University of Southern Queensland

Multi-Method Approaches for Sleep EEG Analysis and Sleep Stage Classification.

A Thesis submitted by

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ABSTRACT

Sleep plays a fundamental role in human well-being, and understanding its intricate effects remains a crucial research area. Sleep electroencephalogram (EEG) signal analysis offers a promising direction for uncovering hidden singularities in sleep data. This thesis introduces innovative approaches for untangling sleep stage characteristics from EEG data.

Studied and inspired by the matching pursuit (MP) method, this research firstly developed a multitapers and convolution (MT&C) method that can decompose EEG data based on a dictionary. The MT&C method leverages controlled wavelets to compute spectral estimation, offering a robust basis for sleep EEG analysis, visual guidance, and stage scoring. By adhering to the Rechtshaffen and Kales sleep scoring manual (R&K rules) and the American Association of Sleep Medicine standards (AASM), both the MP and MT&C methods demonstrate an improved classification accuracy. Experimental results on healthy subjects demonstrated an accuracy of 79.4% and 87.6% for the MP and MT&C, respectively. While the MP and MT&C methods differ in definition, they complement each other and contribute to the advancements of sleep EEG analysis.

This thesis further examines the identification and classification of sleep spindles using a new spindles across multiple channels (SAMC) method. The SAMC implements multitapers and convolution to extract the spectral density estimation across multiple EEG channels, providing a comprehensive understanding of the behaviours and characteristics of the sleep spindles across the scalp. The SAMC method performs better than existing approaches, showcasing its potential to accurately identify and categorise sleep spindles.

Lastly, this study employed an advanced time-frequency analysis and incorporated a powerful deep learning model. The proposed method achieves significant performance improvements by employing the MT&C for initial feature extraction and utilising advanced techniques of visual geometric group, squeeze-and-excitation blocks, and scaled exponential linear units with batch normalisation. Across three diverse

databases, the average accuracy and precision of 87% demonstrated the potential of these techniques in enhancing sleep stage classification.

Overall, this thesis contributes to the field of sleep research by introducing novel multi-method approaches for sleep EEG analysis, sleep stage classification, and spindle identification. The findings highlight the potential for improving understanding and possible diagnosis of sleep-related phenomena, offering new insights into sleep quality and its impact on human health and well-being.

Rationale: This research stems from the critical importance of understanding sleep's effects on human well-being. The focus on EEG signal analysis arises from the potential to uncover hidden aspects of sleep data, contributing to improved diagnosis and comprehension of sleep-related phenomena.

Contributions:

- Introduction of novel multi-method approaches for sleep EEG analysis, sleep stage classification, and spindle identification.
- Development of the MP and MT&C methods, enhancing sleep EEG analysis and classification accuracy.
- Innovation of the SAMC method, outperforming existing approaches in sleep spindle identification.
- Integration of advanced time-frequency analysis and deep learning techniques, significantly improving sleep stage classification across diverse databases.

The findings of this thesis offer new insights into sleep quality and its profound impact on human health and well-being.

CERTIFICATION OF THESIS

I, Ignacio Zapata, declare that the thesis entitled *"Multi-Method Approaches for Sleep EEG Analysis and Sleep Stage Classification"* is not more than 100,000 words in length, including quotes and exclusive of tables, figures, appendices, bibliography, references, and footnotes. The thesis contains no material that has been submitted previously, in whole or in part, for the award of any other academic degree or diploma. Except where otherwise indicated, this thesis is my own work.

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Student and supervisors' 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, Zapata et al., (2022).

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Author	Percent	Tasks Performed
Zapata, I. A.,	70%	Methodology design and implementation, analysis, simulations, interpretation, documentation of the entire paper.
Li, Y., & Wen, P	30%	Significantly improved the manuscript, interpretation, and analysis.

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Li, Y., & Wen, P	25%	Significantly improved the manuscript, interpretation, and analysis.
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Author	**Percent**	**Tasks Performed**
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ABBREVIATIONS, ACRONYMS & NOTATIONS

EEG	Electroencephalogram
MP	Matching pursuit
AASM	American Association of Sleep Medicine
MT&C	Multitapers and convolution
R&K	Rechtshaffen and Kales
SAMC	Spindles across multiple channels
SVM-Q	Support vector machines with Q factor
CNN	Convolutional Neural Networks
PSG	Polysomnography
SDE	Spectral density estimation
SD	Spectral density
VGG	Visual geometric group
SELU	Scaled exponential linear unit
SE	Squeeze-and-Excitation blocks
BN	Batch normalisation
ML	Machine learning
DL	Deep learning
AR	Accuracy rate
CCC	Lin's Concordance Correlation Coefficient
PPV	Positive predicted value
REM	Rapid eye movement
NREM	Non-rapid eye movement
W	Awake/wake
S1	stage 1
S2	stage 2
S3	stage 3
SWS	slow-wave-sleep
SCN	Suprachiasmatic nucleus
SOL	Sleep onset latency
CV	Cardiovascular

EMG	Electromyography
EOG	Electrooculogram
AC	Alternating current
F	Frontal
T	Temporal
C	Central
P	Parietal
O	Occipital
M1/M2	Right/Left mastoid
z	Vertex positioned
A1/A2	Left/Right earlobe region
LOC/E1	Electrode positioned at left eye
ROC/E2	Electrode positioned at right eye
ICA	Independent component analysis
IC	Independent component
CCA	Canonical correlation analysis
IVA	Independent vector analysis
BSS	Blind source separation
STFT	Short-time Fourier transform
FT	Fourier transform
CWT	Continuous wavelet transform
DWT	Discrete wavelet transform
HHT	Hilbert-Huang transform
WPT	Wavelet packet transform
EMD	Empirical mode decomposition
SST	Synchro-squeezing transform
MMP	Multichannel MP
MT	Multitapers
FFT	Fast Fourier transform
STE	Single tapers estimation
SVM	Support vector machines
k-NN	k-Nearest Neighbours
SNR	Signal-to-noise ratio

SGD	Stochastic Gradient Descent
AI	Artificial Intelligence.
Hz	Hertz
μV	microvolts
sec.	Second/s

CHAPTER 1

INTRODUCTION

For many years, extensive research has been dedicated to the field of polysomnography (PSG), with the primary objective of untangling and establishing the complex connections between sleep, neuronal activities, and body functions (Haustein et al., 1986). The study of sleep and its associated brain activity through electroencephalogram (EEG) signals has long been a topic of interest in the sleep research community. Understanding the intricacies of sleep EEG patterns and accurately classifying sleep stages is vital for diagnosing sleep disorders, uncovering underlying mechanisms, and improving sleep quality and human well-being.

Manual sleep scoring is the traditional and commonly employed method for categorising sleep stages based on visual inspection of EEG signals. However, it is time-consuming, subjective, and prone to inter-observer variability (Danker-Hopfer et al., 2009; Himanen & Hasan, 2000; Mayeli et al., 2022). Consequently, there is a growing need for automated approaches to analyse sleep EEG data efficiently and reliably, which can provide objective and consistent sleep stage classifications (Bagur et al., 2018; Chediak et al., 2006).

Many machine-learning methods have recently emerged for sleep stage scoring (Aboalayon et al., 2016a; Al Ghayab et al., 2019; Haustein et al., 1986; Lee et al., 2022). Most of them operate as black boxes, yielding an outcome without providing a comprehensive internal process that medical professionals can interpret. The operations of those systems often involve irrelevant features that do not align with established definitions of sleep stages. Therefore, understanding the final output of such methods becomes challenging for medical experts. This thesis aims to address the challenges by introducing innovative multi-method approaches for sleep EEG analysis and sleep stage classification (Rudin, 2019).

The first part of this thesis focuses on developing novel approaches to identify the parameters and characteristics of sleep stages from EEG data (Zapata et al., 2022). The objective is to implement time-frequency analysis on the sleep EEG data, to extract, identify and evaluate characteristics and parameters of brain waves embedded in the data. This research studied the matching pursuit (MP) method, which discomposes signals based on a dictionary containing a collection of wavelets created from a core function. MP provides a comprehensive framework that is attractive for analysing and interpreting the embedded features of sleep stages. However, due to the computational demands of the MP method, a more computationally friendly alternative, the multitapers and convolution (MT&C) method, was developed. Nevertheless, valuable insights from the MP were brought into the MT&C method, resulting in a refined approach combining the strengths from both techniques.

The MT&C method utilises controlled wavelets to compute the spectral density estimation of a signal, providing a robust basis for sleep EEG analysis. This study is to develop methods that combine features relevant to the characteristics and patterns of the sleep stages from EEG signals. Therefore, adhering to the time-frequency analysis of the Rechtshaffen and Kales (R&K rules) sleep scoring guidelines and the American Academy of Sleep Medicine standards (AASM), the proposed method can identify the sleep characteristics from the EEG data, that not only have relevance to the classification methods, but can also be associated to each sleep stage, and provide the bases from which each stage was classified (Grigg-Damberger, 2012; Kushida et al., 2005; Nir et al., 2011; Pevernagie et al., 2009; Zapata et al., 2022).

At the outset of this study, both the MP and the MT&C methods exhibited improved classification accuracy. Preliminary experimental results on healthy subjects demonstrated an accuracy of 79.4 and 87.6 for the MP and MT&C methods, respectively. While the MP and the MT&C methods differ in definition, they have the potential to complement each other and thus can contribute to sleep EEG analysis.

Furthermore, this thesis investigates the integration of machine learning techniques to enhance EEG classification performance further. The combination of these methods holds the potential for improving the sleep stages classification and the promise to increase the repertory of machine learning algorithms for comparison (Haustein et al., 1986; Y. Huang et al., 2022; Novelli et al., 2010; Rezaie et al., 2018; Siuly et al., 2022).

The identification and categorisation of sleep spindles are also explored using a "spindles across channels" (SAMC) method. The SAMC uses the MT&C to extract spectral density estimation (SDE) across multiple channels, providing a comprehensive understanding of the behaviour and characteristic of sleep spindles. The SAMC method performs better than existing approaches, showcasing its potential to accurately identify, categorise, and visualise sleep spindles (Zapata et al., 2023).

Lastly, this thesis merges into automatic sleep stage classification by implementing advanced time-frequency analysis and incorporating powerful deep learning models. By implementing the MT&C method for initial feature extraction and employing techniques, such as visual geometric group (VGG), squeeze-and-excitation blocks (SE), and scaled exponential linear unit (SELU) with batch normalisation (BN), the proposed method achieves significant performance improvements. Across three different databases, an average accuracy and precision of 87% demonstrate the potential of these techniques in enhancing sleep stage classification.

Overall, this thesis contributes to the field of sleep research by introducing novel multi-method approaches with the defined features for sleep EEG analysis, sleep stage classification, and spindle identification. Implementing the MT&C method, integrating machine learning techniques, exploring sleep spindle identification with the SAMC method, and applying advanced deep learning models collectively, the outcomes of this study have enhanced the understanding of sleep-related phenomena, improved sleep stages classification, and ultimately promoted better sleep health and well-being.

1.1. Study Overview and Motivations

Sleep stage classification is a tenuous task with limitations such as being time-consuming, fatigue-induced biases, lack of inter-score validity, and subjectivity. Those limitations can lead to significant obstacles in the development of diagnosing sleep problems (Chediak et al., 2006; Fernandez Guerrero & Achermann, 2019; Haustein et al., 1986; Himanen & Hasan, 2000; Hori et al., 2001; Kushida et al., 2005; Novelli et al., 2010; Parrino et al., 2009; Rezaie et al., 2018). Furthermore, even though there are defined benchmarks for sleep stage scoring, such as the K&R rules and the AASM standards, most automatic methods used for stage classification operate as black boxes, producing results without offering a straightforward process that users can interpret. Those models often incorporate incongruent features to established sleep stages

definitions, leading to difficulties in comprehending the final output for medical experts (Danker-Hopfer et al., 2009; Lee et al., 2022; Moser et al., 2009; Rudin, 2019).

This study aims to address the limitations and challenges by introducing innovative multi-method approaches. The following sections provide an overview of the critical components of this study and the motivations behind each research direction.

1.1.1. Analysing Sleep EEG Data for Sleep Stage Classification

The first aspect of this research focuses on developing advanced methodologies for sleep EEG data analysis towards sleep stage classification. Exploring signal decomposition and analysing methods like the MP and the MT&C in the EEG data enables the identification of characteristics and parameters that can be linked to sleep stages classification (Zapata et al., 2022). The motivation of this research is to enhance diagnostic capabilities and a deeper understanding of sleep EEG patterns.

1.1.2. Integration of Machine Learning Techniques

In order to enhance the classification performance and explore alternative algorithms, this study incorporates several machine learning (ML) techniques such as linear regression, decision trees, random forest, support vector machines, into the sleep EEG analysis. By leveraging the power of a ML method, the objective is to improve the precision, robustness, and applicability of sleep stages classification (Zapata et al., 2022). This research direction is driven by the aspiration to unleash the potential of automated approaches and mitigate the dependency on manual scoring, thereby expediting the diagnosis of sleep-related disorders with heightened accuracy and showing the relevance and bases of each score.

1.1.3. Sleep Spindles Identification and Categorisation

Sleep spindles are transient neural oscillatory events that occur during specific sleep stages and have been linked to memory consolidation and cortical plasticity. This study introduces the SAMC method to visualise, identify, and categorise sleep spindles in the EEG data (Zapata et al., 2023). By harnessing the capabilities of the MT&C, this approach stipulates a comprehensive understanding of the characteristics of spindles and their spatial distribution over the scalp. It aims to uncover the intrinsic mechanisms of sleep spindles, their role in the brain activity and their potential implications for cognitive processes, expanding our understanding of sleep-related brain activity.

1.1.4. Integration of Advance Time-Frequency Analysis and Deep Learning

The concluding aspect of this research explores advanced time-frequency analysis techniques and deep learning models for automatic sleep stage classification. The

extraction of informative features using the MT&C and incorporating innovative methodologies, such as visual geometric group, squeeze-and-excitation blocks, and scaled exponential linear unit with batch normalisation strives to improve the accuracy and precision of sleep stage classification (Zapata et al., n.d.). The motivation of this research direction is to leverage state-of-the-art techniques in deep learning and signal analysis to enhance the comprehension and classification of sleep stages, with the eventual goal of contributing to a more precise sleep stage classification and subsequent improvement of sleep disorders diagnosis.

In brief, this study incorporates multiple research techniques to revolutionise sleep EEG analysis and sleep stage classification. With the introduction of innovative methodologies, integration of ML techniques, incorporation of sleep spindles characteristics, and consolidation of signal analysis and deep learning models, this study aims to advance the field and provide valuable insights into sleep-related phenomena, ultimately contributing to enhancing sleep health and well-being.

1.2. Research Problems

This section presents the primary research challenges that motivate this study, establishing the bases for the proposed multi-method approaches in sleep EEG analysis and sleep stage classification.

Problem statement:

Sleep is a fundamental aspect of human health, contributing significantly to overall well-being and cognitive function. However, the pervasive issue of sleep disorders has emerged as a global concern, affecting millions of individuals across diverse demographic groups. As we delve into the intricate landscape of sleep health, it becomes imperative to explore the prevalence, impact, and societal implications of sleep disorders on a global scale.

Despite the critical role that sleep plays in maintaining physical and mental health, an alarming number of individuals worldwide suffer from sleep disorders. According to the World Health Organization (WHO), almost 30% of adults globally experience frequent sleep-related difficulties, encompassing conditions such as insomnia, sleep apnea, and restless leg syndrome (WHO, Global Health Observatory Data, 2022). These disorders not only compromise the quality of life for affected individuals but also pose substantial challenges to public health systems and economies.

The impact of sleep disorders extends beyond mere inconvenience, as mounting evidence links inadequate sleep to a many of health issues, including cardiovascular diseases, obesity, and mental health disorders (Buysse et al., 2010; Dietz & Nagel, 1967; Edinger et al., 1991; Esposito et al., 2019; Goldman et al., 2007b; Gulia & Kumar, 2018; Lam, 2006; Patel et al., 2023; Skarpsno et al., 2017; Wang et al., 2018; Watson et al., 2015).

Despite the pervasive nature of sleep disorders, the existing methods for analysing sleep electroencephalogram (EEG) data and classifying sleep stages face notable limitations. Current approaches often struggle with accuracy and efficiency, hindering the timely and precise diagnosis of sleep-related conditions. This deficiency not only compromises the quality of life for affected individuals but also contributes to the escalating economic burden on healthcare systems globally.

Within this context, the present thesis endeavours to address the critical gaps in sleep EEG analysis and sleep stage classification. By leveraging multi-method approaches, incorporating advanced time-frequency analysis and deep learning models, this research aims to provide innovative solutions to enhance the accuracy and reliability of sleep stage classification. The ultimate goal is to contribute to the improvement of diagnostic tools and therapeutic interventions for sleep disorders.

Global Statistics on Sleep Disorders:

Let us briefly examine the staggering prevalence of sleep disorders on a global scale. The National Sleep Foundation reports that sleep-related problems are estimated to cost the United States alone over $94 billion annually in medical expenses and lost productivity [3]. In Europe, sleep disorders affect nearly 45 million people, resulting in a substantial economic burden exceeding €45 billion each year (Baranowski & Jabkowski, 2023; Huyett & Bhattacharyya, 2021).

These statistics underscore the urgent need for advancements in sleep research, particularly in the realm of EEG analysis and sleep stage classification. By improving the accuracy of these methodologies, we can make significant strides toward mitigating the far-reaching consequences of sleep disorders on individuals and society.

Considering this, the following sections of the thesis will delve into the proposed multi-method approaches, their implementation details, and the experimental results demonstrating their superiority over existing methods. Through this research, we aspire to contribute not only to the academic discourse on sleep disorders but also to the practical improvement of diagnostic and treatment modalities.

1.2.1. Manual Sleep Stage Scoring

The dependence on manual sleep stage scoring comprises substantial challenges regarding time consumption, subjectivity, and inter-observer verification. The manual scoring is susceptible to expert fatigue, personal biases, and inconsistency in interpretation (Berry et al., 2017; Chediak et al., 2006; Danker-Hopfer et al., 2009; Grigg-Damberger, 2012; Haustein et al., 1986; Himanen & Hasan, 2000; Hori et al., 2001; Kushida et al., 2005; Lee et al., 2022; Moser et al., 2009; Novelli et al., 2010; Parrino et al., 2009; Rezaie et al., 2018; Rosenberg & Van Hout, 2013; Ruehland et al., 2011; Zapata et al., 2023). This research addresses these limitations and postulates innovative automated methods that offer unbiased, consistent, and efficient sleep stage classification, diminishing sleep experts' personal biases and improving sleep-related diagnostic accuracy for sleep disorders.

1.2.2. Automatic Sleep Stage Classification Methods

Numerous automatic sleep stage classification methods have emerged in recent years, employing various techniques. However, a common characteristic among many methods is the black box design, which introduces uncertainty in the classification output. This uncertainty arises primarily due to the lack of interpretable explanations for a classification result. Moreover, these methods often employ features not aligned with the established parameters for sleep stage scoring, further contributing to the challenges in achieving accurate and interpretable outcomes (Al Ghayab et al., 2019; Danker-Hopfer et al., 2009; Grigg-Damberger, 2012; Hori et al., 2001; Lee et al., 2022; Rudin, 2019). The research problem at hand is to identify parallel approaches that can effectively combine automation in sleep stage scoring while establishing a coherent structure that defines the output of the method. The ultimate objective is to leverage the capabilities of automatic methods while also enabling a visual interpretation of the extracted features. By achieving this, the aim is to generate a more reliable and confident output that medical experts can readily interpret.

1.2.3. Computational Demands of Sleep EEG Analysis

The computational requirements by some of signal analysis techniques for sleep EEG data, such as the MP method, can be excessively high, especially when analysing large databases, limiting their practical applications. This research is to find alternative approaches, like the MT&C method, that strike the balance between computational efficiency and accuracy. However, completely disregarding the MP method may not adequately address the problem. Thus, there is a need to integrate the valuable insights

from the MP method into more computationally feasible approaches while ensuring the preservation of critical signal characteristics.

1.2.4. Unveiling the Characteristics of Sleep Spindles

Sleep spindles, crucial markers of brain activity during sleep, hold significant potential in understanding memory consolidation and cortical plasticity. However, its precise characteristics, distribution, and functions of sleep across different cortical areas still need to be better understood. This research is to explore advanced time-frequency analysis techniques and implement machine learning algorithms to improve the accuracy, robustness, and generalisation of sleep stage classification. That involves extracting informative features, selecting appropriate classification models, and integrating innovative methodologies to enhance the performance of sleep stage classification algorithms.

By addressing these research problems, this study aims to contribute to the field of sleep EEG analysis and sleep stage classification, offering innovative solutions to improve diagnostic capabilities, advance our understanding of sleep-related phenomena, and ultimately enhance sleep health outcomes for individuals.

1.3. Research Questions and Main Objectives

The following five fundamental concerns govern the objectives of this research:

1. How to improve sleep stages classification and detect abnormal events with features and parameters from EEG wave definitions.
2. How to improve the computational power of the algorithm using more effective signal decomposition kernels.
3. How to improve the overall performance of sleep EEG classification using the resolution that time-frequency analysis provides.
4. How to achieve accuracy across multiple EEG databases with different types of sleep EEG data collection devices.
5. How to integrate time-frequency features with machine learning and deep learning algorithms to classify sleep stage classification.

The main objectives of this research are:

- To develop new methods for sleep stage classification capable of improving performance and accuracy.
- To generate visualisations and direct connections between the extracted features by a proposed method and EEG definitions to help experts validate the findings.

Initially, a set of methods used for time-frequency analysis are implemented to extract key features from EEG data based on EEG-wave definitions. Then, based on the findings and performance of each characteristic, they are selected to perform the task where they have the most relevance.

Specifically, the primary goals of this research are:

- To develop a method that combines multiple signal analysis techniques to identify and predict sleep stages and abnormal waves in EEG data.
- To improve the performance of the methods by integrating different signal analysis methods to generate features that have a high correlation with the definitions of EEG waves.
- To develop wavelets, dictionaries and kernels associated with specific wave types found in EEG data.
- To apply methods on different types of EEG databases and to improve their accuracies.
- To generate visualisations associated with the findings in the EEG data.
- To develop, test, train and validate machine learning and deep learning algorithms for sleep stage classification.

1.4. Research Contribution, Outcomes and Significance

This section highlights the main contributions of this research in the field of sleep EEG analysis and sleep stage classification, emphasising the evolution and novel insights gained through the proposed multi-method approaches. The methods developed within this thesis have been disseminated through publication in high quality journals (such as *Sleep* and *IEEE Access*) focusing on detecting and analysing sleep characteristics in EEG signals. The outcomes of the research have been critically reviewed and summarised, explicitly evaluated the precision of their classification. Extensive experiments have been conducted in this study to investigate the performance of the proposed methods thoroughly. Furthermore, comparisons have been made with recently reported algorithms utilising a variety of similar and different databases.

The implemented algorithms of the proposed methods were coded using Python versions 3.9, 3.11 and 3.12, alongside MATLAB R2018a through R2023a. The databases used in this study were the St. Vincent's Database (Heneghan et al., 2008), DREAMS Database (Stephanie Devuyst. et al., 2005), CAP Sleep Database (O'Reilly et al., 2014). Numerous papers have extensively employed these databases to

investigate and analyse sleep EEG. Please refer to Chapters 3, 4 and 5 for further database information. The methods were evaluated utilising various analytical tools, including accuracy rate (AR), Lin's concordance correlation coefficient (CCC), positive predicted value (PPV), F-measure, precision, and recall. Detailed information can be found in Chapters 3-5 for a more comprehensive understanding of these evaluation metrics.

This research project aims to develop innovative methods for automatically identifying the sleep EEG characteristics associated with different sleep stages based on well-defined criteria such as the R&K rules and the AASM standards. Sleep stage scoring involves the identification of distinctive patterns within the EEG signals to classify them into awake (W), stage 1 (S1), stage 2 (S2), stage 3 (S3) and rapid eye movement (REM) sleep stages. Each stage exhibits unique wave characteristics characterised by specific frequency rage, which can be leveraged for their identification.

The current manual sleep stage scoring process is time-consuming and mentally exhausting for experts, who often spend extensive hours analysing EEG recordings. The subjectivity, biases and fatigue associated with manual scoring can lead to inconsistent or conflicting sleep stage scoring. In this context, this thesis aims to automate the identification of sleep characteristics by integrating signal analysis, machine learning, and deep learning techniques. By automating the identification of sleep stages/spindles, this research seeks to reduce the time and effort experts require to analyse EEG signals, overcoming the limitations of black-box approaches commonly used in automated methods. Moreover, the proposed method can be utilised by experts for sleep stage scoring, streaming the process and potentially lowering the cost of treatment as they can automatically analyse patient recordings.

Additionally, the proposed methods offer features relevant to the characteristics of sleep stage definitions, giving the option of visualising features, providing meaningful insights to medical experts, and supporting the outcomes of the classification methods. This feature visualisation aids in enhancing the understanding of the scoring process, enabling experts to identify specific characteristics and further refine their assessments.

In summary, this research project aims to improve the understanding and accuracy of sleep stage scoring by automatically identifying sleep stage characteristics using an integration of signal analysis, machine learning, and deep learning techniques. The proposed methods have the potential to streamline the scoring process, reduce cost, and

provide visual support to medical experts, thereby enhancing the overall sleep stage classification approach.

The following contributions have been made to address the research questions and accomplish the objectives.

1.4.1. Development of the Innovative Techniques

EEG data are complex, non-stationary recordings of brain activity, collected using sensible electrodes on the scalp to detect and measure the voltage fluctuations resulting from the neuronal interactions. However, EEG data collection is challenging due to the susceptibility to noise that are from various sources, including muscle movement, external device frequencies, and even electrode connectivity issues.

Given the significance of EEG data as a fundamental source of information, this research prioritised the study, analysis, and the development of signal pre-processing and analysis methods.

This study makes notable contributions to the field by introducing innovative approaches for sleep EEG analysis and sleep stage classification. By integrating the MT&C method and incorporating valuable insights from the MP method, this study provides a practical and efficient solution for untangling sleep stage parameters from EEG data. Moreover, this research explores the integration of machine learning techniques, advanced time-frequency analysis, and deep learning models, pursuing the boundaries of automated sleep stage classification. These advancements aim to enhance the performance, accuracy and precision of the proposed classification algorithms.

1.4.2. Enhance Sleep Stage Classification Accuracy

One of the primary contributions of this research is the improvement in sleep stage classification accuracy. The proposed approaches achieved notable performance improvements by leveraging advanced methodologies and combining multiple techniques, including the MT&C method, machine learning algorithms, and deep learning models. These advancements enable more accurate and reliable sleep stage classification, facilitating improved diagnoses and a better understanding of sleep-related disorders.

1.4.3. Comprehensive Analysis of Sleep Spindles

This thesis contributes to understand sleep spindles by introducing the SAMC method. This novel approach uses the MT&C to identify and categorise sleep spindles in EEG data, comprehensively analysing spindle characteristics and their distribution across the cortical areas. The insights gained from this method contribute to a deeper

understanding of the role of sleep spindles and their distribution over the scalp, which is an exciting approach to persuade the comprehension of the role of spindles in memory consolidation, cortical plasticity, sleep stages, and other cognitive process.

1.4.4. Integration of Advance Techniques

Another significant contribution of this thesis is to incorporate advanced techniques, including time-frequency analysis, machine learning algorithms, and deep learning models. The proposed approaches confirmed enhanced performances in sleep EEG analysis and sleep stage classification by adopting these techniques. The integration of these techniques provided more comprehensive and accurate analyses of sleep patterns, enabling improved diagnostic capabilities and facilitating personalised sleep health interventions.

Overall, this thesis contributes to the field of sleep EEG analysis and sleep stage classification by introducing innovative approaches, improving classification accuracy, enhancing the understanding of sleep spindles, and integrating advanced techniques. The findings of this research have the potential to revolutionise sleep research, improve current deep learning and machine learning methods, expand clinical practice, and ultimately contribute to better sleep health outcomes for individuals.

1.5. The Structure of the Thesis

This section highlights the connections and interrelationships between the chapters of the thesis, illustrating the logical progression of the research and the cohesive nature of this study.

1.5.1. Chapter 1: Introduction

- It provides an overview of the research problem, objectives, and the significance of the study.
- It sets the stage for the subsequent chapters by outlining the gaps in the current sleep EEG analysis and sleep stage classification methods.

1.5.2. Chapter 2: Literature Review & Methodology

- It facilitates a thorough review of the existing literature and research about time frequency signal analysis, sleep EEG signal analysis, sleep stage classification criteria, and related methodologies.

- It provides a broad understanding of the current state of the sleep EEG fields, highlighting the limitations and challenges in manual scoring and automated approaches.
- It lays a foundation for subsequent chapters by identifying research gaps and establishing the need for innovative multi-method approaches.
- It presents the relevant techniques employed in this thesis, including the description of the MT&C method, the MP method, and others.
- It discusses EEG pre-processing steps, feature extraction methods, and the integration of several machine learning and deep learning techniques such as convolutional neural networks, recurrent neural networks, feedforward neural networks.
- It details the implementation and experimental setup to evaluate the proposed methods.

1.5.3. Chapter 3: Sleep EEG Analysis and Sleep Stage Classification

- It emphasises developing and evaluating the MT&C method for EEG analysis and sleep stage classification.
- It proposes two methods to classify sleep stages, one is a state-of-the-art that uses the parameters from the R&K rules and the standards from the AASM, and the other is the SVM machine learning method.
- It evaluates the experimental results, including accuracy rate and performance metrics and compares them with some existing methods.
- It highlights the significance of the findings for improving the accuracy, efficiency, and objectivity of sleep stage classification.

1.5.4. Chapter 4: Sleep Spindle Identification

- It implements the identification of spindles in different EEG channels and combines them to propose the SAMC method for sleep spindle identification and categorisation.
- It presents the experimental results, including the agreement rate, positive predictive value, and sensitivity of the proposed method compared to other approaches.
- It discusses the implications of the findings for understanding the characteristics and distribution of sleep spindles across different cortical areas.
- It highlights and demonstrates the limitations of current manual scoring and their implication on automated methods, postulating a need to implement a

collaborative classification validation to improve further accuracy on manual and automatic scoring.

1.5.5. Chapter 5: Advanced Time-Frequency Analysis in Alliance with Deep Learning for Sleep Stage Classification

- It investigates the integration of advanced time-frequency analysis techniques and deep learning models for sleep stage classification.
- It describes implementing these techniques, including feature extraction methods, model architectures, and training procedures.
- It presents the experimental results, showcasing the performance improvements in sleep stage classification, and compares them with current studies.

1.5.6. Chapter 6: Discussing and Conclusion

- It summarises the key findings from each chapter and discusses their implications.
- It analyses and interprets the results, addressing the research questions and objectives.
- It offers insights into the limitations of the proposed approaches, potential work for future research, and practical implications of the research outcomes.

