SLEEP CHARACTERISTICS AND STAGES DETECTION AND ANALYSIS USING ELECTROENCEPHALOGRAM (EEG)

A Thesis submitted by

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QUOTES

*Said the Prophet **Muhammad** peace be upon him and his family*

"The best person is the one who benefits all human beings"

Believe the Messenger of Allah

ABSTRACT

An electroencephalogram (EEG) signal is an efficient tool for identifying and diagnosing neurological diseases. In addition, it is very important for assisting patients with a disability to interact with their environment through a brain-computer interface. It can also assist scientists and experts to understand the most complex part of the human body, the brain. However, finding effective techniques to detect sleep characteristics and sleep stages using EEG signals is still a challenging task in sleep research, as visual detection requires advanced skills, as well as time, and effort. For example, visual scoring of sleep characteristics such as sleep spindles and k-complexes is very time consuming, subjective and sometimes does not work accurately because it requires experts to identify the presence or absence of sleep characteristics in EEG recordings. Consequently, automatically detecting and analysing sleep characteristics and stages will help sleep experts and clinical doctors to work more efficiently in diagnosing sleep disorders. This project aims to develop new and more efficient techniques to identify the characteristics of sleep stage 2 in EEG signals.

Two new techniques were proposed in this thesis to detect sleep spindles: firstly, a wavelet Fourier analysis and statistical model was used. In this method, firstly an EEG signal was divided into segments using a sliding window technique. The size of the window was 0.5 seconds with an overlap of 0.4 seconds. Then, wavelet Fourier analysis (WFA) was used to extract statistical features from each 0.5s EEG signal. The extracted features were used as inputs to a Kruskal-Wallis nonparametric one-way analysis variance to select the important features. Finally, four classifiers: a least-square support vector machine (LS-SVM), K-nearest neighbours, a k-means algorithm and a C4.5 decision tree, were used to detect the sleep spindles as well as to evaluate the performance of the proposed approach. The proposed WFA method was tested on two different EEG databases.

Secondly, a novel approach based on a time frequency image (TFI) and a fractal technique (FD) was proposed to identify sleep spindles in EEG signals. This method was employed in this thesis to investigate the main relationships between behaviours of sleep spindles in EEG signals and changes in the nonlinear features. In addition, this method was designed to improve the classification accuracy rate and to reduce the execution time. In this study, a short time Fourier transform (STFT) was applied to obtain a TFI from each EEG segment. Then, a box counting method was then applied to estimate and discover the FDs of EEG signals, as well as to extract the features of interest. Different sets of features were extracted from each TFI after applying a statistical model to the FD of each TFI. Subsequently, four popular machine learning methods (LS-SVM, Naive Bayes, k-means and a neural network) were employed to evaluate the performance of the suggested algorithm. The obtained results demonstrated that both methods performed well and were effective in detecting sleep spindles in the EEG signals. The FDs algorithm coupled with the TFI technique improved the classification accuracy rate and reduced the execution time compared to the WFA method. The developed methods using fractal dimensions were applied to identify other sleep characteristics such as k-complexes in sleep stage 2.

Additionally, in this research, a new method was proposed for the detection of k-complexes in EEG signals based on fractal and frequency features. A dual-tree complex wavelet transform (DT-CWT) was applied to analyse EEG recording signals into frequency bands for features extraction. To select the most important feature, the extracted features were analysed. Subsequently hybrid features based on fractal and frequency features were employed to detect the k-complexes. The extracted features were then forwarded to an ensemble classifier to detect the k-complexes in EEG signals in addition to evaluating the performance of this method.

Finally, an undirected graph was used to extract the most important features from FDs. The extracted features were forwarded to the LS-SVM and k-means as classifiers to evaluate the performance of the proposed feature extraction technique and to detect k-complexes with high accuracy rate and smaller execution time. The proposed method was tested on whole EEG databases. The methods developed in this thesis aim to effectively score sleep characteristic wave forms and correctly identify the discriminative characteristics of sleep stage 2 such as sleep spindles and k-complexes using EEG signals. Furthermore, the research indicates that the proposed techniques

are both practical and effective for identifying and studying the brain behaviour of sleep disorders.

Those methods can assist in the presentation of the most important clinical information about patients with sleep disorders. The outcomes from this project will help sleep experts and clinical doctors to improve their working efficiency and accuracy and will potentially reduce medical costs.

CERTIFICATION OF THESIS

This thesis is the work of Wessam Abbas Hamed AL-Salman except where otherwise acknowledged, with the majority of the authorship of the papers presented as a thesis by publication undertaken by the student. The work is original and has not previously been submitted for any other award, except where acknowledged.

Principal Supervisor: Professor Dr. Yan Li

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Student's and supervisor's signatures of endorsement are held at the University.

STATEMENT OF CONTRIBUTION

This section presents details of contributions by the various authors for each of the papers presented in this Thesis by Publication. The following detail is the agreed share of contribution for candidate and co-authors in the presented publications in this thesis:

Chapter 3, Al-Salman et al., (2019)

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Author	Percent	Tasks Performed
Al-Salman, W	70%	Designed the method, simulation, analysis, interpretation, wrote entire draft of paper.
Li, Y and Wen, P.,	30%	Significantly improved the manuscript, interpretation, and analysis.

Chapter 4, Al-Salman et al., (2018)

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Author	Percent	Tasks Performed
Al-Salman, W	70%	Designed the method, simulation, analysis, interpretation, wrote entire draft of paper.
Li, Y and Wen, P.	30%	Significantly improved the manuscript, interpretation, and analysis.

Chapter 5, Al –Salman et al., (2019)

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Author	Percent	Tasks Performed
Al-Salman, W.	70%	Developed the method, simulation, analysis, interpretation, wrote entire draft of paper.
Li, Y.	20%	Help with methodology design, significantly improved the writing of the manuscript, interpretation.
Wen, P.	10%	Suggested edits to manuscript, interpretation

Chapter 6, Al-Salman et al., (2019)

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Author	Percent	Tasks Performed
Al-Salman, W	65%	Developed the method, simulation performing, analysis, interpretation, wrote entire draft of paper,
Li, Y.	25%	Significantly improved the writing of the manuscript, interpretation.
Wen, P.	10%	Suggested edits to manuscript, interpretation of the manuscript, interpretation.

LIST OF PUBLICATIONS

1. **Al-Salman, W.,** Li, Y & Wen, P., 2019. ' Detecting sleep spindles in EEGs using wavelet Fourier analysis and statistical features',*Biomedical Signal Processing and Control*,vol. 48, pp.80-92.*doi.org/10.1016/j.bspc.2018.10.004*

2. **Al-Salman, W.,** Li, Y., Wen, P. & Diykh, M., 2018. 'An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequency image', *Biomedical Signal Processing and Control,* vol. 41, pp.210-221. *doi.org/10.1016/j.bspc.2017.11.019*

3. **Al-Salman, W.,** Li, Y., & Wen, P., 2019. 'K-complexes Detection in EEG signals using fractal and frequency features coupled with an ensemble classification model', *Neuroscience, 422, pp.119-133. doi.org/10.1016/j.neuroscience.2019.10.034*

4. **Al-Salman, W,** Li, Y., & Wen, P. 2019, 'Detection of EEG K-complexes Using Fractal Dimension of Time Frequency Images Technique Coupled with Undirected Graph Features', *Journal of Frontiers in Neuroinformatics*, 13, 45. *doi:10.3389/fninf.2019.00045*

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LIST OF ACRONYMS & ABBREVIATIONS

EEG	Electroencephalogram
WFA	Wavelet Fourier analysis
LS-SVM	Least-square support vector machine
FD	Fractal dimension
TFI	Time frequency image
STFT	Short time Fourier transform
DT-CWT	Dual-tree complex wavelet transform
EMG	Electromyography
FMRI	Functional magnetic resonance imaging
MRI	Magnetic resonance imaging
EOG	Electrooculography
SPECT	Single photo emission computed tomography
EMG	Electromyography
CNS	Central nervous system
F	Front
T	Temporal
C	Central
P	Parietal
O	Occipital
NREM	Non-rapid eye movement
REM	Rapid eye movement
R&K	Rechtschaffen or Kales
AASM	American Academy of sleep medicine
S1	Stage 1
S2	Stage 2
S3	Stage 3
S4	Stage 4
AWA	Awake
SWS	Slow wave stage
SS	Sleep Spindels

NOTATION

SVM	Support vector machine
KNN	The k-nearest neighbour
ANN	Artificial neural network
NB	Naïve Bayes
C4.5	Decision tree
MASS	Montreal Archive of Sleep Studies
MLP	Multilayer perceptron
TEO	Teager energy operator
MP	Matching Pursuit
DWT	Discrete wavelet transform
MELM-GRBF	Generalized radial basis function extreme learning machine
D3	Wavelet detail coefficient at level 3
α	Alpha
β	Beta
θ	Theta
δ	Delta
γ	Gamma
S	**S**econd
μV	Amplitude
Hz	Hertz
TQWT	Tunable Q-factor wavelet transform
ROC	Receiver operating characteristics curve
MCC	Mathew's correlation coefficient
ACC	Accuracy Rate
KPP	Kappa coefficient
TPR	True positive rate
PPV	Positive precision rate
NPV	Nagative predictive value
FPR	False poeitive rate
PR	Precision rate

CHAPTER 1

INTRODUCTION

The human brain is a complex network comprising billions of neurons which are capable of processing information quickly and efficiently. It is a central part of the nervous system and is considered to be one of the most important parts of the human body. The brain uses electrical signals to send different commands and information to body organs through a system of neurons (Lindsay & Norman 2013; Radocy & Boyle 2012). These signals are responsible for various human functions such as attention, memory, emotions and action. They control our movements and receive and store information (Carlson 2002a; Purves et al. 2004; Siuly et al. 2012).

In recent years, many researchers have used scientific techniques, such as Electromyography (EMG), Electroencephalography (EEG), Electrooculography (EOG) signals, positron emission tomography (PET), magnetic resonance imaging (MRI), functional magnetic resonance imaging (fMRI), and single photo emission computed tomography (SPECT) for analysing human brain activity (He & Liu 2008; Sitaram et al. 2007; Vaughan et al. 1998; Wolpaw et al. 2002). These techniques help clinicians, sleep experts and neuroscientific researchers to deeply explore the brain structure, and its mechanisms. However, clinical research has shown that EEG signals are the most commonly used techniques to collect and analyse brain signals (Blankertz et al. 2007; Grosse-Wentrup et al. 2009) because, as well as being reliable, EEGs are inexpensive and easy to use.

An EEG is an electrical signal obtained by using electrodes attached to the human scalp. It measures electrical brain activity and is an efficient tool for identifying and diagnosing neurological diseases (Akin & Akgul 1998; Fu et al. 2014; Yasmeen & Karki 2017). Furthermore, EEGs are normally utilized to diagnose patients with a sleep

disorder based on clinical applications such as identification of sleep stages (Jansen et al. 1989; Ranjan et al. 2018; Redmond & Heneghan 2006; Shimada, Shiina & Saito 2000). Many researchers have used EEG signals as a tool to discover abnormal brain activities and sleep disorders using a variety of techniques (Faust et al. 2015; Salem, Naseem & Mehaoua 2014; Zhang & Parhi 2014; Zhu, Li & Wen 2014) which are used to extract and select discriminative features, as well as to classify EEG recordings. Most of these techniques fall under three categories: time domain; different transformation techniques; and other approaches.

Although these techniques have obtained relatively promising results, there is an urgent demand to develop new techniques to enhance the diagnosis of sleep disorders, and to improve its efficacy in terms of precision and speed because an increase, for example, in the accuracy of the identification of sleep stages can bring significant improvements in the diagnosis, and therefore the treatment, of sleep disorders (Al-Qazzaz et al. 2015; Al-Salman et al. 2018; Bankman & Gath 1987; Herrera et al. 2013; Ocak 2008; Sinha 2008).

Clinical research has shown that EEG signals exhibit different patterns of waves in sleep stages depending on the state of a person whether asleep, awake or anesthetized. Traditionally, the detection of those patterns in sleep stages, such as sleep spindles and k-complexes, depends on visual inspection that is carried out based on the knowledge of clinicians. The accuracy and reliability of manual scoring are based on the experience of experts, makeing the process tiresome. Visual scoring of those waveforms such as sleep characteristics requires much time and is a tedious workload, and a very demanding process because it requires appropriate qualifications and skills, expenditure, and more physical effort from experts (Acır & Güzeliş 2004a; Amin et al. 2016; Kayikcioglu, Maleki & Eroglu 2015; Lee et al. 2004; Zarjam, Mesbah & Boashash 2003). It is also a subjective process and susceptible to error meaning that a decision made by two experts relating to EEG signals could vary even with the same EEG recording(Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Kemp et al. 2000; Miranda, Aranha & Ladeira 2019; Silber et al. 2007). However, developing an automatic technique to detect all the patterns in sleep stages is an ongoing challenge because typically thousands of those patterns could occur in each EEG recording (Agarwal et al. 1998; Al-Salman et al. 2018), having significant impacts on sleep

research; therefore, an automatic approach would help experts to carry out EEG staging accurately.

This thesis focuses on developing novel methods for analysing and detecting the important characteristics of the sleep stages: sleep spindles in EEG signals, and then applying those developed methods to detect k-complexes; one of the distinctive transiting bio-signal waveforms in sleep stages that is often used to score sleep stages.

These proposed methods can be used to detect and analyse EEG signals into different categories. The proposed methods will be useful to identify sleep disorders correctly and efficiently, detecting the typical patterns in sleep stage 2 of EEG signals. Finally, the outcomes of this study could help sleep experts and clinical doctors to improve their efficiency and accuracy and may therefore reduce medical costs. Moreover, they may help to decrease the cost of treatment for patients because of one of the benefits of the proposed methods is that it can run automatically to check the patient's recording.

1.1 Study Overview and Motivation

Sleep stages scoring is an important process in sleep research as any errors in the scoring of the patient's sleep electroencephalography (EEG) recordings can lead to critical problems (Malafeev et al. 2018; Weiner & Dang-Vu 2016). The sleep stages are connected through different physiological and neuronal characteristics such as sleep spindles and k-complexes that are used in sleep stages identification by physiology experts and researchers, who normally rely on their experience to manually recognize them. The process of discriminating sleep stages visually is called sleep scoring. Although the visual inspection of sleep scoring has been used as a standard method for a long time, it has some deficits and limitations. First of all, it is expensive, and requires a high cost; it takes a great deal of effort and it is also error-prone(Gao, Turek & Vitaterna 2016). Moreover, it is a subjective process, meaning that decisions made by two sleep experts could vary even in the same sleep recordings. Furthermore, the scoring process is carried out by a sleep specialist under either the Rechtschaffen and Kales (R&K) (Rechtschaffen 1968) or the American Academy of Sleep Medicine (AASM) guidelines. The AASM has been developed to tackle some issues in the R&K guidelines (da Silveira, Kozakevicius & Rodrigues 2017; Ebrahimi et al. 2008; Putilov

2015; Rechtschaffen 1968; Tsinalis, Matthews & Guo 2016). Developing an automatic approach to classify sleep stages could have significant impacts on sleep research by helping experts to carry out EEG staging accurately and to relieve the burdens of visual inspection (Al-Salman et al. 2018; Lucey et al. 2016; Mousavi, Afghah & Acharya 2019).

Much clinical research has revealed that individual sleep stages exhibit unique electroencephalogram (EEG) patterns and characteristics that reflect human sleep states (Al-Salman et al. 2018). Analysing those brain waveforms is an important task for aiding neurologists to score and analyse EEG sleep signals. Two of the distinctive transiting bio-signal waveforms that are often used to score sleep stages are sleep spindles and k-complexes (Camilleri, Camilleri & Fabri 2014; Miranda, Aranha & Ladeira 2019; Richard & Lengelle 1998; Weiner & Dang-Vu 2016).

Sleep spindles are the most important transient events used to detect stage 2 in EEG signals. They are defined as a series of distinct waves are within a frequency range of 11-16 Hz with a minimum duration of 0.5 seconds (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Iber et al. 2007; Lajnef et al. 2015), while a k-complex includes a large-amplitude transient waveform with a single negative sharp wave followed by a positive sharp wave, and it has a relatively sharp amplitude that is more than ±75μV (Al-Salman, W, Li, Y & Wen, P 2019; Bremer, Smith & Karacan 1970; Da Rosa et al. 1991; Noori et al. 2014; Pohl & Fahr 1995; Rodenbeck et al. 2006; Strungaru & Popescu 1998; Woertz et al. 2004; Yücelbaş et al. 2018b). In Chapters 3, 4, 5 and 6, a detailed discussion about sleep spindles and k-complexes is provided. Identifying those occurrences in EEG signals is an ongoing challenge because they require high visual skills from experts.

Recently, various attempts, have been made to identify transient events in sleep EEGs such as sleep spindles and k-complexes. Those various attempts, based on research, have been used for different transformation techniques such as Fourier, wavelet, Teager energy operator and short-time Fourier transform (Al-Salman et al. 2018; Bankman et al. 1992; Duman et al. 2009; Erdamar, Duman & Yetkin 2012; Huupponen et al. 2007; Lajnef et al. 2015; Sinha 2008) to identify sleep spindles or k-complexes. Those techniques are often combined with a support vector machine, a genetic algorithm, least square support vector machine, k-means, Naïve Bayes and a neural

network (Acır & Güzeliş 2004b, 2005; Al-Salman, W, Li, Y & Wen, P 2019; Al-salman & Li 2019; Jansen & Desai 1994; Ocak 2008) and most of this research work has limitations.

The main challenge of those techniques is how to detect sleep spindles or k-complexes from complicated EEG signals in an acceptable time and with as high accuracy as possible. In addition, the current studies aim to detect and analyse sleep characteristics in EEG signals using a specific period of time. Based on the literature, it was found that many studies were conducted with one window size, and one database and were used to detect sleep characteristics. Although some of those studies obtained relatively good results, it is still necessary to develop new techniques, firstly to cope with these limitations, and secondly, to achieve a high level of accuracy with less execution time, because an increase in the accuracy of sleep characteristics identification can make significant improvements in the diagnosis of sleep disorders.

Hence, the main goals of this thesis are to develop efficient methods that are as accurate as possible to analyse and detect the most important characteristics of the sleep stages such as sleep spindles and k-complexes in EEG signals. These methods focus on two stages: reducing the dimensionality of the EEG data by extracting and selecting the most appropriate features, and detecting sleep spindles and k-complexes in EEG signals by employing those extracted features, within an acceptable time and with as high an accuracy as possible. In chapters 3, 4, 5 and 6, a detailed description of those stages is provided.

1.2 Research Problems

EEG signals contain a large amount of information (data) with several categories that exhibit brain activities. Researchers have observed that some of this information during recording EEGs could be irrelevant data because it presents noise and artefact. Therefore, to reduce unrelated information from EEG recordings, and to extract the discriminative features, an automatic method is required to extract appropriate features and classify the extracted features by suitable methods. Those processes mainly depend on visual inspection that is carried out based on the knowledge of clinicians (experts), who visually examine the EEG recording (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Diykh & Li 2016; Diykh, Li & Wen 2017;

Hernández-Pereira et al. 2016; Kutlu, Kuntalp & Kuntalp 2009; Siuly & Li 2015; Siuly & Zhang 2016; Subasi & Ercelebi 2005). However, it is often difficult to recognize people who have sleep disorders through visual inspection of EEG recordings. Furthermore, visual inspection methods are unsuitable to produce credible results because the accuracy and reliability of the manual scoring are based solely on the experience of experts. In addition, it is very time consuming, subjective, requires high skills from experts, is not a satisfactory procedure unless carried out based on the knowledge of clinicians, and is prone to errors. Improved analysis and classification of EEG signals automatically will lead to better diagnostic techniques for sleep disorders and to the detection of sleep characteristics. Thus, developing new methods to detect sleep characteristics from complicated EEG signals is the main goal of this thesis. It can reduce the time and effort of experts and can give a more accurate diagnosis of sleep disorders. The performance of the developed approaches has been evaluated using several assessment tools which are related to the field of detection methods, such as accuracy, sensitivity, specificity, F-score, kappa coefficient, the receiver operating characteristic (ROC) curve, k-cross-validation, and Mathew's correlation coefficient (MCC). These measuring tools are used to check the ability of the detection methods and performance for identifying sleep characteristics (Al-Salman et al. 2018; Hernández-Pereira et al. 2016; Ranjan et al. 2018; Wessam, Li & Wen 2019). In chapters 3, 4, 5 and 6, a detailed description about those tools was provided.

Recently, many methods have been developed to extract the desired features from EEG signals and then use these features to classify different EEG categories. Based on previous studies in the literature (Acharya et al. 2005; Da Rosa et al. 1991; Halász 2005; Kiymik, Subasi & Ozcalık 2004; Knoblauch et al. 2003b; Knoblauch et al. 2003a; Kuriakose & Titus 2016; Lajnef et al. 2015; Nonclercq et al. 2013; Patti, Chaparro-Vargas & Cvetkovic 2014; Saifutdinova et al. 2015; Strungaru & Popescu 1998; Vu et al. 2012; Yücelbaş et al. 2018a; Zhuang, Li & Peng 2016), it seems that most of those studies focused on detecting sleep spindles and k-complexes had limitations. For example, many did not achieve high levels of accuracy. It was time consuming to perform the required analyses; no execution time was mentioned in all previous studies; and they were too complicated for practical applications.

Furthermore, it was found that many studies were conducted with one window size and were used to detect sleep characteristics. Furthermore those studies employed one or two assessment tools to evaluate the performance results. Maximum accuracy ranging from 75% to 94 % was reported for the datasets. In our research project we obtained an increase of 3.8% in comparison with other sleep studies, an improvement which is considered significant in sleep treatment. Finally, most of those methods were conducted and tested with one database or small databases rather than a huge dataset which made them unsuitable to use in real-time applications.

To overcome these limitations, this thesis has proposed techniques for detecting the most important characteristics of sleep stages: sleep spindles and k-complexes. Those algorithms were presented to reduce the time taken, and to extract and select the desired features carefully. Thus, this thesis will focus on the following question:

How to enhance the performance of sleep stage scoring in EEG signals by developing advanced detection techniques?

This question led to the following sub-questions:

a. How to detect and analyse the sleep characteristics of the EEG signal, such as sleep spindles and k-complexes in an efficient way with a high classification accuracy?

b. How to enhance the performance of sleep characteristics detection in EEG signals through developed methods to achieve a high level of accuracy with less executive time?

c. How to reduce the feature space of the EEG recordings to represent the transient events in EEG sleep stages scoring?

The main objectives are:

1- To develop new methods for the sleep characteristics detection, that will result in good detection results (performance, accuracy, and processing speed).

2- To improve the working of existing detection methods and reduce the efforts required to efficiently detect transient events in EEG signals.

Based on the experimental results, the developed methods can achieve good detection performance through identifying all the characteristics of sleep stage 2 in EEG signals.

In addition, these methods can be applied to different types of EEG databases.Thus, the hypothesis in this study is that detection of the characteristics of sleep stages such as sleep spindles and k-complexes in EEG signals can be improved using fractal dimension algorithms and hybrid transformation characteristics.

1.3 Contribution of the Thesis

The characteristics of EEG signals in their natural state are nonstationary, complex and nonlinear, so it is challenging to extract the appropriate features from big EEG data sets for classification (Al Ghayab et al. 2018; Kabir et al. 2018; Li & Wen 2009; Selesnick 2011a). The work presented in this thesis focuses on how to detect the possible occurrences of sleep characteristics in EEG signals with a high classification accuracy and less execution time, and how to study the brain behaviour of sleep disorders. In addition, this study focuses on the analysis of the EEG signals, extracting and selecting the most appropriate features, making more efficient use of time, reducing irrelevant data, and investigating the most suitable classification methods using various machine learning classification methods. Thus, in this thesis, four techniques, as shown in Figure 1.1, have been developed for detecting sleep characteristics: the sleep spindles and k-complexes, from EEG signals have been detected successfully with high performance (classification accuracy) using the proposed detection methods.

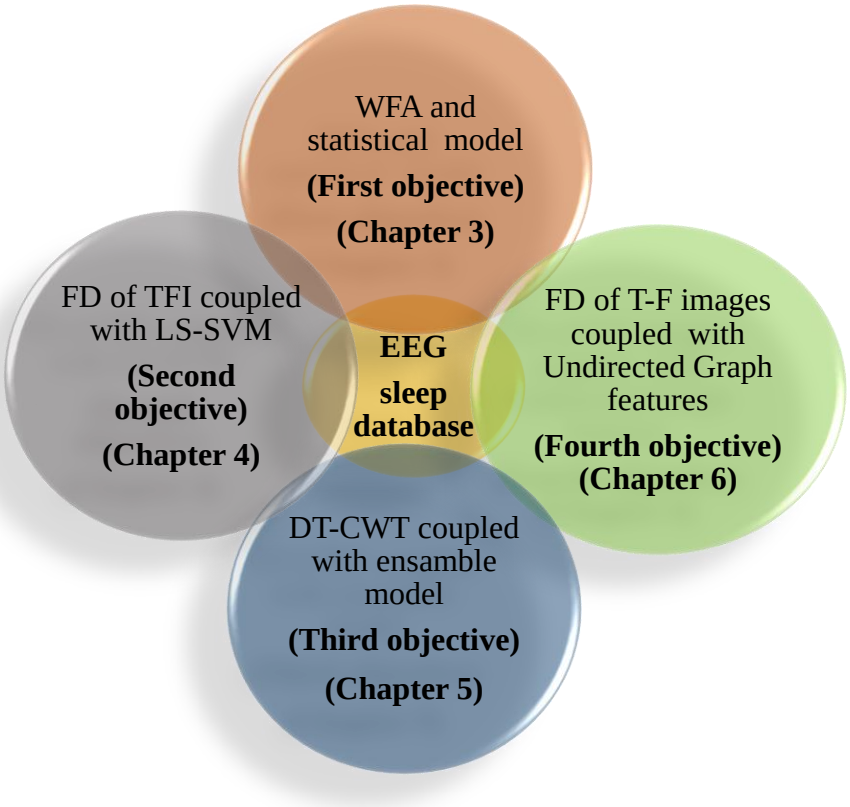


Figure 1.1: Types of proposed methods developed in each chapter to detect the characteristics of sleep stage 2 in EEGs

The developed methods in this thesis have been published in various journals, relating to the detection and analysis of the sleep characteristics in EEG signals. Those research works were reviewed and summarised in terms of the precision of their classification.To investigate the performance of those proposed methods, extensive experiments have been undertaken in this study. In addition, they were compared with recently reported algorithms with different and/or the same databases. The following contributions have been made to answer the research questions and achieve the objectives:

1- Developing a robust method for the detection of the sleep characteristics such as sleep spindles in EEG signals, thus improving the detection results in terms of accuracy.
2- Improving the developed methods by presenting new extraction techniques that can improve the classification accuracy rate with less execution time.
3- Designing a new method to analyse and identify other sleep characteristics such as k-complexes in the EEG signals.

4- Introducing an efficient feature extraction method from the whole EEG databases based on undirected graph features to detect k-complexes that can improve the classification performance as well as improving system performance.

These several proposed methods have been implemented in Matlab R2018a.The databases used in this study are the Dream sleep spindles and the Montreal archive of sleep studies Databases (Devuyst et al. 2011; O'Reilly et al. 2014). They have been used by many researchers for detecting sleep characteristics: sleep spindles and k-complexes. More details regarding the database have been provided in chapters 3, 4, 5 and 6. Furthermore, each method was evaluated using different EEG signals acquired from different channels and different detection metrics tools. These metrics are the accuracy rate (ACC) , sensitivity (SEN), specificity (SPE), precision rate (PR) or positive prediction rate (PPR), F-measure rate, Mathews's correlation coefficient (MCC), Kappa coefficient (KPP) and k-cross-validation. The receiver operating characteristic (ROC) curve was used to evaluate the classification accuracy for the proposed algorithms. The ROC curve depends on four parameters: the true positive rate (TPR) or recall rate (RR), false positive rate (FPR), positive predictive value (PPV) or precision rate (PR), and negative predictive value (NPV). A brief discussion about these four contributions is provided below.

1.3.1 Sleep spindles detection using Wavelet Fourier analysis and statistical featutres

A robust approach based on hybrid transform and statistical features was presented to detect sleep spindles in EEG signals with a high level of accuracy. This approach includes two phases: testing and training. The same preprocessing and extraction techniques were applied for both phases to identify sleep spindles. Firstly, an EEG signal was divided into segments using a sliding window technique. The size of the window was 0.5 seconds with an overlap of 0.4 seconds. Then, a discrete wavelet transform was used to decompose each EEG segment into a set of details and approximation coefficients. Among these parameters, the wavelet detail coefficient at level 3 was selected and passed through the fast Fourier transform to identify the desired frequency bands. Ten statistical characteristics were extracted from each band. To select the most important features and to reduce the dimensions of the features, the

Kruskal-Wallis nonparametric one-way analysis variance is used. As a result, a set of features is selected to represent each of the 0.5 second EEG segments. Furthermore, four different window sizes of 0.25s, 1.0s, 1.5s and 2.0s were also tested in this study to detect all the possible occurrences of the sleep spindles in the original EEG signals. Finally, four popular machine learning methods: a least square support vector machine (LS-SVM), k-nearest, k-means and C4.5 decision tree were used as detectors or trained models in order to detect the sleep spindles. From the experiments in Chapter 3, it can be observed that the proposed method worked very well compared with other existing methods. It also gave better results with 0.5s window than the others. It produced a good detection accuracy rate compared with other existing methods. The method efficiently detected the spindles in EEG signals, and assisted sleep experts to analyse EEG signals. However, this method needs some further improvements to increase the accuracy rate and reduce the execution time by using an effective nonlinear method. More details of this approach are given in Chapter 3. The content of the chapter was published by the Journal of *Biomedical Signal Processing and Control, vol. 48 (2019), pp.80-92, doi.org/10.1016/j.bspc.2018.10.004.*

1.3.2 EEG sleep spindles detection based on fractal dimension (FD) coupled with time frequency image (TFI)

To increase the accuracy rate of sleep spindles classification, to reduce the execution time and to improve the proposed method FD algorithm coupled with TFI was investigated and used in this study to detect the sleep spindles, as can be seen in Chapter 4. Moreover, this method provided many improvements to the method introduction in Section 1.3.1 above. The EEG signal is divided into segments using a sliding window technique. In this study, a TFI is obtained from each EEG segment after applying a short time Fourier transform (STFT). A box counting method is applied to each TFI to calculate the fractal dimension, as well as to extract the features of interest. Then, different sets of statistical features are extracted from each FD of the TFI. Finally, a least square support vector machine (LS-SVM) classifier is applied to discover the best combination of the features and to classify the extracted features. For further investigation of the proposed method, different classifiers, including a k-means, Naïve and neural networks, are also employed. The experimental results in Chapter 4 show that the proposed method with the LS-SVM classifier achieves a high

accuracy compared with other recent studies, and reveals that the proposed method outperforms the others. The obtained results in Chapter 4 show that the fractal dimension algorithm increased the classification accuracy, decreased the execution time and effectively identified the sleep spindles compared with the other methods. As a result, this method can help neurologists and researchers to identify and analyse sleep spindles in EEG signals accurately with less execution time. Details of this approach are given in Chapter 4. The content of this chapter was published by the Journal of *Biomedical Signal Processing and Contro, vol. 41 (2018): pp.210-221, doi.org/10.1016/j.bspc.2017.11.019*

1.3.3 Fractal and frequency features coupled with an ensemble classification model to detect k-complexes EEGs

To detect the k-complexes in EEG recordings, a dual- tree complex wavelet transform (DT-CWT) is utilized and coupled with an ensemble model. EEG signals are first partitioned into segments, using a sliding window technique. Then, the DT-CWT is used to divide each EEG segment into a set of real and imaginary parts. After that, a total of 23 fractal and frequency features are tested from each sub-band. Then the extracted features are analysed. This analysis found that not all the extracted features and their combinations have the same effect for detecting the characteristics of stage 2 EEG waveforms, as shown in Chapter 5. As a result, 12 hybrid features are employed to detect the k- complexes. The extracted features are forwarded to an ensemble classifier to detect the k-complexes in EEG signals. The detection metrics using the accuracy, sensitivity, specificity, kappa coefficient, F-score, and Matthews's correlation coefficient have been used to evaluate this work. The results in Chapter 5 indicate that, by using the ensemble classifier, its classification accuracy is higher than that obtained by the individual classifiers. The experimental results in Chapter 5 showed that the performance of the proposed method was very satisfactory, with good detection accuracy rate. This method can therefore lead to the development of an effective tool for the scoring of automatic sleep EEG stages and can be useful for doctors and neurologists for the early diagnosis of sleep disorders. Finally, this study can be applied efficiently for real-time detection of k-complexes. The details of this

technique are provided in Chapter 5. This chapter was published to the journal of *Neuroscience, 422, pp.119-133*

1.3.4 Detection of EEG K-complexes Using Fractal Dimension of Time-Frequency Images Technique Coupled with Undirected Graph Features

This method provided many improvements to the method introduced in Section 1.3.2 above to improve the detection performance of k-complexes with a whole database. The preprocessing techniques in Section 1.3.2 were developed to produce a new improvement technique to detect k-complexes, and to achieve excellent results in terms of detection accuracy and processing time. An efficient method is proposed to detect k-complexes from EEG signals based on the fractal dimension (FD) of time frequency (T-F) images coupled with undirected graph features. This method as a texture descriptor was developed to make the detection system more robust with a shorter processing time and a good detection rate. The EEG signal is first divided into segments using a sliding window technique. The size of the window is set to 0.5 second (s) with an overlap of 0.4 second (s). Then, each 0.5s EEG segment is passed through a spectrogram of short time Fourier transform (STFT) to obtain the T-F images. Next, FD as a texture descriptor for each T-F image is calculated based on the box counting method. The vector of FD from each T-F image is then mapped into an undirected graph. The structural properties of the graphs are used as the representative features of the original EEG signals for the input of a least square support vector machine (LS-SVM) classifier. Key graphic features are extracted from the undirected graphs and then used as the key features to detect k-complexes in this study. Finally, the extracted graph features are then forwarded to the LS-SVM to identify k-complexes in EEG signals and to evaluate the performance of the proposed feature extraction technique. To investigate the performance of the proposed method, comparisons are also made with several existing k-complexes detection methods in which the same datasets are used. The performance achieved superior results, in terms of detection accuracy, sensitivity, and specificity to other existing methods in the literature, as shown in Chapter 6. Thus, the performance of the proposed method was very satisfactory, in terms of detection accuracy and the processing time.The proposed method can help physicians with diagnosing sleep disorders and potentially it can reduce medical costs. The details of this technique are provided in Chapter 6, the contents of which were

published in the Journal *Frontiers in Neuroinformatics*, *13:45. doi: 10.3389/fninf.2019.00045*

1.4 Research Outcomes and Significance

The aim of this research project is to develop novel methods for the detection of the EEG characteristics of sleep stages, such as sleep spindles and k-complexes in EEG signals. Sleep stages scoring is a process to separate an EEG signal into the six sleep stages of Awake, Stage 1 , Stage 2, Stage 3, Stage 4 and rapid eye movement sleep. Each stage has unique characteristics such as sleep spindles and k-complexes. Sleep stages can be recognised using those characteristics. Experts may spend a long time analysing a patient's recordings in order to classify the stages. This thesis aims at identifying those sleep characteristics automatically so that sleep stages can be identified easily, thus reducing the time and effort that experts spend on analysing EEG signals to identify sleep stages. Experts can use these methods for scoring the sleep stages. Moreover, these methods will help to decrease the cost of treatment for patients because one of their benefits is that they can run automatically to check the patient's recordings. This software package is easy to use, without the need to have extensive training. Moreover, traditional visual inspection is time-consuming and may cause fatigue. Thus, this research will help to reduce the cost of treatment.

1.5 Connections Between Chapters

This thesis focuses on detecting and analysing the characteristics of sleep stages of EEG signals, such as sleep spindles and k-complexes. In addition, it attempts to design and develop a new method to extract and select the representative features of sleep spindles and k-complexes from EEG recordings. This research uses a hybrid transformation and statistical features to detect the most important bio-signals, waveforms, in sleep stages 2 (Chapter 3). It proposes a new detection method based on the fractal dimension algorithm coupled with time-frequency images to study the behaviour of sleep spindles in EEG signals (Chapter 4), which improves the classification rate with less execution time. To detect the second most significant characteristics (k-complexes) in sleep stage 2, hybrid features coupled with an ensemble model were introduced (Chapter 5). This method extracts and selects the

most relevant data and ignores irrelevant data from EEG signals, while simultaneously detecting k-complexes by blending a fractal technique with the undirected graph approach. This approach is provided for features extraction in the nonlinear method (Chapter 6).

1.6 Structure of the thesis

This thesis consists of seven chapters and each chapter provides important information on the study. The thesis schematic is shown in Figure 1.1. The rest of the thesis is structured as follows:

Chapter 2 provides an overview of sleep characteristics detection techniques and the background knowledge of the human brain. Firstly, this chapter introduces brief details about the background knowledge of surrounding information on the human brain, an overview of EEG signals, sleep stages, the concept of some sleep characteristics: sleep spindles and k- complexes and how they affect sleep disorders. This chapter then introduces briefly the concepts of classification, including its methods and the structure. This chapter then focuses on concepts relating to detection of sleep spindles and k- complexes.

Chapter 3 integrates the hybrid transform technique and statistical features for detecting sleep spindles in EEG signals. This chapter introduces a suitable machine learning classifier by using four popular classification methods: Least square support vector machine (LS-SVM); K-nearest neighbour; Decision tree; and k-means. This chapter provides a comparative study between the proposed methods and other existing methods in terms of accuracy, sensitivity and specificity. This chapter presents as a published journal article in Biomedical signal processing and control (Al-Salman, Wessam, Yan Li, and Peng Wen. "Detecting sleep spindles in EEGs using wavelet Fourier analysis and statistical features." ***Biomedical Signal Processing and Control,*** *Volume 48 (2019): Pages 80-92. Online URL: https://doi.org/10.1016/j.bspc.2018.10.004).*

Chapter 4 introduces a new method based on the fractal dimension (FD) algorithm coupled with time frequency images (TFIs) for the detection of sleep spindles in EEG signals. A LS-SVM is used in this study as a classifier. This method was designed to identify sleep spindles in sleep stage 2 as a way to improve the classification rate with less execution time. This chapter also presents as a published journal article in Biomedical signal processing and control (Al-Salman, Wessam, Yan Li and Peng Wen. "An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequency image." ***Biomedical Signal Processing and Control***, *Volume 41 (2018): Pages 210-221: Online URL: https://doi.org/10.1016/j.bspc.2017.11.019).*

Chapter 5 provides a dual tree complex wavelet transform (DT-CWT) based on fractal and frequency features for detecting other sleep characteristics in EEG signals such as k-complexes. This algorithm decomposes each EEG segment into a number of sub-bands (real and imaginary parts); an ensemble model based on a combination of three classification techniques including a LS-SVM, k-means and Naive Bayes, and is used as a classifier to evaluate the proposed algorithm. This chapter presents as a published journal article in Frontiers in Neuroscience (Wessam, Al-Salman, Yan Li, and Peng Wen. "K-complexes detection in EEG signals using fractal and frequency features coupled with an ensemble classification model." ***Neuroscience*** , *Volume 422, (2019), Pages 119-133, Online URL: https://doi.org/10.1016/j.neuroscience.2019.10.034).*

Chapter 6 integrates the undirected graph technique and the fractal dimension method for detection of the k-complexes. This chapter also investigates a suitable machine learning classifier by using two popular classification methods: LS-SVM and k-means. This chapter provides a comparative study between the proposed technique and other existing methods in terms of accuracy. This chapter presents as a published journal article in Neuroinformatics (Al-Salman, Wessam, Yan Li, and Peng Wen. "Detection of EEG K-complexes using fractal dimension of time frequency images technique coupled with

undirected graph features." ***Frontiers in Neuroinformatic***, *Volume 13 (2019)Pages 45, Online URL: https://doi:10.3389/fninf.2019.00045.*

Chapter 7 presents a summary and the findings of this study. This chapter also provides information relating to future work.

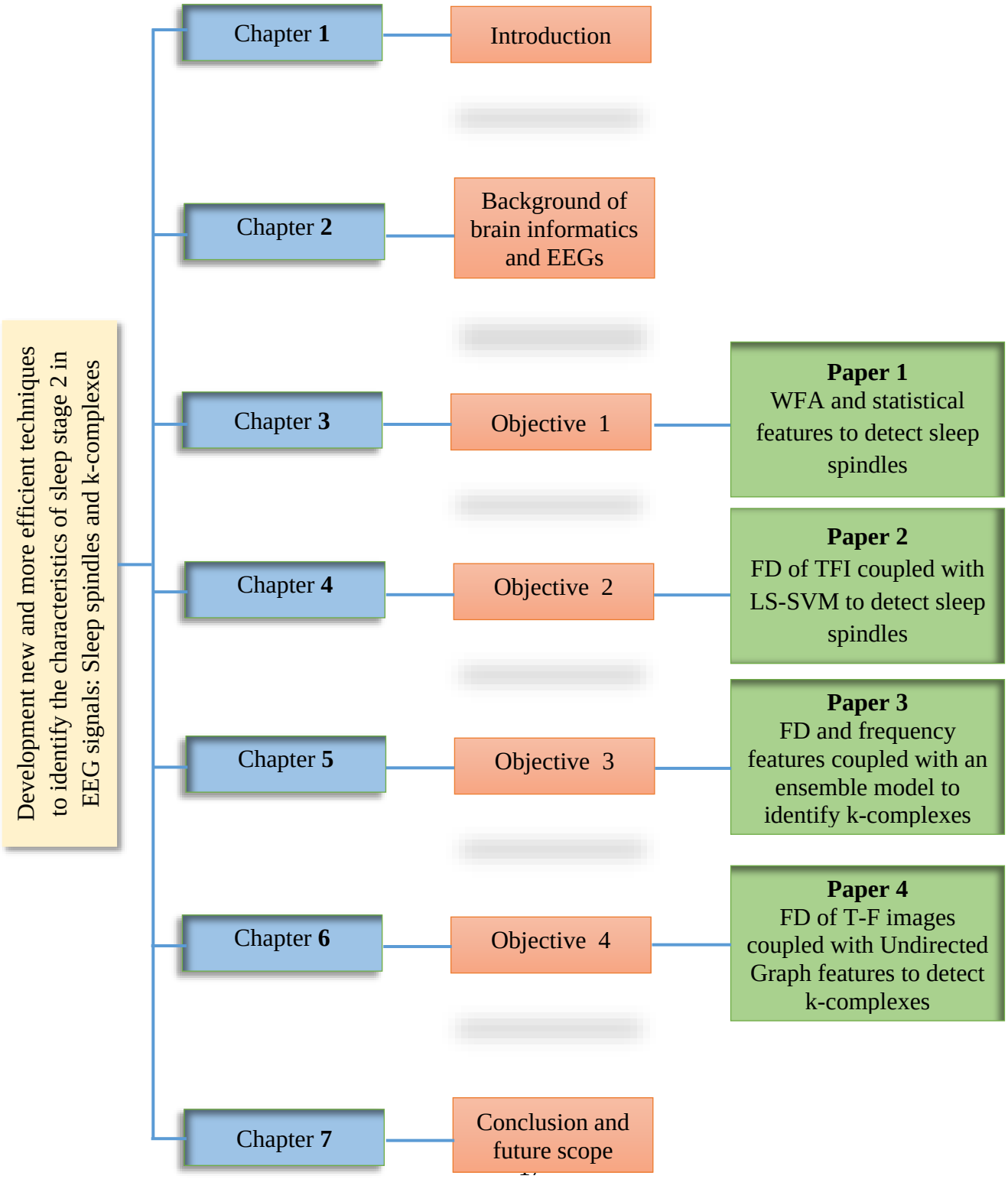


Figure 1.2: Shows thesis flowchart for seven chapters.

CHAPTER 2

OVERVIEW OF BACKGROUND KNOWLEDGE OF BRAIN INFORMATICS AND EEG SIGNAL CLASSIFICATION

The main purpose of this research is to develop new methods for detecting and analysing the important characteristics of the sleep stages in EEG signals: sleep spindles and k-complexes. Those methods could help doctors to diagnose, evaluate and treat several neurological diseases, relating to sleep disorders. Before providing the overview of the detection, this chapter begins with Section 2.1 introducing the human brain (brain EEGs), including brain structures and their functions. Section 2.2 provides the necessary information related to the background knowledge about sleep EEGs: sleep stages and sleep characteristics. Section 2.3 introduces an overview of techniques of analysis and detection in EEG signals (classification techniques), while Section 2.3.1 discusses, in general, the concept of classification algorithms of EEG signals. In order to have a broad understanding of the detection of sleep characteristics in EEG signals, this chapter also provides an overview of detection techniques including the methods described in the literature for the detection of sleep characteristics in EEG signals, as shown in Section 2.3.2. All these terms have been briefly discussed in this chapter.

Chapter 2 Background of brain informatics and EEGs classification

2.1 Brain EEGs

In order to understand brain EEGs, Section 2.1.1 provides an overview of the background knowledge related to the EEG signal to introduce some terminologies and other information related to this research. Section 2.1.2 introduces the neurophysiological aspects of the human brain. This section particularly focuses on the structure of neurons and the neural system. As a general concept, Section 2.1.3 provides an overview of EEG signals and their nature. Section 2.1.4 explains the electrode placement system. Finally, Section 2.1.5 briefly describes the concept of rhythms in EEG signals and provides the necessary information about brain activity.

2.1.1 Background knowledge of Brain Structures and Their Functions

The brain is one of the most complex parts of the human body. It receives instructions (comments) from the sensor organs and then sends outputs to the neurons. The human brain is partitioned into three main parts: cerebrum, cerebellum and brainstem (Gray 2002), and each part of the brain is associated with different human activities. Figure 2.1 shows the three major parts of the brain (Sanei & Chambers 2013; Sanei & Chambers 2007). These three parts of the brain are briefly presented as follows:

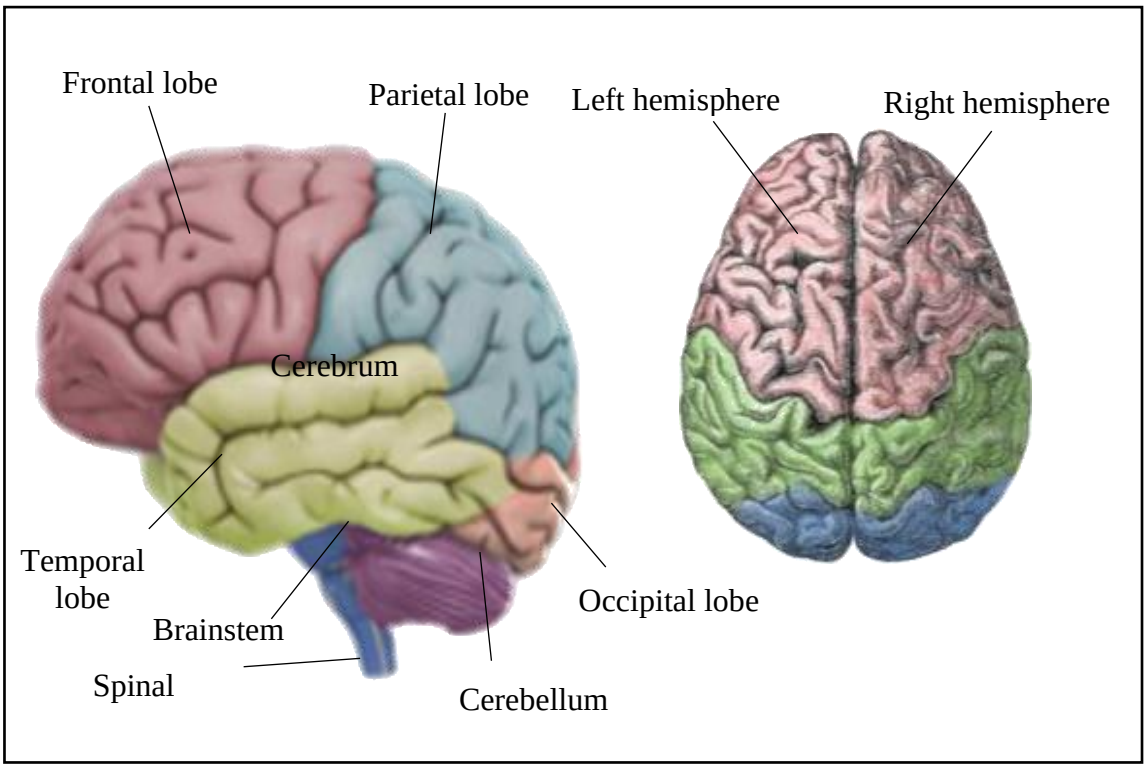


Figure 2.1: Anatomical areas of the main parts of the brain (Gray 2002; Standring 2015)

2.1.1.1 The Cerebrum is the largest and most important part of the human brain. It usually performs the most important functions of the brain, those associated with motions, motor functions and movements. It consists of two hemispheres: right and left side (Davey 2011), as shown in Figure 2.1. The first is associated with creativity while the second is related to logical abilities. Furthermore, each side of the hemisphere is divided into four sub-parts (lobes): frontal lobe, parietal lobe, occipital and temporal lobes. These lobes are responsible for many functions such as problem solving, recognition, orientation and movement, visual processing and speech, as well as perception and memory (Purves et al., 2004; Carlson, 2002a).

2.1.1.2 The Cerebellum is the second largest structure of the brain and contains more than half of the brain neurons. The location of the cerebellum is in the lower back of the head. This part of the brain is normally responsible for many functions in the brain such as the control of muscle movement, balance and posture. It is divided into three lobes: anterior, posterior, and flocculonodular. The first and second lobes are associated with the responses of motor movements. The flocculonodular lobe is associated with maintaining balance (Hall 2015).

2.1.1.3 The Brainstem is located at the posterior part of the brain (underneath the limbic system) and continues to the end of the spinal cord. The brainstem works like a bridge to connect the cerebrum with the spinal cord to pass the brain's commands to the body organs. It is associated with vital life functions such as consciousness, balance, breathing, mouth movement and control of movements of the eyes (Hall 2015; Siuly et al. 2012).

2.1.2 The neural system of the human brain (Neurophysiology of the human brain)

The brain normally contains billions of neurons which keep the brain active and maintain the electrical charge of the brain (Herculano-Houzel 2009; Tatum IV 2014) Neurons have the same parts as other cells and they share the same characteristics. Neurons use electrochemical signals to transmit commands produced by the brain and pass messages from one cell to another. Neurons have three main parts: cell nucleus

(soma), dendrites and long axon (Nunez & Cutillo 1995; Sanei & Chambers 2007). The structure of a neuron is presented in Figure 2.2.

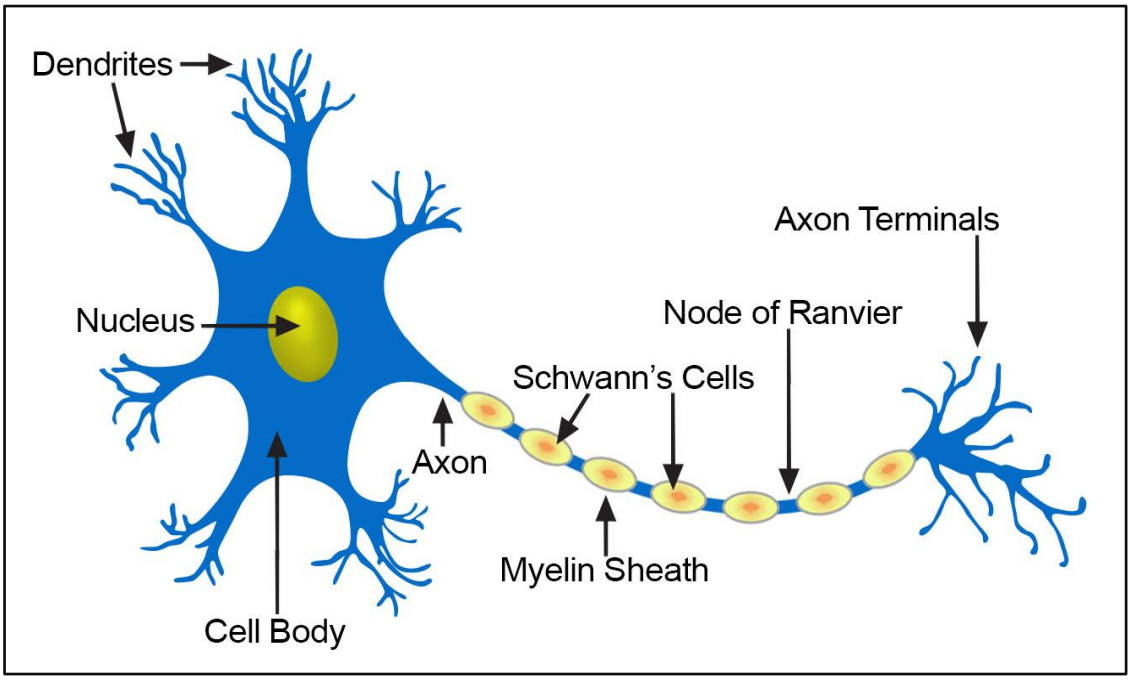


Figure 2.2: Structure of a typical neuron (Sanei & Chambers 2013; Carlson 2002)

Each part of the neuron is responsible for a specific task. The cell body (cell nucleus) is the control centre of the cell and is responsible for maintaining the integrity of genes and for controlling the activities of the cell by regulating gene expression (Carlson 2002b; Purves et al. 2004). The axon is the last part of the neuron and it is called a nerve fibre. The long axon transmits the signal between the cells (Atwood & MacKay 1989). It is a special cellular extension which arises from the cell body at random and is up to one metre long in humans. An axon is sometimes more than one meter long in other species. These axons spread an electrical signal between nerve cells and tissues in the brain in a non-attenuating manner. When electrical signals are reached, in an area in which the neurons are connected, new axons called dendrites receive those signals. The dendrite is a short part of the neuron located at the end of each cell. It consists of many receptors that receive a neurotransmitter from other cells. It can be represented in the form of thin structures extending for hundreds of micrometers and it branches several times. This process of branching multiple times leads to a complex tree-like structure.

The neural system is formed by using a small main unit called a neuron cell. It is responsible for three major functions. These functions are sensory input, integration and motor output, and they describe the following:

2.1.2.1 The sensory input

The sensory input distinguishes and monitors the environment and the changes that occur in the human body. It also describes the response of the skin, eyes, ears and nose, when they receive stimuli. Furthermore, these functions normally record the presence of a change from homeostasis or a particular event in the environment, known as a stimulus (Brodal 2004; Noback et al. 2005).

2.1.2.2 The integration stage or association areas

The integration stage is a very important part of the central nervous system (CNS) as it manipulates the information received by sensory inputs and then makes decisions. It consists of the brain and the spinal cord.

2.1.2.3 Motor output or response

The response or motor output sends an order to the effector organs on the basis of the stimuli perceived by sensory structures which could be muscles or glands. The motor output is either involuntary or conscious. For example, contraction of smooth muscles, regulation of the cardiac muscle, and activation of glands are involuntary (Brodal 2004; Noback et al. 2005).

As mentioned previously, the CNS consists of two main units. These units are the brain and the spinal cord. The first unit can control most functions in the body such as speech, memory, and thoughts. In addition, the brain is associated with the spinal rope (spinal cord) through the brainstem. The spinal cord function transmits the signals between the brain and the body. Thus, any dysfunctions in the spinal rope could lead to a disruption in the transfer of information between the body and the brain. However, there are several lines of defence such as bones and spine that protect the central nervous system from injury. Figure 2.3 illustrates the nervous system structure.

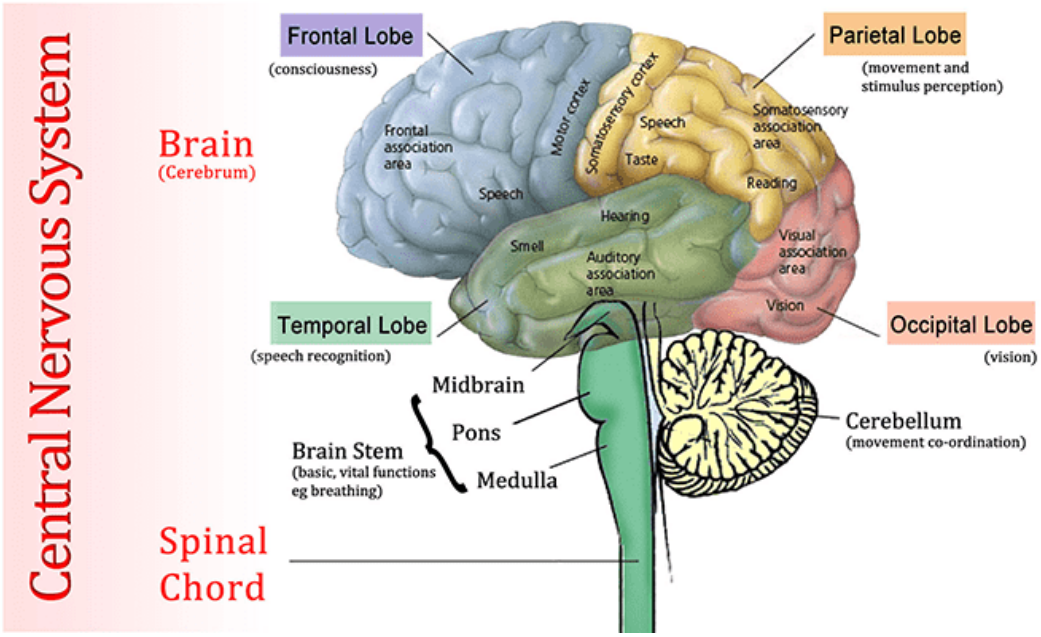


Figure 2.3 : The central nervous system (Sanei & Chambers 2007)

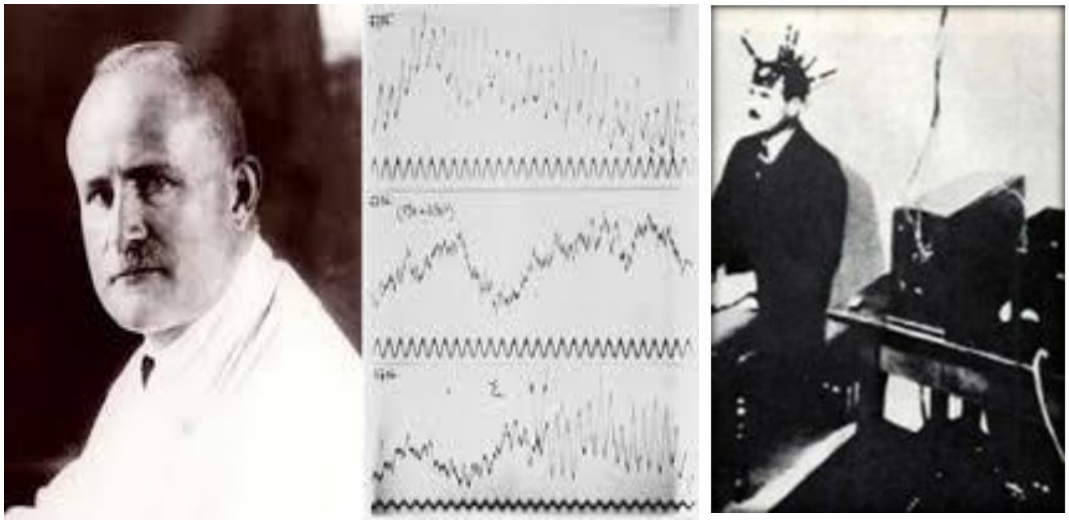
2.1.3 Overview of EEG recordings

The brain consists of cells called neurons or nerve cells (Holmes & Khazipov 2007; Mellinger et al. 2007; Ramadan et al. 2015). The number of neurons in the human brain is approximately 10^{10}. Neurons communicate with each other through electrical impulses which occur at regular intervals. Those electrical impulses can be recorded as electroencephalogram (EEG) signals using electrodes placed on the scalp. The EEG signals require a short time to collect data from the brain.

EEG signals are considered to be an electrophysiological monitoring approach which measures the change of voltage in the swapped ions of the brain's neurons (Niedermeyer & da Silva 2005), used to record the electrical activity of the brain using electrodes placed on the scalp. Physicians and scientists use EEG signals in clinical research to trace abnormalities, such as sleep disorders, brain tumours, brain injuries and epileptic seizures, in the brain's behaviours as well as to study brain functions to diagnose neurological diseases (Adeli, Zhou & Dadmehr 2003; Felton et al. 2007; Hazarika et al. 1997; Orhan, Hekim & Ozer 2011; Rao, Lakshmi & Prasad 2012; Siuly & Li 2012; Van Erp, Lotte & Tangermann 2012).

In 1842, several studies, were conducted to record activities produced by the brain. One of the first was undertaken by Richard Caton, who was a physician practising in Liverpool, and who recorded brain activities. Following Caton's early work, the first recording of EEG signals was in 1875, also by Caton (Collura 1993; Lindsley 1936; Loomis, Harvey & Hobart 1935; Morshed & Khan 2014), which was considered to be the first work to examine brain activity. During this study, electrical activity was recorded from the brains of animals, for example cats, monkeys and rabbits. It was also observed that the cerebral hemispheres of animals released electrical signals.

Thereafter, in 1924, Hans Berger recorded the first human EEG recording and that was published in 1929 (Berger 1929; Haas 2003). Berger was a neuropsychiatrist from the University of Jena in Germany and in his research, he established one of the most important developments in human history, which was a tool to record the activity of the human brain (Millett 2001). Moreover, Berger noticed in his experiment that the rhythms of brain signals changed with an individual's state of consciousness, for example during sleep disorders and epileptic seizures. Figure 2.4 shows the first EEG recording.



Hans Berger (1873-1941)

An EEG recording made by Berger

Patient during recording EEG signal

Figure 2.4: An EEG signal being recorded by Hans Berger (Berger 1929)

To record the brain activity, researchers need to use a number of small discs called electrodes placed in different locations on the surface of the scalp with a conductive glue or paste. Each electrode is connected to an attached amplifier and to an EEG recording machine. Then, all electrical signals of the brain are converted into wavy lines on a computer screen for analysis and further processing, as shown on Figure 2.5.

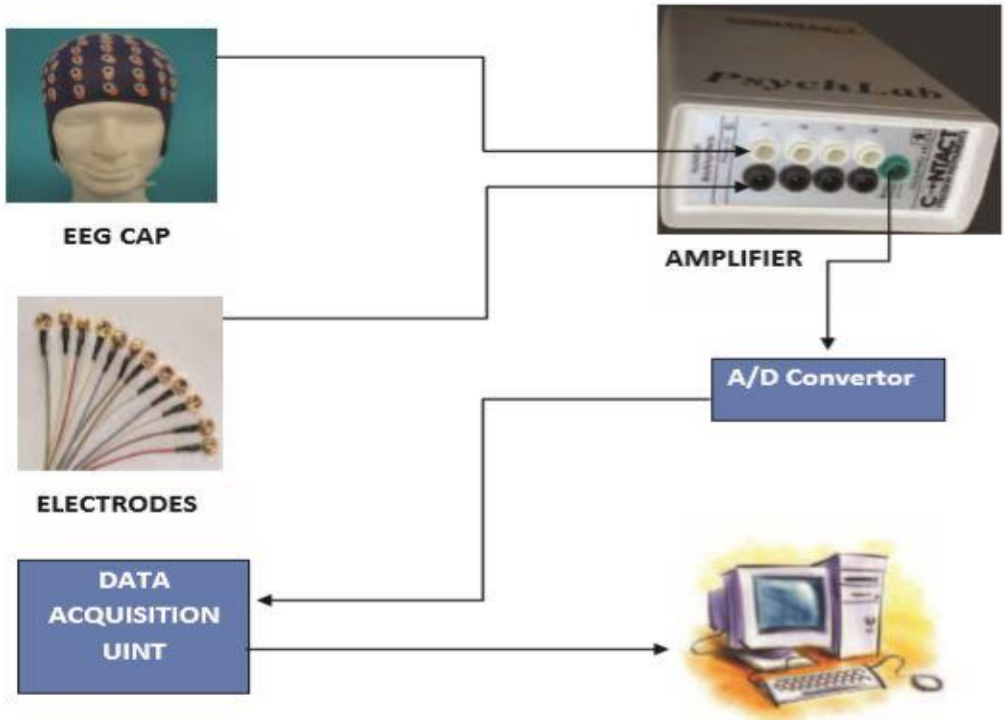


Figure 2.5: EEG acquisition systems (Jasper 1958)

There are two types of recorded EEG signals: multi-channel and single-channel EEG recordings. These recordings normally depend on the number of electrodes that are used to capture these signals. Based on clinical research, single EEG recordings (single channel) can usually be obtained by using one pair of electrodes, while using more than one pair of electrodes at the same time leads to multi-channel EEG recordings. The number of possible electrodes needed to obtain EEG signals is between 1 and 256, depending on the targeted scalp location and the required signals. Those electrodes use the standard international system which describes the locations of electrodes on the scalp.

2.1.4 Electrods Placement System

The standard system of recording the brain activity is called the 10-20 electrode system or international 10–20 system (Jasper, H. H. 1958; Klem et al. 1999; Mason & Birch 2003; Nicolas-Alonso & Gomez-Gil 2012; Teplan 2002; Towle et al. 1993). It is a standard way to describe the locations of electrodes on the scalp. The location of electrodes is determined according to the distance among neighbouring electrodes, as shown in Fig 2.6. There are two points on the scalp that help to determine the electrode positions, called Nasion and Inion. The first is located at the front of the head, alongside the eyes, while the second is located at the back of the head.

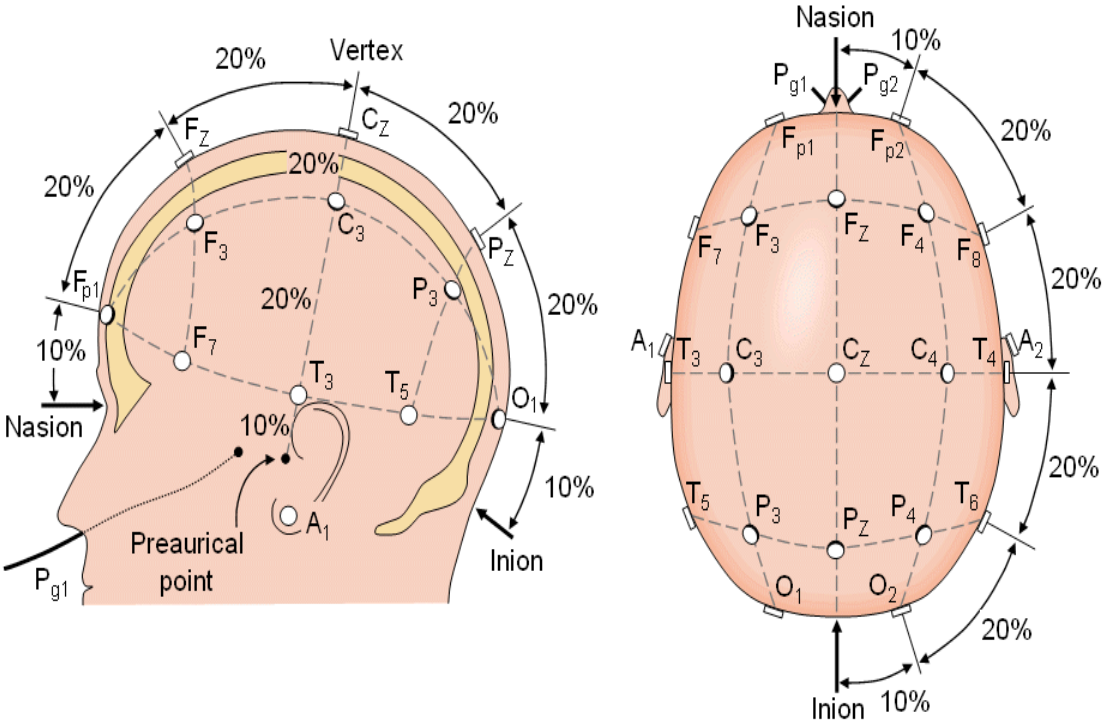


Figure 2.6: A short explanation for location of electrodes on the scalp using the international 10-20 system(Abhang & Gawali 2015; Jasper, H. 1958; Klem et al. 1999)

The numbers 10 and 20 come from the distance between each pair of electrodes that is either 10% or 20% of the total left right or front back of the human skull (Abhang & Gawali 2015; Towle et al. 1993). Furthermore, each electrode has a letter and number to identify the hemisphere location and lobes, as shown in Figure 2.6. These letters are F, T, C, P and O which correspond to the placement of the electrodes, as shown in Table 2.1. For instance, the letter F denotes the front of the skull, T refers to the temporal lode, C is used to identify the centre of skull, P refers to the parietal section of the skull and the letter O denotes the occipital, while the letter Z refers to

the electrodes that are placed on the midline area. In addition, there are two types of numbers which are associated with the location of an electrode. Those numbers are used to denote the electrodes placed in the right or left sides of the scalp. The odd number refers to the electrode position placed on the left hemisphere, while the electrodes with even numbers are placed to the right side of the skull. Table 2.1 presents a short explanation of the locations of all electrodes.

Table 2.1: Observation for each lobe

Electrode	Lobe
F	Front
T	Temporal
C	Central
P	Parietal
O	Occipital

To record sleep EEGs such as the characteristics of sleep stages, the electrodes C_Z-A_1, O_1-A_1, C_3-A_1, F_{P1}-A_1 and C_3 are commonly used, as shown in Figure 2.6. Moreover, the electrodes Fpz-Cz / Pz-Oz are mainly used in recording sleep stages. However, sometimes an alternative electrode placement such as C_4-A_1/ C_3-A_2 could be employed to record EEG signals. EEG signals normally symbolize the different voltages for two electrodes. For that reason, there are numerous ways, named montages, of reading EEG signals (placement of the electrodes). The type of montages that are used to collect a number of EEG channels are presented as an example in Table 2.2. Thus, EEG signals could be monitored with one of the following montages that are illustrated as follows:

2.1.4.1 Bipolar Montage

This montage uses two neighbouring electrodes to record one EEG channel (Niedermeyer & da Silva 2005; Nunez & Pilgreen 1991). The entire montage consists of a sequential number of channels. Two electrodes generate one signal channel, for example, electrode Fp_1 and F_3 produce the channel Fp_1-F_3. The next electrodes are F_3 and C_3 that produce the channel F_3-C_3, and so on, as shown in Figure 2.6. Each channel

represents the voltage differences between two electrodes that are used ((Fisch & Spehlmann 1999; Niedermeyer & da Silva 2005; Siuly & Li 2012).

2.1.4.2 Referential montage

With this montage, there is no standard method of using electrodes to score EEG signals, and each channel with a referential montage represents the differences between one particular electrode and a particular reference electrode. Midline positions of electrodes are often used to record EEG signals compared with other positions because they do not amplify the signals in one hemisphere. Another popular method of using a referential montage is that of using electrodes A_2 and A_1, as references; to take a physical or mathematical average of electrodes set to the earlobes (Nunez & Pilgreen 1991).

2.1.4.3 Average montage

This montage uses an average signal (ARef)) of all the amplifiers which are considered to be a common reference for each channel (Fisch & Spehlmann 1999). The outcomes of all the amplifiers are quantified and then their rates are calculated (Siuly & Zhang 2016).

2.1.4.4 Laplacian montage

Each channel with a Laplacian montage represents the difference between an electrode and a weighted average of the surrounding electrodes (Fisch & Spehlmann 1999; Nunez & Pilgreen 1991; Suily 2012).

The patterns of EEG signals are very important for understanding brain activities because they identify, for example, morphological features of EEG signals in each sleep stage or for examine rhythmic activities (frequency bands) associated with different mental activities or conscious states. The rhythmic activities in EEG signals can be divided into five categories. The most common wave patterns of EEG signals will be discussed in the next section in cases where individuals are in a state of wakefulness, sleep or suffering from a brain disorder.

Table 2.2: Shows an examples of montage type for EEG recordings

Type of montages		
Bipolar montage	**Referential Montage**	**Average reference montage**
F_{p1}-F_3	F_{p1}-A_1	F_{p1}-ARef
F_3-C_3	F_3-A_1	F_3- ARef
C_3-P_3	C_3-A_1	C_3- ARef
P_3-O_1	P_3-A_1	P_3- ARef
F_{p1}-F_7	F_7-A_1	F_7- ARef
F_7-T_3	T_3-A_1	T_3- ARef
T_3-T_5	T_5-A_1	T_5- ARef
T_5-O_1	O_1-A_1	O_1- ARef
F_{p2}-F_4	F_{p2}-A_2	F_{p2}- ARef
F_4-C_4	F_4-A_2	F_4- ARef
C_4-P_4	C_4-A_2	C_4- ARef
P_4-O_2	P_4-A_2	P_4- ARef
F_{p2}-F_8	F_8-A_2	F_8- ARef
F_8-T_4	T_4-A_2	T_4- ARef
T_4-T_6	T_6-A_2	T_6- ARef
T_6-O_2	O_2-A_2	O_2- ARef

Fp = Frontal polar; F = Frontal; C= Central; P=Parietal; T = Temporal; O=Occipital;

2.1.5 Rhythms of EEG signals (Brain activity)

An EEG recording contains an array of signals which are usually described using two terms: rhythmic activities and wave transients (Fisch & Spehlmann 1999; Thut, Miniussi & Gross 2012; Wang 2010; Zaehle, Rach & Herrmann 2010).The rhythmic activities (brain waves) depend on the number of electrodes used to record them. They are defined as electric rhythmic changes or frequency bands. The rhythmic activities are normally divided into five frequency bands: Delta **(δ)**, Theta **(θ)**, Alpha **(α),** Beta **(β)** and Gamma **(γ)** based on their frequencies and using different methods such as a wavelet transform or fast Fourier transform (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Klimesch et al. 1998; Niedermeyer & da Silva 2005; Suily 2012; Vaughan, Wolpaw & Donchin 1996; Wolpaw et al. 2002). These waves usually fall within the range of 0.5-32 Hz (Teplan 2002) and are used to measure brain waves, as shown in Figure 2.7 . The following sub section briefly illustrates those rhythmic activities:

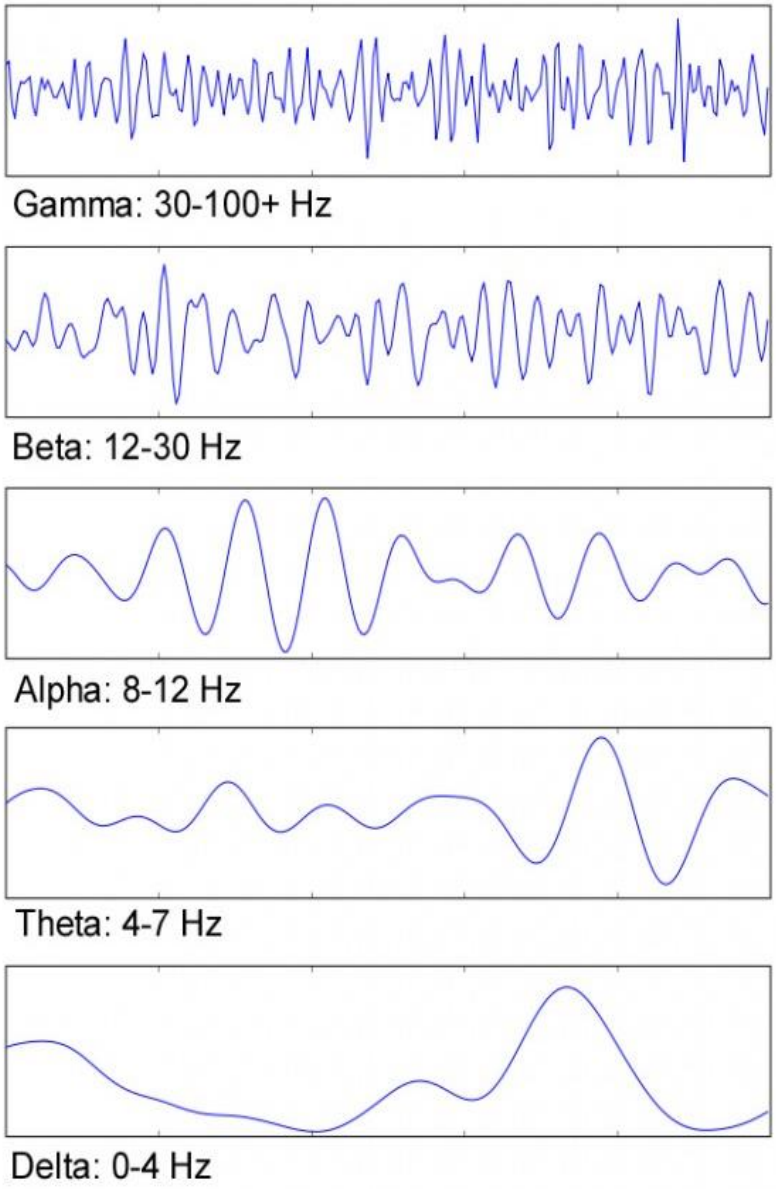


Figure 2.7: Example of five frequncy bands of EEG rhythms (Lotte 2008)

2.1.5.1 Alpha waves contain frequencies between 8 Hz and 12 Hz with an amplitude of 30-50 μV at the awake state (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Gerrard & Malcolm 2007; Klimesch 1999). The alpha wave normally appears in the posterior regions of the head on both sides. It is also called the posterior basic rhythm and mainly appears in adults when their eyes are closed and they are relaxed. The most important regions in the brain to record the alpha waves are the occipital and parietal regions which are located at the back of the skull.

2.1.5.2 Beta waves have a frequency range of 13 Hz to 30 Hz. The maximum amplitude is less than 20 μV and the beta wave appears on the parietal and frontal regions of the scalp. Beta waves are related to many phenomena such as thinking, active concentration and body movements (Pfurtscheller & Da Silva 1999; Suily 2012).

In addition, beta wave activity is associated with several brain disorders such as autism and intellectual disability as well as the effects of drugs and epilepsy which are caused by repeating part of the chromosomes, in particular Chromosome 15 (Frohlich et al. 2016). There are two types of beta waves: beta I waves and beta II waves. The first type has low frequencies which disappear during mental activity, while the second has high frequencies which appear during tension and intense mental activity. The beta waves are normally associated with active attention, and solving concrete problems..

2.1.5.3 Gamma waves have frequencies between 30 Hz and 100 Hz with an amplitude less than 2 μV peak-to-peak when a human is attending to something or experiencing some sensory stimulation. In addition, it has the lowest amplitude compared to other frequency bands. The gamma activity is related to several cognitive and motor functions. Gamma waves also denote a number of neurons working together as a network to help these functions work effectively (Niedermeyer & da Silva 2005).

2.1.5.4 Delta waves contain a frequency range between 0.5 Hz and 4 Hz frequency with an amplitude of less than 100 μV. In addition, the shape of the delta wave demonstrates the highest amplitudes and the slowest waves. Delta wave activity is normally associated with deep sleep, but can also be associated with the awake stage with some sleep cases relating to brain disorders. It also appears in EEG signals when the human is asleep.

2.1.5.5 Theta waves have a frequency range between 4 Hz to 7 Hz with an amplitude greater than 20 μV. They mainly occur in the parietal and temporal regions during sleep. In addition, this type of brain activity can be seen when people are drowsy (Cahn & Polich 2006). Theta waves normally increase in EEG signals during times of emotional stress such as frustration and disappointment. Thus, increasing the number of theta waves in the brain may lead to abnormal activity such as deep midline disorders, metabolic encephalopathy or diffuse disorders. Finally, this type of wave in EEG signals is normally associated with relaxed and creative states.

Clinical research has revealed that during EEG recordings, individual sleep stages exhibit unique features, patterns and characteristics that reflect human sleep states. These patterns, which appear during sleep stages, are called sleep spindles and k-complexes. In addition, vertex waves and sharp waves can be seen during epileptic seizures. These patterns are transient rather than rhythmic waveforms, so detecting and identifying them is more difficult than detecting rhythmic activities.

This research focuses firstly on developing new and robust methods to identify sleep spindles in EEG signals. Secondly, it suggests new methodologies to identify k-complexes, which are the second important characteristics of sleep stages in EEG signals. The following section provides more details about sleep stages and their characteristics: sleep spindles and k-complexes and how these transient waveforms affect human brain neurons.

2.2 Sleep EEGs

In order to understand the sleep EEGs, Section 2.2.1 provides an overview of the background knowledge related to human sleep and sleep stages in EEG signals. General concepts about sleep stages are also discussed in this section. Section 2.2.2

provides brief details about the characteristics of sleep stage 2 and how those characteristics affect human brain disorders.

2.2.1 Sleep EEG signals and human sleep

Sleep is one of the primary functions of the brain and during sleep, some neurons in the human body become inactive (Aboalayon et al. 2016; Huang et al. 2014). Any disorders in the human sleep cycle can lead to lifelong complications in which the mental and physical performances of an individual can be damaged (Aboalayon et al. 2016). In addition, sleep deprivation can cause many problems for the body of a human; for example, it causes reductions in the body temperature, heart rate variability, and growth hormone release, while also leading to memory loss, lack of concentration and drowsiness (Koshino et al. 1993; Kubicki, Scheuler & Wittenbecher 1991; Mousavi, Afghah & Acharya 2019). These problems are significant and extensive. According to the World Health Organisation (WHO), in the United States, around 50-70 million people suffer sleep disorders foor example apnoea and insomnia at some stages in their lives.

Sleep is a dynamic process which consists of two main stages: rapid eye movement (REM) and non-rapid eye movement (NREM). The latter type of sleep (NREM) is classified into four stages: : stage 1, stage 2, stage 3 and stage 4 (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman, W, Li, Y & Wen, P 2019; Al-Salman et al. 2018; Al-salman & Li 2019; Stepnowsky et al. 2013). Humans typically spend approximately 75% of the night in NREM sleep and up to 25% in REM sleep. Thus, the sleep cycle of a subject is normally divided into six stages in the sleep staging procedure: Awake, stage 1, stage 2, stage 3 and stage 4, and REM. The normal sleep cycle is shown in Figure 2.8.

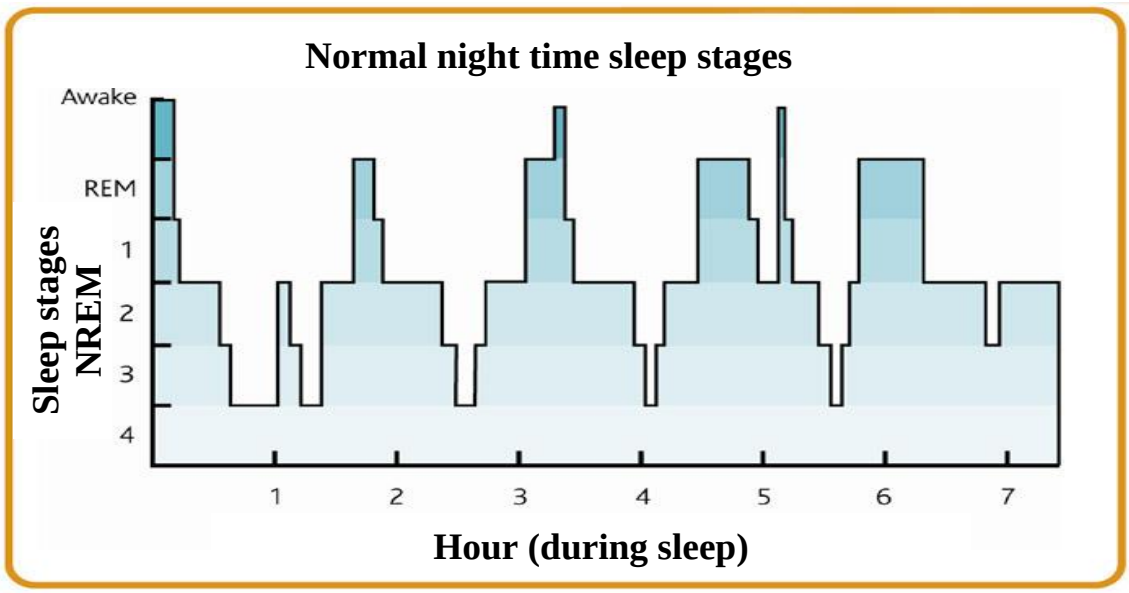


Figure 2.8: The human sleep cycle (https://www.talkaboutsleep.com

Sleep stages scoring is an important process in sleep research as any errors in the scoring of the sleep electroencephalography (EEG) recordings of the patient can lead to critical problems. The sleep stages are connected through different physiological and neuronal characteristics that are used in sleep stages identification by sleep experts and researchers. The process of discriminating sleep stages visually is called sleep staging or sleep scoring. Normally, it is carried out visually by experts according to the criteria of Rechtschaffen and Kales (R&K) (Rechtschaffen 1968) or the guidelines of the American Academy of Sleep Medicine (AASM) (Berry et al. 2012; da Silveira, Kozakevicius & Rodrigues 2017; Ebrahimi et al. 2008; Putilov 2015; Tsinalis, Matthews & Guo 2016). One of the major shortcomings of these criteria is the use of arbitrarily defined thresholds to identify the sleep stages which can lead to unreliable outcomes and poor agreement between experts (Su & Smith 1974; Vu et al. 2012). Although the visual analysis of EEG recording (sleep scoring) has been used as a standard method for a long time, it has some deficits and limitations. First of all, it is expensive, requires a high cost and effort, and is error-prone. In addition, it is also a subjective process that means decisions made by two experts of EEG signals could vary even in the same sleep recordings. Thus, the low and widely varying inter-rater agreement adds to the complexity of the overall scoring process and diagnostic utility. The Cohen's κ coefficient of inter-rater manual scoring ranges between 0.46 to 0.89 (Parekh et al. 2015; Stepnowsky et al. 2013). Some studies have reported an even lower κ coefficient (Devuyst et al. 2010; Devuyst et al. 2011).

According to the guidelines proposed by R&K (Al-Salman, W, Li, Y & Wen, P 2019; Wessam, Li & Wen 2019), a human sleep cycle is divided into two main parts: NREM and REM. The NREM includes four stages: Stage 1 (S1), Stage 2 (S2), Stage 3 (S3) and Stage 4 (S4) as well as awake (AWA), as shown on Figure 2.9.

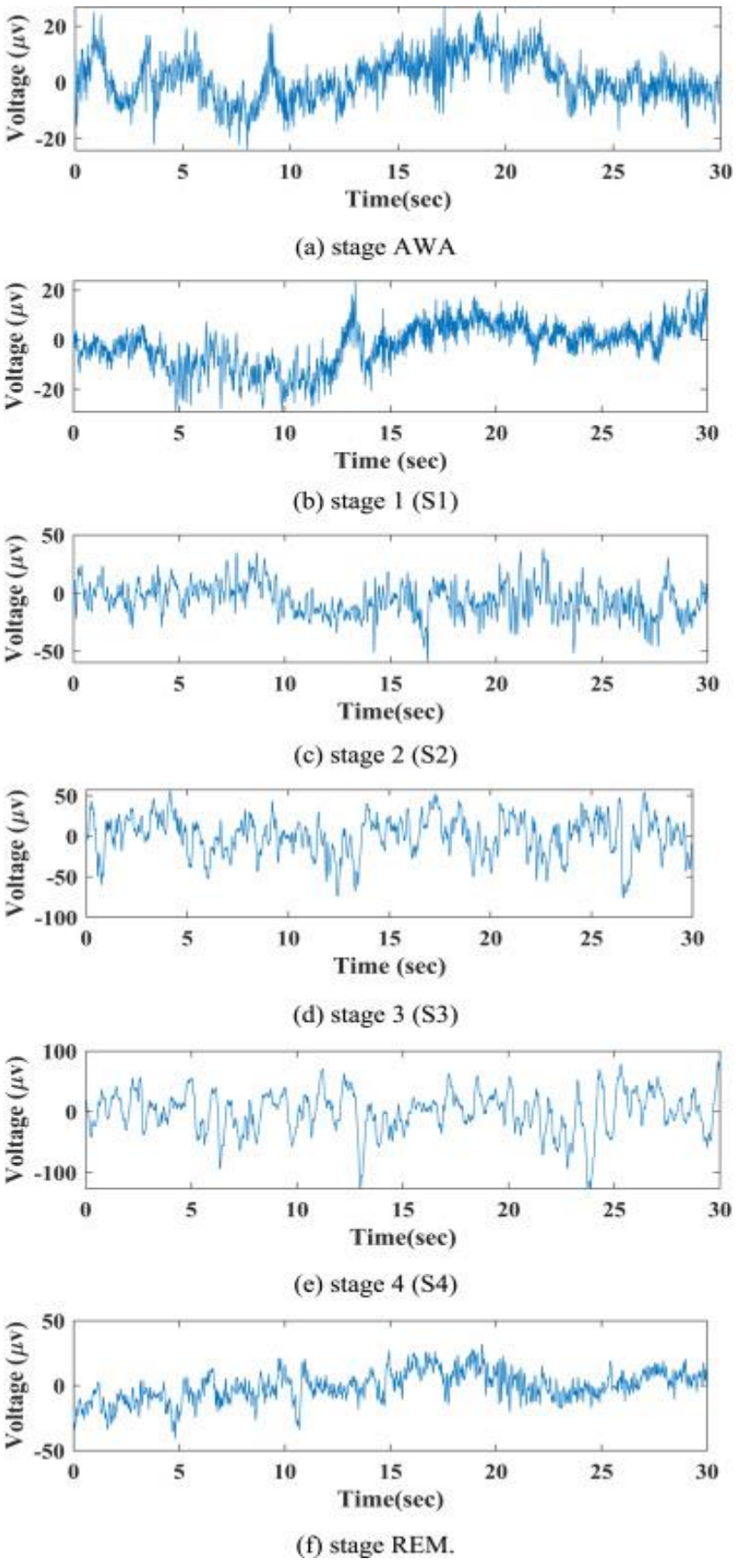
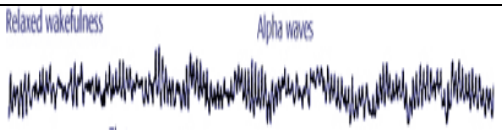
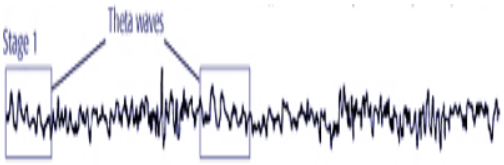
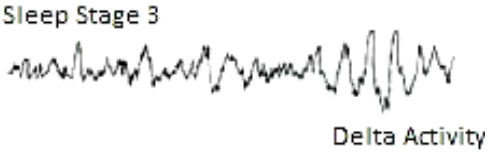


Figure 2.9: Typical 30-second EEG signals of different stages of sleep from Sleep-EDF dataset.

Each stage has a distinct set of associated physiological, and neurological features. Table 2.3 shows EEG signals showing different sleep stages and their characteristics.

Table 2.3: EEG sleep stages, their characteristics and waveforms.

Sleep stages	**Characteristics**	**Amplitude (uV)**	**EEG waveforms**
Awake	Low voltage and fast waves, High frequency (15-50 Hz)	less than 50	
Stage 1 (drowsiness)	Alpha waves drop out (8–13Hz), while beta activity is increased (4-8Hz), positive spikes appear with 14-16 Hz.	50-100	
Stage 2 (light sleep)	Symmetric, synchronous theta rhythms, vertex waves, having k-complexes and spindles (12-14Hz)	50-150	
Stage 3 (deep sleep)	Delta activity, slow of rhythm at 2–4 Hz	100-150	
Stage 4 (very deep sleep)	Delta (0.5-2Hz) activity, more slowing of waves. S3 and S4 are similar and combined as a SWS, appeared in the frequency of 0-4Hz	100-200	
REM sleep	Low amplitude sawtooth waves. Mixed frequency (15-30Hz);	less than 50	

In 2002, the American Academy of Sleep Medicine (AASM) presented a different version of sleep stage scoring (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Diykh & Li 2016; Peker 2016) in which the NREM was reduced to 3 stages, with S3 and S4 combined into one stage: the slow wave stage (SWS). Furthermore, in the AASM guidelines the allocated times for S1 and SWS were changed, and a minimum of three EEG derivations from the frontal, central, and occipital regions were recorded. The AASM also considers body movement as a sleep stage (Gao, Turek & Vitaterna 2016). The following subsections clarify the sleep stages in detail.

2.2.1.1 Sleep Stage 1 is a transition stage between wakefulness and sleep and usually cycles between 1 to 5 minutes. During S1, breathing slows and heartbeat becomes regular, while blood pressure and brain temperature decrease. Clinical research shows that people may suffer from sudden muscle contractions followed by a sensation of falling. In addition, the brain waves change during stage1 transition from unsynchronized beta (12-30Hz) and gamma (25-100Hz) waves to more synchronised beta and gamma waves.

2.2.1.2 Sleep Stage 2 is the baseline of sleep and the theta activity is clearly demonstrated in this stage. Moreover, during stage 2, the human body starts to recover from muscle stress and fatigue and reduces brain activity preparing the body for transition into a deep sleep from which it is hard to wake up. Although S2 and S1 produce a similar range of theta waves, sleep spindles and k-complexes appear in S2 only (Bolón-Canedo, Sánchez-Maroño & Alonso-Betanzos 2013; Camilleri, Camilleri & Fabri 2014; Rodenbeck et al. 2006).

Sleep spindles are defined as short bursts of brain activity in the range of 12-14 Hz for about half a second, while k-complexes exhibit short negative high voltage peaks followed by slower positive k-complexes. They have a frequency of 33 Hz and an amplitude of 100 μV (Cătălin et al. 2018). More details about sleep spindles and k-complexes will be explained in the next section.

2.2.1.3 Sleep Stage 3 and 4 (SWS) are categorised as slow wave sleep, and the corresponding EEG waves have high amplitudes. Stages 3 and 4 are referred to as deep sleep that occurs in the first half of the night. Stages 3 and 4 produce similar brainwaves, 50% of which are delta waves, making it hard to classify them.

2.2.1.4 The REM stage is associated with a unique brain wave pattern, and EEGs reveal continuous mixed activity (theta wave with some delta waves, alpha waves, and beta waves) and 40 ± 80 mV amplitude. During this stage, breathing becomes faster, more irregular and slower. In addition, the cycle of sleep from deep sleep to awake can easily happen and dreams can be remembered if the waking period is too long (Williams, Karacan & Hursch 1974).

During the awake stage, the brain waves become very slow, and more synchronized, with an increase in amplitude. Thus, the EEG signals during the awake stage and REM exhibit different patterns, characteristics, and features, making the separation of these stages more accurate. As mentioned before, two of the most important bio-signal waveforms in sleep stage 2 are sleep spindles and k-complexes.

Developing accurate algorithms to detect the characteristics of sleep stages and to score a patient's EEG recordings could help sleep experts and clinicians work more efficiently in diagnosing sleep disorders. In this thesis, four methods are developed to analyse and detect the most important characteristics of sleep stage 2 in EEG signals: sleep spindles and k-complexes, thus, helping the physician with early detection of sleep disorders. In the next section, we discuss these important characteristics.

2.2.2 Characteristics of sleep stage 2 in EEG signals

This section provides more details about the characteristics of sleep stage 2: sleep spindles and k-complexes, and how they affect human brain disorders.

2.2.2.1 Sleep Spindles

Sleep spindles are the most important transient events to detect sleep stage 2 in EEG signals. They are defined as a series of distinct waves within a frequency range of 12 and 14 Hz with a minimum duration of 0.5 second (s) (Berry et al. 2012; Devuyst et al. 2006; Grigg-Damberger et al. 2007; Imtiaz & Rodriguez-Villegas 2014; Rechtschaffen 1968; Warby et al. 2014). These intervals have been

extended to be between 11Hz and 16Hz (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Clemens, Fabo & Halasz 2005; Devuyst et al. 2006; Fang et al. 2019; Huupponen et al. 2007; Huupponen et al. 2003; Huupponen et al. 2000; Iranmanesh & Rodriguez-Villegas 2017; Ktonas et al. 2009; Kulkarni et al. 2019; Schimicek et al. 1994; Warby et al. 2014). Some studies have reported that the minimum and maximum durations of sleep spindles are 0.5s and 3s, respectively (Duman et al. 2009; Jankel & Niedermeyer 1985; Kabir et al. 2015; Yücelbas et al. 2016), with an amplitude from 5 μV to 25 μV (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Miranda, Aranha & Ladeira 2019; Nonclercq et al. 2013; Zeitlhofer et al. 1997). Figure 2.10 shows an example of sleep spindles.

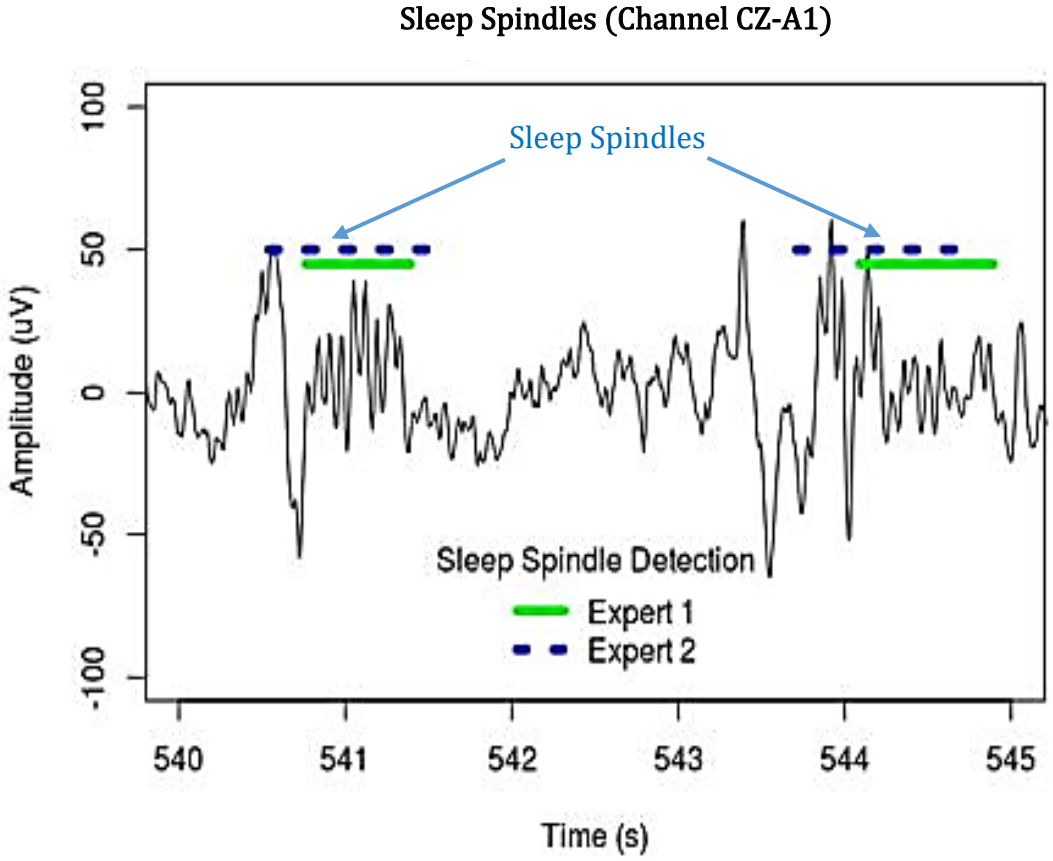


Figure 2.10: Example of sleep spindles detection from EEG data by experts (Miranda, Aranha & Ladeira 2019)

The presence or absence of sleep spindles in EEG sleep signals has a high impact on the memory consolidation of humans (Adamczyk et al. 2015; Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Barakat et al. 2011; Cox, Hofman & Talamini 2012; Diekelmann & Born 2010; Diekelmann, Wilhelm & Born 2009; Fogel et al. 2014; Fogel et al. 2012; Lafortune et al. 2014; Lajnef et al. 2015; Morin

et al. 2008; Nishida, Nakashima & Nishikawa 2016; Schabus et al. 2004; Vorster & Born 2015). From EEG recordings, it is observed that any change in the density of sleep spindles can result in some sleep disorders, such as insomnia, epilepsy, affective disorders, schizophrenia, dementia, mental retardation, neurodegenerative diseases and autism (De Maertelaer et al. 1987; Ferrarelli et al. 2007; Ferrarelli & Tononi 2010; Ktonas et al. 2009; Latreille et al. 2015; Limoges et al. 2005; Niedermeyer & Ribeiro 2000; Uygun et al. 2018; Wamsley et al. 2012; Wei et al. 1999; Zhuang, Li & Peng 2016). These are important changes because the sleep spindles result from the interaction of several regions of the brain such as the cortex, the thalamic reticular nucleus, and the hippocampus (Adamczyk et al. 2015; Ferrarelli & Tononi 2010; Steriade 2006). More details regarding sleep spindles have been presented in chapters 3 and 4.

Consequently, automatically detecting and analysing sleep spindles in EEG signals can help sleep experts in diagnosing sleep disorders. Traditionally, the detection of sleep spindles depends mainly on visual inspection that is carried out based on the knowledge of clinicians; trained experts in sleep clinics. The accuracy and reliability of the manual scoring are based on the experiences of experts; the inter-human agreement is estimated to be around 80% - 90% and the degree of consent is 70 ± 8% (Campbell, Kumar & Hofman 1980; Wendt et al. 2012; Żygierewicz et al. 1999). Visual scoring of these morphologically distinct waveforms such as sleep spindles is very time consuming, subjective and prone to errors because there are typically thousands of sleep characteristics, such as spindles occurring in each EEG recording (Acır & Güzeliş 2004b; Al-Salman et al. 2018; Nonclercq et al. 2013). Identifying sleep spindles in EEG signals visually requires high skills from experts and a high level of vigilance. Thus, reliable detection of sleep spindles is very appealing because it would enhance the accuracy, speed and inter-rater agreement of sleep spindles scoring. However, developing an automatic approach to identify those occurrences in sleep stages is an ongoing challenge (Al-Salman et al. 2018).

2.2.2.2 K-complexes

As mentioned above, k-complexes and sleep spindles patterns are the key characteristics of sleep stage2, and consequently, they are often used to identify and determine NREM stage 2. Because of this significance, the identification of k-complexes and sleep spindles in an epoch is very important for sleep experts in diagnosing sleep disorders.

K-complexes were first discovered in 1937 by Loomis, Harvey and Hobart III (1938) and this was considered to be one of the most important events in sleep EEG studies. K-complexes are important in studying the functional roles in diagnosing sleep disorders; it has also been observed they occur concomitantly with apneic events in patients with sleep apnea (Van Erp, Lotte & Tangermann 2012). In some studies a k-complex is defined as a temporary transient waveform which is observed by a negative sharp wave followed by a positive sharp wave, and it has a relatively sharp amplitude that is more than ±75μV (Devuyst et al. 2011; Halász 2005; Noori et al. 2014; Richard & Lengelle 1998; Rodenbeck et al. 2006). In other studies (Camilleri, Camilleri & Fabri 2014; Gala & Mohylova 2009; Yücelbaş et al. 2018b), the definition of k-complexes is exactly the opposite. It is seen as a positive sharp component and is followed immediately by a negative sharp wave. This temporary waveform appears in all sleep stages, but mainly occurs in sleep stage 2, and presents in 12-14 Hz waves (Al-Salman, W, Li, Y & Wen, P 2019; Jansen & Desai 1994; Wessam, Li & Wen 2019). The waveforms duration of k-complexes is between 0.5s and 1.5s.

Moreover, in other studies (Al-salman & Li 2019; Bremer, Smith & Karacan 1970; Da Rosa et al. 1991) it was reported that the duration of k-complexes is between 0.5s and 1.0s; the minimum peak to peak amplitude value of the k-complexes is around 100 μV. Most of the early studies showed that k-complexes could appear many times during stage 2 with a maximum time duration between 0.5s to 1.5s. Some studies have reported that the maximum time duration of k-complexes is between 1s to 3s (Bankman et al. 1992; Cash et al. 2009; Devuyst et al. 2010; Erdamar, Duman & Yetkin 2012; Pohl & Fahr 1995; Rechtschaffen 1968; Strungaru & Popescu 1998; Vu et al. 2012) and this is one of the standard markers of sleep stage 2. However, although other waveforms, such as delta, theta and alpha waves, are relatively easy to detect, an automated detection approach of k-complexes in EEG signals is a challenging problem (Bankman et al. 1992; Vu et

al. 2012). Examples of EEG signals with k-complex events are shown in Figure 2.11 (Miranda, Aranha & Ladeira 2019).

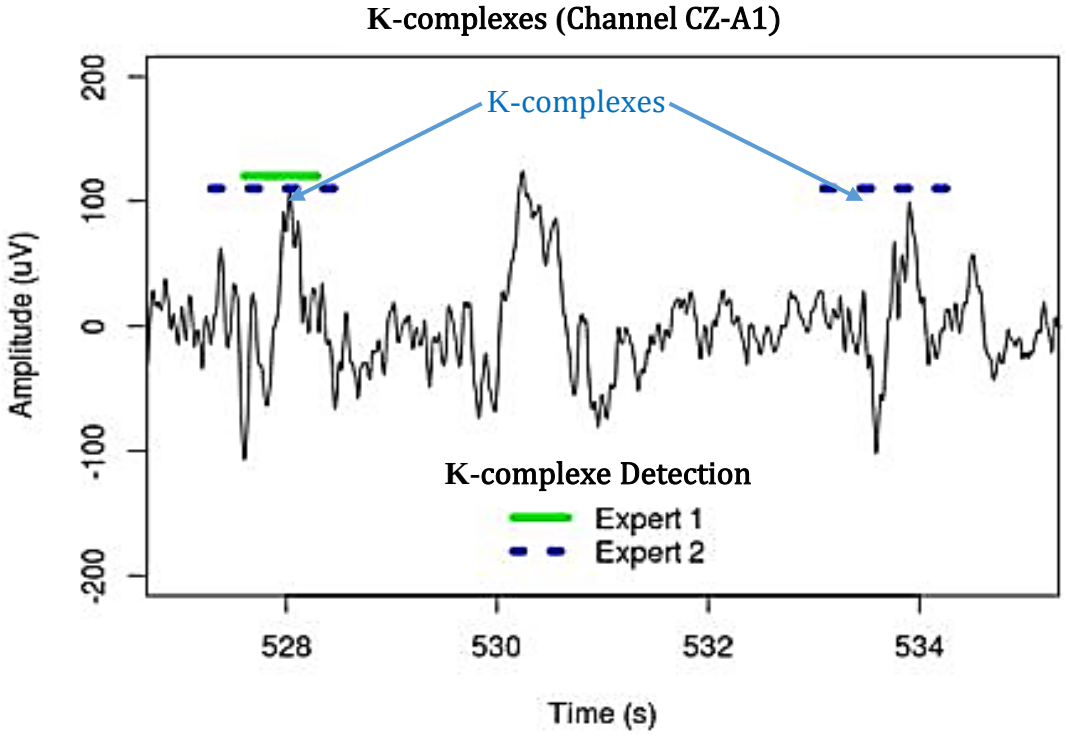


Figure 2.11: Example of k-complexes waveform detected from EEGs by two experts (Miranda et al. 2019).

2.3 Overview of EEGs analysis and classification techniques

Before providing an overview of the classification techniques, this section introduces firstly the generated concept about analysing and classifying EEG signals. Usually, EEG recordings generate and contain a huge amount of information about human activities and the functions of the brain. Classification of EEGs in biomedical research plays a significant role in diagnosing brain disorders, especially in sleep stages. Developing efficient classification methods is vitally important to analyse EEG signals, to extract desired and discriminative features, and to reduce a large amount of EEG data. To analyse and classify these features, there are several procedures researchers must follow. Figure 2.12 shows the main steps of these procedures. The steps are divided into three phases:

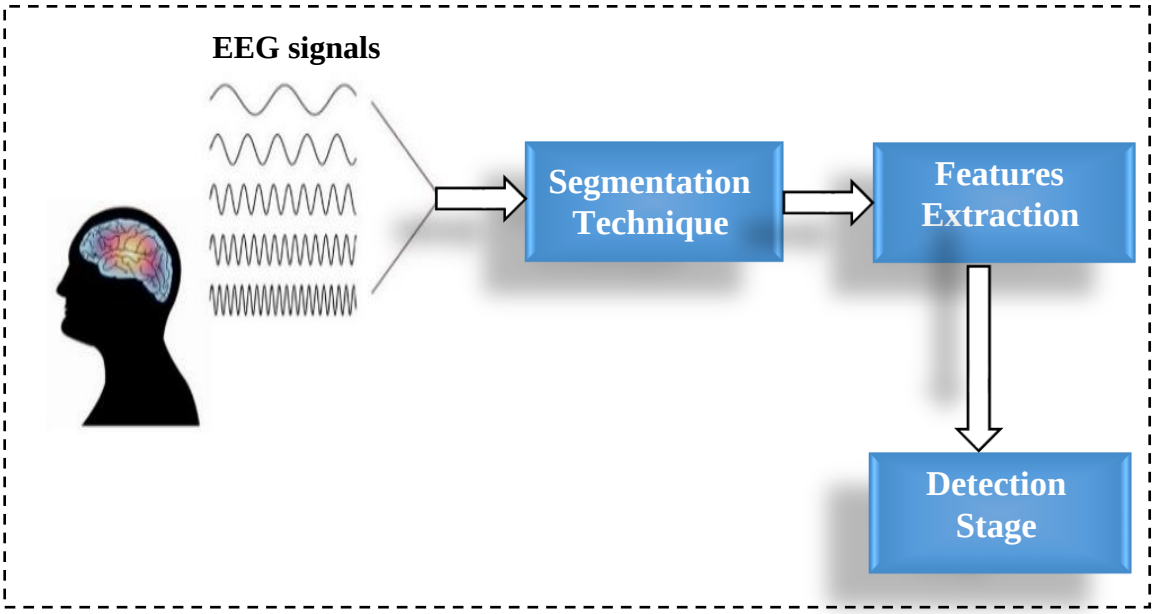


Figure 2.12: Block diagram of EEG signal processing

1- The first phase is the segmentation phase. In this phase, the EEG signals are segmented into small epochs using sliding window techniques. The size of sliding windows was determined empirically during the training phase. For example, sleep experts have observed that the characteristics of sleep stages such as sleep spindles and k-complexes normally appear in EEG signals for 0.5 seconds to 2 seconds. For that reason, the segmentation technique is important in this research to detect those morphologies in sleep stages. Figure 2.13 shows an example of EEG signals being partitioned into segments of 0.5s with an overlapping segment of 0.4s using a sliding window technique. More details regarding the segmentation technique are provided in Chapters 3, 4, 5 and 6.

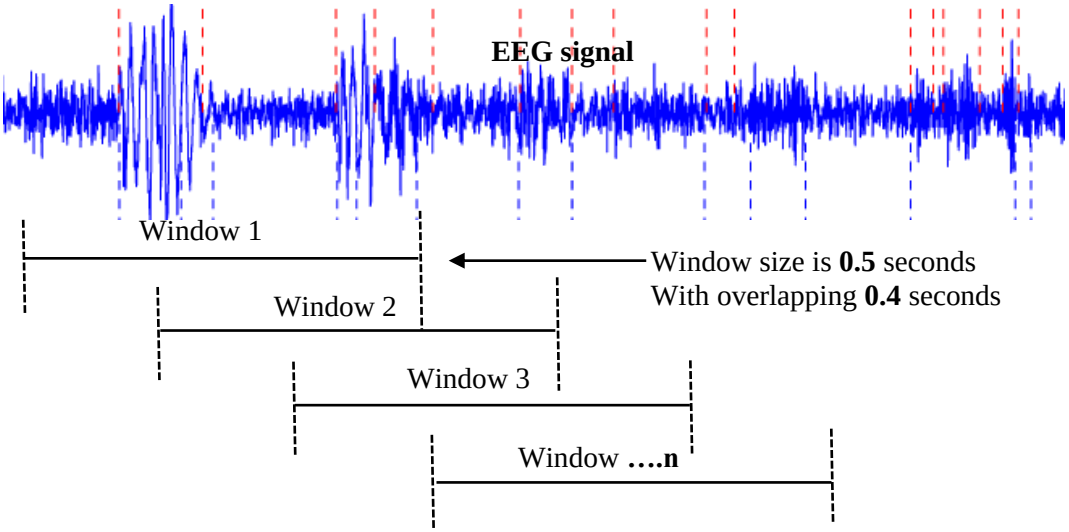


Figure 2.13. An example of using the sliding window method.

2- The second phase is the features extraction and selection phase, which is used to select and derive representative features from EEG signals by applying different signal processing methods (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Kumar & Bhuvaneswari 2012). In this phase, the EEG signals are analysed and the key features are extracted. This step is important as a way to reducing the dimensionality of EEG data and to keep important information while the irrelevant data are eliminated. Those two phases are excellent techniques to use to extract relevant features and accurately describe EEG signals in order to obtain high quality EEG detection. The detailed description of extraction techniques of sleep spindles and k-complexes was given in Chapters 3, 4, 5 and 6.

3- The final phase is the detection stage, in which the extracted features are forwarded to different classifiers (classification algorithms) to detect brain disorders in humans during sleep stages. This phase depends on the quality of pre-processing and extraction methods to obtain a high performance using the proposed method. For example, the relevant extracted features of the sleep characteristics, such as sleep spindles and k-complexes are classified by using classifiers to produce trained models. The detectors can detect different types of sleep characteristics based on extracted features. However, many studies using unsupervised learning algorithms or pre-processing methods have been used to detect the characteristics of the sleep stages, leading to an increase in the processing time for the detection stage. Thus, the aim of using supervised learning algorithms on this stage is to obtain high system performance with less execution time for the testing phase. More details regarding those three phases are provided in Chapters 3, 4, 5 and 6.

In this thesis, we will firstly start with the detection of sleep spindles as an experiment and we will then use this developed method to detect other characteristics in sleep signals such as k-complexes. These methods could assist sleep specialists to diagnose sleep disorders as early as possible. The next sections explain in detail some current methods and detection techniques which are used to detect sleep spindles and k-complexes in sleep Stage 2.

2.3.1 Concept of classification techniques

Classification techniques are commonly used for identifying and diagnosing brain disorders and are the most popular techniques in the field of biomedical research to identify a number of features in different groups, depending on particular characteristics of EEG signals. During the classification algorithms, the input data (vector of features) are classified into groups based on certain categories which are determined by particular features. Those features are normally described by vectors which work as descriptions of instances or classes (Li & Wen 2009; Li & Wen 2010; Li, Wu & Yang 2011; Lotte 2008; Suily 2012). Furthermore, the aim of the techniques is to allocate class labels to the extracted features by observing a set of data on specific issues. Algorithms that are utilized to detect or classify the extracted characteristics from EEG signals are known as classifiers. The classification techniques are divided into two types based on the usage of the features vector: supervised classification and unsupervised classification, as shown on Figure 2.14.

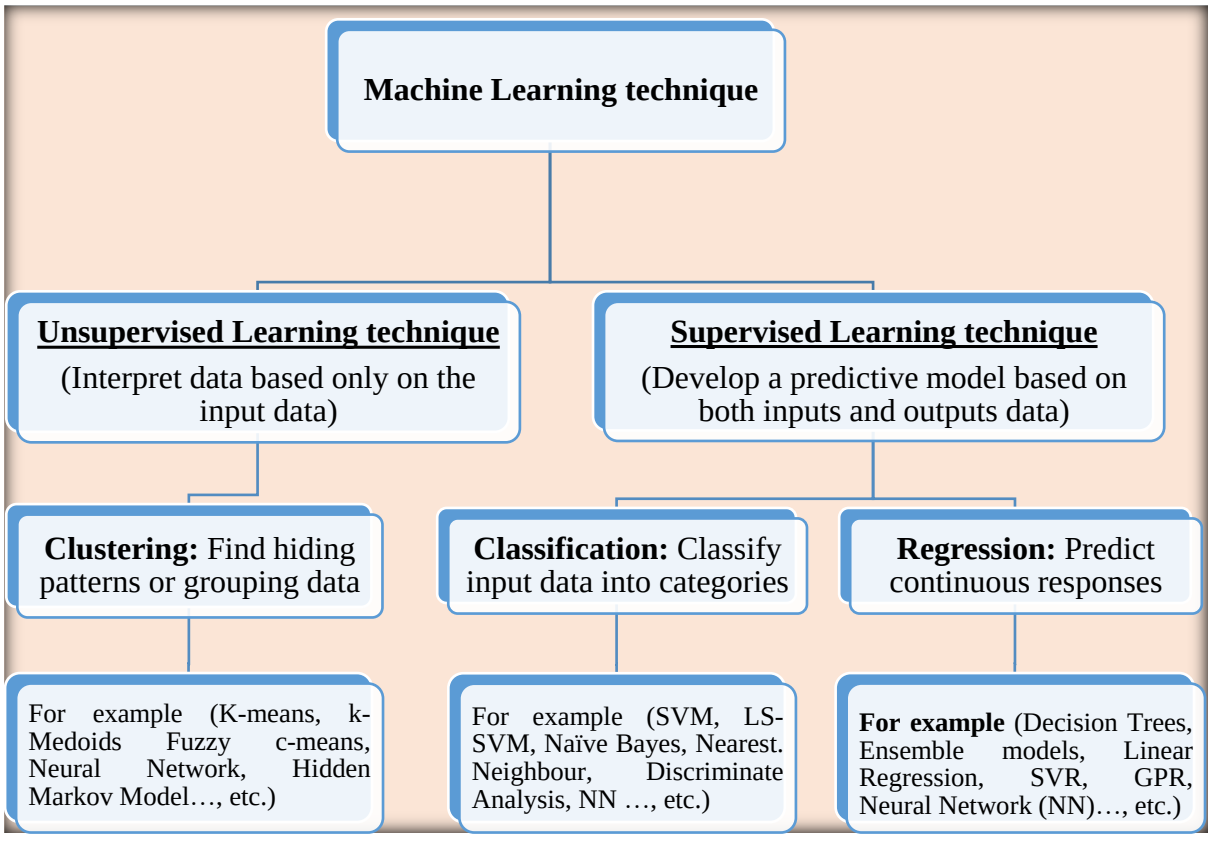


Figure 2.14. Types of classification learning algorithms; Supervised and Unsupervised Machine Learning Algorithms

The first type of classification technique (supervised classification) requires labelling all the input data, while the action with unsupervised classification does not require the labelling of input data to a known class (Huang et al. 2014), as shown in Figure 2.15.The architecture of unsupervised classification depends on dividing data into groups according to the similarities or differences among their elements. However, both those methods have a number of important parameters that require training from a dataset. More details regarding those two types of classification techniques are provided in the next section.

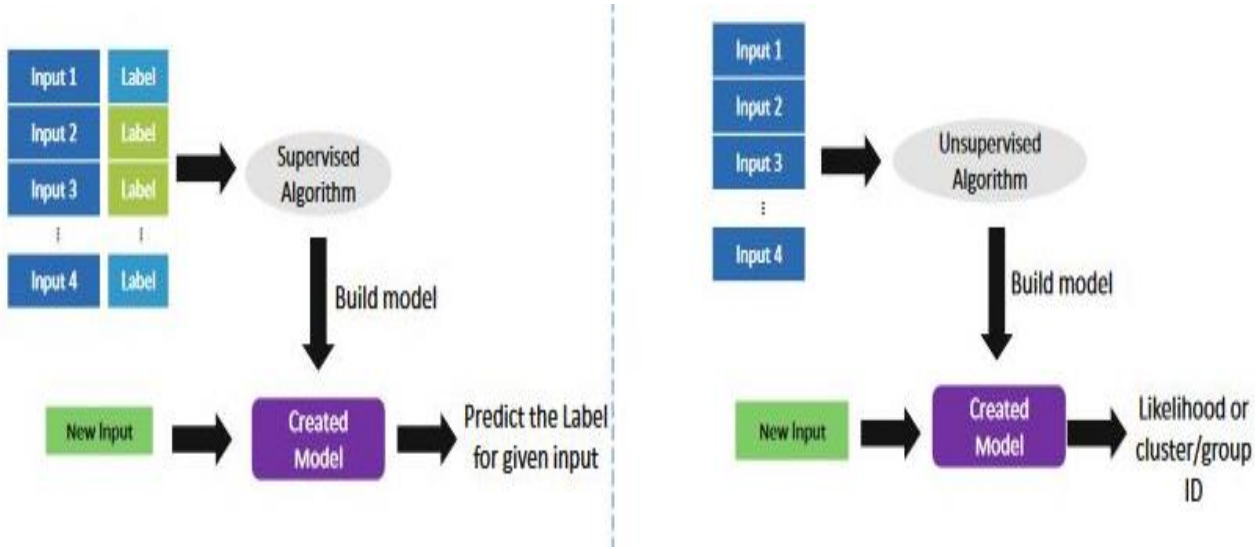


Figure 2.15. Supervised vs. unsupervised machine learning algorithms

2.3.1.1 Supervised and unsupervised learing classification algorithms

The supervised classification algorithm, is one of the algorithms associated with machine learning that deals with a set of data and normally has some information about the dataset. With the supervised technique, the classification model produced based on the class labels information which is given during the training dataset to train the classifier. The supervised approach generally assumes that a set of training data would have a set of relevant labelled instances which refer to the correct output (Brunelli 2009; Duda, Hart & Stork 2012; Morin et al. 2008). There are many supervised classification learning algorithms, such as support vector machine (SVM), least square support vector machine (LS-SVM), decision trees, neural networks (NN), logistic regression linear regression, Bayesian network classifier, fuzzy K-nearest-

neighbour (KNN), Adaboost algorithms, linear discriminant analysis (LDA), Naive Bayes classifier and K-nearest-neighbour (KNN) algorithms.

In the supervised classification approach, the database is typically partitioned into two sets: a training dataset and a testing dataset.The classifier is constructed using the training dataset. Then, the performance of the trained classifier is evaluated by using the testing dataset. This process of evaluation is often repeated for the different parameters of the constructed classifier. Subsequently, the parameters of the classifier are optimized, and selected carefully during the training phase, in order to be ready for assigning the class labels to the features with unseen class labels. Thus, the main goal to learn a procedure is to maximize the testing accuracy on the testing dataset.

This study used supervised learning algorithms to produce the trained models and to detect sleep spindles and k- complexes. During the experiments, all the EEG databases used in this study were divided into two groups of data: the training and testing datasets as shown in Figure 2.16. The training dataset is used to train the classifier and build the trained model (proposed method) to detect sleep characteristics, while the testing dataset is used for evaluating the performance of the trained model.

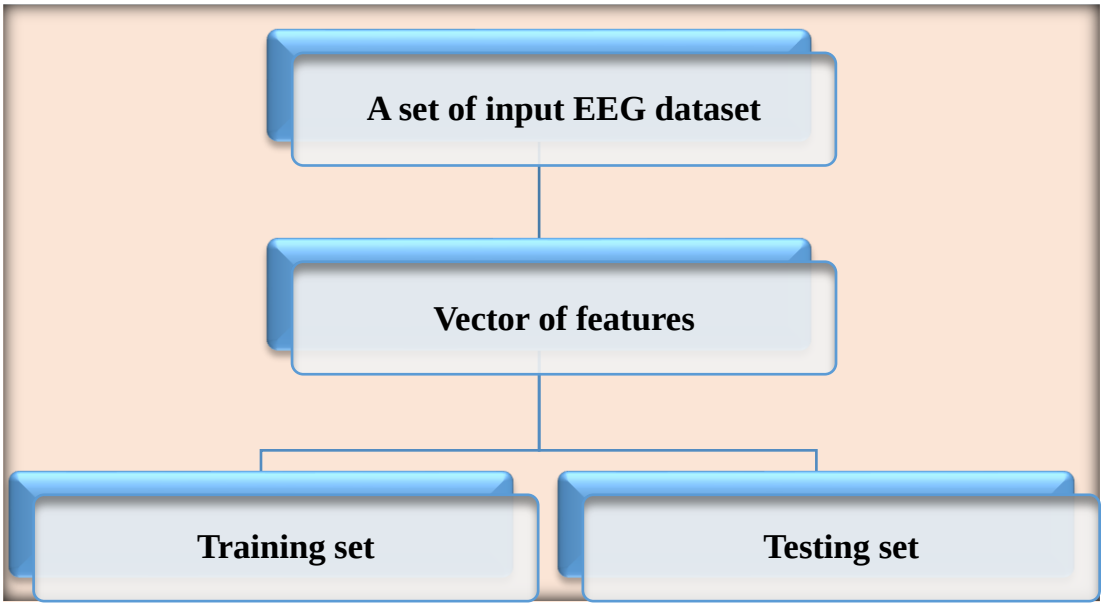


Figure 2.16: Shows training and testing dataset.

The unsupervised classification approaches involve grouping the unlabeled input data (vector of features) into classes to determine hidden patterns. Normally, an unsupervised classification algorithm assumes that the training data has not been labelled and attempts to find the inherent patterns in the data to determine the correct

output value for a new instance data (Brunelli 2009). In this type of learning algorithm, the class label information is not available even for a small number of data (Suily 2012).

Among the common aspects of unsupervised learning approaches, for example, are k-means clustering, hierarchical clustering, hidden Markov models, independent component analysis (ICA), categorical mixture model and principal component analyses (Al-Salman et al. 2018; Hartigan & Wong 1979; Jolliffe 2011; Oberski 2016; Rabiner & Juang 1986), and so on. A combination of two classification learning algorithms (supervised and unsupervised) has been explored (Chapelle, Scholkopf & Zien 2009), leading to semi-supervised algorithms, which use a combination of the small set of labelled data and a large set of unlabelled data.

In this thesis, different techniques to extract the critical features from the EEG signals and to detect sleep spindles and k-complexes have been employed: fractal dimensions coupled with time-frequency images, fractal and frequency features based on DT-CWT, hybrid transform and statistical models, and fractal techniques of time-frequency images coupled with an undirected graph feature. In addition, least square support vector machine (LS-SVM), support vector machine classifier (SVM), k-means, artificial neural network (ANN), Naïve Bayes (NB), k-nearest, decision tree C4.5 and ensemble model are used as tools to classify the extracted features and to perform the classification. More details about those classifiers, which are used as tools to detect sleep spindles and k-complexes, are provided in Chapters 3, 4, 5 and 6. This section gives a brief explanation for each of the classifiers used in this research.

2.3.1.1.1 K-nearest Neighbour Classifier

The k-nearest neighbour (KNN) is a simple supervised classification algorithm which classifies the input data based on a similarity metric such as Euclidian distance. The KNN classifies and assigns each population into the most common class relating to its neighbours (Bablani, Edla & Dodia 2018; Li et al. 2018). The KNN does not require prior learning about the input population as the KNN refers to a lazy learning algorithm. More details are provided in Chapter 3.

2.3.1.1.2 Least Square Support Vector Machine (LS-SVM) Classifier

Because of the popularity of the LS-SVM, it has been widely used to tackle binary classification problems and regression analysis using data analysis and pattern recognition. It has also been used widely in EEG classification research, for example, classification of sleep stages and epileptic seizures, motor image, and alcohol. The quality of LS-SVM predication results depends on how the γ and σ parameters are chosen, as well as the kernel function (Abdel-Hadi et al. 2015; Al-Salman et al. 2018; Al-salman & Li 2019; Li & Wen 2010). The parameters are selected empirically during the training phase. More details are provided in Chapters 3, 4, 5 and 6

2.3.1.1.3 Naïve Bayes Classifier

Naïve Bayes is an efficient and effective technique for classification and it is commonly used in pattern recognition. It operates based on Bayes' theorem and posterior hypothesis. It is an uncomplicated approach, making it useful for high dimensionality data. The main assumption of Naïve Bayes is that the effect of each attribute of a class $\boldsymbol{x}$ on a given class is dependent on the attributes of other classes (Amin et al. 2017; Machado, Balbinot & Schuck 2013).The Naïve Bayes uses two procedures in the training phase to determine the most popular class for each attribute: a maximum probability algorithm and a feature probability distribution. More details are provided in Chapters 4 and 5.

2.3.1.1.4 K-means Classifier

K-means is one of the unsupervised classification methods and is mainly designed to solve clustering problems. It has been widely used to classify data in different fields, such as digital images' classification, time series and biomedical data analysis. The method separates a given population into a number of clusters based on defining $\boldsymbol{k}$ centroids for each cluster. The process is achieved by minimizing the Euclidean distance between an observation and the cluster centroid (Al-salman & Li 2019; Manjusha & Harikumar 2016; Orhan, Hekim & Ozer 2011). Each observation belonging to the given population is associated with the nearest centroid. This step is repeated at each iteration to obtain the first level of clustering, and the new $\boldsymbol{k}$ centroids are

calculated. In this thesis, the k-means classifier is employed to identify sleep spindles and k-complex waves in EEG signals. More details are provided in Chapter 6.

2.3.1.1.5 Decision Tree C4.5 Classifier

Decision tree C4.5 is one of the most popular classification techniques and uses inductive inference tools in pattern recognition. It uses by the splitting criteria (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Rawal & Agarwal 2019; Sharma, Agrawal & Sharma 2013; Wang et al. 2014). It is a flowchart organised as a tree structure that classifies states by sorting them based on the attribute value. A decision tree consists of decision nodes and leaves. Each node in tree C4.5 denotes a feature in an instance to be classified. All branches refer to the test result, and each leaf node holds the label of class. It classifies the instances from the start based on their attribute value and it generates the best rule for the classification of the data set. In this research, the decision tree C4.5 has been used to detect the characteristics of sleep stages in EEG signals. More details regarding C4.5 are provided in chapter 3.

2.3.1.1.6 Artificial Neural network Classifier

Artificial Neural Networks (ANNs) are powerful tools for classification research; with nonlinear structures which are dependent on the function of the human brain. They are commonly used in classification research for processing neurobiological signals extracted by different methods such as EEG and EMG and have been used by many researchers to identify various kinds of brain activities, for example, epileptic seizures and sleep disorders (Al-Salman et al. 2018; Subasi & Ercelebi 2005; Wu, Yang & Sun 2010; Yasmeen & Karki 2017).