The following diagram shows the thesis and chapters workflow:

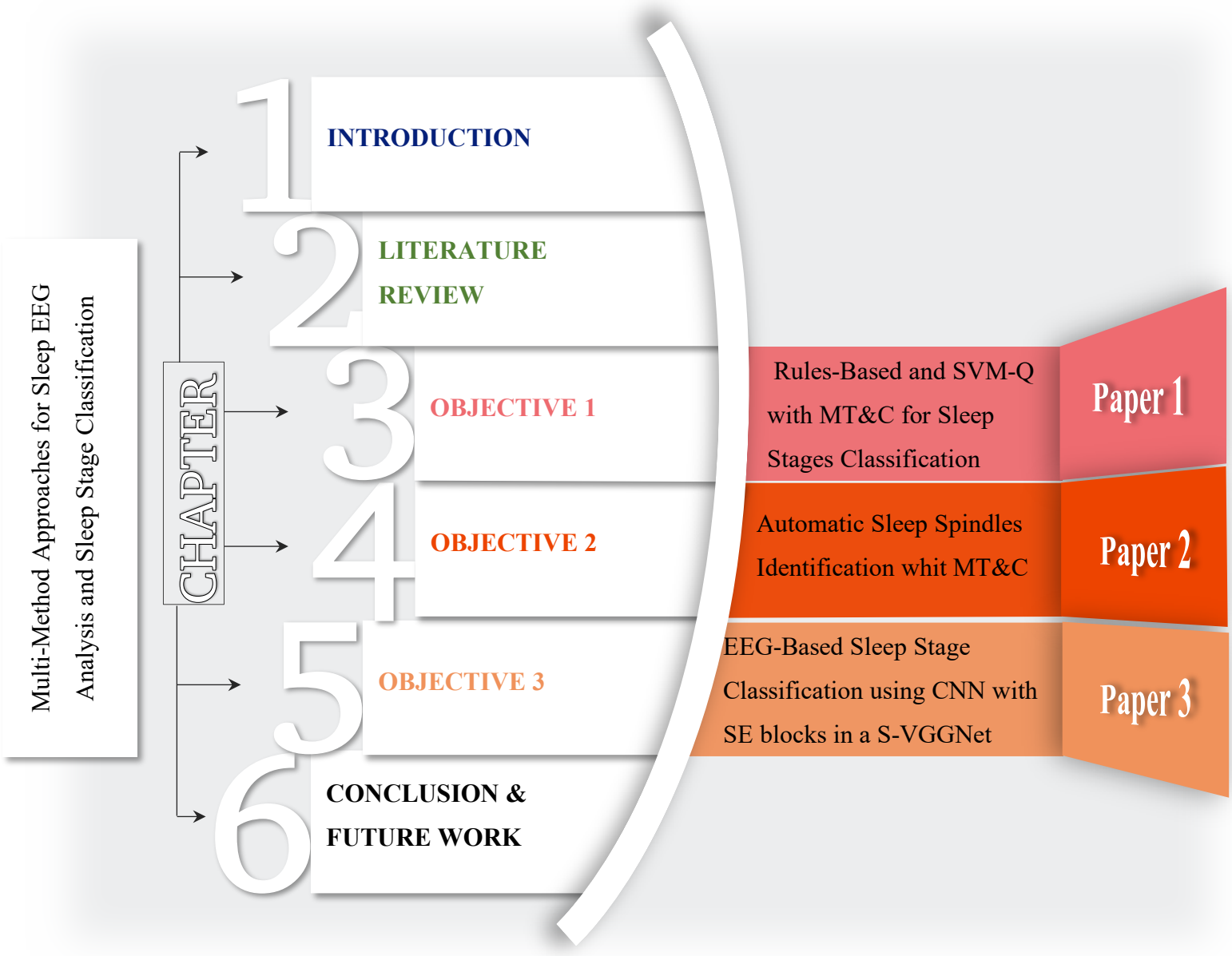

Figure 1.1.5-1: Thesis Flowchart

Examining the connection between the chapters makes it evident that each chapter builds upon the previous one, establishing a cohesive narrative that addresses the proposed research problem from multiple angles. The subsequent chapters delve into specific aspects of the sleep EEG analysis, implementation of machine learning for stage classification, spindle identification, and integration of signal analysis with a deep learning method to classify sleep stages. Conclusively, the discussions and the conclusion chapter synthesise the findings, highlighting their significance and

providing a road map for future research. These chapters constitute a comprehensive and integrated exploration of multi-method approaches for sleep EEG analysis and sleep stage classification, contributing to the advancements in the field and enhancing our understanding of sleep-related phenomena.

CHAPTER 2

LITERATURE REVIEW

This chapter comprehensively reviews the existing literature on sleep, sleep EEG, sleep stages, sleep characteristics, time-frequency signal analysis, sleep stage classification, machine learning, deep learning, and related methodologies. Its primary aim is to establish a strong foundation for the subsequent chapters by synthesising prior research, identifying gaps in knowledge, and advocating for adopting innovative multi-method approaches in this field.

This chapter is organised into five sections. Section 2.1 delves deeply into the concept of sleep, encompassing its characteristics, sleep physiology, stages, sleep EEG, and relevant technical aspects, such as basic montages, rhythms, noise, and EEG signal pre-processing. Continuing the exploration, Section 2.2 presents a comprehensive overview of time-frequency signal analysis, specifically focusing on the implementation and suitability of the MP and MT&C methods for analysing EEG data.

Lastly, Section 2.3 critically examines various sleep stage classification methods while shedding light on the limitations of the existing approaches that rely on black-box techniques. Furthermore, it explores the most promising machine and deep learning methods for feature extraction and classification, aiming to enhance accuracy, efficiency, and other essential capabilities for analysing sleep EEG signals.

2.1. Sleep, Sleep EEG and EEG Signal Pre-processing

This section delves into the absorbing world of sleep, sleep EEG, EEG signal noise and EEG signal pre-processing to unravel the mysteries and lay the foundations of a deeper understanding of sleep and sleep EEG. The sleep EEG, which records electrical brain activity during sleep, holds valuable insights into the intricacies of sleep patterns. This section starts by examining the fundamentals of sleep, understanding its significance in analysing sleep stages and unwavering sleep characteristics. Subsequently, this section embarks on a journey into the realm of sleep EEG signal pre-processing and its

significance, where it uncovers the methodologies and techniques employed to enhance the quality and interpretability of EEG data.

2.1.1. Sleep: Functions, Mechanisms, and Adaptations

Before delving into the world of sleep EEG and the valuable insights it offers into the brain's electrical activity during sleep, it is essential to comprehend sleep physiology, its functions, mechanisms, adaptations, and elements that could cause adverse effects on it. This section dives into the fundamental aspects of human sleep, encompassing its vital functions, underlying mechanisms, remarkable adaptations that play a crucial role in overall human well-being, and the adverse sleep-affecting elements.

2.1.1.1. Sleep

Sleep plays a fundamental role in humans' mental and physical health. The quantity and quality of sleep are essential for almost every aspect of the physiological system. Its significance goes further than the physiological, having significant relevance in the cognitive and emotional processes, directly influencing analytical performance and overall health (Berry & Wagner, 2015; Y. Liu et al., 2016).

From the cognitive standpoint, sleep is vital for memory consolidation, information processing and synaptic plasticity. Sleep directly impacts the brain's ability to adapt and recognise its neural connections in response to experience, learning and environmental stimuli. It aids in organising and solidifying newly acquired knowledge, facilitating critical thinking abilities, and enabling problem-solving. Additionally, sleep fosters emotional regulation and psychological stability, enabling individuals to manage stress and maintain a stable state of mind (Baranwal et al., 2023; Berry & Wagner, 2015; Institute of Medicine (US) & Committee on Sleep Medicine and Research, 2006).

Regarding the role of sleep in human physical health, sleep significantly influences circulatory health, neural system, immunity, reproductive health, and hormone regulation, among many others. Sufficient and qualitative sleep supports physiological rejuvenation, enhancing physical stamina and vitality, and wires the body's immune response, protecting against illnesses and facilitating prompt recovery from daily draining routines. A regular sleep schedule improves the conservation of the biological clocks, reduces sleepiness during the day, and permits subjects to wake up and fall asleep more easily (Baranwal et al., 2023).

2.1.1.2. Sleep Physiology

The sleep-wake cycle, also known as the circadian rhythm, is created by the central neural networks and regulated by complex relationships of neural and hormonal factors. The transit from awake to sleep and its stability involves inhibiting ascending arousal systems that stimulate wakefulness. The suprachiasmatic nucleus (SCN) (Figure 2.1.1) is between the optic chiasm and the hypothalamus. It serves as the body's biological clock, coordinating the timing of various biological processes, including sleep and wakefulness. The circadian clock is driven by endogenous physical oscillations, with cycles of approximately 24 hours, where external cues such as light and darkness synchronise the SCN, helping to maintain a regular sleep schedule (Baranwal et al., 2023; Berry & Wagner, 2015; Y. Liu et al., 2016).

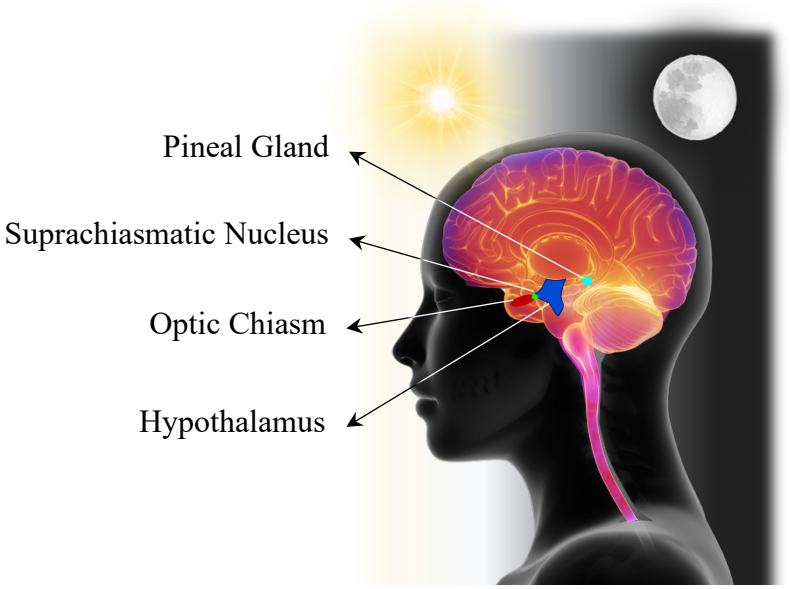

Figure 2.1.1: Suprachiasmatic nucleus & biological clock.

The retina detects the light signals and transfers them as electrical impulses through the optic chiasm to the brain, signifying daylight. The reception of light activates the production of the hormone Cortisol, which stimulates its production in the early hours of the day. Conversely, low light inputs trigger melatonin secretion by the pineal gland or the hormone of darkness. In normal cases, melatonin levels rise in the evenings and peak in the early morning, impacting sleep regulatory mechanisms (Baranwal et al., 2023; Berry & Wagner, 2015; Y. Liu et al., 2016).

Humans cycle through different sleep stages throughout the night, each with unique characteristics and physiological components. The stages go from wakefulness through non-rapid eye movement (NREM) to REM.

NREM sleep is divided into three sub-stages: stage 1 (S1), stage 2 (S2) and stage 3 (S3). S1 is a state of drowsiness, meaning that the subject is transitioning between wakefulness to sleep, and theta waves characterise it. S2 is a middle stage characterised by constant spindles and k-complexes events. S3, or slow-wave-sleep (SWS), is considered the deepest stage of sleep, and slow delta waves govern it (Antony et al., 2018; Armitage, 1995; Baranwal et al., 2023; Fogel & Smith, 2011; Koupparis et al., 2013; Schönauer & Pöhlchen, 2018).

Rapid eye movements, desynchronisation of brainwaves activity that resembles wakefulness and vivid dreaming characterise REM sleep. This paradoxical state is where the brain becomes highly active, and the muscles experience temporary paralysis to prevent individuals from acting out their dreaming (Armitage, 1995; Baranwal et al., 2023).

Sleep regulation involves the interaction of neurotransmitters (Figure 2.1.2) like acetylcholine, serotonin, and norepinephrine, critical in transitioning between wakefulness and sleep stages.

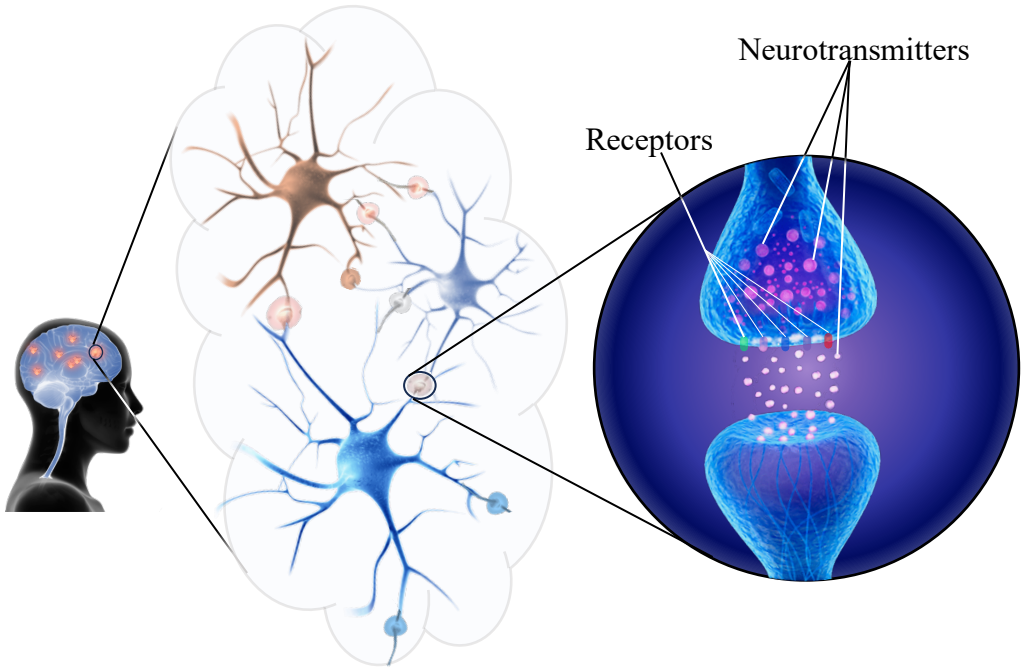

Figure 2.1.2: Connections between neurons and neurotransmitters.

Moreover, melatonin, a hormone produced by the pineal gland (in Figure 2.1.1), is induced in response to darkness, producing feelings of sleepiness and assisting in regulating the sleep-wake cycle (Baranwal et al., 2023).

Sleep deprivation triggers sleep homeostasis or driver, a regulatory mechanism that helps maintain the balance between sleep and wakefulness. It ensures that the body

obtains the right amount of rest needed for optimal functioning. The concept of sleep homeostasis is based on the idea that the longer the individual stays awake, the greater the need for sleep becomes (Baranwal et al., 2023).

Sleep is far from being a passive state of rest. Instead, while sleeping, the brain and the neurons remain highly active, carrying out vital functions such as cellular reparation, immune system strengthening, and memory consolidation. As a result, sleep holds enormous significance for cognitive functions and learning, as it promotes synaptic plasticity in the brain and consolidation of information.

Sleep serves diverse functions, including physiological and cognitive restoration, memory consolidation, brain plasticity, and hormone regulation. Its mechanisms involve complex integrations between neurotransmitter systems, circadian rhythm, and sleep homeostasis. During human life, sleep has undergone adaptations now embedded in the genes, providing unique advantages for survival and well-being. Understanding the functions, mechanisms, and adaptations of sleep enhances the appreciation for this essential aspect of life and its profound impact on health and cognitive function.

2.1.1.3. Causes and Consequences of Sleep Deficiency

Different external factors can influence sleep physiology, including environmental factors such as noise, temperature, and light exposure (Dimitriou et al., 2015; Xu et al., 2021). These factors can potentially disrupt sleep quality and unsettle the body's biological clock. Lifestyle choices, such as caffeine consumption (Brice and Smith 2002; O'Callaghan, Muurlink, and Reid 2018), irregular sleep schedules (Sack et al., 2007), and excessive use of electronic devices before bedtime (Hale & Guan, 2015; Kato et al., 2018; Twenge et al., 2019), can also impact sleep. Furthermore, medications (Doghramji & Jangro, 2016; Liguori et al., 2021), medical conditions (Lewandowski et al., 2011; Phillips et al., 2008), and mental health disorders (Freeman et al., 2020; Mulyadi et al., 2021) may play a role in influencing both duration and quality of sleep. The health and lifestyle of individuals rule the duration and intensity of each sleep stage. For instance, age, diet, and vices or bad habits are highly correlated with sleep quality. In the case of age, it has been reported that the REM stage is highly predominant in newborns, while it tends to shorten in older adults (Al-Jumeily et al., 2015; Bazil & Walczak, 1997; Edwards et al., 2010; Elobeid et al., 2012; Goldberger, 2000; Rajbhandari et al., 2021; Shen et al., 2023; Vitiello et al., 2004; Ye et al., 2020).

Similarly, several studies indicate that high-carbohydrate diets could reduce sleep onset latency (SOL) and SWS while increasing the REM stage. At the same time, high-fat

diets reduce sleep efficiency and REM and increase SWS and arousal (St-Onge et al., 2016).

As for the lifestyle of individuals, several studies implied that the consumption of tobacco, caffeine, alcohol, and certain medications are associated with a high prevalence of insomnia and many other health issues (Brice and Smith 2002; Doghramji and Jangro 2016; Hussain et al., 2022; Liguori et al., 2021; O'Callaghan et al., 2018).

Sleep deficiency, which includes insufficient or excessive sleep, disordered breathing while sleeping, and insomnia, is connected to an elevated probability of insulin resistance and a predominant risk of developing diabetes mellitus. Similarly, acute sleep restriction, in the long run, could impact growth and muscle repair. Sleep disorders can also lead to the central suspension of testosterone, generating sexual dysfunction. Likewise, sleep fragmentation alters the balance of ghrelin and leptin hormones that stimulate hunger and satiety, causing unhealthy eating patterns and adverse health effects (Baranwal et al., 2023).

During normal sleep cycles, the cardiovascular (CV) system steps into resting mode, the heart rate slows down, and the blood pressure dips, shifting from a sympathetic tone to a more relaxed pitch. Abnormal sleep patterns increase the automatic activity stress of the CV system, growing the likelihood of hypertension, cardiac arrhythmia, endothelial dysfunction, coronary artery disease, stroke, and myocardial infarction (Baranwal et al., 2023; Dettoni et al., 2012; Lavie, 2008; X. Li et al., 2021; Rajbhandari et al., 2021).

Sleep and the immune system have a bidirectional relationship, as sickness can disrupt sleep, altering its duration and intensity, and sleep enhances the immune system. Sleep loss and disturbances reduce natural killer cell activity and antibody production, increasing infections and potential cancer risks. Additionally, sleep deprivation leads to the release of inflammatory cytokines, elevating the risk of cardiovascular and metabolic disorders. In the same way, insomnia has been associated with a decrement in post-influenza vaccine antibodies, and shorter sleep duration increases susceptibility to upper respiratory infection (Baranwal et al., 2023; Dettoni et al., 2012; Prerau et al., 2017).

The glymphatic system, active during sleep, removes waste proteins from the brain, and the disruption of this system could contribute to neurodegenerative conditions like Alzheimer's. Sleep plays a crucial role in memory consolidation, enhancing long-term storage and enabling the formation of new associations. Moreover, sleep disorders like

insomnia increase the risk of depression, addictions, and anxiety (Baranwal et al., 2023).

In addition to the conditions already mentioned resulting from sleep deficiency, bad habits, and inadequate nutrition, numerous other physiological systems are impacted, extending influence over sleep quality (Baranwal et al., 2023; Boostani et al., 2017; Minecan et al., 2002).

Neurophysiological technologies such as EEG facilitate comprehensive brain behaviour data acquisition. This information has been instrumental in unveiling novel insights and enriching the comprehension of neuronal interactions during diverse human activities (Aboalayon et al., 2016b; Emmady & Anilkumar, 2023; Feinberg et al., 1969; Fernandez Guerrero & Achermann, 2019).

2.1.1.4. Sleep Architecture

Sleep architecture refers to the structure characterised by a rhythmic cyclin process that alternates from the three sub-stages in the NREM and the REM stage Figure 2.1.3. The complete sleep architecture has neuronal restorative benefits, and its disruption could cause significant consequences. The optimum sleep architecture of a night sleep has between four and five sleep cycles, each of approximately 90 minutes. The sleep cycle starts with S1, transitioning smoothly into S2 and S3, and finalising in the REM stage. During the first half of sleep, the SWS stage is predominant. While in the second half, the REM stage prevails (Zieleniewska et al., 2019).

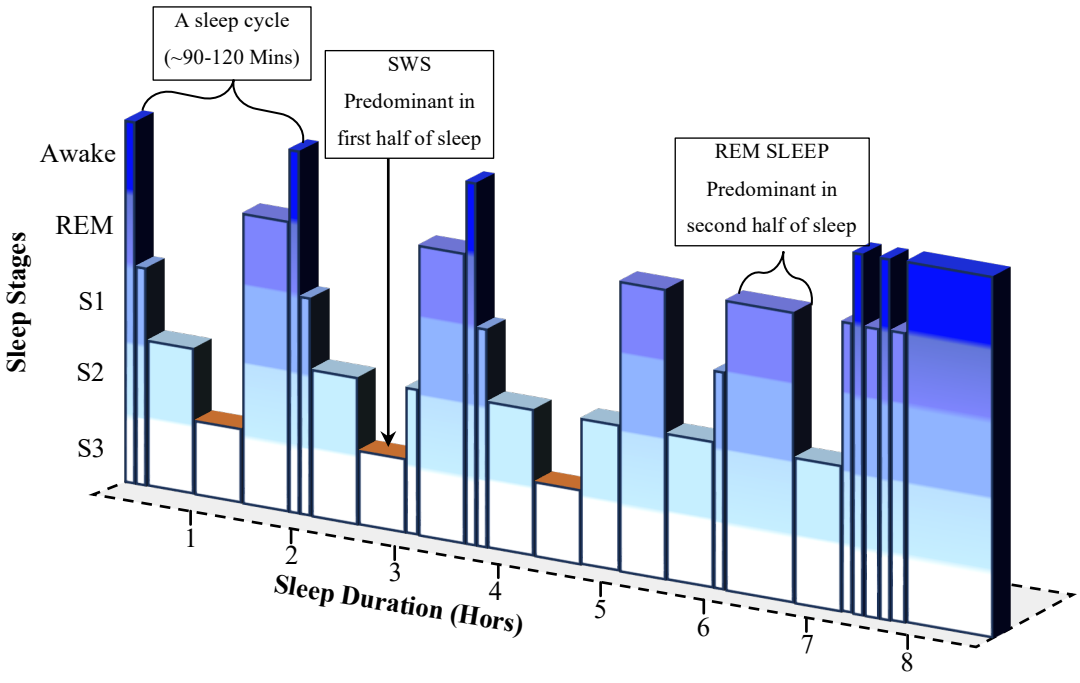

Figure 2.1.3: A normal night sleep structure.

Each sleep stage plays specific functions in the brain, and their interaction and cyclic patterns contribute to achieving optimum sleep (Baranwal et al., 2023; Chokroverty and Thomas 2014; Limoges et al., 2005; Malhotra and Avidan 2014; O'Reilly et al., 2014; Terzano et al., 2001).

2.1.1.4.1. Wake Stage

The initial minutes in a typical EEG recording often consist of wake (W) stage patterns. During a relaxed wake stage, the EEG will exhibit alpha activity, comprising more than 50% of the epoch. When the subject relaxes and alternates opening and closing their eyes, the EEG will display a combination of beta and alpha activities, or predominantly alpha, if the eyes remain closed. Additionally, the electromyography (EMG) data, which supplements the PSG examination, will reveal high muscle tone with large amplitudes caused by muscle contractions and artifacts. Similarly, the electrooculogram (EOG), also part of the PSG, will show abrupt changes indicating eye blinking and rapid eye movement. As the subject further relaxes, entering an early drowsy state with closed eyes, the alpha activity will become more pronounced, and the EMG and EOG signals will shift to a subdued state. The movement of subjects or rolling in bed is also reflected in the EOG data, as paroxysmal events have high-amplitude activity and increased artifacts. Transitioning from the W stage, subjects usually proceed to S1 Stage but may occasionally enter REM sleep or stage S2 directly, particularly under pathological conditions of sleep deprivation (Chokroverty & Thomas, 2014; Malhotra & Avidan, 2014; Terzano et al., 2001).

2.1.1.4.2. Sleep Stage 1

Stage 1 (S1) is the lightest among all sleep stages and represents a transition from wakefulness to stage 2 (S2). It constitutes approximately 5% of total nocturnal sleep. The EEG patterns in the S1 stage are characterised by low voltage and fast EEG activity. However, sometimes those patterns pose challenges in the identification of this stage. Scoring the S1 stage typically occurs when more than half of the epoch exhibits theta activities (4-7 Hertz (Hz)), interspersed with low beta activity amplitudes. The power of beta activity in S1 is generated below 75 microvolts (μV), although brief bursts of theta activity with amplitudes lower than 75 μV may also occur. The percentage of alpha activity in the S1 stage is usually less than 50%. In the later stages of S1, it is possible to find vertex sharp waves (VSWs). However, sleep spindles, k-complexes and rapid eye movement are never components of this stage. The VSWs are occasionally found as a characteristic feature in the last epochs of the S1. These localised paroxysmal

waves, with frequencies between 3 to 6Hz, exhibit high-negative voltage with a sharp surface, followed by a positive component generated over the Cz electrode (Baranwal et al., 2023; Rodenbeck et al., 2006).

Arousals, also characteristic of the S1 stage, are abrupt paroxysms of brain activity that can last between 10% to 50% of the epoch duration. When the duration of these arousals exceeds 50%, the epoch is scored as W. Physiologically, during the S1 stage, the breathing becomes shallow, the heart rate becomes regular, the blood pressure decreases, and the subject exhibits minimal body movement. The S1 is characterised by a levitating sensation, a wandering mind, and dreams changing from reality to illusions (Baranwal et al., 2023).

2.1.1.4.3. Sleep Stage 2

Stage 2 (S2), or intermediate sleep, is one of the most predominant stages comprising of around 50% of a night's sleep, especially in adult subjects. It is characterised by a predominant activity of theta waves, with irregular surges of faster activity. The alpha activity evidenced in the EEG is minimal, and the amplitude could erupt from time to time, as the one seen in S1. The delta activity in S2 must be less than 20% of the epoch. Otherwise, the stage is scored as S3. Spindles and the k-complexes are the primary characteristics of S2, and during its early events, they are usually sporadic (Baranwal et al., 2023; Chokroverty & Thomas, 2014).

Spindles, recognised for being a symmetric synchronised sinusoidal EEG activity localised on the central vertex region with frequencies between 8 and 16Hz, could last from 0.5 seconds to 2 seconds. Spindles usually have an occasional activity in ordinary cases. However, it could change in subjects treated with depressant drugs, increasing the activity of spindles (Bandarabadi et al., 2020; Caspary et al., 1996; Chokroverty & Thomas, 2014; Clawson et al., 2016; Cox et al., 2017; Devuyst et al., 2011; M. A. Kramer et al., 2021; Lafortune et al., 2014; Tsanas & Clifford, 2015; Warby et al., 2014).

K-complexes, sharply polyphasic or monophasic slow waves with a high-pitched negative deflection with a smaller positive deflection, stand out from the other waves. K-complexes are predominantly localised on the central vertex, and their duration should last at least half a second (Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

There are two types of k-complexes spontaneous and evoked. The spontaneous k-complexes arise from unidentified circumstances or endogenous brain activity, and the

evoked k-complexes are triggered by external stimuli such as noise. The k-alpha complexes are a variation of ether spontaneous and evoke k-complexes, and the simultaneous occurrences of ether k-complexes and alpha waves characterise them.

Regular patterns for scoring S2 in the EEG are low k-complexes incidences and high amplitude of spindle activity. In the case of EOG and EMG activity, there is no defined criterion for S2 (Baranwal et al., 2023; Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

Arousals from S2 could lead to a default S1 or W stage, so if the EEG alpha activity persists for less than 50% of the epoch, it is scored as S1, and if the alpha activity persists for over 50%, it is scored as W. However, when the first half of the following epoch exhibits S2 features like spindles, k-complexes or high-amplitude of theta or delta activity, it is scored as S2 (Baranwal et al., 2023).

During S2 sleep, various physiological functions dimmish, including blood pressure, gastrointestinal secretions, brain metabolism, and cardiac activity, and as the subject descends deeper into sleep, they become more disconnected from the external world and progressively harder to awake (Baranwal et al., 2023; Chokroverty & Thomas, 2014; Malhotra & Avidan, 2014; Terzano et al., 2001).

2.1.1.4.4. Sleep Stage 3

The SWS or sleep stage 3 (S3) comprises sub-sections R and K. However, they are collected on a single stage as their distinction does not have a clear clinical significance. The S3 is characterised by synchronised high-amplitude slow waves with frequencies between 0.5 to 5 Hz (delta waves). S3 is usually between S2 and REM, covering approximately 20% of the total sleep time in healthy subjects. The physiological aspect of S3 is distinguished by having the highest threshold for arousal, and subjects experience parasomnias and diffuse dreaming. The eyes cease their movement entirely, and the hormone secretion peaks. Similarly, to S2, there are no defined criteria for scoring S3 regarding the EOG and EMG activity (Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Kemp et al., 2000; Rodenbeck et al., 2006).

When a subject is suddenly woken up from S3, they can experience sleep inertia which is disorientation or confusion, and it can last for several minutes, invalidating the subject from normal functioning and rational thinking. The sleep inertia events could increase in exceptional cases when a subject suffers from sleep deprivation or is prescribed central nervous system medication (Baranwal et al., 2023; Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

The scoring of S2 has several characteristics. First, it must contain a delta wave dominance between 20% and 50% of the epoch with high amplitude in the patterns of sawtooth waves. Second, the eyes must be inactive, and the muscle tone must significantly reduce compared to other stages. Moreover, while sleep spindles and k-complexes are common characteristics of S2, their presence may occur in S3 with a clear presence of delta activity (Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

2.1.1.4.5. REM Stage

The paradoxical sleep stage or REM typically appears around 90 to 120 minutes after sleep onset in adults. REM in the early stages of sleep is brief, but its prevalence intensifies as the night progress, exhibiting its dominance and robustness. Comprising approximately 20 to 25% of the total sleep duration, the REM stage is distinguished by low-amplitude brain waves exhibiting a mixture of frequencies between delta and alpha waves. The brain waves during this stage exhibit small and irregular patterns, often accompanied by pronounced bursts of eye movement, which are detected in the EOG activity (Baranwal et al., 2023; Berry & Wagner, 2015; Chokroverty & Thomas, 2014). In contrast to the physiological activity in the NREM stages, REM is characterised by increased blood pressure and pulse, which could occasionally fluctuate. Furthermore, the breathing becomes irregular, the oxygenation of the brain increases, and the sexual sensorial organs of the subject may become aroused or stimulated. In the REM stage, the body temperature regulation ceases, gradually drifting into the environment temperature.

In the cases of acute sleep deprivation, consumption of antidepressants, or the presence of a pathological condition such as narcolepsy-catalepsy syndrome, the REM stage could experience abrupt termination, resulting in a short latency period. Additionally, various disorders related to REM sleep, including obstructive sleep apnea and parasomnias, may become more pronounced during this specific period.

The scoring of the REM stage is based on the low amplitudes and mixed frequencies evidenced on the EEG. Moreover, the EOG exhibits dynamic activity characterised by active rapid eye movements, while the EMG signal indicates a low chin tone. Notably, the absence of rapid eye movement does not necessarily signify REM's start or end. Instead, if the EEG continues exhibiting low amplitude and mixed frequencies without k-complexes or sleep spindles, and a low chin tone, the subsequent stages can still be classified as REM. The eye movement in REM resembles the eye patterns of an awake subject with eyes open, making the EMG signals crucial for distinguishing the REM

stage. Specifically, the chin tone of an awake subject is typically high, in contrast to the low-chin tone observed during REM stage sleep (Baranwal et al., 2023; Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

In the REM stage, the observed wave patterns typically fall within the frequency range of 2Hz to 6Hz and exhibit a sawtooth appearance. However, the exact amplitude characteristics of these waves remain undefined. On occasions, the chin and limb EMG activity could evidence irregular short bursts denominated transient muscle activity, but they cannot surpass 0.25 seconds (Chokroverty & Thomas, 2014).

Abnormal REM sleep disorder, characterised by the notable absence of normal REM sleep atonia or muscle paralysis, may cause injuries and sleep disruption in subjects, as subjects end up acting out their dreaming. Some REM sleep stages can be classified into phasic or tonic. The phasic REM, which has a high correlation with dreaming, is characterised by an intermittent and brief muscle contraction or phasic twitching of the facial and genioglossal muscles and the middle ear muscle. This type of REM also presents the arousal of sexual sensorial organs (Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

The tonic REM, distinguished by a significant reduction of the EMG activity in the skeletal muscles and the absence of EOG activity, is usually associated with EEG patterns that show low voltage activations. This type of REM seems to be influenced by the locus coeruleus (Chokroverty & Thomas, 2014).

The scoring of the REM stage will continue until sufficient variations in the EOG, EMG and EEG signal exist, evidencing any other sleep stage. For instance, if the epoch meets the criteria for S1 or W, it will be assigned accordingly. Additionally, if k-complexes or sleep spindles are observed in the first half of the epoch, and rapid eye movement is not detected, the epoch will be scored as S2, even if the chin muscle tone is low (Baranwal et al., 2023; Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

2.1.2. Sleep EEG

Sleep EEG is a widely used technique for studying the brain's electrical activity during sleep. This technique was first used in 1930 to measure brain waves during sleep by Loomis, who a few years later published a study about the potentials in the human brain during sleep (Loomis AL et al., 1935). That preliminary research proposed a set of markers that showed the patterns of sleep and awake subjects. However, it was only in 1968 that the R&K (Rechtschaffen & Kales, 1968) rules were established as a standard guideline for visual sleep stage scoring. A decade later, the AASM slightly modified

these guidelines from R&K rules. Since then, the research community has embraced and refined both principles (Berry et al., 2017; Danker-Hopfer et al., 2009; Grigg-Damberger, 2012; Moser et al., 2009; Novelli et al., 2010; Rosenberg & Van Hout, 2013; Ruehland et al., 2011; Tzimourta et al., 2018).

2.1.2.1. EEG Monitoring

Several types of EEG montages are used to capture specific aspects of brain activity and aid in EEG data analysis. However, the electrodes used for activity monitoring and sleep stage classification comprise only a portion commonly employed in clinical EEG monitoring.

The montage of the EEG technique involves placing electrodes on the scalp to detect and capture the voltage fluctuations resulting from the interaction of neurons. These voltage measurements offer valuable insights of the subject's brain physiology (Berry & Wagner, 2015).

One of the main objectives of the EEG recordings is to identify wakefulness and the various sleep stages. The AASM guidelines (Rosenberg & Van Hout, 2013) advise the use of a minimum of four electrodes: right-frontal (F4), right-central (C4), right-occipital (O2), and contralateral left-mastoid (M1). These electrodes are combined to form bipolar channels F4-M1, C4-M1 and O2-M1. In addition to these four electrodes, backup electrodes are advised on the left side of the head, including left-frontal (F3), left-central (C3), left-occipital (O1), and contralateral right-mastoid (M2), as seen in Figure 2.1.4.

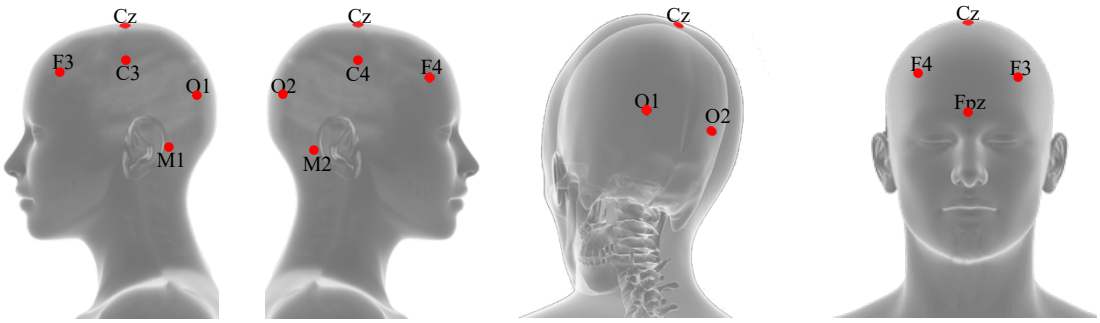

Figure 2.1.4: Basic EEG Electrodes for sleep monitoring. C: Central; F: Frontal; O: Occipital; M: Mastoid; Cz: Central midline (vertex); Fpz: Frontopolar midline.

Despite the theoretical sufficiency of the mentioned montage for detecting a posterior dominant rhythm during wakefulness and the primary sleep architecture, it exhibits significant limitations in adhering to the minimum prescribed montage. Also, limiting the EEG recording to only one hemisphere can be impaired due to localised brain

lesions or misconnections of electrodes. This approach could also fail to detect pathological conditions, especially if the contralateral hemisphere is affected.

The standard montage system to record EEG activity is the international 10-20 system. It refers to the standard approach to locate electrodes on the scalp, which is determined based on the distance of neighbour electrodes, as seen in Figure 2.1.5.

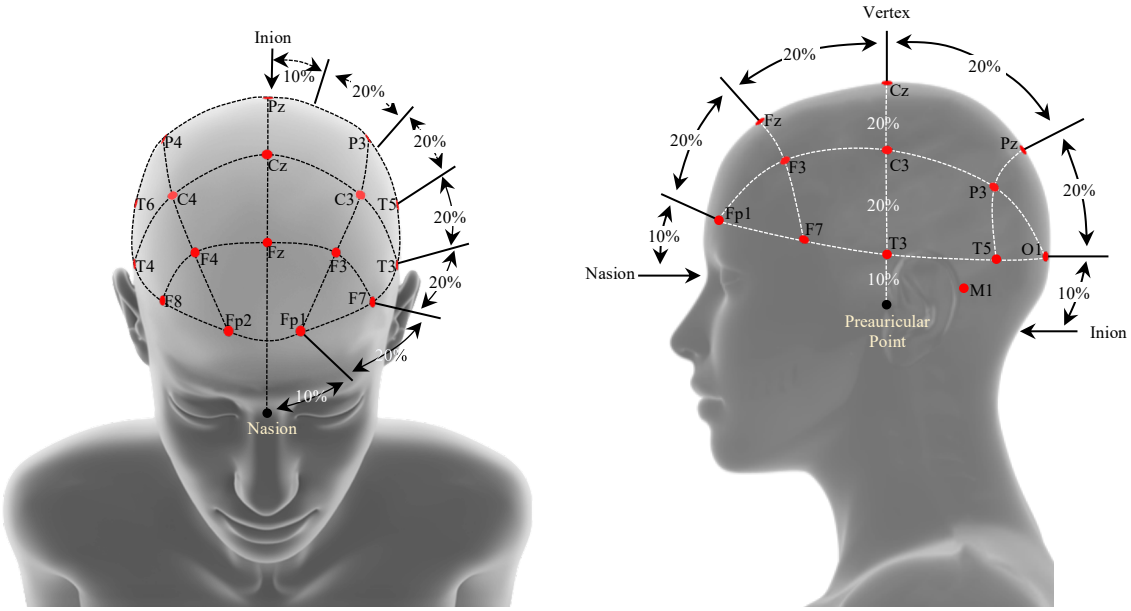

Figure 2.1.5: 10-20 montage international system.

The nomenclature of the electrodes is determined by their specific placement on the scalp, where designations such as F (frontal), T (temporal), C (central), P (parietal) and O (Occipital) are employed. Under the 10-20 international system, even-numbered subscripts denote electrodes on the right side of the head, while odd-numbered subscripts correspond to those on the left side. The central electrodes positioned at the vertex, dividing the two brain hemispheres, are labelled with letters representing the scalp region and the subscript "z". The 10-20 international system also incorporates two additional electrodes at the earlobe region, denoted as M1 and M2 or A1 and A2 in the AASM guidelines (Berry et al., 2017; Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Grigg-Damberger, 2012; Malhotra & Avidan, 2014; Moser et al., 2009; Novelli et al., 2010; Parrino et al., 2009; Ruehland et al., 2011; Siuly et al., 2010; Siuly & Li, 2015).

2.1.2.2. EEG Channels

The methodologies implemented in EEG alternating current (AC) amplifiers differ across montages and electrodes. These AC are implemented to amplify the voltage

variations among electrodes, allowing low-voltage recordings to be superimposed over high-voltage electrical noise (Berry, 2012).

The EEG channels, also known as derivations, represent the voltage difference between two electrodes, and their standard convention is based on the resultant upward deflection of the voltage changes. It is essential to note that some channels, such as the airflow and chest effort, may not pertain to electrical currents (Berry, 2012; Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Rodenbeck et al., 2006).

According to the AASM standard, the recommended EEG derivations and backup derivations for sleep staging are presented in Table 2.1.2. The backup channels replace potential misreading or problematic channels (Berry, 2012; Berry & Wagner, 2015; Chokroverty & Thomas, 2014).

In addition to EEG data, EOG signals often included in a recording can offer valuable insights for sleep stage scoring. EOG data are considered to originate from the cornea

Table 2.1.2: EEG derivations recommended for sleep stages.

RECOMMENDED EEG DERIVATIONS

Recommended Main Derivations	Recommended Backup
F4-A1	F3-A2
C4-A1	C3-A2
O2-A1	O1-A2

and the retina sections of the eyeballs. While a positive current is attributed to the cornea, a negative current is associated with the retina, and the collected data are based on the potential differences between them. The electrodes used to collect the EOGs are positioned in close proximity to the eyes, and they are subscripted as E1 or LOC for the left eye and E2 or ROC for the right. The E1 electrode is placed below the left outer canthus, whereas the E2 is placed above the right outer canthus. The purpose of these opposite placements is to capture both vertical and horizontal movements, enhancing the assessment of sleep stages (Baranwal et al., 2023; Berry, 2012; Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Rosado Coelho et al., 2018; Tzimourta et al., 2018).

The AASM recommended using E1-A2 and E2-A2 as the appropriated EOG derivations, with both employing the right mastoid (A2) as the reference electrode. These derivations allow the identification of artifacts or EEG activity transmitted to the EOGs, resulting in in-phase deflections, as seen in the diagram in Figure 2.1.6, at the second of 5-6 (k-complex). Conversely, eye movement often generates out-of-phase deflection in the EOG channels, which usually is not reflected in the EEGs, as seen in the diagram shown in Figure 2.1.6, at the second of 2-3 (eye-moving during the REM

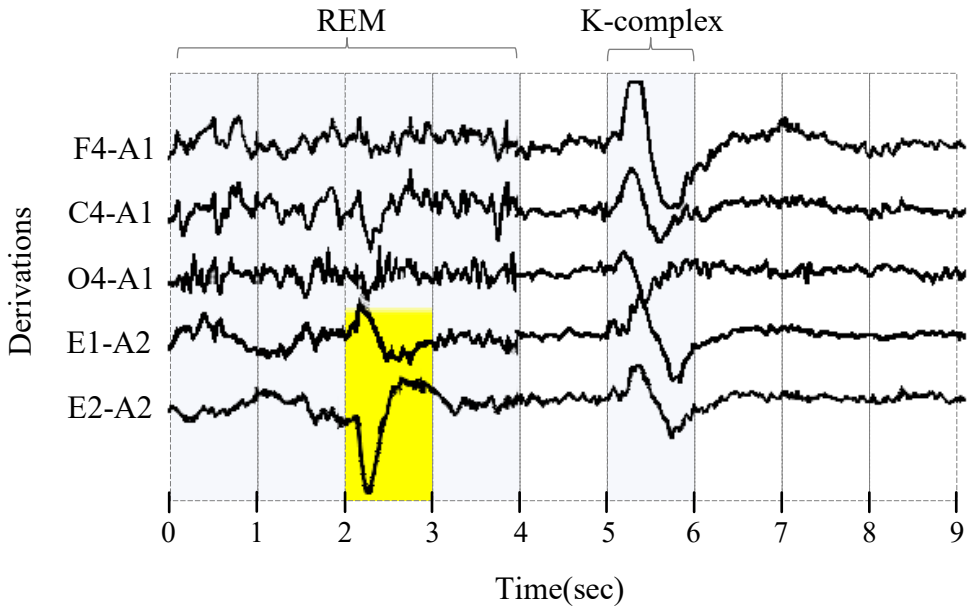

Figure 2.1.6: EEG deflections reflected on the EOG (K-complex at the second of 5-6), and EOG deflection sat the second of 2-3.

stage highlighted in yellow).

Other recorded data that are highly advised to include in the EEG monitoring for REM sleep staging is the EMG. EMG data are from a set of electrodes that monitor the activity of the chin muscles. During REM, the muscle activity in this specific area significantly diminishes. Its amplitude diminishes to the extent that it could reach the lowest amplitude activity observed in the NREM stages, or even lower. However, the EMG data are not used to identify the transition from NREM to REM, as in many cases, EMG activity could reach the REM levels during NREM well before the transition occurs (Baranwal et al., 2023; Berry, 2012; Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Rodenbeck et al., 2006).

2.1.2.3. EEG Wave Forms Related to Sleep Stages

Identifying distinctive characteristics in the EEG and establishing their correlation with sleep patterns are fundamental for sleep staging. The activity within the EEG data can be characterised by its frequency, amplitude, and shape. Signals that exhibit clear

distinctions in frequency and amplitude are often referred to as electric rhythmic signals, whereas those displaying specific characteristics in their shape are termed wave transients.

2.1.2.3.1. Rhythmic Signals

Rhythmic signals are associated with the sleep stages based on their respective proportions of appearance, and they play an essential role determining sleep transitions and scoring. Gaining insights into these waveforms is crucial for accurately classifying sleep stages and identifying abnormal patterns stemming from sleep deprivation or medical conditions. The EEG recordings typically encompass several predominant wave patterns, notably the alpha, theta, delta, REM theta, and the beta and gamma waves.

Alpha Waves

Alpha waves (Figure 2.1.7) are a predominant type of rhythmic electrical activity evidenced during wakefulness and relaxed states. These waves are commonly present when the eyes are closed and are characterised by being in the frequency range of 8-13Hz.

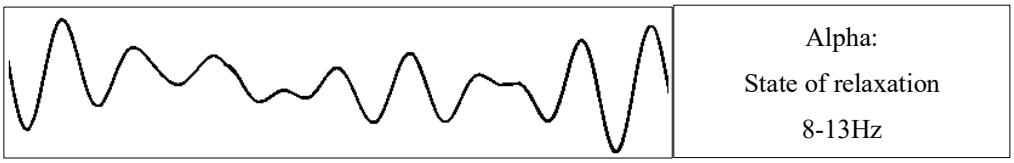

Figure 2.1.7: Alpha waves

Alpha waves are frequently present in the posterior sides of the head on either side. However, the regions primarily used to trace these waves are the parietal and occipital regions. During the transition from wakefulness to sleep, alpha activity diminishes, leading to the onset of sleep stages.

Theta Waves

Theta waves are another important waveform observed in the EEG during sleep (Figure 2.1.8). They are characterised by a frequency range of 4-7Hz, exhibiting amplitudes surpassing 20μV. Primarily detected during the NREM sleep, theta waves are notably present in sleep stages S1 and S2.

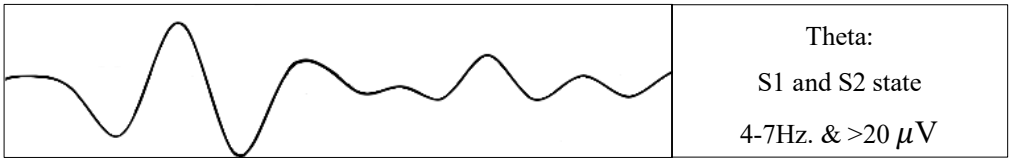

Figure 2.1.8: Theta waves

Theta waves are associated with drowsiness and early states of sleep, signifying sleep onset. They can be identified in the parietal and temporal scalp regions. Studies have reported increased theta waves during emotional events such as stress, frustration and distress, suggesting that excessive occurrences of theta waves might indicate abnormal brain activity, such as diffuse and middle disorder or metabolic encephalopathy (Berry & Wagner, 2015; Cahn & Polich, 2006; Chokroverty & Thomas, 2014; Kaulen et al., 2022; Rajendran et al., 2022; Tzimourta et al., 2018).

Delta Waves

Sleep delta waves (Figure 2.1.9), characteristic of SWS, exhibit slow frequencies ranging from 0.5 to 4Hz and high amplitudes between 75 and 150μV. They are predominately observed during deep sleep and are associated with restoring physical and mental well-being.

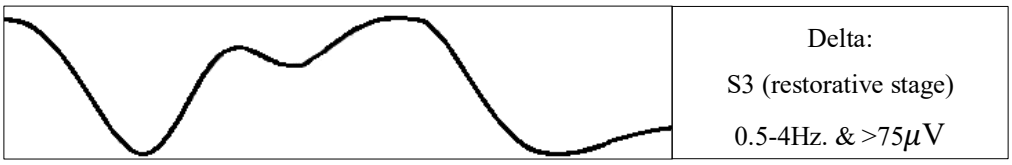

Figure 2.1.9: Delta waves

Furthermore, sleep delta waves are associated with anaesthesia, epileptic seizures,

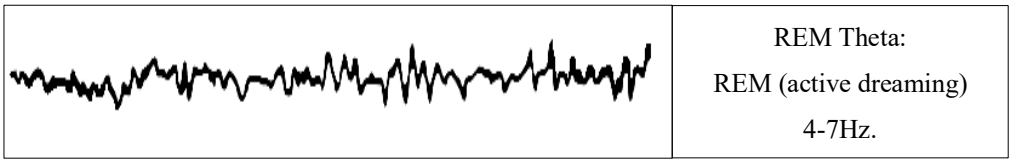

Figure 2.1.10: REM theta waves

coma, and vegetative state. Although they are generally diffuse across the scalp, the posterior region is considered the area for their identification. From a neurophysiological perspective, these waves signify oscillatory dynamics of cortical up and downstate, indicative of the subject's loss of consciousness (Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Frohlich et al., 2021).

REM Theta Waves

During the REM sleep, the EEG exhibits theta waves (Figure 2.1.10) with a frequency range of 4-7Hz. REM theta is characterised by the dreaming phase of sleep and is associated with increased brain activity, vivid dreaming, and rapid eye movement.

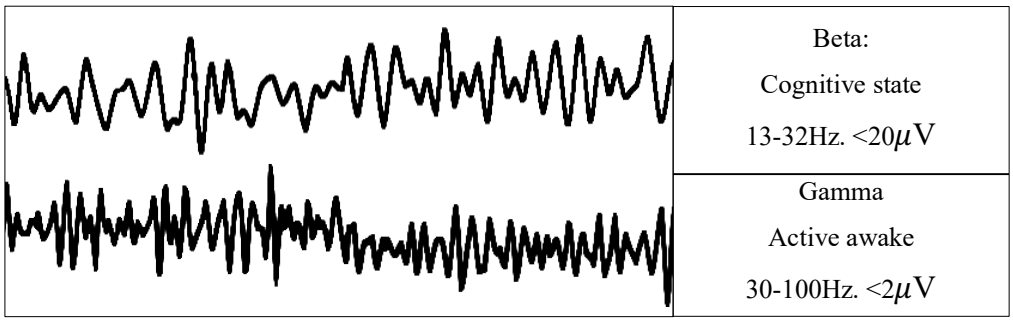

Figure 2.1.11: Beta and gamma waves

REM theta waves are also associated with the brain's ability to integrate and store information collected during the day or from previous experiences, contributing to memory formation and learning. Additionally, this type of waves are associated with emotion regulation and processing.

Beta and Gamma Waves

Beta and gamma waves (Figure 2.1.11) fall within the frequency ranges of 13-30Hz and 30-100Hz, respectively, displaying amplitudes of less than 20μV and 2μV, respectively. Although these waves do not precisely correspond to distinct sleep stages, they are markers for the active wakefulness stage or cognitive activity.

2.1.2.3.2. Sleep Wave Transients

Sleep wave transients are short-lived and temporary fluctuations observed during rhythmic brain activity. These waveforms typically exhibit certain shapes, characterised by abrupt amplitude, frequency, and phase changes. The analysis of these wave transients holds substantial importance in sleep stage classification and the identification of abnormal brain activity, as they can carry critical information about

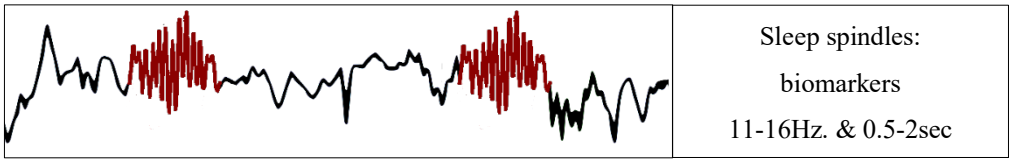

Figure 2.1.12: An example of Sleep spindle (red waves)

specific events or physiological responses.

Sleep Spindles

Sleep spindles (Figure 2.1.12) have distinctive wave patterns observed during the NREM sleep stages. They are characterised by a brief burst of oscillatory activity with frequencies ranging between 11Hz and 16Hz and lasting between 0.5 and 2 seconds. Sleep spindles are predominantly observed in stage S2 (Antony & Paller, 2017; Kabir et al., 2015; Kinoshita et al., 2020; Patti et al., 2018; Weiner & Dang-Vu, 2016).

Sleep spindles play a crucial role in sleep physiology and have been closely linked to cognitive functions and memory consolidation. They are involved in transferring information from the hippocampus to the neocortex, thereby contributing significantly to the consolidation of newly acquired memories and cognitive processes (Antony et al., 2018; Fogel & Smith, 2011; Schönauer & Pöhlchen, 2018; Wamsley et al., 2012). A more comprehensive and in-depth discussion on spindles can be found in Chapter 4.

K-Complex

K-complexes (Figure 2.1.13) are transient waveforms observed in NREM sleep, characterised by a negative deflection followed by a slower positive component. These waves are considered arousal responses, influenced by various internal and external stimuli (Caporro et al., 2012; Ioannides et al., 2019; Koupparis et al., 2013).

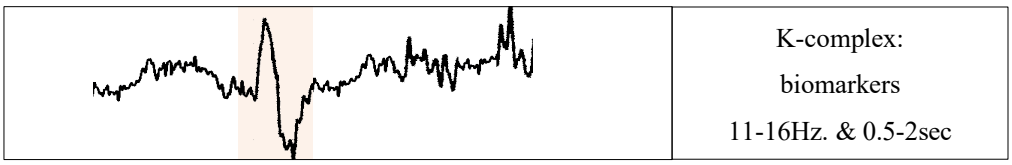

Figure 2.1.13: K-complex (orange area)

K-complexes typically exhibit a frequency around 33Hz and can last for approximately 0.5 to 1.5 seconds, with amplitudes exceeding 100μV. Although direct associations with specific functions have not been established, it is believed that they may contribute to sleep maintenance (Caporro et al., 2012; Ioannides et al., 2019; Koupparis et al., 2013).

Sleep Vertex Sharp Waves

Sleep vertex sharp transients (Figure 1.1.14) are distinctive characteristics observed in sleep EEG recordings, primarily during the REM stage and the transition between light and deep stages of NREM sleep.

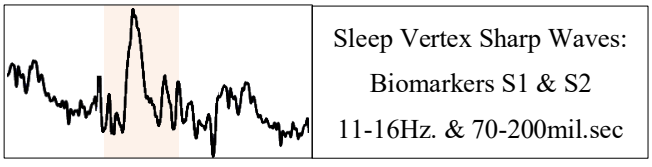

Figure 2.1.14: Vertex sharp waves (orange area)

Vertex sharp waves are defined by a negative sharp deflection followed by a slower positive component. Their occurrence is localised at the central areas of the scalp, giving rise to the term "vertex". These waveforms are considered a regular aspect of sleep architecture and indicate healthy sleep. They are associated with periods of cortical neuron deactivation, manifesting during stages S1 and S2 or through their

transition (Berry & Wagner, 2015; Chokroverty & Thomas, 2014; Danker-Hopfer et al., 2009; Frauscher et al., 2020; Vyazovskiy et al., 2009).

2.1.2.4. EEG Artifacts Mitigation Techniques in Sleep Research and Beyond

Various artifacts can significantly affect the accuracy of EEG recordings, including muscle movements and noise. Muscle movements encompass involuntary activities, such as eye blinking, jaw clenching, and facial expressions, which generate electrical interference often reflected in the EEG activity. Conversely, noise refers to unwanted electrical signals or interference that can contaminate the EEG recordings.

In order to mitigate the adverse impact of muscle movement and noise artifacts, it is imperative to employ a range of signal processing techniques, such as filtering and artefacts removal algorithms. Properly addressing these artifacts is of paramount importance to ensure the validity and reliability of EEG findings in sleep research and relevant applications (X. Chen et al., 2019; Muthukumaraswamy, 2013).

EEG Muscle Movement

Muscle movement, or EMG activity, refers to the electrical signals generated by muscle contractions. These contractions, resulting from eye movements, jaw clenching, facial expressions, and heart rhythms, usually manifest in the EEG as electrical interference. Such interference contaminates the signals of interest, posing challenges in accurately assessing brainwave activity (X. Chen et al., 2019; Muthukumaraswamy, 2013).

Muscle movements pose problems during sleep, when a subject lacks control over their movement. Episodes of muscle movement can suppress or conceal sleep events and patterns, thereby obstructing specific characteristics of interest related to sleep stages. This phenomenon obstructs the accurate identification of sleep-related events (Criswell & Cram, 2011).

Various techniques are available to remove or reduce muscle movement artifacts, although some may be more controversial than others. Nonetheless, the primary objective of all these techniques is to eliminate or minimise the impact of muscle activity during sleep.

Accurately removing muscle artifacts from EEG recordings is fundamental to comprehending cognitive neuroscience experiments. Artifacts arising from movement, such as chewing and brow wrinkling, as well as frontal muscle, exhibit power spectral with a bandwidth of 20-300Hz, with the majority of power concentrated in the lower frequency ranges (Criswell & Cram, 2011). Temporal muscles may show a bandwidth of 40-80Hz, while posterior head muscles like trapezius, sternocleidomastoids, and

splenius capitis display higher peak frequencies up to 100Hz. Notably, smaller facial muscles may extend their activity to frequencies as high as 600Hz. Studies have reported peak frequencies around 30-60Hz for chewing and 30-40Hz for frontalis muscle activity (O'Donnell et al., 1974). Moreover, the power of muscle artifacts varies based on factors such as specific muscles involved, the force of contraction, the direction, and the gender of the subjects (Kumar et al., 2003).

The widespread amplitudes of muscle activity, around 1000fT and 100μV, recorded in temporal EEG electrodes and sensors poses a significant challenge, making it problematic to distinguish muscular artifacts from neural oscillations, even after employing screening techniques. Experiments utilising neuromuscular blockade have demonstrated the presence of muscle contamination in EEG recordings, especially in the high-frequency range (20-100Hz) (Herrmann & Demiralp, 2005; Muthukumaraswamy, 2013).

The contamination of the frequency spectrum is most pronounced around 20Hz, with approximately five times more power at 40Hz and around 10 times more power at 80Hz during the non-paralysed state (NREM). The electrodes located at the edges of the electrode montage, typically employed for scalp-recorded muscle activity, are more problematic regarding frequency contaminations. Moreover, cognitive sleep stages further increase EMG activity, contaminating EEG recordings (Muthukumaraswamy, 2013; O'Donnell et al., 1974; Whitham et al., 2007).

While adaptive filters and blind source separation techniques effectively suppress ECG and EOG artifacts, eliminating EMG artifacts poses significant challenges due to their complex features like high amplitudes, wide frequencies spectra and broad anatomical distributions, as mentioned before (X. Chen et al., 2019; Jung et al., 2000).

Muscle artifacts can distort signals even after standard pre-processing methods, affecting EEG-based quantitative and qualitative measures. Traditional approaches involve discarding corrupted EEG segments and low-pass filtering, but these methods may lead to the loss of valuable brain signals (X. Chen et al., 2019; McMenamin et al., 2011).

To overcome the limitations of classical filtering, to some extent, techniques like adaptive filtering and Kalman filtering have emerged to remove muscle artifacts. Adaptive filtering generates a signal correlated with the muscle artifact using a reference muscle signal, while Kalman filtering is based on Bayesian filtering, recursively estimating the state of a dynamic system (Brunner et al., 1996; X. Chen et

al., 2019; Fatourechi et al., 2007). Both techniques along with additional filters, were applied on the data pre-processing for the proposed methods in Chapters 3 and 4. Additionally, as the methods implemented in these chapters involved signal decomposition using wavelet transform, additional indirect denoise methods were applied.

Source separation algorithms, such as independent component analysis (ICA), canonical correlation analysis (CCA), and independent vector analysis (IVA), have been proposed for denoising EEG by separating EEG and EMG sources into different components and removing muscle-related components during reconstruction. However, muscle artifacts can still contaminate most ICs, and additional measures, such as adaptive filtering and wavelet transform, are used to address this issue (Barlow, 1984; X. Chen et al., 2019; Goncharova et al., 2003a; Gotman et al., 1981) . The ICA, CCA, IVA, adaptive filtering and wavelet transform were employed in the data pre-processing in Chapters 4 and 5.

The CCA, which is an addition of the blind source separation (BSS) technique, measures the linear relationship between two datasets and solves the BSS problem by maximising correlations between canonical variates while ensuring that they are non-interrelated within each dataset (Albera et al., 2012; Daly et al., 2012; Sweeney et al., 2012; Urigüen & Garcia-Zapirain, 2015). The IVA, a generalisation of ICA for multiple datasets, addresses the permutation problem in the frequency domain for rhythmic signals separation (mentioned in the previous subsection). It ensures mutual independence within each dataset and maximum dependence across multiple datasets. In this context, datasets refer to each EEG derivation or bipolar channel, meaning that the ICA or IVA use each derivation to create the generalisation, addressing the permutation problem based on the rhythmic signals (X. Chen et al., 2017, 2019; Chiu et al., 2014; Jiang et al., 2017; Jung et al., 2000; Ko & Fox, 2009; Urigüen & Garcia-Zapirain, 2015).

Despite extensive research efforts to mitigate muscle artifacts, effectively eliminating their influence remains challenging. Neuromuscular blockage studies have revealed that broadband muscle activity significantly affects even seemingly clean resting EEGs (X. Chen et al., 2019; Goncharova et al., 2003b).

Muscle artifact removal is crucial not only for the data used in this study to improve the quality of the sleep stages characteristics but also for long-term health monitoring and other complex signal experiments, making it an important and pressing issue to be

addressed in future studies (X. Chen et al., 2019; Chiu et al., 2014; Mishra & Singla, 2013; Vos et al., 2010).

In our research, we have applied different signal pre-processing techniques over time, modifying and improving them to find the best EEG signal pre-processing methods that enhance signal quality. However, as it was outside the scope of our objectives, we did not postulate any methods or approaches to improve it.

EEG White Noise

EEG noise refers to unwanted electrical signals or interference that can contaminate EEG recordings. These noise signals can originate from various sources, such as environmental factors, electrical equipment, and physiological processes unrelated to brain activity. EEG noise can impede the accurate interpretation and analysis of brainwave patterns during sleep.

White noise is a random signal with constant power density across all frequencies, which is usually manifested in EEG recordings as a relatively uniform distribution of electrical activity. This undesirable noise masks and obstructs specific brainwave patterns and sleep-related events of significant relevance for interpreting sleep stages.

Among the most common sources of white noise in EEG recordings are electrical interference, equipment limitations, and misconnections of electrodes with the scalp. Some events highly affected by white noise are sleep spindles, k-complexes, and rapid eye movement (Dement & Kleitman, 1957; Rudzik et al., 2018).

Several techniques are employed to minimise the effects of white noise in EEG signals, including signal filtering, advanced signal processing algorithms, and improved electrode placement. Additionally, high-quality recording equipment has significantly enhanced signal-to-noise ratio reduction, especially equipment equipped with electromagnetic shield technology.

Section 2.1 presents a comprehensive and in-depth discussion of different aspects of sleep, including its characteristics, sleep physiology, sleep EEG, and relevant technical aspects, such as basic montages, rhythms, noise, and EEG signal pre-processing. This section lays the foundation for the subsequent research studies and plays a pivotal role in shaping the methodology and approach adopted throughout the thesis.

The discussion on sleep characteristics and physiology deepened our understanding of the dynamic nature of sleep and its essential role in restorative processes, memory consolidation, and overall well-being. By exploring the different sleep stages, along with their characteristics and EEG waveforms, valuable insights into the brain's activity

during various sleep phases were gained. This knowledge proves fundamental in identifying the key features used in sleep stages classification, thus facilitating accurate and reliable identification of sleep stages in the research studies. Such a foundation proves essential for the creation of the "Rules-based method" implemented in Chapter 3, as well as in the identification of spindles in Chapter 4.

Furthermore, the subsection on sleep EEG, encompassing basic montages, rhythms, noise, and EEG signal pre-processing, establishes the necessary foundations and tools to handle and analyse sleep EEG recordings effectively. A profound understanding of EEG signal pre-processing, artifact removal, and data normalisation ensures the acquisition of high-quality data for subsequent analysis, ultimately enhancing the accuracy and validity of the research outcomes.

The information collected in Section 2.1 is instrumental in guiding the direction and development of the multi-method approaches for sleep EEG analysis and sleep stage classification. It constructed a critical foundation for this thesis, providing the necessary theoretical background and technical expertise for the successful execution of the studies. The comprehensive discussion on sleep characteristics, physiology, stages, sleep EEG, and its technical aspects lays the groundwork for developing innovative multi-method approaches with the potential to transform sleep EEG analysis and sleep stage classification. Applying this knowledge contributed to significant enhancements in sleep state classification accuracy and holds significant applications for sleep medicine, neuroscience, and personalised sleep health interventions. The information conveyed in Section 2.1 enriches our understanding of sleep. It guides us in selecting and implementing the postulated methods discussed in Section 2.2, intending to address existing challenges in sleep stage classification, as discussed in Section 1.3.