The architecture of a typical neural network consists of three layers: an input layer, a hidden layer and the output layer. In this thesis, the ANN has been used to identify sleep spindles in EEG signals. More details regarding the ANN are provided in Chapter 4.

2.3.1.1.7 Ensamble Classafier

In this research an ensemble classifier, which includes various single classifiers, is used to identify the targeted EEG segment based on different

criteria. The final decision of classification is made based on voting. One of the common ensemble approaches for generating diversity aggregation (bagging) was used in this thesis to classify the characteristics of the extracted features into one of the sleep characteristics. The approach was developed by (Breiman 1996). It is one of the most effective machine learning algorithms used to resolve any classification problem by considering the decision of multi-classifiers. Based on the bagging technique, each individual classifier has been trained separately and combined with other classifiers according to an appropriate criteria (Han, Sun & Wang 2015; Raza et al. 2019; Satapathy, Jagadev & Dehuri 2017). More details are provided in Chapter 4.

However, the performance of those classifiers depends greatly on the characteristics of the data to be classified. In addition, there is no single classifier working most effectively on all given problems. A variety of empirical tests have been employed to compare the performance of the classifier to elicit the characteristics of the data that determine a classifier's performance. The confusion matrix and measures of accuracy are commonly used to evaluate the quality of the classification methods. In the last few years, receiver operating characteristic (ROC) curves have also been used to evaluate the performance of classification algorithms based on the trade-off between true- and false-positive rates. This research uses several measures: accuracy, sensitivity, specificity, F-score and Kappa coefficient, to assess the performance of the proposed methods. The confusion matrix and ROC curves are also used to evaluate the performance. More details regarding those classifiers and metrics are provided in Chapter 3, 4, 5 and 6.

2.3.1.2 Structure of the sleep characteristics classification

A classification process includes two phases: the feature extraction phase and the classification phase. The extraction for the most important EEG signals features values is done at the extraction phase. The classification phase requires a classifier to determine the correct class of the EEG signals based on the extracted features. The concept of EEG signals classification as an example of sleep spindles (SS) is provided in Figure 2.17. From this figure, it can be seen that appropriate EEG signal features

were extracted from the SS features space. At the SS features space, the SS features are divided into two classes, the SS and Non-SS.

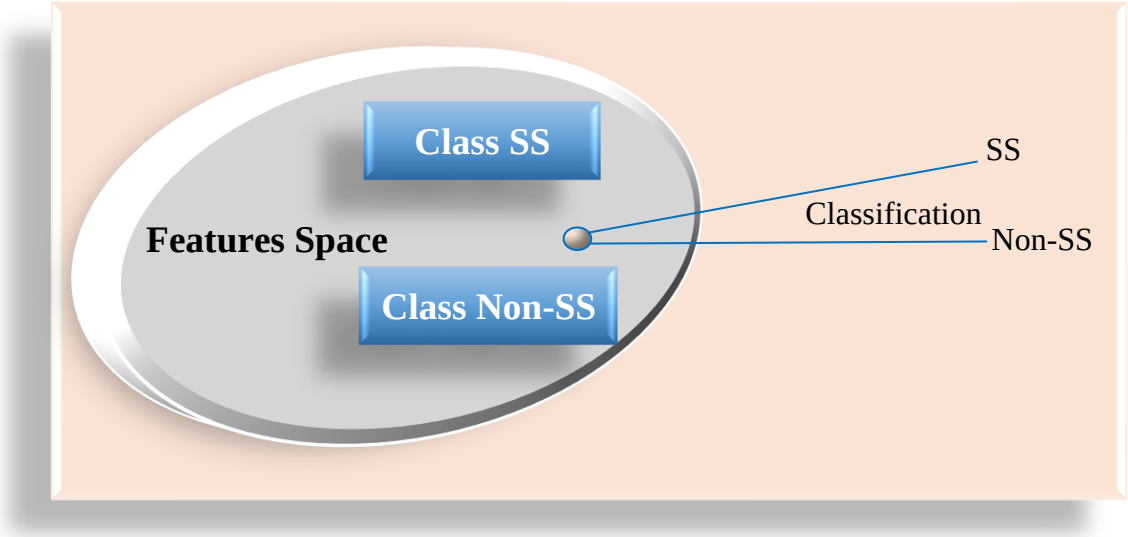


Figure 2.17: An example of the process of the sleep spindles classification in EEGs

In this thesis, four extraction methods: WFA technique, FD of TFI technique, DT-CWT technique and FD of TFI technique coupled with Undirected Graph were utilized to extract the most critical features from EEG signals and were then used to identify sleep spindles and k-complexes. At the same time, different machine learning algorithms, LS-SVM, k-means, artificial neural network, Naïve Bayes, k-nearest, decision tree, and ensemble model were used as tools to perform the classification stage (phase) to detect and train the extracted features.

2.3.2 Commonly used methods for the detection of characteristics

Researchers have developed many methods for the detection of sleep characteristics in EEG signals. These methods fall into a number of different categories: time domain, frequency domain, different transformation techniques, and other methods. In this section, we focused on reviewing sleep spindles and the detection of k-complexes. All those studies were implemented with the same database as was used in the projects of the DREAM sleep spindles Database and Montreal Archive of Sleep Studies (Devuyst et al. 2011; O'Reilly et al. 2014). More details about these databases are provided in Chapters 3, 4, 5 and 6. In previous studies, various methods have been used for the detection of sleep spindles and k-complexes. The detection accuracy of EEG sleep spindles and k-complexes reported in the literature has varied. A range of the maximum accuracy of 75% and 94 % was reported for the datasets.

However, accurate methods are very important in order to extract the discriminative features from EEG signals because these significantly affect the results of detecting sleep spindles and k-complexes. For example, if the extracted features using these proposed methods are not accurate and not relevant to the EEG signals, the correct detection results will be low. A brief summary of the previous research is provided below.

2.3.2.1 Time domain methods used for the detection of the sleep spindles and k-complexes in EEGs

In the time domain, the processing shows how the EEG signal changes with time because time domain features come from a non-stationary property of the EEG signal. Statistical properties of those features change over time, but time domain features assume the input data as a stationary signal (Lei, Wang & Feng 2001; Phinyomark, Phukpattaranont & Limsakul 2012). Hence, a variation of features can be obtained in time domain features when the EEG signals are recorded through dynamic movements. Researchers have developed many methods to detect sleep spindles and k-complexes in relation to a specified period of time using a variety of techniques.

Acır and Güzeliş (2004b) used a combination of artificial neural networks to, firstly, eliminate the segments of non-sleep spindles from an EEG signal and to secondly separate the remaining EEG segments of sleep spindles. These segments were separated by using two classifiers: a radial support vector machine and a backpropagation neural network. A classification sensitivity of 94.6% was reported. Using autoregressive modelling for features extraction in EEG signals, sleep spindles can easily be detected. This method was firstly reported by Görür et al. (2003). The model parameters were obtained using the correlation function of the EEG signal as the second-order characteristics. In their study, the size of the window was set to 0.5s and the classification method was trained using the extracted features. Further, all data sets were divided into six folds to train and test the classifiers. 5 folds out of 6 were used in the training set and the remaining 1 fold for testing. This process was repeated six-times by considering each possible combination. The obtained results were investigated using two classifiers: a multilayer perceptron (MLP); and a support vector machine (SVM). The obtained accuracies were 93.6% and 94.4% for the MLP and the SVM, respectively. Based on the high performances of the proposed method, the

researchers reported that an autoregressive model could be used as a feature extraction method.

In 2000, Huupponen et al proposed a method based on autoassociative multilayer perceptron networks to identify sleep spindles. An EEG signal, from the channel C_4-A_1, was segmented using a window size of 1.0s. The receiver operating characteristic curve (ROC) curve was used in that study to evaluate the proposed method. Average sensitivity of 75% was reported.

In the last few decades, various detection methods have been used to identify sleep spindles in EEGs using different classifiers; for example, using artificial neural networks, support vector machines, radial basis support vector machine, Bayesian classification and decision trees (Acır & Güzeliş 2004b; Babadi et al. 2011; Boser, Guyon & Vapnik 1992; Duman et al. 2009; Güneş et al. 2011; Kabir et al. 2015; Shimada, Shiina & Saito 2000; Wendt et al. 2012). The results they obtained were no higher than those in this thesis. More details regarding sleep spindles detection methods were provided in Chapters 3 and 4.

Regarding the k-complexes detection methods, time domain features were also used to detect k-complexes in EEG signals. Bankman et al. (1992) presented a method based on artificial neural networks. In that study, 14 features were extracted from each row of EEG signals to detect k-complexes. Then, each row of EEG recordings was used as input to the artificial neural networks classifier. In that work, the k-complexes detection was achieved in two stages: training stage and testing stage. The same pre-processing and extraction techniques were applied for both phases. In the training stage, 200 segments of EEG k-complexes and non-k-complexes were used, while in the testing stage, 51 k-complexes segments and 49 non- k-complexes were also utilized to test the classification method. To enable more accurate evaluation of the proposed method, the extracted features were also classified using a linear discriminant classifier. The six cross-validations were also applied in that study. An average sensitivity of 90% was obtained with an 8% false-positive rate. Based on the study, using the extracted features provided a significantly better performance than using the original EEG data.

Another study was presented by Zamir et al. (2014), in which the features extraction and optimization-based procedure model, based on solving a sequence of the linear least square problem, was used to detect k-complexes in EEG signals. The

performance of the proposed method was evaluated on the basis of one expert scoring. In their study, 12 different classifiers were used to evaluate the performance of the proposed method. All these classifiers were used with their default sets of parameters. They reported that the most accurate classifier was a logistic model tree. An average accuracy of 74% was obtained with that classifier. Sherif et al. (1977) utilized a mathematical description of the k-complexes morphology to apply a matched filter. Average sensitivity and specificity rates of 85, 44% and 52, 43% respectively were recorded.

In 2009, Gala et al suggested a method to identify k-complexes using a clustering approach and a neural network classifier. In their study, two features: average amplitude, and frequency, were extracted from each 30s EEG signal and then used as inputs to a neural network classifier to detect k-complexes and non k-complexes EEG segments.

Several methods have been employed for the detection of k-complexes in EEG signals. These include artificial neural networks (Güneş et al. 2011; Jansen 1990; Strungaru & Popescu 1998), methodology frameworks (Jobert et al. 1992; Koley & Dey 2012), fuzzy recognition (Pohl & Fahr 1995), knowledge based systems (Jansen & Desai 1994), morphological component analysis (Lajnef et al. 2015), non- smooth optimization and classification methods (Moloney et al. 2011) and fuzzy artificial neural networks (Ranjan et al. 2018). Features extraction methods based on the detection approach using artificial neural networks (Bankman et al. 1992) and a hybrid-synergic coupled machine learning approach (Vu et al. 2012) have been studied to discriminate k-complexes segments and non k-complexes segments in EEG signals. Features extraction methods based on amplitude and duration measurements have also been employed in recent studies (Hernández-Pereira et al. 2016) to identify k-complexes from non-k-complexes segments. In that study, five classifiers were used to classify the extracted features from a row of EEG signals into the k-complexes segment and non-k-complexes segment. Among all the classifiers tested, the support vector machine obtained the best results with an accuracy of 88.69%. The classification performance was significantly improved at 36% when the correlation-based feature selection (CFS) algorithm was used.

2.3.2.2 Methods used for detection of sleep spindles and k-complexes based on different transformation techniques

Transformation techniques, such as discrete wavelet transform (DWT), Fourier transform (FF), short time Fourier transform (STFT), Teager energy operator (TEO), and wavelet packet decomposition (WPD), were applied to categorize EEG frequencies in a specific range by which the sleep spindles or k-complexes were detected (Akin & Akgul 1998; Camilleri, Camilleri & Fabri 2014; Imtiaz & Rodriguez-Villegas 2014; Krohne et al. 2014; Lajnef et al. 2015; Patti, Chaparro-Vargas & Cvetkovic 2014; Tang & Ishii 1995) . The process using those techniques demonstrates that the number of the EEG signals fall within frequency bands through a number of frequencies. Thus, these techniques are normally used to analyse EEG signals with regard to the frequency and the bands. In this section, we will show a variety of methods which have been used in order to identify sleep spindles and k-complexes using different transformation approaches.

Duman et al. (2009) proposed a short time Fourier transform (STFT), multiple signal classification and Teager Energy Operator (TEO) to identify sleep spindles. An EEG signal, from channel C3-A2, was segmented using a window size of 2.0s. In their study, wavelet transform was firstly used and then applied using the STFT on a 2s window to detect sleep spindles. Subsequently, a TEO was used to measure the duration of the sleep spindle. An average sensitivity and specificity of 93% and 88% were reported, respectively.

The STFT was also used with different classifiers such as a support vector machine, a multilayer perception, a supervised approach such as clustering technique and a k-means to recognize the segments of sleep spindles from non-sleep spindles segments. In their study, the maximum classification accuracy was 92.4% (Causa et al. 2010; Costa et al. 2012; Da Costa, Ortigueira & Batista 2013; Duman et al. 2005; Estévez et al. 2007; Gorur et al. 2002; Patti, Chaparro-Vargas & Cvetkovic 2014; Ventouras et al. 2005).

Using a wavelet packet transform and TEO for features extraction in EEG signals, sleep spindles can easily be detected. This method was firstly reported by Ahmed, Redissi and Tafreshi (2009). In that study, a window of 1.28s without overlapping was considered. The TEO was used to improve periodic activity in segments of the EEG containing spindles, while the wavelet packet transform was applied to determine the

location of sleep spindles accurately in the time-frequency domain. They reported an accuracy of 93.7%.

There are several types of wavelet transform approaches, including wavelet transform; discrete wavelet transform; wavelet packet decomposition; short time Fourier transform and continuous wavelet transform, combined with different classification algorithms such as neural networks, and support vector machines. These approaches have been applied to determine the sleep spindles from EEG recordings (Acır & Güzeliş 2004b, 2004a; Akin & Akgul 1998; Bódizs et al. 2009; Da Costa, Ortigueira & Batista 2013; Durka & Blinowska 1996; Durka, Ircha & Blinowska 2001; Estévez et al. 2007; Gorur et al. 2002; Hekmatmanesh, Noori & Mikaili 2014; Huupponen et al. 2000; Lajnef et al. 2015; Parekh et al. 2015; Saifutdinova et al. 2015; Tsanas & Clifford 2015; Yücelbas et al. 2016).

In relation to the k-complexes detection approaches, various efforts to automatically identify k-complexes have been reported in the literature (chapters 5 and 6). Some of the literature dealt with k-complexes detection (Bremer, Smith & Karacan 1970; Devuyst et al. 2010; Erdamar, Duman & Yetkin 2012; Henry, Sauter & Caspary 1994; Jansen & Desai 1994; Kam et al. 2004; Parekh et al. 2015; Pohl & Fahr 1995; Strungaru & Popescu 1998; Tang & Ishii 1995) using the recording for the whole night whilst others dealt with the classification issue (Al-salman & Li 2019; Bankman & Gath 1987; Bankman et al. 1992; Hernández-Pereira et al. 2016; Jansen et al. 1989; Jansen 1990; Noori et al. 2014; Richard & Lengelle 1998; Shete et al. 2012; Vu et al. 2012; Zacharaki et al. 2013; Zamir et al. 2014) utilizing EEG segments of a steady length. Those methods are normally applied to analyse EEG signals in both time and frequency domains at the same time. The important analysis approaches in frequency domain, such as discrete wavelet, are wavelet transforms.

Using the discrete wavelet transform (DWT) parameters to identify k-complexes in human EEGs, k-complexes can easily be classified. This method was firstly proposed by Tang and Ishii (1995).The DWT parameters were used to determine the time duration and amplitude of k-complexes. In that study, the 4th order B-spline wavelet function basis was used, as it was shown to provide a better predication. A different set of features was extracted and then used as input to the principle of the minimum distance classification to identify k-complexes in EEG signals. That classifier was designed and used in that study in order to decide the thresholds of recognition criteria.

In their study, they attained 87% sensitivity and 10% false positive rate. More recently, Lajnef et al. (2015) used a tunable Q-factor wavelet transform for the detection of k-complexes. In their study, k-complexes were detected based on a threshold in two stages: the transient component to identify k-complexes and time-frequency representation. The EEG database was collected from 14 subjects. The performance of the proposed method was evaluated using ROC curves. It was reported that the proposed method could be a valuable alternative to manual k-complex detection methods. An average sensitivity and false positive rate of 81.57% and 29.54% respectively were reported.

Yücelbaş et al. (2018b) used a method to detect k-complexes automatically based on time and frequency analyses. In their study, an EEG signal was decomposed using a discrete wavelet transformation. In that study, db2 and db4 wavelet functions were used, which are the most similar to k-complexes, and EEG recordings from the C_4-A_1 and C_3-A_2 channels were also used. The obtained results of the proposed method were compared with singular value variational model decomposition to determine the location of k-complexes in EEGs. An average accuracy rate of 92.29% was achieved.

Parekh et al. (2015) detected the k-complexes based on a fast non-linear optimization algorithm as a model. That model consisted of a transient, low frequency, and oscillatory component. The first one captured the non-oscillatory transient waveform (k-complexes) in the EEG signals, while the function of the oscillatory component was to admit a sparse time-frequency representation. In that study, only the F-score result was reported. An average F-score of 0.57% for the detection of the k-complexes was achieved.

Cătălin et al. (2018) proposed a STFT, and continuous wavelet transform (CWT) to identify k-complexes from EEG signals. They reported that evaluating the results of algorithms reveals that false k-complex detection is as important as real k-complex detection.

However, since some of those techniques such as Fourier methods, discrete wavelet transformation, and wavelet transform may not be appropriate for non-stationary signals, or signals with short-lived components, alternative approaches have been sought (Siuly & Li 2012; Suily 2012). Furthermore, it must be noted that although a variety of methods have been used, only one or two measures have been employed to evaluate the performance of the proposed methods. This research uses a number of

measures: accuracy, sensitivity, specificity, F-score and Kapps coefficient to assess the performance of the proposed methods. The confusion matrix and ROC curves are also used to evaluate the performance. More details regarding detection methods of sleep spindles and k-complexes were provided in Chapters 3, 4, 5 and 6.

2.3.2.3 Other methods to detect sleep spindles and k-complexes in EEG signals

The EEG signals are non-stationary in nature, and can be processed in an efficient way by using a combination of algorithms or nonlinear methods (Al Ghayab et al. 2018; Bajaj et al. 2017). A variety of useful techniques have been used to detect sleep spindles and k-complexes, such as a combination of time domain features and frequency domain features (Al-Salman, Wessam, Li, Yan & Wen, Peng 2019; Al-Salman et al. 2018; Güneş et al. 2011).

In 2011, Güneş et al. made an attempt to recognize sleep spindles in the time and frequency domains. In their research, a six-time domain, 65 frequency domain and 10 time and frequency domain features were extracted from an EEG signal. The time-domain features were extracted from each raw EEG, while frequency-domain features were extracted after applying welch spectral analysis. Then, statistical measures were applied and used to reduce the number of features from 65 to 4. Finally, three types of features set: 6 time domain, 4 frequency domain, and 10 both time and frequency domain features were used as inputs to the artificial neural network with Levenberg–Marquardt to classify sleep spindles. The obtained results of the proposed method were evaluated by physicians who were sleep experts. They reported that the proposed algorithm could confidently be used to automatically detect sleep spindles in EEGs. An average accuracy of 93.84% was achieved.

Nonclercq et al. (2013) examined sleep spindles using amplitude-frequency analysis. Filtered EEG signals were segmented into small epochs, with a window size of 0.5 s and an overlap of 0.25s. Then a statistical model was utilized to obtain a vector of features. The most significant features were selected after applying a principal component analysis and a sequential features selection technique. The selected features were then fed to a classifier. The proposed recognition system was assessed against the scoring of two sleep scoring experts using information obtained from seven healthy child and six adult patients, respectively, suffering from different pathologies.

An average specificity and sensitivity of 94% and 78.5% were reported, but the authors did not report results for accuracy

Liang et al. (2012) developed an adaptive neuro-fuzzy inference system (ANFIS) for sleep spindle detection. In that study, a window size of 0.5s was employed. Two features were extracted: sigma index and energy of sigma. Those features were used as input to the fuzzy interface system to identify sleep spindles. Average sensitivity and specificity of the ANFIS were 94.09% and 96.76%, respectively. A method has been presented to permit the power of bumps of EEG to be used in automated detection of sleep spindles (Najafi et al. 2011). In 2012, Babadi et al. proposed a method based on a data-driven Bayesian algorithm for sleep spindles detection on the EEG.

Using a band-pass filter for features extraction in EEG signals, sleep spindles can be easily detected. This method was first reported by Schimicek et al. (1994). In that study, the pass filter of 11.5-16Hz with peak-to-peak amplitude of 25 μV as a fixed amplitude threshold were used to identify sleep spindles. Later algorithms proposed a novel deep learning strategy based on a single EEG channel to identify sleep spindles from EEG signals (Kulkarni et al. 2019). The other approach detected sleep spindles based on the shape of the waveform. This approach considered that the shape of sleep spindles was an application consisting of two thresholds. The higher threshold was used to localize activity bursts in sigma frequency, while the lower one was utilized to estimate the duration of sleep spindles (Ferrarelli et al. 2007).

Recently, many researchers have detected sleep spindles based on a Matching Pursuit (MP) and filtering technique. Żygierewicz et al. (1999) presented an MP method to detect sleep spindles. The maximum sensitivity reported in that study was 90%. Schönwald et al. (2006) also employed the MP method to detect sleep spindles based on the amplitude, frequency, and duration characteristics of the signals. An average sensitivity and specificity of 80.6% and 81.2% respectively were achieved. Durka and Blinowska (1996) utilized a set of parameters which were extracted by the MP method to detect sleep spindles. In that study the sleep spindles in EEG signals were detected according to the changes in the extracted parameters, position, frequency, width, amplitude and phase. An average sensitivity of 82% was reported.

A variety of methods, such as pre-processing, threshold, band pass filtering and amplitude thresholding, and Tunable Q-factor wavelet transform (TQWT) combined with morphology component analysis and artificial intelligence, have been proposed

to identify sleep spindles in EEG signals. These methods were used to extract the desired features from EEG signals and then classify these features into sleep spindles and non-sleep spindles segments using different classifiers (unsupervised or supervised techniques), for example, artificial neural networks, likelihood, decision tree and support vector machines (Bódizs et al. 2009; Duman et al. 2009; Duman et al. 2005; Ferrarelli et al. 2007; Gais et al. 2002; Gorur et al. 2002; Held et al. 2004; Huupponen et al. 2006; Huupponen et al. 2007; Martin et al. 2013; Norman et al. 1992; Parekh et al. 2014; Schimicek et al. 1994; Selesnick 2011a, 2011b). More details regarding methods of detecting sleep spindles were reported in Chapters 3 and 4.

Regarding the k-complexes detection methods, Camilleri et al. (2104) suggested switching multiple models to detect k-complexes in EEG signals. The advantage of this approach is that it offers a unified framework for detecting multiple transient events within background EEG data. They obtained 74.75% sensitivity. An earlier study was presented by Henry, Sauter and Caspary (1994), in which the k-complexes were classified based on matched filtering. Each segment was decomposed into a set of orthonormal functions and wavelets analysis. In that study, different criteria: miss detection, false alarm rate, and robustness were used and applied to evaluate the proposed method. They reported that the proposed method was unable to distinguish events in which the patterns were very close.

In order to identify k-complexes in EEG recordings, Hernández-Pereira et al. (2016) presented a comparative study over the k-complex classification task based on 14 features extracted from each EEG signal. Those features were based on amplitude and duration measurements obtained from EEGs to be classified. The performance of the proposed approach has been evaluated using the receiver operating characteristic (ROC) curve. The researchers employed five popular classifiers to evaluate the proposed method. Their methodology had a 91.40% accuracy rate.

A variety of reliable methods have been proposed to identify k-complexes in EEG signals (Bankman et al. 1992; Berry et al. 2012; Camilleri, Camilleri & Fabri 2014; Devuyst et al. 2010; Erdamar, Duman & Yetkin 2012; Hernández-Pereira et al. 2016; Jaleel et al. 2013; Jobert et al. 1992; Kam et al. 2004; Koley & Dey 2012; Moloney et al. 2011; Parekh et al. 2015; Richard & Lengelle 1998). They proposed the threshold technique, non-smooth optimization, switching multiple models, Fuzzy threshold, join time and time frequency domain, methodological framework, and matched filtering

combined with different classifiers to detect the morphology of k-complexes. They reported that it was very difficult to obtain satisfactory performance results because there was a wide diversity in EEG and k-complexes appearances among subjects. More details regarding k-complexes detection methods were presented in chapters 5 and 6.

In summary, from the literature, it is be observed that there are numerous signal processing techniques used for the feature extraction and detection stages, but there are limitations. The drawbacks of these methods, for example, are that they do not produce sufficient accuracy for the detection of sleep spindles and k-complexes in EEG signals and do not work well when the data size is very large. In addition, all the methods above have used only a part of the database in their study. Furthermore, these methods may require a long time to gain results because no execution time was mentioned in all previous studies. Moreover, many sleep studies were conducted with one window size and they were tested on a single-channel EEG signal. In addition, the current studies were used to detect and analyse a specific characteristic of sleep such as sleep spindles or k-complexes in EEG signals using one database.The average of accuracy for detection of sleep spindles and k-complexes was between 68%-92%. To overcome these limitations this research aims to introduce novel methods for the detection of the sleep spindles and k-complexes in EEG signals.

2.4 Summary of chapter

This chapter provides an overview of the detection of sleep stages characteristics in EEG signals and also provides necessary background knowledge related to the sleep characteristics: sleep spindles and k-complexes. Firstly, this chapter presents an outline of the concept and structure of the human brain and its functions, an overview of EEG signals, the fundamentals of sleep stages, sleep characteristics: sleep spindles and k-complexes that appear during sleep stages and how they affect sleep disorders of the human brain. The classification concept is also discussed in this chapter.

Following this overview, this chapter discusses the detection of sleep spindles and k-complexes in EEG signals and also reviews which methods were utilized for the detection of sleep spindles and k-complexes in the previous study. Based on previous studies in the literature, it seems that there are limitations associated with the existing methods that are used to detect sleep spindles and k-complexes. Hence, the development of new detection algorithms is needed for a reliable diagnosis of

neurological diseases, such as sleep disorders. In the next chapter, a new method based on wavelet Fourier analysis and statistical features coupled with a least square support vector machine (LS-SVM) classifier is introduced to detect sleep spindles in EEG signals. This proposed method is also tested and investigated to identify sleep spindles in EEG signals with two different EEG recordings (databases) acquired from different channels.

CHAPTER 3

DETECTING SLEEP SPINDLES IN EEGS USING WAVELET FOURIER ANALYSIS AND STATISTICAL FEATURES

3.1 Introduction

Sleep stages scoring is an important process in sleep research as EEG recordings play an essential part in the diagnosis of sleep disorders such as apnea and insomnia, so any errors in the scoring of the patient's EEG recordings can lead to critical problems. Developing a new technique to classify and analyse EEG signals is, therefore, a significant factor in the field of biomedical research. One of the most important bio-signal waveforms in sleep stage EEG signals is sleep spindles. To relieve some of the burdens of visual scoring such as cost and human error, various techniques have been developed to detect sleep spindles more effectively.

The content of this chapter is an exact copy of a published article in the *biomedical signals processing and control journal* by AL-Salman et al. (2019). It explains a new method based on wavelet Fourier analysis with statistical features to detect sleep spindles in EEG signals. In the proposed method, sleep spindle detection is achieved in two phases: a training phase and a testing phase. This study aims to establish a method to determine an optimal classification method to extract features by using a combination of discrete wavelet transform and fast Fourier transform. This chapter focuses on three main points: segmentation techniques, extracted features and detection results. Firstly, an EEG signal was divided into segments using a sliding

window technique. The size of the window is 0.5 s, with an overlap of 0.4 s. Secondly, a wavelet Fourier analysis (WFA) technique is used to extract features from each EEG segment. Then, Kruskal-Wallis nonparametric one-way analysis variance is applied to select the important features and to reduce the dimensionality of the data, representing each of the 0.5 s EEG segments. Finally, the extracted features are forwarded to four classifiers to detect the sleep spindles: K-nearest neighbours, a least-squares support vector machine (LS-SVM), a K-means algorithm and a C4.5 decision tree. The experimental results demonstrated that the proposed feature extraction algorithm with the LS-SVM classifier produces the best performance, when compared to the other three classifiers.The results were also compared with other existing methods, based on some performance evaluation measures, and an evaluation showed that the proposed method is better than the other methods examined. It also yielded a high detection rate compared with the state-of the art approaches using the same database. The proposed method has been tested on two different EEG databases: DREAMS datasets and Montreal Archive Sleep Studies.

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Detecting sleep spindles in EEGs using wavelet fourier analysis and statistical features

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ABSTRACT

One of the more difficult tasks in sleep stage scoring is the detection of sleep spindles. Developing an effective method to identify these transitions in sleep electroencephalogram (EEG) recordings is an ongoing challenge, as there are typically hundreds of such transitions in each recording. This paper proposes a statistical model and a method based on wavelet Fourier analysis to detect sleep spindles. In this work, spindle detection is achieved in two phases: a training phase and a testing phase. An EEG signal is first divided into segments, using a sliding window technique. The size of the window is 0.5 s, with an overlap of 0.4 s. Then, each EEG segment is decomposed using a discrete wavelet transform into different levels of decompositions. The wavelet detail coefficient at level 3 (D3) is selected from these parameters, and this is passed through a fast Fourier transform to identify the desired frequency bands $\{\alpha, \beta, \theta, \delta, \gamma\}$. Ten statistical characteristics are extracted from each band. Nonparametric Kruskal-Wallis one-way analysis of variance is used to select the important features, representing each of the 0.5 s EEG segments. To detect all possible occurrences of sleep spindles in the original EEG signals, four different window sizes of 0.25, 1.0, 1.5 and 2.0 s are also tested. Finally, the extracted features are used as the input to four classifiers to detect the sleep spindles: a least-squares support vector machine (LS-SVM), K-nearest neighbours, a K-means algorithm and a C4.5 decision tree. The obtained results demonstrate that the proposed method yields optimal results with a window size of 0.5 s. The maximum averages of accuracy, sensitivity and specificity are 97.9%, 98.5% and 97.8%, respectively. This method can efficiently detect spindles in EEG signals, and can assist sleep experts in analysing EEG signals.

1. Introduction

Sleep spindles are one type of transient waveforms in non-rapid eye movement (NREM) sleep, often encountered in stage 2 sleep (stage 2). They can be used to identify stage 2 NREM through changes in their amplitudes. Their duration is typically between 0.5 and 2.0 s [14,25,7,1,4]. According to the Rechtschafen and Kales (R&K) criteria, the frequency range of sleep spindles is between 12 Hz and 14 Hz. This interval was extended to 11 Hz to 16 Hz after the American Academy of Sleep Medicine (AASM) released a new version of their sleep scoring guidelines in 2002 [37,16,15,43,23]. Fig. 1 shows an example of sleep spindles in multi-channel EEG signals, taken from [15]. The CZ-A1 channel shows a sleep spindle occurring at 23 s and another at 26 s with a different amplitude.

The detection of sleep spindles is one of the critical tasks in the recognition of stage 2 sleep, as their characteristics mean they require a great deal of effort to identify visually. Manual inspection is subjective and time-consuming, since there are typically hundreds of spindles in each EEG recording. Consequently, automatic approaches for spindle detection have been developed [2,8,18,32,34]. Most of the existing automatic methods were designed to detect both sleep spindles and K-complexes simultaneously, but are generally used to detect only one of these. Some sleep spindle detection methods have been developed based on the analysis of EEG signals using a discrete wavelet transform or fast Fourier transform [2]. These transformation techniques are applied to categorize the frequencies of EEGs within a specific range, thus allowing sleep spindles and K-complexes to be detected [7]. Gorur et al. [21] utilized a short-time Fourier transform to decompose EEG signals. In their study, two different classifiers were employed:

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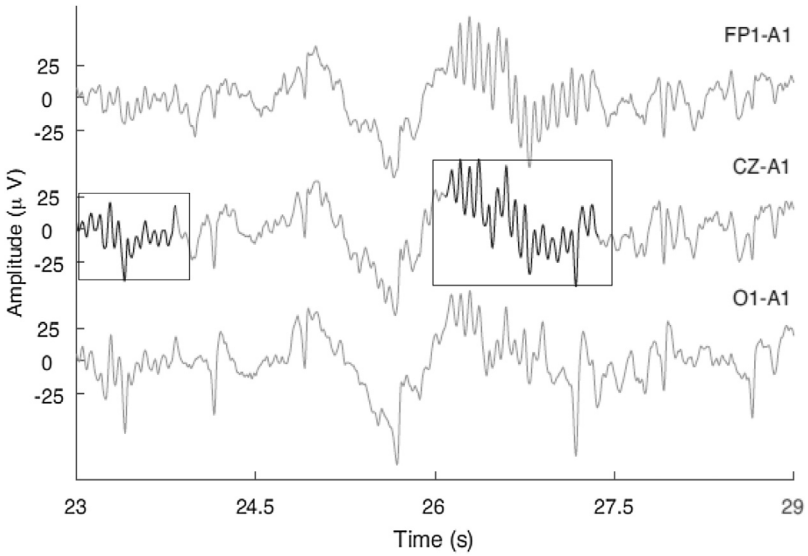

Fig. 1. An example of sleep spindles from the DREAMS database: 6 s of EEG recording containing two spindles [15].

a support vector machine and a multilayer perceptron; classification accuracies of 95.4% and 88.7% were achieved using these two classifiers. Ahmed et al. [1] detected sleep spindles by applying a wavelet packet transform and the Teager energy operator. They reported an accuracy of 93.7%. Patti et al. [35] also employed a short-time Fourier transform with an adaptive window size to extract four features: sigma power, sigma index, sigma index 2 and sigma power 2. A supervised approach was used to cluster the extracted characteristics.

Yucelbas et al. [45] used a fast Fourier transform, autoregressive multiple signal classification and a Welch filter to identify sleep spindles. The detection phase was carried out by a neural network classifier. Duman et al. [18] proposed a short-time Fourier transform, multiple signal classification and a Teager energy operator to identify sleep spindles. Güneş et al. [22] made an attempt to recognize sleep spindles in the time and frequency domains. In their research, six time-domain and 65 frequency-domain features were extracted from an EEG signal. Nonclercq et al. [30] examined sleep spindles using time features. The filtered EEG signals were segmented into small epochs, and a set of statistical characteristics were then extracted to form a vector of features. The most significant features were selected after applying principal component analysis and a sequential features selection technique. The selected features were then fed to a classifier.

Wavelet Fourier analysis were used to improve the performance of glaucoma classification [47], and were also employed in speech recognition [49,27,40], proving that a combination of wavelet and Fourier transforms is an effective approach to extract the desired frequencies from a signal. In this paper we use the hybrid wavelet Fourier analysis to extract key features from EEG data for detecting sleep spindles, which is innovative and efficient as sleep characteristics in EEG signals are conditionally detected based on either wavelet or Fourier transform.

In the study, a single-channel EEG signal is firstly divided into small segments using a sliding window technique, and the length of the window is determined empirically. Each EEG segment is passed through a wavelet transform. After decomposing each EEG segment into different frequency levels, the level 3 (D3) detail is selected, since it yields better results than others. A fast Fourier transform is applied to D3, and a set of 10 statistical features are extracted. An LS-SVM is used to differentiate the EEG segments into spindles and non-spindles. To determine the best window size, various window sizes of 0.25 s (s), 0.5 s, 1.0 s, 1.5 s and 2.0 s were tested, and it was found that a length of 0.5 s was more efficient than other window sizes. The extracted features were also forwarded to a C4.5 decision tree, and K-means and K-nearest neighbour classifiers. The results show that the proposed method combined with the LS-SVM gives better results than those obtained by the other classifiers. Comparisons are also made with previous research studies, and the results show that the proposed method outperforms the other techniques.

The rest of this paper is organised as follows: Section 2 describes the EEG datasets used. In Section 3, the main steps of the proposed method are explained. Section 4 discusses the simulation phase and reports the results. Section 5 presents the conclusions of this study.

2. EEG data and pre-processing

In this study, two publicly available databases are used for the proposed method to identify sleep spindles in EEG signals. The two databases are the DREAMS datasets (Devusty, 2011) [15] and Montreal Archive Sleep Studies (MASS) (O'Reilly et al., (2014) [42]. The following section briefly explains the details of the datasets.

2.1. The dream sleep spindles database

The sleep database includes eight recordings from different participants, recorded at the Circuit Theory and Signal Processing Lab at the University of Mons-TCTS Laboratory [15]. The eight subjects had various pathologies (dysomnia, restless legs syndrome, insomnia, apnoea/hypopnoea syndrome), and were aged between 31 and 53 years. Three EEG channels of CZ-A1 or C3-A1, FP1-A1 and O1-A1, two channels of electrooculography (EOG) data of P8-A1 and P18-A1 and one channel of electromyography (EMG) were recorded from each subject. The data were sampled at frequencies of 200 Hz, 100 Hz and 50 Hz. Sleep EEG data of 30 min durations were scored and all sleep spindles were detected manually by two experts, and the starting and ending times were also marked. All recordings were scored according to the R&K criteria. The first expert scored all eight recordings, while the second expert annotated six of the eight. Thus the automated detection results in this paper were compared with the detection of only the first expert.

In this study, EEG recordings from the CZ-A1 channel were used, sampled at 200 Hz. Table 1 illustrates the number of sleep spindles for each subject, the maximum and minimum duration of the sleep spindles, and the number of epochs with and without spindles. The database, along with additional information, is

Table 1
Number of sleep spindles in each EEG recording.

Subject ID.	Number of segments with sleep spindles	Number of segments without sleep spindles	Maximum spindle duration (s)	Minimum spindle duration (s)
1	52	3547	1.6700	0.5000
2	60	3599	1.4600	0.4900
3	5	1795	1.4600	0.6100
4	44	1799	1.8000	0.3900
5	56	1219	1.2800	0.5000
6	72	2342	1.3000	0.5000
7	18	1869	1.2200	0.5000
8	48	4589	1.8900	0.5400

Table 2
The number of sleep spindles in each EEG recording.

Subject ID.	Number of segments with sleep spindles	Number of segments without sleep spindles	Minimum spindle duration (s)	Maximum spindle duration (s)
1	708	30320	0.5 s	1.6s
2	1141	32360	0.5 s	1.2s
3	1156	28640	0.5 s	1.2s
4	810	27600	0.5 s	1.0 s
5	1040	18958	0.5 s	1.3s
6	905	20280	0.5 s	1.1s

publicly available online at: http://www.tcts.fpms.ac.be/~devuyst/Databases/DatabaseSpindles/

2.2. Montreal archive of sleep studies database

The database was recorded from 19 subjects: 8 males and 11 females. The subjects aged between 30–55 years. The EEG signals were recorded in a 20 min intervals during one night. The EEG signals were sampled at 256 Hz. Each EEG recording included 19 EEG channels, four channels of EOGs, one channel of EMG and one channels of ECG channels. In this database the visual scoring of sleep spindles was carried out also by two experts. The first expert annotated 19 recordings, including sleep spindles according to the AASM rules, while the second only annotated 15 out of 19 recordings. In this study, the EEG scoring from different subjects were chosen randomly, and EEG recordings from the C3 channel were used, all sampled at 256 Hz. The datasets can be accessed through https://massdb.herokuapp.com/en/. Table 2 shows the sleep spindles for each subject, their maximum and minimum duration of the sleep spindles used in this research. The experiments were conducted using Matlab software (Version: R2015) on a computer with the following settings: 3.40 GHz Intel(R) core(TM) i7 CPU processor machine, and 8 GB RAM.

3. Methodology

Spindle detection is achieved using two phases: training and testing. The EEG signals are divided into segments using a sliding window technique, and the size of the window was set to 0.5 s after an extensive simulation. Each EEG segment is passed through a wavelet Fourier transform to identify the desired frequency bands $\{\alpha, \beta, \theta, \delta, \gamma\}$. Ten statistical characteristics are extracted from each band, and 50 features are selected to represent each of the EEG segments. The extracted features are used as input for four classifiers: LS-SVM, K-nearest neighbour, K-means and the C4.5 decision tree. For further analysis, windows of 0.25, 1.0, 1.5 and 2.0 s were also tested, and our findings showed that the 0.5 s window gave better results than the others. Fig. 2 illustrates the process used in the proposed method. The wavelet and Fourier transform functions in Matlab 2015b were utilized in this implementation.

3.1. EEG signals stratification

Sleep spindles in EEG data mainly occur during sleep stage 2 from 10 Hz to 15 Hz. They can be recognized according to their low amplitude and high frequency. Sleep experts have observed that sleep spindles normally appear in EEG signals for 0.5 s to 2.0 s. A sliding window technique was utilized by Li et al [29] for the classification of EEG signals. It was also utilized by Al-Salman et al [4] and Zhuang et al [48] to detect sleep spindles in EEG signals. Their results showed that applying a sliding window technique helped to improve satisfactory classification results. In this study, a whole EEG signal is divided into segments using the sliding window technique. The window size used is 0.5 s with an overlapping of 0.4 s. Fig. 3 shows an EEG signal being partitioned into overlapping segments.

3.2. Wavelet fourier analysis (WFA)

A discrete wavelet transform (DWT) and fast Fourier transform (FFT) are commonly used to transform a signal into the frequency domain. FFT is applied to obtain the spectral information of signals, while DWT is used to analyse the waveforms of signals. The literature suggests that combining DWT with FFT could be a robust and efficient way to extract important frequency information from non-stationary signals [40,47]. Tarasiuk et al. [40] showed that by applying FFT to the wavelet coefficients, the most important frequency information of the signals were obtained with a few required multiplications. After testing different wavelet functions, the Daubechies wavelet function of order six (db6) was used in this study, as it was shown to provide better predication [13].

Suppose a signal, x, can be decomposed into different frequencies using a DWT, which is defined as follows [11,17,31,29]:

$$D_{\psi}(a, b) = \frac{1}{\sqrt{a}} \int_{-\infty}^{\infty} x(t)\,\psi\left(\frac{t-b}{a}\right) dt \tag{1}$$

where a is a scale parameter and b is a translation parameter, $D_{\psi}(a, b)$ denotes the discrete wavelet coefficients and ψ is the wavelet function.

To decompose the signal x, a series of low-pass filters (LPF) and high-pass filters (HPF) must be used. The HPF and LPF are used with scaling and wavelet functions, which are defined as:

$$\emptyset_{a,b}(x) = 2^{a/2}\, h(2^{a} x - b) \tag{2}$$

$$\Psi_{a,b}(x) = 2^{a/2}\, g(2^{a} x - b) \tag{3}$$

where $\emptyset_{a,b}(x)$ is a scaling function based on a low-pass filter, and $\Psi_{a,b}(x)$ is a wavelet function based on a high-pass filter.

The EEG signals have a non-stationary nature. Processing EEG signals by passing them through filtering techniques helps to reveal hidden patterns in signals. As sleep spindles have unique frequency patterns that cannot be detected without filtering EEG signals, we use these filters to process the signals.

The decomposition procedure starts by passing a signal through the filters. The detail (D1) and the approximation (A1) were obtained from the first level of the decomposition through which EEG signals passed through the high pass and low pass filters. For further decomposition, the same process can be performed for A1. This process is repeated to obtain the desired output.

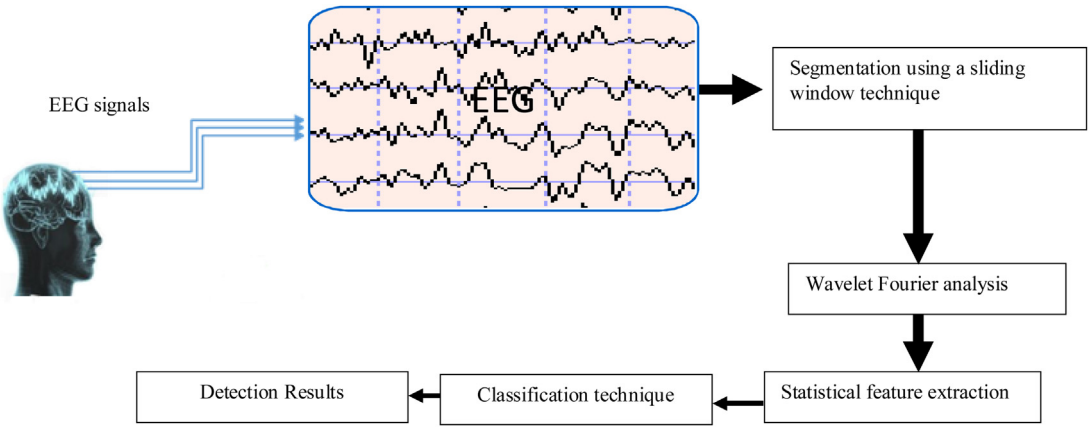

Fig. 2. Block diagram for sleep spindles detection methodology.

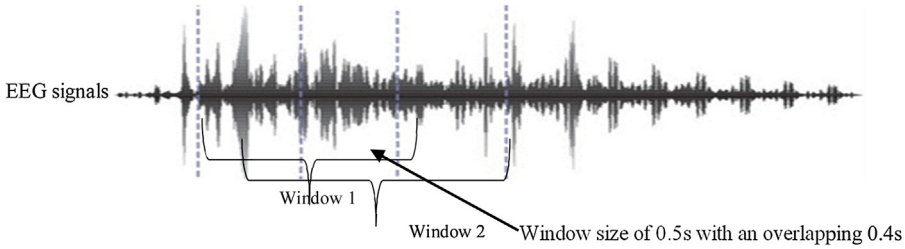

Fig. 3. An example of segmenting an EEG signal into windows.

To obtain the desired frequencies, FFT is applied separately to each level of the wavelet detail coefficients, D1–D5. FFT is defined as:

$$X\left(e^{jw}\right) = \sum_{n=-\infty}^{\infty} x(n)e^{-jwn} \tag{4}$$

where the time index n is discrete, and w is the normalized angular frequency. The transform pair of the DFT is defined as:

$$X(k) = \sum_{n=0}^{N-1} x(n)W_N^{nk} \longleftarrow x(n) = \frac{1}{N}\sum_{k=0}^{N-1} X(k)\,W_n^{-nk} \tag{5}$$

After the application of FFT, the EEG signals are normally defined as the congregation of five basic frequency bands: alpha (α), beta (β), gamma (γ), delta (δ) and theta (θ). They are distinguished by their different frequency ranges, as discussed below.

Alpha waves contain frequencies between 8 Hz and 13 Hz, and have an amplitude of less than 10 μV in the awake state. Beta waves have a frequency range of 13–30 Hz; their maximum amplitude is less than 20 μV, and they appear in the parietal and frontal regions of the brain. There are two types of beta waves: beta I and beta II. The former has low frequencies which disappear during mental activity, while the latter has high frequencies which appear during tension and intense mental activity. Theta waves have a frequency range of between 4 Hz and 8 Hz, and an amplitude of less than 100 μV. They mainly occur in the parietal and temporal regions during sleep. Delta waves have a frequency range of between 0.5 Hz and 4 Hz and an amplitude of less than 100 μV. Gamma waves have frequencies of between 30 Hz and 100 Hz with a peak-to-peak amplitude of less than 2 μV in humans when attending to sensory stimulation.

A number of experiments were conducted to investigate the effective levels of DWT. It was found that D3 provided better representative characteristics for identifying the sleep spindles in EEG signals. D3 was thus passed to FFT to obtain the most significant frequencies for detecting sleep spindles. Fig. 4 shows the algorithm used to extract the statistical features and to determine the number of the decomposition levels using the WFA.

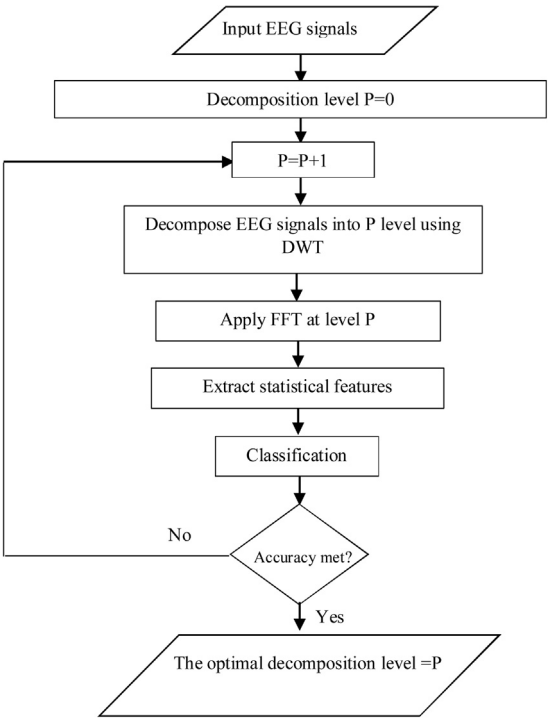

Fig. 4. Algorithm flowchart for determining the decomposition level number.

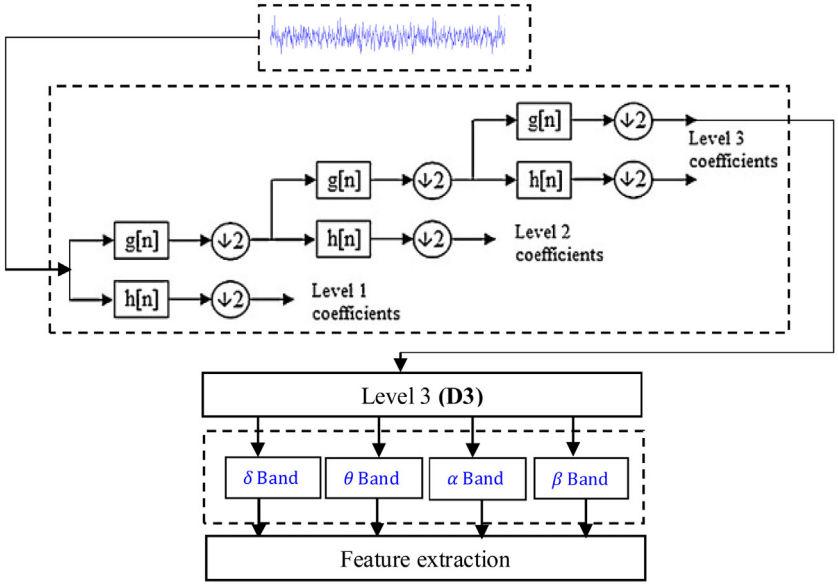

Fig. 5. A graphical diagram of the proposed method for the main steps of the features extraction using the WFA.

Table 3
P-value of the selected features; features in bold are not used in this work, as they are insignificant.

Band	F1	F2	F3	F4	F5	F6	F7	F8	F9	F10
1	1.1578e-51	1.1952e-78	3.1358e-59	2.7878e-51	4.1558e-78	3.4778e-78	5.1555e-65	6.8748e-89	5.7894e-81	4.7578e-97
2	3.0025e-22	9.4526e-45	3.9852e-45	1.3452e-12	5.1052e-75	2.3352e-10	7.0052e-45	6.0142e-75	1.1452e-18	2.1792e-10
3	4.2352e-23	2.1209e-23	1.0082e-62	2.1102e-67	1.1302e-65	1.1092e-14	4.0052e-12	7.1252e-16	2.2152e-11	1.2102e-21
4	3.234e-90	1.1700e-37	3.1204e-78	0.2774e-47	1.3214e-10	1.9694e-22	4.2171e-51	2.2032e-54	1.2374e-21	1.1370e-76
5	0.0121	0.0345	0.0478	0.0187	0.2541	0.2414	0.2654	0.2414	0.2412	0.1231

3.3. Feature extraction and segmentation

To reduce the dimensionality of EEG data and to extract useful information, 10 statistical features are extracted from each band to represent EEG data. These 10 statistical features are the *median, maximum, minimum, mean, mode, range, standard deviation, variation, skewness* and *kurtosis* [20,28,38,42]. Fig. 5 shows the main steps of the feature extraction process. The features were extracted from five bands ($\alpha, \beta, \theta, \delta, \gamma$). Many studies have reported that most of the features extracted from EEG signals are not likely to work for large datasets. Computational hypothesis testing is a powerful statistical approach for evaluating the extracted features.

In this paper, nonparametric Kruskal-Wallis one-way analysis of variance was used to determine the most powerful features [10]. Features from γ band were not chosen, as they were not significant in classifying the sleep spindles ($p < 0.05$) [39]. Table 3 shows an example of these features, and those shown in italic are insignificant. However, only four bands (α,β,θ,δ) were used in this work, since these features can shed a light on the issue, as reported in the literature [16]. To represent the EEG data associated with a symmetric distribution, the *mean* and *standard deviation* features are used, while *median* and *range* have been shown to be the appropriate measures for a skewed distribution. The other features are used to extract other important information from the EEG data.

3.4. Classification

The features extracted from each EEG segment were used as the input for the LS-SVM as well as K-means, K-nearest neighbour and C4.5 decision tree classifiers. The performances of these classifiers were compared in terms of classification accuracy. Based on the literature [29, 30, 31, 17 4], we found that those four classifiers are considered the most popular and effective methods in biomedical signal classification. The training parameters of the selected classifiers were presented in Table 4.

Table 4
Classifiers' parameters used during the experiments.

Classifier	Parameters
LS-SVM	RBF kernel, γ=10 and σ = 1
K-nearest neighbour	K = 7 is used, which denotes the number of the nearest neighbours.
k-means	k, c_i and x_k, where k is the number of clusters and k = 2. c_i is the centre of the clusters and c_i=1, and x_k is the data points.
Decision tree	Inputs = training_ patterns (training set); Outputs = test_targets (sleep spindles and non-spindles segments)

3.4.1. K-nearest neighbour

K-nearest neighbour is one of the most straightforward learning methods [44]. This algorithm depends on Euclidian distance to compute the similarity between the training case and the case in the classification record. A record is kept in order to store the classification performance and similarity results. Several distance metrics are used to define the distance in the K-nearest neighbour algorithm. Based on the training session, the Euclidean distance is used in this paper. In order to classify an instance, the similarity with K-nearest neighbours is computed, and the class corresponding to the maximum number of votes is assigned as an output class of the instance. A total of *k* different values of the K-nearest neighbour classifier were tested. It was found from simulation that the best results were achieved for $k = 7$.

3.4.2. Decision tree

C4.5 is the most widely used inductive inference tool in pattern recognition. The tree construction follows a top-down approach, in which the tree construction starts from a training set or tuples. A tuple is a collection of attributes and a class value. An attribute may have a continuous or discrete value, while a class can have only discrete values. A decision tree consists of decision nodes and leaves. At each decision node, an attribute is specified, which is tested for its ability to classify a training sample. Initially, the root node is associated with the whole training set and the weight value for each case is set to one. In order to construct a decision tree, the C4.5 algorithm employs a 'divide and conquer' approach; the attribute with the highest information gain is selected for testing at a node, and a child node is then created for each possible outcome of the class. This process is repeated for each attribute associated with each node, leading to the selection of the best attribute for the node [36,19].

3.4.3. LS-SVM

The LS-SVM is a powerful approach in the field of biomedical signals classification [9,4], and has been widely used in EEG classification research. Siuly et al. [29] used the LS-SVM to classify motor image data, and Al Ghayab et al. [3] also employed the LS-SVM to identify epileptic seizures. It was used for the detection of sleep spindles in EEG signals in our previous work [4]. The LS-SVM depends on two hyper parameters, γ *and* σ. Those parameters can influence the classification accuracy negatively if they are elected improperly. In this paper, the LS-SVM parameters were selected empirically during the training phase. The radial basis function (RBF) kernel was used. The parameters were set to $\gamma = 10$ and $\sigma = 1$ after a series of experiments were conducted and the polynomial kernel chosen.

3.4.4. K-means

K-means is considered one of the simplest approaches in biomedical data classification. This algorithm partitions observations into a number of groups, according to similarities or dissimilarities among the patterns. Each observation is associated to the group with the nearest centroid. This approach has been widely used to classify data in different fields such as digital image classification, time series and biomedical data analysis. The K-means algorithm identifies the cluster centre and other elements by reducing the squared errors based on an objective function. The main objective of using a clustering algorithm is to identify the cluster centre and to associate each element having the same characteristics with the nearest cluster centre. In K-means clustering, the Euclidean distance is usually used as the dissimilarity measure. This was used by Orhan et al., [33] to detect epileptic EEG signals, and by da Costa et al., [12] for the detection of sleep spindles. The most important parameters used in the K-means algorithm are k, c_i and x_k, and the algorithm is defined as follows:

$$k_{means} = \sum_{i=1}^{k} \sum_{k} ||x_k - c_i||^2 \tag{6}$$

where k is the number of clusters, c_i represents the centres of the clusters, and x_k represents the data points. In this paper, the number of data points refers to all the data mentioned in Section 3, and the clustering number is two (sleep spindles/non-sleep spindles).

3.5. Statistical measures for evaluating performance

The performance of the proposed method is evaluated and tested using several statistical measures k-fold cross-validation, sensitivity, specificity and accuracy. This section gives a brief description of each statistical measure used.

- **K-fold cross-validation:** This is a popular measure of assessing the classification accuracy, and is used to describe the performance of the proposed method. The dataset is divided into six subsets of equal size; each subset contains an equal number of EEG segments that includes sleep spindles and non-sleep spindles. One of these subsets is used as the testing set, while the remaining subsets are used as the training set. All subsets are tested in turn. The testing classification accuracy for all subsets is calculated and recorded, and their average accuracy is computed below.

$$\text{Performance} = \frac{1}{6}\sum_{1}^{6} \text{accuracy}^{(R)} \tag{7}$$

where $accuracy^{(R)}$ is the accuracy over the results from six iterations.

- **Sensitivity or true positive rate (TPR) or Recall:** This is used to estimate the performance of the classification method by measuring the proportion of the actual positive prediction. It is defined as [45]:

$$\text{Sensitivity (SEN)} = \frac{\text{TP}}{\text{TP} + \text{FN}} \tag{8}$$

where TP means the actual sleep spindle waves that are correctly detected using the proposed method, and FN means the actual sleep spindles that are incorrectly marked as non-sleep spindles.

- **Accuracy:** This refers to as the number of correctly classified cases, and is calculated by dividing the aggregation of the classification results by the total number of the cases. The accuracy is defined as:

$$\text{Accuracy (ACC)} = \frac{\text{TP} + \text{TN}}{\text{Total number of cases}} \tag{9}$$

where TN is the actual non-sleep spindles that are correctly classified using the proposed method as non-sleep spindles.

- **Specificity:** This is used to calculate the proportion of actual negative prediction. It is defined as :

$$\textit{Specificity (SPE)} = \frac{TN}{TN + FP} \tag{10}$$

where FP refers to the number of sleep spindles that are incorrectly determined by the proposed method.

- **Kappa coefficient:** This measures the agreement in the performance between two models. It is defined as below:

$$\text{Cohen's kappa coefficient (k)} = \frac{\frac{\text{TP}+\text{TN}}{\text{N}} - \text{Pre}}{1 - \text{Pre}} \tag{11}$$

$$\text{Pre} = \frac{\text{TP} + \text{FN}}{\text{N}} \cdot \frac{\text{TP} + \text{FP}}{\text{N}} + \left(1 - \frac{\text{TP} + \text{FN}}{\text{N}}\right) \cdot \left(1 - \frac{\text{TP} + \text{FP}}{\text{N}}\right), \quad \text{and N} = (\text{TP} + \text{FP} + \text{TN} + \text{FN}) \tag{12}$$

- **F-score:** This is one of the most important measurements used to show the overlap between the sets of true spindles and the spindles found using the proposed method. The F-score is defined as a harmonic means of precision *(PPV)* and recall *(TPR)* [26]:

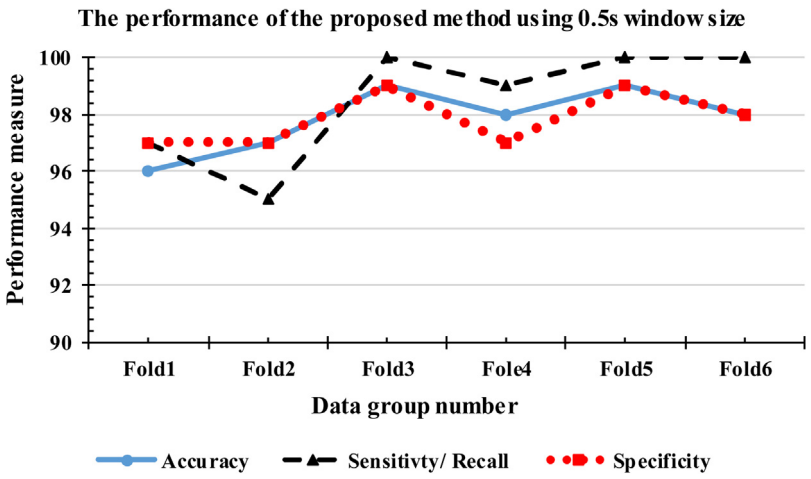

Fig. 6. Performance of the proposed method using a window size of 0.5 s.

$$F - \text{Score} = 2 \cdot \frac{(PPV \cdot TPR)}{PPV + TPR} \quad (13)$$

where PPV is the precision or positive predictive value, calculated as:

$$\text{Precision}\,(PPV) = \frac{TP}{TP + FP} \quad (14)$$

4. Experimental results

To evaluate the performance of the proposed method, extensive experiments were conducted using the dataset discussed in Section 2. The datasets were divided into six groups with no overlap, and the proposed method was applied to all groups. In the training phase, all LS-SVM parameters were determined and adjusted. The wavelet and Fourier transform functions in Matlab 2015b were utilized in this implementation, and the experiments were carried out using Matlab 2015b on a computer with 8GB RAM, i7 processor CPU, 3.40 GHZ Intel (R) i7.

4.1. Spindles detection using a window size of 0.5 s

A window size of 0.5 s was used to separate the EEG signals into segments, with an overlap of 0.4 s A vector of 4 × 10 extracted characteristics was fed to the LS-SVM. Fig. 6 shows the results obtained using the proposed method with a window size of 0.5 s. The performance of the proposed method was evaluated in terms of accuracy, sensitivity and specificity. The dataset was divided into six subsets. The proposed method was tested six times and all the results obtained were recorded. At each iteration, one group was used as a testing set and the rest as the training set.

From Fig. 6, we can see that the proposed method achieves a high performance, with an average accuracy, sensitivity (recall) and specificity of 97.9%, 98.5% and 97.8%, respectively. The results demonstrate that the lowest accuracy using the proposed method is 96% for the LS-SVM classifier.

To assess the discrimination capability of the proposed method, a receiver operating characteristics (ROC) curve was established in this paper. The ROC is a suitable metric in studying the dependency of sensitivity (recall) and specificity. It is an essential and significant method to recognize the performance of the binary classifier, and it is commonly used in medical decision making. The relationships among true positive rate (recall), false negative rate, false positive rate and true negative rate were investigated in this study using the ROC curve. The receiver operating characteristics (ROC) curve for different classification tasks is shown in Fig. 7. From the obtained results, we can be noticed that the proposed method correctly predict the sleep spindles in EEG signals. The area under the resulting ROC (AUC) was calculated in this study. The AUC is a portion of the area under the ROC curves. The highest area under the curve of 0.97 was recorded for classification take with the LS-SVM classifier.

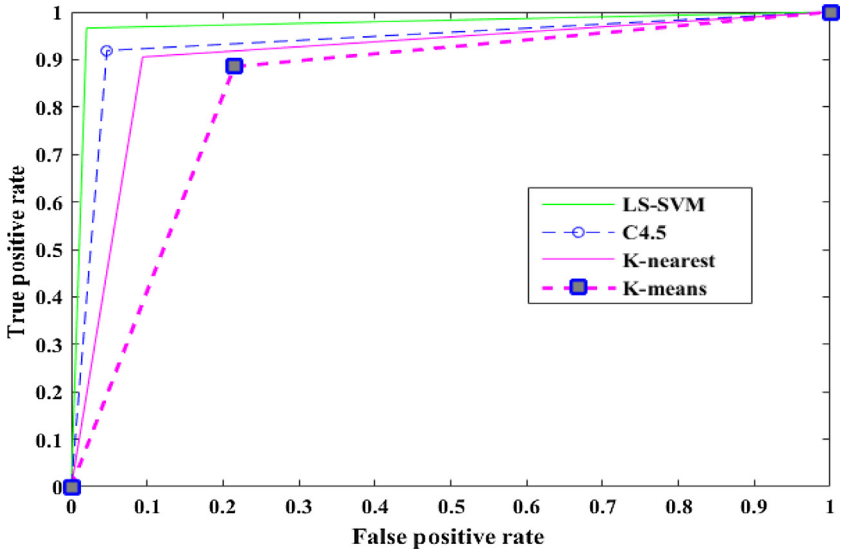

Fig. 7. Receiver operating characteristics curve for sleep spindles and non- spindles EEG signals (relation of recall using four classifiers).