2.2. Time-Frequency Signal Analysis

Time-frequency analysis serves as a powerful tool for examining the temporal dynamics of non-stationary signals, such as EEG recordings, thereby extracting valuable information about diverse brainwave activities during sleep (Al-Fahoum & Al-Fraihat, 2014; Weis et al., 2009). This section provides a comprehensive overview of time-frequency signal analysis techniques, particularly emphasising the implementation and suitability of MP and MT&C methods for EEG data analysis.

The analytical approach of time-frequency analysis enables examining frequency content changes over time (Miwakeichi et al., 2004), unveiling the interactions between

different frequencies during specific events or states. Given the inherent complexity and variability of sleep stages and events, time-frequency analysis is significant in comprehending the dynamic brain processes during sleep (Al-Fahoum & Al-Fraihat, 2014; Boashash, 2015; Claasen TA & Mecklenbräuker W, 1980; Debnath, 2001; W. Liu et al., 2016; Qiang et al., 2011).

Throughout sleep, subjects experience internal physiological changes regarding brain activity. These changes, which can be visualised as an EEG activity across different frequency bands (Rhythmic Signals) over the course of sleep, can be extracted using different techniques.

2.2.1. An Overview of Key Signal Processing Analysis Techniques

Various methods and algorithms have been implemented to generate features from EEG data. While some of these methods implement minimal signal processing techniques (Alickovic & Subasi, 2018; ElMoaqet et al., 2022; Längkvist et al., 2012; N. Mei et al., 2017; Sun et al., 2019; Yulita et al., 2017), others heavily rely on this approach (Aboalayon et al., 2016b; Ghasemzadeh et al., 2019; Längkvist et al., 2012; N. Mei et al., 2017; Moser et al., 2009; Yi Li et al., 2009; Zapata et al., n.d., 2022, 2023; Zhu et al., 2014). A prominent example of signal processing is time-frequency analysis, which enables the evaluation of signals based on specific parameters, including time, frequency and power.

One of the techniques used in EEG signal processing is the short-time Fourier transform (STFT). This widely used technique applies the Fourier transform (TF) to short signal segments to visualise their frequency content. While STFT provides a fixed time and frequency resolution, making it suitable for stationary signals, it limits the ability to analyse non-stationary signals with time-varying frequency content. This technique is highly computationally efficient, easy to implement, and enables visualisation of the time-frequency representation. However, it could generate inadequate resolution for non-stationary signals, leading to the smearing of time-frequency features (Canal, 2010; Casson & Rodriguez-Villegas, 2011; Castagna & Sun, 2006; Hyvärinen et al., 2010; Zabidi et al., 2012).

Another technique is the continuous wavelet transform (CWT), which uses a wavelet function to assess the similarity between the signal and a scaled wavelet version, providing time-frequency representations. Despite offering variable time and frequency resolution, making it suitable for non-stationary signals, it requires selecting an appropriate wavelet function, which could affect the quality of the representation. The

CWT offers better time-frequency localisation, revealing transient and frequency changes. It is also suitable for analysing signals with time-varying frequency content. However, it is computationally more demanding than STFT, and the choice of the wavelet kernel function will have a direct implication on the accuracy of the method (Casson & Rodriguez-Villegas, 2011; Castagna & Sun, 2006; Hamaneh et al., 2014).

The Discrete Wavelet Transform (DWT) method is a variant of the CWT that divides the signal into sub-bands of varying frequency ranges. In contrast to the CWT, the DWT uses a discrete set of wavelet scales and positions, offering a multi-resolution signal analysis. This process enhances computational efficiency while retaining time-frequency localisation. DWT's multi-resolution property also makes it well-suited for denoising and compression applications. However, the DWT exhibits limited frequency resolution compared to CWT, which might be a concern in specific applications requiring fine frequency discrimination. Besides, DWT lacks phase information, a critical aspect in certain contexts, potentially restricting its use in applications where phase relationships are required (Allen & MacKinnon, 2010; Chaovalit et al., 2011; Sundararajan, 2016; Zhenyu Guo et al., 1994).

The Hilbert-Huang transform (HHT) technique is a data-driven method that decomposes a signal into intrinsic mode functions and a time-frequency distribution known as the Hilbert Spectrum. Compared to other methods, the HHT is a practical approach to handling non-stationary and nonlinear signals. Its adaptability and versatility make it particularly well-suited for analysing such complex signals. One of the notable advantages of HHT is its ability to resolve mode mixing, allowing for improved localisation of time-frequency components. However, the mode mixing in the HHT can lead to ambiguous interpretations, posing a challenge in some instances. Additionally, special attention is required when dealing with boundary conditions and end effects to ensure accurate results and mitigate potential inaccuracies in the analysis (Allen & MacKinnon, 2010; Castagna & Sun, 2006; Gerla et al., n.d.; Oweis & Abdulhay, 2011; Yi Li et al., 2009).

The Stockwell transform (S-transform) is a time-frequency representation technique that combines elements of STFT and CWT, resulting in enhanced resolution and localisation compared to STFT. It offers improved time-frequency localisation, making it suitable for analysing non-stationary signals with oscillatory components of varying frequencies. However, its computational intensity is superior to STFT due to the use of CWT, and the choice of parameters may influence the quality of the representation

(Allen & MacKinnon, 2010; Castagna & Sun, 2006; Jian-Zhong Xue et al., n.d.; Minecan et al., 2002; Murmu & Bhattacharya, 2011; Yan et al., 2015).

On the other hand, the wavelet packet transform (WPT) is an extension of DWT that allows further decomposition of sub-bands into smaller frequency components, providing a more detailed and versatile signal analysis. The WPT offers multi-resolution and adaptability to different signal characteristics, making it suitable for analysing complex signals with a hierarchical decomposition. Nonetheless, its computational complexity is increased compared to DWT, and careful selection of wavelet packets is required, as it can affect the quality of the representation (Allen & MacKinnon, 2010; Castagna & Sun, 2006; Zandi et al., 2010).

The empirical mode decomposition (EMD) is a signal decomposition technique that separates the signal into intrinsic mode functions, each representing different oscillatory modes. It offers an adaptive and data-driven representation of the signal, making it suitable for analysing non-stationary and nonlinear signals. The absence of predefined basis functions allows the EMD to adapt to diverse signal structures. However, EMD is limited by mode mixing, which can lead to ambiguous interpretations, and requires careful handling of end effects and boundary conditions (Allen & MacKinnon, 2010; Castagna & Sun, 2006; Sweeney-Reed et al., 2018; Sweeney-Reed & Nasuto, 2007; Zhenyu Guo et al., 1994).

In contrast, the synchro-squeezing transform (SST) is a method that enhances the localisation and energy concentration of time-frequency components in a signal, thereby providing improved resolution for analysing non-stationary signals. The SST enhances the accuracy of feature extraction in terms of time-frequency localisation, and it is well-suited for signals with varying frequency components. However, SST's computational demands are higher compared to some other time-frequency techniques, and the selection of parameters may influence the quality of the time-frequency representation (Allen & MacKinnon, 2010; Castagna & Sun, 2006; Mert & Akan, 2018; Ozel et al., 2019).

MP is an iterative algorithm that adaptively selects elementary waveforms from a predefined dictionary to decompose a signal into a sum of these wavelets, thus extracting time-frequency features. The MP efficiently captures non-stationary features in the signal, making it suitable for complex signal structures. Additionally, MP can achieve high time-frequency resolution even with a small dictionary. However, its computational complexity increases with the number of iterations and the signal's

sample rate, and proper parameter tuning is necessary, which may impact the quality of the representation (Mallat & Zhifeng Zhang, 1993; Wen et al., 2016, 2017).

Conversely, the MT&C method employs multiple tapered windows to calculate the power spectral density and analyses non-stationary signals with high-resolution frequency analysis. Compared to standard window-based methods, the MT&C offers enhanced frequency resolution and proves robust against noise, making it suitable for detecting low-intensity frequency components. However, the MT&C requires careful selection of appropriate tapers, as this choice significantly affects the quality of the analysis. Moreover, it is computationally more demanding than standard window-based methods but considerably less than the MP (Babadi & Brown, 2014; Park, Lindberg, & Vernon, 1987; Prerau et al., 2017).

This section has provided a comprehensive insight into various signal processing methodologies. Among the diverse range of techniques explored, the MP and MT&C were selected for their unique advantages in handling non-stationary signals with high-resolution frequency analysis. The ability of the MP method to effectively capture time-frequency analysis features using elementary waveforms from a predefined dictionary makes it well-suited for complex signal structures. At the same time, the MT&C implements multiple taper windows allowing for an enhanced frequency resolution and robustness against noise, making it particularly useful for detecting low-intensity frequency components. Moreover, the comparative analysis revealed that combining the MP and MT&C can balance analytical accuracy and robustness, underscoring their relevance and applicability in signal-processing tasks.

2.2.2. Matching Pursuit (MP) Applications

MP, an algorithm introduced nearly three decades ago, is a valuable tool for identifying the singularities within EEG data. As a greedy or weak-greedy algorithm, MP computes the adaptive nonlinear expansion of a signal by employing a redundant dictionary of sparse approximations (Mallat & Zhifeng Zhang, 1993). Despite not being as extensively utilised for signal decomposition as other methods, several domains have employed its potential (Ali et al., 2014; S. Chen et al., 2018; A. Kaur & Budhiraja, 2014; Mourad et al., 2016; Wen et al., 2016, 2017; J. Zhao & Bai, 2017). This prominence positions MP as a promising candidate for disentangling diverse characteristics in sleep stage classification and detecting abnormal waves.

Durka et al., (2015) proposed the parametrisation of time-frequency structure in transient sleep EEG. By employing cross-validation, they used MP decomposition to

identify sleep spindles. The application yielded a predominantly root mean square distribution of 97th percentiles (Durka et al., 2015).

Malinowska et al., (2009) parameterised key elements characterising sleep stages based on visual analysis criteria for sleep EEG classification. MP was employed as a primary method to decompose the signal into individual waves, which were subsequently classified according to sleep EEG parameters. Comparing their proposed method to multiple expert scorings, they achieved an accuracy of 73% and observed a discrepancy of 25% between experts (Malinowska et al., 2009).

Another approach by Durka et al., (2005) involved a pre-processing EEG time series using multichannel MP (MMP) with an inverse method. The discomposed signal obtained through MMP was mapped to identify specific characteristics of interest, such as sleep spindles. The algorithm automatically detected 578 spindles on the first night and 692 on the second night of EEG recordings from a single subject, with standard deviations of 120 and 316, respectively (Durka et al., 2005).

In Benar et al., (2009), MP was implemented to extract EEG signal characteristics. Utilising a voting technique for atom selection in each iteration, the authors aimed to find the most descriptive atom in every trial waveform, facilitating the estimation of variability levels across trials (Bénar et al., 2009).

2.2.3. Applications of Multitapers

Multitapers (MT) is a commonly used in time-frequency analysis and spectral estimation, not only in sleep stage classification and multi-trial EEG data analysis but also in various domains requiring comprehensive signal analysis (Babadi & Brown, 2014; M. X. Cohen, 2014). The origins of MT trace back to Thomson's pioneering work in 1982, designed to analyse the harmonics in time series data. Subsequent improvements by Thomson et al., (1987) extended its application to estimate the frequency oscillation of the Earth. Over time, MT has gained prominence as an effective method for signal analysis and decomposition in numerous research areas (Babadi & Brown, 2014; M. X. Cohen, 2014; Das & Babadi, 2020; Lindberg & Park, 1987; Park, Lindberg, & Thomson, 1987; Park, Lindberg, & Vernon, 1987). Presently, MT is extensively used for spectral density estimation in EEG data, not only for sleep stage classification but also for identifying abnormal activities in awake subjects (L. Cohen, 1989; M. X. Cohen, 2014).

A study by Jeyaseelan and Balaji (2015) delved into the spectral characteristics of waves using the MT method. Their experiments revealed that MT-generated spectral

estimation outperformed fast Fourier transform (FFT)-based methods. By varying the number of tapers, they observed improved autonomy, reduced inconsistencies, and smoother spectral peaks with a well-defined estimation of utmost frequencies (Jeyaseelan & Balaji, 2015).

Babadi and Brown (Babadi & Brown, 2014) conducted a comprehensive analysis of the MT spectral and standard non-parametric spectral estimation, applying it to anaesthetic and sleep EEG data. Their experiments demonstrated that specifying the spectral resolution of a taper resulted in more precise frequencies within the resolution, enabling the identification of elements within that specific range. Their study shed light on MT's ability to discern spectral estimations from diverse signals (Babadi & Brown, 2014; Das & Babadi, 2020).

Prerau et al., (2017) reviewed the neurophysiology of sleep EEG data using MT-based spectral analysis (spectrogram). Their work showcased how MT is a valuable tool for presenting EEG data in a well-defined manner, providing faster and better results for expert sleep stage classification. The spectrogram representation facilitated the identification of oscillatory mechanisms for each sleep stage, making the visualisation of EEG data more accessible to match with the hypnogram, compared to the original signal. Their results demonstrated a close correspondence between the hypnogram generated by expert classification and the spectrogram produced by the MT method (Prerau et al., 2017).

These referenced papers exemplify how integrating different signal analysis methods can reveal distinct, relevant entities in specific fields. While MP relies on a range of equations and algorithms to create complex dictionaries with a targeted focus on various wavelet or atom representations, MT aims to develop a kernel function to identify single targets within a signal without decomposition, thereby improving performance and extracting spectral estimations of individual components. Building upon the idea of combining multiple signal analysis methods or tools tailored to the diverse elements encountered in EEG data analysis, the ultimate goal is to extract and integrate the best components of each technique to enhance the accuracy and performance of a robust method across databases. This research aims to deliver original contributions in analysing a range of EEG waves mapped to their definitions, resulting in a potentially applicable method to other domains.

2.2.4. The Relationship Between Matching Pursuit and Multitapers with Convolution

Both MP and MT&C methods involve the use of a kernel. MP utilises a Gabor kernel to generate a dictionary of wavelets, while the MT&C employs tapers that are subsequently convoluted with the data. The Gabor kernel emerged as a critical component with outstanding results in MP through extensive experimentation and literature review. Hence, this study adopts the Gabor kernel as a central equation due to its high performance in localising target signals based on given parameters, making it particularly suitable for the complexity of EEG signals.

The Gabor function developed for the MP and then implemented in the MT&C shares similar elements with the original equation (Eq.1), as applied in Mallat & Zhang (Mallat & Zhifeng Zhang, 1993).

$$g_\gamma(t) = K(\gamma)\, e^{-\pi\left(\frac{t-u}{s}\right)^2} \cos(\omega(t-u)+\phi) \tag{1}$$

However, some modifications have been introduced to optimise the efficiency of the process. In the original equation, a Gaussian function (first part of Eq.1) contains an adjustable Gaussian window, creating a complex and extensive dictionary. In contrast, the Gaussian widow has been substituted with Eq.2 in the updated equation, featuring a new standard deviation (Eq.3) used solely to define the sine and cosine functions. This adjustment results in variable-sized atoms, thereby reducing the size of the dictionary without compromising the chance of matching the wavelets from the discomposed signal (Gribonval, 2001; Kuś et al., 2013; Loza & Principe, 2016; Mallat & Zhifeng Zhang, 1993).

$$Gussian\ Window = e^{\left(\frac{(-t^2)}{(2S^2)}\right)} \tag{2}$$

Where $\boldsymbol{t}$ is the time of the signal, and S is the standard deviation.

$$(S) = \frac{\tau}{(2\pi f)} \tag{3}$$

Where τ refers to the number of cycles of the wavelet and f refers to the signal frequency.

To create the complex wavelet for this study (Eq.4), the cosine element from the original equation (the second part of Eq.1) has been replaced with Eq.4 to incorporate both the sine and cosine elements into a single complex wavelet, effectively preventing exponential growth of the dictionary (Ahmed et al., 1974; M. X. Cohen, 2014; Strang, 1999b, 1999a; Zeng & Fu, 2008).

$$e^{(i\,2\,\pi\,f\,t)} \tag{4}$$

In simple terms, the Gabor function used in this study (Eq.5) is characterised by two phases, as in sine and cosine, embedded into a single imaginary atom or complex wavelet, as inspired by Cohen (2014) in the book of "Analysing Neural Time Series Data" (M. X. Cohen, 2014).

$$g_\gamma(t) = e^{\left(\frac{(-t^2)}{(2\,S^2)}\right)} e^{(i\,2\,\pi\,f\,t)} \tag{5}$$

To illustrate the concept of a complex wavelet, imagine observing a spring in a 3-dimensional space (Figure 2.2.4 left). From this perspective, the entire structure of the spring can be seen. However, when looking at the side of the spring in a 2-dimensional space (*Figure 2.2.1 right*), only one side can be seen, known as the real part, while the other side remains hidden, referred to as the imaginary part.

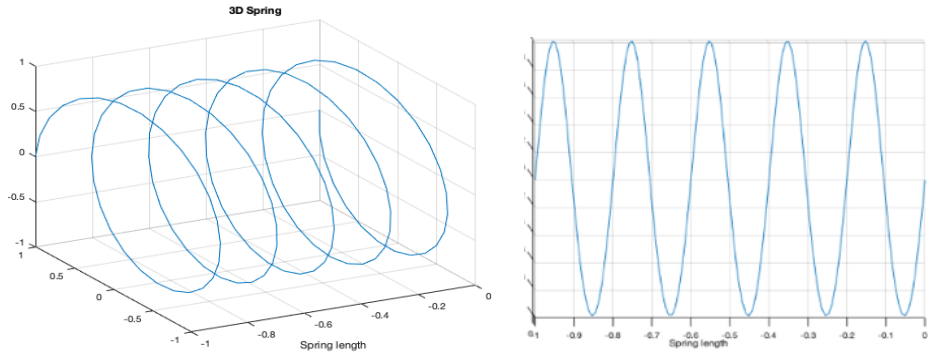

Figure 2.2.1: Left: Spring in a 3D space; Right: String in 2D space**.**

The same principle has been adopted for the method of the MT&C, according to Cohen (2014). This approach allows for the creation of a complex sub-dictionary or wavelet with reduced magnitude, where redundancy is preserved while the size is diminished, thereby enhancing computational efficiency, particularly for an extensive signal decomposition, as is the case for EEG signals (Strang, 1999a; Thomson, 1982; Wen et al., 2017; Zeng & Fu, 2008; J. Zhao & Bai, 2017).

2.2.4.1. Time Shift of the Gabor Function for the MT&C

In order to construct a redundant dictionary of sparse approximations using the Gabor function, the appropriate selection of a time shift between atoms is crucial, as it determines the size and redundancy of the dictionary. While time shifts may not be essential for many atomic functions, they play a fundamental role when dealing with functions containing localised time-frequency atoms, such as the Gabor function. Typically, when generating a Gabor function, the time scale in the equation serves as a reference for creating the atom, and the atom is centred at time zero, resulting in a symmetric distribution on the x-axis with equal negative and positive parts (Figure 2.2.2

(left)). However, if the time scale passed into the functions is set to 0 to n+, the atom will only have half of its symmetric distribution, as shown in Figure 2.2.2 (right) (for more specification on the dictionary kernel, refer to Appendix B).

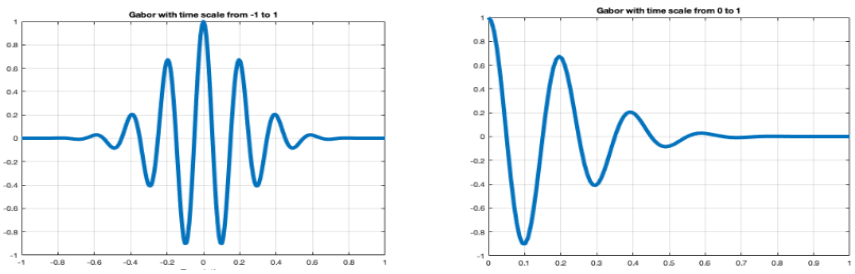

Figure 2.2.2: Left: Gabor atom with time scale from n^- to n^+.
Right: Gabor atom with time scale from 0 to n^+.

In order to generate a robust dictionary, the Gabor function needs to generate atoms across all time scales, implying that every time an atom is generated, the next atom must be time-shifted. The distance between atoms (time-shifted) was based on a current application like 'Haar Transform' and 'Chirplet Transform', where the atoms are generated every two points or 1/(Fs/2) (Fs refers to the sample rate of the signal). However, further trial and error analysis was implemented, and it was found that when the time shift was applied to every single point (1/Fs), the signal decomposition did not improve, but the size of the dictionary increased exponentially (Choi & Williams, 1989; Gribonval, 2001; Weis et al., 2009). Moreover, the signal decomposition started to lose its accuracy when the time-shift was set to every 8 points or more (1/(Fs/8+)) (Figure 2.2.3 (Left)). Therefore, the time shift selected for the Gabor function was between two and four points (Figure 2.2.3 (right)) (for more specifications on the size of the dictionary, refer to Appendix A).

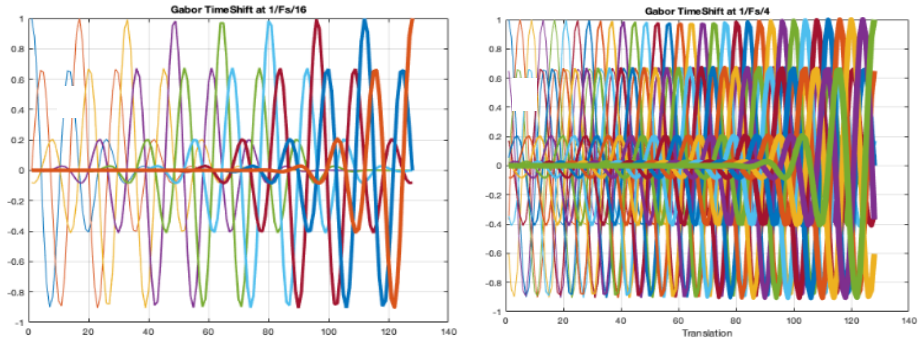

Figure 2.2.3: Left: Time shift every 16 points between atoms.
Right: Time shift every 4 points between atoms.

2.2.4.2. MP Feature Extraction

The MP signal decomposition is performed by iteratively searching a dictionary for an atom that best describes a part of the signal and subtracting it. This process is then repeated for several iterations on the remaining signal. Any remaining signal after the iterations is regarded as residual. In this study, the MP method utilises 30 iterations to decompose each 30-second EEG epoch, resulting in the signal being decomposed into 30 atoms.

The decomposed signal generated by MP closely approximates the original signal, resulting in slight differences between the decomposed and original signals. These differences can be seen as noise data. To reconstruct the signal, all the generated atoms must be computed along with their coefficients and residuals.

Subsequently, each atom obtained from the MP decomposition is analysed based on the EEG wave definitions to identify specific wavelet characteristics and associate them with a particular phenomenon (Figure 2.2.4) (Roebuck et al., 2014).

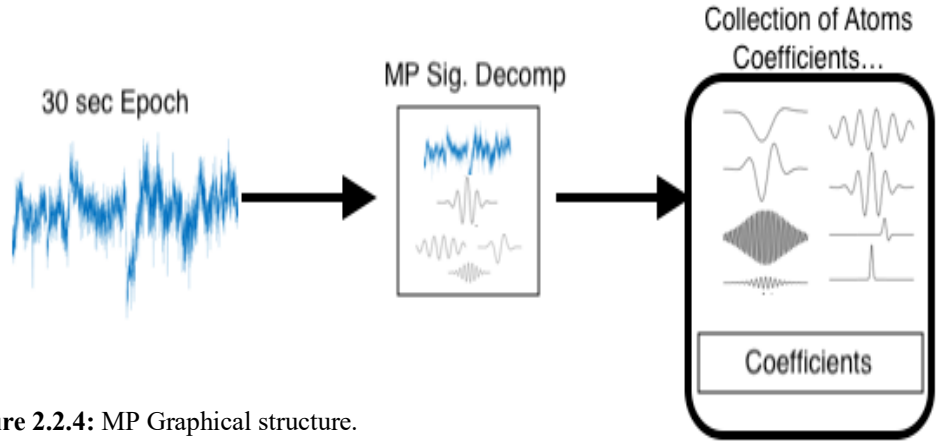

Figure 2.2.4: MP Graphical structure.

2.2.4.3. Theoretical Basis of the MT&C and its Applications to EEG Analysis

Multitapers (MT) are utilised to generate the spectral estimation (SE) or spectra density estimation (SDE) of a signal, breaking down a waveform into various oscillation components based on their frequencies. The SDE reveals the time-frequency characteristics of a signal represented by taper parameters. The core principle behind the SDE lies in Fourier transform (FT) analysis, which decomposes a complex signal into a series of raw sine waves. This principle is well-suited for EEG analysis, as each taper can represent distinct activity in the EEG signal generated by neuronal oscillations across the brain (M. X. Cohen, 2014).

The MT&C used in this research adopts the concept of a dictionary from MP but without the dictionary itself, meaning that it will generate a collection of atoms relevant

to the EEG data and the sleep parameters. The atoms in the MT&C will be referred to as tapers or wavelets, and they are generated using the same Gabor function applied in MP. The tapers in the MT have a fixed predefined frequency, and the number of tapers will vary based on user requirements. For this research, we employ 30 wavelets, each representing a frequency from 0.2Hz to 30Hz. In a way, this can be linked to the number of iterations applied in MP.

Prior to the implementation of the MT in EEG data analysis, spectral estimation was calculated using a periodogram. However, concerns arose about its bias. Further details on this topic are discussed in Appendices C.

Variance estimation of the spectrum is crucial for most time-series data analysis, particularly in EEG data analysis (M. X. Cohen, 2014), as it requires significant temporal resolution to identify general components in small time windows. Single tapers estimation (STE) is utilised to reduce the bias of the periodogram and increase the variance. Although increasing variance can pose challenges in signal analysis, there are ways to mitigate this issue, such as computing the cross-average of each section window (epoch) to cancel out noise. Nonetheless, this process can be tedious. Alternatively, multitapers spectral estimation is employed, which exhibits superior statistical properties compared to the STE.

In the TM, some temporal precision is sacrificed to enhance the signal-to-noise ratio in the time-frequency domain, which usually significantly impacts the gamma waves of the signals. Though, modifications in the MT function can improve that temporal precision. However, gamma waves are not the primary concerns in this study (L. Cohen, 1989; M. X. Cohen, 2014).

2.2.4.4. Functionality of the MT&C

The underlying theory behind the functionality of the MT&C method is to generate a set of Slepian tapers, wavelets, or Gabor atoms, each of which is mutually orthogonal and possesses unique characteristics such as frequency, power, and phase. Every wavelet can independently estimate the spectral density of the signal within a specific time window. The computation of a signal's spectral estimation is achieved through a convolution process (see Figure 2.2.5), where the kernel function (taper or wavelet) multiplies the raw signal generating a dot-product at each time point by sliding the wavelet across the signal.

This process is implemented for each kernel, resulting in multiple new signals being generated if there are, for instance, five kernels at different frequencies. Each of these

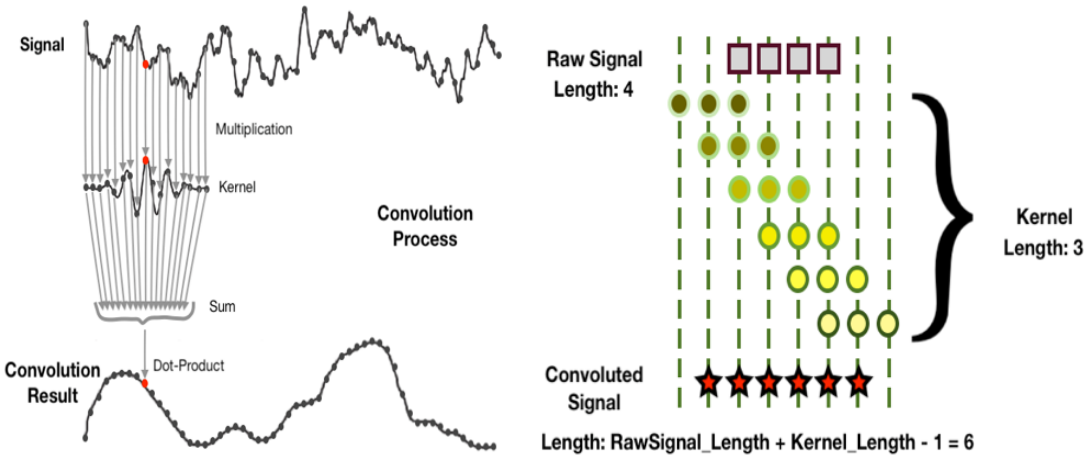

Figure 2.2.5: Convolution process for a single point (Left), convolution process and convolution signal length (right).

new signals represents the frequency content of the respective wavelet in the original signal. In other words, if a wavelet has a frequency of 10Hz (as shown in Figure 2.2.6), the convoluted wavelet will generate a signal that will provide information about the instance, power, and amplitude of the frequency component tenth in the raw signal (Park, Lindberg, & Thomson, 1987; Park, Lindberg, & Vernon, 1987). For more comprehensive information on dot-product and convolution, please refer to Appendix D.

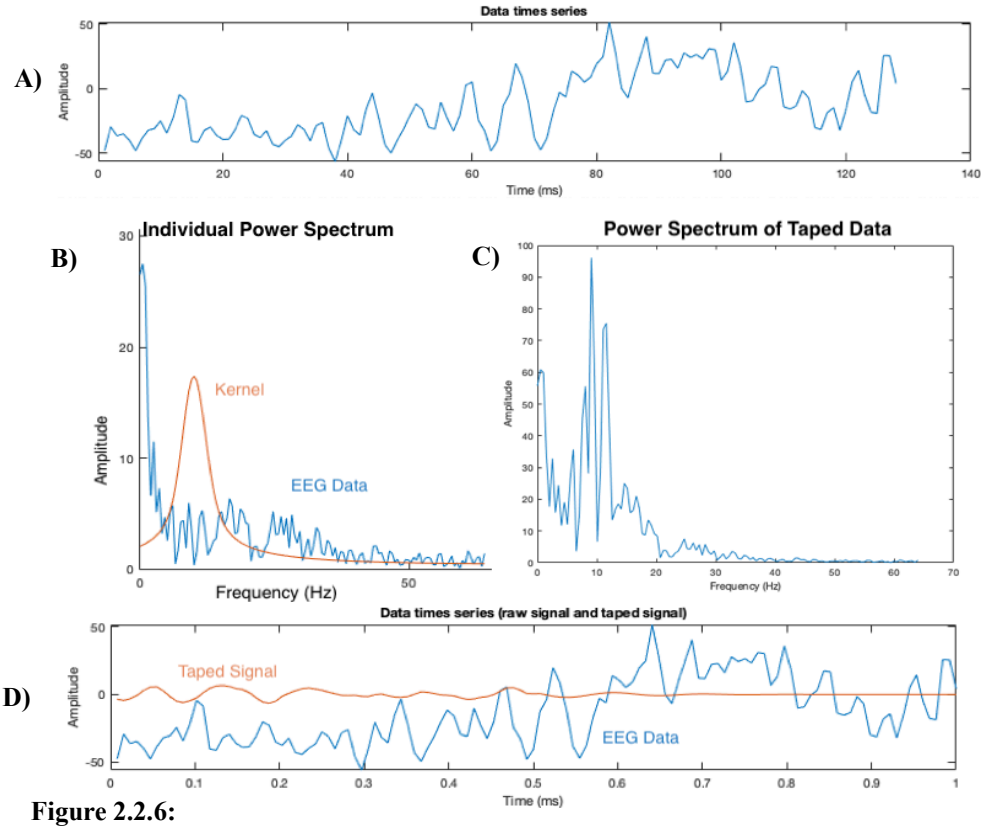

Figure 2.2.6:
(A): EEG Data in time-series,
(B): EEG Data and wavelet in the frequency spectrum,
(C): EEG Data and wavelet convoluted in the frequency spectrum,
(D): EEG Data and taped data in time-series.

In conclusion, this section has provided a comprehensive overview of time-frequency signal analysis techniques, specifically focusing on the MP and MT&C methods for EEG data analysis. The analytical approach of time-frequency analysis proves invaluable in examining the temporal dynamics of non-stationary signals like EEG recordings during sleep. The diverse range of signal processing techniques explored here highlights the strengths and limitations of each method, enabling researchers to make informed choices based on specific analysis requirements.

The MP and MT&C methods have emerged as promising candidates for handling non-stationary signals with high-resolution frequency analysis. MP's adaptability in capturing time-frequency features using elementary waveforms and MT&C's utilisation of multiple tapered windows for enhanced frequency resolution make them well-suited for complex signal structures and detecting low-intensity frequency components. The comparative analysis reveals that both methods balance analytical accuracy and robustness, making them relevant and applicable in signal processing tasks.

Moreover, this study unravelled the relationship between the MP and MT&C methods, indicating the central role of the Gabor function in both approaches. Modifications were introduced to optimise the efficiency of the Gabor function, ensuring reduced dictionary size without compromising signal-matching accuracy.

The applications of the MP and MT&C in EEG data analysis have been demonstrated through various studies. MP proves valuable in identifying sleep spindles and classifying sleep stages, while the MT&C offers improved spectral estimation and facilitates expert sleep stage classification. However, it was not employed directly due to the significant computational demands of MP, especially when applied to extensive signal decomposition as required for sleep EEG data. Instead, its more attractive characteristics were extracted and integrated into the MT&C approach.

The combination of different signal analysis methods shows promise in extracting distinct features and enhancing the accuracy and performance of robust methodologies.

In summary, this section contributes to a deeper understanding of time-frequency signal analysis techniques, emphasising the relevance of the MP and MT&C methods in EEG data analysis. Their unique advantages and insights gained from various applications position these methods as practical tools in comprehending complex brainwave activities during sleep and other fields of study. This research has demonstrated their applications and effectiveness of these methods, as evidenced and documented in Chapters 3, 4 and 5.

2.3. Limitations and Embracing Innovative Techniques in Sleep EEG Analysis

The accurate classification of sleep stages is of utmost importance in sleep medicine and research, as it provides valuable insights into an individual sleep architecture and overall health. Section 2.3 critically examines sleep stage classification methods, shedding light on their limitations, particularly those relying on black-box techniques. This section explores the most promising machine and deep learning methods for feature extraction and classification in sleep EEG analysis. By embracing innovative techniques, we aim to enhance the accuracy, efficiency, and other essential capabilities for analysing sleep EEG signals.

2.3.1. Limitations of Existing Sleep Stage Classification Methods

Existing sleep stage classification methods face several limitations that can impact their accuracy and overall utility. The following are some of the more common limitations associated with these methods (Dequidt et al., 2023; H. Kim & Choi, 2018; Y. Kim et al., 1992; C. Li et al., 2022; Lin et al., 2002; Onton et al., 2016; Podvezko, 2007; Siuly et al., 2010; Younes et al., 2015).

Inter-score Variability: Manual scoring methods often exhibit discrepancies among different scorers in their interpretations of sleep patterns, resulting in inconsistencies in the classification of sleep stages. This subjectivity can undermine the reliability and comparability of sleep data across studies and sleep clinics. Three common issues identified in manual scoring are errors stemming from poor interpretation by scorers, scorer's bias, and equivocal scoring, often influenced by fatigue or apophenia (Danker-Hopfe et al., 2004; Loredo et al., 1999; Magalang et al., 2013; Younes et al., 2016; Younes & Hanly, 2016).

The problem of inter-score variability not only affects patients, medical experts, and researchers but also extends to most supervised and semi-supervised automatic methods that rely on labels marked by scorers or experts (Kuna et al., 2013; Loredo et al., 1999; Norman et al., 2000; Younes & Hanly, 2016).

Lack of Standardisation: While manual scoring methods based on the R&K rules and the AASM standards provide a framework, there is still a degree of variability in the applications of these rules across different sleep laboratories. The absence of standardised scoring criteria can delay the reproducibility and comparability of research findings (Jobert et al., 2013; Norman et al., 2000; Pevernagie et al., 2009).

Time-Consuming and Labour-Intensive: Manual scoring of sleep stages is time-consuming, particularly for long sleep recordings. The requirement for skilled human

experts to visually analyse data renders it impractical for large-scale studies and real-time clinical applications. Additionally, the necessity for inter-score agreement further complicates and hinders the practicality and reliability of this approach to some extent (Chediak et al., 2006; Danker-Hopfe et al., 2004; Jobert et al., 2013; Kuna et al., 2013; Rosenberg & Van Hout, 2013; Younes & Hanly, 2016).

Challenges with Complex Sleep Patterns: Some sleep disorders like sleep apnea and parasomnias present complex sleep patterns that challenge manual and automated classification methods. These disorders often require additional diagnostic tests and expert evaluation. Automated black-box approaches may yield efficient outcomes, but they lack the essential information of particular interest to medical professionals. Moreover, the methodology used to generate such outcomes is not easily interpretable by medical experts, rendering it irrelevant and illegible. As a result, addressing these challenges necessitates the development of comprehensive and interpretable sleep stage classification methods that can assist medical experts in understanding and interpreting the results effectively (Gulia & Kumar, 2018; Hamida & Ahmed, 2013; Lam, 2006; D. Zhao et al., 2019).

Subject's Sleep Variability: Sleep patterns can vary significantly across different nights for the same subject due to factors like stress, medications, or lifestyle changes. Both manual and automated methods struggle to capture this nocturnal variability adequately. Therefore, sleep variability presents a significant challenge for sleep research and somnology (Brunner et al., 1996; Buysse et al., 2010; X. Chen et al., 2019; Edinger et al., 1991; McMenamin et al., 2011; Sweeney et al., 2012; Urigüen & Garcia-Zapirain, 2015).

Artifact Sensitivity: Automated sleep stage classification methods can be sensitive to artifacts and noise in polysomnographic EEG data, resulting in misclassifications. The pre-processing stage poses a significant challenge, and it lacks a consistent methodology in sleep EEG research to implement artifact removal techniques and mitigate this issue reliably and effectively (Brunner et al., 1996; Chiu et al., 2014; Muthukumaraswamy, 2013).

In addition to the limitations mentioned above, manual and automated sleep stage classification face additional challenges, including the inadequate representation of sleep stage patterns and the applicability of existing methods to diverse populations. The limitations in representing sleep patterns are particularly noticeable in the NREM stages S2 and S3, where the boundaries between them are not always clearly defined,

leading to confusion and misinterpretation by both automatic methods and experts (Goldman et al., 2007a, 2007b; Grandner & Rosenberger, 2019). Moreover, the adaptability of existing methods to diverse populations raises significant concerns. Many of these methods have been developed based on specific demographic groups or sleep disorders, which hinders their generalisation to diverse populations, such as children or individuals with comorbidities (Grandner & Rosenberger, 2019; Kubek et al., 2022).

Addressing these limitations and developing more robust and accurate sleep stage classification methods is crucial for advancing sleep research, diagnosis, and treatment of sleep disorders. Integrating cutting-edge machine learning algorithms, incorporating more extensive and diverse datasets, and exploring hybrid approaches could improve sleep stage classification in the future.

2.3.2. Machine Learning Methods for Feature Extraction and Classification

Sleep EEG data contains valuable information about different sleep events and conditions. The accurate classification of sleep stages relies on extracting and classifying relevant features from these signals. Machine learning methods, such as rule-based, support vector machines (SVM), random forest, and k-nearest neighbours (k-NN), among others, are employed to extract and classify features from EEG data. This section delves into the efficacy of these techniques in capturing pertinent features and patterns associated with different sleep stages. Moreover, it highlights the significance of interpretability and explainability during the feature extraction process, facilitating a deeper understanding of the discriminative properties of the extracted features.

2.3.2.1. Rules-Based Classifier

A rules-based classifier is a type of machine learning (ML) model that makes decisions based on predefined rules and conditions. These rules are usually derived from domain knowledge or expert input and are then implemented to classify data into different categories or classes. Rules-based classifiers differ from other machine learning methods in several aspects. While traditional ML models are well-suited for various tasks and data types, the rules-based method may not be optimal for all scenarios (Angelov & Gu, 2018; Farid et al., 2016; B. Liu et al., 2000; Xu et al., 2020).

Rule-based classifiers offer high interpretability due to their transparent decision-making process, which is easily understandable by humans. Each rule represents a

specific condition leading to a particular classification, facilitating clear model reasoning. These classifiers do not need the training phases seen in other machine learning models, as experts manually define the rules, reducing the dependence on large, labelled datasets and complex optimisation algorithms. The simplicity of rule-based classifiers ensures low computational overhead, enabling quick predictions on new data, making them ideal for real-time or time-critical applications. Moreover, these classifiers seamlessly incorporate domain knowledge, allowing experts to input their expertise directly into the model by defining rules and facilitating the integration of prior knowledge into the classification process (Angelov & Gu, 2018; Farid et al., 2016; B. Liu et al., 2000; Xu et al., 2020). These characteristics are prominently demonstrated in Chapter 3, where one of the classifiers was created based on the sleep stage rules from the R&K and AASM standards.

The limitations of rule-based classifiers are evident compared to more high-level models like neural networks or decision trees. Their limited eloquence obstructs their ability to capture complex patterns or high-order interactions within data. Additionally, the risk of rule overfitting poses a significant concern. Adding too many rules can lead to excellent performance on the validation set but poor generalisation to new, unseen data. Moreover, the heavy reliance on domain experts for rule definitions introduces expert bias, potentially leading to biased classification outcomes. Also, as the number of rules increases, the model's scalability, manageability, and interpretability become challenging, making maintenance and modification awkward. Lastly, rule-based classifiers may struggle to generalise effectively to new domains or unseen data if the rules are overly specific to the training data or fail to account for complex patterns not explicitly defined in the rule set (Angelov & Gu, 2018; Farid et al., 2016; B. Liu et al., 2000; Xu et al., 2020).

In the context of signal analysis, particularly in sleep EEG, a notable concern revolves around the susceptibility to artifacts, which can considerably influence the classification and rules employed. This issue became apparent in the rules-based method as discussed in Chapter 3, specifically when classifying data from the St. Vincent database, wherein some subjects exhibited sleep pathologies. Consequently, the method's performance was not as robust as when assessed on other databases comprising healthy subjects. Thus, the sensitivity to artifacts played a pivotal role in the observed inferiority of the method's performance.

2.3.2.2. Support Vector Machines for Feature Extraction and Classification

Support vector machines (SVMs) are a robust supervised learning algorithm for binary classification tasks. In the context of sleep EEG analysis, SVMs can extract relevant features by learning the optimal hyperplane that separates different sleep stages in the feature space. The discriminative features identified by SVMs are subsequently used for classifying sleep stages (Dagher, 2008; Lajnef et al., 2015; Siuly & Li, 2012).

One of SVMs' strengths is its ability to handle non-linear and complex feature spaces. The kernel trick allows SVMs to implicitly transform the original feature space into a higher-dimensional space, enabling the capture of intricate patterns and non-linear relationships presented in sleep EEG data. SVMs focus on identifying support vectors or data points near the decision boundary, representing the most relevant features for classification (Alickovic & Subasi, 2018; Lajnef et al., 2015).

However, one limitation of SVMs is its lack of inherent interpretability. While the identified support vectors play a crucial role in classification, understanding the individual feature's significance can be challenging. To address this, feature importance scores can be applied to improve the relevance of different features and their contributions to sleep stage classification.

By incorporating SVMs as part of the feature extraction and classification process, the proposed method aims to enhance the performance and accuracy of sleep stage classification, providing valuable insights into sleep EEG analysis and its association with various sleep stages (Alickovic & Subasi, 2018; Dagher, 2008; Lajnef et al., 2015; Siuly & Li, 2012; Zapata et al., 2022).

In addition to the conventional SVMs, a variant known as SVM with Q factor (SVM-Q) offers an additional feature extraction and classification approach in sleep EEG analysis. SVM-Q extends the traditional SVM by incorporating a Q factor, representing a signal quality measure, into the feature selection process and classification. This additional parameter enhances the discriminative power of SVMs, especially when dealing with noisy or low-quality signals often encountered in sleep EEG data (Dagher, 2008; Nefedov et al., 2009; Suthaharan, 2016).

The Q factor is calculated based on the signal-to-noise ratio (SNR) of EEG data, which quantitatively measures the signal's reliability and accuracy. By considering the Q factor during the feature extraction stage, SVM-Q can prioritise selecting features with higher signal quality, effectively mitigating the impact of noise and artifacts on the classification performance (Nefedov et al., 2009; Suthaharan, 2016).

The integration of SVM-Q into sleep stage classification holds promise for an improved accuracy and robustness, as it addresses one of the challenges posed by noisy EEG signals. SVM-Q can help to ensure that the selected features are more relevant to the underlying sleep stage patterns, leading to better generalisation and performance across different datasets (Dagher, 2008; Nefedov et al., 2009; Suthaharan, 2016).

Furthermore, the interpretability aspect of SVM-Q can also be enhanced by utilising the Q factor to highlight the importance of features with higher signal quality, providing a clearer understanding of the contributions of individual features to the classification outcome, aiding medical experts in validating the relevance of the selected features in relation to the scored sleep stages (Dagher, 2008; Zapata et al., 2022).

In conclusion, SVM-Q represents a valuable extension of traditional SVMs in sleep EEG analysis, offering the potential to overcome the limitations posed by noisy EEG signals and providing more reliable and interpretable feature extraction and classification. By incorporating SVM-Q alongside other feature extraction techniques, such as the previously mentioned the MT&C and SE-VGGNet-S-BN methods, the proposed multi-method approach aims further to enhance the accuracy and robustness of sleep stage classification, ultimately contributing to advancements in sleep physiology research and improving the diagnosis and treatment of sleep disorders (Zapata et al., 2022).

2.3.2.3. Random Forest

Random Forest (RF) is an ensemble learning technique that relies on decision trees to improve accuracy and generalisation. Constructing multiple decision trees and combining their outputs allows an RF algorithm to identify informative features associated with different sleep stages in the context of sleep EEG analysis (Biau & Scornet, 2016).

The effectiveness of an RF algorithm relies on its ability to handle large feature sets and automatically select essential ones based on their contribution, reducing misleading connections in decision trees. This adaptability makes it well-suited for dealing with multidimensional sleep EEG features, passed from the MT&C method, and capturing complex relationships and interactions between features.

Furthermore, RF provides a level of interpretability and explainability by generating feature importance scores, which offer insights into the relative importance of various features during the classification process. These scores facilitate interpreting extracted features and their discriminative characteristics (Biau & Scornet, 2016).

Although RF was not directly utilised in the algorithms presented in this study, it proved valuable insight when incorporated with other methodologies, such as the Rule-based method and the SVM. By combining RF with these approaches, we were able to leverage their respective strengths, resulting in enhanced sleep stage classification and a deeper understanding of sleep EEG analysis. Adding SVM for classification enhanced the overall performance of the system, providing a more comprehensive and accurate classification of sleep stages.

2.3.2.4. k-Nearest Neighbours

k-Nearest Neighbours (k-NN) is an intuitive and straightforward instance-based learning algorithm proficient in classifying data points by evaluating their proximity to a k-NN within a feature space. Particularly relevant in sleep EEG analysis as a feature extraction method, k-NN excels in identifying crucial features based on their influence on the class labels of neighbouring data points. Regarding effectiveness, k-NN adeptly captures local patterns and feature dependencies in sleep EEG signals, identifying clusters of similar sleep stages through the proximity of feature vectors, thus effectively handling spatially correlated EEG data. The inherent interpretability of k-NN is one of its notable strengths, as its classification decision relies on the majority class among the k-NN, making the role of individual features in determining classification easily comprehensible. As a result, this attribute furnishes valuable insights into the discriminative properties of the extracted features, thereby enhancing the overall interpretability and explainability of the process.

Several algorithms were employed for testing and performance analysis, including k-NN, logistic regression, Naïve Bayes, linear discrimination, Gaussian process, and hidden Markov models. However, it was observed that the Rules-based method and SVM exhibited superior performance. As a result, these two approaches were employed as the primary research methods that are presented in Chapter 3 Click or tap here to enter text.

2.3.2.5. Interpretability and Explainability

Interpretability and explainability are important in the feature extraction process for sleep EEG data. As sleep stage classification directly affects medical decisions and patient treatment, understanding the basis of classification becomes crucial for clinical acceptance and trust in automated systems. Interpretable models allow sleep experts to validate the relevance of extracted features and identify potential biases or artifacts that could impact classification results.

Moreover, interpretability is crucial in providing researchers with valuable insights into the physiological significance of specific features associated with different sleep stages. By understanding the discriminative properties of the extracted features, novel discoveries can emerge, leading to the development of targeted and effective treatments for sleep disorders (H. Kaur et al., 2022; Linardatos et al., 2020; Oviedo et al., 2022).

In conclusion, machine learning methods, such as rules-based, SVMs, random forest, and k-NN, among others, serve as valuable tools for feature extraction and classification from sleep EEG signals. These techniques effectively capture relevant features and patterns related to various sleep stages, enabling accurate sleep stage classification. The emphasis on interpretability and explainability during the feature extraction process empowers researchers and clinicians to gain insights into the discriminative nature of the extracted features, thereby facilitating a better understanding and utilisation of automated sleep stage classification systems.

Consequently, integrating the MT&C with different machine learning algorithms establishes a direct connection between the classification and interpretation of the features. The features align with the principles and patterns of the R&K rules and AASM standards, making them relevant to signal analysis. They can be recognised and distinguished by experts as in manual scoring.

2.3.3. Deep Learning Methods for Sleep Stage Classification

In recent years, deep learning models have shown remarkable success in various fields, including computer vision, natural language processing, and sleep stage classification. In this section, we explore the applications of deep learning models, such as CNNs, VGGNet, and the integration of advanced techniques like batch normalisation, SE, SELU activation, max-pooling, flatten layer, transformation layer, loss function optimisation using stochastic gradient descent (SGD), and learning rate decay, in sleep stage classification.

2.3.3.1. Convolutional Neural Networks and VGGNet

CNNs and visual geometric group network (VGGNet) have transformed the field of image classification, but their applications extend beyond visual data. In the context of sleep stage classification, these deep learning models offer a powerful and practical approach to analyse EEG data, which can be represented as 2D spectrograms in the time-frequency domain (Dequidt et al., 2023; Ji et al., 2022; Kaulen et al., 2022; H. Kim & Choi, 2018; C. Li et al., 2022; S. Liu & Deng, 2015; Perslev et al., n.d.; Simonyan & Zisserman, 2014; Tzimourta et al., 2018).

CNNs are designed to automatically learn hierarchical features from spatial data, making them well-suited for tasks like image recognition. However, the time-frequency representation of EEG data, in the form of spectrograms, shares similarities with images. This similarity allows CNN algorithms to recognise patterns and structures within the spectrograms, enabling them to efficiently capture the intricate temporal and spectral characteristics of different sleep stages (Ji et al., 2022; S. Liu & Deng, 2015; Perslev et al.; Simonyan & Zisserman, 2014).

VGGNet, a deep CNN architecture, has demonstrated its effectiveness in various image classification tasks. It consists of multiple convolutional layers, each followed by a max-pooling layer, creating a deep, sophisticated network that can extract hierarchical features from input data (Rodriguez-Martinez et al., 2023). The adaptability of VGGNet makes it an excellent candidate for processing EEG spectrograms, where it can automatically learn relevant features that distinguish different sleep stages (Y. Mei et al., 2021; Raja et al., 2021).

By training VGGNet on large datasets of labelled EEG spectrograms, the model can learn to identify and classify sleep stages based on the extracted features. The stacking of convolutional and pooling layers allows the model to progressively learn higher-level representations, enabling it to recognise complex temporal and spectral patterns indicative of different sleep stages (Ji et al., 2022; Y. Mei et al., 2021; Raja et al., 2021; Supratak et al., 2017).

In summary, CNNs, specifically VGGNet, have proven their capabilities in image classification tasks. When applied to sleep stage classification with EEG spectrograms, they can effectively learn and distinguish the characteristic features of different sleep stages, as documented in Chapter 5 (Zapata et al., n.d.). Leveraging the power of deep learning, these models offer a promising avenue to enhance the accuracy and efficiency of sleep stage classification, ultimately contributing to advancements in sleep medicine, research, and personalised sleep health interventions.

2.3.3.2. Integration of Advanced Techniques in a VGGNet Model

To enhance the performance of deep learning models for sleep stage classification, the integration of advanced techniques has shown significant benefits. These techniques optimise the training process, improve generalisation, and increase the model's robustness. In this section, we explore the incorporation of batch normalisation, squeeze-and-excitation (SE) blocks, SELU activation, max-pooling, a flattening layer, and a transformation layer for data augmentation.

Batch normalisation is a technique that activates the intermediate layers of a deep neural network. By normalising the activations within each mini-batch during training, batch normalisation reduces internal covariate shifting, stabilises training, and accelerates convergence. The application of batch normalisation helps prevent overfitting. It improves the model's ability to generalise to unseen data, making it an essential component in deep learning models for sleep stage classification (Ioffe & Szegedy, n.d.-a, n.d.-b; Santurkar et al., n.d.).

SE blocks aim to recalibrate the importance of different feature maps within a CNN. During training, SE blocks learn to assign higher weights to the most discriminative feature maps and lower weights to less informative ones, effectively enhancing the representation of essential features. By incorporating SE blocks, the deep learning model becomes more adaptive to the most relevant information, leading to improved performance in sleep stage classification tasks (Hu et al., 2019; Siuly & Li, 2012; Zapata et al., n.d.).

SELU (Scaled Exponential Linear Unit) is a self-normalising activation function that addresses the vanishing and exploding gradient problems commonly encountered in deep networks. A SELU activation helps maintain the mean and variance of the activations close to one, ensuring stable training with deep architectures. The utilisation of a SELU activation further enhances the robustness of the model and enables efficient training of deep neural networks for sleep stage classification (Z. Huang et al., 2020; Zhang & Li, 2018).

Max-pooling is a down-sampling operation that reduces the spatial dimensions of feature maps, capturing the most salient information. After convolutional layers, the flattening layer reshapes the 2D feature maps into a 1D vector, preparing them to be fed into fully connected layers for further processing. Max-pooling and the flattening layer facilitate feature extraction and dimensionality reduction, improving the model's efficiency and ability to learn discriminative patterns (Rodriguez-Martinez et al., 2023; You et al., 2021).

Data augmentation is crucial in training deep learning models, especially when data are limited. The transformation layer can perform various transformations on the EEG spectrograms, such as rotations, shifts, and flips, generating diverse variations of the original data. Augmenting training datasets with these variations increases its diversity, helping the model generalise better to different recording conditions and variations in sleep EEG data.

In conclusion, the integration of advanced techniques, such as batch normalisation, Squeeze-and-Excitation (SE) blocks, SELU activation, max-pooling, flatten layer, and data augmentation using a transformation layer, enhances the capabilities of deep learning models for sleep stage classification. These techniques improve convergence, prevent overfitting, and promote stable and efficient training. By leveraging these advancements, researchers and clinicians can develop more accurate and robust sleep stage classification models, leading to better insights into sleep physiology and more effective sleep health assessments, as presented in Chapter 5.

2.3.3.3. Learning Sleep EEG Signals Patterns from MT&C Features

Learning EEG signal patterns from the MT&C features using deep learning models offers a potent approach to extracting intricate and contextually relevant information from sleep EEG recordings. Deep learning models enhance adaptability, generalisation, and robustness in sleep stage classification with their capacity for automatically learning hierarchical representations. Architectures like CNNs facilitate hierarchical learning, capturing complex patterns and relationships within MT&C features of the sleep EEG spectrograms. Deep learning models excel in adapting to variations in sleep EEG recordings caused by differences in individuals, sleep habits, and recording conditions. Deep learning models improve generalisation by learning discriminative features directly from the MT&C features, surpassing traditional feature extraction methods that may require laborious manual engineering. This advancement significantly eases the burden on researchers and clinicians.

Moreover, deep learning's capacity to learn non-linear representations empowers models to capture intricate EEG signal patterns related to sleep stages. The adoption of end-to-end learning streamlines the classification process, ensuring seamless integration of the MT&C features, optimising learning, and enhancing overall performance. In conclusion, deep learning models revolutionise sleep stage classification, advancing our understanding of sleep physiology and elevating patient care through its robust and adaptable capabilities.

2.4. Chapter Summary

This chapter delves into the foundational aspects essential for the multi-method approach in sleep EEG analysis and sleep stage classification. Section 2.1 provides a comprehensive discussion on sleep characteristics, physiology, stages, sleep EEG, and technical aspects, forming a critical foundation for the subsequent research studies. This

knowledge enriches our understanding of sleep and guides the selection and implementation of postulated methods discussed in Section 2.2 to address challenges in sleep stage classification. Additionally, Section 2.2 explores time-frequency signal analysis techniques, highlighting the suitability and advantages of the MP and MT&C methods in EEG data analysis. The combination of the MP and MT&C offers enhanced accuracy and performance, as demonstrated through various applications, including sleep spindle identification and sleep stage classification. However, due to computational demands, the insights from MP are integrated into the MT&C approach. Section 2.3 delves into deep learning models, such as CNNs, that excel in learning hierarchical representations from the MT&C features of sleep EEG spectrograms. These models embrace end-to-end learning, streamlining the classification process, enabling efficient integration of the MT&C features, optimising learning, and elevating overall performance. By revolutionising sleep stage classification, deep learning models enhance our understanding of sleep physiology and improve patient care through their powerful and adaptable capabilities. Overall, this chapter lays the groundwork for innovative approaches, offering insights into the potential transformation of sleep EEG analysis and sleep stage classification in sleep medicine, neuroscience, and personalised sleep health interventions.

CHAPTER 3

Rules-Based and SVM-Q Methods with Multitapers and Convolution for Sleep EEG Stages Classification

3.1. Introduction

The classification of sleep stages through analysing sleep EEG signals is vital in comprehending the underlying phenomena that occur during sleep. It aids in understanding the neurocognitive processes that take place while the body is at rest, particularly during sleep, which plays an essential role in the body's recovery and overall well-being. The content of this chapter is an exact copy of an original study published by **IEEE Access,** an *IEEE Xplore Journal, 2022, 10th edition, DOI: 10.1109/ACCESS.2022.3188286*.

The study introduces a novel approach for sleep stage classification, employing the time-frequency analysis method of the MT&C. The primary goal of this approach is to decipher the parameters that define sleep stages from EEG data by effectively computing the spectral estimation of the signal using a set of controlled wavelets. In this context, the research explores two distinct methods for sleep stage classification: a rules-based approach and a support vector machine with a quadratic equation (SVM-Q) classifier.

The chapter begins by underscoring the significance of EEG data in understanding the neurocognitive processes during rest, with sleep being a critical component of the body's recovery process and overall well-being. While manual scoring has long been the traditional method for sleep stage classification, it is not without limitations, primarily due to its subjectivity and time-consuming nature. Thus, to address these limitations and enhance the efficiency of sleep stage classification, this research proposes a novel time-frequency analysis approach utilising the MT&C to extract essential features from EEG data.

Moreover, the chapter provides an overview of the methodology employed, encompassing the pre-processing of EEG data, the extraction of features, and the classification techniques applied. The MT&C method stands as the primary feature

extraction approach used, with the extracted features subsequently employed in both the SVM-Q classifier and the rules-based classification, facilitating the categorisation of sleep stages based on known parameters and characteristics.

To highlight the novelty of the research, the introduction emphasises integrating Gabor wavelets with the MT&C method and introducing the rules-based classification based on R&K rules. Consequently, the chapter sets the stage for the subsequent sections which delve into the technical intricacies of the methodology and present the experimental results and comparisons.

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Rules-Based and SVM-Q Methods With Multitapers and Convolution for Sleep EEG Stages Classification

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ABSTRACT Sleep EEG signals analysis is an approach that helps researchers identify and understand the different phenomena concealed within sleep EEG data. This research introduces a time-frequency analysis approach to untangle the parameters of the sleep stages classification from EEG data. This approach computes the spectral estimation of a signal based on a set of controlled wavelets using a multitaper with convolution (MT&C) method. In this study, the MT&C methods is implemented to extract the features from a single sleep EEG data channel. Then two separated approaches are applied for sleep stage classification. The first one is based on the EEG waves characteristic definitions of sleep stages (named as Rules-based method) to directly classify each 30 second EEG segment after the feature extraction. The second approach uses a support vector machine with quadratic equation (SVM-Q) classifier to classify the sleep stages based on experts' scoring. The experimental results are evaluated, and the outcomes show an overall accuracy of 90% with an average sensitivity of 96.2% and an average specificity of 93.2% using an SVM-Q classifier and an 87.6% accuracy for the Rules-based method on healthy subjects. On the other hand, the accuracy on subjects with abnormal sleep EEG data is of 78.1% with the SVM-Q classifier and 73.4% with the Rules-based method.

INDEX TERMS Multitapers, support vector machine, SVM-Q, spectral estimation, sleep EEG, sleep stages, sleep rules, spectra density estimation (SDE).

I. INTRODUCTION

The electroencephalography (EEG) data represents the neurocognitive process of an individual and the interactions between neurons in the brain [1]–[3]. Its complexity creates a real-world challenge for researchers to generate various algorithms that are able to accurately identify the cognitive dynamics in a certain time frame in which cognition appears. An optimum time to analyse the cognitive dynamics of the human brain is while it is resting, as most of the body functions are partially suspended.

Sleep is essential not just because humans spend one-third of our lives sleeping, but also because it is a recovery process, and its quality dictates the neurological and physiological status of individuals. Therefore, sleep analysis has been a focus of scientific research for many decades, and there are a large number of algorithms dedicated to the analysis of the physiological dynamics of sleep. However, many EEG sleep analysis algorithms face enormous dilemmas due to the variation of their results for individuals and between databases. Often some algorithms perform better than others, yet none of them produces a flawless result [4]–[6].

Manual scoring has been used as the main method for sleep stages classification, and it is still one of the most common practices applied today, although it is time-consuming and subject to expert's fatigue and personal biases [7], [8].

This research introduces a methodology to unveil the characteristics of sleep stages based on EEG data using a time-frequency method, multitapers with convolution (MT&C).

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of such resolution became blurry, allowing them to identify only the elements within the spectral resolution. That study gave an insight into how MTs was capable of identifying an accurate spectral estimation for different types of EEG signals.

Prerau *et al.* [30] presented a review of the neurophysiology of sleep EEG data using the spectral analysis generated by the MTs spectrograms. They demonstrated how the MTs method could be used as an effective tool to present a more defined way to visualize EEG data, producing better and faster results of classifying sleep stages. They found that the spectrograms allowed them to identify the embedded oscillatory mechanisms of each particular sleep stage and create a visual representation that was easier to map with their hypnogram compared to the original signal. Their results showed a very close relationship between expert's labels and the spectrograms produced by the MTs method.

B. EXISTING STUDIES FOR RESULT COMPARISONS

The performance of the proposed methods in this paper are compared against four other similar studies that used the same databases as the ones proposed in this research.

The first study by Zhu *et al.* [3] combined a deep belief networks approach with bi-directional long short-term memory to improve the performance and time efficiency for sleep stages classification using the St. Vincent's University Hospital database. That paper reported an average accuracy of 68.6% with good performance on Stage 2, but very low accuracy on REM stage.

The second study by Chokroverty *et al.* [4] proposed the use of a deep belief network to extract representative features and automatically classify sleep stages. That study reported an average accuracy of 65.3%.

The third study by Diykh *et al.* [5] presented a sleep stages classification method using two-stage networks. In the first step, the network combined the hand-crafted features with a network generated feature. In the second step, the network combined a sequence learning process with a prediction model that classified sleep stages using a training and testing approach. That approach produced an average accuracy of 78.6%.

Aboalayon *et al.* [6] proposed a method based on a U-Network architecture. The aim of that method was to generate a spontaneous temporal scale based on the sequences of the labels produced from mapping sequential inputs of a subjective length. So, the final prediction was given by classifying each single time-point in a signal and attaching those classifications over static intervals. That study used both the St. Vincent's University Hospital database and the CAP Sleep database. That approach produced an average accuracy of 72.8% for the St. Vincent's database and 67.8% for the CAP Sleep database.

III. EXPERIMENTAL DATA

In this study, three databases were used, two open-access from PhysioNet [31] and one private database from our industry partner. The first open-access database is the St. Vincent's University Hospital and the University College Dublin Sleep Apnea Database (St. Vincent's Database) published by Heneghan [32]. The second database is the Cyclic Alternating Pattern of EEG Activity During Sleep Database (CAP Sleep Database) published by Terzano *et al.* [33]. The database from our industry partner known as the Delica Database is for closed access and is used for testing.

A. ST. VINCENT'S DATABASE

The St. Vincent's Database was published in 2007 and revised in 2011. That database contains a full overnight polysomnogram EEG data from a three-channel Holter of 25 adult subjects with suspected sleep disorders. For that database, the subjects were randomly selected from a group of individuals over 18 years of age, who were not under any medication, and did not present any cardiovascular diseases, or dysautonomia.

The hypnograms from the database were manually labelled by a sleep technologist using the R&K rules [9].

TABLE 2. St. Vincent's data information (from 12 subjects).