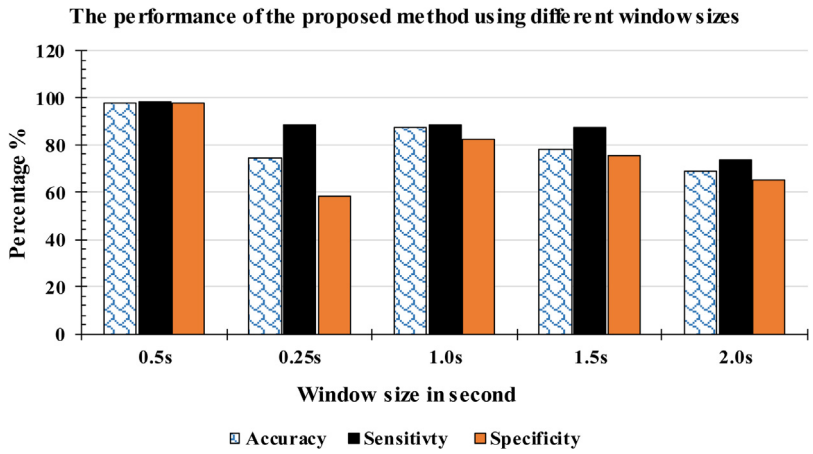

Fig. 8. Performance of the proposed method with different window sizes.

4.2. Effect of different window sizes

To detect all possible occurrences of the sleep spindles in the original EEG signals, and to assess the ability of the proposed method to identify the sleep spindles, four other window sizes of 1.0 s, 1.5 s and 2.0 s were also tested. The EEG signals were first segmented based on a window size of 1.0 s with an overlap of 0.8 s. The features described in Section 3.3 were extracted, and the datasets were divided into six subsets. The proposed method was then applied separately to each group. Fig. 8 shows the performance of the proposed method in terms of accuracy, sensitivity and specificity using different window sizes. It was observed that the proposed method has the capacity to detect sleep spindles at a window size of 1.0 s. The obtained results were compared with the scoring by an expert 1. There was only slight disagreements between the proposed method and the expert's scoring.

A second experiment was conducted using a window size of 1.5 s. From the results in Fig.8, it can be seen that the accuracy in some groups was degraded as the window size increased. The obtained results were compared with the scoring by an Expert 1. It was shown that, there were large disagreements between the proposed method and Expert1 in some datasets.

Fig. 8 also shows the experiment results using a window size of 2.0 s A maximum accuracy of 68% was obtained. It appears that it was difficult to detect sleep spindles in EEG signals with this window size, which makes sense since the most of the occurrences of sleep spindles have a window size of 0.5 s. Several previous studies used a window size of 0.25 s with an overlap of 50%, which was also tested in this research. The maximum accuracy was 74.5% and the results are shown in Fig. 8. It appears that this window was too short to detect sleep spindles. It was, therefore, found that a window size of 0.5 s yielded the best results among those examined. The findings in this paper confirm that sleep spindles occurring in EEG signals have an average duration of 0.5 s. All the results in Figs. 6 and 8 were carried out using the LS-SVM classifier.

4.3. Performance evaluation based on different classifiers

The extracted features from each EEG segment were forwarded separately to the LS-SVM, K-means, C4.5 decision tree and K-nearest neighbour classifiers in order to determine the best classifier for detection of sleep spindles. In these experiments, a window size of 0.5 s was used. The results obtained from these classifiers were compared in terms of accuracy, sensitivity and specificity. The results shown in Table 5 demonstrate the performance of the proposed method and the LS-SVM is better than the other three classifiers.

Table 5
Performance evaluation using different classifiers.

Classifier	Accuracy	Sensitivity	Specificity
LS-SVM	**97.9%**	**98.5%**	**97.8%**
K-nearest neighbour	90%	95%	89%
C4.5	93%	92%	91%
K-means	89%	90%	86%

Table 6
Performance from all classifiers using different window sizes.

		Classifiers			
Window size	Performance	LS-SVM	C4.5	K-means	K-nearest neighbour
1.0 s	*Accuracy*	**87.1%**	82%	79%	80.1%
	Sensitivity	88.3%	81%	78%	84%
	Specificity	82.3%	76%	71%	70%
1.5 s	*Accuracy*	**78.1%**	73%	69%	70.1%
	Sensitivity	87.6%	80%	78%	83%
	Specificity	75.8%	69%	64%	67%
2.0 s	*Accuracy*	**68.6%**	64%	60%	61%
	Sensitivity	73.5%	66.5%	64.5%	69.5%
	Specificity	65.3%	59.3%	54.3%	57.3%
2.5 s	*Accuracy*	**74.5%**	69.6%	65.6%	66.6%
	Sensitivity	88.3%	81.3%	79.3%	84.3%
	Specificity	58.5%	52.5%	47.5%	50.5%

To shed more light on the comparison, the performance of the proposed method was also compared based on 6- fold cross validation. The EEG data was divided into six folds. The plot boxes for each fold based on 6-fold cross validation is shown in Fig. 9. According to the results in Fig. 8, it was observed that there was an improvement achieved with the proposed method to detect the sleep spindles in EEG signals when the LS-SVM classifier was used to classify the features compared to the k-means, K-nearest neighbour and C4.5 classifier. It is clear from these results, the extracted features based on the WFA coupled with the LS-SVM classifier have better ability to distinguish the sleep spindles in EEG signals. In addition, we can see that the highest accuracy obtained by the LS-SVM was 97%, while the lowest accuracy was from K-means with 89% accuracy.

4.4. Performance evaluation of other classifiers with different window sizes

The performances using different classifiers and different window sizes were assessed in this section. Four experiments were conducted, each using a different window size. The performance from these four classifiers were tested individually, using window sizes of 0.25, 1.0, 1.5 and 2.0 s. The results were recorded. Table 6

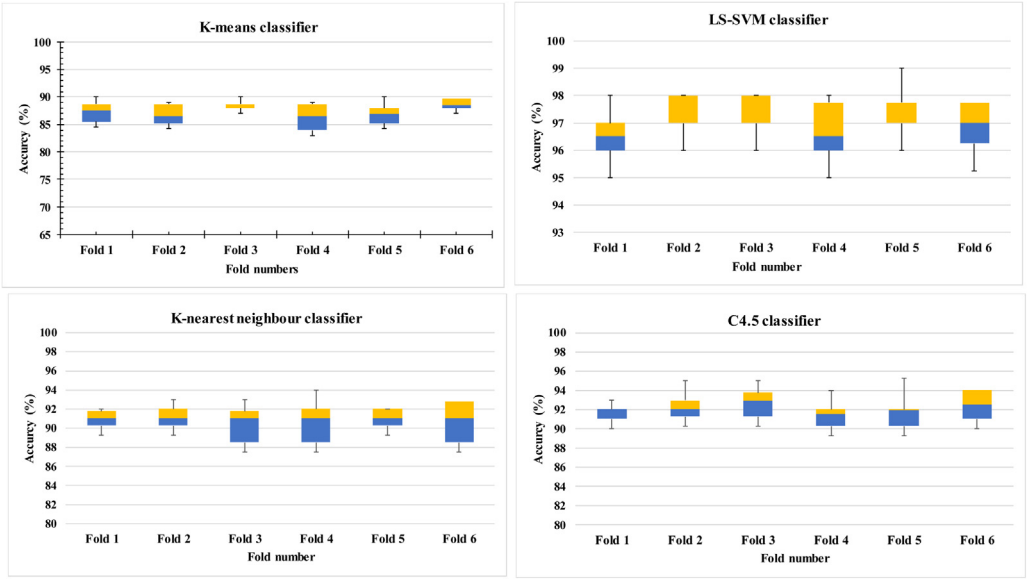

Fig. 9. The classification accuracy based on 6-fold cross validation.

shows the classification results in terms of accuracy, sensitivity and specificity. From these results, it can be seen that the LS-SVM achieved the highest performance among all the classifiers.

4.5. Comparison with previous studies

To evaluate the proposed method, comparisons were also made with previous studies. To carry out a fair comparison, all the selected studies were conducted using the same datasets as described in Section 2. Table 7 presents a comparisons of the results of the proposed method and those of [24,35,21,15,30,41,48,34,45,46]. Some of those studies did not report specificity or accuracy in their results, and they are marked with (-) in Table 7.

Imtiaz et al., [24] detected sleep spindles based on two features: Teager energy and spectral edge frequency. A window size of 0.25 s with an overlap of 50% was used in their study. They obtained an accuracy, sensitivity and specificity of about 91%, 80% and 98%, respectively, in detection of sleep spindles. In comparison, our method outperformed that approach, even though the proposed method was applied to larger datasets containing all the EEG recordings in the database. Another study was reported by Patti et al., [35], in which sleep spindles were identified based on a Gaussian mixture model. A window size of 1.5 s without overlap was used in this study. Four features were employed for detection, and the maximum sensitivity was 74.9%, while our proposed method attained 98.5% sensitivity with a window size of 0.5 s. Gorur et al. [21], applied a short-time Fourier transform to distinguish EEG sleep spindles, using a static Hamming window of 0.5 s. They achieved an average of 95.4% accuracy using an SVM and 88.7% with a neural network, which are lower than the results obtained using our method.

Another study was reported by Devuyst et al., [15] in which a systematic assessment method was applied to detect sleep spindles, using a window size of 0.5 s with an overlap of 0.1 s. Average values for sensitivity and specificity of 70.20% and 98.6% were reported, respectively, and these are lower than the results achieved in the current study. Nonclercq et al. [30], detected sleep spindles using amplitude-based feature extraction, with a window size of 0.5 s and an overlap of 0.25 s A specificity and sensitivity of 94.2% and 78.5 were obtained, which was comparable to those achieved in this paper, but the authors did not report results for accuracy. Tsanas et al. [41], detected sleep spindles based on a continuous wavelet transform and local weighted smoothing, reporting sensitivity and specificity of 76% and 92%, respectively. It can be seen that the sensitivity of 96.8% obtained by our method is higher than that reported by Tsanas et al., [41].

Another study was presented by Zhuang and Peng [48] in which sleep spindles were detected based on a sliding window-based probability estimation method. An EEG signal was passed through a Mexican hat wavelet transform, and a set of wavelet coefficients were employed. A window size of 1.0 s with an overlap of 50% was used in that study. An average sensitivity of 50.98%, f-score of 0.58% and a specificity of 99% were reported. Although the average specificity in that study was higher than those by our proposed method, our method achieved higher values of sensitivity and f-score of 98.5% and 0.71%, respectively, and also higher than those from Zhuang and Peng [48]. An optimization algorithm to estimate the components in the proposed signals model was presented by Parekh et al. [34], for the detection of K-complexes and sleep spindles in EEG signals. In that study, sleep spindles and k-complexes were detected separately, based on low-frequency and oscillatory components. A window size of 1.28 s was used for the STFS without overlap. The authors reported approximately 96.4% accuracy, 70% sensitivity, 97.8% specificity, 0.70 f-score and 0.67% kappa coefficient for sleep spindles detection. Thus, our method gave better results than other methods in terms of accuracy, sensitivity, f-score and kappa coefficient, with a window size of 0.5 s and an overlap of 0.4 s.

The proposed method was also compared with other methods in which different datasets were used. One study was reported by Yucelbas et al., [45] in which sleep spindles were detected using an FFT, autoregressive multiple signal classification and a Welch filter. The detection phase was carried out by a neural network classifier. A maximum accuracy of 84.84% was reported, although the results changed when principal component analysis was used, which gave a maximum accuracy of 94.8%. According to the results, the proposed method performed better than that of Yucelbas et al., [45]. A second study reported by Yucelbas et al. [46], used an STFT artificial neural network, EMD and DWT to detect sleep spindles in EEG signals. The average sensitivities in that study were 55.9%, 100% and 99.4%, respectively. In addition, an average specificity using those method of 69.62%, 78.45% and 70.75% were reported. Our method obtained a higher classification specificity. In summary, compar-

Table 7
Performance comparison of the proposed method and other existing methods.

Author	Method	Accuracy	Sensitivity	Specificity	F-score	Kappa coefficient
Imtiaz et al. (2013)	Teager energy and spectral edge frequency	91%	80	98%		
Patti et al. (2014)	Gaussian mixture model	–	74.9%.	–		
Gorur et al. (2002)	Short-time Fourier transform with an SVM and neural network	95.4%, 88.7%	–	–	–	–
Devuyst et al. (2011)	Systematic assessment method	–	70.20%	98.6%	–	
Tsanas et al.(2015)	Continuous wavelet transform with Morlet basis function		76%	92%	–	–
Nonclercq et al. (2013)	Sleep spindle detection using amplitude-based feature extraction	–	78.5	94.2	–	–
Zhuang and Peng (2016)	Sliding window-based probability estimation method to detect sleep spindles	–	50.98%	99%	0.58	
Parekh et al (2015)	Optimization algorithm for the detection of K-complex and sleep spindles	96.4%	70%	97.8%	0.70	0.67
Yucelbas et al. (2016)	FFT, autoregressive multiple signal classification and Welch filter to identify sleep spindles	84.83% without PCA 94.8% with PCA	–	–	–	–
Yucelbas et al. (2016)	STFT- artificial neural network, empirical mode decomposition and DWT	– – –	55.9%, 100% and 99.42%	69.6% 78.45% 70.75%	– –	– –
The proposed method	Statistical features and wavelet Fourier analysis	**97.9%**	**98.5%**	**97.8%**	**0.71**	**0.90**

isons with previous studies shows that using WFA was effective and appropriate for the detection of sleep spindles in EEG signals. It was also found that the window of 0.5 s gives better results than 2.0 s. 1.0 s, 1.5 s and 0.25 s.

5. Discussion

Sleep spindles are important transient events indicating sleep stage 2 in EEG signals. In this study, a new technique is presented for the detection of sleep spindles based on wavelet Fourier analysis and statistical features, which gives better results compared with using Fourier and wavelet transforms, separately. Our findings show that not all the frequency bands obtained through the wavelet Fourier transform are useful in detecting sleep spindles. As a result, only features from the δ, θ, α, β bands were used in this research. Further investigations and discussions are as follows:

1 The wavelet decomposition level was determined based on the accuracy of sleep spindles detection. At each level, the wavelet coefficients were investigated by extracting the features mentioned in section 3.3. The extracted features were forwarded to the LS-SVM classifier. The accuracy of the sleep spindles detection at each level was calculated against the bio-marks flagged by the sleep experts. The accuracies were recorded and compared with those from other wavelet levels. It was showed that D3 provided the best features vector to identify the sleep spindles. Fig.10 shows the accuracies of the sleep spindles detection against the wavelet coefficients of D1-D5. From Fig. 10 it can be noticed that the best detection accuracy of the sleep spindles was obtained from D3.
2 The performance of the proposed method was also tested using F-score and kappa coefficient measurements. These were computed for each subject, and the average results were investigated. The average F-scores and kappa coefficients for the proposed method were 0.71 and 0.90, respectively. Based on the literature, the results obtained for F-score and kappa coefficient provided evidence that the proposed method has the potential to classify sleep spindles and non-spindles in EEG signals.
3 In our experimental results, we used single-channel sleep EEG signals. The execution time of the algorithm was recorded over a one-hour period of EEG recordings, and the results showed that the proposed method typically took an average of 165.36 s to process one hour of a single-channel EEG signal, beginning with pre-processing the EEG signal and ending with the classification phase. In future work, we aim to detect sleep spindles using multi-channel EEG signals.

Table 8
Six-fold cross-validation using the four classifiers (MASS dataset).

Classifier	Average accuracy	STD
K-nearest neighbour	93.2%	2.3
C4.5	94%	1.9554
k-means	94%	1.8602
LS-SVM	**97.5%**	**1.5620**

4 The proposed method was also evaluated using Montreal archive of sleep studies (MASS) dataset [32]. The same methodology in section 2 was used in which D3 coefficients were also passed to Fourier transform to obtain the desired features. The LS-SVM was used as a classifier to categorize the extracted features. The feature set was divided into six subsets. The proposed method was tested 6 times and all the obtained results were recorded. Fig. 11 shows the results obtained using the proposed method with MASS database. It is clear that the proposed method achieved quite similar results using to the Dream Sleep Spindles database. An average accuracy, sensitivity and specificity of the proposed method of 97.5%, 99.1% and 96.5% were obtained.

For further investigations, each group of the dataset (MASS) was tested using 6 cross validation times. Table. 8 shows that the average accuracy of all the classifiers exceeded 93%. In addition, we can see that the maximum accuracy obtained by the LS-SVM is 97%, while the minimum accuracy is 93%, which was from k-nearest

5 The proposed method was conducted and tested with different mother wavelet functions reported in Alyasseri et al., [5,6] such as symlet, biorthogonal and coiflet functions. The proposed method was also tested with sym 7, coif 3 and bior3.9 mother wavelets. It was showed that Daubechies wavelet function at order 6 (db6) provided better results than other functions. Fig. 12 shows the comparison results among different wavelet functions. Based on the results in Fig. 12, db6 produced the best performance compared with other functions, in terms of accuracy, sensitivity and specificity. The finding shows that the second highest accuracy, sensitivity and specificity were yielded by coif3 mother wavelet. However, the performance of sym7 mother function

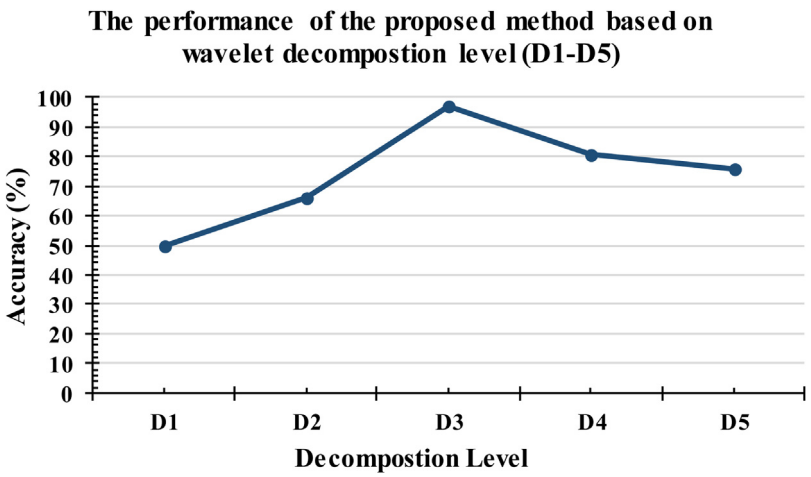

Fig. 10. Accuracy of sleep spindles detection by LS-SVM vs. the decomposition level of wavelet coefficient.

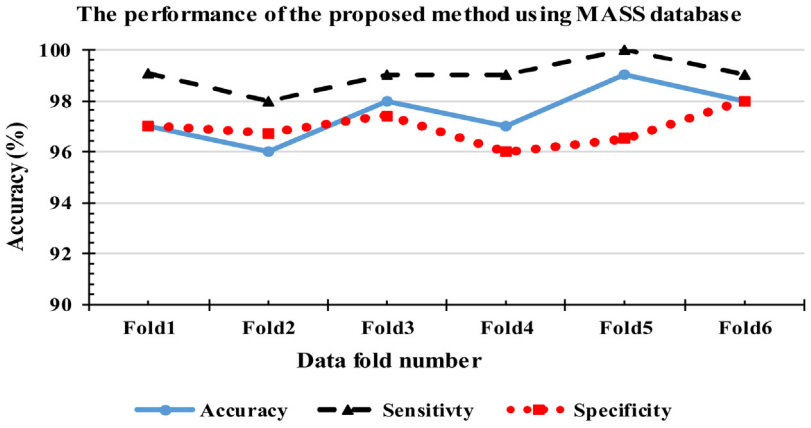

Fig. 11. Performance of the proposed method using a window size of 0.5 s and MASS database.

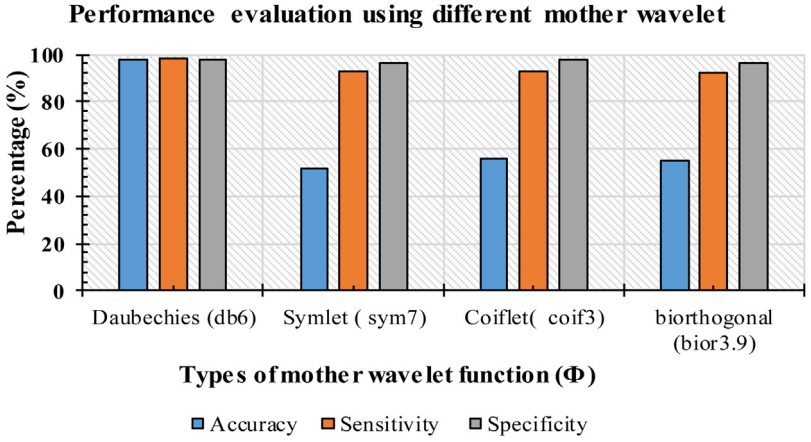

Fig. 12. Performance of the proposed method using different wavelet functions database.

was recorded the lowest classification results. The experimental results with the LS-SVM classifier show that using Daubechies wavelet function at order of 6 (db6) is an effective method for sleep spindles detection. It gave the best classification results compared with those by sym7, bior3.9 and coif3 mother wavelet functions. This properly is the reason why Daubechies wavelet function is commonly used to detect and evaluate the transient waves in EEG signals.

6 Finally, from Table 7, it can be seen that the performance results obtained from this study are better than those from others. This is the main advantage of the proposed method. The performance of the proposed method depends on individual channel signals. We found that it was hard to have high classification results when it was applied to a different EEG channels such as the C3-A1. However, one of the limitations of our proposed method is that it does not perform well with the C3-A1 channel. Two recordings from the C3-A1 channel were tested in this study. An average of

78%, 85% and 74% were obtained for the accuracy, sensitivity and specificity using the proposed method. The experimental results show that the proposed method gives better results with the CZ-A1 channel than with the C3-A1 channel.

6. Conclusion

In this paper, an automatic sleep spindles detection method is presented. The method applies the wavelet-Fourier analysis with statistical features to extract the important features from sleep EEG signals. In this process, the EEG signals were segmented into small windows of 0.5 s with an overlapping of 0.4 s. Ten statistical features were extracted from each window segment after applying a wavelet-Fourier transformation. The LS-SVM was used to classify the sleep spindles using the extracted features. The performance of the proposed method was evaluated using different measures of accuracy, sensitivity and specificity. The obtained results were also compared with the other existing methods. The evaluation results show that the proposed method is the best among all the methods in terms of accuracy, sensitivity, specificity, F-score and kappa coefficient. Furthermore, C4.5 decision tree, k-means and k-nearest classifier were also implemented for comparisons, and the results were compared with those by the LS-SVM.

In this study, it was found that the length of 0.5 s gives better results than 2.0 s. 1.0 s, 1.5 s and 0.25 s. The outcomes of this study can help the physicians with diagnosing sleep disorders and potentially it can reduce the medical costs. Future work will be conducted to verify the possibility of using less number of features and a shorter window size in sleep spindles detection using EEG signals. In addition, we will apply the proposed method to identify sleep spindles by using multi-channel EEG signals.

Conflicts of interest

The authors declare no conflicts of interest for this work.

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3.2 Chapter Summary

Al-Salman et al. (2019) implemented an innovative method based on the wavelet-Fourier analysis (WFA) with statistical features to extract the important features from sleep EEG signals. Ten statistical features were extracted from each 0.5 EEG segment after applying a WFA. Thereafter, the key features were forwarded to four classifiers: LS-SVM, C4.5 decision tree, k-means, and k-nearest to detect the sleep spindles. The experimental results revealed that the proposed feature extraction method combined with the LS-SVM classifier was capable of differentiating those sleep spindles with an excellent performance, compared to existing methods. Moreover, four other window sizes of 1.0s, 1.5s, and 2.0 s were also tested to assess the ability of the proposed method to identify the sleep spindles. It was also found that the window of 0.5s using the LS-SVM classifier gave better results than a window size of 2.0. 1.0, 1.5 and 0.25s. Thus, the proposed method was able to efficiently detect spindles in EEG signals, and could therefore assist sleep experts in analysing EEG signals. This method was therefore able to assist physicians in diagnosing sleep disorders quickly and efficiently and by speeding up the process of diagnosis, it could potentially reduce medical costs. Al-Salman et al. (2019) demonstrated that using the WFA method had the potential to improve the method of classification and to therefore detect sleep spindles with high rate of accuracy and a shorter execution time.

This study will attempt to validate to further validate the robustness and generalization ability of the proposed methods, as presented in Chapter 3, and to investigate the efficacy of the proposed methods relative to other benchmark approaches., As a way of establishing these benefits, a comparison of the proposed methods to some of the more recently reported approaches (the recent state-of-the-art and advanced classifiers) in the literature will be undertaken. Among those studies, for example, one by Kulkarni et al. (2019) developed a deep neural network framework integrated for online spindle detection (SpindleNet), where the bandpass filtered signal (9–16 Hz) and the power features were fused to distinguish spindles and non-spindles. An average sensitivity, specificity, and F1- score of 90.07%, 96.19%, and 0.75 on the MASS dataset respectively were achieved. A deep convolutional neural network was also used to a binary classification task of clinical relevance, namely detecting sleep spindles (Usai and Trappenberg, 2019; Chambon, et al., 2019; You et al., 2021; Loza

and Colgin , 2021; Lacourse et al., 2019). In their studies, the accuracy rate was not mentioned.

LaRocco et al., (2018) introduced a new framework (namely Spindler) for spindle detection enabled by parametric analysis. Matching studies with Gabor atoms were used to decompose the EEG signal and then the spindle was computed for each point in a fine grid of parameter values. Spindler achieved the average F1-score of 0.57% and 0.67% on MASS-SS2 dataset. Using wavelet synchrosqueezed transform (SST) and random under-sampling boosting (RUSBoost) to identify sleep spindles in EEG signals, spindles can easily be detected. This method was firstly proposed by Kinoshita et al (2020). The proposed method used the SST for feature extraction and RUSBoost for the classifier construction. The performance of the proposed method was validated using an open-access database called the Montreal archive of sleep studies cohort 1 (MASS-C1), which showed an F-measure of 0.70% with a sensitivity of 76.9% and a positive predictive value of 61.2%. Based on the results in Chapter 3, it was found that the proposed technique outperformed the state-of-the-art works.

To sum up, it can be concluded that the research in Chapter 3 has established a successful algorithm for reliable classification of sleep spindles in EEG signals. The research results in this Chapter indicate that the proposed method can assist neurologists and sleep specialists in diagnosing and monitoring sleep disorders. However, investigations using other techniques, such as fractal dimension and time-frequency images, also improved the accuracy rate and reduced the execution time. The next chapter will discuss EEG sleep spindles detection based on fractal dimensions coupled with time-frequency image.

CHAPTER 4

AN EFFICIENT APPROCH FOR EEG SLEEP SPINDLES DETECTION BASED ON FRACTAL DIMENSION (FD) COUPLED WITH TIME FREQUNCY IMAGE (TFI)

4.1 Introduction

In Chapter 3, the DWT and FFT techniques denoted as WFA and based on the LS-SVM classifier were developed to detect sleep spindles in EEG signals. According to the results in Chapter 3, it was found that this combination of techniques yielded promising results to detect sleep spindles in EEG signals. In addition, those results observed that the sleep spindles exhibited nonlinear behaviours with high processing of execution time. One of the most effective non-linear methods to identify sleep spindles, to improve the classification accuracy and to reduce the complexity time is the FDs algorithm coupled with TFI.

In this chapter, the details presented here are an exact copy of a published paper in *Journal of biomedical signal processing and control* by Al-Salman et al. (2019). It proposes a robust extraction method to detect sleep spindles in EEG signals. In this chapter, a new combination of the fractal dimension (FD) algorithm and time-frequency image (TFI) is used to further improve the performance discussed in Al-Salman et al. (2019). This chapter employs a short time Fourier transform (STFT) to

obtain TFI and then applies a box counting method to estimate the FD of EEG signals and to extract the discriminative features from each TFI. The extracted key features are evaluated by using four popular machine learning methods: a k-means, Naive Bayes, neural network and least square support vector machine. Furthermore, the proposed method is evaluated using two publicly available databases: Dream sleep spindles and Montreal archive of sleep studies, and is also compared with several existing methods reported in the literature. The results of the evaluation revealed that the proposed method outperformed the existing methods and achieved a high classification accuracy, sensitivity, and specificity for sleep spindles with different channels. Furthermore, processing required only a short execution time compared with the previous method. As a result, the classification rate and execution time were improved.

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An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequency image

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ABSTRACT

Detection of the characteristics of the sleep stages, such as sleep spindles and K-complexes in EEG signals, is a challenging task in sleep research as visually detecting them requires high skills and efforts from sleep experts. In this paper, we propose a robust method based on time frequency image (TFI) and fractal dimension (FD) to detect sleep spindles in EEG signals. The EEG signals are divided into segments using a sliding window technique. The window size is set to 0.5 s with an overlapping of 0.4 s. A short time Fourier transform (STFT) is applied to obtain a TFI from each EEG segment. Each TFI is converted into an 8-bit binary image. Then, a box counting method is applied to estimate and discover the FDs of EEG signals. Different sets of features are extracted from each TFI after applying a statistical model to the FD of each TFI. The extracted statistical features are fed to a least square support vector machine (LS_SVM) to figure out the best combination of the features. As a result, the proposed method is found to have a high classification rate with the eight features sets. To verify the effectiveness of the proposed method, different classifiers, including a K-means, Naive Bayes and a neural network, are also employed. In this paper, the proposed method is evaluated using two publically available datasets: Dream sleep spindles and Montreal archive of sleep studies. The proposed method is compared with the current existing methods, and the results revealed that the proposed method outperformed the others. An average accuracy of 98.6% and 97.1% is obtained by the proposed method for the two datasets, respectively.

1. Introduction

Sleep scoring is a challenging task in sleep classification research due to the characteristics of the sleep stages vary [12,31,39]. According to the Rechtsaffen and Kales (R&K) guidelines [49], a human sleep cycle is divided into two main parts: the non-rapid eyes movements sleep (NREM) and rapid eyes movements sleep (REM), where the NREM includes four stages namely: Stage 1 (S1), Stage 2 (S2), Stage 3 (S3) and Stage 4 (S4).

The guidelines of the R&K have been modified by the American Academy of Sleep Medicine (AASM) in 2002. The AASM presented a different version of sleep scoring [28] by which the NREM is reduced to three stages, with S3 and S4 are combined into one stage as slow wave stage (SWS). Much clinical research have revealed that individual sleep stages exhibit unique electroencephalogram (EEG) patterns and characteristics that reflect human states whether he/she is awake or asleep. Those characteristics of sleep stages reflect the changes in brain neurons and muscles at each sleep stages [11]. Analyzing those brain waveforms is an important task for neurologists to score and analyse EEG sleep signals [17,29].

Two of the important transiting bio-signal waveforms in sleep stages are sleep spindles and k-complexes that are often used to score sleep stages [28]. Sleep spindles are the most important transient events to detect sleep stage 2 in EEG signals. They are defined as a series of distinct waves which are within a frequency range of 11–16 Hz with a minimum duration of 0.5 s (s) [60,28]. Some studies reported that, the minimum and maximum durations of sleep spindles are 0.5 s and 3s, respectively [30,60,13], with an amplitude from 5 μV to 25 μV [34]. The presence or absence of sleep spindles in EEG sleep signals has a high impact on the memory consolidation of humans [35,42]. From EEG recordings, it is observed that any change in the density of sleep spindles can result in some sleep disorders, such as insomnia and schizophrenia and autism [20,59]. Consequently, automatically detecting and analyzing sleep spindles can help experts in diagnosing sleep disorders.

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Traditionally, the detection of sleep spindles mainly depends on visual inspection that is carried out based on the knowledge of clinicians or sleep expert. The accuracy and reliability of the manual scoring are based on the experiences of experts. Visual scoring of sleep spindles is very time consuming, subjective and prone to errors due to there are typically thousands of sleep spindles occurred in each EEG recording [1]. Identifying sleep spindles in EEG signals visually requires high skills from experts. However, developing an automatic approach to identify those marked occurrences in the sleep stages is an ongoing challenge.

Various attempts were made in identifying sleep spindles based on Fourier, wavelet and hybrid transforms [16,27,54,26]. Machine learning methods, such as support vector machines, neural networks, and genetic algorithms, were also employed to classify the extracted features by those transformation techniques [2,3,38]. Yücelbaş et al. [61] used a short time Fourier transform (STFT) combined with an artificial neural network to detect sleep spindles in EEG signals. The STFT was also used as a feature extractor by da Costa et al. [14]. The extracted features were fed to a K-means to recognize the segments of sleep spindles from non-sleep spindles segments. Estévez et al. [18] propounded a merge neural gas model with the STFT to analyse EEG signals. A maximum sensitivity of sleep spindles detection was 62.9%. Güneş et al. [24] utilized the STFT to decompose an EEG signal. The most discriminating features were extracted from the frequencies of interest. The extracted features were forwarded to two machine learning methods: a support vector machine and a multilayer perceptron to detect sleep spindles.

Recently, many researchers reported the detection of sleep spindles based on a matching pursuit and filtering techniques. Ventouras et al. [58] utilized a bandpass filter with an artificial neural network to detect sleep spindles. The obtained results in terms of sensitivity and accuracy were reported. In that study, an average of 87.5% accuracy was achieved. Żygierewicz et al. [66] presented a matching pursuit method to detect sleep spindles. The maximum sensitivity reported in that study was 90%. Schönwald et al. [52] also employed the matching pursuit to detect sleep spindles based on the amplitude, frequency, and duration characteristics of the signals. An average of sensitivity and specificity of 80.6% and 81.2% were achieved, respectively.

According to the literature, we found that the fractal dimension has been proved to be an efficient approach to explore the hidden patterns in digital images and signals. It has been used to analyse EEG signals to trace the changes in EEG signals during different sleep stages, and also was employed to recognize different digital images patterns. Yang et al., [63] and Sourina et al. [56] applied a fractal dimension technique to analyse sleep stages in EEG signals. Ali et al. [7] also utilized a fractal dimension technique for voice recognition. Furthermore, a time frequency image (TFI) has been used to analyse different types of EEG signals, such as EEG sleep stages signals. Bajaj and Pachori [9] identified EEG sleep stages based on time frequency images. Fu et al., in [22] used a time frequency image as a features extractor for epileptic seizures classification. Bajaj et al., [8] also classified alcoholic EEGs based on time frequency images.

Although the existing methods have achieved some good results in sleep spindles detection, a considerable amount of further improvement on the existing methods are still in demand. In this paper, the fractal dimension combined with time frequency images is used to detect sleep spindles in EEG signals. Firstly, each EEG signal is partitioned into segments of 0.5s. Then, each segment is transformed into a time frequency image using a short time Fourier transform (STFT). Each TFI is converted into a binary image. The box counting technique is applied to each TFI and the statistical features are extracted from the FD. Different set of statistical features are extracted and tested from the FDs to figure out the best combination of features for detecting sleep spindles. Different classifiers are also used to validate the proposed method. The obtained results showed that the proposed method achieved a high accuracy for detecting sleep spindles in EEG signals.

The rest of this paper is organized as follows: Section 2 describes the EEG datasets used. Section 3 presents the methodology of the proposed method. The experimental results are explained in Section 4. Finally the discussions, conclusions and future work are provided in Section 5.

2. Experimental EEG data

In this study, two different datasets were used to evaluate the proposed method for detecting sleep spindles in EEG signals. Those databases that are publicly available are: the DREAMS datasets (Devusty) [15] and Montreal Archive Sleep Studies (MASS) (O'Reilly et al. [40]. The following section briefly explains the details of the two datasets.

2.1. The dream sleep spindles dataset (Datsaet-1)

The EEG data sets used in this paper were collected through the Dream Project at University of Mons-TCTS Laboratory (Devyust et al.). The sleep EEG data sets were recorded from eight subjects with various sleep diseases, such as dysomnia, restless legs syndrome, insomnia, and apnea/hypopnea syndrome. The subjects were aged between 30 and 55 years. The signals were recorded in 30 min intervals during a whole night. The recorded signals were scored, and the ending and starting time instances of the sleep spindles were marked. Six of the EEG recordings were sampled at 200 Hz, while the other two recordings were sampled at 100 Hz and 50 Hz. Each EEG recoding included with two EOG channels of P8-A1 and P18-A1, three EEG channels of CZ-A1 or C3-A1, FP1-A and O1-A1, and one EMG channel. The sleep spindles in the Dream database were detected manually by two experts. The first expert scored all the eight recordings, while the second expert annotated six recordings out of the eight EEG recordings. In this study, the CZ-A1 channel and the EEG recording sampled at 200 Hz were used. The subjects selected were subject IDs 2, 4, 5, 6, 7 and 8. Table 1 shows the number of the segments that were used in this research. The dataset along with additional information is publicly available from: http:\\www.tcts.fpms.ac.be/~devuyst/Database/DatabaseSpindles.

2.2. Montreal archive of sleep studies (Dataset-2)

The database was recorded from 19 subjects: 8 males and 11 females. The age of the subjects was between 30–55 years. The EEG signals were recorded in 20 min intervals during a whole night. The EEG signals were sampled at 256 Hz. Each EEG recording included 19 EEG channels, four Electrooculography (EOG), electromyography (EMG) and Electrocardiography (ECG) channels. In this database the visual scoring of sleep spindles were carried out aslo by two experts. The first expert annotated 19 recordings, including sleep spindles according to the AASM rules, while the second only annotated 15 out of 19 recordings, including sleep spindles according to the R&K criteria. In this study, the EEG scoring from six subjects were chosen randomly. The subjects selected were subject IDs 1, 2, 7, 9, 14 and 18. Table 2 shows the number of segments that were used in this research. The datasets can be accessed through *http://www.ceams-carsm.ca/en/MASS*. Tables 1 and 2 included five columns: namely, subject ID, the number of segments with sleep spindles, the number of all segments in all EEG signals, minimum and maximum sleep spindles. The experiments were conducted using Matlab software (Version: R2015) on a computer with the

Table 1
The number of segments for each subject (Dataset-1).

Subject ID.	No. of segments with sleep spindles	No. of all segments in EEG signals	Minimum Spindle Period (second)	Maximum Spindle Period (second)
ID2	60	3599	0.5s	1.1s
ID4	44	1799	0.5s	1.8s
ID5	56	1219	0.5s	1.2s
ID6	72	2342	0.5s	1.5s
ID7	18	1869	0.5s	1.3s
ID8	48	4589	0.5s	1.9s
Total	**298**	**15417**	–	–

Table 2
The number of segments for each subject (Dataset-2).

Subject ID.	No. of segments with sleep spindles	No. of all segments in EEG signals	Minimum Spindle Period (second)	Maximum Spindle Period (second)
ID1	1040	28958	0.5s	1.3s
ID2	1141	32360	0.5s	1.2s
ID7	905	20280	0.5s	1.1s
ID9	810	27600	0.5s	1.0s
ID14	708	30320	0.5s	1.6s
ID18	1156	28640	0.5s	1.2s
Total	5760	**168150**	–	–

following settings: 3.40 GHz Intel(R) core(TM) i7 CPU processor machine, and 8 GB RAM.

3. Methodology

In this study, an efficient technique to detect sleep spindles is presented based on a short time Fourier transform (STFT) and the original EEG signals are divided into segments by a sliding window technique. The size of the window is set to 0.5 s with an overlapping of 0.4s. Then, each EEG segment is passed through the STFT to obtain its time frequency image (TFI). The obtained TFI is transformed into an 8-bit binary image. Then, a box counting method is applied to each TFI to calculate the fractal dimension, as well as to extract the features of interest. Eight statistical features are extracted from each FD of the TFI. The extracted features are used as the input to different classifiers, including a LS_SVM, K-means, Naive Bayes and a neural network. For further investigation, different features sets, including two, four, six and eight features sets, from each TFI, are tested. Comparisons are then made with the previous studies. The obtained results showed that the proposed method provided better classification results than the other methods. Fig. 1 depicts the methodology of the proposed method.

3.1. Segmentation

In this paper, a sliding window is used to segment the EEG signals into small intervals. A window size of 0.5 s is empirically selected and used to separate EEG signals with an overlapping of 0.4s. Different window sizes are tested and applied in order to figure out the best window size. The obtained results from the proposed scheme revealed that a window of 0.5 s gives better results than other window sizes. Fig. 2 shows an EEG signal being divided into segments with an overlapping of 0.4s.

3.2. Spectrogram

The main formula of the STFT is defined as [8,9]:

$$X(n,\omega) = \sum_{m=-\infty}^{\infty} x[m]\, w[n-m]\, e^{-jwn} \tag{1}$$

where $x[m]\, w[n-m]$ is a short time of signal X at time n.

The discrete STFT can be formulated as

$$X(n,k) = X(n,\omega)|_{\omega} = \frac{2\pi k}{N} \tag{2}$$

where N refers to the number of discrete frequencies.

Before calculating the Fourier transform, the centered function $w = [m]$ at time n was multiplied with signal X. The Fourier transform is an estimate at time n, and the window function of signal X is considered close to time n. To obtain the STFT, a fixed positive function was used, which is denoted as$w[m]$. However, the spectrogram can be formulated as:

$$S(n,k) = |X(n,\omega)|^2 \tag{3}$$

An EEG signal is transformed into time frequency domain. Then, the spectrogram of the STFT is applied to obtain the time frequency images (TFIs) of the EEG signals. The STFT spectrogram is defined as the normalized and squared magnitude of the STFT coefficients.

The STFT coefficients are obtained using a sliding window in time domain in order to divide the signals into smaller blocks. Each block is then analyzed using Fourier transform to determine their frequencies. Thus a time varying spectrum can be obtained. Based on Eqs. (1) and (2), the spectrogram of the signal can be calculated from the square of the discrete STFT.

Based on the literature, it is found that the spectrogram is an effective approach to analyse non-stationary and periodic signals. In this paper, the spectrogram is applied to each EEG segment to obtain the TFIs.

3.3. Fractal dimension based on box counting method (BCM)

Fractal is a scale which is used to represent a geometric pattern that cannot be represented by a classical geometry. It allows to measure the degree of complexity of an object. Based on fractal concept, each figure is presented using a series of fragments that each one can be represented as a figure. Those fragmented parts can be used to reflect the original image. There are some criteria used to define the fractal:

(1) Fractal is a simple structure with small scales.

(2) Fractal cannot be described using the traditional Euclidean geometry.

One of the main fractal features is that it possesses scaling properties. By using a fractal, an one-dimension object can be segmented into n equal parts. Each part can be scaled down by a ratio $of\, r = \frac{1}{n}$.

Another example is for two-dimensional objects. For example, a square area in a plane, which can be separated into n self-similar

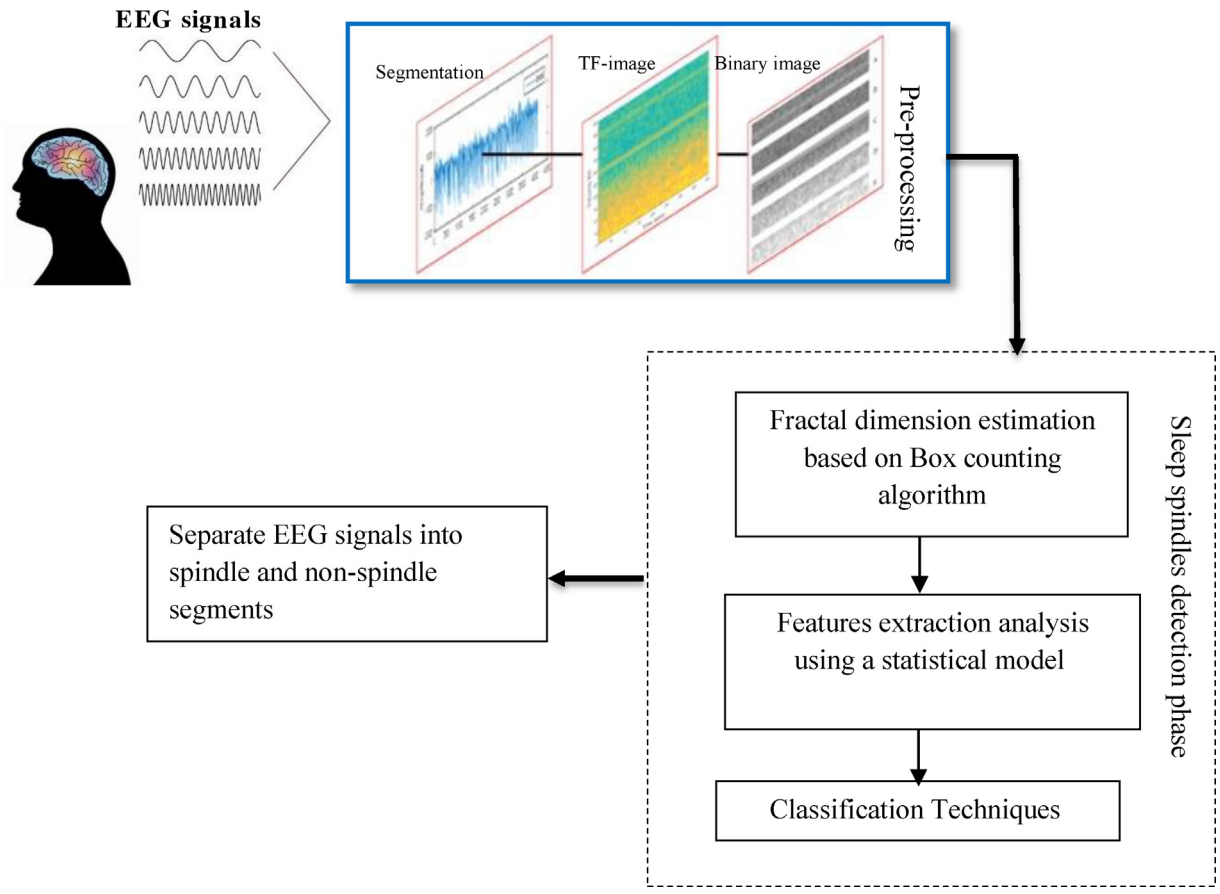

Fig. 1. The methodology of the proposed method for sleep spindles detection.

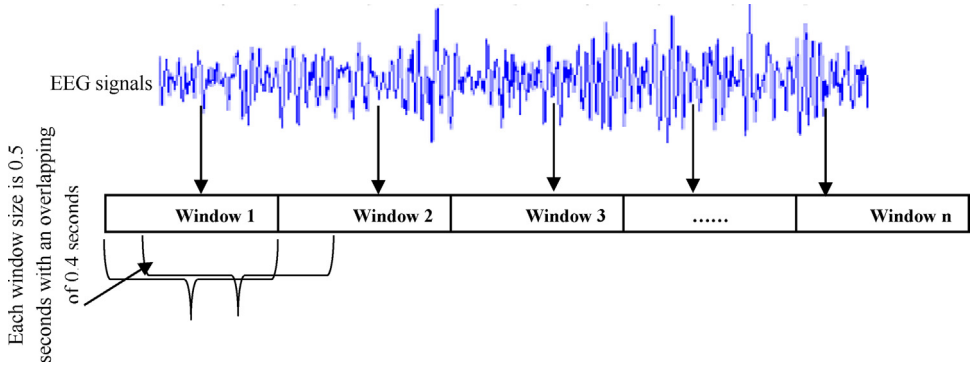

Fig. 2. An example of segmenting an EEG signal into windows.

parts, with each one scaled by a factor of $r = \frac{1}{\sqrt{n}}$. Further, a solid cube is an example of three-dimensional objects, which could also be partitioned into n little cubes with each one is scaled down by a ratio of $r = \frac{1}{\sqrt[3]{n}}$. D-dimensional self-similar objects are, therefore, scaled down by a factor of $r = \frac{1}{\sqrt[D]{N}}$. They can be partitioned into n smaller parts, with each one is scaled down by a factor of $r = \frac{1}{\sqrt[D]{N}}$.

As a result, a self-similar object of N parts can be scaled by a ratio r from the whole. Its fractal or similarity dimension is given by:

$$D = \frac{Log\,(N)}{Log\left(\frac{1}{r}\right)} \tag{4}$$

The fractal dimension is normally not an integer number. For example, von Koch curve is constructed from four sub-segments. Each one is scaled down by a factor of $\frac{1}{3}$. By applying the above equation, the fractal is equal to 1.26. The obtained results are often a non-integer value that is greater than one and less than two.

Extracting features from images is a common step that is used in various image applications, by which the important features, such as texture and color features can be pulled out. A fractal dimension (FD) technique is one of the powerful methods to extract the hidden patterns in images [45]. It is commonly used to explore the key patterns in biomedical signals and images [37]. It has been used to analyse and classify EEGs, EMG and ECG [62,21,32]. The term of fractal dimension refers to any fractal characteristics, such as information dimensions, capacity dimensions and correlation dimensions [47]. In this paper, the capacity dimensions are used.

A box counting algorithm is one of the fractal dimension methods, which is used to obtain the FD of an image or a signal [50,61]. In this paper, the box counting algorithm is used to estimate the FD of

Table 3
The numbers of non-empty grid (box size) in ten scale.

Box size δ	1	2	4	8	16	32	64	128	256	512	1024
No. of box $N(\delta)$	435823	110918	28205	7321	1973	571	166	42	12	4	1
Log$(1/\delta)$	0	0.30102	0.60205	0.90308	1.20411	1.50514	1.80617	2.10720	2.40823	2.70926	3.01029
logN (δ)	5.6393	5.04500	4.45032	3.8645	3.29512	2.75663	2.22201	1.62324	1.07918	0.60206	0

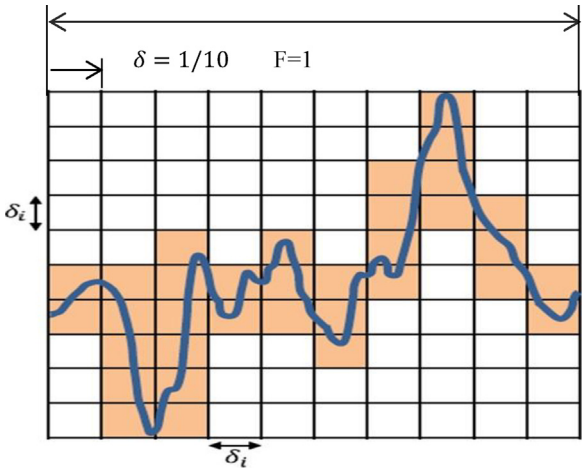

Fig. 3. An illustration of the box counting algorithm to create the size (δ) and the numbers of boxes N_δ.

a TFI to detect sleep spindles in EEG signals. Each TFI is converted into a gray scale image. Each gray scale image is then translated into a binary image before applying the box counting algorithm.

To convert a grayscale image into a binary image, a predefined threshold value (δ) is used based on the following equation.

$$Im\,(p(i)) > \delta \rightarrow 1; Im\,(p(i)) < \delta \rightarrow 0 \quad (5)$$

where Im is an image, $p\,(i)$ refers to the ith pixel, and δ is a predefined threshold. Each pixel value is set to 0 or 1, based on Eq. (5). If the pixel value is greater than or equal to the threshold, then the pixel is set to 1, otherwise 0.

The main concept of the box counting method can be described as follows: assume **X** is a TFI, and we need to determine the FD of **X**. The following equation is used [60,45].

$$D_\beta = \lim_{\delta \to 0} logN(\delta)/\log(1/\delta) \quad (6)$$

where D_β is a fractal dimension, $N(\delta)$ is the total number of boxes, and δ is the size of boxes that is required to cover image **X**. In order to cover the entire TFI in this paper, different sizes of boxes are tested and $N(\delta)$ and δ are determined. For example, to estimate the FD of a TFI, firstly, the TFI is normalized by rescaling it from the size of n x n to the size of m x m. We use an image scaling technique called nearest neighbour to rescale the TFIs. A TFI is converted from one resolution/dimension to another one without losing the visual content. Nearest neighbour is one of the fastest and simplest forms of rescaling techniques. During enlarging (upscaling), the empty spaces will be replaced with the nearest neighbouring pixels. For shrinking, the pixel sizes are reduced. One of the TFIs is used as a reference image or a base image to construct a new scaled image. This new rescaled image is used to rescale other IFIs. The number of the boxes that are required to cover a TFI and the size of each box are then investigated. That means at each iteration, a different number of boxes with different sizes of boxes are tested until the values of δ and N are decided. Fig. 3 shows an example of how to create the size and the number of boxes using the box counting algorithm. By using Eq. (6), the fractal of each TFI can be obtained from a slope of the least square fit of $\log N(\delta) = versus - \log(1/\delta)$.

Table 3 shows the number of the boxes that are required to cover the entire TFI by which the FD can be estimated.

If the box size $\doteq$ is 32 and the number of boxes that are required to cover the curve is 571, based on the equation , $\log N(\delta) = versus - \log(1/\delta)$, the fractal value for the sixth features (*FD6)* is equal to 1.788. The same procedure is applied to get all the features. The fractal dimension values are between 1 and 2 and all the FD values are non-integer.

3.4. Extracted features

As mentioned before in Section 3.3, the FD is calculated after transferring an EEG signal into a TFI using the STFT. The obtained result of the TFI is converted into an 8-bit binary image. To extract the features from each image, the box-counting algorithm is applied to each TFI and a set of statistical features are then extracted based on the fractal estimation values. Each element in the fractal dimension features is computed using Eq. (6) and the fractal is obtained based on the slope of least square best straight line. Ten fractal dimension features are extracted from each TFI, and they are denoted as FD = {*FD1, FD2, FD3 . . . FD10*}, where the number of the features corresponding to the number of iterations used to cover each TFI. Different numbers of boxes with different sizes of boxes are tested until an optimal number of boxes is obtained to cover the whole TFI. At each iteration, a fractal feature is extracted. The procedure is repeated 10 times in this paper when the maximum number of boxes to cover the whole TFI is reached. As a result, 10 features are extracted. A statistical model is then used to extract the statistical characteristics of the fractal dimension features and the number of the features is reduced to eight [63].

Different combinations of these statistical features including two, four, six and eight features sets, are tested in this paper to find out the best combination to represent each TFI. Table 4 presents the formulae of the eight statistical features.

- $F_{mean} = mean\,(FD)$
- $F_{max} = max\,(FD)$
- $F_{meadin} = median\,(FD)$
- $F_{SD} = standard\ deviation\,(FD)$
- $F_{min} = min\,(FD)$
- $F_{Sk} = skewness\,(FD)$
- $F_{rang} = Range\,(FD)$
- $F_{ku} = kurtosis\,(FD)$

Where N is the length of *FD*, m is the *mean* of the *FD* [16,34,53].

3.5. Classifiers

To evaluate the performance of the proposed method to detect sleep spindles in EEG signals, different classification methods are used and tested. The features extracted from each TFI are used as the input to the LS_SVM as well as to a K-means, Naïve Bayes and neural network classifiers. The used classifiers are briefly discussed in this section.

3.5.1. Least square support vector machine (LS_SVM)

The LS_SVM is a robust method for signals regression and classification. It is a popular classifier due to its high accuracy and with a

Table 4
Definitions of the statistical features.

No.	Features name	Formula	No.	Features name	Formula
1	*mean (FD)*	$F_{mean} = \frac{1}{N}\sum_{n=1}^{N} FD_n$	5	*standarddeviation (FD)*	$F_{SD} = \sqrt{\sum_{n=1}^{n}(FD_n - m)^{\frac{2}{n-1}}}$
2	*max (FD)*	$F_{max} = \max[FD_n]$	6	*Range (FD)*	$F_{rang} = F_{max-}F_{min}$
3	*min (FD)*	$F_{min} = min\,[FD_n]$	7	*skewness (FD)*	$F_{Sk=}\sum_{n=1}^{N}(FD_n - m)\frac{3}{(N-1)SD^3}$
4	*median (FD)*	$F_{meadin} = \left(\frac{N+1}{2}\right)^{th}$	8	*kurtosis (FD)*	$F_{ku} = \sum_{n=1}^{N}(FD_n - m)\frac{4}{(N-1)SD^4}$

minimum execution time. Many researchers have used the LS_SVM in EEG signals classification. It was used by Suily et al. [55] for the motor image classification, also by Al Ghayab et al. [6] for detecting the epileptic EEG signals.

The LS_SVM depends on two hyper parameters, γ and σ. The two parameters can positively or negatively affect the performance of the proposed method. It is necessary to choose those parameters carefully in order to obtain the desired classification results. In this study, the radial basis function (RBF) kernel was used, and the optimum values for γ and σ are set to $\gamma = 10$ and $\sigma = 0.5$, selected during the training session.

3.5.2. K-means

The K-means is widely used to classify data in various fields, such as biomedical signals, digital images and time series classification. It is generally known as a clustering algorithm [41,19]. The architecture of this classifier depends on dividing data into groups according to their similarities or differences among their elements. The K-means identifies the cluster center and other elements by reducing the squared errors based on an objective function. The main objective of using a clustering algorithm is, firstly, to identify the cluster center. Secondly, it associates each element which has the same characteristics with the nearest cluster center. In this paper, K-means is used to distinguish between sleep spindles and non spindles segments.

3.5.3. Neural network

The backpropagation algorithm of a neural network is a supervised learning algorithm. It is commonly used in classification research [10]. It was used by Bishop et al. [25] to classify k-complexes in sleep EEG signals. The connection weights in each iteration are updated. The architecture of a typical neural network consists of three layers, namely, an input layer, a hidden layer and the output layer. The input layer is fed with the input features. The second layer is a hidden layer. It has five neurons with an activation function of $y(x) = 1/(1 + e^{-\sigma x})$. The number of the hidden layer and neurons are determined empirically. The value of σ is set to 1. The number of iterations is set to 1000, the target error is set to 10e-5. The learning rate is set to 0.05.

3.5.4. Naïve bayes (NB)

Naïve Bayes is an efficient and effective technique for classification and it is commonly used in pattern recognition. It works based on the applications of Bayes' rules and posterior hypothesis. The Naïve Bayes assumes that each attribute influences differently on a given class. It has received a great attention from many researchers as it is simple and fast [4]. Puntumapon et al. [46] used a naïve classifier for classifying cellular phone mobility. Rakshit et al. [48] also employed this classifier to classify left and right movement patterns in EEG signals. In this paper, Naïve Bayes is also employed to detect sleep spindles.

3.6. Performance evaluation

The accuracy, sensitivity and specificity measurements are used to evaluate the performance of the proposed method to detect sleep spindles [64,51,65]. The main formulas of those statistical measurements are defined as.

Sensitivity (SEN) or true positive rate: It is used to estimate the performance of the classification method by measuring the proportion of the actual positive predication. It is defined as:

$$Sensitivity\ (SEN) = \frac{TP}{TP + FN} \tag{7}$$

where TP (true positive) means the actual sleep spindle waves that are correctly detected using the proposed method, FN (false negative) shows the actual sleep spindles that are incorrectly marked as non-sleep spindles.

Accuracy: it refers to the number of correctly classified cases. It is calculated by dividing the aggregating of classification results by the number of cases. The accuracy is defined as:

$$Accuracy\ (ACC) = \frac{TP + TN}{Total\ number\ of\ the\ cases} \tag{8}$$

where TN (true negative) is the actual non-sleep spindles that are correctly classified using the proposed method as non-sleep spindles

Specificity: it is used to calculate the proportion of the actual negative predication. It is defined as.

$$Specificity\ (SPE) = \frac{TN}{TN + FP} \tag{9}$$

where FP (false positive) refers to the number of sleep spindles that are incorrectly determined by the proposed method.

F-score*:* it is one of the most important measurements that are used to show the overlapping between the sets of true sleep spindles and the found sleep spindles by using the proposed method. F-score is defined as a harmonic mean of precision *(PPV)* and recall *(TPR):*

$$F - Score = 2x\frac{(PPV.TPR)}{PPV + TPR} \tag{10}$$

where PPV is precision or positive predictive value that is calculated as

$$Precision\ (PPV) = \frac{TP}{TP + FP} \tag{11}$$

Kappa coefficient: it measures the performance agreement between two models. It is defined as.

$$Cohen's\ Kappa\ Coefficient\ (k) = \frac{pr\,(a) - pr\,(e)}{1 - pr\,(e)} \tag{12}$$

where *pr(a)* and *pr(e)* represent the actual agreement and chance agreement respectively.

Table 5
The performance of the proposed method based on two features set.

Dataset-1				Dataset-2		
Fold	sensitivity%	specificity%	accuracy%	sensitivity%	specificity%	accuracy%
Fold1	73	75	78	39.2	87.6	81.9
Fold2	76	72	74	55	85	79
Fold3	74	76	76	77	81	77
Fold4	75.5	74	77	60	80	81
Fold5	72	73	75	76	83	80
Fold6	76	75	76.5	72	79	75
average	**74.41**	**74.16**	**76.03**	**63.2**	**82.6**	**78.9**

K-cross-validation: It is a popular measure to assess the classification accuracy. It is used to describe the performance of the proposed method. The dataset is divided into k equal subsets. One of them is used as the testing set, while the rest subsets are used as the training set. All the subsets are tested. The testing classification accuracy for all the subsets are calculated and recorded.

In this paper, $k = 6$ (6-cross-validation) is used. Therefore, the average accuracy is computed as below.

$$\text{Performance} = \frac{1}{6}\sum_{1}^{6} accuracy^{(R)} \tag{13}$$

where $accuracy^{(R)}$ is the accuracy for the 6 iterations.

Receiver Operating Characteristics (ROC): The ROC curve is a suitable metric in studying the dependency of sensitivity and specificity. The relationships among true positive rate, false negative rate, false positive rate and true negative were investigated in this paper using the ROC. The ROC curve represents by a graph in which the false positive rate is plotted on the x-axis while the true positive rate is plotted on the y-axis. The left lower point (0, 0) indicts the method dose not commit false positive errors and dose not obtain true positive rate, while the upper right point (1, 1) represents the opposite strategy. The perfect point in the ROC is represented by the point (0, 1).

4. Experimental results

In this study, the proposed method is developed to detect sleep spindles based on fractal dimension and time frequency image. All the experiments were conducted with the databases discussed in Section 2. The EEG signals were divided into segments using a sliding window technique. The size of the window was set to 0.5 s with an overlapping of 0.4s. Then, the EEG signal was, firstly, converted to a TFI using a STFT. Each TFI was converted into an 8-bit binary image. The fractal dimension based on the box-counting method was used to extract the desired features from each TFI. The obtained results showed that the extracted features using the box counting algorithm yielded accurate results. The experiments were conducted using Matlab software (Version: R2015) on a computer with the following settings: 3.40 GHz Intel(R) core(TM) i7 CPU processor machine, and 8 GB RAM.

The number of square boxes that were required to cover the entire curve is investigated in this paper. Eight statistical features were extracted after obtaining the FDs based on the box-counting method. Those features were considered as the key features, and were then forwarded to different classifiers of LS_SVM, K-means, Nave Bayes and a neural network. For further investigation and to evaluate the performance of the proposed method, different sets of features, including two, four, six and eight features, were used to detect sleep spindles. The results were discussed in the next section. According to the experimental results, the proposed method with eight features achieved high classification results, with an average accuracy of 98.6% for Dataset-1, and 97% for Dataset-2.

4.1. Two features set

Two features $\{F_{mean}, F_{max}\}$ were tested to detect sleep spindles in EEG signals. In this case four boxes of size 512 were considered in this experiment to extract the FDs. Each TFI was presented as a vector of two statistical features. According to the obtained results, two features set was not good enough to distinguish the sleep spindles with an acceptable accuracy. Table 5 reports the obtained results in term of accuracy, sensitivity and specificity in each fold based on the two features for the both datasets. The 6-cross validation was used in this paper. An average accuracy, sensitivity and specificity of 76%, 74.4% and 74.1% for Dataset-1, while the average accuracy, sensitivity and specificity of 78.9%, 63.2% and 82.6% for Dataset-2 were recorded. To obtain a higher accuracy, the number of features was increased to four features in the next experiment.

4.2. Four features set

Four features were also investigated. The four features of $\{F_{mean}, F_{max}, F_{meadin}, F_{SD}\}$ were extracted from the FDs of each TFI. In this experiment, 64 boxes of size 128 were considered to extract the estimates of the fractal dimensions for each TFI. The accuracy, sensitivity and specificity were increased by about 7% when the number of features was increased to four. Table 6 shows the obtained results for the both datasets.

We can notice that there are differences in the results when the number of features was increased. Because the box size and the number of boxes used to extract the FDs were covered most

Table 6
The performance of the proposed method based on four features set.

Dataset-1				Dataset-2		
Fold	sensitivity%	specificity%	accuracy%	sensitivity%	specificity%	accuracy%
Fold1	84	86	89	65.5	98.2	88
Fold2	81	84	88	75	90	86
Fold3	83	82.6	84.6	79	89	84
Fold4	80.5	84	85	81	91	87
Fold5	83	85.5	84	76	86	85
Fold6	82	87	86	72	84	84
average	**82.25**	**84.85**	**86.1**	**74.75**	**89.7**	**85.6**

Table 7
The performance of the proposed method based on six features set.

Dataset-1				Dataset-2		
Fold	sensitivity%	specificity%	accuracy%	sensitivity%	specificity%	accuracy%
Fold1	96	96	99	79.6	97.8	90.6
Fold2	95	98	95	74	92	91
Fold3	94.5	94	97	69	96	97
Fold4	97	95	96	80	97	93
Fold5	94	97	97	79	94	91
Fold6	93	98	99	78	96	90
average	**94.9**	**96.3**	**97**	**76.6**	**95.4**	**92.1**

Table 8
The performance of the proposed method based on eight features set.

Dataset-1				Dataset-2		
Fold	sensitivity%	specificity%	accuracy%	sensitivity%	specificity%	accuracy%
Fold1	97	97.6	99	93.7	99	98.1
Fold2	95	96	98	92	95	98
Fold3	96	97.5	99	96	97	97
Fold4	96	99	98.7	97	98	95
Fold5	98	98	99	99	99	99
Fold6	99	97	98	95	94	96
average	**96.8**	**97.5**	**98.6**	**95.4**	**97**	**97.1**

of the image region. Also, the proposed method provides a better performance by using the four features. The average accuracy, sensitivity and specificity of the proposed method with Dataset-1 is 86.1%, 82.25% and 84.85%, respectively. The average accuracy, sensitivity and specificity of 85.6%, 74.5% and 89.7% for Dataset-2 were recorded. Our finding showed that there were no big differences in results when the proposed method was evaluated with two different datasets. It is clear that, the proposed method achieved quite similar results using two different channels.

4.3. Six and eight features

In this case, a vector of six features including {F_{mean},F_{max}, F_{meadin}, F_{SD}, F_{min}, F_{Sk}} were extracted and used to detect sleep spindles. Table 6 shows the performance of the proposed method based on the six features with the both datasets. The experimental results showed that the classification performance by the six features set were better than that by the four features set with an increase of 8%. The proposed method was also tested with eight features of {F_{mean},F_{max}, F_{median}, F_{SD}, F_{min}, F_{Sk}, F_{rang}, F_{ku}}. It was noticed that the accuracy, sensitivity and specificity were slightly increased, but there were no big differences between using the six or eight features set. The performance results based on the eight features set by the proposed method with two datasets are presented in Table 8. Tables 7 and 8 show that the six and eight features sets using the two datasets yielded quite similar results. From the obtained results, it is clear that increasing the number of the features to eight can increase the performance of detecting sleep spindles. The obtained results demonstrated that the proposed method yielded the best performance with an average accuracy of 98.6% and 97.1% with Dataset-1 and Dataset-2, respectively. Figs. 4 and 5 demonstrate the classification accuracy against the number of the features. From Fig. 4 one can notice that the proposed scheme achieves better results with an average accuracy of 98% using six and eight features with Dataset-1. Fig. 5 shows the average accuracy of 97.1% using Dataset-2. The above results show that the proposed method has potentials to classify EEG signals for sleep spindles and non-spindles segments.

Fig. 6 presents the classification accuracy based on the number of the features for the both datasets. From Fig. 6, it was found that the eight features set yielded the best accuracy with the both

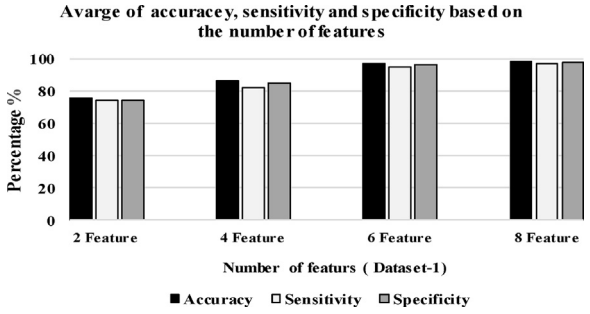

Fig. 4. The accuracy, sensitivity and specificity percentages with the number of the features for Dateset-1.

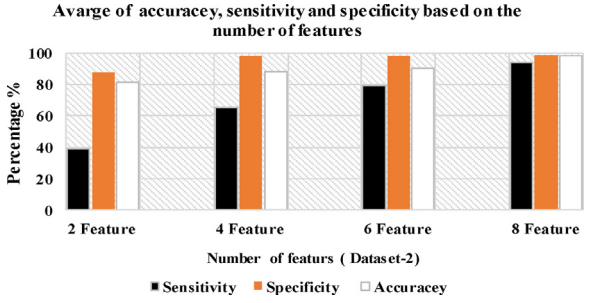

Fig. 5. The accuracy, sensitivity and specificity percentage with the number of the features for Dateset-2.

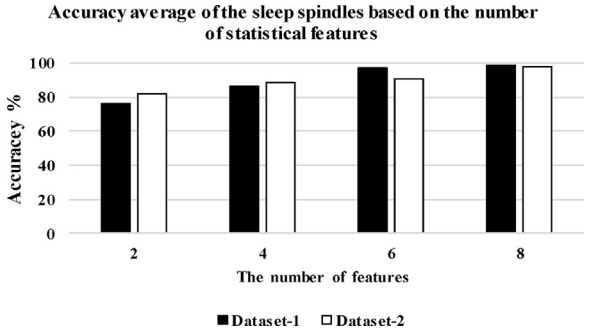

Fig. 6. Classification accuracy based on the number of the features.

Table 9
The performance of the proposed method based on F-score and Kappa coefficient.

Type of Database	Measurements	
	F-score	Kappa coefficient
Dataset-1	0.95	0.87
Dataset-2	0.89	0.83

databases when compared to the results with another features, including two, four, six and eight features sets. It was observed that there were relationships between the number of the features and the accuracy. Based on the above results, the proposed method obtained an average of 98.6% and 97.1% accuracy with eight features set for the two datasets, separately.

For further evaluation, the performance of the proposed scheme were also tested using different metrics, including F-score and kappa coefficient. Table 9 reports the average of measurements for the both datasets. The averages of F-score and kappa coefficient were 0.95% and 0.87% for Dataset-1, while the average of F-score and kappa coefficient were 0.89 and 0.83 for Dataset-2. All the results in Tables 5–9 were carried out using the LS_SVM classifier.

5. Comparison of study

To evaluate the proposed method, extensive experiments were conducted to detect sleep spindles in EEG signals. The extracted features were fed into the LS_SVM as well as to the neural network (NN), Naïve Bayes and K-means to evaluate the performance of the proposed method. We also compared the performance of the proposed method with other existing studies that used the same datasets as described in Section 2. Finally, the complexity time was computed to evaluate the speed of the proposed method in sleep spindles detection.

5.1. Comparison with different classifiers

In this section, the performance of the proposed method was compared using accuracy, sensitivity, specificity and F-score with different classifiers, including the LS_SVM, the NN, K-means and Naïve Bayes. Fig. 7 presents the results of the comparisons. Different numbers of segments were selected randomly from the two datasets. The eight statistical features set was considered in the comparisons.

Based on the obtained results in Fig. 7, the proposed method achieved better results with LS_SVM than the other classifiers. One can see that the best accuracy is 98.6% by the LS_SVM. Furthermore, the sensitivity and specificity with the same classifier are 96.8% and 97.5%, respectively. The second highest accuracy, sensitivity and specificity 94.6%, 93% and 94%, respectively, were recorded with K-means classifier. For further investigation in terms of the efficiency of the proposed method, F-score was assessed for all the classifiers. The proposed method with the LS_SVM classifier yielded the highest F-score value as 0.95.

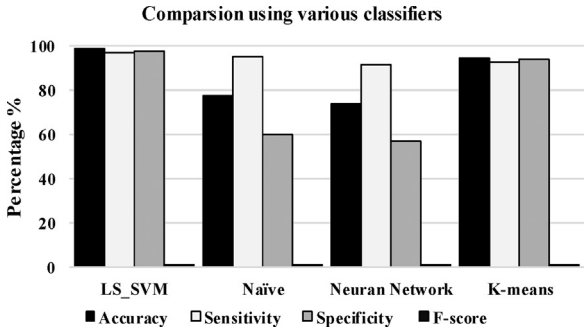

Fig. 7. The performance of the proposed method based on different classifiers.

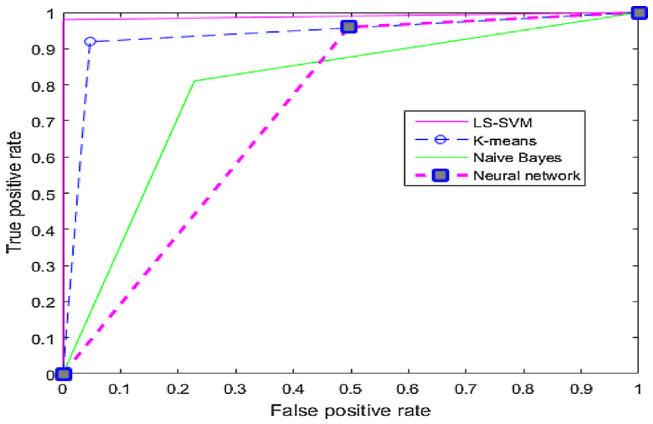

Fig. 8. The ROC curves for the four classifiers.

The evaluation results for all the classifiers were supported by using Receiver Operating Characteristics (ROC) curve. From Fig. 8, it is clear that the biggest area under the ROC curve was constructed by LS_SVM. The second best results was obtained with K-means classifier, and the area under the ROC curve for artificial neural network was generally lower than other classifiers. The results of the area under the curve of 0.98 reported were from LS_SVM classifier. From those results, it was evidence that the LS_SVM was the best classifier for detecting sleep spindles in EEG signals.

5.2. Performance evaluation based on time complexity

Comparisons in terms of the time complexity were made for the both datasets. Fig. 9 shows the results of the comparisons based on the number of segments and complexity time for each classifier. Different numbers of segments were used to compare our proposed method using those classifiers. All the segments were randomly selected from the both datasets. According to the results, the performance of the proposed method with the LS_SVM is better than those by other classifiers. The minimum time execution of the proposed methods with the LS_SVM was 0.41second(s) when dealing with 100 segments. In addition, one can see that the time slightly increased when the number of the segments was between 200 and 500. On the other hand, the maximum time of the proposed method increased to a record of 10.0 s with 1500 segments. From Fig. 9, it is clear that the longest time was consumed by the NN classifier.

5.3. Comparison with histogram representation

Form the literature, the previous studies that used a time frequency image to extract features from EEG signals were developed

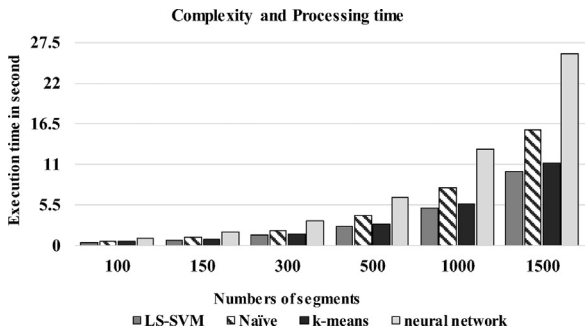

Fig. 9. Time complexity comparisons with different numbers of segments from the both datasets.

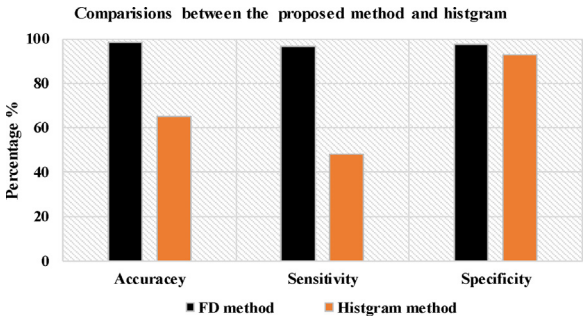

Fig. 10. Comparison of the performance of the proposed method based on histogram and fractal dimension features.

based on analyzing the characteristics of histograms. The characteristics of the TFI histograms were used by Bajaj and Pachori [9] to identify EEG sleep stages and to classify alcoholic EEG signals. They were also used by Fu et al. in [22] to detect epileptic seizures in EEG signals. In this paper, the characteristics of the TFI histograms were also investigated. The obtained results were compared with those by the fractal dimension technique. In this experiment, the histogram features were extracted from each TFI and the performance of the proposed method was evaluated in terms of accuracy, sensitivity and specificity. All experiments were made with the both datasets. Eight statistical features of $\{F_{mean}, F_{max}, F_{median}, F_{SD}, F_{min}, F_{Sk}, F_{rang}, F_{ku}\}$ were extracted from each TFI histogram. The extracted features were fed to the LS_SVM. From Fig. 10, we can notice that the maximum accuracy, sensitivity and specificity obtained by the histogram dimensional features were 65%, 48% and 93%. It is clear that the obtained results are lower than those obtained by fractal dimension. Based on the results, extracted features from TFIs using the box counting method achieved high classification rates than the histogram features.

5.4. Comparison with the existing methods

To evaluate the performance of the proposed methods, the comparisons with other existing algorithms were made. All the selected studies were conducted using the same databases as described in Section 2. Table 10 shows the comparisons among the proposed method and those from Nonclercq et al. [36], Imtiaz et al. [30], Patti et al. [43], Ahmed et al. [5], Gorur et al. [23] and Devuyst, S., et al. [15], Kuriakose, et al. [33], Zhuang and Peng [65], Patti et al. [44] and Yucelbas et al. [64]. Those studies were conducted using Dataset-1. The proposed method was also compared with some studies in which Dataset-2 was used. The comparison studies were made by Tsanas et al. [57], Saifutdinova et al. [51] and Patti et al. [44]. Based on the results in Table 10, the proposed method yields the best results comparing with the others.

Nonclercq et al. [36] used a 0.5 s window size with an overlapping 125 ms. The maximum sensitivity and specificity in that study were 75.1% and 94%, respectively. The obtained results using the proposed methods were better than those by Nonclercq et al. [36]. Another study was presented by Devuyst, et al. [15]. The used window in that study was 0 0.5 s with an overlapping 0.1 ms. The maximum sensitivity and specificity achieved were 70.20% and 98%, respectively. We can observe that the proposed method performed better than those by Devuyst, S., et al. [15].

Table 10
The performance comparisons of the proposed method with other existing methods.

Authors	Method	ACC (%)	SEN (%)	SPE (%)	F-score(%)	KA(%)	WS (s)	OVR (s)	DB
Nonclercq et al.	Sleep spindles detection using amplitude based features extraction	–	–	94	–	–	0.5	0.25	DB-1
Imtiaz et al.	Teager energy and spectral edge frequency	91	80	96	–	–	0.25	50	DB-1
Devuyst et al.	a systematic assessment method	–	80.3	97.6	–	–	0.5	–	DB-1
Imtiaz et al.	Line length	–	83.6	87.9	–	–	1.0	50	DB-1
Kuriakose, et al.	Transformation coefficients as known Karhunen-level transform	–	86.9	93.5	–	–	0.5	–	DB-1
Gorur et al.	a short time Fourier transform with a SVM and neural network		95.4 88.7	–	–	–	0.5	–	DB-1
Ahmed et al.	Wavelets packets Energy Ratio and Teager Energy Operator	93.7	–	–	–	–	1.28	–	DB-1
Tsanas et al.	Continuous wavelet transform with Morlet basis function		76	92	0.46	0.66	1.0	–	DB-2 DB-1
Patti et al.	Gaussian mixture model	–	74.9	–	–	–	1.5	–	DB-1
Zhuang and Peng	Utilize a sliding window- based probability estimation method		50	99	0.58		1.0	50	DB-1
Patti et al	Random Forest classifier		71.2	96.73	–	–	–	–	DB-2
Yucelbas et al.	Fast Fourier transform, autoregressive, multiple signal classification and Welch filter	84 without PCA							Private
Yucelbas et al.	Fast Fourier transform, autoregressive, multiple signal classification and Welch filter	94with PCA	–	–	–	–	–	–	Private
Parekh et al	Optimization algorithm for the detection k-complex and sleep spindles.	96	71	96	0.69	0.67	1.0	75	DB-1
Saifutdinova et al.	used an empirical mode decomposition to detect sleep spindles in EEG signals	–	–	–	0.40	–	–	–	DB-2
Proposed method	**Time frequency image based on fractal dimension**	**98.6**	**96.8**	**98.2**	**0.95**	**0.87**	**0.5**	**0.4**	DB-1
Proposed method	**Time frequency image based on fractal dimension**	**97.1**	**95.4**	**97**	**0.89**	**0.83**	**0.5**	**0.4**	DB-2

where ACC = accuracy, SEN = sensitivity, SPE = specificity, KA = kappa coefficient, WE = window size, OVR = an overlapping, s=second and DB = dataset.

Imtiaz et al. [30] reported a Teager energy and spectral edge frequency method to detect sleep spindles. In this study, a window size of 0.25 s with an overlapping of 50% was considered, and over 91% of sleep spindles were detected correctly. However, the proposed method archived a 98.6% accuracy, higher than the method by Imtiaz et al. [30].

Patti et al. [43] used a Gaussian mixture model to identify sleep spindles in EEG signals. A window size of 1.5 s without overlapping was employed. Four features were extracted and forwarded to a classifier to detect sleep spindles. An average sensitivity of 74.9% was reported. In comparison, the proposed method achieved more than 96.8% sensitivity with a 0.5 window size. Most recently, Ahmed et al. [5] introduced a wavelet packet transform and Teager energy operator algorithm for detecting sleep spindles. A window of 1.28 s without overlapping was considered. From the results in Table 9, we can see that the proposed method yielded a better classification accuracy, comparing to those by Patti et al. [43] and Ahmed et al., [5].

Gorur et al. [23] used a short time Fourier transform to distinguish EEG sleep spindles. They used the same window size of 0.5 s without overlapping. In that study, the maximum average of sensitivity using the SVM and the NN was 95.4% and 88.7%, respectively. According to the results, one can see that the sensitivity of 96.8% by the proposed method is higher than those by Gorur et al. [23]. Another study presented by Zhuang and Peng [64], in which the sleep spindles were detected based on a sliding window-based probability estimation method. An EEG signal was passed through a Mexican hat wavelet transform. A set of wavelet coefficients were employed. A window size of 1.0 s with an overlapping of 50% was used in that study. An average 50.98% sensitivity and 99% specificity were reported. Although the average specificity in that study was higher than our proposed method, but we achieved the highest sensitivity and accuracy of 96.5% and 97.9%, respectively, comparing with those by Zhuang and Peng [64].

Tsanas et al. [57] detected sleep spindles based on a continuous wavelet transform and local weighted smoothing. The paper reported a sensitivity and specificity of 76% and 92%, respectively. It is clear that the proposed method achieved better accuracy, sensitivity and specificity compared with the existing methods. Patti et al. [44] applied a Random Forest classifier to detect sleep spindles. Three channels in the central EEG signals, including CZ, C3 and C4, were utilized for detecting sleep spindles. A window size of 0.5 s without overlapping was used in that study. Three features of Alpha Ratio, Sigma index and spindle band ratio were employed for the detection. The maximum sensitivity and specificity of 71.2% and 96.73% were reported, respectively.

Another study presented by Saifutdinova et al. [51] used an empirical mode decomposition to detect sleep spindles in EEG signals. The average F-score in that study was 40.72%, and 48.59%. The proposed method obtained a high classification F-score compared with the results presented by Saifutdinova et al. [51]. The proposed method was also compared with other methods in which different datasets were used.

Yucelbas et al. [64] presented the sleep spindles detection results using a fast Fourier transform, autoregressive, multiple signal classification and Welch filter. The detection phase was carried out by a NN classifier. An average accuracy of 84.8% was reported. In that study, the results changed when a principle component analysis was used. The maximum accuracy was 94%. The proposed method performed much better than those by Yucelbas et al. [64]. In summary, the comparisons with the previous studies showed that using time frequency image based on fractal dimension is effective and suitable to detect sleep spindles in EEG signals.

6. Conclusion

In this paper, a new method to detect sleep spindles in EEG signals was presented. The proposed method applied time frequency image and fraction dimension techniques to detect sleep spindles with a high classification accuracy and low execution time.

A window size of 0.5 s with an overlapping of 0.4 s was adopted in this study. The EEG signals were converted into time frequency images by using spectrogram of a short time Fourier transform. A box counting algorithm was applied to calculate the fractal dimensions (FDs) from each TFI. Eight statistical features were extracted from each FD. Those features were passed to different classifiers, including the least square support vector machine, K-means, neural network, Naïve Bayes classifiers to figure out the best classification method to detect sleep spindles. The best results of 98.6% accuracy, 96.8% sensitivity and 97.5% specificity were achieved with Dateset-1. It was found that using the TFI with the fractional dimension can improve the detection of sleep spindles. The outcomes of this study can help sleep experts to efficiently analyse EEG signals. In the future work, we will apply the proposed method to detect K-complexes in EEG signals.

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4.2 Chapter Summary

Al-Salman et al. (2018) identified sleep spindles using fractal dimensions and statistical model features. The efficiency of the fractal dimension (FD) algorithm and time-frequency image (TFI) in the sleep spindles detection was investigated for extraction features and reduction of a large amount of EEG recordings. One of the most important findings in this chapter is that the use of FD techniques to detect sleep spindles gave high classification results, accuracy, F-score and kappa coefficient, and low execution time. The effectiveness of the proposed method was tested with two databases acquired from different EEG sources, with different types of measurements and with other state of the art approaches. It was found that using the TFI with the fractional dimension improved the accuracy of detecting sleep spindles. Furthermore, the proposed method increased the possibility of analysing and detecting other sleep characteristics in EEG signals, thus enabling physicians to diagnose and treat sleep disorders.

The performance of the proposed method, as presented in Chapter 4, was compared with other recent methods that used advanced classifiers such as the deep convolutional neural network and other classifiers. All those studies used the same database as describe in this chapter. Among those studies, for example, one by Chen et al., (2021) proposed an efficient method to distinguish between sleep spindles and non- sleep spindles by a generic framework based on deep neural networks for accurate spindle detection. Firstly, time window applies to adapting to the significantly varied durations of spindles in EEG. Then, convolutional neural networks (CNNs) were used to obtain the regulated deep features of EEG epochs with variable-lengths. These regulated deep features were mixed with the entropy of EEG epochs to support spindle classification. They achieved an average F-score of 0.67%. Based on the obtained results, the proposed method yielded a higher F-score compared with Chen et al., (2021). Kulkarni et al., (2019) introduced a novel deep learning approach for single-channel sleep spindles detection, where the envelope of bandpass filter signals (9-16 Hz) and power features was used to distinguish sleep spindles and non-sleep spindles. An average sensitivity, specificity, and F-score of 90%, 96.1%, and 0.75% were reported, respectively. The results were less sensitive to the proposed method. Other studies were presented by You et al., (2021) and Chambon et al., (2018), who introduced a new method based on a deep learning approach to detect sleep spindles

in EEG signals, but they reported that the deep learning approach has not been fully investigated in the context of automatic sleep spindles in EEG signals. The average of F-score results they achieved was 0.73%, which was less sensitive than the proposed method.

Several recent methods have been employed for the detection of sleep spindles in EEG signals using different classifiers. These include a novel deep learning approach (Kulkarni et al.,2019), a generic framework based on a deep neural network (Chambon et al.,2019), an adaptive framework (You et al., 2021), genetic programming coupled with k-nearest neighbors classifier (Parekh et al., 2017), multivariate classification of EEG epochs (Lachner-Piza et al., 2018), and a two-stage approach for sleep spindle detection using single-channel EEG (Jiang et al., (2021), Time Domain Features (Fatima et al., 2020). The results they obtained were no higher than those in this thesis. An average classification accuracy rate for the detection of sleep spindles was 95.9% by (Kulkarni et al.,2019) which is considered less than obtained by the proposed method in Chapter 4. In comparison to these more recently published papers, the sensitivities measured for the same dataset using the proposed method were more sensitive and are therefore still considered to be state of the art method at the time of this thesis submission.

Both Al-Salman et al. (2019) (discussed in Chapter 3) and Al-Salman et al. (2018) showed that the proposed method yields a better performance for all sleep spindles detection compared with other recent studies. Furthermore, the proposed method made it possible to analyse other EEG signals, which assisted physicians to diagnose and treat brain disorders. Al-Salman et al. (2018) suggested that the FD features combined with statistical model features could be used to detect all the occurrences of sleep characteristics, such as spindles and k-complexes, in EEG signals efficiently. The next chapter will discuss EEG k-complexes detection based on fractal and frequency features coupled with ensemble model classifier.

CHAPTER 5

K-COMPLEXES DETECTION IN EEG SIGNALS USING FRACTAL AND FREQUENCY FEATURES COUPLED WITH AN ENSEMBLE CLASSIFICATION MODEL

5.1 Introduction

In Chapter 3, the wavelet Fourier analysis and statistical features were presented to detect sleep spindles in EEG signals. In Chapter 4, a new method based on the FD algorithm and TFI technique was proposed to analyse and identify sleep spindles with high accuracy rate and low complexity time. However, to analyse and detect other sleep characteristics in EEG signals such as k-complexes, a novel method was presented in this chapter. K-complexes are important transient bio-signal waveforms in sleep stage 2.

Detecting k-complexes visually requires a highly qualified expert. Furthermore, detecting k-complexes in EEG signals using transformation techniques, such as a wavelet transform and Fourier transform does not give the promising results that EEG signals do because the EEG signals have a nonstationary and nonlinear natural. In previous research, Al-Salman et al. (2018) reported that the fractal dimension based features achieved promising results for analysing EEG signals as well as for detection sleep spindles. As a result, the concept of the fractal algorithm was used in this study to identify the second most important characteristics of sleep stage 2: k-complexes.

Chapter 5 Fractal and Frequency feature coupled with an Ensemble model to detect k-complexes in EEG signals.

The content of this chapter is an exact copy of a published paper in the neuroscience journal (2019). It presents an efficient method for detecting k-complexes from electroencephalogram (EEG) signals based on fractal and frequency features coupled with an ensemble model of three classifiers. The proposed method has a number of phases to analyse large amounts of EEG recordings and to identify k-complexes. In the first phase, EEG signals are first partitioned into segments, using a sliding window technique. In the second phase, each EEG segment is decomposed into a number of sub-bands by using a dual-tree complex wavelet transform (DT-CWT) method. Ten sub-bands are obtained after four levels of decompositions, and the high sub-bands are considered in this research for feature extraction. Lastly, fractal and frequency features are extracted from each sub-band and then forwarded to an ensemble classifier to detect k-complexes. The proposed method was tested with Dream sleep database published in Chapter 4. The performance of the ensemble detector was evaluated with the LS-SVM, k-means and Naive Bayes detector, through a 6-fold cross-validation procedur. Moreover, comparisons were also made with existing k-complexes detection approaches for which the same datasets were used. The experimental results demonstrate that the proposed feature extraction algorithm with the ensemble model produces the best performance compared with the other studies and with individual classifiers. Also, the proposed approach was evaluated using several performance measurement metrics for k-complex detection methods. The results reveal that the proposed approach is efficient in identifying the k-complexes in EEG signals.

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K-complexes Detection in EEG Signals using Fractal and Frequency Features Coupled with an Ensemble Classification Model

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Abstract—K-complexes are important transient bio-signal waveforms in sleep stage 2. Detecting k-complexes visually requires a highly qualified expert. In this study, an efficient method for detecting k-complexes from electroencephalogram (EEG) signals based on fractal and frequency features coupled with an ensemble model of three classifiers is presented. EEG signals are first partitioned into segments, using a sliding window technique. Then, each EEG segment is decomposed using a dual-tree complex wavelet transform (DT-CWT) to a set of real and imaginary parts. A total of 10 sub-bands are used based on four levels of decomposition, and the high sub-bands are considered in this research for feature extraction. Fractal and frequency features based on DT-CWT and Higuchi's algorithm are pulled out from each sub-band and then forwarded to an ensemble classifier to detect k-complexes. A twelve-feature set is finally used to detect the sleep EEG characteristics using the ensemble model. The ensemble model is designed using a combination of three classification techniques including a least square support vector machine (LS-SVM), k-means and Naïve Bayes. The proposed method for the detection of the k-complexes achieves an average accuracy rate of 97.3 %. The results from the ensemble classifier were compared with those by individual classifiers. Comparisons were also made with existing k-complexes detection approaches for which the same datasets were used. The results demonstrate that the proposed approach is efficient in identifying the k-complexes in EEG signals; it yields optimal results with a window size 0.5 s. It can be an effective tool for sleep stages classification and can be useful for doctors and neurologists for diagnosing sleep disorders.

Key words: K-complexes, dual-tree complex wavelet transform, fractal dimensions, ensemble model, EEG signals.

INTRODUCTION

In the context of sleep research, sleep scoring is a difficult task due to its irregular behaviors of electroencephalogram (EEG) signals. Rechtschaffen (1968) suggested a set of guidelines. Based on these guidelines, experts divide a human sleep EEG recording into six sleep stages namely: Awake, Stage 1 (S1), Stage 2 (S2), Stage 3 (S3) and Stage 4 (S4), and rapid eye movement (REM) sleep (Gala and Mohylova, 2009; Peker, 2016). Each stage has a distinct set of associated physiological, psychological, and neurological features.

The four stages of S1, S2, S3, and S4 are classified as the non-rapid eye movement (NREM) sleep. Sleep exerts significant influence on human health as poor sleeping quality can cause a disturbance to the immune system. The first stage (S1) of sleep is a transition stage which lasts between 1 and 10 min. During S1, breathing slows down and heartbeat becomes regular, blood pressure and brain temperature decrease. Clinical research shows that people can suffer from sudden muscle contractions followed by a sensation of falling. However, during Stage 2, the human body starts to recover from muscle stress and fatigue. The brain activity is reduced for moving into a deep sleep (S3 and S4) from which it is hard to wake up. Although, S1 and S2 produce a similar range of theta waves, sleep spindles and k-complexes mainly appear in Stage 2 (Gorur et al., 2002). During REM stage, EEGs reveal continuous mixed activity (theta wave with some delta, alpha, and beta waves) and 40 ± 80 mv amplitude, while in S3 (slow wave sleep) EEGs show more than 20% delta

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Abbreviations: DT-CWT, dual-tree complex wavelet transform; DWT, discrete wavelet; EEG, electroencephalogram; HFD, Higuchi's fractal dimension; LS-SVM, least square support vector machine.

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waves and the amplitude can achieve 150 mv. Stages 3 and 4 are referred to as deep sleep that are combined as one (Williams et el., 1974; Ranjan et al., 2018).

Each sleep stage exhibits unique waveforms and patterns which are used by experts to detect abnormal patterns in sleep EEG recordings. One of these waveforms is the k-complexes (Parekh et al., 2015; Berry, et al., 2012; Zacharaki et al., 2013). In 2002, The American Academy of Sleep Medicine (AASM) defined k-complexes as large-amplitude transient waveforms. These waveforms have a single negative sharp wave followed by a positive sharp wave (Bankman et al., 1992). This inconsistency in the shapes peaks of k-complexes results from the non-periodic nature of EEG signals. Most early studies show that k-complexes can appear many times during S2, with a maximum duration between 0.5 s and 1.5 s. The frequency range of k-complexes is between 8 Hz and 16 Hz (Rodenbeck et al., 2006; Noori et al., 2014). However, Stage 2 can also be recognized by other transient waveforms, such as sleep spindles. The detection of those transient waveforms in EEG signals based on visual inspection is tedious, time consuming, and requires expert skills. Automatic detection approaches have thus been developed to identify k-complexes based on different transformation techniques (Al-salman et al., 2018).

Automatic detection approaches have thus been developed to identify k-complexes based on different transformation techniques combined with different machine learning such as support vector machine, decision tree and artificial neural network (Lajnef et al., 2015; Al-Salman et al., 2019; Parekh et al., 2015). Richard and Lengelle (1998) used a linear filtering approach in time and frequency domains to identify sleep k-complexes in EEG signals. An average sensitivity and false positive rate of 90% and 9.2% were reported in their study. Tang and Ishii (1995) utilized the discrete wavelet (DWT) for recognizing k-complexes in EEG signals. In that study, they obtained an 87% sensitivity and a 10% false positive rate.

Kam et al. (2004) proposed a method using a hidden Markov model based on a continuous-density to identify k-complexes in EEG signals. In their study, the false positive rate was reported around 7%, while the sensitivity classification was 85.3%. Research reported by Devuyst et al. (2010), employed a likelihood threshold to detect k-complexes. An average sensitivity of 60.94% and 61.72% respectively, were recorded. Erdamar et al. (2012) detected k-complexes based on the characteristics of EEG signals such as amplitude and duration properties. The obtained results were evaluated using a receiver operating curve. The paper reported an accuracy of 91%. Vu et al. (2012) applied a hybrid-synergic classifier to distinguish EEG k-complexes. They achieved an average of 90% accuracy and 70% sensitivity.

Bankman et al. (1992) presented a method based on artificial neural network. In that study, 14 features were extracted from the raw EEG signals to detect k-complexes. An average sensitivity of 90% was obtained with an 8% false positive rate. Based on the study, using the extracted features provided a significantly better performance than the original EEG data. Another study was presented by Hernández-Pereira et al. (2016), in which k-complexes were detected based on 14 features extracted from each EEG signal. The extracted features were then used as input to different classifiers to identify the k-complexes. An average classification accuracy rate of 91.40% was recorded using a features selection method. Krohne et al. (2014) utilized a wavelet transformation for detecting k-complexes. Four features were extracted from each sub-band. An average sensitivity of 74% was recorded. A pattern matching wavelet method to identify k-complexes in EEG signals was presented by (Patti et al., 2016). The average sensitivity in that study was 84%. Those studies were conducted using data from the same database used in this paper.

More recently, Lajnef et al. (2015) detected k-complexes using a tunable Q-factor wavelet transform. An average sensitivity and false positive rate of 81.57% and 29.54% were reported respectively. Parekh et al. (2015) proposed a method based on a non-linear optimization algorithm to recognize the k-complexes. The maximum F-measure in their study was reported at 0.57%. Our previous work, (Al-Salman et al., 2018, 2019) reported that fractal dimension based features achieved promising results for analyzing EEG signals and for detecting sleep spindles and k-complexes. This research focuses on developing an accurate method to detect k-complexes in EEG signals. Detecting those wave forms can contribute to identify sleep S2 correctly in EEG signals. The study will help advance the knowledge in sleep research and assist experts with new technologies.

In this study, firstly, a dual-tree complex wavelet transform (DT-CWT) is used to decompose an EEG signal into real and imaginary parts. High sub-bands from four levels of decompositions are used for features. The fractal dimensions and frequency features are extracted from each sub-band to detect the k-complexes in EEG signals. The extracted feature sets are evaluated to identify the best combination of features for detecting k-complexes. An ensemble classification model is used to classify the extracted features into k-complexes and non k-complexes segments. Our findings revealed that the proposed method is promising to detect k-complexes in EEG signals.

EXPERIMENTAL PROCEDURES

Proposed method

To detect the k-complexes in EEG recordings, the DT-CWT is utilized and coupled with an ensemble model. A sliding window approach is employed to divide EEG signals into segments. A window size of 0.5 s is adopted with an overlapping of 0.4 s that is chosen empirically. Then, the DT-CWT is used to decompose each EEG segment to a set of real and imaginary parts. After testing, 12 fractal dimension and frequency features are employed, and forwarded to an ensemble classifier to detect the k-complexes in EEG signals. The results obtained using the ensemble classifier are compared with those obtained by a single classifier of a LS-SVM, Naive Bayes and k-means, separately. The results indicate that, by using the ensemble classifier,

classification accuracy is higher than those obtained by the individual classifiers. Fig. 1 outlines the methodology of the proposed method. All the experimental results were obtained in a Matlab 2015b environment on a computer that has the features of: 3.40 GH Intel (R) core (TM) i7 processor machine and 8.00 GB RAM.

EEG recordings and data acquisition

The EEG database for k-complexes detection was acquired in a sleep laboratory of a Belgian hospital using a digital 32-channel polygraph (BrainnetTM Sys-tem of MEDATEC, Brussels, Belgium). It is important to highlight that all EEG recordings on this database were from patients with various sleep pathologies: dystonia, restless legs syndrome, insomnia, apnea/hypopnea syndrome (Devuyst et al., 2011; Al-Salman et al., 2019; Devuyst et al., 2010). The k-complexes database, which has been made available by the University of MONS - TCTS Laboratory and University Libre de Bruxelles—CHU de Charleroi Sleep Laboratory, can be accessed online at http://www.tcts.fpms.ac.be/~devuyst/Databases/DatabaseKcomplexes. The k-complex datasets that were publically available included 10 recordings acquired from 10 subjects. The sleep EEG data were collected in 30-minute intervals of the central EEG channel for a whole night PSG recording for k-complexes scoring. The sampled rate used to preprocess EEG signals was 200 Hz. Each recording included three EEG channels: The CZ-A1 or C3-A1, FP1-A1 and O1-A1; two EOG channels (P8-A1, P18-A1); and one submental EMG channel. The recordings (from subjects) in the EEG database were given to two experts who independently scored k-complexes according to the manual (Berry et al., 2012) and their recommendations in (Devuyst et al., 2010). The CZ-A1 channel EEG recordings sampled at 200 Hz were utilized for detecting the k-complexes in this research. Also for this study, we chose randomly six subjects out of ten that were scored by Expert 1 as a benchmark since the annotations of Expert 2 were not available for all subjects. (Miranda et al., 2019). More details regarding the EEG database were provided by (Al-Salman et al., 2019; Lajnef et al., 2015; Parekh et al., 2015; Miranda et al., 2019). Examples of EEG signals with k-complex events are shown in Fig. 2 (Miranda et al., 2019).

Signals stratification

EEG signals are segmented into small intervals using a sliding window technique. Li and Wen (2011) utilized a segmentation technique for classifying EEG signals. A sliding window with an overlapping was used by (Zhuang et al., 2016; Al-salman et al., 2018) to detect sleep spindles. Kam et al. (2004) also used a sliding window method to identify k-complexes. A sliding window with an overlapping was also used by (Al-Salman et al., 2019) to identify k-complexes. Their results demonstrated that using the sliding window technique helped to improve classification results.

In this paper, we supposed that **Y** was an EEG signal having **X** data points, where $\mathbf{Y} = \{y_1, y_2, y_3 \ldots y_x\}$. Each 30 s EEG segment was divided into sub-segments of **T,** where, $\mathbf{T} = \{m_1, m_2, m_3 \ldots m_x\}$ using a sliding window technique. The size of a sliding window was determined empirically based on an extensive number of experiments during the training phase. The previous work by (Al-Salman et al., 2018, 2019) showed that the sliding window technique gave accurate results in EEG signals segmentation for detecting the characteristics of sleep S2, such as sleep spindles and k-complexes. As sleep spindles and k-complexes occur during stage 2 for about 0.5–2 s, we tested various window sizes (such as 1.0 s, 1.5 s and 2.0 s) and overlapping lengths to identify the optimal segment size. However, we made the window length between 0.5 and 2 s. We used the same technique in (Al-Salman et al. 2018; Al-Salman et al., 2019a,b). We selected 0.5 s window length based on our simulation results. The simulation results showed that the window size of 0.5 s was most optimal for identifying EEG characteristics than other window sizes. More details about the window size is explained in the results section. Fig. 3 provides an example of EEG signals partitioned into intervals of 0.5 s with an overlapping of 0.4 s.

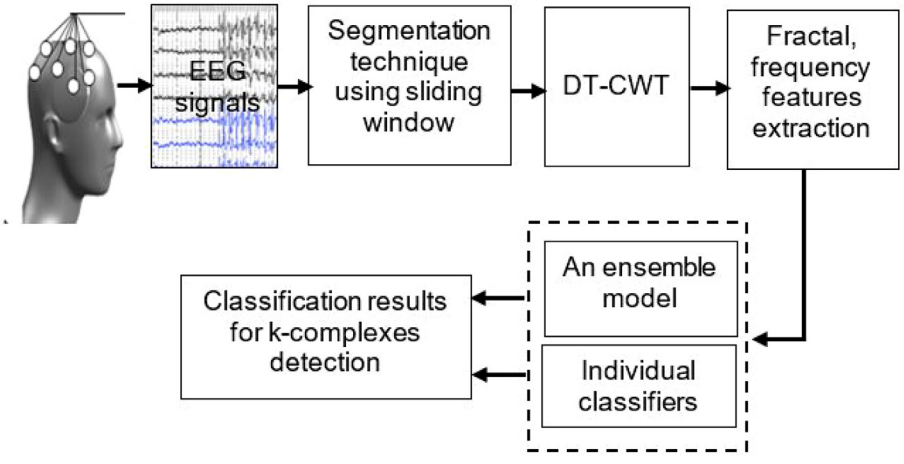

Fig. 1. Block diagram of the k-complexes detection method using fractal and frequency features based on the DT-CWT and HFD algorithms coupled with an ensemble model.

Dual-tree complex wavelet transform (DT-CWT)

The discrete wavelet transform (DWT) is a spectrum analysis technique. It was often used in various research studies to analyse non-stationary signals such as EEG signals. Due to the characteristics of EEG signals change over time, using the DWT often causes the problems of aliasing, shift variance, lack of directionality and limited directional information (Baraniuk et al., 2005; Li et al., 2017; Liu et al., 2012). Those drawbacks could be addressed by using a dual tree complex wavelet transformation (DT-CWT). The DT-CWT

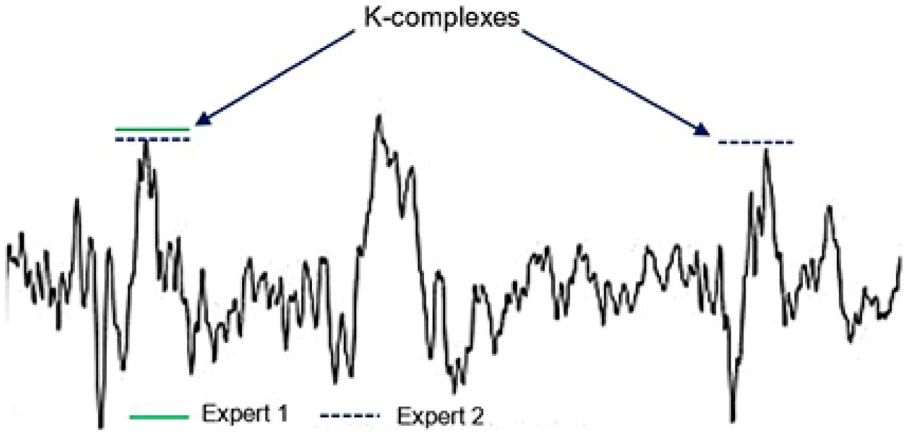

Fig. 2. Example of k-complexes waveform using the CZ-A1 channel identified from EEG data by two different experts (Miranda et al., 2019).

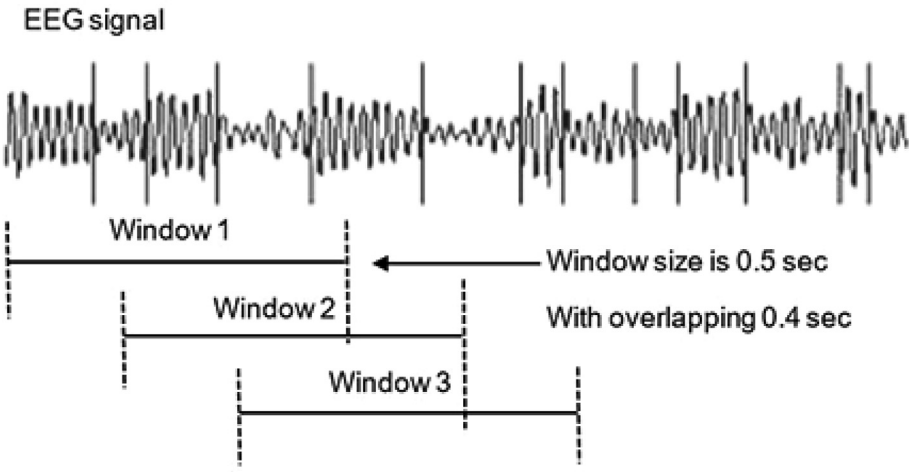

Fig. 3. Example of EEG signals partitioned into small segments using sliding window techniques. A window size of 0.5 s was used with an overlap of 0.4 s.

decomposes a signal into different levels to obtain the most significant frequency sub-bands. It employs two DWT trees (Das et al., 2016; Selesnick et al., 2005). The top tree represents the real part of the complex wavelet coefficients while the bottom tree represents the imaginary part as illustrated in Fig. 4. It has many characteristics, such as an approximate shift invariance, better directional selectivity, limited redundancy and independency of the number of scales.

In this study, EEG signals are passed through the DT-CWT to obtain the high and low frequency sub-bands. Each segment is decomposed into four levels, namely, four sub-bands of y1, y2, y3, y4 including sub-band z4, based on the four levels of decompositions. For example, in the first level of the decomposition, each EEG segment is decomposed into a higher frequency component y1 and a lower frequency component z1. Then, in the second level, z1 is decomposed into y2 and z2 as the higher and lower frequency components, respectively (Das et al., 2016). As the results, each DT-CWT coefficient has two parts of real and imaginary components. 10 sub-bands are obtained after the four levels of decomposition. The sub-bands for both real and imaginary parts are presented as (y1, 1), (y1, 2), (y2, 1), (y2, 2), (y3, 1), (y3, 2), (y4, 1), (y4, 2), (z4, 1) and (z4, 2). For example, the first sub-band for the real and imaginary parts are represented as (y1, 1), (y1, 2), respectively. Then, fractal and frequency features are extracted from each sub-band and used to study the behaviours of the k-complexes in EEG signals.

Fractal dimension based on Higuchi's algorithm (HFD)

A fractal dimension (FD) technique has been proved to be an efficient method for analyzing the characteristics of EEG signals (Finotello et al., 2015; Xiao et al., 2005; Prieto et al., 2011; Smitha and Narayanan, 2015; AL-Salman et al., 2018, 2019). More details are provided in our previous work by (Al-Salman et al., 2018, 2019a, b). In this study, Higuchi's Algorithm is used to estimate the FD from each sub-band of the DT-CWT. The Higuchi's fractal dimension (HFD) algorithm is used to measure the FDs of EEG signals. To calculate the FDs based on the HFD, the following steps are considered (Accardo et al., 1997; Higuch, 1988). Let $\frac{\pi}{3}$ be a time series to be analyzed. Starting from the first point in the time series, the algorithm constructs Y_x^r as a new time series, which is defined as:

$$Y_x^r = \left\{ Y(x),\ Y(x+r),\ Y(x+2r),\ \ldots, Y\left(x + \frac{(N-x)}{r} r\right) \right\}, \text{for } r = 1, 2, \ldots, r \tag{1}$$

where x is the initial point of the time series, and r is the time interval between two data points. The length of the curve $L_x(r)$ is calculated for each of the r time instance, and the curve Y_x^r is:

$$L_x(r) = \frac{\sum_{i=1}^{\frac{N-x}{r}} |Y(x+i.r) - Y(x+(i-1)r)|(n-1)}{\frac{N-r}{r} r} \tag{2}$$

where N is the length of the original time series Y, and $(N-1)/[(N-x)/r]\ r)$ is a normalization factor. An average length was computed for all the time series, having the same scale r, as the mean of the r length $L_x\ (r)$ for $x = 1, \ldots, r_{max}$, where r_{max} is a free parameter. This procedure was repeated many times for each r. The mean value (average length) of the curve length for each r was calculated as

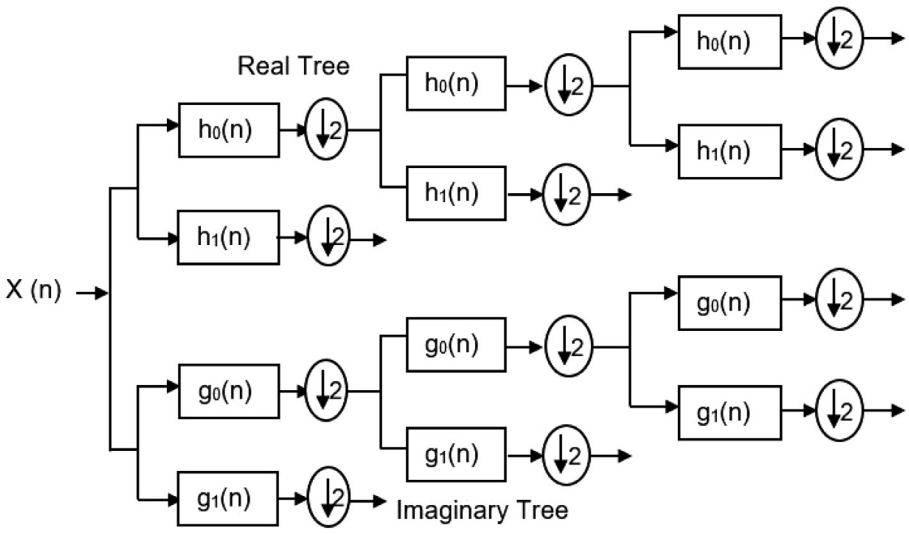

Fig. 4. EEG signals decomposed using DT-CWT. Four sub-bands (y1, y2, y3, y4) including sub-band z4 are obtained based on four levels of decomposition. $g_0[n]$ and $h_0[n]$ presents the real tree while $g_1[n]$ and $h_1[n]$ show the imaginary tree for each level of DT-CWT.

$$L(r) = \sum_{x=1}^{r} L_x(r) \quad (3)$$

The total average length for $L(r)$ is proportional to r^{-D}, where D is the FD by Higuchi's method. In the curve of $\log(L(r))$ vs $\log(1r)$, the slop of the least square's linear best fit is the estimate of the FDs (Accardo et al., 1997; Esteller et al., 2001). In this paper, the HFD is applied to calculate the FDs from each sub-band after the DT-CWT decomposition. 13 features were extracted from the FDs, and then reduced to three: standard deviation, mean energy and skewness. These features were used along with the frequency features as the input to the ensemble classifier to detect k-complexes. Our findings showed that the extracted features from the FDs based on the HFD and DT-CWT coupled with the ensemble classifier achieved better results in comparison to those by other methods. More details are explained in the experimental results section.

Features extraction method

Fractal and frequency features were used in this study to detect k-complexes. Fig. 5 shows the main steps of the features extraction process. A total of 13 statistical features are extracted, including {minimum, range, median, mean, skewness, maximum, standard deviation, variation, mode, kurtosis, Hurst exponent, Mean Energy, Permutation entropy} based on fractal dimension, and 9 frequency features of {f1, f2, f3, f4, f5, f6, f7, f8, f9} were extracted from each sub-band. A short explanation of the frequency features is given in Table 1 (Vu et al., 2012; Nguyen-ky et al., 2009; Şen et al., 2014; Al Ghayab et al., 2019; Al-Salman et al., 2018). After testing, eventually 12 hybrid features of {f1, f2, f3, f4, f5, f6, f7, f8, f9, standard deviation, mean energy, skewness} were used to detect the k-complexes in this study. Those features are then forwarded to an ensemble model to identify k-complexes in EEG signals. Fig. 6 shows a schematic diagram for k-complex with amplitude and time labels for one segment in EEG signals.

Classification algorithms to analysis EEG data

The ability of the proposed approach to detect k-complexes in EEG signals is tested based on serval classifiers. Three classification algorithms of LS-SVM, k-means and Naïve Bayes are combined to design an ensemble classifier in this paper. The final decision for the classification was made using a voting scheme based on the weights of the three classifiers. The chosen classifiers and their tuning parameters are explained in this section. The chosen classifiers and their tuning parameters are explained in this section. Table 2 shows the optimum parameters for each individual classifier, which were combined to form

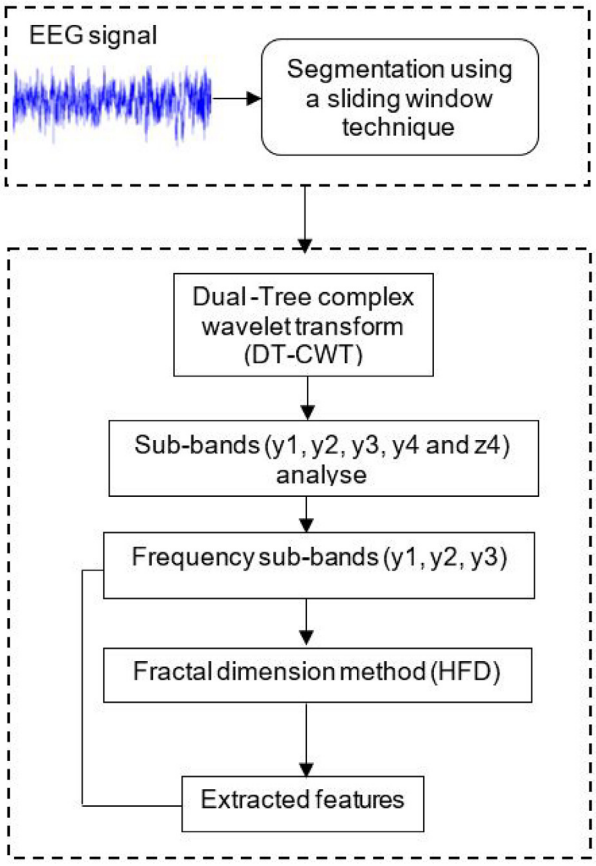

Fig. 5. Graphical diagram of features extraction from higher sub-band (y1, y2 and y3) of the DT-CWT and fractal dimension of the HFD algorithm.

Table 1. Formula of the statistical features.

Features	Formula	Explanation
*f*1	X_{max}	The max amplitude
*f*2	X_{min}	The min amplitude
*f*3	$X_{max} - X_{min}$	Peak to peak amplitude
*f*4	$\lvert p_{max} - p_{min}\rvert$	Distance between max and min data points
*f*5	$\lvert f2\rvert/\lvert f1\rvert$	The ratio between the max amplitude and the min amplitude
*f*6	$\lvert p_{middel} - p_{start}\rvert$	Duration of positive curve
*f*7	$\lvert p_{middle} - p_{end}\rvert$	Duration of negative curve
*f*8	$\lvert p_{start} - p_{end}\rvert$	Duration of the sharp wave (prospective k-complex)
*f*9	$X_{start} - X_{end}$	Differences between the first point and the min negative wave
*f*10	$X_{SD} = \sqrt{\frac{\sum_{n=1}^{N}(x_n - X_{Mean})^2}{n-1}}$	Standard Deviation; Where $X_n = 1, 2, 3, \ldots.., n$, is a time series, N is the number of data points
*f*11	$X_{Ske=} \sum_{n=1}^{N}(x_n - X_{Mean}) \frac{3}{(N-1)X_{SD}^3}$	Skewness feature where X_{Mean} is a mean for 0.5 s EEG signals
*f*12	$X_{Mean\ energy} = \frac{1}{N}\sum_{n=k-N+1}^{k} x[n]^2$	Mean energy features; where X_n is a time series

the ensemble model (Al-Salman et al., 2019; Diykh et al., 2016). More details regarding those three individual classifiers were provided in our previous work (Al-Salman et al., 2018; Al-Salman et al., 2019a,b). Based on the literature (Al-Salman et al., 2018, 2019; Li and Wen. 2011; Orhan et al., 2011; Rakshit et al., 2016; Shete et al., 2013; Li and Wen, 2010); we found that those three classifiers of LS-SVM, K-means and Naïve Bayes algorithms are considered the most popular and effective methods in biomedical signal classification. Many researchers have used the above three classifiers individually to classify EEG signals (Da cost et al, 2013; Jansen et al, 1990; Kantar and Erdamar, 2017; Puntumapon and Pattara-Atikom, 2008; Rakshit et al., 2016; Shete et al., 2013; Li and Wen, 2010).

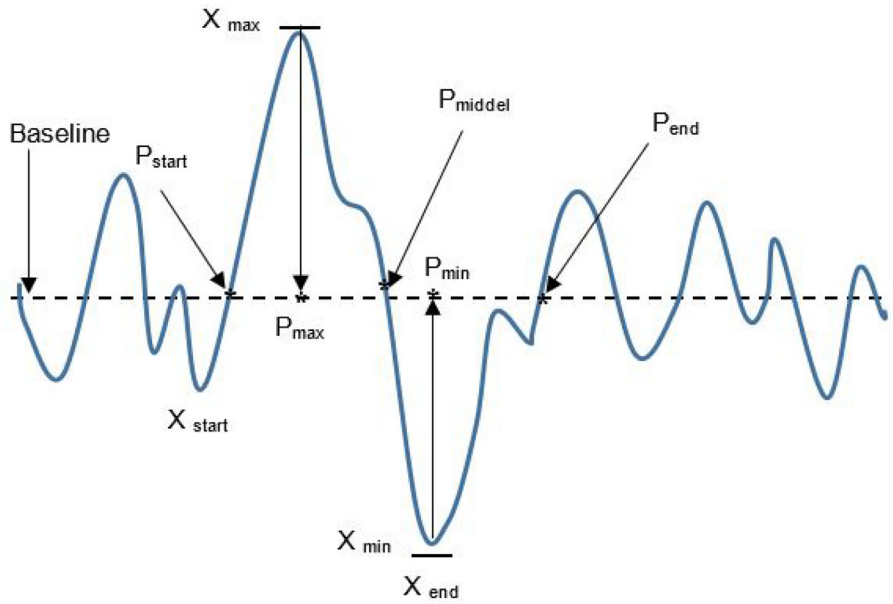

Fig. 6. Schematic diagram for a k-complex with amplitude and time labels for one segment in EEG signals.

Least square support vector machine (LS-SVM). Suyken and Vandewalle proposed a modified version of the original support vector called the least square support vector machine (LS-SVM). It is widely used to tackle binary classification problems. It was used by (Al-Salman et al., 2018, 2019; Zhu et al., 2014) to detect sleep spindles. We used the LS-SVM classifier as part of the ensemble model. The main parameters, γ, σ and the kernel function are carefully selected during the training phase. In this study, the radial basis function kernel *(RBF_kernal*) was used. It can be defined as:

$$RBF\_kernal_{(x,x_k)} = \exp(-||x - x_k||)^2/2\sigma^2 \quad (4)$$

Naïve Bayes classifier. Naïve Bayes algorithm classifies the input sample using two concepts: Bayes' rules and posterior hypothesis. The main assumption of Naive Bayes is that each input value influences a given class in a different way. It is used in two procedures in the training phase to determine the most common class for each attribute. These procedures are a maximum probability algorithm and features probability distribution. They are used by many researchers. Al-Salman et al. (2018) employed the Naïve Bayes classifier in their study to distinguish sleep spindles. In this work, the Naïve Bayes classifier is employed under the ensemble model to detect k-complexes

K-means classifier. The k-means classifier is commonly used to identify data in various fields such as signals in time series and biomedical signal processing. It was used by Orhan et al. (2011) to classify EEG epilep-

Table 2. classifiers' parameters used during the experiments.

Classifier	Parameters
LS-SVM	$\gamma = 10$, $\sigma = 1$ and kernel is RBF.
Naïve Bayes	The EEG k-complexes refer to class nodes while the feature nodes represent the statistic features of FDs as well as the frequency features
k-means	k, c_i and x_k, where k is the number of clusters , $k = 2$, while c_i is the centre of clusters and $c_i = 1$, and x_k is the data points

tic seizures. It is known as an unsupervised classification method and is mainly designed to solve clustering problems. The main mechanism of the k-means classifier is the division of a training sample into classes based on the similarities or differences within them. Each observation is associated with one group with the nearest centroid. An objective function, which reduces the squared errors, is used by the k-means to determine the cluster centre along with other elements. The k-means algorithm aims to associate each element in the training sample with other elements that have the same characteristics. In this paper, the k-means is used as a classifier technique along with the ensemble model.

The ensemble model

In this paper, an ensemble classifier based on the three single classifiers of k-means, LS-SVM and Naïve Bayes, is constructed and employed to identify k-complexes with a weighing scheme. The final decision of the classification was made based on voting (Gao et al., 2017). The ensemble technique for generating a variety of aggregation (bagging) was used to detect the k-complexes. An example of the bagging algorithm with the three classifiers to build the ensemble model is shown in Fig. 7.

The bagging ensemble technique uses a different set of training data to train individual classifiers. The training set is randomly divided into several subsets using a bootstrap aggregation method. Each individual classifier is trained separately and combined with other classifiers with a weighting scheme. All classifiers are trained together for the final prediction.

A weight is calculated for each classifier based on their error rates. A lower value error rate is considered more accurate for that classifier and it is assigned with a higher weight. The voting weights of the classifiers are calculated based on the following equation (Han et al., 2011; Lafta et al., 2017):

$$\omega i(C_t) = \log \frac{1 - error(C_t)}{error(C_t)}, \ 1 \leq (C_t) \leq 3 \quad (5)$$

where $\omega i(C_t)$ is the weight of a classifier's vote, error(C_t) is the error rate of its classifier. The proposed weighted bagging ensemble can be explained using the following example:

Step 1: A classifier is first trained individually, and the ErrRate is calculated for each classifier. For example, based on Eq. (5), the weights for the three classifiers are assigned as w_k-means (KM) = 0.47, w_ Naïve Bayes (NB) = 0.31 and w_LS-SVM = 0.73.

Step 2: The prediction results from individual classifiers are: k-means predicts 0 (Class 0, means that a non k-complex is detected); LS-SVM predicts 1 (Class 1, means k-complexes are detected), and Naïve Bayes predicts 0.

Step 3: Based on the weighted votes of the ensemble model, the prediction results are

Class 0: KM + NB = > 0.47 + 0.31 = 0.78; Class 1: LS-SVM = > 0.73

Finally, based on the above result, Class 1 gained the lower value than Class 0. The final ensemble classifier flags the segment as Class 0 (a non-k-complexes segment).

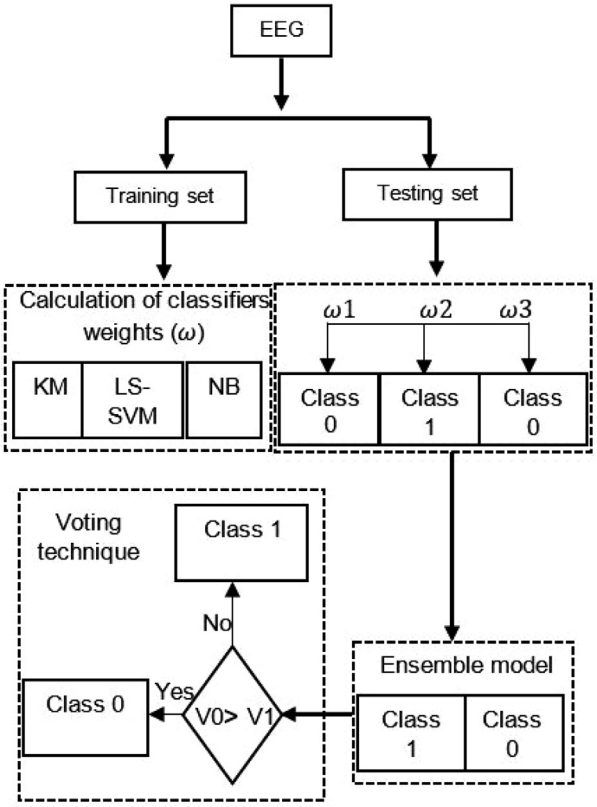

Fig. 7. Architecture of an ensemble model that is designed using a combination of three classifier including a least square support vector machine, k-means and Naïve Bayes , and the voting concept was used in the classification phase.

Discriminability evaluation and statistical analysis

In this study, several assessment metrics along with k-fold cross validation are utilized to evaluate the performance of the proposed approach. These metrics are sensitivity, accuracy, specificity, confusion matrix, Cohen's kappa coefficient and Matthews's correlation coefficient. Further details about the metrics' are provided in (Al-Salman et al., 2019, 2018; Al Ghayab et al., 2019). A brief explanation of the metrics is provided in this section.

Accuracy measure. It is used to evaluate the performance of a classification algorithm based on dividing the number of the samples (cases) correctly classified by the total number of samples. The true positive (TP) means the actual k-complexes waves that are correctly detected. The true negative (TN) is the actual non-k-complexes that are correctly marked as non-k-complexes. Classification accuracy is defined as:

$$\text{Accuracy} = \frac{\sum \text{TP} + \sum \text{TN}}{\sum \text{Total number of cases}} \times 100 \quad (6)$$

Sensitivity measure. It is a statistic metric used to test the quality of a classifier based on measuring the proportion of the actual positive prediction. The false negative (FN) shows the actual k-complex that are incorrectly marked as non k-complexes.