Sleep Stage	The Number of Stages
Awake	2309
Stage 1	1348
Stage 2	1746
Stage 3 & Stage 4	3309 & 343 (3652)
REM	995
Total:	10051

B. CAP SLEEP DATABASE

The CAP Sleep Database contains the EEG, electrooculography (EOG), electromyography (EMG), respiration signals and electrocardiography (ECG or EKG) polysomnograms of 108 subjects divided into eight groups, from which the non-pathology subject group is used on this research. The hypnograms were made by an expert trained at the Sleep Centre using the R&K rules [9].

The non-pathology datasets from CAP Sleep Database comprise 16 healthy subjects of mixed genders in an age range of 25 to 42, who were not on any medication that could alter the central nervous system. The data of each subject contains around 9 hours of an overnight sleep recording. The datasets are available in a sampling rate of 256 hertz (Hz).

C. DELICA DATABASE

The Delica Database contains the EEG, EOG, EMG and EKG of an overnight sleep from three different healthy subjects from 17 to 23 years old. That database uses a sampling rate of 500Hz in a frequency band of 0.05 to 100Hz. The data from that database has not been filtered or modified. It has five individual EEGs channels (F4, C3, C4, O1, O2, A1, A2), four EOGs (two vertical electrooculograms and two horizontal electrooculograms) and three EKGs (one right and two left).

TABLE 3. CAP Sleep data information (from 11 subjects).

Sleep Stage	The Number of Stages
Awake	985
Stage 1	390
Stage 2	4107
Stage 3 & Stage 4	874 & 1551 (2425)
REM	2174
Total:	10081

TABLE 4. Delica database (from 3 subjects).

Sleep Stage	The Number of Stages
Awake	467
Stage 1	311
Stage 2	934
Stage 3	319
REM	587
Total:	2618

IV. METHODOLOGY

This research uses one main feature extraction method for the general features and one supplementary method to extract the features of muscle movement (MM). Then, the features are classified into stages using two different approaches.

A. EEG DATA AND DATA PROCESSING

This study uses the EEGs from C3-A2 and C4-A1 channels for the MT&C feature extraction method, and the right (R) and left (L) EOGs channels together with the C3-A2 and C4-A1 for the MM feature extraction method. In the case of the EEGs used in MT&C, those bio-signal channels were selected in accordance with R&K [9] as they are the main channels to score sleep stages using sleep EEG data. The data from the EEG channels were filtered using a notch filter and a bandpass filter. The starting frequency of 0.2Hz on the notch filter were selected to avoid negative frequencies as described in [34]–[36], and the top frequency of 50Hz in the notch filter as well as in the bandpass filter were designated to exclude frequencies over 50Hz which were not relevant to this study.

In the case of the MM feature extraction method, additional filters were applied in the right (R) and left (L) EOG channels as well as in the EEG data. Accordingly, considering that the features from the MM method reflect the outsized increase of the amplitudes (over 15Hz) in sleep EEG data whenever there is muscle movement in subjects, all four channels used in this method were filtered above the alpha range (15Hz) using a high-pass filter.

The average of signal to noise ratio (SNR) in the CAP database [33] is around 0.0198 decibels (dBs). For the St. Vincent's database [32] the SNR is around 0.132 dBs and 0.223 dBs for the Delica database. That noise corresponds to the high amplitudes, and high or abrupted frequencies (>30Hz, 50Hz) that are removed from the data for the sleep stages classification. Also, the segments that are flagged as noisy due to constant muscle movement and awake are deducted from the data that is used for sleep analysis. It's unclear what preprocessing and denoising methods were applied in the two open-source EEG databases (CAP and St Vincent's). But we applied xx denoise method before used all the EEG data.

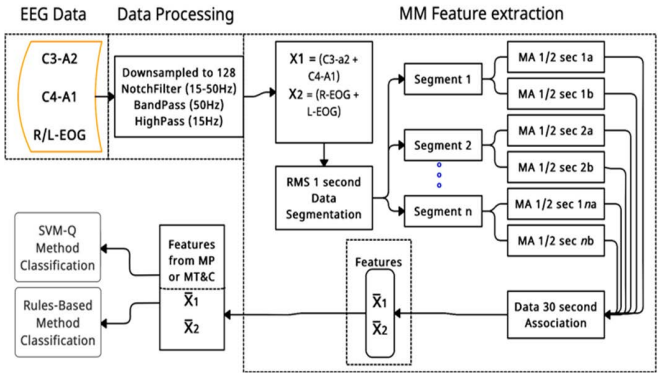

FIGURE 1. MM feature extraction diagram.

B. FEATURE EXTRACTION

Feature extraction was conducted using two individual methods of the MM and MT&C. The features obtained from the MM method are integrated with those from the MT&C. For the MT&C feature extraction, the data was segmented in epochs of 30 seconds to match the hypnograms for the sleep stage scoring. The data were segmented in epochs of one second to compute bipolar differences and then it was grouped back to epochs of 30 seconds to match the hypnograms in the MM feature extraction.

1) MM FEATURE EXTRACTION

The Muscle movement or MM characteristic features were originally defined by the R&K rules [2] and used in many other studies when analysing EEG data for sleep stages classification [7], [8], [10], [23], [24], [35].

Fig. 1 shows the algorithmic form diagram in the MM feature extraction. Firstly, the sleep EEG and EOGs data were pre-processed, then the EEGs from C3-A2 and C4-A1 channels were integrated into a single signal (X1), so did the R-EOG and L-EOG channels (X2). After that, the data were segmented into one second epoch and the root mean square (RMS) was calculated for each epoch. The moving average (MA) technique was then used to smooth out the small fluctuations for every 0.5 second of the input data to highlight the outliers from those high amplitudes. Then the data were grouped back into 30 second epochs and the mean ($\bar{x}$) of the entire data was computed and passed as features $\bar{X}1$ and $\bar{X}2$.

The sensitivity analysis surrounding the relationship of the MM features and awake stage was based on the correlation between all awake instances on the hypnogram and the high amplitudes found on the MM features. It was established that

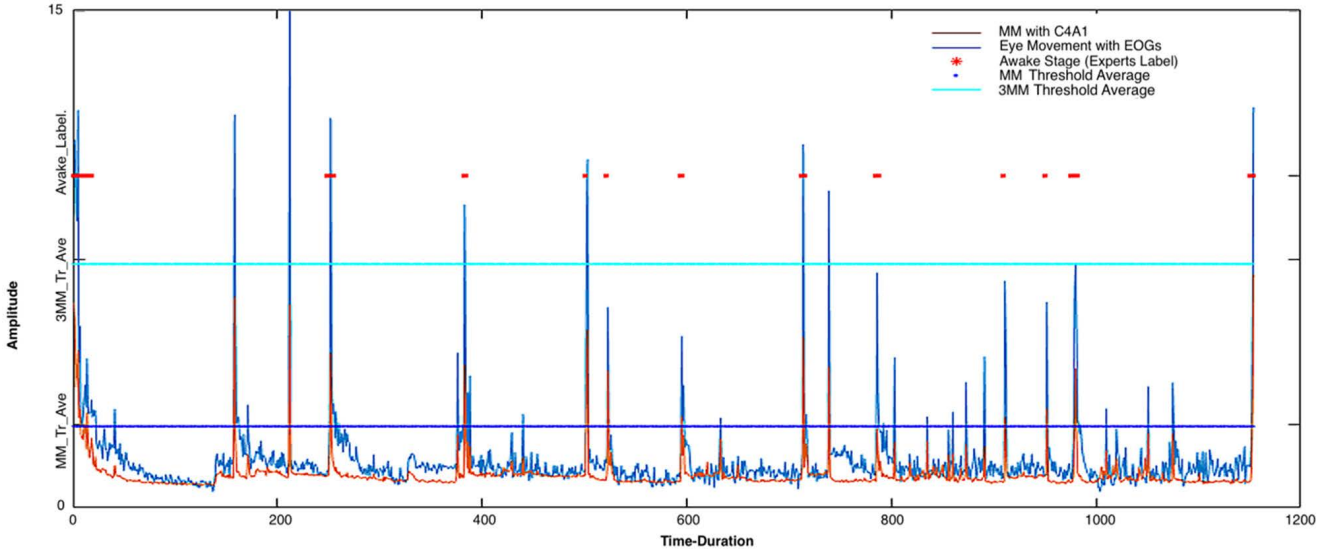

FIGURE 2. Correlation between muscle movement and eye movement using the features from MM method.

awake stages and high amplitudes on frequencies above 15Hz have a significant correlation with the number of instances (artifacts) found on each awake stage. Consequently, by calculating the number of artifacts in each epoch and smoothing them out using a moving average function, most of the awake stages were defined by using the MM features from the EEG bipolar channel (BC) called MM-BC and the EOGs called MM-EOG [37]. Muscle movement was determined when the MM-BC and the MM-EOG surpassed the general average (Tr_Ave) of the MM-BC, as seen in Fig. 2.

Using the features from MM method the muscle movement was determined when the MM-BC was three times larger than its general average (3MM_Tr_Ave) as shown in Fig. 2. Likewise, when the artifacts in one of the surrounding epochs were above the general mean of the signal, and its artifacts on the current epoch were above the mean, that epoch also were given the MM status. Parallel to that analysis, the MM was also validated using the SVM-Q classification method from MATLAB. It was found that the final MM features had a high correlation with the wake stage, and by using the MM from C3-A2 or C4-A1, the classification tool was able to predict an average classification accuracy of 87.7% for awake stages using a support vector machine (SVM).

2) MT&C FEATURE EXTRACTION

This main feature extraction in this study is the MT&C method. It generates a spectra density estimation (SDE) from a signal by convoluting predefined wavelets with a row signal. The predefined wavelets are orthogonal to each other in terms of frequency, and they are generated using the Gabor function.

The Gabor kernel is selected as the main function after intensive literature review [15], [24], [39]–[41] and experiments performed and compared with other kernels like Haar, Laplacian, Sobel, and a combination of them. The Gabor function in (1), which is used to create the wavelets that convolute the signal, is a permutation of a Gaussian function in [15], [38], [39] with an imaginary cosine wave as used in [24], [40].

$$g_k(t) = e^{\left(\frac{(-t^2)}{(2S^2)}\right)} e^{(i2\pi f_k t)} \tag{1}$$

where $g_k(t)$ is the Gabor wavelet, $e^{\left(\frac{(-t^2)}{(2S^2)}\right)}$ is the Gaussian window, $e^{(i2\pi f_k t)}$ is an imaginary cosine wave, t is the time instance which also represents the duration of the wavelet *(1 second with the sample rate* (R) *of the raw signal)* and *fk* is the frequency, which also refers to a specific the wavelet, meaning that each wavelet is referenced by the frequency used to generate it.

Naturally, a cosine wave ($e^{(i2\pi f_k t)}$) is a constant infinite oscillatory wave, that by itself does not present much meaning to the interpretation of fluctuated signals as the ones presented in EEG sleep data [41], [42], [44]. Therefore, it is used together with the Gaussian function ($e^{\left(\frac{(-t^2)}{(2S^2)}\right)}$), which is a window that transforms the cosine wave into a wavelet with specific characteristics (f_k) that allows to identify specific elements in fluctuating signals. From the Gaussian function, there is an adjustable standard deviation (S) (described in (2)) that allows to modify the size or range of the wavelet, meaning that S in the Gaussian function defines the width of the wavelet.

$$S = \frac{n}{(2\pi f_k)} \tag{2}$$

where n is the number of cycles of the wavelet, and f_k is the frequency of the signal at level k.

The kernel function implemented here is based on Mallat [39], in combination with the one by Cohen [24], [40] in an attempt to reduce the complexity of the wavelet used in

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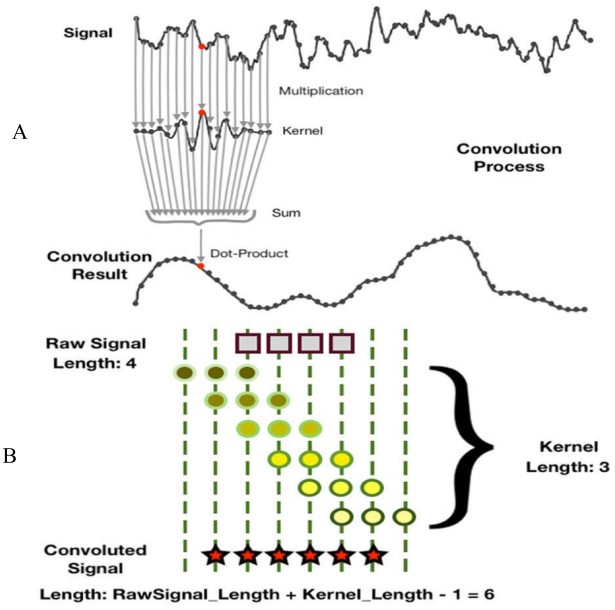

FIGURE 3. (A) Convolution process for a single point (red mark). (B) Convolution process and convolution signal length.

the MT&C by creating a complex wavelet, where redundancy is not compromised, but its size is reduced, improving the computational power, especially for extensive signals decomposition [45].

The number of wavelets used in the MT&C are associated to the frequencies that are desired to be extracted from an EEG signal [46]. Considering that each wavelet (g_k) can offer an autonomous estimation of the spectral density function (SDE(f_k)) of a signal within a time-window. The SDE of the signal is computed with a convolution process as shown in (3), and graphically represented in Fig. 3.

$$SDE(f_k) = \sum_{t=R\left(-\frac{1}{2}R\right)}^{n} (g_k(t)X_{w_t}) \tag{3}$$

where R *is the sampling rate,* t is one second (duration of the wavelet) and it starts from $t - (1/2R)$, and it goes up to $w+(1/2R)$ with increments of $1/R$. $g_k(t)$ is the kernel function in the frequency instance k with t duration. X_{w_t} is the original EEG data with t duration from the total duration w.

Based on SDE(f_k), $g_k(t)$ multiplies the original signal X_{w_t} and generates a dot-product for every point in X_{w_t}. This process is achieved by sliding each wavelet across the signal (X_{w_t}), meaning that if there are five kernels at different frequencies, the convolution will generate five different new signals, where each one contains the information related to the wavelet at the frequency. For instance, if the wavelet has a frequency of 15, the generated signal will show the instance, the power, and the amount of frequency (15) in the evaluated signal [28].

As described in (3), the dot-product between a wavelet and a signal is the sum of all points of the wavelet with a t duration multiplied by the signal of the same duration (red mark in Fig. 3(A). In other words, it is generated by convoluting every point of the kernel against the input signal. Considering that the maximum power a wavelet is in its centre, we must pad a $0.5R$ of zeros at the beginning and at the end of the original signal. Otherwise, if no additional points are added into the original signal, the first and the last 1/2 second of the resulting signal will not have an unbiased meaning. Those new extra points in the signal will have a value of zero to cancelling biased values and noise in the resulting signal, which means that the rightmost point of the kernel will be lined up with the leftmost point of the original signal at the start and the end of the convolution. The size of the resulting signal will be equal to the size of the original signal plus the size of the kernel minus one. The minus one occurs because the kernel overlaps the raw signal by one (Fig. 3(B)).

In general, the MT&C method behaves like a filter, where the signal is passed through a tunnel named kernel, which bypasses the frequencies that are outside it, resulting in a new signal that will only have amplitude wherever the frequency from the kernel is present [24], [46].

C. MT&C FUNCTIONALITY

Fig. 4 shows the algorithm structure for the MT&C feature extraction and classification method, where the data from one sleep EEG channel (C3-A2 or C4-A1) is pre-processed and segmented into epochs of 30 seconds. Subsequently, each epoch is convoluted to generate its SDEs. The resulting SDEs from each epoch are then grouped in wave bands, and their results are the MT&C features.

1) MT&C ALGORITHM

The MT&C algorithm includes four elements: an array that contains the data from one sleep EEG channel, a minimum frequency, a maximum frequency, and the number of frequencies that the algorithm is going to retrieve from the signal. The algorithm creates a linearly spaced vector from the minimum to the maximum frequency. The distance between individual frequencies will vary according to the number of frequencies requested by a user. Based on each element of the linearly spaced vector, the algorithm will then generate one Gabor atom using (3). Each wavelet generated will be convoluted across the signal [47].

The MT&C algorithm returns a matrix with all applied frequencies, a 2D matrix with the average power for each evaluated frequency and a matrix with the spectrogram.

D. FEATURE DIMENSIONALITY REDUCTION

The features generated from the MT&C method are a series of multidimensional descriptive matrices which can become problematic to be applied in the sleep stages classification methods. There is, therefore, a customised dimensionality reduction section for each classifier. The matrices from the MT&C are reduced to 30 features. Each feature represents the power spectrum presence on each of the frequencies, which are sorted in an ascending order based on the frequency.

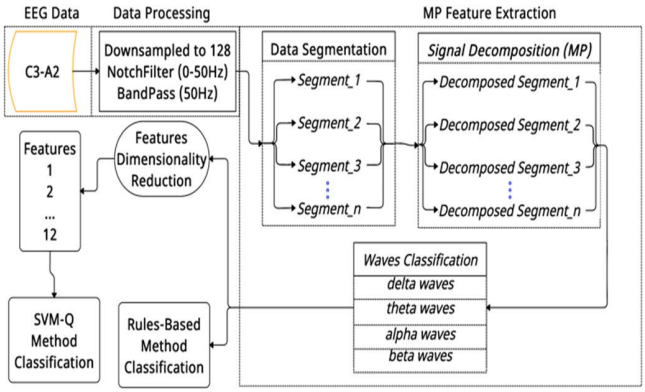

FIGURE 4. Feature extraction and classification using MT&C.

Those features are then grouped with the two features from the MM method before they are passed to the next phase of the classification.

E. SLEEP STAGES CLASSIFICATION WITH THE SVM-Q

The SVM-Q was implemented in this study after carefully analysing other supervised classifiers like decision trees, discriminant analysis, naïve bayes classifier, nearest neighbour classifier and ensemble classifier. It was found that the SVM-Q have better performance and accuracy over the other classifiers. SVM classifiers, also known as binary classifiers, are popular supervised learning algorithms used for regression and classification. The idea behind the SVMs is to find a hyperplane that denotes clear distinction between features into distinctive domains [48]. The quadratic kernel in the (4) is computed using quadratic optimization approach [49].

$$K(x, y) = \left(x^T * y + c\right)^2 \tag{4}$$

The SVM-Q classifier is fed with 32 features (30 from the MT&C and two from the MM), along with the expert labels. 70% of the data were used as the training data and the remaining 30% was divided equally for testing and validation. There are five main parameters used by the SVM-Q classifier used are. 1) The regularisation of the 'c' variable that defines the trade-off rate between the model minimization complexity and the minimization of the training error. 2) The box constrain level, that variable changes the number of support vectors (SVs) used in the classification algorithm, it is set individually for each subject and the computational power requirements fluctuates based on the number of the SVs used. 3) The kernel scale, by default it uses heuristic procedure to select the kernel scale value, however, in some instances the kernel scale is manually set. The algorithm splits the elements of the predictor matrix on the number of the kernel scale and then it applies the kernel norm to generate the main matrix. 4) The multiclass method, those variables have two options, ether one-vs-one or one-vs-all. When one-vs-one is applied, the classifier trains one learner for each pair of classes, which allows the learner to distinguish one class from another. When one-vs-all method is applied, the classifier trains one learner against each class, that allows the class to distinguish each class from all others. 5) The standardise data and non-standardise data, that parameter specifies whether or not to scale every coordinated distance. In some cases (for some subjects), where the predictors have a substantial scale difference, standardization improves the prediction.

1) RULES-BASED CLASSIFICATION

Fig. 5 shows the classification workflow diagram in the Rules-based classification method. The first step is to identify clear MM instances from sleep or very relaxed stages. So, any stage that contains a constant beta activity and active EOG movement is scored as Awake.

a: STAGE 3

To identify sleep Stage 3, all the spectral coefficients are analysed against each wave frequency sections. For instance, if the band frequency delta is predominant over every other band (theta, alpha or beta), and theta is smaller than delta but larger than alpha and beta, the stage is scored as Stage 3 [50].

b: STAGE 2

If the power spectrum is predominant between theta and delta (mostly theta), and at the same time are much larger than alpha and beta, then, the epoch is scored as sleep Stage 2.

c: STAGE 1

Stage 1 is scored only when the spectral coefficient of low-alpha (8-10Hz) is smaller than 40%, and the spectral coefficient of theta is higher than 40%.

d: REM

If the power spectrums across alpha, theta and delta bands are considerably low and close to each other, which at the same time are larger than the beta amplitude, the epoch is scored as REM.

2) PERFORMANCE MEASUREMENT METRICS

The performance of this study is evaluated using three measurement metrics: accuracy, sensitivity and specificity [51]. The accuracy metric is based on the number of the correct assessments, true positive (TP) and true negative (TN), divided by the total number of assessments, TP, TN and false positive (FP) and false negative (FN), as shown in (5). The measurement shows the percentage rate of the correct classification in terms of all [52], [53].

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{5}$$

The sensitivity metric, which is defined as the TP divided by the sum of the TP and FN as shown in (6), shows the ability of the algorithm to identify a specific sleep stage in terms of others [52].

$$Sensitivity = \frac{TP}{TP + FN} \tag{6}$$

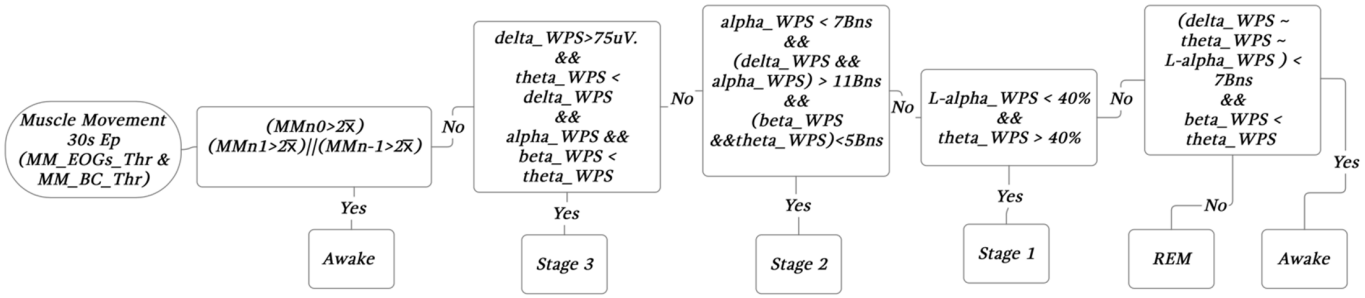

FIGURE 5. Rules-based classification method for MT&C features *(WPS = wavelet power spectrum)*.

The specificity metric, which is based on the TN divided by the sum of FP and TN as in (7), is the ability of the algorithm to exclude specific stage from others [52].

$$Specificity = \frac{TN}{FP + TN} \tag{7}$$

V. EXPERIMENTAL RESULTS

The algorithms presented in this research are evaluated using a set of experiments with the databases mentioned in Section 2. The results from the SVM-Q classifier and the Rules-based classification are compared with one another and with other existing studies that used the same databases. The features used for the classifications are from the MT&C in conjunction with the MM features.

The experiments consisted of four parts: A) graphical analysis using the MT&C against experts hypnograms; B) stages classification using the Rules-based classification and the SVM-Q classifier; C) Results comparisons between the Rules-based method and the SVM-Q; and D) Results comparison with the others in the literature as discussed in Section 2.2.

A. GRAPHICAL ANALYSIS OF THE MT&C

After generating the spectral estimation of the EEG data, it was visualized on a heat-map to identify and analyse the common element between the hypnogram generated by the experts and the spectral estimation generated by the MT&C method, as seen in Fig. 6.

Fig. 6 shows the correlation between the spectral estimation in respect to each sleep stage. The most prominent distinction was on Stages 2 and 3, where the amplitudes were highly concentrated on the delta wave range (green/yellow and red-wide colours in heat-map Fig. 6). Another sleep stage that is highly distinctive is the Awake stage. There the beta waves range (light blue lines between 13 Hz and 30 Hz) becomes evident when the subject enters into Awake stage. In the case of REM, the spectral estimation of the frequencies becomes quiet, with low amplitudes in varying ranges between low-alpha (L-alpha, 8-10 Hz) and delta. It has also been found that during REM, the MM-EOG factor becomes quite active and the MM factor from C4-A1 and C3-A2 remains quiet as seen in Fig. 6 (EOG & MM factors are at the bottom side on Fig. 6). For Stage 1, it was found that the amplitudes in the spectrogram started to do a smooth transition from L-Alpha to theta wave range, the amplitudes on that stage were low and transitory.

B. EXPERIMENTAL RESULTS WITH THE SVM-Q CLASSIFIER AND THE RULES-BASED CLASSIFICATION

The number of features generated by the MT&C was given by the number of specific frequencies which are directly related to the number of wavelets applied. It was found that when the number of specific frequencies were larger than 40, not only did the size of the matrix increase massively but so did the computational power required to generate the spectral estimation. Moreover, when the "lined spaced vector" between one frequency to the next was higher than 1, the descriptive values of the frequencies after the convolution did not match the parameters of the sleep stages. The best outcomes were achieved when there was a "lined spaced vector" between 1 to 29, and a 0.2 element was attached to that vector. The 0.2 element was incorporated to match the EEG sleep parameters of delta waves. The Rules-based classification for the MT&C features was applied based on the graphical analysis of the MT&C and the classification criteria stated in Table 1.

It was found that the accuracy of the sleep stages classification with the Rules-based method using the features from the MT&C and the datasets from St. Vincent's database was good, however, the accuracy of the sleep stages classification on healthy subjects was considerably better (CAP Sleep Database) [54]. The average accuracy in sleep classification on the St. Vincent's database was 73.4%, with an average specificity of 81.8% and an average sensitivity of 87.7%. While the average accuracy of the sleep stages classification on the CAP Sleep Database was 87.6%, as seen in Fig. 7 with an average sensitivity of 93.1% and an average specificity of 91.6%. In Fig.7 (confusion matrix) it can be seen that most of the stages had a good performance, however, Awake stage and Stage1 had a significant number of FPs (36.5% and 36.4%) compared to the number of the evaluated stages (416 for Awake stage and 264 for Stage1). The performance of the other sleep stages (Stage 2, Stage 3 and REM) in terms of FPs were significantly better with FPs rates between 18.1% and 5% (Fig. 7 far-right column).

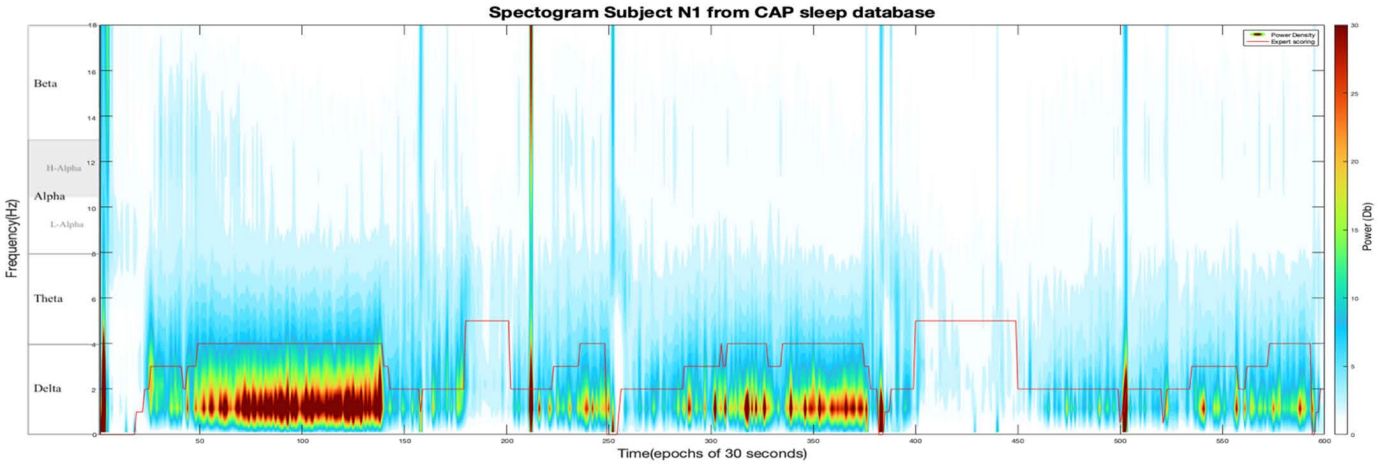

FIGURE 6. Spectrogram generated by the MT&C feature extraction. It shows the distribution of the power across 30 frequencies (1-30Hz) over one night sleep. The distribution of frequencies is contrasted with labels from an expert (red-line: 0 = awake, 1 = stage 1, 2 = stage 2, 3 and 4 = deep-sleep stage, 5 = REM).

TABLE 5. Methods accuracy on St. Vincent's database.

Methods	Main Channel	Other Channels	Features	Average Accuracy	Accuracy /stage (%)				
					Aw	S1	S2	S3	REM
MT&C-rules	**C3A2**	**C3A2**	**32**	**73.4%**	**78**	**63**	**86**	**80**	**83**
MT&C(SVMQ)	**C3A2**	**C3A2**	**32**	**78.1%**	**80**	**60**	**82**	**78**	**67**
qBi-LSTM [11]	------	C3A2, C4A1, EMG, EOG	28 features	68.6%	75	75	90	69	34
DBN [12]	------	C3A2, C4A1, EMG, EOG	28 features	65.38%	68	33	76	88	60
BLSTM+WDBN [13]	C3A2	No mentioned	40 features	78.6%	81	57	83	88	84
U-Time [14]	C3A2	EOG, EMG	No mentioned	72.8%	75	51	79	86	73

TABLE 6. Methods accuracy on CAP Sleep Database.

Methods	Main Channel	Other Channels	Features	Average Accuracy	Accuracy /stage (%)				
					W	S1	S2	S3	REM
MT&C-Rules	**C3A2**	**C3A2**	**32**	**87.6%**	**97**	**84**	**82**	**89**	**86**
MT&C(SVMQ)	**C3A2**	**C3A2**	**32**	**90%**	**92**	**85**	**87**	**89**	**95**
U-Time [14]	C3A2	EOG, EMG	No mentioned	67.8%	78	29	76	80	76
CNN [14]	C3A2	EOG, EMG	No mentioned	68%	77	35	76	78	76
CNN-LSTM [14]	C3A2	EOG, EMG	No mentioned	65%	77	28	69	77	75

In terms of FNs, all stages predictions perform significantly good, with FNs rates between 2.9% and 17.4%, as seen in Fig.7 bottom row. Most of the stages had FNs with the immediately following stage except by Stage 2 which had FNs with Stage 3 and REM.

As seen in Tables 5 and 6, the performance of the SVM-Q classifier was slightly better than the classification with the Rules-based method. The best results were archived with the combination of the SVM-Q classifier with the features generated from the CAP Sleep Database. The average accuracy of the SVM-Q classifier using the MT&C features from the St. Vincent's Database were of 78.1%, with an average sensitivity of 82.2% and average specificity of 93.9%. And the average accuracy of the SVM-Q classifier using the MT&C features with the CAP Sleep Databa was of 90.1%, with an average sensitivity of 96.2% and average specificity of 93.2%.

Fig. 8 (boxplot) shows the accuracy range of each stage on a different test performed in each subject from CAP Sleep Database using the Rules-based method.

Fig. 9 (confusion matrix) shows the classification results of the sleep stages classification on the Delica Database using the SVM-Q classifier, it had an average accuracy of 80%, an average sensitivity of 87% and average specificity of 90.5%. In Delica Database the SVM-Q classifier also performed better than the Rules-based method which archived and average accuracy of just under 78% using the same number of subjects as in the SVM-Q classifier.

Considering the SNR mentioned on section V.A, it is noted that the performance of the algorithms has a high correlation

TABLE 7. Methods performance on all three databases used (St. Vincent's, CAP Sleep and Delica) with the proposed methods.