It is defined as:

$$\text{Sensitivity (Sen)} = \frac{\sum \text{TP}}{\sum \text{TP} + \sum \text{FN}} \times 100 \quad (7)$$

Specificity measure. It is utilized to calculate the average of negative cases that are correctly marketed by the proposed method. The false positive (FP) refers to the number of k-complexes that are incorrectly determined by a classifier. The main formula of specificity is defined as:

$$\text{Specifcity(Spe)} = \frac{\sum \text{TN}}{\sum \text{TN} + \sum \text{FP}} \times 100 \quad (8)$$

Matthews's correlation coefficient (MCC). MCC is a metric used to test the quality of a classifier. It provides a balanced evaluation. The MCC uses the sensitivity and specificity to examine the performance of the proposed model. The MCC returns a value between −1 (worst) and 1 (best), while 0 indicate a results no better than a random prediction. It is defined as (Patti et al., 2016):

$$\text{MCC} = \frac{\sum(\text{TP} \times \text{TN}) - \sum(\text{FP} \times \text{FN})}{\sqrt{(\text{TP}+\text{FP}) \times (\text{TP}+\text{FN}) \times (\text{TN}+\text{FP}) \times (\text{TN}+\text{FN})}} \quad (9)$$

F-measure. It is one of the most important measurements used to show overlapping between the two sets. It is defined by weighted sensitivity and precision.

$$\text{F} - \text{measure} = \frac{\text{Precision x Recall}}{\text{Precision} + \text{Recall}} \quad (10)$$

Kappa coefficient statistic. It is a statistical measure used to evaluate the agreement between two classification results. In this paper, it is employed to evaluate the agreement between two models, the proposed method and expert (Expert 1). It is defined as:

$$\text{Kappa Coefficient} = \frac{\text{accuracy} - \text{P}_e}{1 - \text{P}_e};$$

where P_e is a probablity of random agreement (11)

K-fold cross-validation statistic. This is a popular measure for assessing classification accuracy, and is used to describe the performance of the proposed method. The datasets are divided into six subsets of equal size with each subset contains an equal number of EEG segments that include k-complexes and non-k-complexes. One of these subsets is used as the testing set, while the remaining subsets are used as the training set. All subsets are tested in turn. The testing classification accuracy for all subsets is calculated and recorded, and their average accuracy is computed below.

$$\text{Performance} = \frac{1}{\text{k}} \sum_{1}^{\text{k}} \text{accuracy}^{(\text{k})}; \quad \text{k} = 6 \text{ in this study} \quad (12)$$

In this paper, the 6-fold cross-validation is used as the accuracy isn't improved after k > 6. The motivation to use the k-fold cross validation technique is that when we fit a model, we are fitting it to a training dataset. Without cross validation we only have information on how our model performs to the in-sample data. Ideally we would like to see how the model performs when we have new data in terms of accuracy of its predictions. In this paper, we used 6-fold cross validation in order to distribute our dataset in six sub-groups. In each testing run we used one sub-group for the training and others for the testing

Experimental results

A number of experiments were conducted to evaluate the performance of the proposed method. The datasets used in the experiments were described in Section 2. The fractal and frequency features were used to identify the k-complexes. Each segment with 0.5 s of EEG data was passed through the DT-CWT to decompose the signal into different frequency sub-bands (high and low frequencies). The high sub-bands are considered in this paper. A set of fractal and frequency features were extracted from each sub-band. Table 3 presents the obtained results based on the proposed method. All the experimental results were obtained in a Matlab 2015b environment on a computer that has the properties of:

Table 3. The obtained results for k-complexes detection.

Assessment tools	Fold No.						
	Fold −1	Fold −2	Fold −3	Fold −4	Fold −5	Fold −6	Average
Accuracy	97%	97%	98%	97%	97.2%	98%	97.3%
Sensitivity	95%	94%	96%	95%	93%	94%	94.5%
Specificity	99%	97%	97%	98%	99%	98%	98%

3.40 GH Intel (R) core (TM) i7 processor machine and 8.00 GB RAM.

Features analysis

Feature selection is important for EEG waveforms detection. In this section, the extracted features were analysed for their ability to detect the k-complexes. Fig. 8a–d provide the box plots for some fractal and frequency features. Fig. 8a shows the FDs of the k-complexes. The values of the fractal dimensions ranged between 1.0 and 2.0. One of the statistical features extracted from the fractal dimension was mean energy. It showed a high performance for identifying the k-complexes. Fig. 8d presents the plot boxes of the mean energy. It was noticed that it generated different values by which the k-complexes can be detected. However, with the k-complexes, mean energy generated takes values between 1.5 and 2.0. The main reason for this is that k-complexes normally have higher amplitudes than other waves in EEG signals. This feature was employed to recognize the k-complexes.

On the other hand, *variance* showed a negative reflection for the detection of the k-complexes. Fig. 8c shows box plots of *variance*. From Fig. 8c, we can see that this feature had similar values for the k-complexes and the non-k-complexes. Consequently, this feature was not considered in this study. Another feature, which is *peak to peak (f3),* was investigated. Based on the obtained results, peak-to-peak showed a significant ability to identify the k-complexes compared with non k-complexes segments. Fig. 8b shows the box plots of *peak-to-peak* for both k-complexes and non k-complexes. It was noticed that it was sufficient to identify the k-complexes from the non k-complexes in EEG segments.

Standard deviation was also employed as a feature in this study. It was used to measure the dispersion and skewness of EEG signals. Based on the results, the standard deviation feature can be used to distinguish the characteristics of sleep Stage 2, such as k-complexes.

Based on the features analysis, it was found that there was a positive relationship between the number of the extracted features and classification accuracy rate. Several experiments were conducted using different sets of features. 12 fractal and frequency features were tested separately. The importance of each feature was recorded based on the classification results. The 12 features were then ranked in descending order. The final features vector obtained is {*f1, f2, f3, f4, f5, f6, f7, f8, f9, standard deviation (SD), mean energy (ME), skewness (SK)*}. The features set was chosen based on the optimisation phase. During the training phase, different features were tested individually, and their corresponding accuracies were recorded. The features were ranked based on their classification performance, and the most influential features were selected. Fig. 9 shows the 12 features ranked based on their importance. We can see that *f3* is considered the most important one among the 12 features.

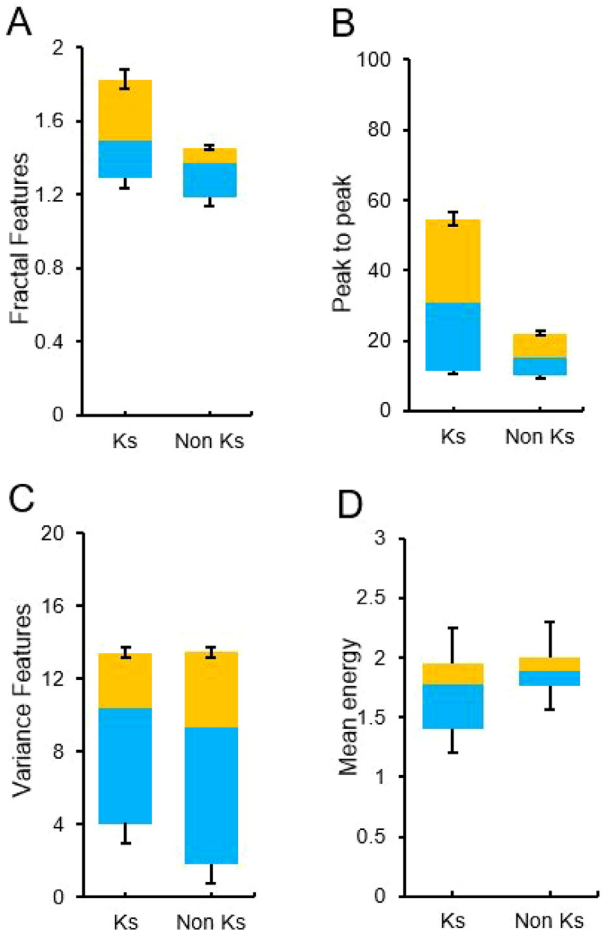

Fig. 8. Box plots for EEG k-complexes (Ks) and Non-k-complexes (Non-Ks) by using different features. **(A)** Shows the *fractal dimension feature* for Ks and Non-Ks. **(B)** Shows the minimum and maximum *peak-to-peak* values for Ks and Non-Ks. **(C)** Presents *variance features* for both Ks and Non-Ks. **(D)** shows the box plot for *mean energy* features. The x-axis shows the values of features for both Ks and Non-Ks in EEG signals.

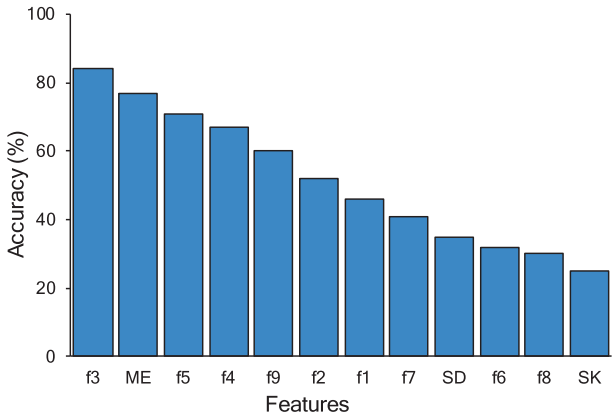

Fig. 9. Frequency and fractal features based on the classification accuracy rate for each feature; 12 features were ranked based on their importance. The x-axis shows the type of features while the y-axis presents the accuracy percentage for each feature.

Classification and cross validation

Table 3 shows the classification results based on accuracy, sensitivity and specificity. The results demonstrated that the minimum accuracy was 97%. The obtained results were compared with the experts' scoring (Expert1), and it was noticed that there were agreements between the proposed method and the expert's scoring. All the results in Tables 3 and 4 were carried out using the ensemble classifier.

6-Fold cross-validation using different classifiers

The classification performance was evaluated with the individual classifiers based on 6-fold validation, namely: LS-SVM, k-means, Naïve Bayes classifiers. The EEG data was divided into six folds (groups) and each group was tested in turns. The features extracted from each 0.5 s of an EEG segment were forwarded to those classifiers separately to identify the best classifier to detect k-complexes. The results obtained by those classifiers were compared with the proposed ensemble classifier. All parameters of the individual classifiers were selected in the training phase. Comparison of the individual classifiers and the ensemble classifier according to the obtained results were made in terms of accuracy. Table 4 shows all the performances based on 6-fold cross validation. The results demonstrate that there is a big improvement in the classification results when the ensemble classifier was used to detect the k-complexes in EEG signals. For the performances of the individual classifies, the LS-SVM achieved the highest accuracy among all the three classifiers with an average accuracy of 90.9%. The second highest performance was achieved by Naïve Bayes classifier. The k-means classifier recorded the lowest accuracy. Based on the obtained results in Table 4, the best detection results were achieved by the ensemble classifier gaining an average accuracy of 97.3%. It is clear that there were improvements in results when the ensemble classifier was adopted to detect the k-complexes in this study.

Performance evaluation of the proposed method using different window sizes

To evaluate the performance of the proposed method for detecting k-complexes in EEG signals, the window sizes of 1.0 s, 1.5 s and 2.0 s were tested in this paper. The average accuracies of the proposed scheme were recorded from the 6-fold cross evaluation. The accuracies against the expert's scoring using different window sizes were reported in Fig. 10. Our findings show that the proposed method achieved the highest results when the window size of 0.5 s with overlapping 0.4 s was used.

Table 4. The detection accuracy comparison by all the classifiers based on 6-fold cross validation.

Classifier type				
	LS-SVM	Naive Bayes	k-means	Ensemble
Fold-1	91%	87.3%	82.3%	96.7%
Fold-2	93.1%	86.2%	80.9%	97.3%
Fold-3	90.1%	87.1%	84.7%	98%
Fold-4	87.9%	85%	75.8%	97%
Fold-5	91.1%	87%	80.1%	97.2%
Fold-6	92.4%	88%	83.2%	98%
Average	90.9%	86.7%	81.2%	97.3%

Performance evaluation of the proposed method based on single and multi-sub-bands

The performance of the proposed method was evaluated based on the signal and multi sub-bands. Tables 5 and 6 show the corresponding values of accuracy, sensitivity and specificity from the single and multi sub-bands, respectively. Our findings show that the features obtained from the higher frequency sub-bands (y1, y2, and y3) gave more accurate results than those from the low-frequency sub-bands (y4 and z4). Based on the results presented in Table 6, the performance of the proposed approach improved significantly when the extracted features from the higher sub-bands were adopted.

However, the results from low sub-bands were not significant and they recorded lower accuracy compared with the other sub-bands. Table 5 shows the accuracy obtained by using the proposed method from a single sub-band.

Furthermore, *p*-value was used in this study to determine the significant features based on a hypothesis test that is used to test the validity of features selection. *P*-value is a number between 0 and 1 and is interpreted in the following way: a small *p*-value ($p \leq 0.05$) indicates a strong indication against the null hypothesis, while a large *p*-value (> 0.05) indicates weak evidence against the null hypothesis.

Performance evaluation of the proposed method based on the number of segments and execution time

The performance of the proposed method was also evaluated through execution time. Fig. 11 shows the

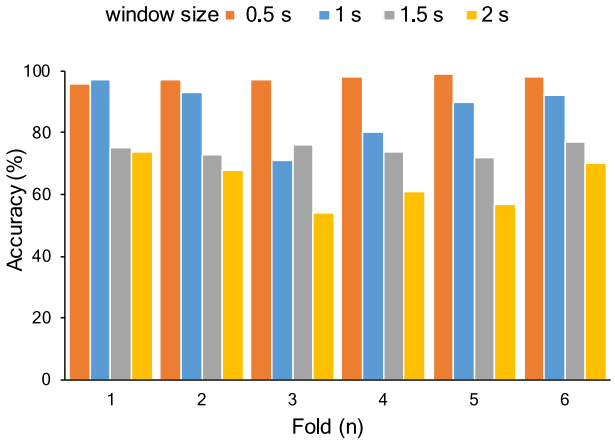

Fig. 10. The performance of the proposed method using different window sizes of 0.5 s, 1.0 s, 1.5 s and 2.0 s based on 6-fold cross-validation. The average accuracy of the proposed method was recorded from each fold using those window sizes. The results demonstrate that the proposed approach achieved the highest results with a window size 0.5 s compared with others of 1.0 s, 1.5 s, and 2.0 s.

Table 5. The reported results by the proposed method using single sub-band.

Name of sub-band	Accuracy	Sensitivity	Specificity	*P*-value
Sub-bands 1 (y1)	86.92%	81.6%	84.3	3.3359-E3
Sub-bands 2 (y2)	89.91%	87.5%	86.4	2.20058E-5
Sub-bands 3 (y3)	90.54%	93.2%	88.9%	2.4268E-6
Sub-bands 4 (y4)	75.13%	78%	80.1%	0.01329
Sub-bands 5 (z4)	71.65%	64.2%	68.3%	0.34026

Table 6. The reported results by the proposed method using multi-level decomposition sub-band.

Name of sub-band	Accuracy	Sensitivity	Specificity	*P*-value
Sub-bands 1,2 (y1,y2)	95 %	92.45	96.1%	2.4014E-5
Sub-bands 1,3 (y1,y3)	93.79%	91.3%	94.5%	3.4253E-4
Sub-bands 2,3 (y2,y3)	95.28%	93.7%	95.2%	4.6242E-5
Sub-bands 1,2,3 (y1,y2,y3)	97.3%	94.5%	98.1%	2.7523E-10

complexity time for the ensemble classifier and the individual classifiers. We assume that the number of the segments is Y, and the time to extract features for one segment is Z. The total classification time (T) depends on the processing time (L) of the classifier used. The total complexity and processing time (T) are T = Y*Z + L. To compute the performances of the four classifiers, the same computer having the same settings was used, with the same input data segments. The complexity time of the proposed method was recorded for each classifier.

From Fig. 11, the lowest execution time was recorded with the k-means classifier compared with other classifiers. The results show that the ensemble classifier recorded the highest execution time to detect the k-complexes compared to the three individual classifiers as the implementation of the ensemble classifier depended on the summation of the execution times by the three individual classifiers. In return, the proposed method yielded a high performance classification. Apparently, there is a trade-off between the performance and the computation speed.

The performance of the proposed method was also compared with the other three classifiers based on the number of segments. In this study, the same number of segments were used for comparison and the number of segments were selected randomly from the database. Those segments were divided into a training set and a testing set, and were then forwarded to the ensemble model as well as to the k-means, Naïve Bayes and LS-SVM classifiers to identify k-complexes. Fig. 12 shows the obtained results by the proposed method using the ensemble classifier and the other three classifier. We can see from the obtained results that the performance of the proposed scheme was the best.

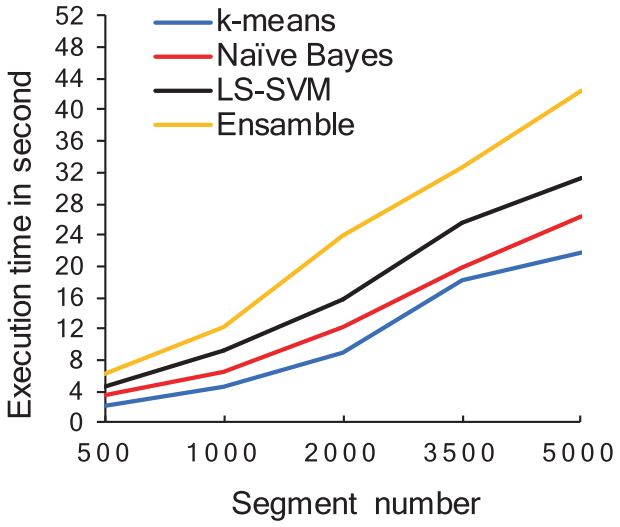

Fig. 11. Execution time for the ensemble model and the other three classifiers of LS-SVM, Naïve Bayes and k-means, based on the segment number.

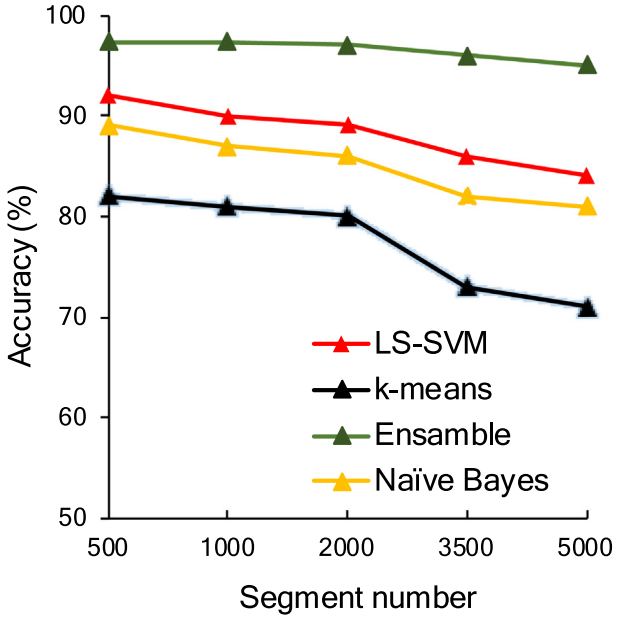

Fig. 12. Shows the performance comparison between the proposed method and other classifiers: LSSVM, K-means and Naïve Bayes based on the number of segments. The x-axis shows the number of segments, while the y-axis presents the accuracy by the proposed method.

Comparisons with k-complexes classification methods

To evaluate the proposed method, its performance was compared with the state of the art of k-complexes' detection in term of accuracy, sensitivity and specificity. The same EEG recordings were used in all the comparison studies. Table 7 presents the comparison results. The best classification accuracy rates among the methods are highlighted in bold font in Table 7. The proposed method reported the highest results compared with those by (Patti et al., 2016; Krohne et al., 2014; Erdamar et al., 2012; Devuyst et al., 2010; Vu et al., 2012; Kantar and Erdamar, 2017; Migotina et al., 2010; Hernandez-Pereira et al., 2016; Bankman et al., 1992).

Patti et al. (2016) used pattern matched wavelets to detect k-complexes. They achieved an average detection sensitivity of 84%. In that study, various thresholds for wavelet coefficients were applied to detect k-complexes. The maximum wavelet coefficient for a k-complex ranged within the scales of 0.5 s to 2.0 s. Our proposed method reported higher results than those by Patti et al. (2016). Another study was presented by Krohne et al. (2014), in which the k-complexes were identified based on a discrete wavelet transform. In their study, a different mother wavelet was tested to determine the best wavelet function. A different set of features including peak-to-peak amplitude, positive amplitude, RelDelta, mean and slop of the rise were extracted from each of the sub-bands. The average sensitivity of 74% was recorded. They obtained a smaller sensitivity compared with that of the proposed method. Erdamar et al. (2012) employed the teager energy operator to identify k-complexes in EEG signals. A different set of features of amplitude, minimum and maximum duration and slope of the rise were utilized. Based on the obtained results shown in Table 7, their classification results were lower than those by the proposed method.

Devuyst et al. (2010) used a fuzzy threshold to extract features. They applied an algorithm to detect the waves in EEG signals based on likelihood thresholds. An average sensitivity of 61.72% with expert1 and 60.94% with expert2 were obtained. Their results were lower than those by the proposed method. Vu et al. (2012) employed a hybrid-synergic machine learning method to detect the k-complexes in EEG signals. In that study, a set of 29 features were extracted from each 0.5 s of an EEG segment, and were then analysed separately based on the classification accuracy rate. Representative instance classifier based on multi-instance learning and single-instance learning was used to classify those features into k-complexes and non-k-complexes. An average accuracy of 90% and sensitivity of 70% were reported. Based on these results, the proposed method used a set of 12 features and yielded better results compared with that of Vu et al. (2012). Kantar and Erdamar (2017) used a combination of features combined with a support vector machine classifier to detect the k-complexes in EEG signals. They reported 70.8% sensitivity and 85.29% specificity. Thus, we can see that the proposed method gave better results than Kantar and Erdamar (2017). Another study was presented by Migotina et al. (2010), in which the k-complexes were detected using fuzzy decision with hjorth parameters. Their fuzzy decision was based on a number of hjorth parameters, which were defined experimentally. In that study, the performance of the detection system was compared to the visual human scoring. The average sensitivity and specificity of 86% and 82% were reported, respectively. Based on the results, the proposed method reported higher results compared with Migotina et al. (2010).

Bankman et al. (1992) detected k-complexes in EEG signals using a different set of features combined with a neural network classifier. 12 features were extracted from each EEG signal and then used as inputs to the neural network classifier to identify k-complexes. An average sensitivity of 90% was reported. Our method obtained a higher classification sensitivity compared with that by Bankman et al. (1992). Hernández-Pereira et al. (2016) also detected the k-complexes based on a different features' selection method. 14 frequency features were extracted and then used as inputs to several different

Table 7. Comparisons among the proposed approach with other studies in the literature.

Authors	Method	ACC	SEN	SPE	FPR
Patti et al. (2016)	Pattern matched Wavelets by 400 and 700 thresholds.	–	84%	–	–
Krohne et al. (2014)	Wavelet transformation and different features threshold.	–	74%	–	–
Devuyst et al. (2010)	Features extraction based on fuzzy thresholds for Scorers 1 and 2.	–	61.72% 60.94%	–	19.62%
Erdamar et al. (2012)	Teager energy operator coupled with a wavelet transform based on features such as amplitude and duration.	91%	85.3%	–	0.07%
Vu et al. (2012)	Features extraction by a hybrid-synergic machine learning method.	90%	70%	–	–
Bankman et al. (1992)	12 features combined with a neural network.	–	90%	–	–
Kantar and Erdamar (2017)	Three features with support vector machine.	–	70.8%	85.29%	–
Hernández-Pereira et al. (2016)	14 frequency features and support vector machine classifier.	91.40%	–	–	6.2%
Migotina et al. (2010)	Hjorth parameters and fuzzy decision	–	86%	82%	–
The proposed method	Fractal and frequency features coupled with ensemble model	97.3%	94.5%	98%	0.019%

Accuracy = ACC, Sensitivity = SEP, Specificity = SPE and False positive rate = FPR.

classifiers. In that study, different machine learning methods including a support vector machine (SVM), artificial neural network and logistic regression were investigated. A maximum accuracy of 91.4% was recorded using a SVM classifier. From the results in Table 6, we can see that the proposed method obtained a better classification accuracy compared with Hernández-Pereira et al. (2016). In summary, the comparisons with the previous studies show that using the DT-CWT for a combination of features is an effective and suitable method to detect k-complexes in EEG signals

DISCUSSIONS

In this work, the fractal and frequency features were employed to analyse EEG sleep characteristics. Two sets of optimal features were selected to classify the transient waveform (k-complexes) in sleep EEG signals. Three fractal features and nine frequency features were extracted from each EEG segment as the feature vector. They were then forwarded to an ensemble classifier to detect the k-complexes. Further investigations and discussions are as follows:

The performance comparison of the proposed method with the DWT

The performance of the DT-CWT was compared with a discrete wavelet transformation (DWT). The same features in Section 2 were extracted from the DWT and those features were forwarded to the ensemble model to detect k-complexes. We can see that the results obtained by using the DWT are lower than those obtained by the DC-CWT. Fig. 13 shows the comparisons by the DWT and DT-CWT.

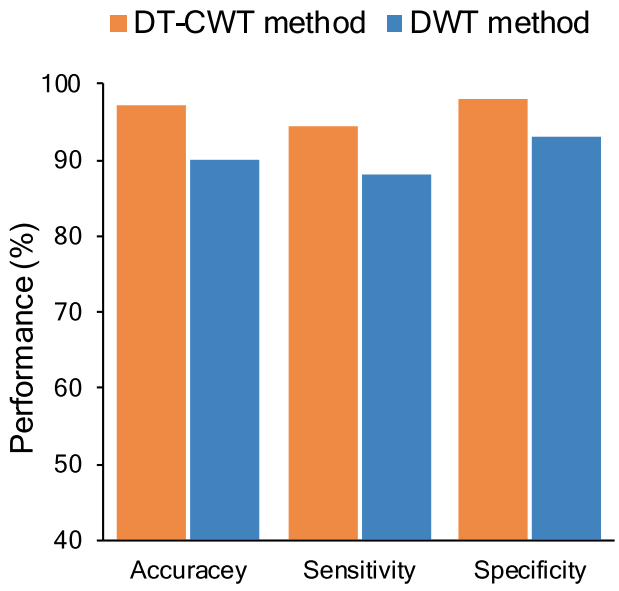

Fig. 13. Results obtained by the DWT and DT-CWT. The same methodology in the section of Experimental procedures was used to extract features. The performance of the proposed method was evaluated in terms of accuracy, sensitivity, and specificity.

Table 8. The performance of the proposed method with different fractal algorithms.

algorithm	Accuracy	Sensitivity	Specificity
Katz's method	72.3%	65.7%	84.2%
Box counting method	91%	87%	92%
Higuchi's method	97.3%	94.5%	98%

The performance comparison of the proposed method with different algorithm for FD

Two algorithms, box-counting and Katz's were utilized to extract 12 features. The algorithms used the same methodology as that described in Section EXPERIMENTAL PROCEDURES. The extracted features were fed into the ensemble model to identify k-complexes. The characteristics of those methods were also used by Salmasi et al. (2016) to analysis EEG signals. In their work, the HFD algorithm achieved higher classification rates than the box-counting and Katz's methods. In this paper, to evaluate the performance of the HFD algorithm, two algorithms for FDs including Katz's and box counting were used to extract the fractal dimension features. The comparison results of the box counting and Katz's method, as well as the HFD algorithm were presented in Table 8. The performance of the proposed method is evaluated in term of accuracy sensitivity and specificity.

However, for further evaluation, F-score, Kappa coefficient and Mathew's correlation coefficient (*MCC*) measurements were used to evaluate the performance of the proposed scheme. They were computed in each fold and the averages of all the results were considered. The proposed method achieved an average classification rate of F-score, Kappa coefficient and *MCC* of 0.87%, 0.93% and 0.921%, respectively. Based on the literature, the results obtained by F-score, Kappa coefficient and *MCC* provided the evidence that the proposed method surpassed other methods in the identification of the k-complexes and non-k-complexes segments.

Finally, we showed that the DT-CWT combined with an ensemble machine can be used to identify k-complexes efficiently. The proposed method is compared with individual classifiers as well as with several existing k-complexes detection methods in which the same datasets were used as in this paper. It was proved that the proposed methodology attained a good performance in term of detecting k-complexes. It was also observed that using fractal and frequency features gave good classification accuracy for the detection of the characteristics of sleep Stage 2. This study suggests that the DT-CWT combined with an ensemble machine can be used to identify the k-complexes efficiently. This method can help physicians diagnose sleep disorders and potentially reduce medical costs.

CONFLICT OF INTERESTS

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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Chapter 5 Fractal and Frequency feature coupled with an Ensemble model to detect k-complexes in EEG signals.

5.2 Chapter Summary

Al-Salman et al. (2019) presented an innovative method to extract the most significant features from EEG databases, Dream project at University of Mons-TCTS Laboratory. A sliding window technique was used to divide EEG signals into small segments. A window size of 0.5s with an overlapping of 0.4s was considered in this study. DT-CWT was applied to decomposed each segment into four sub-bands. Thereafter, fractal and frequency features were extracted from each sub-band. The key features were forwarded to the ensemble model to detect the k-complexes. The experimental results observed that using fractal and frequency features gave reasonable classification accuracy for the detection of the characteristics of sleep Stage 2, compared to existing methods. Furthermore, the proposed method was compared with individual classifiers as well as with several existing k-complexes detection methods in which the same datasets were used. The results show that the proposed feature extraction method combined with the ensemble model outperforms other techniques in k-complexes detection. In addition, this method is capable of differentiating the variety of EEG categories (k-complexes and non-k-complexes) with an excellent performance, compared to existing methods. The obtained results clearly demonstrated that using DT-CWT based on the ensemble model technique has the potential to improve the classification and to identify k-complexes in EEG signals.

However, using only six subjects of EEG recording was not enough to detect k-complexes with high accuracy and low execution time. Considering other technique, such as fractal and graph features, reduced the processing execution time, decreased the dimensionality of EEG data and improved the results with all datasets. The next chapter will discuss k-complexes detection of a whole dataset based on the fractal dimension of time-frequency images technique coupled with undirected graph features. This method improved performance by reducing the execution time with a whole dataset.

CHAPTER 6

DETECTION OF EEG K-COMPLEXES USING FRACTAL DIMENSIONS OF TIME FREQUNCEY IMAGES TECHNIQUE COUPLED WITH UNDIRECTED GRAPH FEATURES

6.1 Introduction

In Chapter 5, the fractal and frequency features combined with the ensemble mode classifier was presented to identify k-complexes in sleep stage 2 with a high accuracy rate and high processing of execution time. This scheme was implemented and tested on a benchmark EEG database which used only six subjects out of ten. However, to reduce the execution time, to decrease the dimensionality of EEG data, and to improve the results with all datasets a novel method to identify k-complexes, based on fractal graph features, is presented in this chapter; it was conducted and tested with a whole dataset.

In previous research, Al-Salman et al. (2018) reported that the fractal dimension based features achieved promising results for analysing EEG signals as well as for the detection of sleep spindles. As a result, the concept of the fractal algorithm was used in this study to identify the k-complexes with the lowest execution time and the highest classification results.

Chapter 6 Detection K-complexes Using FD of TFI Coupled with Graph Featutres

In this chapter, the details presented here is an exact copy of a published paper in *Journal of Frontiers in Neuroinformatics* by Al-Salman et al. (2019). They explain a new method based on a fractal dimension (FD) of time frequency images (TFI) technique coupled with undirected graph features. The method was employed to analyse and identify k-complexes in EEG signals during sleep stage 2. There were four steps in the process.

Firstly, an EEG signal was divided into smaller segments using a sliding window technique. Secondly, each segment was passed through a spectrogram of short time Fourier transfer to obtain the TFI; FD were then discovered in EEG signals to each TFI. Thirdly, the structural properties of the undirected graph were used to extract the discriminative features from each FDs; and lastly, these features were forwarded to a least square support vector machine (LS-SVM) and k-means classifier to detect k-complex and non k-complex segments. The proposed method was tested with a whole EEG database, and it was also compared with other existing methods, based on a number of performance evaluation measures. The findings of this study shows that the proposed method yields better classification results than other existing methods in the literature.

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Detection of EEG K-Complexes Using Fractal Dimension of Time Frequency Images Technique Coupled With Undirected Graph Features

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K-complexes identification is a challenging task in sleep research. The detection of k-complexes in electroencephalogram (EEG) signals based on visual inspection is time consuming, prone to errors, and requires well-trained knowledge. Many existing methods for k-complexes detection rely mainly on analyzing EEG signals in time and frequency domains. In this study, an efficient method is proposed to detect k-complexes from EEG signals based on fractal dimension (FD) of time frequency (T-F) images coupled with undirected graph features. Firstly, an EEG signal is partitioned into smaller segments using a sliding window technique. Each EEG segment is passed through a spectrogram of short time Fourier transform (STFT) to obtain the T-F images. Secondly, the box counting method is applied to each T-F image to discover the FDs in EEG signals. A vector of FD features are extracted from each T-F image and then mapped into an undirected graph. The structural properties of the graphs are used as the representative features of the original EEG signals for the input of a least square support vector machine (LS-SVM) classifier. Key graphic features are extracted from the undirected graphs. The extracted graph features are forwarded to the LS-SVM for classification. To investigate the classification ability of the proposed feature extraction combined with the LS-SVM classifier, the extracted features are also forwarded to a k-means classifier for comparison. The proposed method is compared with several existing k-complexes detection methods in which the same datasets were used. The findings of this study shows that the proposed method yields better classification results than other existing methods in the literature. An average accuracy of 97% for the detection of the k-complexes is obtained using the proposed method. The proposed method could lead to an efficient tool for the scoring of automatic sleep stages which could be useful for doctors and neurologists in the diagnosis and treatment of sleep disorders and for sleep research.

Keywords: electroencephalogram, k-complexes, structural undirected graph, fractal dimensions, box counting and time frequency images

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INTRODUCTION

Sleep can be divided into different sleep stages that include mainly non-rapid eyes movements (NREM) sleep, rapid eyes movements (REM) sleep etc. NREM sleep can be further divided into four stages of drowsiness (S1), light sleep (S2), deep sleep (S3) and very deep sleep (S4). Recently, the NREM sleep were reduced by American academy of sleep medicine (AASM) into three stages in which S3 and S4 were combined into one stage as slow waves stages (SWS) (Rechtschaffen and Kales, 1968; Iber et al., 2007; Ranjan et al., 2018). **Figure 1** shows the sleep stage signals and their characteristics (Fraiwan et al., 2012). Analysis of these sleep waveforms based on their characteristic features of different stages is an important phase in sleep studies as each sleep stage has different characteristic waveforms. One of those important waveforms occurred in electroencephalogram (EEG) signals and changed over a short time are sleep spindles and k-complexes waves. K-complexes and sleep spindles patterns are the key characteristics of S2, and consequently they are often used to identify S2.

In 1993 k-complexes were first discovered by Loomis et al. (1938). A k-complex includes a large-amplitude transient waveform with a single negative sharp wave followed by a positive sharp wave, and it has a relatively sharp amplitude that is more than ± 75 μV (Bremer et al., 1970; Richard and Lengelle, 1998; Lajnef et al., 2015). This transient bio-signal waveform occurs in all sleep stages, but mainly occurs in sleep stage 2, and it presents in 12–14 Hz waves (Jansen and Desai, 1994). Moreover, in another study (Bremer et al., 1970) it was reported that the minimum peak to peak amplitude value of the k-complexes is around 100 μV. Most of these early studies showed that k-complexes could appear many times during stage 2 with a maximum time duration between 0.5 and 1.5 s. Some studies reported that the maximum time duration of a k-complexes is between 1 and 3 s (Pohl and Fahr, 1995; Lajnef et al., 2015; Hernández-Pereira et al., 2016; Ghanbari and Moradi, 2017; Al-Salman et al., 2018). Examples of EEG signals with and without k-complexes events are shown in **Figure 2** (Yücelbaş et al., 2018a).

The k-complexes are very important in both children's and adults' sleep studies and the diagnoses of neurophysiologic and cognitive disorders (Bremer et al., 1970; Strungaru and Popescu, 1998; Lajnef et al., 2015). Reliable methods for the analysis and detection of the k-complexes in sleep EEG signals are of great importance for sleep research and clinical diagnosis (Kokkinos and Kostopoulos, 2011). Traditionally, k-complexes are visually examined and marked in an all-night sleep EEG recording by one or two well-trained experts. This process is time consuming, specialist dependent, and tedious, due to the fact that there are typically 1 to 3 k-complexes per minute in stage 2 for young adults (Amzica and Steriade, 2002; Kam et al., 2004; Ghanbari and Moradi, 2017; Ranjan et al., 2018). Therefore, the auto detection of k-complexes is a very important research topic.

In this paper, the fractal dimension (FD) combined with undirected graphs is used to detect k-complexes in sleep EEG signals. Firstly, EEG signal is divided into segments of 0.5 s. Each segment is transformed into a time frequency (T-F) images using a short time Fourier transform (STFT). Secondly, a box counting algorithm is applied to each of the T-F image to calculate their FD. Ten FDs are extracted from each T-F image, and are mapped to undirected graphs to extract the features of interest. The least square support vector machine classifier is used to validate the proposed method. The performance is measured in term of accuracy, sensitivity, and specificity. The performance of the proposed method was compared with several existing methods in the literature. The results demonstrated that the proposed method achieved a high classification accuracy rate for detecting k-complexes in EEG signals.

The remainder of this paper is organized as follows: Section "Related Work" descripts the EEG data used in this paper. Section "EEG Data Description" illustrates the details of the proposed methodology. The experimental results are explained in section "Proposed Method." Finally, the conclusion is provided in section "Experimental Results."

RELATED WORK

Several automatic methods have been developed to detect and analyze the k-complexes. Those approaches used different transformation techniques, such as Fourier transform, wavelet transform, spectral analysis, matching pursuit and autoregressive modeling (Camilleri et al., 2014). So far, no studies have been presented to identify k-complex transient events based on their waveform characteristics, such as a textural descriptor, non-linear features or their graph connections.

Bankman et al. (1992) used a method based on different set of features to detect k-complexes in sleep EEG signals. 14 features were extracted from EEG signals and then used as input into a neural network. The researchers reported an average of sensitivity and false positive rate (FPR) of 90 and 8.1%, respectively. Another study was presented by Hernández-Pereira et al. (2016), in which k-complexes were also detected based on 14 features extracted from each sleep EEG signal. The features were then forwarded to different classifiers to identify k-complexes. An average accuracy of 91.40% was reported using the features selection method.

Tang and Ishii (1995) proposed a method to identify k-complexes based on the discrete wavelet transform (DWT) parameters. The DWT parameters were used to determine the time duration and amplitude of k-complexes. In their study, they obtained 87% sensitivity and 10% FPR. More recently, Lajnef et al. (2015) used a tunable Q-factor wavelet transform for the detection of k-complexes. An average sensitivity and FPR of 81.57 and 29.54% were reported, respectively.

Another study was presented by Richard and Lengelle (1998), in which the k-complexes were recognized based on a joint linear filter in time and time-frequency domains. The k-complexes and delta waves were identified with an average sensitivity and FPR of 90 and 9.2%, respectively. Yücelbaş et al. (2018b) used a method to detect k-complexes automatically based on time and frequency analyses. In their study, an EEG signal was decomposed using a DWT. An average accuracy rate of 92.29% was achieved.

Noori et al. (2014) used a features selection using a generalized radial basis function extreme learning machine (MELM-GRBF)

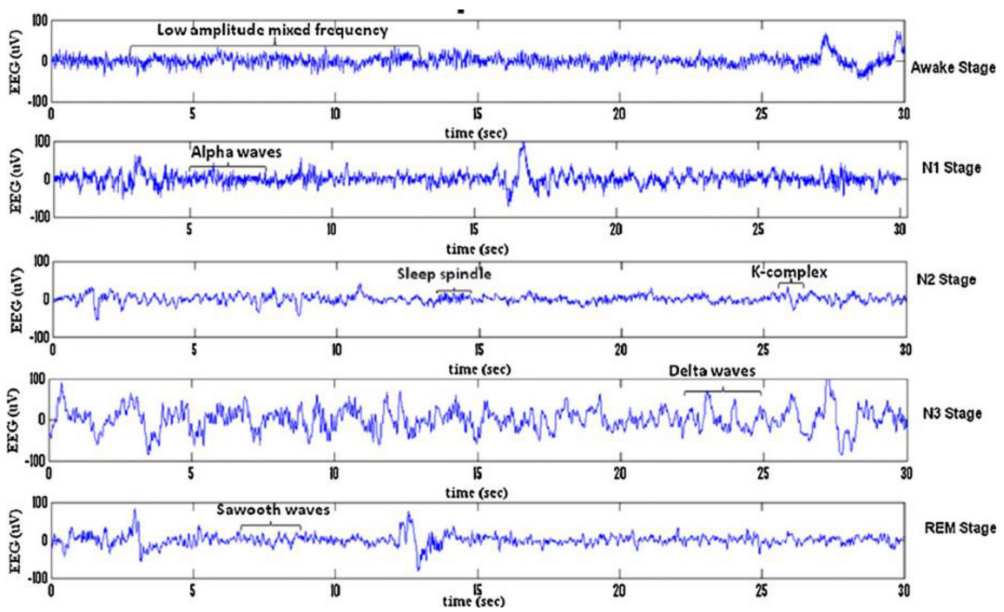

FIGURE 1 | Typical EEG signals of 30 s belonging to sleep stages for a subject: awake stage, N1, N2, S3, N4, and REM stage.

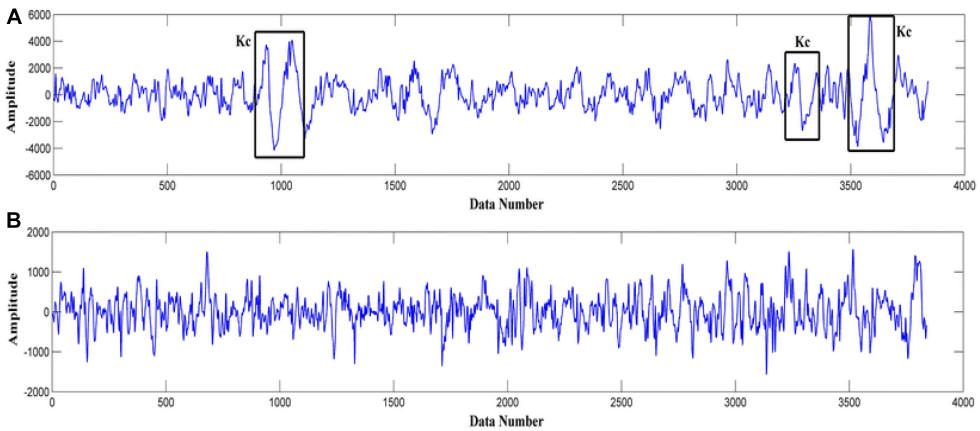

FIGURE 2 | EEG signal examples: **(A)** with k-complexes events. **(B)** without k-complexes.

algorithm to detect k-complexes. In their study, fractal and entropy features were employed. The EEG signals were divided into segments using a sliding window technique. The size of the window was set to 1.0 s. An average sensitivity and accuracy of 61 and 96.1% were reported. Researchers in Zacharaki et al. (2013) utilized two steps to detect k-complexes. In the first step, the k-complex candidates are selected, while the number of k-complexes is reduced in the second step using a machine learning algorithm. In that study, four features, including peak-to-peak amplitude, standard deviation, and a ratio of power and duration of the negative sharp wave, were extracted from each segment. An average sensitivity of 83% was reported.

Parekh et al. (2015) detected the k-complexes based on a fast non-linear optimization algorithm. In that study, only F-score result was reported. An average F-score of 0.70 and 0.57% for the detection of the sleep spindles and the k-complexes were achieved, respectively. Another study was presented by Henry et al. (1994), in which the k-complexes were classified based on matched filtering. Each segment was decomposed into a set of orthonormal functions and wavelets analysis.

Devuyst et al. (2010) used a likelihood threshold parameters and features extraction method to detect k-complexes. The performance of the detection was assessed against to two human experts' scorings. An average of sensitivity rate of 61.72 and 60.94% for scorer 1 and scorer 2 were obtained. Migotina et al. (2010) presented a method based on Hjorth parameters and employed fuzzy decision to identify k-complexes. In that study, the performance of the proposed method was compared with the visual human scoring to evaluate their results. All those methods

for classifying k-complexes in sleep EEG signals were based on linear features. So far waveform characteristics based features, such as a textural descriptor, and graph network connections, have not been used for the detection of k-complexes.

According to the literature, we found that the FD as non-linear features has been proven to be an efficient approach to explore the hidden patterns in digital images and signals (Prieto et al., 2011; Finotello et al., 2015). It has been used to analyze and classify EEG signals to trace the changes in EEG signals during different sleep stages, and has also been employed to recognize different digital image patterns. Yang et al. (2007) and Sourina and Liu (2011) employed a FD approach to analyze sleep stages in EEG signals.

Fractal dimension technique was also used by Ali et al. (2016) for voice recognition. Time frequency (TF) images were also used by Bajaj and Pachori (2013) to classify sleep stages. Bajaj et al. (2017) also identified alcoholic EEGs based on T-F images. Based on our previous study (Al-Salman et al., 2018) we found that time frequency images coupled with FD yielded promising results in analyzing and detecting sleep spindles in sleep EEG signals. Furthermore, undirected graph properties have been used to analyze and study brain diseases (Vural and Yildiz, 2010; Wang et al., 2014). Some studies reported that undirected graphs can be considered as one of the robust approaches to characterize the functional topological properties in brain networks for both normal and abnormal brain functioning (Sourina and Liu, 2011; Li et al., 2013). The relevant techniques were employed in image processing as a powerful tool to analyze and classify digital images (Sarsoh et al., 2012).

Recently, a graph approach was used in Diykh et al. (2016) to classify sleep stages. However, in this work, we have combined the fractal features with properties of undirected graphs to detect k-complexes in sleep EEG signals. Based on our knowledge, fractal graph features approach has not been used in k-complexes detection before.

EEG DATA DESCRIPTION

The EEG datasets used in this paper were collected by the Dream project at University of Mons-TCTS Laboratory (Devuyst et al., 2011). The sleep EEG data sets that were publically available included 10 recordings acquired from 10 subjects: 4 males and 6 females using a digital 32-channel polygraph (BrainnetTM system of MEDATEC, Brussels, Belgium) (Devuyst et al., 2010). The sleep EEG data sets were collected in a 30 min interval of the central EEG channel for a whole night. The datasets were sampled at frequency of 200 Hz. Three EEG channels (CZ-A1 or C3-A1, FP1-A1 and O1-A1) and one submental EMG channel were recorded from each subject. The k-complexes in this database were detected visually by two experts. The first expert scored all the ten recordings, while the second expert only annotated five recordings out of the 10 EEG recordings. Therefore, the CZ-A1 channel EEG recordings sampled at 200 Hz, all recording by expert 1, were used for detecting the k-complexes in this study. The information about for the database is shown in **Table 1**. For more information, please refer to the following website gives details. The dataset with additional information is publicly available from http://www.tcts.fpms.ac.be/~devuyst/Databases/DatabaseKcomplexes.

TABLE 1 | Database information from dream database.

Subject ID	Sex	Age	K-complexes scored by expert 1	K-complexes scored by expert 2
ID1	Man	20	34	19
ID2	woman	47	45	8
ID3	Woman	24	12	3
ID4	Woman	23	78	14
ID5	Woman	27	39	20
ID6	Man	23	28	–
ID7	Man	27	11	–
ID8	Woman	46	4	–
ID9	Man	27	5	–
ID10	woman	21	16	–

PROPOSED METHOD

In this work, a new method is presented based on time-frequency image and graph features to detect k-complexes in EEG signals. An illustration is given in **Figure 3**. The EEG signal is firstly divided into segments using a sliding window technique. The size of the window is set to 0.5 s with an overlapping of 0.4 s. Then, each 0.5 s EEG segment is passed through the spectrogram of STFT to obtain the time-frequency images (T-F images). FD as a texture descriptor for each T-F image is calculated based on the box counting method. The vector of FD from each T-F image is then mapped into an undirected graph. Three features of *{degree distributions, Jaccard coefficient, and cluster coefficient}* from each graph are extracted and used as the key features to detect k-complexes in this study. Those features are then forwarded to a least square support vector machine (LS-SVM) classifier to detected k-complexes in EEG signals.

Segmentation

Sleep experts have observed that k-complexes normally appear in EEG signals for 0.5 to 2 s. The sliding window technique was utilized by Siuly et al. (2011) for the classification of EEG signals. It was also utilized by Al-Salman et al. (2018) and Zhuang et al. (2016) to detect sleep spindles in EEG signals. Kam et al. (2004) employed the sliding window method to detect k-complexes in their study. Their results showed that applying a sliding window technique helped to improve satisfactory classification results. As sleep spindles and k-complexes occur during stage 2 for about 0.5 to 2 s, we tested various window sizes of 1.0, 1.5, and 2.0 s and overlapping lengths to identify the optimal segment size. However, we made the window length between 0.5 and 2 s. We used the same technique in Al-Salman et al. (2018, 2019). We selected 0.5 window length based on our simulation results. The simulation results showed that the window size of 0.5 s was more optimal for identifying EEG characteristics than other window sizes. **Figure 4** shows the EEG signal being dividing

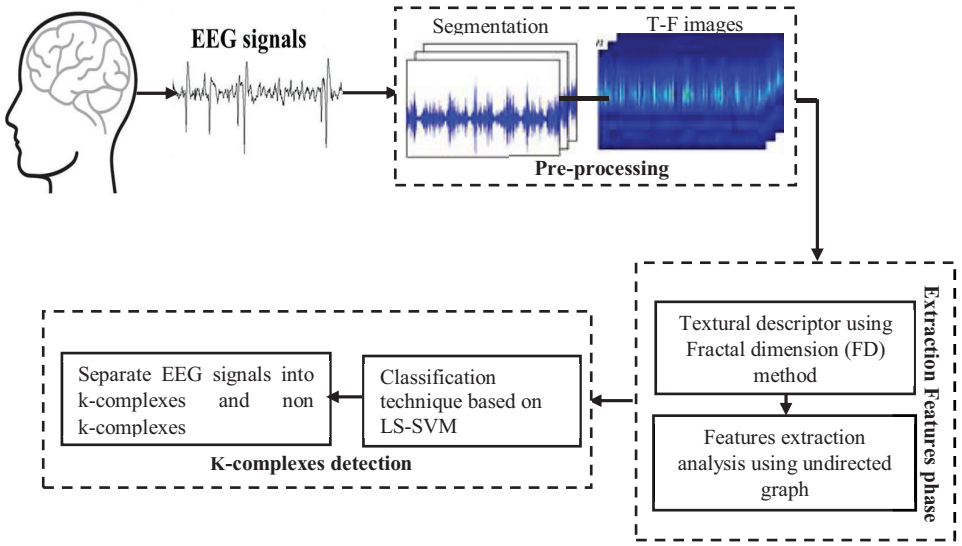

FIGURE 3 | The methodology of the proposed method for k-complexes detection.

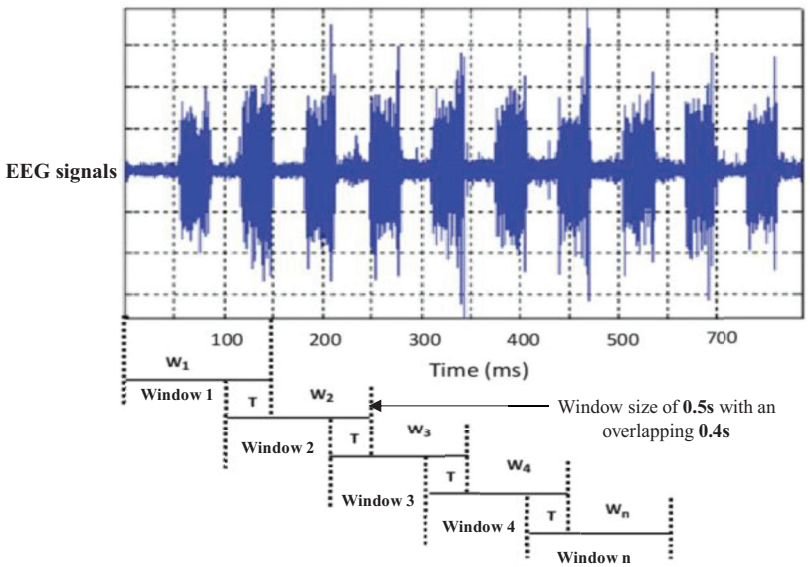

FIGURE 4 | An example of segmenting an EEG signal into windows using a sliding window technique.

into 0.5 s segments with an overlapping of 0.4 s using a sliding window technique.

Spectrogram of STFT

Spectrogram of STFT is normally defined as the normalized, square magnitude of the STFT coefficient (Bajaj et al., 2017; Al-Salman et al., 2018). The STFT is defined as:

$$S(n, \omega) = \sum_{x=-\infty}^{\infty} y[x]w[n-x]e^{-jwn} \quad (1)$$

where $y[x]w[n-x]$ is a short time of signal $S(n, \omega)$ at time n, and the discrete of STFT can be formulated as:

$$S(n, k) = S(n, \omega)|_{\omega} = \frac{2\pi k}{N} \quad (2)$$

where N refers to the number of discrete frequencies.

Before Fourier transform was calculated, the centered function $w = [x]$ at time n was multiplied with signal S. The Fourier transform is estimated at time n, and the window function, $w = [x]$ centered at time n, of signal $S(n, \omega)$ is considered close to time n. A fixed positive function was used to obtain the STFT, which is

denoted as $w[x]$. Thus, the spectrogram can be formulated as:

$$SP(n, k) = |S(n, \omega)|^2 \quad (3)$$

The signal is divided into smaller blocks to obtain the STFT coefficients using the sliding window. After each block is transformed through a Fourier transform, their spectrum is obtained. As the result, the spectrogram of the signal can be calculated from the square of the discrete STFT by using Eqs 1 and 2. **Figure 5** shows examples of an EEG segment with a k-complex and an EEG segment without a k-complex event were transformed into a time frequency image using the STFT. According to the literature, the spectrogram is more effective for analyzing non-stationary signals (Siuly and Li, 2012). In this paper, the spectrogram is applied to each EEG segment to obtain the T-F images.

Fractal Dimension

Fractal dimension allows us to measure the degree of complexity of an object. With FD, each figure can be depicted by a series of fragments. Those fragmented parts can be represented as a small copy of the original figure (Al-Salman et al., 2018).

Extracting features from EEG signals is a common step to obtain the key information. The FD technique is one of the most powerful methods to extract the hidden characteristics from EEG signals (Nunsong and Woraratpanya, 2015) as well as to explore the key patterns in biomedical signals and image processing (Prieto et al., 2011). The FD is commonly used to analyze and classify EEGs signals (Finotello et al., 2015). Based on our previous work (Al-Salman et al., 2018), it was found that extracting features from FD could reduce the complexity of computation time and also increased the detection accuracy.

In this paper, the box counting algorithm is employed and applied to estimate the FD (capacity dimensions) of a T-F image to identify k-complexes in EEG signals. The box counting method can be described as follows: Suppose that **M** is a T-F images and we need to calculate the FD of **M**. The following main formula is utilized.

$$Dim = \lim_{r \to 0} \frac{\log N(r)}{\log(1/r)} \quad (4)$$

Based on the equation above, Dim is a FD, $N(r)$ is the total number of boxes, and r is the size of boxes that are required to cover image **M**. To cover the entire T-F image, different sizes of boxes are tested, and $N(r)$ and r are determined. **Figure 6** presents an example illustrating how the number and size of boxes were created. More details about the box counting algorithm is provided in our previous work (Al-Salman et al., 2019).

Features Extraction Based on Fractal Graphs

Different window sizes of 0.5, 1.0, 1.5, and 2.0 s were tested in this study to investigate the most suitable number of boxes required to cover the curve. The number of the boxes that are required to cover the entire T-F images using 0.5 s is shown in **Table 2**, while **Table 3** presents the number of boxes with different sizes of windows. As mentioned before, the FD is calculated after transferring an EEG segment into T-F images using the STFT. Then, the box-counting algorithm is applied on each T-F image to extract the features of interest. The values of those features range between 1.0 and 2.0. Each element in the FDs is calculated based on $\log N(r)/\log(1/r)$. By using the slope of a least square best straight line, the fractal is obtained. From each T-F image, ten FD features as a vector are extracted from each TFI.

For example, if the box size r is 16, the size of window is 0.5, 1.0, 1.5, and 2.0 s and the number of boxes is 1232, 1973, 2357 and 3351, respectively, as shown in **Table 3**. Based on the equation of $\log N(r)/\log(1/r)$, the fractal value for the seventh feature (*FD7*) is 1.204 with window size 0.5 s, as shown in **Table 2**. However, to obtain 10 FDs from each T-F image, the same procedure is repeated 10 times. In general, the FD values are between 1.0 and 2.0 and all the FD values are non-integer. Based on the experimental results during the training phase, the proposed method provides better classification results using a window size of 0.5 s than the window sizes of 1.0, 1.5, and 2.0 s. More details regarding windows sizes will be presented in section Experimental results.

Structure and Construction of Graph Properties

Undirected graph properties have been used to analyze and study brain diseases (Vural and Yildiz, 2010; Wang et al., 2014). The graph may be considered as one of the more robust tools to characterize the functional topological properties in brain networks for both normal and abnormal brain functioning (Stam et al., 2007; Li et al., 2013). It is widely used to identify EEG signals such as sleep stages, as well as to classify digital images (Sarsoh et al., 2012; Diykh et al., 2016). In this study, the structure of graph properties is employed to identify k-complexes from EEG signals.

An undirected graph can be described as a set of nodes and edges. A graph is a pair of set $\boldsymbol{G} = (\boldsymbol{V}, \boldsymbol{E})$, where $\boldsymbol{V}$ is a set of nodes in a graph and $\boldsymbol{E}$ is a set of connections between the nodes of graphs. Each pair of nodes in a graph is connected by a link. The connection denotes that there are relationships between each pair of nodes in a graph (Blondel et al., 2004; Migotina et al., 2010; Bernhardt et al., 2015). The Euclidean distance has been used in this study as a similarity measure (Huang and Lai, 2006). The edges between the first point and others are calculated using the Euclidean distance. **Figure 7** shows a vector of FD as example **X** = {1.2, 1.4, 1.3, 0.7, 1.9, 2.2, 0.3, 2.0, 2.8, 4.6, 12.2, …}, being transferred into an undirected graph which is obtained from the TFIs based on Eq. 4. To construct the undirected graph, each data point in **X** was considered to be a node in a graph. v_1 is the first node in the graph corresponding to the first point in the vector **X** with a value of 1.2. The edges between this point and the others were calculated based on Euclidean distance. More details about Euclidean distance were provided in Zhang and Small (2006), Zhu et al. (2014), and Jain et al. (1999). Consequently, a distance matrix (adjacency matrix) is produced according to Eq. 7. Based on the proposed method, the undirected graph can be characterized with its degree distributions, cluster coefficient and Jaccard coefficient. The next section provides more details in relation to the undirected graph characteristics.

To build the adjacency matrix, we assume that there are two nodes, v_1 and v_2, in an undirected graph. Those nodes are

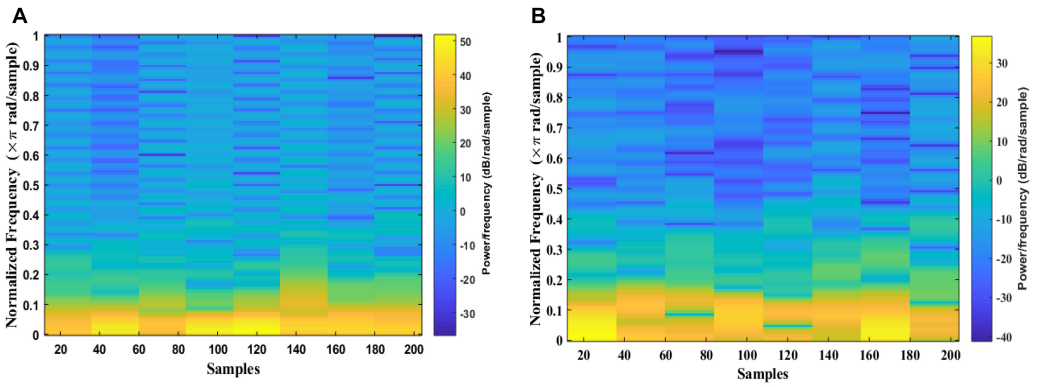

FIGURE 5 | Time-Frequency Image of an EEG segment by the STFT: **(A)** with k-complexes events. **(B)** without k-complexes.

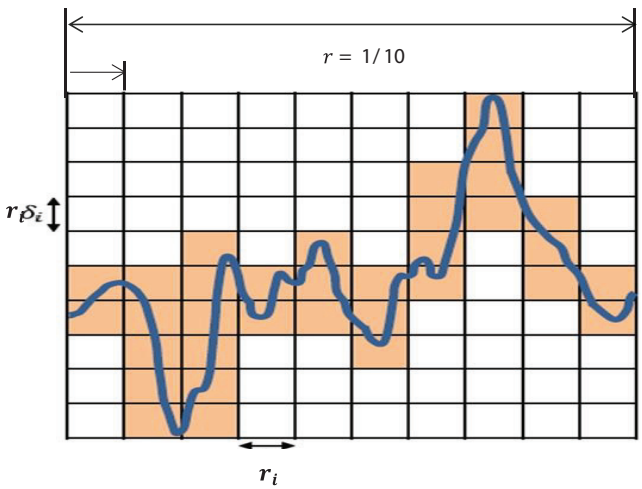

FIGURE 6 | An illustration of the box counting algorithm to create the size and the numbers of boxes.

TABLE 2 | The number of boxes in ten scale according to the box size by using 0.5 s window sizes.

Box size *r*	**1**	**2**	**4**	**8**	**16**	**32**	**64**	**128**	**256**	**512**	**1024**
No. of box *N*(*r*)	277925	70406	17805	6418	1232	360	105	34	12	4	1
log(1/*r*)	0	0.30102	0.60205	0.90308	1.20411	1.50514	1.80617	2.10720	2.40823	2.70926	3.01029
log *N*(*r*)	5.4439	4.8476	4.2505	3.6645	3.0906	2.4857	2.0212	1.5315	1.0792	0.6021	0

connected if the distance (d) between v_1 and v_2 is less than or equal to a pre-determined threshold as explained in the following (Boccaletti et al., 2006; Huang and Lai, 2006; Lacasa and Toral, 2010; Zhu et al., 2014; Diykh et al., 2016).

$$(v_1, v_2) \in E, \text{ if } d(v_1, v_2) \leq thr \tag{5}$$

where ***thr*** is the pre-determined threshold. Since the structure of the graph is generally biased by the number of existing edges, statistical measures should be calculated on graphs of equal degree ***k***. Therefore, the threshold was defined in this study by adopting the mean degree as an appropriate threshold scheme to reveal the informative network topology which is the average number of edges per nodes of the graph. More details about adopting the mean degree as the threshold was provided in Sporns and Zwi (2004), Stam et al. (2007), Dimitriadis et al. (2009, 2010), and Micheloyannis et al. (2009).

$$k = \frac{1}{n}\sum_{i=1}^{n} B(v_i, v_j); \quad n = \text{number of node}; \tag{6}$$

Graph ***G*** can be described by giving a square matrix T × T called adjacency matrix *B*. This matrix is used to describe the connection between all the nodes of the graph. The adjacency matrix contains zeros in its diagonal. Thus it is considered to be

TABLE 3 | The number of the boxes in seven scales using different window size of 2.0, 1.5, 1.0, and 0.5 s.

Box size *r*	1	2	4	8	16	32	64
No. of box *N*(*r*) using 2.0 s	536322	136667	34827	8966	3351	614	168
No. of box *N*(*r*) using 1.5 s	572994	145071	36542	9222	2357	615	168
No. of box *N*(*r*) using 1.0 s	435823	110918	28205	7321	1973	571	166
No. of box *N*(*r*) using 0.5 s	277925	70406	17805	6418	1232	360	105

a symmetrical matrix. The value of this matrix is equal to zero if there is no connectivity among two nodes (v_1 and v_1), and otherwise it is equal to one (Boccaletti et al., 2006). However, the connectivity matrix of an undirected graph is symmetric as $B(v_i, v_j) = B(v_j, v_i)$.

$$B(v_i, v_j) \begin{cases} 1, & \text{if } (v_i, v_j) \in E \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

It is clear from **Figure 7** that the node v_{11} of Euclidean distance has no connection to any other nodes in the graph. That means that this node is an isolated point in the graph. In this paper, all the graphs have been constructed with the same number of nodes. The next section provides more details in relation to the undirected graph characteristics.

Graph Features

In this study, the adjacency matrix of a graph ***G*** has been used to extract the statistical features. Those statistical features of a graph can be used for the detection of k-complexes from EEG signals in this paper. The following section describes the important features that can be extracted from graph ***G*** (Li et al., 2013; Fang and Wang, 2014; Diykh and Li, 2016).

Degree distributions (DD) of the graph

The DD of graph ***G,*** denoted by ***P*(*k*)**, is defined to the proportion of nodes with degree ***k*** partitioned by the total number of nodes in the graph (Stam and Reijneveld, 2007; Zhu et al., 2014; Diykh et al., 2016). It is obtained by counting the number of nodes having degree ***k*** divided by the total number of nodes (Zhu et al., 2014). The DD is defined as:

$$P(k) = \frac{|\{v|d(v) = k\}|}{U} \tag{8}$$

where $d(v)$ refers to the degree of node v, while U is the total number of nodes in the graph. For example, in **Figure 7**, $P(k) = \left(\frac{3}{10}, \frac{2}{10}, \frac{5}{10}, \frac{2}{10}, \frac{3}{10}, \frac{2}{10}, \ldots, \frac{n}{10}\right)$.