Methods	Database	Features	Average Specificity (%)	Average Sensitivity (%)	Average Accuracy (%)	SNR (dBs)
MT&C-Rules	St. Vincent's	32	81.8	87.7	73.4	
MT&C(SVM Q)	St. Vincent's	32	93.9	82.2	78.1	0.132
MT&C-Rules	**CAP Sleep**	**32**	**91.6**	**93.1**	**87.6**	
MT&C(SVMQ)	**CAP Sleep**	**32**	**93.2**	**96.2**	**90.1**	**0.0198**
MT&C-Rules	Delica	33	83.4	88.4	77.5	
MT&C(SVMQ)	**Delica**	**33**	**90.5**	**87**	**80**	0.223

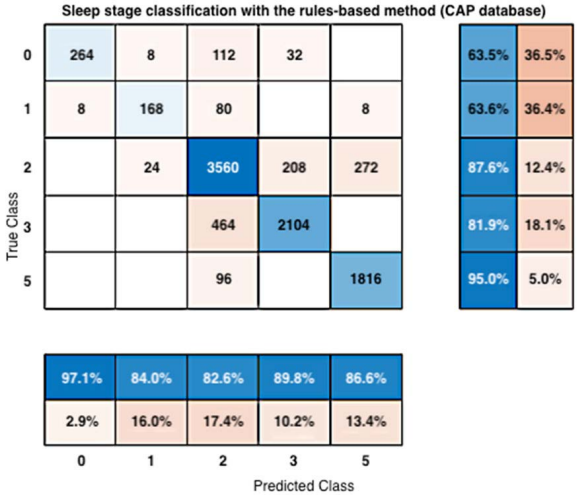

FIGURE 7. Confusion Matrix for 9224 predicted stages from 10 different subjects with features from MT&C using the Rules-based classification method *vs* expert labels for CAP Sleep Database.

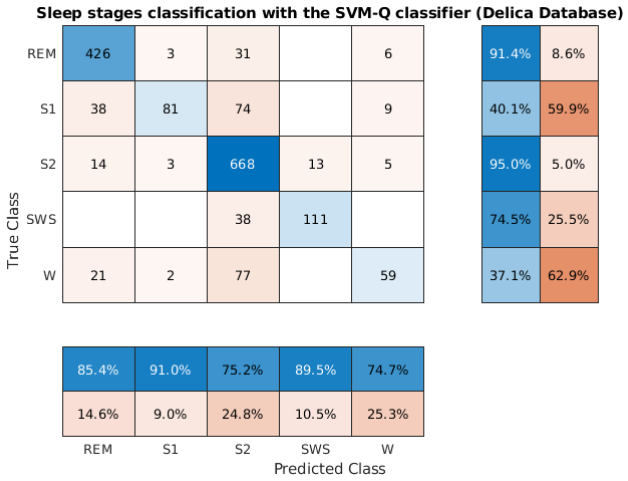

FIGURE 9. Confusion Matrix for 1679 predicted stages from 3 different subjects with features from MT&C using the SVM-Q classifier method *vs* expert labels for Delica Database.

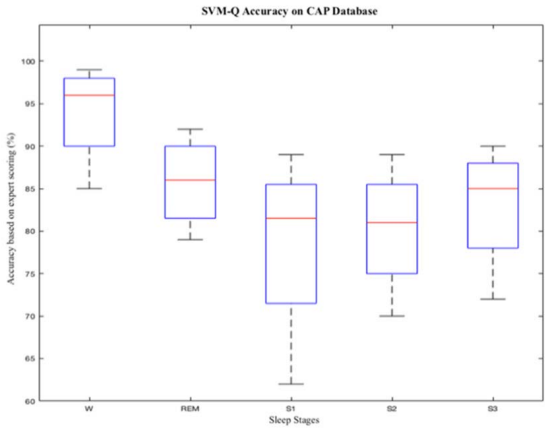

FIGURE 8. Accuracy on the CAP Sleep Database using the Rules-based classifier.

with the SNR of a database. As seen in Table 7, the results from the CAP database with lower SNR (mentioned in section V.A) preformed significantly better that the other databases that have a greater SNR (St. Vincent's and Delica databases).

C. COMPARISONS OF THE PROPOSED METHODS WITH OTHER EXISTING SLEEP CLASSIFICATION STUDIES

To verify the performances of the proposed methods, a comparison with other classification methods that used the same databases was conducted. For the St. Vincent's Database, the studies from Gorriz *et al.* [55], Sun *et al.* [13] and Peslev *et al.* [14] were used. The comparison performances were listed in Table 5. For the CAP Sleep Database, the study from Peslev *et al.* [14] was used, their comparison performances are listed in Table 6. The performances by the proposed methods and those reported in [13] and [14], [55] were very similar with the St. Vincent's Database. It is evidence that the performances of the proposed methods were significantly better than those from [14] for the CAP Sleep Database, as listed in Table 6.

VI. CONCLUSION

This paper applies time frequency analysis methods to sleep EEG data and identifies a significant difference in performance accuracies between healthy subjects and subjects with abnormal sleep patterns. It was found that the both

classification methods, the Rules-based and SVM-Q classifiers, struggled the most in trying to predict Stage 1 in subjects with abnormal sleep EEGs. Even though that the SVM-Q performed better that the Rules-based method in subjects with abnormal sleep EEGs, it had a very low performance in classifying the REM stage compared to the Rule-based method on the same type of subjects [37].

It can be concluded that the features from the MT&C with the data from healthy subjects were more descriptive in terms of the correlation to the sleep stages that the ones from subjects with abnormal sleep. The performance of both classifications was considerably better when using the data from the CAP Sleep Database and the data from Delica Database.

It is very clear that the SVM-Q classifier performs better in accuracy over the Rules-based method. However, the Rules-based classifier has lots of potential for future improvements. For instance, as new descriptive features are incorporated into the Rules-based classifier algorithm, it has the possibility to identify more detailed elements from each stage, which at the same time will improve the classification of stages that are uncleared or controversial. The Rules-based classifier algorithm has the potential to show a graphical interpretation of the events that took place in each particular stage, which will also help experts on identification of particular characteristics.

More importantly, this study suggests that by using similar principles as the ones applied by the MT&C, sleep stages classification can be improved. For instance, this method could use an additional descriptive wavelet method to identify specific characteristics in sleep stages like spindles and k-complexes, improving the performance and the accuracy of this sleep EEG classification method.

In summary, the applied methods in this research not only produce a good sleep stages classification on different sleep EEG databases as show in table 7, but it can also display the actual events that take place in each stage by visualizing the features produced by the MT&C method. This means that the sleep stages predictions are performed by the spectral estimation generated and then displayed in the spectrogram, which gives a graphical description of the events inside each stage.

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3.2 Chapter Summary

Chapter 3 presents the results and findings of the research study on sleep EEG data analysis using a time-frequency analysis approach with multitapers and convolution. The application of the MT&C with SVM-Q and rules-based classifiers has shown promising results in sleep stage classification. The research demonstrates that these methods can achieve high accuracy, sensitivity, and specificity in classifying sleep stages, particularly in datasets with normal sleep EEG patterns.

The SVM-Q classifier performed slightly better than the rules-based method in subjects with abnormal sleep patterns, but both approaches performed well on the datasets from healthy subjects. The study also revealed challenges in classifying stage 1 in subjects with abnormal sleep EEGs, and further improvements are needed in this aspect.

The paper concludes that the MT&C method, in conjunction with SVM-Q and rules-based classifiers, holds great potential for improving sleep stage classification accuracy. The approach provides accurate classifications and allows for visualising the events within each stage through spectrogram representations. This graphical interpretation can aid experts in identifying specific characteristics and further enhance the classification process.

The research suggests that incorporating additional descriptive wavelet methods into the rules-based classifier could lead to better identification of specific characteristics in sleep stages, potentially improving accuracy. The innovative methodology of this study opens new avenues for future research to explore further and enhance sleep stage classification.

In summary, the research presented in this chapter contributes to advancing the field of sleep EEG analysis and classification. The proposed approach holds promise for improving sleep stage classification and providing valuable insights into sleep physiology and neurological processes during rest. As the study continues to evolve, it offers the potential for more accurate sleep stage classifications, which can have significant implications for sleep research, clinical diagnosis, and personalised treatment strategies.

CHAPTER 4

Automatic sleep spindles identification and classification with multitapers and convolution

4.1. Introduction

Sleep spindles are hallmark events in EEG data, that take place during NREM sleep. They are characterized by transient bursts of rhythmic brain activity lasting between 0.5 and 2 seconds. These neurophysiological events have been under the attention of sleep researchers due to their enigmatic nature and complexity. The study of sleep spindles poses several challenges, such as the variability in their occurrence across individuals, age-related changes, variations in spindle characteristics, and their transit across the scalp. Despite these challenges, discovering the secrets of sleep spindles holds great importance as they are believed to play a crucial role in memory consolidation, cognitive processes, and overall sleep quality.

Moreover, their association with various neurological and psychiatric conditions highlights the potential of sleep spindles as diagnostic and prognostic biomarkers. Therefore, understanding the intricacies of sleep spindles and their significance opens promising avenues for advancing sleep research, cognitive neuroscience, and clinical applications. This chapter presents an exact copy of a published paper in

Sleep Research Society Journal by Zapata et al. 2023, August Edition,
DOI: 10.1093/sleep/zsad159

The article focuses on sleep spindles, transient surges of oscillatory neural activity during NREM sleep stages 2 and 3. These spindles have been associated with memory consolidation and plasticity in the brain, making them a subject of interest for researchers studying sleep mechanisms and their connections with neurological functions.

Chapter 4: Automatic sleep spindles identification and classification with multitapers and convolution

The study proposes a new method called the "*spindles across multiple channels*" (SAMC), which identifies and categorises sleep spindles in EEG data during NREM sleep. The SAMC method utilises a MT&C approach to generate the SDE of spindles across channels and scores them when present across multiple channels. The method provides the characteristics of the identified spindles, such as duration, power, and event areas. The SDE can also be used to represent spindles graphically.

The proposed method is evaluated using three open-access EEG databases: the NAP EEG BD, Dreams DB, and SS2-MASS. The results are compared with other state-of-the-art spindle identification methods, demonstrating the superiority of the SAMC method with an agreement rate, average positive predictive value, and sensitivity of over 90% across all three databases. The proposed method can potentially enhance the understanding of spindle behaviour across the scalp and accurately identify and categorise sleep spindles.

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Original Article

Automatic sleep spindles identification and classification with multitapers and convolution

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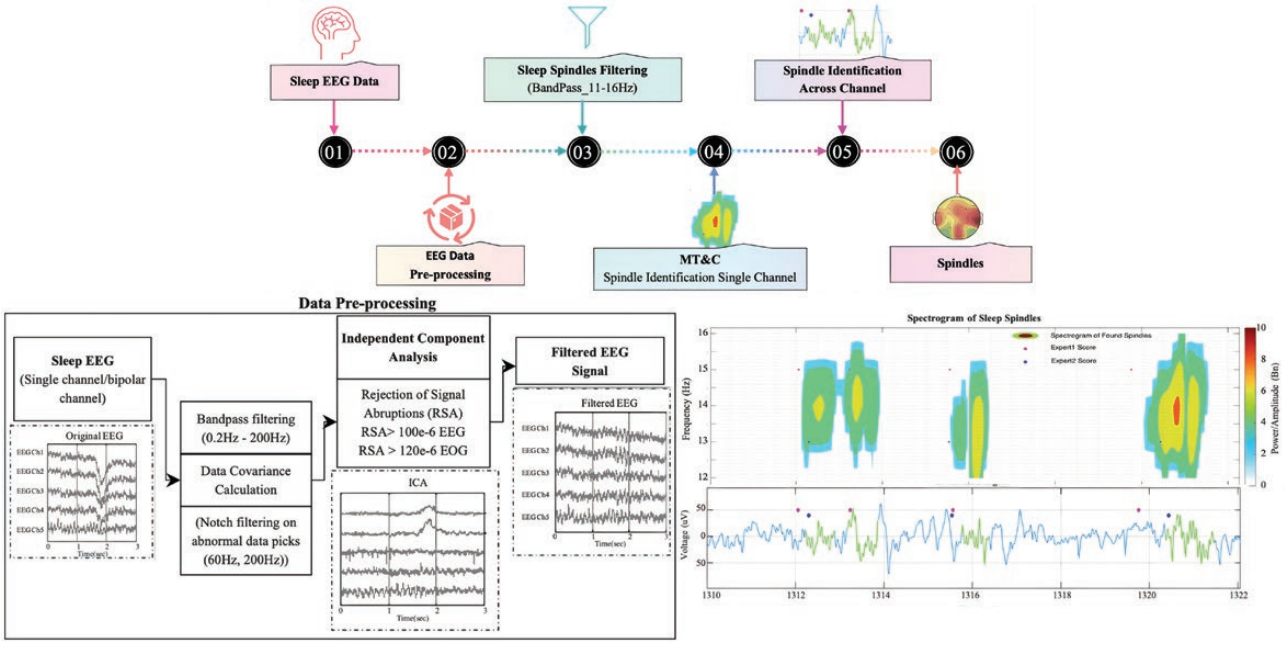
Abstract

Sleep spindles are isolated transient surges of oscillatory neural activity present during sleep stages 2 and 3 in the nonrapid eye movement (NREM). They can indicate the mechanisms of memory consolidation and plasticity in the brain. Spindles can be identified across cortical areas and classified as either slow or fast. There are spindle transients across different frequencies and power, yet most of their functions remain a mystery. Using several electroencephalogram (EEG) databases, this study presents a new method, called the "spindles across multiple channels" (SAMC) method, for identifying and categorizing sleep spindles in EEGs during the NREM sleep. The SAMC method uses a multitapers and convolution (MT&C) approach to extract the spectral estimation of different frequencies present in sleep EEGs and graphically identify spindles across multiple channels. The characteristics of spindles, such as duration, power, and event areas, are also extracted by the SAMC method. Comparison with other state-of-the-art spindle identification methods demonstrated the superiority of the proposed method with an agreement rate, average positive predictive value, and sensitivity of over 90% for spindle classification across the three databases used in this paper. The computing cost was found to be, on average, 0.004 seconds per epoch. The proposed method can potentially improve the understanding of the behavior of spindles across the scalp and accurately identify and categories sleep spindles.

Key words: multitapers; spectral estimation; sleep EEG; sleep spindles; spectra density estimation (SDE)

Graphical Abstract



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Statement of Significance

Sleep spindles are a pattern of brain waves that occur during nonrapid eye movement. They have been presumed to correlate with memory consolidation, sleep quality and aging significantly. To identify and classify spindles, we developed a method named "spindles across multiple channels" (SAMC) that combines multiple channels to identify spindles. This method does not require training or expert's labels. Instead, it uses the definitions and parameters of the spindles from the Rechtshaffen and Kales sleep criteria. The SAMC method uses time–frequency analysis to generate spindle-like wavelets by using multitapers (MTs) technology. The wavelets from the MTs are then convoluted with the EEG data to extract the spindles components. This process is performed on each EEG channel, and then the spindles are scored if there is a spindle presence agreement across channels. Overall, this method provides a substantial spindle classification improvement over other methods, with easy use for analyzing and tracking spindle behaviors.

Introduction

Polysomnography (PSG) has been under continuous research for many years. It aims to understand and identify the links between neuronal behaviors with body functions. Sleep spindles are one of those neuronal comportments that have attracted the researcher's interest because of their connections with nonrapid eye movement (NREM), memory consolidation, and mental and physical problems [1, 2].

Understanding sleep mechanisms and their relationships with human brain activities have progressed over the past decades. Research shows that the structure and patterns of electrophysiological features are associated with certain neurological functions or conditions [1, 2]. Limitations, however, remain regarding the associations of specific neuronal behaviors with brain functions. One of those limitations is how to interpret and analyze brain wave structures, like spindles [3, 4].

This paper analyses sleep spindles and their identification from sleep electroencephalogram (EEG) data. The proposed method is a time–frequency analysis using a multitapers and convolution (MT&C) method [5–7] to calculate the spectral estimation of spindles' characteristics in EEG data. Sleep spindles are bursts of energy ranging between 9 and 16 hertz (Hz) frequencies with a pyramidal-like structure that wanes and waxes its oscillations between 0.5 and 2 seconds (s). Spindles are characterized as thalamocortical circuits because they are generated in the thalamus and move forward to the brain's cortex. The shape and duration of sleep spindles are based on the reciprocal interactions between the cortex and the thalamus [8–13].

Up to now, no explicit brain functions are associated with sleep spindles. However, spindles are widely assumed to be associated with memory consolidations and plasticity [14]. Another uncertainty surrounding sleep spindles is their frequency range. Existing studies have defined spindle transient waveforms differently, with some defining them in frequencies between 9 Hz and 16 Hz [15], while others conceptualized spindles in the frequency range of 11 Hz and 15 Hz [8, 16, 17]. Most studies agreed that there are two types of spindles: slow spindles ranging between 9 Hz and 11 Hz or 13 Hz, and fast spindles ranging between 13 and 15 Hz or 16 Hz [18–24].

This research uses the frequency range of 11–16 Hz under the spindle definition and parameters from the Rechtshaffen and Kales sleep criteria (R&K rules) [25], as shown in Table 1. This paper defines a spindle based on the spindle definition and parameters shown in Table 1, which are used to create the tapers for the MT&C method. The tapers are the combination of a kernel function with the parameters of the spindles. Therefore, in this study, the terms of *taper*, *kernel*, and *wavelet* could refer to the same use.

This research aims to develop a new method to interpret, identify, classify, and visualize sleep spindles across multiple EEG channels from subjects, including those with different neurological conditions (unhealthy subjects). Spindles are identified using a method named "spindles across multiple channels" (SAMC), which scores spindles when they are identified across several channels. There are two main reasons for using multichannel EEGs for spindles identification. First, those bio-signals can track the behaviors of spindles across the scalp. Second, it can provide a higher level of certainty as we can isolate spindles from other brain activities with similar wave patterns and structures.

This paper is organized as follows. Section 2 briefs relevant research on sleep spindles and multitapers-based studies. Section 3 introduces the EEG databases (DBs) used in this research. Section 4 describes the MT&C method for identifying sleep spindles. Section 5 presents the research findings from the different experiments. Finally, Section 6 summarizes the research and future work.

Table 1. Spindles parameters used in the proposed method.

Spindles parameters		
Frequency	**Time duration**	**Min amplitude**
11–16 Hz	0.5–2.5 s	13 uV

Related Work

Many studies are dedicated to sleep spindles analysis using different methods to identify their characteristics and connections with human physiology. Yet there are still many concerns surrounding sleep spindles, such as:

- The link between spindle types with specific body functions.
- The consistency of identification across subjects with altered neurological conditions,
- The parameters, particularly the frequency range, used to identify sleep spindles.

Spindles Related Applications

One of the most prominent roles of sleep spindles is its relationship with the NREM sleep [10, 26–28]. For instance, sleep spindles and k-complexes (KCs) are the hallmarks used to distinguish sleep stage 2 or light sleep from other stages [29, 30]. As reported by [26], sleep spindles and KCs are correlated during stage 2 sleep with an incidence of around 68%. However, the occurrences of KCs and spindles have no associations with any of their physical characteristics or the probability of spindles' appearance.

For memory consolidation, spindles are believed to play an important role. A study from [28] suggested that for healthy individuals between middle age and older, the spindle density can be used as a marker to establish the stability of the

neurophysiological characteristics that play a role in cognitive functions and plasticity. They also implied that the duration of the REM stage is directly associated with the integration of neurotransmitters and neuromodulators, which are fundamental parts of our autonomic nervous system.

In terms of the topography of spindles, an early study by [3] indicated that spindle events were independent and located in different cortical areas. However, recent reports suggested that spindles were identified across different cortical areas, and most events occurred simultaneously [31, 32]. Even though some reports try to explain the topography of spindles, some suggestions indicate that spindles are not coherent in their occurrence as they are not regularly phase-locked or have the same frequency ranges [8, 17]. It has been demonstrated that there are two types of spindles so far. Spindles with low peak frequency in the frontal cortex with anteroposterior gradients in their frequency oscillation range of 9–12Hz are called slow spindles. Spindles with a higher peak frequency with nonphase-locked and between 13 Hz and 15 Hz are known as fast spindles [15, 23, 32, 33].

Sleep spindles are a constant indication of abnormal neuronal brain behaviors, not because of specific elements hidden in the spindle waves but due to their absence in sleep EEG recordings. A study by [34] found that spindles were not as frequent in subjects with Asperger's syndrome (AS) compared to normal subjects, although all the other elements in sleep data in AS subjects were normal. Similarly, a report by [35] indicated that the sleep data from subjects with autism spectrum disorders (ASD) were like normal subjects, except for sleep spindles, which were notoriously less in ASD subjects [36]. Another study by [37] showed that subjects with mental retardation have notorious abnormalities across all sleep stages compared to healthy subjects, especially in spindles and KCs, which have disreputable atypical events and low-rate patterns.

Multitapers Related Applications

Multitapers (MTs) are mechanisms of exploration that use time–frequency analysis to extract detailed information from signals and map specific elements of an object or concern. As implemented in [5], MTs were used to identify different frequencies, power, and time of an event present in sleep EEG data to generate features that were directly associated with the sleep physiology based on the R&K rules [25]. They classified sleep stages with an average rate of 87% with the option of visualizing them using a spectral estimation from each epoch. It was seen that MTs were able to represent specific events (e.g., frequency and power).

Babadi and Brown [38] presented a detailed analysis of a spectral and a standard nonparametric spectral estimation from MTs. They applied an MTs-based method to analyze anesthetic and sleep EEG data. They showed that by specifying the spectral resolution of the tapers, the frequencies outside of the taper range resolution became blurry, allowing them to identify only elements within the spectral resolution of the taper. That study gave an insight into how MTs-based methods could identify an accurate spectral estimation for different types of EEG signals [39].

A neurophysiology review from sleep EEG data was presented by [4] using a spectral analysis generated by MTs spectrograms. They demonstrated how an MTs-based method could be used as an effective tool to present a more defined way to visualize EEG data for producing better and faster results in classifying sleep stages. They found that the spectrograms allowed them to identify the underlying oscillatory mechanisms in each sleep stage, creating a visual representation that was easier to map with their hypnogram corresponding to the original signal. Their results showed a very close relationship between expert labels and the spectrograms produced by the MTs method.

Existing Studies for Result Comparisons

The performances of the proposed method in this paper are compared with other studies that used similar methods for spindles identification. The article by Wamsley [16] and implemented in [15] used a wavelet-based algorithm to detect spindles automatically. The algorithm was based on a spectral estimation from a fast Fourier transform, applying a Hanning window to three-second epochs. In the case of [15], they did not compare their results with other studies. The proposed method in this paper is applied to the databases provided by the authors and compared to their results [15].

Experimental Data

This study uses three open-access databases (DBs) to identify spindles by applying the proposed method. All three DBs include spindle labels from experts, as seen in Table 2. The first open-access DB is the NAP EEG BD from Open Science Framework (OSF), published in [12]. The second open-access DB is the Dreams DB from ZENODO, published in [40, 41]. The third open-access DB is the Montreal Archive of Sleep Studies (SS2-MASS), published in [42].

NAP EEG DB

The NAP EEG DB contains the EEG recordings from 22 subjects between 18 and 43 years old, who completed memory tasks before their naps. Each recording includes 62-channel data and two electrooculograms (EOG) electrodes with a sample rate of 1000 Hz. The data from each subject were collected on two separate days. The annotations on the DB are as awake, stage 1, stage 2, stage 3, spindles and KCs.

All annotations were based on 30-second epochs and manually scored. Spindles were scored by visual inspection of anterior–posterior brain regions using the data from channels of F3, F4, C3, C4, O1, and O2, which were positioned and recorded following the 10–20 EEG international system [12].

SS2-MASS C1 DB

The SS2-MASS DB from the MASS-C1 DB was published in 2014. It contains 19 subjects' polysomnographic recordings from three different laboratories of the Centre for Advanced Research in Sleep Medicine, Montreal, Canada. The subjects are between the ages of 18 and 33. The data were recorded using Harmonie software, with an amplifier system Grass Models 12 and 15. This research uses the SS2 DB as it is the only one that contains spindles' labels. The EEG data from the SS2 DB has 19-channel

Table 2. Spindles available on each database and the number of subjects

Number of spindles in the databases		
Database	**Number of subjects**	**Spindles**
NAP	22	2528
SS2-MASS	19	22254
Dreams	8	475

montage (C3, C4, Cz, F3, F4, F7, F8, O1, O2, P3, P4, Pz, T3, T4, T5, T6, Fp1, Fp2, Fpz). It also contains four EOGs, one EMG, one ECG and one Respiratory thermistance. The sample rate of the SS2 DB is 256 Hz for all channels, except for the respiratory thermistance, which was recorded at 54 Hz.

The hypnograms from the SS2 DB contain the labels for spindles and KCs from two experts who manually labeled them using the R&K rules [25]. The labels of the spindles and KCs include approximated coordinates of the start and end of the events [42].

Dreams DB

The Dreams DB contains 30 minutes of sleep recordings from EEG, EOG, and EMG channels for eight subjects between the ages of 31 and 53. The data from that DB has not been filtered. The subjects present different pathologies like dyssomnia, restless legs syndrome, insomnia, and apnoea/hypopnoea syndrome. The DB contains three EEG channels (Cz-A1 or C3-A1, Fp1-A1, and O1-A1), two EOGs (P8-A1 and P18-A1) and one submental EMG. The sample rates are 200 Hz, 100 Hz and 50 Hz, respectively. The data were scored for sleep stages using the R&K rules [25, 40].

Methodology

This research implements the SAMC method to identify and classify spindles. The SAMC method uses the MT&C method [5] to extract the key spindles information from different channels from the three sleep EEG DBs. The proposed method identifies the signal power on frequencies between 11 and 16 Hz. The spindle-like waves are then analyzed and classified in terms of their duration. Identified spindle waves across multiple channels are transformed into logical data (zeros for nonspindle waves and ones for spindle-like waves) to map the spindle-like waves' agreement and duration across all the EEG channels. Independent epochs are rated as a spindle only if they are consistently identified across a particular number of channels surpassing the minimum power and duration criteria of spindles.

Data Preprocessing

All EEG data are preprocessed using the MNE Python Library [43]. As shown in Figures 1 and 2, the EEG data are filtered using a bandpass between 0.2 Hz and 200 Hz. Then the peaks of every channel are computed to generate the covariance. Simultaneously, a notch filter is applied based on the peaks found in the data. After that, chunks of data defined as muscle movements are removed. Removing epochs with muscle movements is based on abnormal amplitude or frequency peaks (characterized in the awake stage) across channels using an independent component analysis (ICA) estimation.

The ICA algorithm separates the EEG signals into statistically independent components. The components in the ICA algorithm are individual signals that were combined during their recording [44–46].

The MT&C Method for Identifying Spindle Waves

The MT&C method is implemented to calculate the sleep EEG spectral density estimation (SDE) using tapers that simulate the characteristics of fast and slow spindles (refer to the spindle parameters in Table 1). The SDE accentuates the signal time–frequency characteristics based on the parameters of the tapers. The tapers are wavelets generated using a Gabor kernel, which is convoluted with the signal, intending to highlight the spectra density of the spindles in sleep EEG data [5]. The tapers in the MT&C are generated using the Gabor function (1) and the parameters of the spindles [44–46].

$$g_k(t) = e^{\left(\frac{(-t^2)}{(2s^2)}\right)} e^{(i\ 2\pi\ f_k\ t)} \quad (1)$$

where $g_k(t)$ is the Gabor taper, which is based on a Gaussian window $e^{\left(\frac{(-t^2)}{(2s^2)}\right)}$ and an imaginary cosine wave $e^{(i\ 2\pi\ f_k\ t)}$. Here "t" in the cosine wave refers to the time duration of the signal, which is the maximum duration of a spindle (2 s), and f_k is the frequency of the taper, which also refers to a Gabor taper [5, 47–49]. Considering that the oscillation of a cosine wave is constant automatic, and infinite, it is combined with a Gaussian function to simulate specific characteristics found in the fluctuated

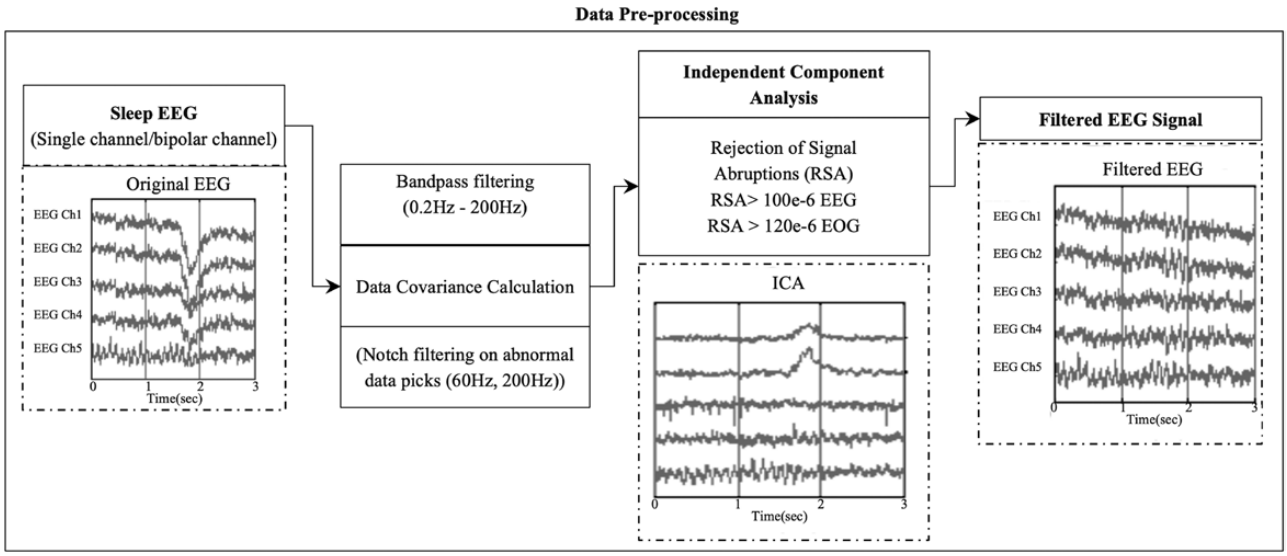

Figure 1. Data pre-processing.

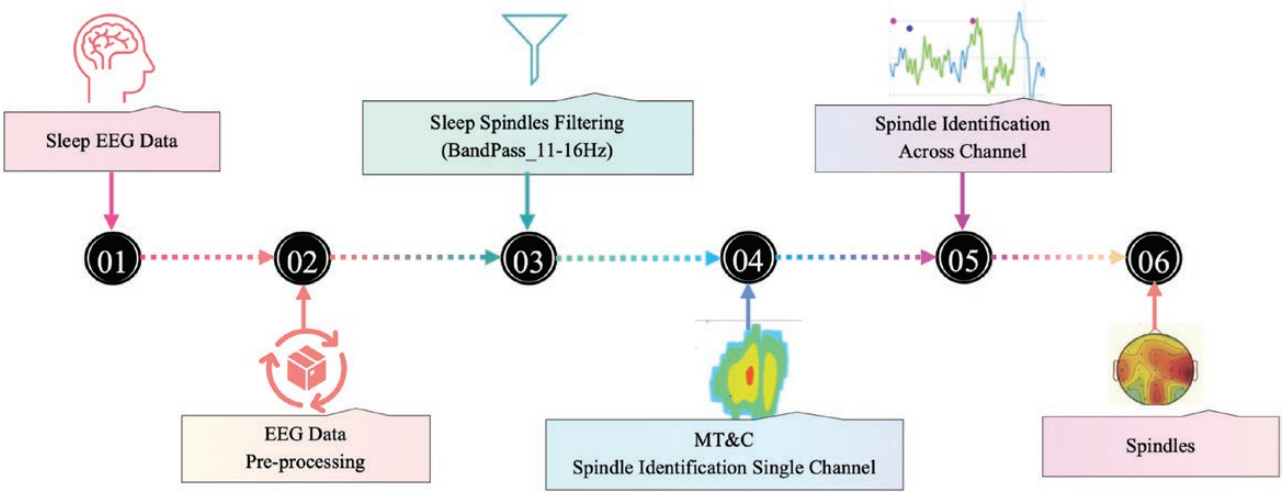

Figure 2. Sleep spindles classification algorithm: (1) Sleep EEG data from databases. (2) Sleep EEG data preprocessing using muscle movement detections from MNE Python Library. (3) Data filtering based on spindles frequency parameters using a Bandpass filter (11–16 Hz). (4) Spindle Identification on single-channel based on parameters from Table 1. (5) Spindle Identification Across Channels (SAMC method) based on a rule of a spindle wave from one channel has 25% agreement with another channel. (6) Resulting spindles are generated in terms of Power, Frequency range, and Time-duration.

signals. The Gaussian function $e^{\left(\frac{(-t^2)}{(2s^2)}\right)}$ behaves like a filter, which only allows passing the oscillations within a section frame. The size of that frame is ruled by an adjustable standard deviation (S) in (2) [5, 48, 49].

$$S = \frac{n}{(2\pi f_k)} \tag{2}$$

where n is a logarithmical space vector between the logarithm 10^{th} of the maximum number of cycles and the logarithm 10^{th} of the minimum number of cycles. f_k is the frequency of the signal at level k. The number of tapers involved in the MT&C method is based on the number of frequencies evaluated for the spindles [5].