Clustering coefficient (CC) of the graph

The CC can be considered as one of most important metrics utilized to characterize both local and global structures of a graph, ***G***. It was used by Stam et al. (2007) and Li et al. (2013) to analyze brain activities. Assume that v_i is a node in the graph. The clustering coefficient of a given node, v_i is calculated as the proportion of the links among v_i's neighbors. For example, the

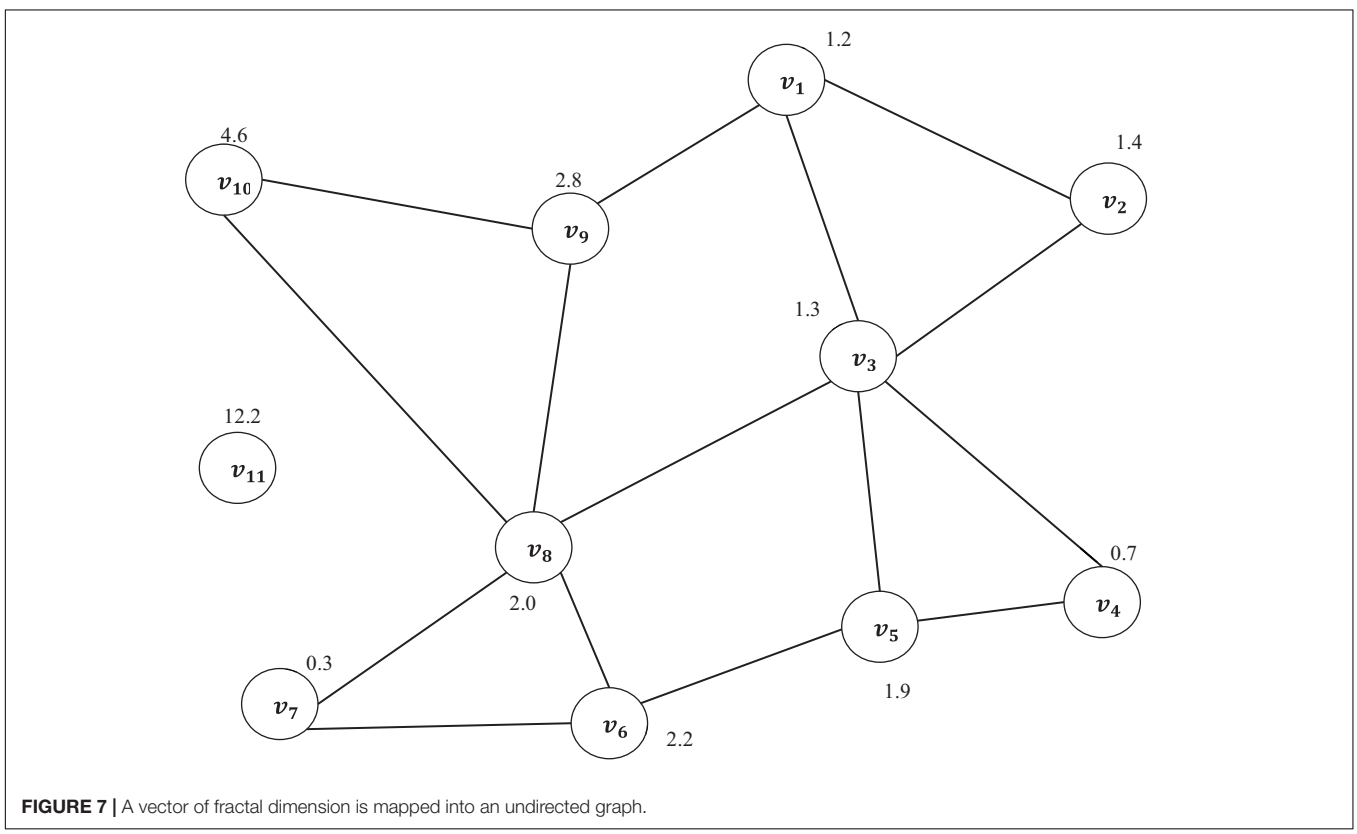

FIGURE 7 | A vector of fractal dimension is mapped into an undirected graph.

CC of node v_s in **Figure 7** is 1 as the node v_s has three neighbors: ($v_4 \rightarrow v_5$, $v_3 \rightarrow v_5$, $v_5 \rightarrow v_6$). Thus, the CC of $v_s = 1$. The average of the CC of all the nodes is measured as:

$$CC = \frac{1}{U}\sum_{i=1}^{U} G_{vi} \tag{9}$$

where U is the number of the nodes in graph $\boldsymbol{G}$ and G_{vi} is the clustering coefficient of node v_i.

Jaccard coefficient of the graph

Jaccard coefficient is used to measure the similarity between two nodes of a graph. Assume v_i and v_j are two nodes in graph $\boldsymbol{G}$. Jaccard coefficient can be defined as a ratio of the set of the neighboring intersection between v_i and v_j to the set of the neighboring unions for the two nodes. Jaccard coefficient was used by Anuradha and Sairam (2011) to classify digital image. It was also utilized by Iglesias and Kastner (2013) to analyze the similarity between two time series. Their results showed that using a Jaccard coefficient helped to improve satisfactory classification results. Jaccard coefficient function is calculated based on the following equation:

$$\mathbf{M}(v_i, v_j) = \frac{|\Gamma(v_i) \cap \Gamma(v_j)|}{|\Gamma(v_i) \cup \Gamma(v_j)|} \tag{10}$$

where $\Gamma(v_i)$ and $\Gamma(v_j)$ are the sets of neighbors of the two nods, v_i and v_j, that have an edge from v_i and v_j, and $\mathbf{M} = [0, 1]$. In this study, for each graph, a Jaccard coefficient vector is computed. **Figure 8** shows the main steps of the features extraction process using the proposed method.

Classification Algorithms

After the three fractal graph features are obtained from each graph, they are forwarded to a LS-SVM classifier to identify k-complexes in sleep EEG signals. For comparison, a k-means classifier is also applied. Based on the literature (Siuly et al., 2011; Siuly and Li, 2012; Al Ghayab et al., 2016; Al-Salman et al., 2018, 2019), we found the two classifiers are considered the most popular and effective methods in biomedical signal classification. The training parameters of the selected classifiers were presented in **Table 4**.

Least Square Support Vector Machine (LS-SVM)

The LS-SVM classifier was first developed by Suyken and Vandewalle (Guler and Ubeyli, 2007) based on the last version of a support vector machine. It is widely used to classify various types of biomedical signals because it has showed great performance results with a high accuracy rate and low execution time. Many researchers used the LS-SVM classifier to classify different characteristic patterns of EEG signals, such as sleep stages, sleep spindles and epileptic seizures (Sengur, 2009; Siuly and Li, 2012, 2015; Bajaj and Pachori, 2013; Al Ghayab et al., 2016; Diykh et al., 2016). It was used for the detection of sleep spindles in EEG signals in our previous work (Al-Salman et al., 2018).

The LS-SVM classifier generally depends on two hyper parameters, γ and σ. Those parameters should be carefully chosen due to they can positively or negatively affect the performance of a method to increase or decrease the classification rate. The radial basis function (RBF) kernels, γ and σ are empirically selected during the training session. In this paper, the optimum values for γ and σ are set to $\gamma = 10$ and $\sigma = 1$.

K-Means

The k-means classifier is a second classifier being employed in this study. It is considered as one of the most popular approaches in biomedical data classification. In general, the k-means classifier is known as a clustering algorithm (Faraoun and Boukelif, 2006; Al-Salman et al., 2018). It partitions observations into a number of groups according to the similarities or dissimilarities among their patterns. The Euclidean distance for a k-means classifier is usually used for the dissimilarity measure. It was used by Al-Salman et al. (2018) for detecting the sleep spindles, and by Orhan et al. (2011) for detecting the epileptic EEG signals. In this research, the k-means classifier is used to distinguish between k-complexes and non-k-complexes waveforms.

Performance Evaluation

In order to evaluate the performance of the proposed method with different EEG categories, the following metrics, accuracy, sensitivity and specificity are used in this paper. The main formulas of those statistical measurements are defined as Tawfik et al. (2016) and Yücelbaş et al. (2018b).

$$\begin{aligned} \text{Accuracy (ACC)} &= \frac{\text{TP} + \text{TN}}{\text{TP} + \text{FN} + \text{FP} + \text{TN}}; \\ \text{Sensitivity (SEN)} &= \frac{\text{TP}}{\text{TP} + \text{FN}}; \\ \text{Specificity (SPE)} &= \frac{\text{TN}}{\text{TN} + \text{FP}} \end{aligned} \tag{11}$$

where TN (true negative) is the actual non-k-complexes that are correctly classified as non-k-complexes. FP (false positive) refers to the number of k-complexes that are incorrectly determined by a classifier. TP (true positive) means the actual k-complex waves that are correctly detected. FN (false negative) shows the actual k-complexes that are incorrectly marked as non-k-complexes. More details for those metrics and other measurements are provided in Al-Salman et al. (2018).

Matthews's Correlation Coefficient (MCC)

MCC is used in machine learning as a measure of the quality of binary classifications. It provides a balanced evaluation of the detector as compared with sensitivity and specificity values, which can be used even if classes are of unequal size. It is defined in Migotina et al. (2010) and Matthews (1975):

$$\text{MCC} = \frac{\text{TP.TN} - \text{FP.FN}}{\sqrt{(\text{TP} + \text{FP})(\text{TP} + \text{FN})(\text{TN} + \text{FP})(\text{TN} + \text{FN})}} \tag{12}$$

F-Score

One of the most important measurements that are used to show the overlapping between the two sets. F-score is defined by weighted sensitivity and precision.

$$\text{F} - \text{score} = \frac{2\text{TP}}{2\text{TP} + \text{FP} + \text{FN}} \tag{13}$$

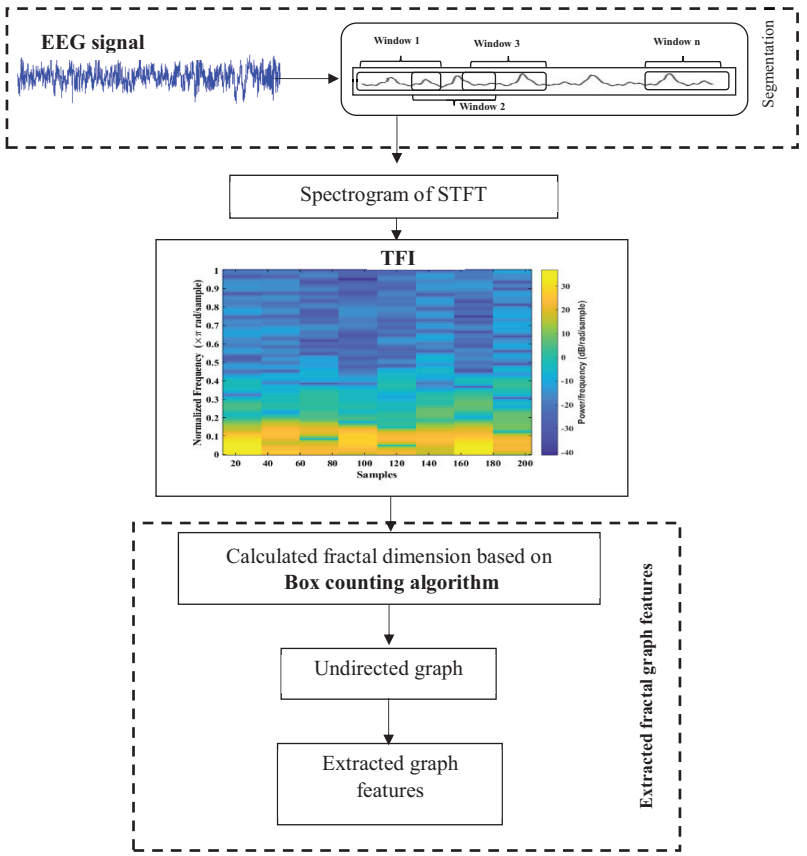

FIGURE 8 | A graphical diagram of feature extraction.

Kappa Coefficient

It is a statistic measure used to evaluate the agreement between two classification results. In this paper, it is employed to evaluate the agreement between two models, the proposed method and expert (expert 1). It is defined as below:

$$\text{Kappa coefficient } (k) = \frac{\frac{\text{TP+TN}}{\text{N}} - \text{pre}}{1 - \text{pre}} \tag{14}$$

where, $\text{pre} = \frac{\text{TP+FN}}{\text{N}} . \frac{\text{TP+FP}}{\text{N}} + \left(1 - \frac{\text{TP+FN}}{\text{N}}\right) . \left(1 - \frac{\text{TP+FP}}{\text{N}}\right)$, and $N = (\text{TP} + \text{FP} + \text{TN} + \text{FN})$.

K-Cross Validation

It is a popular approach used for evaluating the performance of a classification algorithm. It is utilized to estimate the quality of the classification results by dividing the number of correctly classified results by the total of the cases. The datasets in section "EEG Data Description" are separated into ***k*** groups with equal size. Each time, one group is used as the testing set, while the remaining subsets (groups) are used as the training set. All the groups are tested in turn. The testing classification accuracy for all groups is calculated. In this paper, 6- cross-validation is used as the accuracy is not improved after $k > 6$. The average accuracy for all testing subsets is computed below:

$$\text{Performance} = \frac{1}{6} \sum_{1}^{6} \text{accuracy}^{(k)} \tag{15}$$

where accuracy$^{(k)}$ is the accuracy over the six iterations (k = 1, 2, . . ., 6).

TABLE 4 | Classifiers' parameters used in this study.

Classifier	Parameters
LS-SVM	$\gamma = 10$, $\sigma = 1$ and RBF kernel
K-means	k, c_i and x_k, where k is the number of clusters and $k = 2$. c_i is the center of the clusters and $c_i = 1$, and x_k is the data points.

EXPERIMENTAL RESULTS

All the experiments were conducted with the database discussed in section "EEG Data Description" and three structural graph features were extracted from each FD of the T-F images in this study. The features graph were sorted in a descending order based on their importance as shown in **Figure 9**. Based on the obtained results, the proposed method with the three graph features recorded high classification results, with an average accuracy of 97%. All the experimental results were obtained in a Matlab 2015b

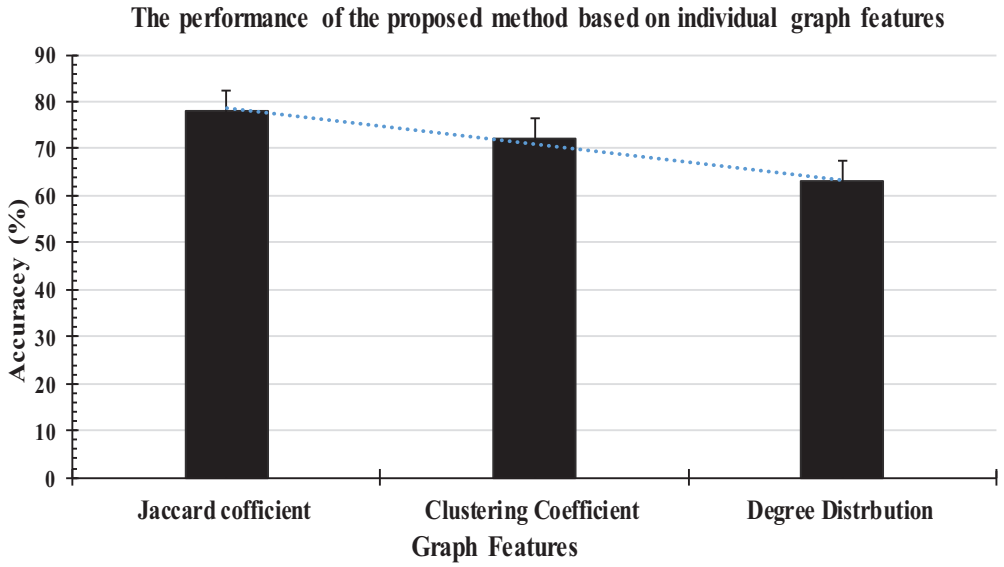

FIGURE 9 | Classification accuracy based on individual graph features.

environment on a computer that has the following features: 3.40 GH Intel (R) Core^{TM} i7 processor machine, and 8.00 GB RAM. The experimental results were evaluated in terms of accuracy, sensitivity, and specificity. The 6-fold cross validation was also used in this study.

According to **Figure 9**, some attributes of a graph, such as the Jaccard coefficient, were more significant that other graph attributes in recognizing k-complexes. To investigate the effectiveness of the characteristics of the graph on the identification of the k-complexes, the mean and standard deviation measurements for each segment were used in this study, as shown in **Figure 10**. From the results in **Figure 10**, we can see that the three of the graph features: Jaccard coefficient, clustering coefficient, and degree distribution can be used as key attributes to differentiate the k-complexes. All the characteristics of the graph have reported reasonable results in term of standard deviation, as shown on **Figure 10**. Based on the literature, the obtained results indicate that the three graph features of *{Jaccard coefficient, clustering coefficient, and degree distribution}* can be used to distinguish between k-complexes and non-k-complexes EEG segments.

The results based on the three features set by the proposed method are presented in **Table 5**. Based on the results in **Table 5**, it was observed that, the three features set of the graph yields the highest accuracy for the detection of k-complexes in EEG signals. The obtained results demonstrated that the proposed method yielded the best performance with an average accuracy, sensitivity and specificity of 97, 96.6, and 94.7%, respectively. All the results in **Table 5** were carried out using LS-SVM classifier with a window size of 0.5 s. For further evaluation, the performance of the proposed method was also tested using a FPR and kappa coefficient. The FPR and kappa coefficient have been calculated for each subject and the average of all the results was investigated. The average of the FPR and kappa coefficient of the proposed method was 0.060 and 0.87, respectively. Based on the literature, the obtained results by the FPR and kappa coefficient provided evidence that the proposed method has the potential to classify k-complexes and non-k-complexes in EEG signals.

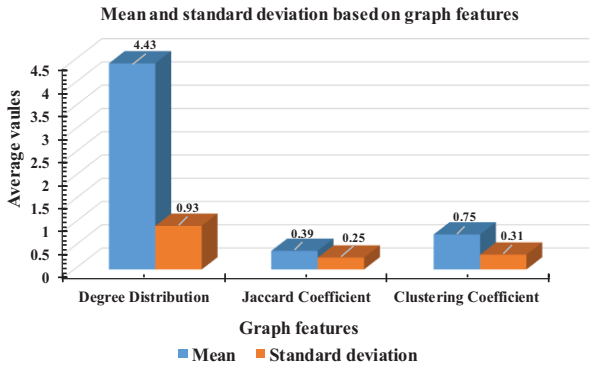

FIGURE 10 | Mean and standard deviation of undirected graph features.

TABLE 5 | The performance of the proposed method based on the DD, JC and CC.

Fold No.	Sensitivity %	Specificity %	Accuracy %
Fold1	97	94	98.2
Fold2	96.3	97.8	97.1
Fold3	97.1	96	97
Fold4	97	94	97.3
Fold5	96	92	95.8
Fold6	97	93	96.8
Average	**96.6**	**94.7**	**97**

Performance of the Proposed Method Based on Different Window Sizes

To detect all possible occurrences of the k-complexes in the original EEG signals, and to assess the ability of the proposed method to identify the k-complexes, three other window sizes of 1.0, 1.5, and 2.0 s were tested in this paper. The features described in Section "Graph Features" were extracted, and the dataset was divided into six subsets. The average accuracies of the proposed method were recorded from the 6-fold cross evaluation. The accuracies against the expert's scoring using different window sizes were reported in **Figure 11**. From the results in **Figure 11**, it can be seen that it was difficult to detect k-complexes in EEG signals with 2.0 s window size, which makes sense since the most of the occurrences of k-complexes have a window size of 0.5 s. Our findings show that, there were large disagreements between the proposed method and the expert (Expert 1) in some datasets when 1.5 s window size was used.

On the other hand, it was observed that the proposed method has the capacity to identify k-complexes at a window size of 1.0 s and there was only slight disagreements between the proposed method and the expert's scoring. Our findings show that the proposed method achieved the highest results when the window size of 0.5 s with overlapping of 0.4 s was used. The maximum accuracy was 97%.

Performance of the Proposed Method Using Receiving Operating Characteristic Curve

The performance of the proposed method was also evaluated based on a Receiving Operating Characteristic (ROC) curve. **Figure 12** depicts the ROC analysis results of the LS-SVM classifier. The ROC is a suitable metric in studying the dependence of sensitivity and specificity. The relationship between the true positive rate and FPR were investigated in this paper using the ROC curve. A good test is the one for which sensitivity (true positive rate) rises rapidly and 1-specificity (FPR) hardly increases at all until sensitivity becomes high (Übeyli, 2008). From **Figure 12**, it is seen that the area value of the ROC curve is 97, which indicates that the LS-SVM model has effectively detected the k-complexes in EEG signals using the extracted features from the graph. Therefore, it is obvious that the fractal graph features well represent the EEG signals and the LS-SVM classifier trained on these features achieves a high classification accuracy.

Performance Comparisons Using Different Classifiers, Different Data-Driven Thresholding Scheme and With Other Existing Studies

Three types of comparisons were conducted in this section. Firstly, the performance of the proposed method was compared with a different classifier, k-means classifier. Secondly, the proposed method was also compared with different data-driven thresholding scheme. Finally, the proposed method was compared with other studies that used the same datasets as described in section "EEG Data Description."

Comparison With K-Means Classifier

Figure 13 shows the comparison results between the LS-SVM and k-means classifiers using the extracted features. The same

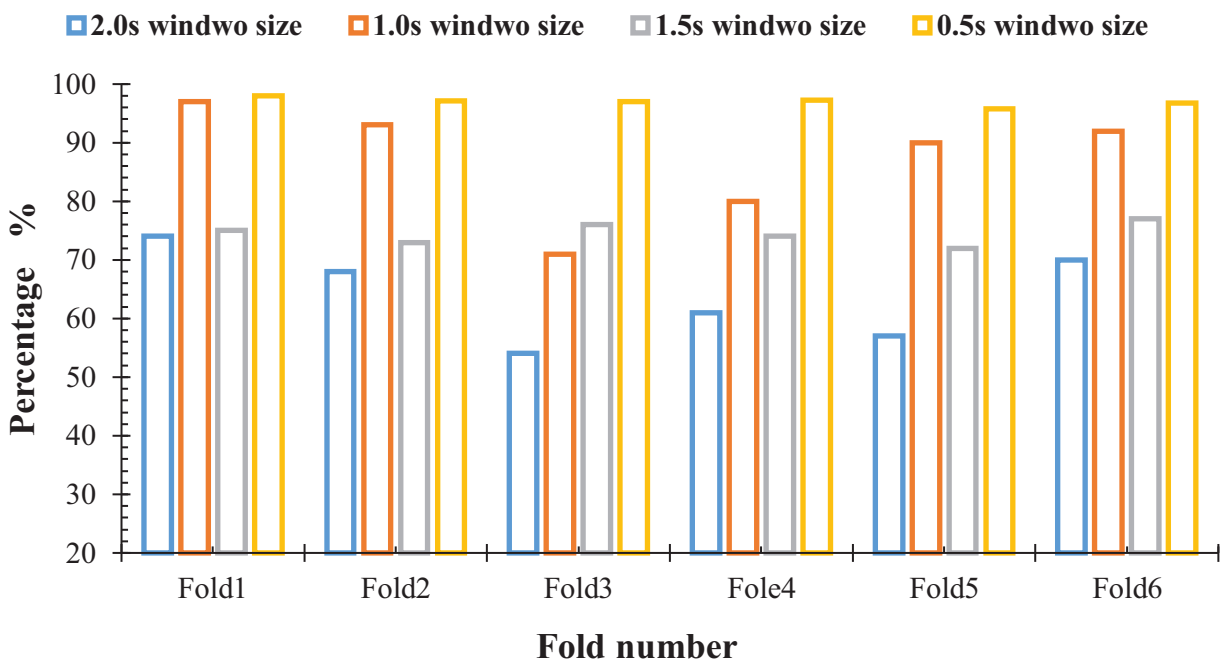

FIGURE 11 | Performance comparisons by the proposed method using different window sizes.

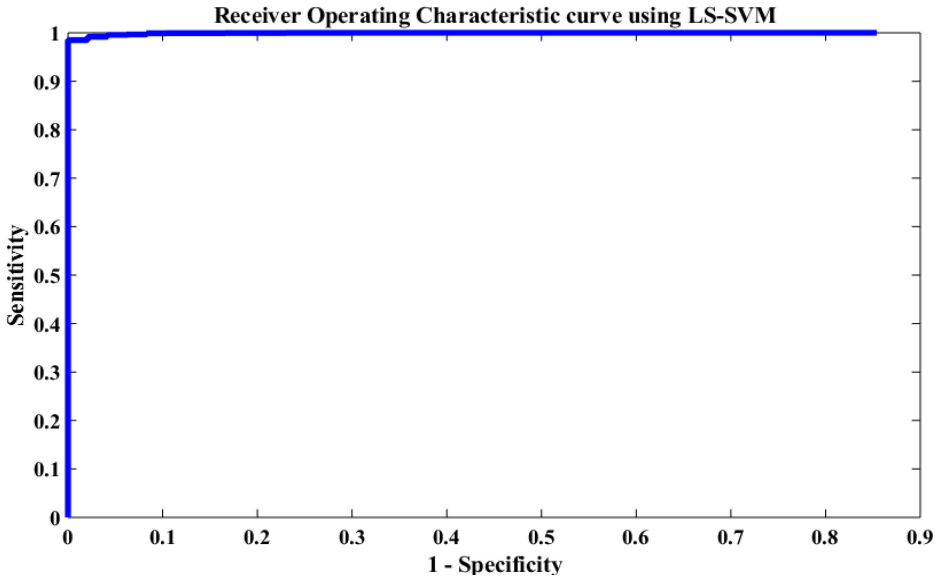

FIGURE 12 | Performance evaluation of the proposed approach using the LS-SVM classifier based on the ROC curve.

number of segments were used. The segments were chosen randomly from the database. The selected segments were separated into a training set and a testing set, and then were forwarded to the classifiers, separately, to identify k-complexes. Based on the results in **Figure 13**, it can be observed that the performance of the proposed scheme using the LS-SVM was better than that by the k-means classifier. The accuracy of the k-means classifier was degraded from 65 to 51% when the number of the segments gets to 4000. In terms of accuracy, sensitivity and specificity, the proposed method based on the LS-SVM classifier outperformed the k-means.

For more investigation, the execution time of the proposed method was calculated based on the LS-SVM classifier as well as to the k-means classifier. **Figure 14** shows the complexity time for the LS-SVM and k-means classifiers. To compute the performances of the two classifiers, the same computer having the same settings was used, with the same input data segments.

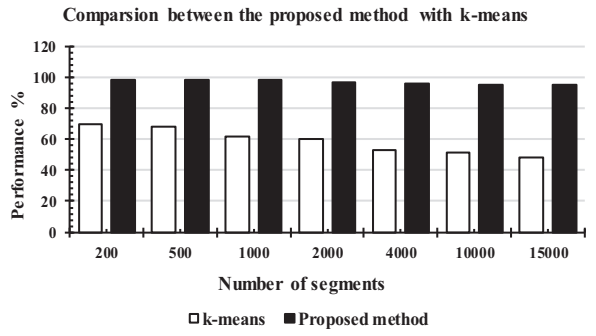

FIGURE 13 | The performance comparison between the proposed method and the k-means classifier.

The complexity time of the proposed method was recorded for each classifier. From **Figure 14**, we observed that the proposed method took an acceptable time although it had more processing steps involved in the algorithm. Based on the obtained results, the highest execution time was recorded with the LS-SVM classifier compared with the k-means classifier. Although converting the fractal features to the undirected graphs take more time, it resulted in more accurate results in k-complexes detection.

To shed more light on the comparison, the performance of the proposed method was also compared with k-means classifiers for detecting k-complexes in EEG signals based on 6-fold cross validation. The EEG data were divided into six folds and each fold was tested six times. The boxplots for each fold based on 6-fold cross validation were shown in **Figures 15**, **16**. According to the results in **Figure 16**, it was observed that there was an improvement achieved with the proposed method to detect the k-complexes in EEG signals when the LS-SVM classifier was used to classify the features compared to the k-means classifier. It is clear from these results, the extracted features based on fractal graphs coupled with the LS-SVM classifier have better ability to distinguish the k-complexes in EEG signals.

Comparison With Different Data-Driven Thresholding Scheme

The proposed method was tested with different data-driven thresholding scheme reported in Dimitriadis et al. (2017a,b) such as minimal spinning tree (MST) and orthogonal minimal spinning tree (OMST). A spanning tree is a subgraph that includes all nodes of the original graph but it has no cycles. The MSTs try to connect simultaneously all the nodes of the graph by minimizing the cost of the total sum of the weighted links. An MST based on the Kruskal algorithm was used in this study to search the MST in an undirected weighted graph and remove redundant edges. On the other hand, the OMSTs try to capture

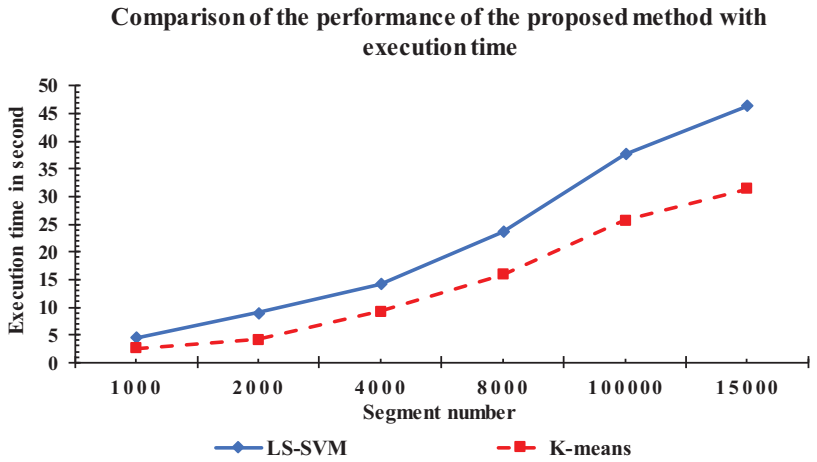

FIGURE 14 | Comparison of the execution time among the proposed method and k-means.

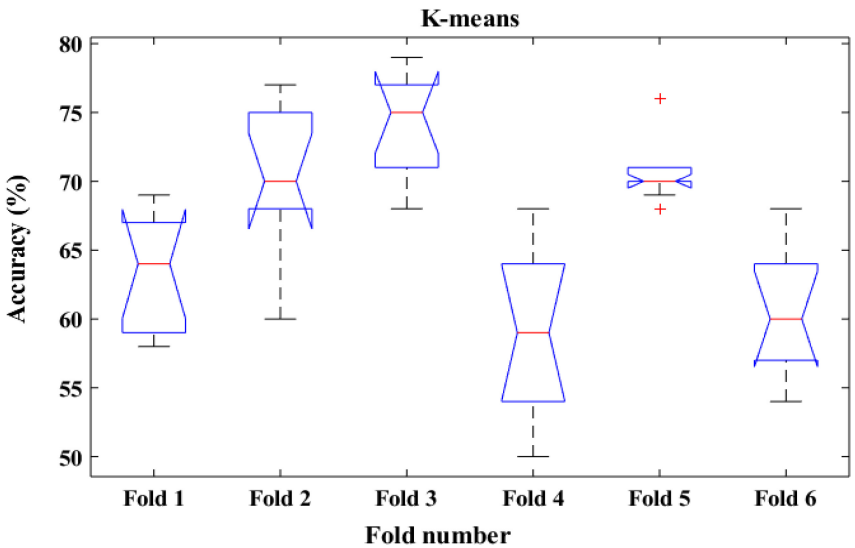

FIGURE 15 | The boxplot of the classification accuracy based on 6-fold cross validation for k-means classifier.

the most significant connections under the constraint of the MST. More details about the data-drive threshold method was provided in Dimitriadis et al. (2017a,b).

In this paper, the proposed method was also compared with MST and OMST approaches; we optimized the mean degree following a step of 0.1 from mean degree = >5 up to mean degree = <8 toward the maximization of accuracy. The best classification performance was obtained when k was 6 and the optimal matching step was 0.2, with an accuracy of 97%, as shown on **Table 6**. The main reason for that is small mean degrees produces more informative features that further improve classification performance. Also, when the mean degree was small, features that contributed more to the classification were also chosen, leading to higher classification accuracy (Breakspear and Terry, 2002; Rutter et al., 2013; Guo et al., 2018). Thus, the experimental results showed that the optimizing mean degree influenced the classification results. Furthermore, the results in **Table 6** indicate that network analysis of an undirected graph to detect k-complexes in EEG signals has been realized in binary graphs using MST, OMST and arbitrary thresholding. However, our findings showed that the proposed method using an arbitrary threshold reported better accuracy, sensitivity and specificity than that of those methods: the MST and OMST. Therefore, in this study, we consider arbitrary thresholding. **Table 6** shows the comparison results among different data-driven schemes.

Comparison With Other Methods Based on Different Measurements

For further evaluation, the performances of the proposed method was compared with other methods based on different metrics, including F-score, recall, precision and Matthews (MCC).

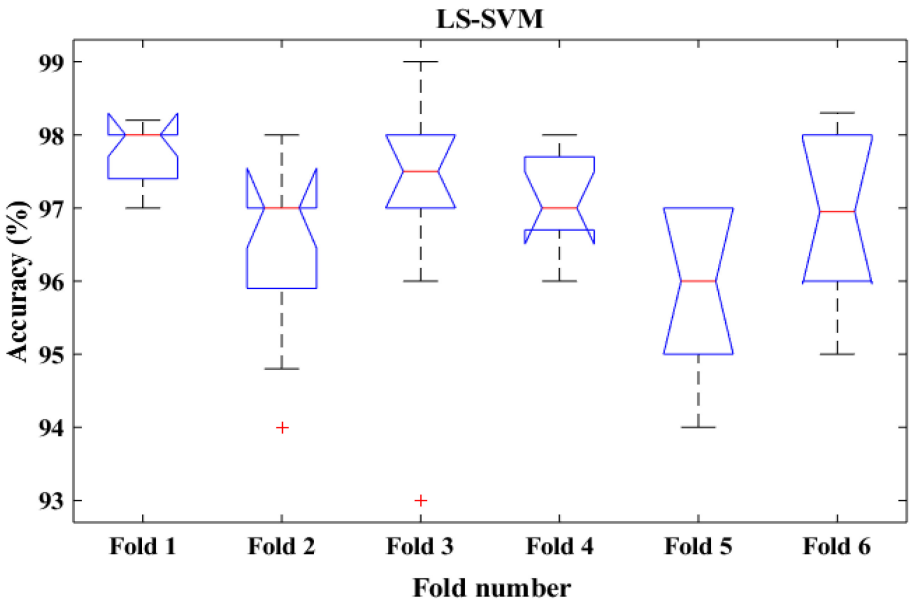

FIGURE 16 | The boxplot of the classification accuracy based on 6-fold cross validation for LS-SVM classifier.

Figure 17 shows the result of comparisons based on different measurements. They were used in different methods to detect k-complexes in EEG signals (Devuyst et al., 2010; Parekh et al., 2015; Ghanbari and Moradi, 2017). They conducted their methods with the same database as used in this study. It can be seen in **Figure 17**, that the proposed detection approach has a better F-score, recall, precision and MCC values compared with those by other methods. The averages of F-score, recall, precision and MCC were 0.77, 0.96, 0.78, and 0.83%, respectively. Our method performed better than other detection methods, and it achieved higher results compared with those by others.

Comparisons With Other Existing K-Complexes Classification Methods

Table 7 represents the performance comparisons among the seven reported methods (Devuyst et al., 2010; Erdamar et al., 2012; Vu et al., 2012; Krohne et al., 2014; Zamir et al., 2015; Patti et al., 2016; Ranjan et al., 2018). All these studies used the same database as discussed in section "EEG Data Description." According to the results in **Table 7**, the proposed method is the best among the seven methods. Additionally, it achieved a high accuracy, sensitivity and specificity of 97, 96.6, and 94.7% compared with those methods.

TABLE 6 | The performance of the proposed method over various thresholding schemes.

Metrics	Types of thresholding schemes		
	MST	OMST	Arbitrary thresholding
Accuracy	89%	94.6%	**97%**
Sensitivity	91%	95%	**96.6%**
Specificity	94.6%	86.2%	**94.7%**

Patti et al. (2016) reported their results of the k-complexes detection with the same database. The average of the sensitivity results they achieved was 84%. The average accuracy was lower than that obtained in this study. Vu et al. (2012) focused on designing a hybrid classifier to detect k-complexes in EEG signals using a hybrid synergic machine learning method. A set of features were extracted from each EEG segment and a representation instance classifier was used to classify the extracted features. Overall, they reported an average of the classification accuracy of 90.2%. Based on the obtained results, the proposed method outperformed the one by Vu et al. (2012).

Another study was made by Devuyst et al. (2010), in which a likelihood threshold was used to detect k-complexes. That study was conducted using the same datasets as the ones used in this paper. The authors reported only true positive rates. The obtained results in our method were higher than those by Devuyst et al. (2010). Ranjan et al. (2018) detected k-complexes using a fuzzy algorithm combined with an artificial neural network. In that study, features were extracted from each EEG segment and then forwarded to a fuzzy neural network algorithm to identify k-complexes in EEG signals. An average accuracy, sensitivity, and specificity of 87.56, 94.04, and 76.2%, were reported, respectively. The classification results were also lower than those by the proposed method. A convert optimization technique was utilized by Zamir et al. (2015) to detect k-complexes. In that study, different features were extracted and ranked based on a feature selection algorithm. The best classification accuracy of 84% was reported. Their accuracy was lower than that of the proposed method.

Erdamar et al. (2012) detected k-complexes using two main stages, including a wavelet transformation combined with a

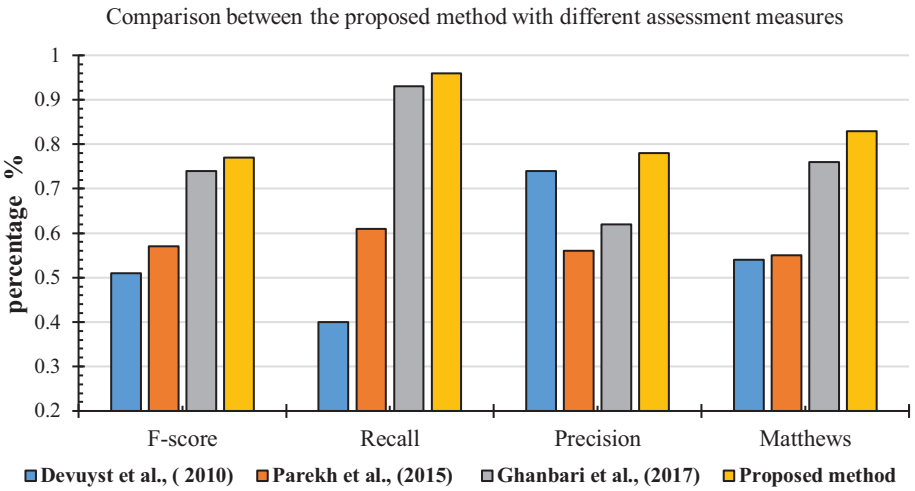

FIGURE 17 | Performance comparison of the proposed method for k-complex detection using different assessment measures.

TABLE 7 | Performance comparisons between the proposed method and other different k-complexes detection approaches with the same datasets.

Authors	Method	Accuracy	Sensitivity	Specificity
Patti et al. (2016)	Pattern matched wavelets using 400 threshold	–	84%	–
Vu et al. (2012)	Hybrid synergic multi-instance learning machine.	90.2%	70.4%	–
Devuyst et al. (2010)	Likelihood threshold		61.72%	
Ranjan et al. (2018)	Fuzzy algorithm combined with artificial neural network	87.56%	94.04%	76.2%
Zamir et al. (2015)	Convert optimization technique	84%		
Erdamar et al. (2012)	Wavelet transformation combined with a Teager energy operator	91%	89	–
Krohne et al. (2014)	Wavelet transformation	–	74%	–
The proposed method	**T-F images coupled with fractal graph features**	97%	96.6%	94.7%

Teager energy operator. In that study, features were extracted based on the amplitude and duration properties of k-complex waveforms. The results from both stages were combined to make a robust method for the detection of k-complexes. In comparison, the proposed method yielded a high classification accuracy than that by Erdamar et al. (2012). Krohne et al. (2014) classified EEG signals into k-complex and non-k-complex segments based on wavelet transformation. In that study, different datasets were used. Their results with both databases were lower than our proposed method. It is clear that the proposed method yielded the highest accuracy compared with the seven other methods using the same datasets.

For further evaluation, the performance of the proposed method was compared with those by Hernández-Pereira et al. (2016), Gala and Mohylova (2009), Ranjan et al. (2018), Noori et al. (2014) based on the types of features and classifiers used. **Table 8** shows the results of the comparison. It can be noticed that the proposed scheme reported the highest accuracy compared with the four other methods. The proposed method obtained an average accuracy of 97% with fractal and graph features. This demonstrated that the proposed approach achieved the best performance in terms of classification accuracy.

TABLE 8 | Comparisons between the proposed method and other studies based on the type of features and classifiers used.

Authors	Features	Classifier	ACC
Hernández-Pereira et al. (2016)	12 frequency features.	support vector machine	91.4%
Gala and Mohylova (2009)	Time and frequency domain features	neural network	63%
Ranjan et al. (2018)	12 Bankman features	fuzzy neural network	86.9%
Noori et al. (2014)	Statistic and fractal features	extreme learning machine	96%
The proposed method	**Fractal and graph features**	**LS-SVM classifier**	**97%**

CONCLUSION

In this paper, the FD technique and undirected graph properties are used to detect k-complexes in EEG signals. In the proposed method, each 0.5 s EEG segment was passed through the spectrogram of the STFT to obtain the time-frequency images (T-F images). Then, the box counting algorithm was applied to each T-F image to calculate the FD. A vector of FD was mapped into an undirected graph to extract the features of interest. Three features were extracted from each graph and they were forwarded to a LS-SVM classifier to identify k-complexes in EEG signals.

The experimental results showed that the graph features achieved better performance for the detection of k-complexes with an average accuracy of 97%.

The proposed method was also compared with other existing methods and with different classifiers to identify the ability of using fractal graph features to detect k-complexes. Based on those comparisons the proposed method achieved the best performance in terms of classification accuracy, sensitivity and specificity. The maximum averages of accuracy, sensitivity and specificity obtained using the proposed method are 97, 96.6, and 94.7%, respectively. The outcomes of this study can help the physicians with diagnosing sleep disorders and potentially it can reduce the medical costs. In our future work, the fully weighted version will be taken into consideration as a new methodology to detect other sleep characteristics such as sleep spindles, Sawtooth waves, Alpha waves, and vertex waves.

AUTHOR CONTRIBUTIONS

WA-S, YL, and PW contributed conception and design of the study and wrote sections of the manuscript. WA-S organized the database and wrote the first draft of the manuscript. WA-S and YL performed the statistical analysis. All authors contributed to manuscript revision, read and approved the submitted version.

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6.2 Chapter Summary

Al-Salman et al. (2019) developed a new method to identify the k-complexes from sleep stage 2 in EEG signals. They used FD and TFI coupled with an undirected graph to extract features which have been used to detect k-complexes in EEG signals. The extracted features, the vectors of FD of each TFI, were transmitted to the undirected graph to firstly reduce the dimensionality of FD and to secondly extract the most discriminating graph features. Features were extracted from each graph and they were forwarded to a LS-SVM classifier to identify k-complexes in EEG signals. The proposed method was tested with all datasets (all EEG recordings) rather than as part of a dataset. The experimental results showed that the graph features achieved better performance for the detection of k-complexes. This study proved that the FDs combined with undirected graph features achieved low execution time with a high classification results.

Al-Salman et al. (2019) demonstrated that the proposed method, based on FDs and TFI coupled with graph features, was promising for the extraction of the features from the EEG data and the selection of the most important features. In addition, it had the potential to detect the most important characteristics of sleep stage 2: k-complexes. The proposed method was also compared with other existing methods, based on different features, and also with different classifiers to identify the usefulness of using fractal graph features to detect k-complexes. Based on those comparisons the proposed method achieved the best performance and it outperformed other methods which used different transformation techniques. Al-Salman et al. (2019) clearly demonstrated that the proposed method has the ability to detect the k-complexes with a high classification results and low execution time. Al-Salman et al. (2019) also suggested that the fractal graph features can be used to identify k-complexes efficiently and without pre-processing.

CHAPTER 7

CONCLUSIONS AND DIRECTIONS FOR FUTURE WORK

7.1 Introduction

The human brain is a complex network that contains billions of neurons, each of which generates small electrical signals. The brain uses the electrical signals through a system of neurons to send instructions to organs of the body and to process different types of information at a specific time. Researchers use several techniques to record electrical signals generated by the brain. One of the most important techniques to detect, record and measure record brain activity is EEG signals.

Analysis and classification methods of EEG signals can help doctors and specialists to detect and identify brain disorders. Normally, EEG signals are recorded using electrodes placed on the scalp using a conductive gel. They have the ability to help the diagnosis and treatment of neurological diseases, sleep disorders, and abnormalities of the brain. However, they are affected by brain diseases, such as sleep disorders, epileptic seizures, autism, and Alzheimer's disease.

A variety of methods have been developed and presented based on time domain and frequency domain to study the characteristics of EEG signals and to investigate their composition. Those methods are commonly used to analyse different types of brain disorders during the recording of EEG signals such as identifying sleep characteristics and sleep stages. Because each recording of the EEG signal has unique patterns and characteristics, previous studies have been unable to develop a robust signal analysis

approach. Practical and effective approaches are therefore in demand to achieve accurate results for EEG classification. Summaries of the analysis and detection techniques have been presented in this chapter. Furthermore, some work limitations have also been discussed for future research guidance.

7.2 Discussion and Conclusions of the Thesis

The research project has aimed to identified sleep stages automatically by detecting the main characteristics in EEG signals. In this research, robust techniques in order have been presented and developed to identify and analyse the most important characteristics of sleep stages: sleep spindles and k-complexes. Four techniques, considered to relate to the main objectives of the thesis, have been developed:

1- Development of a robust technique to analyse and detect sleep characteristics such as sleep spindles in EEG signals based on the hybrid transformation technique. This will improve the detection system performance and has a high accuracy rate.
2- Improvement of the developed method to identify the sleep spindles in EEG signals by presenting new extraction techniques based on FD of TFI that can improve the classification accuracy and reduce the time for the processing of execution.
3- Design of a new method to identify and analyse other sleep characteristics in EEG signals such as k-complexes; the second most important bio-signal waveform in sleep stage 2 based on DT-CWT coupled with fractal and frequency features.
4- Investment in the ability of fractal dimensions in # 2 to develop an efficient feature extraction method to detect k-complexes from the whole EEG database, thus reducing the dimensionality of EEG datasets and improving classification performance with less execution time.

In order to achieve these objectives and to accomplish these techniques, firstly two methods were developed: wavelet Fourier analysis (WFA) with the statistical model, and fractal dimension (FD) technique coupled with time-frequency images (TFI) to detect the sleep spindles in EEG signals. Those methods detected sleep spindles in EEG signals with a high accuracy rate and a shorter execution time. Thereafter, a new method was designed and

developed based on fractal and frequency features coupled with an ensemble classification model to detect the second most important characteristics, such as k-complexes in EEG signals. Finally, for investing in the ability of FD of TFI, another method was developed based on fractal graph features coupled with an LS-SVM classifier to detect k-complexes in EEG signals with high classification results and less execution time. This method tested and evaluated a whole EEG dataset. A summary of the developed methods is provided in the following subsection:

7.2.1 Detection and analysis of sleep spindles in EEG signals

In the first method, wavelet Fourier analysis and the statistical model method were used to detect sleep spindles in EEG signals as seen in Chapter 3. Wavelet Fourier analysis was designed based on discrete wavelet transform (DWT) combined with fast Fourier transform (FFT). This method was applied to extract the important features from sleep EEG signals. In this process, the EEG signals were segmented into small windows of 0.5 second (s) with an overlap of 0.4s. Ultimately, ten statistical features were extracted from each window segment after applying a wavelet-Fourier transformation. Lastly, the LS-SVM classifier was used to classify the sleep spindles using the extracted features. The obtained results were also compared with the other existing methods in the literature. The evaluation results showed that the proposed method was the best among all the methods in terms of detection accuracy. Furthermore, C4.5 decision tree, k-means and k-nearest classifier were also implemented for comparisons, and the results were compared with those by the LS-SVM. To test the effectiveness of the proposed method for detection sleep spindles, Dream sleep spindles; and Montreal archive of sleep studies, were used. These databases were acquired from different EEG channels and recorded by either R& K or AASM guidelines. Further, this technique was conducted and tested with different window sizes: 2.0s. 1.0s, 1.5s, and 0.25s to detect all possible occurrences of sleep spindles in the original EEG signals. The experimental results in this chapter showed that the length of 0.5s reported better results than 2.0s. 1.0s, 1.5s and 0.25s; the WFA method achieved 97.9% classification accuracy. The outcomes of this technique may help physicians to diagnose sleep disorders and potentially to reduce medical costs.

7.2.2 Fractal dimension of Time-frequency images for sleep spindles detection

To improve the classification performance and to reduce the execution time, a robust method to detect sleep spindles in EEG signals was presented as discussed in Chapter 4. The proposed method in Chapter 4 applied time frequency image and fractal dimension techniques to detect sleep spindles with a high classification accuracy and low execution time. In this procedure, each EEG signal was divided into small segments using a sliding window technique. A window size of 0.5s with an overlap of 0.4s was adopted in this study after extensive experiments. Then the EEG signals were converted into time frequency images by using a spectrogram of a short time Fourier transform. A box counting algorithm was applied to calculate the fractal dimensions (FDs) from each TFI. Statistical features were extracted from each FD. This work successfully reduced the extracted features dimension. Lastly, the extracted features were used as the input to the least square support vector machine, K-means, neural network, and Naïve Bayes classifiers to elicit the best classification method to detect sleep spindles and to evaluate the performance of this technique. Furthermore, the proposed method in this study was evaluated using two publically available datasets: Dream sleep spindles and the Montreal archive of sleep studies. An average accuracy of 98.6% was obtained by the proposed method. The experimental results showed that using the TFI with the fractal dimension could improve the detection of sleep spindles and take much less execution time compared to the WFA. The outcomes of this study may help sleep experts to efficiently analyse EEG signals.

7.2.3 K-complexes identifaction in EEG signals.

Al-Salman et al. (2018) clearly demonstrated that using fractal dimension techniques improved the classification results of sleep spindles in the EEG signal. In addition, the excellent results achieved using the fractal algorithm to identify sleep spindles (Al-Salman et al., 2018), motivated an exploration and development of the fractal dimension algorithm to detect k-complexes in EEG signals. Thus, a new method based on fractal and frequency features was developed for detecting the k-complexes in EEG signals as explained in Chapter 5. In this framework, a sliding window technique was used to divide EEG signals into small segments. Each segment was decomposed into four levels (four sub-bands) using a dual-tree complex wavelet transform (DT-CWT) method. Four sub-bands including y1, y2, y3, y4, and z4 were obtained for each part

tree. As a result, the DT-CWT coefficient produced both real and imaginary parts. Ten sub-bands were obtained after four levels of decomposition (five sub-bands for each part), and the high sub-bands were considered in this research for feature extraction. Thereafter, fractal and frequency features were extracted from each sub-band and then forwarded to the ensemble classifier to detect the k-complexes. The results presented indicated that DT-CWT combined with an ensemble machine may be used to identify the k-complexes efficiently. An average accuracy of 97.3% was obtained by the proposed method for the detection of the k-complexes, as shown in Chapter 4. Finally, to evaluate the performance of this algorithm and to compare the obtained results with the ensemble mode, the LS-SVM, k-means and Naïve Bayes classifier were used in this research. Furthermore, the performance of the proposed method was compared with other existing methods of k-complex detection. A review of the literature found that there were no methods using frequency features and fractal dimension characteristics in k-complex detection. The obtained results indicated that using fractal and frequency features gave reasonable classification accuracy for the detection of the characteristics of sleep Stage 2. This method may help physicians to diagnose sleep disorders and potentially to reduce medical costs.

7.2.4 Fractal graph features to detect k-complexes

To reduce the processing of execution time, to decrease the dimensionality of EEG data, and to improve the results with all datasets a novel method to identify k-complexes, based on fractal graph features, was presented in Chapter 6; it was conducted and tested with a whole database. In previous research, Al-Salman et al. (2018) reported that the fractal dimension based features achieved promising results for analysing EEG signals as well as for the detection of sleep spindles. As a result, the concept of the fractal dimension technique was used in this study to identify the k-complexes. This method has been used to improve classification results with less execution time.

In this procedure, each 0.5s EEG segment was passed through the spectrogram of the STFT to obtain the time-frequency images (T-F images). Subsequently, the box counting algorithm was applied to each T-F image to calculate the fractal dimension. A vector of the fractal dimension was mapped into an undirected graph to extract the features of interest. The characteristics of graph features were extracted from each graph and they were forwarded to a LS-SVM classifier to identify k-complexes in EEG

signals. The performance of this method was evaluated through the 6-fold cross validation procedure. The ROC curve was also used in Chapter 5 to evaluate the results of the proposed method. The experimental results showed that the graph features achieved approximately the same performance but took less execution time, for the detection of k-complexes, as shown in Chapter 5. To check whether the developed approaches have advantages or not, the proposed method was also compared with other existing methods in which different transformation techniques were used, and with different classifiers to identify the ability to use fractal graph features to detect k-complexes. Based on those comparisons the proposed method achieved the best performance and it also showed the effectiveness of using fractal graph features to identify k-complexes in EEG signals. Moreover, it could be applied efficiently for real-time applications.

To sum up, it can be concluded that this research project has established new and successful algorithms and techniques for reliable detection of the characteristics of sleep stage2 in EEG signals: sleep spindles and k-complexes. There are many advantages to be gained from using these approaches. They will help doctors, particularly neurologists in the diagnosis and treatment of sleep disorders and other brain-related disorders and for sleep research. Furthermore, the proposed methods in this thesis can help doctors to provide clinical information about patients who suffer from sleep disorders. Another very important benefit of this research is that it will help to decrease the cost of treatment for patients because the proposed methods can run automatically to check the patient's recordings.

7.3 Future Work

This study analyses feature extraction techniques from EEG recordings to detect the most important characteristics of sleep stages in EEG signals: sleep spindles and k-complexes. We believe that the techniques developed in this thesis will provide the potential to analyse EEG signals in the biomedical field as well as the potential to classify and process EEG signals. To enable an improvement in the methods presented in this thesis, we have highlighted a number of key issues which are addressed below.

The WFA and LS-SVM classifier was tested on two databases of EEG signals: Dream sleep spindles and the Montreal archive of sleep studies. Technically, the WFA method was applied to divide the EEG signals into segments using sliding window techniques.

In future work, the WFA method could be used to cluster the EEG data into *m* number of clusters. At the last sub cluster, different types of features: statistical, entropic, linear and non-linear features will be extracted and the characteristics of each feature will be studied to find the harmony among these features. The computational hypothesis test based on the one-way *ANOVA f-test* will test these features and select the most proportional features from each sub-cluster and will then extract the most representative features of raw EEG data. In addition, further work on WFA in EEG signal analysis can be undertaken to improve the method through a decrease in execution time. In the biomedical application, the processing of real time EEG signal data requires high speed techniques. In the near future, the WFA method aims to reduce computational time by using fewer hybrid features and applying parallel processing techniques.

In relation to the time-frequency image (TFI) and the fractal dimension, methods were developed to extract features from the time frequency domain from an offline database collected by Dream sleep spindles and the Montreal archive of sleep studies. This method works well with the both databases and increases the classification accuracy; it decreases the execution time, but it may increase the delay time when implemented with a real-time application. In future work, this method could be executed on a real-time database by using a huge data framework and different deep learning approaches. Additionally, in the detection stage using an ensemble of the classifiers could improve the classification accuracy and the efficiency of the trained models compared with using a single classifier.

In addition, a dual- tree complex wavelet transform (DT-CWT) coupled with an ensemble model was developed to identify k-complexes in EEG signals. This method was used to detect binary EEG classes. This scheme may be extended in the future to test multi-channel EEG signals such as epileptic seizures, and also to be implemented on real time databases. In addition, it was tested with only one database. A planned future work aims to test the proposed method with more than one database or a huge database. In addition, in the future, TQWT a parametric method that depends on Q factor (Q) and redundancy (R) to decompose EEG signals into a number of sub-bands might be used instead of DT-CWT which were set empirically to decompose EEG signals into a number of sub-bands.

Furthermore, this method can be improved to reduce the extraction time using the preprocessing techniques for both phases of testing and training. In relation to the dimensionality reduction for the extracted features, a principal component analysis (PCA) will be used in future work.

One potential problem with EEG signals is that they sometimes contain a variety of noises which can be the result of environmental and physiological factors. The proposed method developed in this study did not attempt to remove the unrelated signals such as noise from raw EEG data. Further investigation and study are required to successfully remove noise without compromising EEG signals for the proposed techniques. In future studies, these methods will be developed to achieve high performances for detecting the characteristics of sleep in EEG signals, after removal of these kinds of unrelated signals (artifacts and noise).

However, to increase the classification results and reduce the execution time of the proposed methods, the multi-fractal dimension, and an undirected graph with deep learning approach will be used. Analysing multi-fractal characteristics of undirected graphs could help to reveal some of the hidden patterns of EEG signals that cannot be detected using fractal dimensions such as vertices and slow waves. In addition, using a multi-fractal attribute to analysing EEG signals could lead to abnormal behaviour in EEG signals that can be difficult to detect using transformation techniques and statistical features.

This thesis studied offline detection methods, but it is desirable for this work to be applied to a real online database to see the impact of this research. This will require more effort. Therefore, all of the proposed methods need to be employed for online detection. This would be a significant achievement in the field of biomedical signal processing for work under difficult conditions.

In summary, these proposed methods can successfully detect the characteristics of sleep stages in EEG signals, such as sleep spindles and k-complexes and efficiently obtain accurate results. However, there is still room for improvement, and therefore more research work needs to be done in the future.

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APPENDICES

A

Matlab simulation code for Chapter 3

Detecting sleep spindles in EEGs using wavelet fourier analysis and Statistical Feature

In this appendix, a simulation code to detect sleep spindles in EEG signals is presented. In this simulation code, some of functions used were from Matlab tool The experiment results were obtained using Matlab programming language version R2018a.

```
%This Program Read each subject and then identify sleep spindles in
EEG signals
% Three Matrix of classification results: Accuracy, Sensitivity and
specificity//each Matrix is included the classification results of
sleep spindles
% the major steps of the methodology:
%
%
%
% 1. Read EEG recordings {the data sets are downloaded from
% http:\\www.tcts.fpms.ac.be/~devuyst/Database/DatabaseSpindles} and
% % http://www.ceams-carsm.ca/en/MASS.
% 2. Each EEG recording was segmented into small segment using
sliding
% window techniques (0.5s with overlapping 0.4s)
% 3. Each EEG segment is decomposed using a discrete wavelet
transform
% (DWT) into different levels of decompositions
% 4. Wavelet detail coefficient at level 3 (D3) is selected and
passed
% through FFT to identify the desired frequency bands.
% 5. Ten statistical characteristics are extracted from each band
% 6. Nonparametric Kruskal-Wallis one-way analysis of variance is
used to select the important features
7. As a result, the extracted features are used as input to the two
LS-SVM and other four classifiers.
% 8. In the classicisation phase, at each time, sleep spindles and
non-sleep spindles EEG segment was detected.
9. Part of  code was presented in this sections A and D ;For further
information regarding Matlab code contact with authors.
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% Read the EEG.rec file, the channel CZ-A1 and C3-A1  is  selected
in this study
% Clear all
disp (' This Program was used to detecte sleep spindles using WFA');
[filename pathname]=uigetfile({'*.rec'},'Select EEG recording');
fulname=strcat(pathname, filename);
[Su2 Su22]=edfread(fulname);
R=Su22(3,:);
%Read the EEG.Hyp file index%
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[filename pathname]=uigetfile({'*.txt'},'Select EEG HYP file');
fulname=strcat(pathname, filename);
Ki=importdata(fulname)
SS=Ki.data
x = inputdlg('Enter Sample Frequncey Rate:',... % Read Sampling of
dataset
             'Sample', [1 50]);
Sample = str2num(x{:});
 SS(:,3)=SS(:,1)+SS(:,2);
[M1,M2]=size(SS);
for i=1:M1
    n1=SS(i,1);
    n2=SS(i,3);
    p1=n1*200;
    p2=n2*200;
    SREc{i}.SP=R(p1:p2);
    SREc{i}.St=p1;
    SREc{i}.ENd=p2;
end
Rec=SREc;
```

```
m=size(SS,1);
d=SS;
tim=200;
sz=100;
k=1;
for i=1:m
    s=d(i,1)*tim;
    e=s+d(i,2)*tim-sz;
    for j=s:e
        sp(k)=j;
        k=k+1;
    end
end
save sp sp
M=R;
[n1 n]=size(M);
dd=sp;
n=size(M,2);
k=1;sz=100;
for i=1:20:n-sz
     Pos_1=i;
Pos_2=i+sz-1;
    feat(k,1:sz)=M(i:i+sz-1);
Pos_mat(k,1)=Pos_1;
Pos_mat(k,2)=Pos_2;
           k=k+1;
end
     save feat feat
disp (' The segmentations were completed, Please press enter to
continue another setp');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
% extracted 10 features based on wavelet Fourier anywise, DWT and
FFT, from 5 sub bund and then reduced to 4 sub-bund;
Wav_w=Wavelat_w(feat);
[Alph_1, Beat_1, Theta_1 ,Delat_1]= ExtractedBund_FFT_w(Wav_w);
    Featutres_Alph=StatisticFeatutres_w(Alph_1);
    Featutres_Beat=StatisticFeatutres_w(Beat_1);
    Featutres_Theat=StatisticFeatutres_w(Theta_1);
    Featutres_Delat=StatisticFeatutres_w(Delat_1);
    Featutres_AllBund=[Featutres_Alph,
Featutres_Beat,Featutres_Theat,Featutres_Delat];
Fea_thear=Featutres_AllBund;
[o1 o2]=size(Fea_thear);
for i=1:o1
     b=find(dd==i);
    if isempty(b)
        Y(i)=0;
    else
        Y(i)=1;
    end
end
Y=Y';
 disp (' The features were extracted based on WFA,Please press enter
to continue');
   Pause;
 %%%%%%%%%%%%%%%%%%%%%%%%%%%% LS_SVM11%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
[ACC,SES, SPE]=LS_SVM11_classifciation_w(Fea_thear,Y)
disp('Classifciation results using WFA')
disp('Accuracy')
disp('________')
```

```
disp('   The performnace of the proposed method as Accuracey=' );
disp(ACC);
disp('-------------------------------------------------------');
disp('Sensitivity')
disp('   The performnace of the proposed method as Sensitivity=' );
disp(SES);
disp('-------------------------------------------------------');
disp('Specifcity')
disp('   The performnace of the proposed method as Specifcity=' );
disp(SPE);
toc
%%%%%%%%%%%%% Comparison with different classifiers%%%%%%%%%%%%%
[ACC,SES, SPE]=LS_SVM11_classifciation_w();
[index] = K_Means_classi (Fea_thear);
Test_targets = C4_5 (Train date, train targets, Test data, inc_node)
      Y_id=Convert_Idx(Y);
      [Acc,rand_index,match]=AccMeasure(Y_id,index);
disp('Classifciation results using WFA')
disp('Accuracy')
disp('________')
disp('   The performnace of the proposed method as Accuracey=' );
disp(Acc);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [ VV ] = Wavelat_w(BB2)
% received The EEG data and  return bund of wavelet coefficient
 RR=BB2;
[n m]=size(RR);
for i=1:n
 Ch=RR(i,:);
 D=wave_w(Ch);
  RE=reshape(D',1,[]);
  Subject1(i,:)=RE;
end
  VV=Subject1;
 end
 function [ DD5 ] = wave_w(CH )
 Ch=CH;
 waveletName='db6';
 level=5;
% Multilevel 1-D wavelet decomposition
 [c0,l0]=wavedec(Ch,level,waveletName);
% 1-D detail coefficients for ch0
 cD1 = detcoef(c0,l0,1); %NOISY
 cD2 = detcoef(c0,l0,2); %GAMMA
 cD3 = detcoef(c0,l0,3); %BETA
 cD4 = detcoef(c0,l0,4); %ALPHA
 cD5 = detcoef(c0,l0,5); %THETA
 cA5 = appcoef(c0,l0,waveletName,5); %DELTA
% Reconstruct single branch from 1-D wavelet coefficients for ch0
 D1 = wrcoef('d',c0,l0,waveletName,1); %NOISY
 D2 = wrcoef('d',c0,l0,waveletName,2); %GAMMA
 D3 = wrcoef('d',c0,l0,waveletName,3); %BETA
 D4 = wrcoef('d',c0,l0,waveletName,4); %ALPHA
 D5 = wrcoef('d',c0,l0,waveletName,5); %THETA
 A5 = wrcoef('a',c0,l0,waveletName,5); %DELTA
 DD5=D3;
end
 function [c,l] = wavedec(x,n,IN3,IN4)
narginchk(3,4);
validateattributes(x,{'numeric'},{'vector','finite','real'},'wavedec
','X');
```

```
validateattributes(n,{'numeric'},{'scalar','integer','positive'},'wa
vedec','N');
if nargin==3
    [Lo_D,Hi_D] = wfilters(IN3,'d');
else
    Lo_D = IN3;   Hi_D = IN4;
end
 s = size(x); x = x(:)';
c = [];
l = zeros(1,n+2);
if isempty(x) , return; end
 l(end) = length(x);
for k = 1:n
    [x,d] = dwt(x,Lo_D,Hi_D);
    c     = [d c];
    l(n+2-k) = length(d);
end
c = [x c];
l(1) = length(x);

if s(1)>1, c = c'; l = l'; end

function varargout = detcoef(coefs,longs,levels,dummy)
% Extract 1-D detail coefficients.
narginchk(2,4);
 validateattributes(coefs,{'numeric'},{'vector','finite','real'},...
    'detcoef','C');
validateattributes(longs,{'numeric'},...
    {'vector','integer','positive'},'detcoef','L');
 nmax = length(longs)-2;
cellFLAG = false;
if nargin>2
    if isnumeric(levels)
        if (any(levels < 1)) || (any(levels > nmax) ) || ...
            any(levels ~= fix(levels)) || isempty(levels)
            error(message('Wavelet:FunctionArgVal:Invalid_LevVal'));
        end
        cellFLAG = (nargin>3);
    else
        cellFLAG = true;
        levels = 1:nmax;
    end
else
    levels = nmax;
end
 first = cumsum(longs)+1;
first = first(end-2:-1:1);
longs = longs(end-1:-1:2);
last  = first+longs-1;
nblev = length(levels);
tmp   = cell(1,nblev);
for j = 1:nblev
    k = levels(j);
    tmp{j} = coefs(first(k):last(k));
end
  if (nargout == 1 && nblev>1) || cellFLAG
   varargout{1} = tmp;
else
   varargout = tmp;
end
 function x = wrcoef(o,c,l,varargin)
```

```
narginchk(4,6)
o = lower(o(1));
rmax = length(l); nmax = rmax-2;
 if o=='a'
    nmin = 0;
    else nmin = 1;
end
if ischar(varargin{1})
    [Lo_R,Hi_R] = wfilters(varargin{1},'r'); next = 2;
else
    Lo_R = varargin{1};  Hi_R = varargin{2}; next = 3;
end
if nargin>=(3+next) , n = varargin{next}; else n = nmax; end

if (n<nmin) || (n>nmax) || (n~=fix(n))
    error(message('Wavelet:FunctionArgVal:Invalid_ArgVal'));
end
 dwtATTR = dwtmode('get');
 switch o
  case 'a'
        x = appcoef(c,l,Lo_R,Hi_R,n);
    if n==0, return; end
    F1 = Lo_R;
   case 'd'
    % Extract detail coefficients.
    x = detcoef(c,l,n);
    F1 = Hi_R;
   otherwise
    error(message('Wavelet:FunctionArgVal:Invalid_ArgVal'));
end
 imin = rmax-n;
x  = upsconv1(x,F1,l(imin+1),dwtATTR);
for k=2:n , x = upsconv1(x,Lo_R,l(imin+k),dwtATTR); end
function [ TT1, TT2, TT3, TT4 ] = ExtractedBund_FFT_w(T)
Denoised_x_total=T;
Test1(1,:)=Delta_bandfilter(Denoised_x_total);
Test1(2,:)=Theta_bandfilter(Denoised_x_total);
Test1(3,:)=Alfa_bandfilter(Denoised_x_total);
Test1(4,:)=Beta_bandfilter(Denoised_x_total);
Test1(5,:)=Gama_bandfilter(Denoised_x_total);
 TT1=Test1;
 TT2=Test2;
 TT3=Test3;
 TT4=Test4;
  end
function y = Gama_bandfilter()
% Calculated the Game bund.
 persistent Hd;
 if isempty(Hd)
    Fstop1 = 30;     % First Stopband Frequency
    Fpass1 = 30.1;   % First Passband Frequency
    Fpass2 = 63.8;   % Second Passband Frequency
    Fstop2 = 63.9;     % Second Stopband Frequency
    Astop1 = 60;     % First Stopband Attenuation (dB)
    Apass  = 1;      % Passband Ripple (dB)
    Astop2 = 60;     % Second Stopband Attenuation (dB)
    Fs     = 200;    % Sampling Frequency
     h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2', Fstop1,
Fpass1, ...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);
```

```
    Hd = design(h, 'equiripple', ...
        'MinOrder', 'any');
         set(Hd,'PersistentMemory',true);
    y=Hd;
end
end
 y = filter(Hd,x);

function y = Alfa_bandfilter()
 persistent Hd;
 if isempty(Hd)

    Fstop1 = 7;     % First Stopband Frequency
    Fpass1 = 7.1;   % First Passband Frequency
    Fpass2 = 12.9;   % Second Passband Frequency
    Fstop2 = 13;     % Second Stopband Frequency
    Astop1 = 60;     % First Stopband Attenuation (dB)
    Apass  = 1;      % Passband Ripple (dB)
    Astop2 = 60;     % Second Stopband Attenuation (dB)
    Fs     = 128;    % Sampling Frequency

    h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2', Fstop1,
Fpass1, ...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);

    Hd = design(h, 'equiripple', ...
        'MinOrder', 'any');

    set(Hd,'PersistentMemory',true);
    y=Hd;
end
end
y = filter(Hd,x);

function y = Theta_bandfilter()
persistent Hd;
 if isempty(Hd)
    Fstop1 = 3.5;   % First Stopband Frequency
    Fpass1 = 3.6;   % First Passband Frequency
    Fpass2 = 6.9;   % Second Passband Frequency
    Fstop2 = 7;     % Second Stopband Frequency
    Astop1 = 60;     % First Stopband Attenuation (dB)
    Apass  = 1;      % Passband Ripple (dB)
    Astop2 = 60;     % Second Stopband Attenuation (dB)
    Fs     = 200;    % Sampling Frequency

    h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2', Fstop1,
Fpass1, ...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);
        Hd = design(h, 'equiripple', ...
        'MinOrder', 'any');

    set(Hd,'PersistentMemory',true);
    y=Hd;
end
end
 y = filter(Hd,x);

function y = Delta_bandfilter()
persistent Hd;
```

```
 if isempty(Hd)
        Fstop1 = 0.5;    % First Stopband Frequency
    Fpass1 = 0.6;    % First Passband Frequency
    Fpass2 = 3.4;    % Second Passband Frequency
    Fstop2 = 3.5;    % Second Stopband Frequency
    Astop1 = 60;     % First Stopband Attenuation (dB)
    Apass  = 1;      % Passband Ripple (dB)
    Astop2 = 60;     % Second Stopband Attenuation (dB)
    Fs     = 200;    % Sampling Frequency
        h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2',
Fstop1, Fpass1, ...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);

    Hd = design(h, 'equiripple', ...
        'MinOrder', 'any');

    set(Hd,'PersistentMemory',true);
    y=Hd;
end
end
y = filter(Hd,x);

function y = Beta_bandfilter(x)
persistent Hd;

if isempty(Hd)
    Fstop1 = 13;     % First Stopband Frequency
    Fpass1 = 13.1;   % First Passband Frequency
    Fpass2 = 29.9;   % Second Passband Frequency
    Fstop2 = 30;     % Second Stopband Frequency
    Astop1 = 60;     % First Stopband Attenuation (dB)
    Apass  = 1;      % Passband Ripple (dB)
    Astop2 = 60;     % Second Stopband Attenuation (dB)
    Fs     = 128;    % Sampling Frequency
     h = fdesign.bandpass('fst1,fp1,fp2,fst2,ast1,ap,ast2', Fstop1,
Fpass1, ...
        Fpass2, Fstop2, Astop1, Apass, Astop2, Fs);

    Hd = design(h, 'equiripple', ...
        'MinOrder', 'any');
         set(Hd,'PersistentMemory',true);
    end
 y = filter(Hd,x);
function [Featutres_Bund]= StatisticFeatutres_w( T )
% calculate 10 statistic features from each sub-band;
RR=T;
[n m]=size(RR);
for j=1:n
 Ch=RR(j,:);
featu=mainpoint(Ch);
    feature(j,:)=featu;
end
  Featutres_Bund=feature;
 end

function [X ] = mainpoint ( Y )
% Receives: A set of EEG data Y
% % Returns: a vector of statistical features X
i=1;
for i=1:10
```

```
 X(1)=max(Y);
 X(2)=range(Y);
 X(3)=std(Y);
 X(4)=min(Y);
 X(5)=mean(Y);
 X(6)=mode(Y);
 X(7)=median(Y);
 X(8)=var(Y);
 X(9)=skewness(Y);
 X(10)=kurtosis(Y);
end
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [ ACC,SEM, SPE] = LS_SVM11_classifciation_w(XX,Y)
tic
X=xx;
y=Y;
gam=10;
sig2=1;
type='classification';
L_fold=6;
[gam, sig2] = tunelssvm({x,y,'c',[],[],'RBF_kernel'}, 'simplex',...
        'leavseoneoutlssvm', {'misclass'});
[alpha,b] = trainlssvm({x,y,type,gam,sig2,'RBF_kernel'});
Yh=simlssvm({x,y,type,gam,sig2,'RBF_kernel'},{alpha,b},Xtest);

 [perc,n,which]=misclass(Ytest,Yh); % Which: contains the indices of
                                     the misclassificated instances
                                    (the first column gives the
                                    row, the second the column index)

n      % is the number of misclassifications
perc   % is the rate of misclassifications (between 0 and 1)
[C,order] = confusionmat(Ytest,Yh);
C
order
Y_latent=latentlssvm({x,y,type,gam,sig2,'RBF_kernel'},{alpha,b},x);
[area,se,thresholds,oneMinusspec,sens,TN,TP,FN,FP]=roc(Y_latent,y);
%[thresholds oneMinusspec sens ];
Accuracy=(TP+TN)/(TP+TN+FP+FN)*100
ACC=Accuracy;
T=TP/(TP+FN);
T1=TN/(TN+FP)
SEM=T*100;
SPE=T1*100;
toc
end
function [ index] = K_Means_classi( X1 )
  x=X1;
      k=2;
      p=100;
          opts = statset('Display','final');
      [idx,ctrs,sumd] =
kmeans(x,k,'Distance','city','Replicates',p,'Options',opts,'start','
uniform','emptyaction','drop');
      index=idx;
  end

function [ Y_id ] = Convert_Idx ( H )
Y=H;
for i=1:length(Y)
```

```
    if Y(i)==0
        Y_id(i)=2;
    else
        Y_id(i)=1;
    end
end
Y_id=Y_id';

end
function [Acc,rand_index,match]=AccMeasure(T,idx)
%Measure percentage of Accuracy;
k=max([T(:);idx(:)]);
n=length(T);
for i=1:k
    temp=find(T==i);
    a{i}=temp;
end
 b1=[];
t1=zeros(1,k);
for i=1:k
    tt1=find(idx==i);
    for j=1:k
       t1(j)=sum(ismember(tt1,a{j}));
    end
    b1=[b1;t1];
end
    Members=zeros(1,k);
    P = perms((1:k));
    Acc1=0;
for pi=1:size(P,1)
    for ki=1:k
        Members(ki)=b1(P(pi,ki),ki);
    end
    if sum(Members)>Acc1
        match=P(pi,:);
        Acc1=sum (Members);
    end
end
 rand_ss1=0;
rand_dd1=0;
for xi=1:n-1
    for xj=xi+1:n
        rand_ss1=rand_ss1+((idx(xi)==idx(xj))&&(T(xi)==T(xj)));
        rand_dd1=rand_dd1+((idx(xi)~=idx(xj))&&(T(xi)~=T(xj)));
    end
end
rand_index=200*(rand_ss1+rand_dd1)/(n*(n-1));
Acc=Acc1/n*100;
match=[1:k;match];
end
function test_targets = C4_5(train_patterns, train_targets,
test_patterns, inc_node)
% Classify using Quinlan's C4.5 algorithm
[Ni, M]     = size(train_patterns);
inc_node    = inc_node*M/100;
Nu          = 10;
discrete_dim = zeros(1,Ni);
for i = 1:Ni,
    Ub = unique(train_patterns(i,:));
    Nb = length(Ub);
    if (Nb <= Nu),
```

```
         discrete_dim(i) = Nb;
        dist            = abs(ones(Nb ,1)*test_patterns(i,:) -
Ub'*ones(1, size(test_patterns,2)));
        [m, in]         = min(dist);
        test_patterns(i,:)  = Ub(in);
    end
end
%Build the tree recursively
disp('Building tree')
tree            = make_tree(train_patterns, train_targets, inc_node,
discrete_dim, max(discrete_dim), 0);
%Classify test samples of EEG
disp('Classify test samples using the tree')
test_targets    = use_tree(test_patterns, 1:size(test_patterns,2),
tree, discrete_dim, unique(train_targets));
%END
function targets = use_tree(patterns, indices, tree, discrete_dim,
Uc)
%Classify recursively using a tree
targets = zeros(1, size(patterns,2));
if (tree.dim == 0)
    %Reached the end of the tree
    targets(indices) = tree.child;
    return
end
dim = tree.dim;
dims= 1:size(patterns,1);
if (discrete_dim(dim) == 0),
    %Continuous pattern
    in              = indices(find(patterns(dim, indices) <=
tree.split_loc));
    targets     = targets + use_tree(patterns(dims, :), in,
tree.child(1), discrete_dim(dims), Uc);
    in              = indices(find(patterns(dim, indices) >
tree.split_loc));
    targets     = targets + use_tree(patterns(dims, :), in,
tree.child(2), discrete_dim(dims), Uc);
else
    %Discrete pattern
    Uf              = unique(patterns(dim,:));
    for i = 1:length(Uf),
        if any(Uf(i) == tree.Nf)
            in      = indices(find(patterns(dim, indices) ==
Uf(i)));
            targets = targets + use_tree(patterns(dims, :), in,
tree.child(find(Uf(i)==tree.Nf)), discrete_dim(dims), Uc);
        end
    end
end
%END use_tree
function tree = make_tree(patterns, targets, inc_node, discrete_dim,
maxNbin, base)
%Build a tree recursively
[Ni, L]                     = size(patterns);
Uc                          = unique(targets);
tree.dim                    = 0;
%tree.child(1:maxNbin)   = zeros(1,maxNbin);
tree.split_loc              = inf;
if isempty(patterns),
    return
end
```

```
if ((inc_node > L) | (L == 1) | (length(Uc) == 1)),
    H                   = hist(targets, length(Uc));
    [m, largest]    = max(H);
    tree.Nf         = [];
    tree.split_loc  = [];
    tree.child      = Uc(largest);
    return
end
for i = 1:length(Uc),
    Pnode(i) = length(find(targets == Uc(i))) / L;
end
Inode = -sum(Pnode.*log(Pnode)/log(2));
delta_Ib    = zeros(1, Ni);
split_loc   = ones(1, Ni)*inf;
for i = 1:Ni,
    data    = patterns(i,:);
    Ud      = unique(data);
    Nbins   = length(Ud);
    if (discrete_dim(i)),
         P   = zeros(length(Uc), Nbins);
        for j = 1:length(Uc),
            for k = 1:Nbins,
         indices     = find((targets == Uc(j)) & (patterns(i,:) ==
Ud(k)));
                P(j,k)  = length(indices);
            end
        end
        Pk          = sum(P);
        P           = P/L;
        Pk          = Pk/sum(Pk);
        info        = sum(-P.*log(eps+P)/log(2));
        delta_Ib(i) = (Inode-sum(Pk.*info))/-
sum(Pk.*log(eps+Pk)/log(2));
    else
         P   = zeros(length(Uc), 2);
          [sorted_data, indices] = sort(data);
          sorted_targets = targets(indices);
           I = zeros(1, L-1);
          for j = 1:L-1,
              P(:, 1) = hist(sorted_targets(1:j) , Uc);
              P(:, 2) = hist(sorted_targets(j+1:end) , Uc);
              Ps        = sum(P)/L;
              P     = P/L;
              Pk      = sum(P);
              P1      = repmat(Pk, length(Uc), 1);
              P1      = P1 + eps*(P1==0);
              info  = sum(-P.*log(eps+P./P1)/log(2));
              I(j)  = Inode - sum(info.*Ps);
          end
          [delta_Ib(i), s] = max(I);
          split_loc(i) = sorted_data(s);
      end
  end
[m, dim]    = max(delta_Ib);
dims        = 1:Ni;
tree.dim    = dim;
Nf      = unique(patterns(dim,:));
Nbins   = length(Nf);
tree.Nf = Nf;
tree.split_loc      = split_loc(dim);
%If only one value remains for this pattern, one cannot split it.
```

```
if (Nbins == 1)
    H               = hist(targets, length(Uc));
    [m, largest]    = max(H);
    tree.Nf         = [];
    tree.split_loc  = [];
    tree.child      = Uc(largest);
    return
end
if (discrete_dim(dim)),
    %Discrete pattern
    for i = 1:Nbins,
        indices         = find(patterns(dim, :) == Nf(i));
        tree.child(i)   = make_tree(patterns(dims, indices),
targets(indices), inc_node, discrete_dim(dims), maxNbin, base);
    end
else
    %Continuous pattern
    indices1            = find(patterns(dim,:) <= split_loc(dim));
    indices2            = find(patterns(dim,:) > split_loc(dim));
    if ~(isempty(indices1) | isempty(indices2))
        tree.child(1)   = make_tree(patterns(dims, indices1),
targets(indices1), inc_node, discrete_dim(dims), maxNbin, base+1);
        tree.child(2)   = make_tree(patterns(dims, indices2),
targets(indices2), inc_node, discrete_dim(dims), maxNbin, base+1);
    else
        H               = hist(targets, length(Uc));
        [m, largest]    = max(H);
        tree.child      = Uc(largest);
        tree.dim                = 0;
    end
end
```

B

Matlab simulation code for Chapter 4

An efficient approach for EEG sleep spindles detection based on fractal dimension coupled with time frequncey image

In this appendix, a simulation code to detect sleep spindles in EEG signals is presented. In this simulation code, some of functions used were from Matlab tool. The experiment results were obtained using Matlab programming language versiona R2018a.

```
%%%%%%%%%%%%%%%%%%%%%%%%%Read EEG data %%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Reading EEG data is same as in the appendix A

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
clear all
FFFFF=feat2; % all the dataset which is content all segments
 [k1 k2]=size (FFFFF);
for Check =1:k1
    % set all parameters as empty in the first time;
        I=  [];II= [];J= [];nn= [];r=  [];df= [];
        x=FFFFF(Check,1:100);
  name=['C:\Users\U1061534\Documents\MATLAB\Checki\SurfacePlot555'
  num2str(Check)];
  spectrogram(x,'yaxis');print(name,'-djpeg','-noui');
  KI=['C:\Users\U1061534\Documents\MATLAB\ Checki \SurfacePlot555'
  num2str(Check) '.jpg' ];
  I=imread(KI );
  II=rgb2gray(I);
  p=imcrop(II,[[145.5 65.5 846 738]]);
  III=im2bw(p);
  [nn, r] = Dim(III);
  df = -diff(log(nn))./diff(log(r));
  DFF = (log(nn))./(log(r));
  FractalBox_ng1(Check,:)=df(1:10);
  disp(['Fractal dimension, Df = ' num2str(mean(df(4:8))) ' +/- '
  num2str(std(df(4:8)))])
end
    Save FractalBox_ng1 FractalBox_ng1
XX=StatisticFeatutre (FractalBox_ng1);
Fea_thear=XX;
[o1 o2]=size (XX);
for i=1:o1
    b=find(dd==i);
    if isempty(b)
        Y(i)=0;
    else
        Y(i)=1;
    end
end
Y=Y';
Y=Y(1:o1);
% LS-SVM Classifier
[ACC, SEM, SPE] =LS_SVM11_classifciation (Fea_thear, Y)
disp('Classification results using FD of TFI features ')
disp('Accuracy')
disp('________')
disp(' The performance of the proposed method as Accuracy=' );
disp(ACC);
disp('-----------------------------------------------------');
disp('Sensitivity')
disp('   The performance of the proposed method as Sensitivity=' );
disp(SEM);
disp('-----------------------------------------------------');
disp('Specificity')
disp('   The performance of the proposed method as Specificity=' );
disp(SPE);
% K-means Classifier
 [index] = K_Means(Fea_thear);
```

```
      Y_id=Convert_Idx(Y);
      [Acc,rand_index,match]=AccMeasure(Y_id,index);
disp('Classification results using FD of TFI')
disp('Accuracy')
disp('_________')
disp('   The performance of the proposed method as Accuracy=' );
disp(Acc);
% Nave Bayes Classifier
disp('Classification results using Naïve Bayes')
disp('            Accuracy    ')
disp('------------------------------------------------------');
disp('%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%% %%%%%%%%');
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%);
[Acc]=Nai_classificationTesting(Fea_thear,Y);
disp('Classification results using Naive')
disp('            Accuracy    ')
disp('________________________________________')
disp('   Sleep Spindles detection, accuracy=' );
disp(ACC_NAVE);
disp('------------------------------------------------------');
end
##################################################################
function varargout = spectrogram(x,varargin)
%SPECTROGRAM Spectrogram using a Short-Time Fourier Transform;
narginchk(1,11);
nargoutchk(0,6);
 if nargout > 0
  [varargout{1:nargout}] = pspectrogram({x},'spect',varargin{:});
else
  pspectrogram({x},'spect',varargin{:});
end
####################################################################
function [boxCounts,resolutions]=Dim(I)
    % this function extracted FD from each T-F images
    maxDim = max(size(I));
    newDimSize = 2^ceil(log2(maxDim));
    rowPad = newDimSize - size(I, 1);
    colPad = newDimSize - size(I, 2);
    I = padarray(I, [rowPad, colPad], 'post');
     boxCounts = zeros(1, ceil(log2(maxDim)));
    resolutions = zeros(1, ceil(log2(maxDim)));
    boxSize = size(I, 1);
    boxesPerDim = 1;
    idx = 0;
    while boxSize >= 1
        boxCount = 0;
          for boxRow = 1:boxesPerDim
            for boxCol = 1:boxesPerDim
                minRow = (boxRow - 1) * boxSize + 1;
                maxRow = boxRow * boxSize;
                minCol = (boxCol - 1) * boxSize + 1;
                maxCol = boxCol * boxSize;
                objFound = false;
                for row = minRow:maxRow
                    for col = minCol:maxCol
                        if I(row, col)
                            boxCount = boxCount + 1;
                            objFound = true;
                        end;
                        if objFound
                            break;
```

```
                        end;
                    end;
                        if objFound
                         break;
                    end;
                end;
            end;
        end;
        idx = idx + 1;
        boxCounts(idx) = boxCount;
        resolutions(idx) =  boxSize;
        boxesPerDim = boxesPerDim * 2;
        boxSize = boxSize / 2;
    end;
    D = polyfit(log(resolutions), log(boxCounts), 1);
#####################################################################
function [XX]= StatisticFeatutres ( T )
% calculate 10 statistic features from each sub-band
% Receives: A set FD of TFI
% Returns: a vector of statistical features X
RR=T;
[n m]=size(RR);
for j=1:n
 Ch=RR(j,:);
featu=mainpoint(Ch);
    feature(j,:)=featu;
end
   XX=feature;
 end
function [X] = mainpoint ( Y )
% Receives: A set of EEG data Y (Raw of FD of TFI)
% Returns: a vector of statistical features X
i=1;
for i=1:8
 X(1)=max(Y);
 X(2)=range(Y);
 X(3)=std(Y);
 X(4)=min(Y);
 X(5)=mean(Y);
 X(6)=median(Y);
X(7)=skewness(Y);
X(8)=kurtosis(Y);
end
end
 ####################################################################
function [hdr, record] = edfread(fname, varargin)
%Read all waveforms/data associated with file 'EEG1.edf':
if nargin > 5
    error('EDFREAD: Too many input arguments.');
end
 if ~nargin
    error('EDFREAD: Requires at least one input argument (filename
to read).');
end
 [fid,msg] = fopen(fname,'r');
if fid == -1
    error(msg)
end
assignToVariables = false;
targetSignals = [];
for ii = 1:2:numel(varargin)
```

```
    switch lower(varargin{ii})
        case 'assigntovariables'
            assignToVariables = varargin{ii+1};
        case 'targetsignals'
            targetSignals = varargin{ii+1};
        otherwise
            error('EDFREAD: Unrecognized parameter-value pair
specified. Valid values are ''assignToVariables'' and
''targetSignals''.')
    end
end
 hdr.ver         = str2double(char(fread(fid,8)'));
hdr.patientID   = fread(fid,80,'*char')';
hdr.recordID    = fread(fid,80,'*char')';
hdr.startdate   = fread(fid,8,'*char')';
hdr.starttime   = fread(fid,8,'*char')';
hdr.bytes       = str2double(fread(fid,8,'*char')');
reserved        = fread(fid,44);
hdr.records     = str2double(fread(fid,8,'*char')');
hdr.duration    = str2double(fread(fid,8,'*char')');
hdr.ns     = str2double(fread(fid,4,'*char')');
for ii = 1:hdr.ns
    hdr.label{ii} = regexprep(fread(fid,16,'*char')','\W','');
end
 if isempty(targetSignals)
    targetSignals = 1:numel(hdr.label);
elseif iscell(targetSignals)||ischar(targetSignals)
    targetSignals =
find(ismember(hdr.label,regexprep(targetSignals,'\W','')));
end
if isempty(targetSignals)
    error('EDFREAD: The signal(s) you requested were not detected.')
end
 for ii = 1:hdr.ns
    hdr.transducer{ii} = fread(fid,80,'*char')';
end
for ii = 1:hdr.ns
    hdr.units{ii} = fread(fid,8,'*char')';
end
for ii = 1:hdr.ns
    hdr.physicalMin(ii) = str2double(fread(fid,8,'*char')');
end
for ii = 1:hdr.ns
    hdr.physicalMax(ii) = str2double(fread(fid,8,'*char')');
end
for ii = 1:hdr.ns
    hdr.digitalMin(ii) = str2double(fread(fid,8,'*char')');
end
for ii = 1:hdr.ns
    hdr.digitalMax(ii) = str2double(fread(fid,8,'*char')');
end
for ii = 1:hdr.ns
    hdr.prefilter{ii} = fread(fid,80,'*char')';
end
for ii = 1:hdr.ns
    hdr.samples(ii) = str2double(fread(fid,8,'*char')');
end
for ii = 1:hdr.ns
    reserved    = fread(fid,32,'*char')';
end
hdr.label = hdr.label(targetSignals);
```

```
hdr.label = regexprep(hdr.label,'\W','');
hdr.units = regexprep(hdr.units,'\W','');
disp('Step 1 of 2: Reading requested records. (This may take a few
minutes.)...');
if nargout > 1 || assignToVariables
    scalefac = (hdr.physicalMax - hdr.physicalMin)./(hdr.digitalMax
- hdr.digitalMin);
    dc = hdr.physicalMax - scalefac .* hdr.digitalMax;
        tmpdata = struct;
    for recnum = 1:hdr.records
        for ii = 1:hdr.ns
          if ismember(ii,targetSignals)
              tmpdata(recnum).data{ii} =
fread(fid,hdr.samples(ii),'int16') * scalefac(ii) + dc(ii);
            else
                fseek(fid,hdr.samples(ii)*2,0);
            end
        end
    end
    hdr.units = hdr.units(targetSignals);
    hdr.physicalMin = hdr.physicalMin(targetSignals);
    hdr.physicalMax = hdr.physicalMax(targetSignals);
    hdr.digitalMin = hdr.digitalMin(targetSignals);
    hdr.digitalMax = hdr.digitalMax(targetSignals);
    hdr.prefilter = hdr.prefilter(targetSignals);
    hdr.transducer = hdr.transducer(targetSignals);
        record = zeros(numel(hdr.label),
hdr.samples(1)*hdr.records);
        disp('Step 2 of 2: Parsing data...');
    recnum = 1;
    for ii = 1:hdr.ns
        if ismember(ii,targetSignals)
            ctr = 1;
            for jj = 1:hdr.records
                try
                    record(recnum, ctr : ctr + hdr.samples(ii) - 1)
= tmpdata(jj).data{ii};
                end
                ctr = ctr + hdr.samples(ii);
            end
            recnum = recnum + 1;
        end
    end
    hdr.ns = numel(hdr.label);
    hdr.samples = hdr.samples(targetSignals);

    if assignToVariables
        for ii = 1:numel(hdr.label)
            try
eval(['assignin(''caller'',''',hdr.label{ii},''',record(ii,:))'])
            end
        end
        record = [];
    end
end
fclose(fid);
   ####################See Code in Appendix A ###################
function [ ACC,SEM, SPE] = LS_SVM11_classifciation (XX,Y)
function [ index] = K_Means_classi( X1 )
function [Acc,rand_index,match]=AccMeasure(T,idx)
      ########################################################
```

C

Matlab simulation code for Chapter 5

K-complexes detection in EEG signals using fractal and frequncey featutres coupled with an ensamble classification model

In this appendix, a simulation code to detect k-complexe in EEG signals is presented. In this simulation code, some of functions used were from Matlab tool. The experiment results were obtained using Matlab programming language version R2018a.

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Reading EEG data is same as in the appendices A and B

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
      Dual_wessam=DualWavalte(feat);
      [Freqnucey_Featutres]=Frequncet_Featutres2018 (Dual_wessam);
     [Fractal_Features] =Feature_weHFD2018 (Dual_wessam);
     [Statistic_Featutres]= Feature_we2018 (Fractal_Features);
     [Statistic_Record]=FeatutresFrom_Record_Statistic
(Statistic_Featutres);

[Frequncey_Record]=FeatutresFrom_Record_Statistic(Freqnucey_Featutre
s);
[Bund1,Bund2,Bund3,Bund4,Bund5,BundAll]=Bund_Dual(Statistic_Record,F
requncey_Record);
 Featutres_AllBund=BundAll;
Fea_thear=Featutres_AllBund;
[o1 o2]=size(Fea_thear);
for i=1:o1
    b=find(dd==i);
    if isempty(b)
        Y(i)=0;
    else
        Y(i)=1;
    end
end
 Y=Y';
 [ACC, SEM, SPE] = Ensamble_Result (Fea_thear, Y);
disp('Classification results using DT-CWT)
disp('Accuracy')
disp('________')
disp('   The performance of the proposed method as Accuracy=' );
disp(ACC);
disp('-------------------------------------------------------');
disp('Sensitivity')
disp('   The performance of the proposed method as Sensitivity=' );
disp(SEM);
disp('-------------------------------------------------------');
disp('Specificity')
disp('   The performance of the proposed method as Specificity=' );
disp(SPE);
%end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [ V ] = DualWavalte ( X )
% Summary of this function goes here
% detailed explanation goes here
% Each 0.5s EEG signals was decomposed into 4 levels using DT-CWT;
% a total of 10 sub-bands are obtained based on four levels of
% decomposition.
% this function was called three sub function to complete the level
of decomposing:
   1- FSfarras
   2- dualfilt1
   3- dualtree

xx=X;
  [n m]=size(xx);
  for k=1:n
  x=xx(k,:);
 J = 4;       % number of stages; 4 sub-bands
```

```
  [Faf, Fsf] = FSfarras;
 [af, sf] = dualfilt1;
  w= dualtree(x, J, Faf, af);
  y= idualtree(w, J, Fsf, sf);
  K_complex10{k}.p=w;
  K_complex10{k}.p1=y;
  err = x - y;
  max(abs(err));
  end

function w = dualtree(x, J, Faf, af)
% Dual-tree Complex Discrete Wavelet Transform
x = x/sqrt(2);
% Tree 1
[x1 w{1}{1}] = afb(x, Faf{1});
for j = 2:J
    [x1 w{j}{1}] = afb(x1, af{1});
end
w{J+1}{1} = x1;
% Tree 2
[x2 w{1}{2}] = afb(x, Faf{2});
for j = 2:J
    [x2 w{j}{2}] = afb(x2, af{2});
end
w{J+1}{2} = x2;
function y = idualtree(w, J, Fsf, sf)
% Inverse Dual-tree Complex DWT
y1 = w{J+1}{1};
for j = J:-1:2
   y1 = sfb(y1, w{j}{1}, sf{1});
end
y1 = sfb(y1, w{1}{1}, Fsf{1});
 % Tree 2
y2 = w{J+1}{2};
for j = J:-1:2
   y2 = sfb(y2, w{j}{2}, sf{2});
end
y2 = sfb(y2, w{1}{2}, Fsf{2});
% normalization
y = (y1 + y2)/sqrt(2);
function [ MM ] = Frequncet_Featutres2018 ( BB2 )
[n m2]=size(BB2)
RR=BB2;
for w1=1:m2
 Ch1=RR{w1}.p
     for A1=1:5
        DD1=Ch1{A1};
for T=1:1
       DD2=DD1{1};
       DD3=DD1{2};
    DD4=[DD2,DD3];
 F1(A1,:)= Frequncey_Features_We(DD4);
     DD1=[];
     DD2=[];
     DD3=[];
     F3=[];
     end
    FFF44{w1}.p=F1;
end
end
 MM= FFF44;
```

```
   end
function [ HH ] = Frequncey_Features_We( X )
FFKomplex=X;
[n m]= size(FFKomplex);
for i=1:n
   [Mxf,I] = max(FFKomplex(i,:));    % max
   [Mif,II] = min(FFKomplex(i,:));    % min
    Dffamplitud=Mxf-Mif;  % diffrences amplitude or peak to peak
    DistMx_mi=I-II;              %distaice betwwen max and min
    Rati= abs(Mif)/abs(Mxf);                %ration
    Sharp=Dffamplitud/DistMx_mi;         %sharp
    Pstart=II+1;
   Pend=I-1;
   pmedil=Dffamplitud;
   Duration=abs(Pstart-Pend);                   %duration
   DurPositiv= abs(pmedil- Pstart);        %duration positive
   DurNagative= abs(pmedil- Pend);           %duration nagative
   Reflectsharp=Mxf/DurPositiv;              %reflect sharp positive
  ReflectshNag=Mxf/DurNagative;       %reflect sharp nagative
   slop=(Mxf-Mif)/(DurPositiv-DurNagative);   %slop
%  Sharpwaves= Dffamplitud/DistMx
% assigned all features above to one vector
    Max11(i)=Mxf;                %max
    Min11(i)=Mif;                %min
    Dff11(i)=Dffamplitud;        % diffrences amplitude
    DistMx_mi11(i)=DistMx_mi;    %distaice betwwen max and min
    Rati11(i)=Rati;              %ration
    Sharp11(i)=Sharp;            %sharpwaves
    Dura11(i)=Duration;          % duration
    DurPosi11(i)=DurPositiv;     % duration posituive
    DurNaga11(i)=DurNagative;    % duration posituive
   Reflectsh11(i)=Reflectsharp;  %reflect sharp positive
   ReflectshNag11(i)= ReflectshNag;  %reflect sharp nagative
   slop11(i)=slop;                   %slop
end
    Max11' ;                  %max
    Min11' ;                  %min
    Dff11' ;          % diffrences amplitude
    DistMx_mi11' ;       %distaice betwwen max and min
    Rati11' ;                  %ration
    Sharp11' ;                  %sharpwaves
    Dura11' ;             % duration
    DurPosi11' ;        % duration posituive
    DurNaga11'  ;        % duration posituive
   Reflectsh11' ;     %reflect sharp positive
   ReflectshNag11' ;    %reflect sharp nagative
   slop11';
%NewFeaturesK_complxes =[ Max11', Min11', Dff11', DistMx_mi11',
Rati11',Sharp11', Dura11',DurPosi11',DurNaga11', Reflectsh11',
ReflectshNag11',slop11'];
  NewFeaturesK_complxes =[ Max11', Min11', Dff11', DistMx_mi11',
Rati11',Sharp11', Dura11',DurPosi11',DurNaga11'];
HH=NewFeaturesK_complxes;
    end
 %%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [ VV ] = Feature_weHFD2018 ( BB2 )
% Detailed explanation goes here
[n m2]=size(BB2)
RR=BB2;
for w1=1:m2
 Ch1=RR{w1}.p
```

```
     for A1=1:5
        DD1=Ch1{A1};
for T=1:1
       DD2=DD1{1};
       DD3=DD1{2};
       DD4=[DD2,DD3];
 F1(A1,:)= FractalHFD(DD4);
     DD1=[];
     DD2=[];
     DD3=[];
     F3=[];
     end
    FFF33{w1}.p=F1;
end
end
 VV= FFF33;
   end
function [ F ] = FractalHFD ( XX )
%Detailed explanation goes here
Text=XX;
[n m]= size(Text);
ff=Text;
for i=1:n
    for r=1:8
   HDF_Kc(i,r)=Higuchi_FD1(ff(i,:), r);
     end
end
F=HDF_Kc;
End
function [HFD] = Higuchi_FD1(serie, Kmax)
control = ~isempty(serie);
assert(control,'The user must introduce a series (first inpunt).');
control = ~isempty(Kmax);
assert(control,'The user must introduce the Kmax parameter (second
inpunt).');
N = length(serie);
X = NaN(Kmax,Kmax,N);
for k = 1:Kmax
    for m = 1:k
        limit = floor((N-m)/k);
        j = 1;
        for i = m:k:(m + (limit*k))
            X(k,m,j) = serie(i);
            j = j + 1;
        end
    end
end
L = NaN(1, Kmax);
for k = 1:Kmax
    L_m = zeros(1,k);
    for m = 1:k
        R = (N - 1)/(floor((N - m)/k) * k);
        aux = squeeze(X(k,m,logical(~isnan(X(k,m,:))))');
        for i = 1:(length(aux) - 1)
            L_m(m) = L_m(m) + abs(aux(i+1) - aux(i));
        end
        L_m(m) = (L_m(m) * R)/k;
    end
    L(k) = sum(L_m)/k;
end
x = 1./(1:Kmax);
```

```
aux = polyfit(log(x),log(L),1);
HFD = aux(1);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [ VV ] = Feature_we( BB2 )
[n m2]=size (BB2);
RR=BB2;
for w1=1:m2
 Ch1=RR{w1}.p;
     for A1=1:5
        DD1=Ch1(A1,:);
     F1(A1,:)= mainpoint(DD1);
      DD1= [];
      end
    FFF33{w1}.p=F1;
end
 VV= FFF33;
   end
function [X ] = mainpoint ( Y )
%  detailed explanation goes here
% Receive:
% the vector of FD and Return the vector of statistic features
i=1;
for i=1:10
  X(1)=std(Y);
  X(2)=skewness(Y);
  X(3)=Energy(Y);
 end
end
function [ KK ] = FeatutresFrom_Record_Statistic ( TT )
FST1=TT;
  [n m2]=size( FST1);
for i=1:m2
    Ch1=FST1{i}.p
    RRR=reshape(Ch1',1,[])
    WWWW(i,:)=RRR;
end
KK=WWWW;
end
function [ F_Rc1, F_Rc2,  F_Rc3,  F_Rc4,  F_Rc5, F_Rc6] = Bund_Dual
( X1,X2)
  GG=X1;
  HH=X2;
SS1=GG(:,1:3);
SS2=GG(:,4:6);
SS3=GG(:,7:9);
SS4=GG(:,10:12);
SS5=GG(:,13:15);

FF1=HH(:,1:9);
FF2=HH(:,10:18);
FF3=HH(:,19:27);
FF4=HH(:,28:36);
FF5=HH(:,37:45);

E1=[SS1,FF1];
E2=[SS2,FF2];
E3=[SS3,FF3];
E4=[SS4,FF4];
E5=[SS5,FF5];

E6=[SS1,SS2,SS3,FF1,FF2,FF3];
```

```
F_Rc1=E1;
F_Rc2=E2;
F_Rc3=E3;
F_Rc4=E4;
F_Rc5=E5;
F_Rc6=E6;
End
function [ACC, SEM,SPE ] = Ensamble_Result ( XXX,YYY )
X2=XXX;
Y2=YYY;
[Acc,Id1,SPE1]=Nai_classificationTesting(X2,Y2);
[ ACC,SEM, SPE,Id2,Ytest]=LS_SVM_classifciationTesting(X2,Y2);
[Id3]=K_Means_Testing(X2);
[n m]=size(Id2);
Idx1=Id1(1:n,1);
Idx2=Id2(1:n,1);
Idx3=Id3(1:n,1);
[Y_id]=Convert_Tes(Idx3);    % k-means index
Y_id2=Id2;
Y_id3=Idx1;
p1=Y_id;
p2=Y_id2;
p3=Y_id3;
[L J]=size(p1);
[Acc,rand_index,match]=AccMeasure(Y_id,Ytest)
T1=1-SPE1;
T2=1-SPE;
T3=1-rand_index;
Wi_N=log2((1-T1)/T1);
Wi_L=log2((1-T2)/T2);
Wi_K=log2((1-T3)/T3);
 F1=Wi_N;
 F2=Wi_L;
 F3=Wi_K;
for i=1:L
    if p1(i)==0 && p2(i)==0 && p3(i)==0
    XXT(i)=-1;
    elseif p1(i)==1 && p2(i)==1 && p3(i)==1
      XXT(i)=1;
    end
if p1(i)==1 && p2(i)==1 && p3(i)==0
    G1=F1+F2;
    G2=F3;
     if G1>=G2
    XXT(i)=1;
     else
          XXT(i)=-1;
    end
 else if p1(i)==1 && p2(i)==0 && p3(i)==1
    G1=F1+F3;
    G2=F2;
    if G1>=G2
      XXT(i)=1;
    else
        XXT(i)=-1;
    end
   else if p1(i)==0 && p2(i)==0 && p3(i)==1
    G1=F1+F2;
    G2=F3;
    if G1>=G2
      XXT(i)=-1;
```

```
    else
        XXT(i)=1;
    end
 else if p1(i)==0 && p2(i)==1 && p3(i)==0
    G1=F1+F3;
    G2=F2;
    if G1>=G2
      XXT(i)=-1;
    else
        XXT(i)=1;
    end
        else if p1(i)==0 && p2(i)==1 && p3(i)==1
    G1=F2+F3;
    G2=F1;
    if G1>=G2
      XXT(i)=1;
    else
        XXT(i)=-1;
    end
   else if p1(i)==1 && p2(i)==0 && p3(i)==0
    G1=F2+F3;
    G2=F1;
    if G1>=G2
      XXT(i)=-1;
    else
        XXT(i)=1;
    end
end
end
 XXT=XXT'
  [u1 u11]=size(XXT)
 [Y_idF]=Convert_Tes1(XXT);
 [u1 u11]=size(XXT);
  Ytest=Ytest(1:u11,1);
[Acc,rand_index,match]=AccMeasure(Ytest,Y_idF);
end
function [ Y_id ] = Convert_Tes ( H )
Y=H;
 for i=1:length(Y)
    if Y(i)==2
        Y_id(i)=1;
    else
        Y_id(i)=-1;
    end
end
Y_id=Y_id';
end
function [ ACC,Id1, SPE1,FF ] = Nai_classificationTe ( XX,BB )
distr='normal';
distr='kernel';
DD=XX;
Y=BB;
[n3 m3]=size(DD);
R=m3+1;
DD(1:n3,R)=Y;
nrows = size(DD,1);
r80 = round(0.75 * nrows);
trainingset = DD(1:r80,:,:);
testset = DD(r80+1:end,:,:);
[k1 k2]=size(trainingset);
x = trainingset(:,1:k2-1);
```

```
y = trainingset(:,k2);
% test set
u= testset(:,1:k2-1)
v=testset(:,k2);
Y=DD(:,R);
% Create a cvpartition object that defined the folds
c = cvpartition(Y,'holdout',.2);
yu=unique(y);
nc=length(yu); % number of classes
ni=size(x,2); % independent variables
ns=length(v); % test set
 for i=1:nc
    fy(i)=sum(double(y==yu(i)))/length(y);
end
 switch distr
        case 'normal'
        for i=1:nc
            xi=x((y==yu(i)),:);
            mu(i,:)=mean(xi,1);
            sigma(i,:)=std(xi,1);
        end
        for j=1:ns
            fu=normcdf(ones(nc,1)*u(j,:),mu,sigma);
            P(j,:)=fy.*prod(fu,2)';
        end
     case 'kernel'
            for i=1:nc
            for k=1:ni
                xi=x(y==yu(i),k);
                ui=u(:,k);
                fuStruct(i,k).f=ksdensity(xi,ui);
            end
        end
        for i=1:ns
            for j=1:nc
                for k=1:ni
                    fu(j,k)=fuStruct(j,k).f(i);
                end
            end
            P(i,:)=fy.*prod(fu,2)';
        end
    otherwise
        disp('invalid distribution stated')
        return
 end
[pv0,id]=max(P,[],2);
for i=1:length(id)
    pv(i,1)=yu(id(i));
end
 confMat=myconfusionmat(v,pv);
conf=sum(pv==v)/length(pv);
ACC=conf*100;
SPE1=conf*100;
Id1=v;
MM=SPE1;
FF=DD;
end
 function [ ACC,SEM, SPE,Id1,Ytest] = LS_SVM_classifciationTe
 (X2,Y2)
Xtest= X2;
Ytest=Y2;
```

```
size(Xtest)
size(Ytest)
gam=10;
sig2=1;
type='classification';
L_fold=6;
[x,y]=Ranad(X2,Y2);
[gam, sig2] = tunelssvm({x,y,'c',[],[],'RBF_kernel'}, 'simplex',...
        'leaveoneoutlssvm', {'misclass'});
[alpha,b] = trainlssvm({x,y,type,gam,sig2,'RBF_kernel';
Yh=simlssvm({x,y,type,gam,sig2,'RBF_kernel'},{alpha,b},Xtest);
[perc,n,which]=misclass(Ytest,Yh); % Which: contains the indices of
                                    the misclassificated instances
                                   (the first column gives the
                                   row, the second the column index)
n % is the number of misclassifications
perc % is the rate of misclassifications (between 0 and 1
[C,order] = confusionmat(Ytest,Yh);
C
order
Y_latent=latentlssvm({x,y,type,gam,sig2,'RBF_kernel'},{alpha,b},x);
[area,se,thresholds,oneMinusspec,sens,TN,TP,FN,FP]=roc(Y_latent,y);
%[thresholds oneMinusspec sens ];
Accuracy=(TP+TN)/(TP+TN+FP+FN)*100
ACC=Accuracy;
T=TP/(TP+FN);
SEM=T*100;
T1=TN/(TN+FP);
SPE=T1*100;
Id1=Yh;
Ytest=Ytest;
disp('Classifciation results using DT-CWT')
disp('Accuracy')
disp('________')
disp('   The performnace of the proposed method as Accuracey=' );
disp(ACC);
disp('-----------------------------------------------------');
disp('Sensitivity')
disp('   The performnace of the proposed method as Sensitivity=' );
disp(SEM);
disp('-----------------------------------------------------');
disp('Specifcity')
disp('   The performnace of the proposed method as Specifcity=' );
disp(SPE);
toc
end
     ###############See Code in Appendix A ###################
function [ index] = K_Means_Testing ( X1 )
   % Input: X1 and X2, are the pair of sleep stages to be classified
   % Output: Accuracy the percentage of corrected classification
   % and sensitivity
 end
 function [Acc,rand_index,match]=AccMeasure(T,idx)
   % Measure percentage of Accuracy and the Rand index of clustering
   % results
   % see the procedure in Appendex A;
end
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

D

Matlab simulation code for Chapter 6

Detection of EEG k-complexes using fractal dimension of time frequncey images technique coupled with undirected graph features.

In this appendix, a simulation code to detect sleep spindles in EEG signals is presented. In this simulation code, some of functions used were from Matlab tool. The experiment results were obtained using Matlab programming language version R2018a.

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

Reading EEG data is same as in the appendix A

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
FFFFF=feat2; % all the dataset which is content all segments
                      % After calculate FD of TFI
Save FractalBox_ng11 FractalBox_ng11
ff2=FractalBox_ng11;
F=ff2;
[k1 K2]=size (ff2)
for k=1:k1
  F1=F (k, :)
  D=dist (F1)
   A=Adj_mat(D)
  [DEG,Lap]=Laplace_matrix_degree(A);
  Jacc_vect(k,:)=Jaccardcoff(A);
  Degree_matrix(k,:)=DEG(:,1)
  Cluster_coff_matrix(k,:)=clustering1(A, 'undirected')
  Degree_matrix(k,:)=averageDegree(A);
end
  Cluster_coff_matrix_2018=Cluster_coff_matrix;
  Degree_matrix2018=Degree_matrix;
  Jacc_vect2018=Jacc_vect;
  A1=Cluster_coff_matrix_2018;
  A2=Degree_matrix2018;
  A3=Jacc_vect2018;
  Featutres_Fractal_Graph2018=[A1,A2,A3];
 save Featutres_Fractal_Graph2018 Featutres_Fractal_Graph2018
 DD_JC2018= [A2, A3];
 DD_CC2018=[A2,A1];
 JC_CC2018=[A3,A1];
 ALL_DD_JC_CC2018=[A1,A2,A3];
 save DD_JC DD_JC2018
 save DD_CC DD_CC2018
 save JC_CC JC_CC2018
 save ALL_DD_JC_CC ALL_DD_JC_CC2018
XX4=ALL_DD_JC_CC2018;
[n m]=size(XX4);
TT1=XX4(:,1:10);
TT2=XX4(:,11:20);
TT3=XX4(:,21:30);
[s s1]=size(TT1);
for i=1:s
     e=TT1(i,:)
     e1=TT2(i,:)
     e2=TT3(i,:)
     EE(i)=sum(e)/s1;
     EE1(i)=sum(e1)/s1;
     EE2(i)=sum(e2)/s1;
end
 RR1=EE';
 RR2=EE1';
 RR3=EE2';
 RR4=[RR1,RR2,RR3];
 Fea_thear=RR4;
 [o1 o2]=size(Fea_thear);
for i=1:o1

    b=find(dd==i);
    if isempty(b)
        Y(i)=0;
    else
```

```
        Y(i)=1;
    end
end
Y=Y';
Y=Y(1:o1);
[ACC, SEM, SPE] =LS_SVM11_classifciation_we(Feathear, Y)
disp('Classification results using Fracatl_graph features ')
disp('Accuracy')
disp('________')
disp(' The performance of the proposed method as Accuracy=' );
disp(ACC);
disp('-------------------------------------------------------');
disp('Sensitivity')
disp('   The performance of the proposed method as Sensitivity=' );
disp(SEM);
disp('-------------------------------------------------------');
disp('Specificity')
disp('   The performance of the proposed method as Specificity=' );
disp(SPE);
% calculate Mean and Standard deviation for graph features
disp(' The data was now read , Please press any Key to continue');
pause;
load Three_Graph_Featutres;
[ZZ_STD, ZZ_mean]=STD_and_Mean2019(Three_Graph_Featutres);
disp('   Classifciation results using STD and mean for CC,DD,JC=' );
disp(ZZ_STD);
disp('-------------------------------------------------------');
disp('   Classifciation results using STD and mean for CC,DD,JC=' );
disp(ZZ_mean);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function varargout = spectrogram(x,var)
%SPECTROGRAM Spectrogram using a Short-Time Fourier Transform
narginchk(1,11);
nargoutchk(0,6);
 if nargout > 0
  [varargout{1:nargout}] = pspectrogram({x},'spect',var{:});
else
  pspectrogram({x},'spect',var{:});
end
function [Y,N] = Laplace_matrix(X1)
 [n m]=size(X1)
for i=1:n
          Deg(i,1)=sum(X1(i,:)==1)
end
Y=Deg
%%%%%%%%%%%% Laplacian Matrix%%%%%%%%%%%%%%%%%%%%%%%%%%%%
for i=1:n
    for j=1:m
        if i==j
          Y1(i,j)=Deg(i)
        else
            Y1(i,j)=0
        end
    end
end
   N=Y1-X1
  End

function [ Y ] = Jaccardcoff( P )
% Receives:
% Adjacency matrix P
```

```
%
Returns:
% Jaccardcoff Y
A=P;
[n m]=size (A)
for i=1:n
    mm1=0;
    for j=1:m
    if (A(i,j)==1)
       mm1=mm1+1;
      nn{i}.mm(mm1)=j;
    end
    end
end
for i=1:n
    for j=1:m
        if (i~=j)
        p= nn{i}.mm
        p2= nn{j}.mm
        interse=intersect(p,p2)
        uni=union(p,p2)
        L1=numel(interse)
        L2=numel(uni)
        Jacca_coff(i,:)=L1/L2
        end
    end
end
Y=Jacca_coff
end
 function coeff = clustering(A, type)
%  The clustering coefficient for each node in the graph is
calculated
n = size(A,1);
 if (nargin>1)
    if strcmp(type,'directed')
        digraph = true;
    elseif strcmp(type,'undirected')
        digraph = false;
    else
        error('Type must be either "directed" or "undirected"')
    end
else
    if all(all(A == A'))
        digraph = false;
    else
        digraph = true;
    end
end
if digraph
    c = sum((A^2) .* A, 2);
else
    c = sum((A^3) .* eye(n), 2);
end
 % Calculate the out degree of the nodes
out = sum(A,2);
% Calculate the clustering coefficient
s = warning('off','MATLAB:divideByZero');
coeff = c ./ (out .* (out - 1));
warning(s);
coeff(out == 0) = 0;
coeff(out == 1) = 0;
```

```
end
function k=averageDegree(adj)
k=2*numEdges(adj)/numNodes(adj);

function [Acc,rand_index,match]=AccMeasure(T,idx)
k=max ([T (:); idx(:)]);
n=length (T);
for i=1:k
    temp=find(T==i);
    a{i}=temp;
end
b1=[];
t1=zeros (1, k);
for i=1:k
    tt1=find (idx==i);
    for j=1:k
       t1(j)=sum(ismember(tt1,a{j}));
    end
    b1=[b1;t1];
end
    Members=zeros (1, k);
    P = perms((1:k));
    Acc1=0;
for pi=1:size(P,1)
    for ki=1:k
        Members(ki)=b1(P(pi,ki),ki);
    end
    if sum(Members)>Acc1
        match=P(pi,:);
        Acc1=sum(Members);
    end
end
 rand_ss1=0;
rand_dd1=0;
for xi=1:n-1
    for xj=xi+1:n
        rand_ss1=rand_ss1+((idx(xi)==idx(xj))&&(T(xi)==T(xj)));
        rand_dd1=rand_dd1+((idx(xi)~=idx(xj))&&(T(xi)~=T(xj)));
    end
end
rand_index=200*(rand_ss1+rand_dd1)/(n*(n-1));
Acc=Acc1/n*100;
match=[1:k;match];
function [ A] = = Adj_mat ( D )
% Receives
% A Graph distance matrix D
% % Returns:
% Adjacency Matrix A1, a threshold
[n m]=size(D)
 for i=1 : n
    e=D(i,:)
    ee=sum(e)/n;
 for j=1:n
     if i ~= j
        if( D(i,j)<=ee)
                          A(i,j)=1
             else
                 A(i,j)=0
             end
        end
    end
```

```
 end
A=A
end

#######compared using different thresholding MST and OMST ######
FractalTFI2019=TFI_ Rev_W(feat2);
[XX1, XX2, XX3, XX5]=Gra_Fe_Extr(FractalTFI2019);
CaluctedAllFeatutresGraph2019using_MST=XX5;
XX4=CaluctedAllFeatutresGraph2019using_MST;
CaluctedAllFeatutresGraph2019using_OMST=XX5;
XX4=CaluctedAllFeatutresGraph2019using_OMST;
[n m]=size(XX4);
TT1=XX4(:,1:10);
TT2=XX4(:,11:20);
TT3=XX4(:,21:30);
[s s1]=size(TT1);
for i=1:s
     e=TT1(i,:)
     e1=TT2(i,:)
     e2=TT3(i,:)
    EE(i)=sum(e)/s1;
    EE1(i)=sum(e1)/s1;
    EE2(i)=sum(e2)/s1;
end
RR1=EE';
RR2=EE1';
RR3=EE2';
RR4=[RR1,RR2,RR3];
Fea_thear=RR4;
  [o1 o2]=size(Fea_thear);
for i=1:o1
      b=find(dd==i);
    if isempty(b)
        Y(i)=0;
    else
        Y(i)=1;
    end
end
Y=Y';
  Y=Y(1:o1);
[ ACC,SEM, SPE]=LS_SVM11_classifciation_we(Fea_thear,Y)
disp('Classifciation results using Dual-Fractal')
disp('Accuracy')
disp('________')
disp('   The performnace of the proposed method as Accuracey=' );
disp(ACC);
disp('-------------------------------------------------------');
disp('Sensitivity')
disp('   The performnace of the proposed method as Sensitivity=' );
disp(SEM);
disp('-------------------------------------------------------');
disp('Specifcity')
disp('   The performnace of the proposed method as Specifcity=' );
disp(SPE);
load Three_Graph_Featutres;
[ZZ_STD, ZZ_mean]=STD_and_Mean2019(Three_Graph_Featutres);
disp('   Classifciation results using STD and mean for CC,DD,JC=' );
disp(ZZ_STD);
disp('-------------------------------------------------------');
disp('   Classifciation results using STD and mean for CC,DD,JC=' );
disp(ZZ_mean);
```

```
function [ XX1, XX2, XX3, XX4 ] = Gra_Fe_Extr(Y )
[k1 k2]=size(Y);
F=Y;
for k=1:k1
    F1=F(k,:);
    D=dist(F1);
    [links,weights]=minimal_spanning_tree(D);
    w=weights;
    A=Adj_mat(D);
    [w_st, ST, X_st] = kruskal2019(A, w);
    Kk=6;
    A= threslold_mean_degree(X_st,kk)
    Jacc_vect(k,:)=Jaccardcoff(A);
    Cluster_coff_matrix(k,:)=clustering1(A, 'undirected')
    [DEG,Lap]=Laplace_matrix_degree(A);
    Degree_matrix(k,:)=DEG(:,1)
end
    XX1=Jacc_vect;
    XX2=Cluster_coff_matrix;
    XX3=Degree_matrix;
    XX4= [Jacc_vect,Cluster_coff_matrix,Degree_matrix];
end
function [Three_Featutres] = CaluctedAllFeatutresGraph2019using_MST
 (Cluster_coff_matrix,Degree_matrix,Jacc_vect )
% Receives:
% Graph Features
% Return average of three graph features
A1=Cluster_coff_matrix;
A2=Degree_matrix;
A3=Jacc_vect;
 Featutres_Fractal_Graph=[A1,A2,A3];
 save Featutres_Fractal_Graph Featutres_Fractal_Graph
 DD_JC=[A2,A3];
 DD_CC=[A2,A1];
 JC_CC=[A3,A1];
 ALL_DD_JC_CC=[A1,A2,A3];
 save DD_JC DD_JC
 save DD_CC DD_CC
 save JC_CC JC_CC
 save ALL_DD_JC_CC ALL_DD_JC_CC
Three_Featutres=ALL_DD_JC_CC ALL_DD_JC_CC ;
 end
function [w_st, ST, X_st] = kruskal(X, w)
      isUndirGraph = 0;w=inatialweight();
     if size(X,1)==size(X,2) && sum(X(:)==0)+sum(X(:)==1)==numel(X)
         if any(any(X-X'))
             isUndirGraph = 0;
         end
         ne = cnvrtX2ne(X,isUndirGraph);
     else
         if size(unique(sort(X,2),'rows'),1)~=size(X,1)
             isUndirGraph = 0;
         end
         ne = X;
     end
     if numel(w)~=length(w)
         if isUndirGraph && any(any(w-w'))
             error('If it is an undirected graph, weight matrix has
to be symmetric.');
         end
         w = cnvrtw2ne(w,ne);
```

```
    end
     N    = max(ne(:));
    Ne   = size(ne,1);
    lidx = zeros(Ne,1);
    [w,idx] = sort(w);
    ne      = ne(idx,:);
    [repr, rnk] = makeset(N);
    for k = 1:Ne
        i = ne(k,1);
        j = ne(k,2);
        if fnd(i,repr) ~= fnd(j,repr)
            lidx(k) = 1;
            [repr, rnk] = union(i, j, repr, rnk);
        end
    end
     % Form the minimum spanning tree
    treeidx = find(lidx);
    ST = ne (treeidx, :);
       % Generate adjacency matrix of the minimum spanning tree
    X_st = zeros(N);
    for k = 1:size(ST,1)
        X_st(ST(k,1),ST(k,2)) = 1;
        if isUndirGraph,  X_st(ST(k,2),ST(k,1)) = 1;  end
    end
      % Evaluate the total weight of the minimum spanning tree
    w_st = sum(w(treeidx));
end
function ne = cnvrtX2ne(X, isUndirGraph)
    if isUndirGraph
        ne = zeros(sum(sum(X.*triu(ones(size(X))))),2);
    else
        ne = zeros(sum(X(:)),2);
    end
    cnt = 1;
    for i = 1:size(X,1)
        v       = find(X(i,:));
        if isUndirGraph
            v(v<=i) = [];
        end
        u       = repmat(i, size(v));
        edges   = [u; v]';
        ne(cnt:cnt+size(edges,1)-1,:) = edges;
        cnt = cnt + size(edges,1);
    end
end

function w = cnvrtw2ne(w,ne)
    tmp = zeros(size(ne,1),1);
    cnt = 1;
    for k = 1:size(ne,1)
        tmp(cnt) = w(ne(k,1),ne(k,2));
        cnt = cnt + 1;
    end
    w = tmp;
end

function [repr, rnk] = makeset(N)
    repr = (1:N);
    rnk  = zeros(1,N);
end
function o = fnd(i,repr)
```

```
    while i ~= repr(i)
        i = repr(i);
    end
    o = i;
end
  function [repr, rnk] = union(i, j, repr, rnk)
    r_i = fnd(i,repr);
    r_j = fnd(j,repr);
    if rnk(r_i) > rnk(r_j)
        repr(r_j) = r_i;
    else
        repr(r_i) = r_j;
        if rnk(r_i) == rnk(r_j)
            rnk(r_j) = rnk(r_j) + 1;
        end
    end
end

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
 function  [links,weights]=minimal_spanning_tree(d)
[N,N]=size(d);, V=[1:N];, r=1;, VT=r;,
 weights=zeros(1,N); links=zeros(1,N);
 V_VT=setdiff(V,VT);
  weights(V_VT)=d(r,V_VT);
 links(V_VT)=r;
 for i=1:N-2
   [edge_weight,u]=min(weights(V_VT));
  node=V_VT(u);
   VT=union(VT,node);
   V_VT=setdiff(V,VT);
  for j=1:N-1-i,
   [weights(V_VT(j)),index]=min( [weights(V_VT(j)),d(node,V_VT(j))]
);,
  if index == 2,  links(V_VT(j))=node;, else, end
    end
 end
 links=[2:N; links(2:N)]';
 weights=weights(2:N)';
  [ignore,list]=sort(weights);
links=links(list,:); weights=weights(list);
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
function [bin thres mdegree]=threslold_mean_degree(graph,kk)
iter=5;
 [d1 d2]=size(graph);
 step=1/iter;
 thres=0;
 bin(1:d1,1:d2)=0;
  thresdeg=zeros(iter,2);
 for i=1:iter
    thres=thres+step;
    bin(1:d1,1:d2)=0;
    for k=1:d1
        for l=(k+1):d2
            if(graph(k,l)>thres)
                bin(k,l)=1;
                bin(l,k)=1;
            end
        end
    end
    [deg] = degrees_und(bin);
      thresdeg(i,1)=mean(deg);
```

```
     thresdeg(i,2)=thres;
 end
 %find the nearest mean degree to kk
 dif=zeros(1,iter);
 for i=1:iter
     dif(i)=abs(thresdeg(i,1) - kk);
 end
 %find the mean degree with the min difference from kk
 [a r]=min(dif);
%find the threhold corresponds to the mean degree
 mdegree=0;
 mdegree=thresdeg(r,1);
 thres=thresdeg(r,2);
     for k=1:d1
         for l=(k+1):d2
             if(graph(k,l) > thres)
                 bin(k,l)=1;
                 bin(l,k)=1;
             end
         end
     end
function [ZZ_STD,ZZ_mean ] = STD_and_Mean2019 (ALL_DD_JC_CC2018)
XX4=ALL_DD_JC_CC2018;
[n m]=size(XX4);
TT1=XX4(:,1:10);
TT2=XX4(:,11:20);
TT3=XX4(:,21:30);
[s s1]=size(TT1);
for i=1:s
     e=TT1(i,:)
     e1=TT2(i,:)
     e2=TT3(i,:)
    EE(i)=sum(e)/s1;
    EE1(i)=sum(e1)/s1;
    EE2(i)=sum(e2)/s1;
end
RR1=EE';
RR2=EE1';
RR3=EE2';
RR4=[RR1,RR2,RR3];
for k=1:s
   u1=TT1(k,:);
   u2=TT2(k,:);
   u3=TT3(k,:);
    LL1(k)=std(u1);
    LL2(k)=std(u2);
    LL3(k)=std(u3);
end
HH1=LL1';
HH2=LL2';
HH3=LL3';
HH4=[HH1,HH2,HH3];
STD_JC=sum(HH1(1:end,1))/s
STD_CC=sum(HH2(1:end,1))/s
STD_DD=sum(HH3(1:end,1))/s
Mean_JC=sum(RR1(1:end,1))/s
Mean_CC=sum(RR2(1:end,1))/s
Mean_DD=sum(RR3(1:end,1))/s
ZZ_STD=[STD_JC,STD_CC,STD_DD]
ZZ_mean=[Mean_JC, Mean_CC,Mean_DD]
end
```