The SDE is computed for each wavelet "g," "k" ("t"), using a sliding window across the entire sleep EEG signal as expressed in (3).

$$\mathrm{SDE}(f_k) = \sum_{t=R\left(-\frac{1}{2}R\right)} (g_k(t)\ X_w) \tag{3}$$

where t is in 2-second intervals, and R is the sampling rate. $g_k(t)$ is the taper k, which is also a kernel function, and X_w is the whole EEG signal.

When the kernel function $g_k(t)$ is convoluted with the original EEG signal, it creates a dot-product for each data point in the EEG signal intending to extract the power present in the signal in terms of the taper parameters [5]. The spectral estimation (ES) from the EEG signal provided by the MT&C method contains the information of the spindles regarding frequency, power, and wavelet duration.

Spindle Identification in One Channel

The first step to identify spindles from the ES data is to identify their amplitude and extract their normalized power, as shown in (4).

$$\begin{aligned} m &= \mathrm{abs}(\mathrm{SDE}(f_k)); \\ p &= \mathrm{sqrt}(m); \\ norm\_power &= \left(\frac{p - \wedge(p)}{\vee(p) - \wedge(p)}\right) \end{aligned} \tag{4}$$

where p is the power, m is the amplitude, and $\mathrm{SDE}(f_k)$ is the spectral estimation of the signal. $sqrt(m)$ is the square root of the amplitude, $\wedge(p)$is the minimum power and $\vee(p)$is the maximum power.

Considering that the MT&C method extracts the powers of EEG signals that match the characteristic of its tapers, all the amplitudes that surpass the power of the peaks (threshold of 0.5 in (4)) are selected as potential spindles. Those spindle candidates are then evaluated based on their duration, determined from the starting point of the power peaks that surpass the threshold to the last point of the power peak. Then based on the number of data points present in the power peak wave, if they are between 0.4 second (a 0.1 second tolerance factor is introduced) and 2 seconds, they are classified as spindles in a single channel.

All the spindles found are gathered in order of events in a set of continuous EEG data. As seen in Figure 3, the spectrogram shows the duration of a spindle, amplitude, and frequency. Fragmented spindles, like the one in the second 1313^{th} in Figure 4, with gaps of 0.10 seconds or less, are scored as a single spindle.

Spindles Identification Across Channels

After identifying spindles on each channel using the MT&C method, the spindle events are presented in Boolean values (ones and zeros), where zeros represent all the null values (power zero or non-spindle), and ones denote the other values (power of spindle different to zero).

To score the spindles using the SAMC method, at least two channels must agree with each other for at least 25% of the spindle event. The criteria for spindle identification across multiple channels are flexible regarding the agreement percentage between spindles and the number of channels that need to be included.

It is essential to mention that some channels are more sensitive to a specific type of spindles (anterior, posterior, or global spindles). Sometimes, mixing opposite channels could result in false negative identification of spindles across channels. The SAMC can be applied to identify and map the behaviors of spindles across the scalp. It can also classify spindles like anterior, posterior, and global spindles.

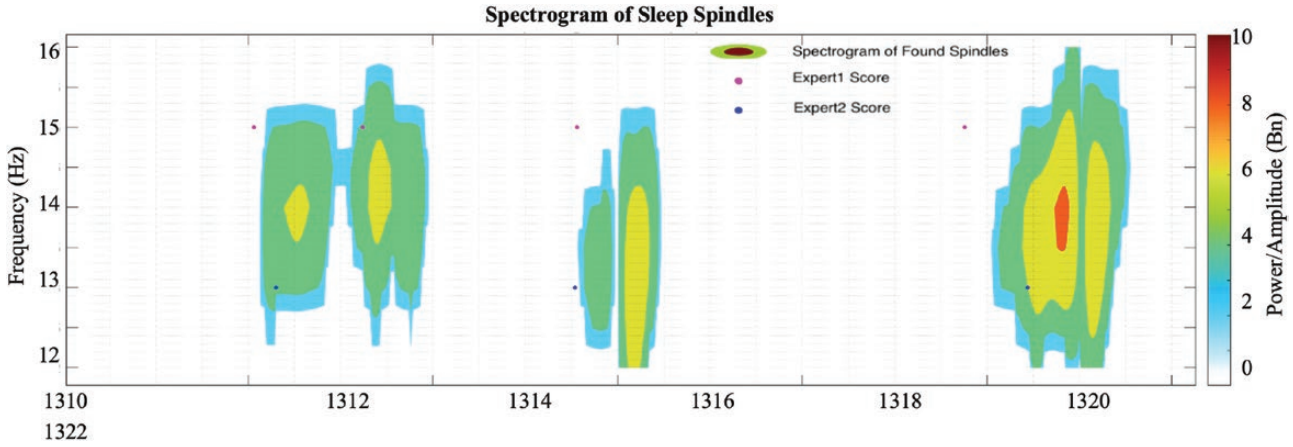

Figure 3. MT&C spectrogram vs expert's score.

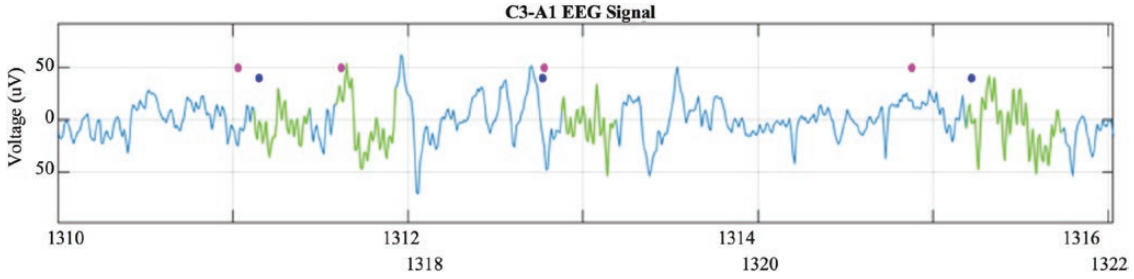

Figure 4. Visualization of classified spindles (green waves) compared to original data (signal in blue) and expert labels (magenta and blue dots).

Performance Measurement Metrics

The performance of this study is evaluated using five measurement metrics: Lin's Concordance Correlation Coefficient (CCC), agreement rate (AR), positive predicted value (PPV), F-measure and sensitivity. Specificity and accuracy are not evaluated for spindle identification because experts usually mark the spindle events that match its definitions/characteristics on the bio-signals like EEGs (True Positives). Most bio-signals are nonspindle events. That means that it is insignificant to identify non-spindles separately. Therefore, true negatives (TN) are not determined. Consequently, specificity and accuracy are not evaluated in this research [50].

In this paper, the CCC method compares the agreement between two entities of the same variable to show the concordance between the results by the proposed method and the scores from the experts. The CCC and AR are also used in this study to analyze the agreement between experts' scores.

Assuming that from n observations, a bivariate set from the same variable is selected *(subscripts x and y)*, with a correlation ρ, variances φ_x^2 and φ_y^2 and the means of μ_x and μ_y [51–55]. Here, X and Y represent the number of spindles identified in a dataset by two different scorers or methods (expert1 and expert2 or by an expert and the proposed method). The CCC between two entities is defined as:

$$\rho_c = \frac{2\rho\ \phi_x\ \phi_y}{(\mu_x - \mu_y) + \ \phi_x^2 + \phi_y^2} \tag{5}$$

where ρ is the correlation between variables $\phi_x$and ϕ_y (the number of spindles scored by the entity x and the entity y on the same DB).

The AR of the spindles considers only the spindles found across channels that agreed with the expert's scores. The spindles also must be within the range of ether-identified spindles with an overlap of at least 0.25 s. It means that the spindles must overlap 0.25 s to score it as a spindle. The AR is defined as:

$$\mathrm{AR}(\%) = \frac{n_1 + n_n}{N_1 + N_n} * 100 \tag{6}$$

where $N_1 + N_n$ is the number of spindles that match both experts, and $n_1 + n_n$ is the number of spindles found by the proposed method that match the spindles identified by the experts [52, 56].

Sensitivity is to evaluate the correctness of measurement in terms of true positives (TP) and false negatives (FN), as shown in Eq. (7). The TPs for this study are conceptualized as the spindles identified by the proposed method that match the expert spindles for at least 0.25 seconds. The FNs are the spindles scored by an expert but not found by the proposed method [51, 57, 58].

$$\text{Sensitivity} \quad = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{7}$$

The PPV shows the probability that the existence of a condition is present on a subject. Apart from the TP, the PPV also uses false positives (FPs) to find its value, as shown in Eq. (8) [50, 57]. An FP refers to the spindles found by the method but not by an expert.

$$\mathrm{PPV} \quad = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{8}$$

The F-measure, which evaluates the binary classification of a system by combining the Precision (PPV) and Recall (Sensitivity) of a model, is defined by Eq. (9) [59].

$$F = \frac{2TP}{2TP + FN + FP} \quad (9)$$

Experimental Results

The spindles detection on a single channel relies primarily on the parameter measurements detected in the data obtained by the MT&C method. When the data are contaminated by any noise like muscle movement, AC power, electronic equipment, a wrong connection of electrodes and even abnormal events like interictal epileptiform spikes, it could trigger an increase of power, causing spindle-like amplitudes [60]. Therefore, EEG data must be adequately denoized and filtered to identify spindles more accurately [61].

The ICA analysis from the MNE Python Library [43], which can remove noisy sections from data, is applied to decrease the number of false positives (FPs) and their impact [44–46].

Evaluation Criteria

The performance evaluation of the proposed method for identifying spindles is based on the spindle labels marked by any of the experts in the DBs (Expert1 or Expert2), which means that the scores from the experts are combined to compare them with the spindles identified by the proposed method.

Spindle durations are considered for the Dreams and SS2-MASS DBs. In the NAP DB, most durations were not included, or it was set by default to one second [8, 20, 25]. In that case, for the evaluation of spindle identification, each duration of the spindles is set to 1.6 seconds (0.4 seconds before the spindle starts and 1 second after its start).

Experimental Results

The proposed method is evaluated using data from the SS2-MASS, NAP and Dreams DBs. The experimental results are presented in Tables 3–7 and discussed in the following three sections. The SAMC classification method is evaluated based on the results obtained from the classification of spindles and compared with the labels generated by the experts on each of the DBs.

The Results for the NAP DB

Tables 3 and 4 present the spindle classification results for the NAP DB. The proposed SAMC approach obtained an agreement rate of 91% with impressive results on sensitivity, PPV and *F*-score of 0.91, 0.82, and 0.86, respectively. However, some disparities were detected between the number of spindles identified by the SAMC method and those labelled by the experts, indicating that the SAMC method identified a substantial 20% additional spindles in the NAP DB. Furthermore, our study revealed that approximately 525 spindles annotated by the experts were outside of the defined spindle duration, for example, less than 0.5 seconds in duration or fragmented with a period lower than 0.5 seconds or over 0.25 seconds between fragments, according to the SAMC method,

The Results for the SS2-MASS DB

In the case of the SS2-MASS DB, our SAMC classification method was implemented using two EEG channels, namely Cz-A1 and C3-A1.

The results presented in Tables 3 and 5 indicate that the method achieved a spindle classification disagreement of less than 4%. In comparison to other existing studies, our proposed method outperformed the Kinoshita method [62], which utilized a synchro-squeezed wavelet transform for feature extraction and RUS-Boost for classification. The Kinoshita method achieved an average PPV, F-score, and sensitivity of 0.61, 0.7, and 0.77, respectively. Similarly, the Patti method [21], which used a weighted system based on channel combination for feature extraction and clustering of Gaussian mixtures for classification, achieved

Table 4: Confusion matrix for the NAP DB

Confusion Matrix for the Nap DB			
		SAMC Classification	
		spindles	Non-spindles
Expert Scores	Spindles	3208 (TP)	308 (FN)
	Nonspindles	665 (FP)	--- (TN)

Table 5. Confusion matrix for the SS2-MASS DB

Confusion Matrix for the SS2-MASS DB			
		SAMC Classification	
		spindles	Non-spindles
Expert Scores	Spindles	15325 (TP)	505 (FN)
	Nonspindles	1191 (FP)	--- (TN)

Table 6. Confusion matrix for the dreams DB

Confusion Matrix for the Dreams DB			
		SAMC Classification	
		spindles	Non-spindles
Expert Scores	Spindles	538 (TP)	10 (FN)
	Non-spindles	51 (FP)	--- (TN)

Table 3. Performance Results of Spindles Classification by The Proposed Method (SAMC) With Expert

Performance Results Of Spindle Classification By The Proposed Method (SAMC) With Expert Scores:								
Database	SAMC	Ex1∪Ex2	Agreement	CCC	AR	Sensitivity	PPV	F-score
NAP DB	4398	3516	3208	0.72	91%	0.91	0.82	0.86
SS2-MASS DB	18352	15830	15325	0.75	96%	0.96	0.92	0.94
Dreams DB	622	548	538	0.82	98%	0.98	0.91	0.94

Table 7. Performance comparison between the SAMC method & other methods

Performance Comparison between SAMC Method & Others				
DB	**Method**	**PPV**	**F-score**	**Sensitivity**
SS2-MASS DB	Kinoshita *et al* [62].	0.61	0.7	0.77
	Patti *et al* [21].	---	0.69	0.74
	Tsanas *et al* [63].	0.16	---	0.83
	SAMC	**0.92**	**0.94**	**0.96**
Dreams DB	Tsanas *et al* [63].	0.33	---	0.76
	Devuyst *et al* [41].	0.74	0.72	0.70
	Kinoshita *et al* [62].	0.55	0.64	0.72
	SAMC	**0.91**	**0.94**	**0.98**

an average F-score and sensitivity of 0.69 and 0.74, respectively. Lastly, the method proposed by Tsanas [63] used a continuous wavelet transform for feature extraction and classification based on the defined parameters of spindles, achieving an average PPV and sensitivity of 0.16 and 0.83, respectively. Notably, our experimental results demonstrate significant performance improvements in terms of all performance evaluation metrics compared to other studies, as summarized in Table 7.

The Results for the Dreams DB

Upon analyzing the Dreams DB, our proposed SAMC method exhibited the highest level of agreement with the combined labels from the two experts. As presented in Tables 3 and 6, the method achieved an average agreement rate of 98%, with a sensitivity, PPV, and F-scores of 0.98, 0.91, and 0.94, respectively. To further evaluate the performance of the SAMC method, its results were compared with other existing methods applied to the Dreams DB. The Tsanas method [63] achieved an average PPV of 0.33 and a sensitivity of 0.76. In contrast, the Devuyst method [40, 41], which used a systematic assessment approach, obtained an average PPV of 0.74 and a sensitivity and an F-score of 0.70 and 0.72, respectively [41]. The Kinoshita method [62], which utilized a synchro-squeezed wavelet transform for spindle classification, achieved an average sensitivity of 0.72, with a PPV and F-score of 0.55 and 0.64, respectively. It is worth noting that the proposed method demonstrated a significant improvement over these existing methods, as illustrated in Table 7.

Discussion

This study presents a new method for spindle detection in sleep EEG signals. The proposed method combines spectral analysis and machine learning techniques to identify spindles across the scalp using sleep EEG data. The method was tested on three different databases (the NAP, SS2-MASS and Dreams DBs), and its performances were compared with other existing methods in the literature.

Overall, the results show that the SAMC outperforms the existing methods in terms of sensitivity, positive predictive value (PPV) and F-score. The SAMC method was also found to be more robust to inter-expert variability, which is an essential consideration in practical applications.

One of the limitations of this study is that the method was primarily tested on EEG signals from healthy subjects (MASS-DB and NAP-DB) as the data available for subjects with sleep pathologies that contain spindle labels were too limited (Dreams DB: 8 subjects). Meaning that it will remain unclear how well the method would perform in patients with sleep disorders. This limitation was due to the restricted access to abnormal Sleep EEG data with spindle labels.

In terms of future directions, exploring how the SAMC method could be applied to other different types of EEG data, performing various mental tasks rather than spindle detection, would be valuable. Overall, the proposed method better suits those applications with different physiological signals like spikes, sharps, and triphasic waves, among other EEG waveforms [64].

The novel method proposed in this study for spindle detection in sleep EEG signals has great promise. With the ability to map spindle behavior across the scalp, the SAMC method could help unfold the links between spindle types and scalp regions. The parameters used in the spindle identification are malleable to application areas and can be visualized on a heat map, as shown in Figure 3. This implies that experts can see the amplitude of the spindles and the frequency range of the events.

The results presented in this study suggest that the SAMC method can be a helpful tool for sleep researchers and clinicians.

In this study, spindles detection on a single channel was also conducted on all the three DBs. Extra spindles (FP) were often identified using a single-channel method compared to the proposed SAMC method. For some FNs generated by the single channel method, it was found that the duration of those spindle-like waves scored by the expert did not last more than 0.5 s. Some events were fragmented with less than 0.5 seconds in each fragment and separated for more than 0.25 s. It was observed that other FN events had a central frequency outside the spindle frequency range (<11 Hz or >16 Hz).

Furthermore, this study revealed that the performance of our proposed method can be further enhanced when a database contains labels from multiple experts, as evidenced in the Dreams and SS2-MASS DBs. Suggesting that the performance of the proposed method could be improved for the NAP DB if a set of labels were available from an additional score.

Table 8. Sleep spindle experts' scoring comparison across databases.

Sleep Spindle Experts' Scoring Comparison Across Databases:						
Database	**Expert 1**	**Expert 2**	**Automatic Score (AS)**	**Agreement**	**CCC**	**AR**
SS2-MASS DB	9338	15556	---	~9064	0.57	E1: >97% E2: >58%
Nap DB	3516	---	---	---	---	---
Dream DB	298	409	528	Expert1 Vs. Expert2: 159 Experts Vs. AS: 138	Expert1 Vs. Expert2: 0.35 Experts Vs. AS: 0.28	E1:<54% E2:<39% AS:<27%

Data Consideration

It is essential to mention that the spindle labels included in NAP, SS2-MASS and Dreams DBs were scored based on the R&K rules [25], which leaves a considerable margin of subjective interpretation, causing label discrepancies between experts [65]. It has been previously documented in [32, 48, 56, 61], and reviewed in this study by comparing expert's spindles labels from the Dreams and SS2-MASS DB as shown in Table 8.

The average agreement rate between the experts on scoring spindles for the Dreams DB was under 50%. In some cases, like for EEG recordings from Subject 1 and Subject 3, the agreement did not reach 25% and 10%, respectively. And when comparing the agreement rate of the labels between both experts and the automatic method provided by the Dreams DB, the average agreement rate was under 60%.

In the case of the SS2-MASS DB, the average agreement between the two experts was under 58%, with an AR for Expert 1 of 97% and 58% for Expert 2, as documented in Table 8.

Conclusion

In conclusion, this study presents a new approach for spindle detection in sleep EEG signals that offers promising results. The proposed SAMC method outperforms several existing methods in terms of sensitivity, PPV, and F-score, as demonstrated in our experimental results using three publicly available databases (the NAP, SS2-MASS and Dreams DBs).

The implementation of the SAMC method brings two significant benefits, as it can focus the spindles on a specific frequency range and map their behavior in the scalp through multichannel visualization of spindles. After the model training, this method does not require expert labels or further training as it only relies on the definition of the spindles and related parameters as defined in Table 1. The experimental results for the three different DBs show that the proposed method achieves an overall agreement rate, positive predictive value, F-score, and sensitivity of over 90% for all three DBs, compared to the scores from more than one expert. Furthermore, it is observed that the SAMC method outperformed other existing methods (Kinoshita [62], Patti [21], Tsanas [63] and Devuyst [41]).

The spindles identified by the proposed method can be visualized across all channels (as shown in Figure 3). This is useful for investigating the links and relationships between spindle types and specific brain regions. It helps us have a more accurate and comprehensive understanding of the behaviours of the spindles across the scalp. Our findings indicate that the proposed method can be further improved by including more annotations from an additional expert. It is believed that the SAMC method can significantly advance our understanding of the sleep dynamics of the spindles. It is hoped that this work will inspire more research in this exciting area.

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Data Availability

The datasets used in the current study are open sources and are available in Open Science Framework (OSF) [12], ZENODO [40, 41], and Montreal Archive of Sleep Studies (SS2-MASS) [42].

Implementation Details

The data were pre-processed using the MNE Python Library [43], and the methods were created and implemented in MATLAB. Since there is no record of the duration of the spindles in some databases, we set them to a default duration of 1.5 seconds when comparing the SAMC method results with the experts' labels.

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4.2. Chapter Summary

Zapata et al., (2023) proposed a novel approach to identify spindles across the brain during NREM sleep using a method named "Spindles Across Multiple Channels" (SAMC). The SAMC method utilises a MT&C approach to identify and classify spindles across multiple EEG channels, providing valuable insights into their characteristics and behaviours.

The results of the SAMC method demonstrated its superiority over existing spindle identification methods, achieving high agreement rates, PPV, and F-scores when compared to expert labels. The ability to visualise spindles across multiple channels enables researchers to investigate the relationships between spindle types and specific brain regions, contributing to a deeper understanding of sleep dynamics and neural activity.

The proposed method holds promise in further advancing sleep research, memory consolidation, cognitive function studies, and potential applications in clinical settings for sleep disorder diagnoses. Future research endeavours may focus on applying the SAMC method to different types of EEG data, exploring its capabilities in various mental tasks, and expanding its applications to other physiological signals beyond spindles. Overall, the SAMC method represents a valuable tool for sleep researchers and clinicians, offering a more accurate and comprehensive analysis of the behaviours of sleep spindles across the scalp.

CHAPTER 5:

EEG-Based Sleep Stage Classification Using CNN with Squeeze-and-Excitation Blocks in a Short-Visual Geometric Group

5.1. Introduction

The study of sleep stage classification is vital in diagnosing sleep-related disorders and understanding the intricacies of sleep physiology. Adopting a multi-method approach is essential to improve the accuracy and robustness of automatic sleep stage classification. Integrating various methods and techniques can provide complementary insights, overcome limitations of individual methods, and enhance the overall performance of sleep stage classification algorithms. Combining the strengths of different methodologies, such as time-frequency analysis, convolutional neural networks (CNNs), and deep learning techniques, a multi-method approach can extract and interpret diverse features from EEG data, leading to more comprehensive and reliable sleep stage classification results. This introductory paragraph sets the stage for further exploration of the benefits and significance of employing a multi-method approach in the subsequent sections of this research study.

This study aims to advance sleep stage classification by employing innovative techniques in EEG analysis. It is important to note that this chapter contains an exact copy of a research paper submitted to

Sleep Research Society Journal by Zapata et al on the 04th of August of 2023.

The article outlines a method that integrates time-frequency analysis and deep learning to enhance the accuracy and performance of sleep stage classification. It explores using EEG data and time-frequency analysis for feature extraction, employing multitapers and convolution. To enhance the feature representation, the study incorporates a visual geometric group network (VGGNet) with squeeze-and-excitation (SE) blocks, scaled exponential linear unit (SELU), and batch normalisation (BN). The proposed method

uses a multi-layer perceptron for sleep stage classification, achieving a significant performance improvement with an average accuracy and precision of 87% across three different EEG databases.

Original Article

EEG-Based Sleep Stage Classification Using CNN with Squeeze-and-Excitation Blocks in a Short-Visual Geometric Group

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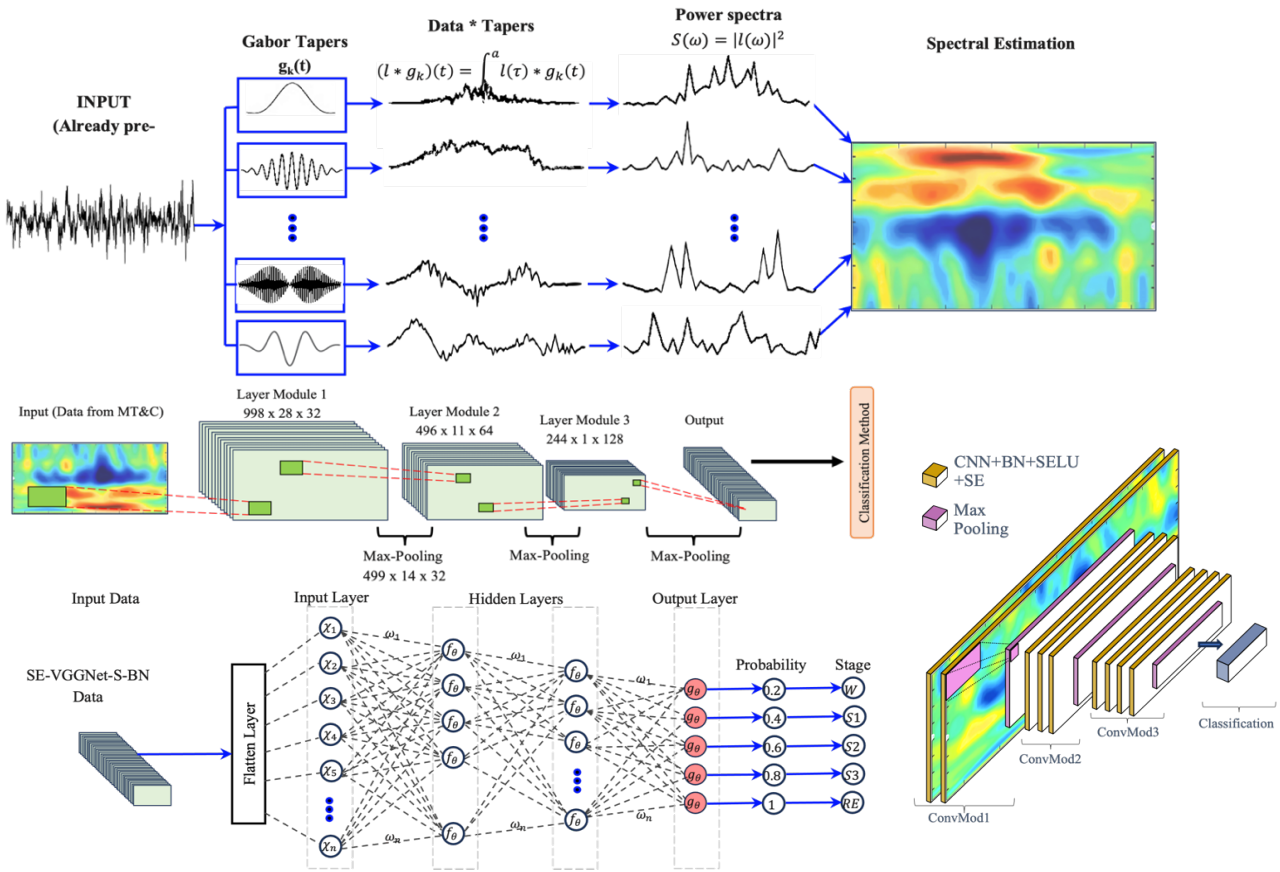
Abstract

Sleep stage classification is commonly used to diagnose sleep-related diseases. Many advanced sleep stage classification methods have been emerged in recent years, which are promising. To improve the performance and accuracy of automatic sleep stage classification, this paper uses EEG data and implements a time-frequency analysis for feature extraction using multitapers and convolution. It then applies a visual geometric group, adding squeeze-and-excitation blocks, scaled exponential linear unit and batch normalisation to refine the features. In the sleep stage classification stage, a multi-layer perceptron is used. This study reports a significant performance improvement with average accuracy and precision of 87% on sleep stage classification from three different databases.

Keywords: Multitapers, Spectral Estimation, Sleep EEG, Deep Learning, Convolutional Neural Network (CNN), Spectra Density Estimation.

Graphical Abstract



Statement of Significance

The research paper presents a significant contribution to the field of sleep stage classification by utilizing Electroencephalogram (EEG) data and implementing a time-frequency analysis for feature extraction using multitapers and convolution. The proposed method combines a visual geometric group network (VGGNet) with Squeeze-and-Excitation (SE) blocks, Scaled Exponential Linear Unit (SELU), and Batch Normalization (BN) to refine the features extracted from EEG data. A multi-layer perceptron is used for the final sleep stage classification. The proposed method integrates two feature extraction methods, effectively capturing essential characteristics and patterns associated with different sleep stages. The comprehensive evaluation using diverse databases enhances the relevance and application of the proposed method in future studies. Overall, this study demonstrates the feasibility and effectiveness of integrating time-frequency analysis and deep learning for sleep stage classification, making valuable contributions to the understanding and diagnosis sleep-related disorders.

1. Introduction

Sleep is a fundamental and indispensable physiological process in the human daily cycle, taking one-third of our lifespan and holding immense significance. Poor sleep has been associated with various health conditions that strongly correlate with different sleep stages [1–4].

Sleep comprises two general phases: rapid eye movement (REM) and non-rapid-eye-movement (NREM). According to the Rechtschaffen and Kales rules (R&K Rules) [5,6], the NREM phase consists of stage 1 (S1), stage 2 (S2), stage 3 (S3) and stage 4 (S4) with frequencies at either alpha (8-13Hz), theta (3.5-7.5Hz) or delta (>3Hz) depending on individual stages [7]. The REM phase has only one stage (REM), and its frequencies vary between theta, beta (16-32Hz) and gamma (>32Hz) [8].

Electroencephalogram (EEG) data collected from the human scalp allow researchers to uncover hidden information that can help us better understand the neural interactions during different human brain activities[1,9–13].

This study proposes a method that implements feature extraction in two steps and classifies them into sleep stages.

Firstly, the preliminary features are extracted using a time-frequency analysis with multitapers and convolution (MT&C) method from [14]. This initial stage transposes the data from lineal time series into spectral data in the frequency domain [2,9]. In feature extraction, we use a convolutional neural network (CNN) in a visual geometric group network (VGGNet) with squeeze-and-excitation (SE) blocks and with an additional scaled exponential linear unit (SELU) and batch normalisation (BN). This is to identify important characteristics in the spectral estimations generated by the MT&C method [3,4,15,16]. Finally, the sleep stage classification is performed using a multi-layer perceptron with the SELU and BN.

This research uses the data from three different EEG databases to train, test and validate the performance of the proposed method. The data is initially pre-processed using the Python library MNE (MEG & EEG analysis and visualisation).

This research aims to contribute with a deep learning method that interprets preliminary features and extracts, identifies, and classifies sleep stages across databases with subjects without and with different neurological conditions.

Combining two feature extraction methods aims to interpret and classify data relevant to the sleep stage characteristic based on medical definitions like the ones based on the R&K rules or the American Association of Sleep Medicine (AASM) standards. Also, the initial extracted features can be used to visually map and identify different characteristics at each sleep stage.

This paper is structured into six sections. The next section offers an overview of the research background, while the third section summarises the EEG databases employed. The fourth section thoroughly discusses the pre-processing, feature extraction, and stage classification methods, emphasising their significance with the proposed methodology. The experimental findings and results are presented in the fifth section. Finally, the last section encompasses the discussion and conclusion, summarising the key aspects of this research and proposing potential directions for future investigations.

2. Related Work

Sleep stage classification is a significant area of research in healthcare, as it helps to identify abnormalities, diagnose sleep disorders, and design appropriate treatment plans. Over the last few years, deep learning (DL) methods have emerged as a promising technology for classifying sleep stages [6,17,18].

Several studies have reported high accuracy rates for sleep stage classification using DL methods. However, the lack of a standardised database, evaluation metrics, and pre-processing techniques poses a challenge to directly comparing their results [9].

2.1. Sleep stage classification

Sleep stage classification has been a popular research area for several decades, from 1930, when the first EEG was used to measure brain waves during sleep, to the implementation of automated methods in the late 1970s.

Several years later, when the first EEG was used on the scalp, Loomis [19,20] published a study about the potentials in the human brain during sleep. That preliminary research proposed a set of markers that showed the patterns of sleep and awake subjects. However, only in 1968 when the R&K rules were established as a standardised guideline for visual sleep stage scoring based on EEG data [5]. Almost a decade later, the AASM adopted the principles from the R&K rules with slight modifications. Since then, the research community has adopted and refined both principles.

Recent studies from Supratak *et al.* [21] and ElMoaqet *et al.* [22] proposed a deep transfer learning method to classify bipolar-channel EEG data using a recurrent neural networks (RNN) method, which is a derivation from convolutional neural networks (CNNs) with an additional bidirectional long short-term memory (BLSTM). Supratak [21] used a bipolar channel from two open-source databases, where the raw EEG data were used directly without pre-processing. ElMoaqet [22], on the other hand, first transferred their EEG data into images using a Fourier synchronisation transform (FST) and continuous wavelet transform (CWT) before classification. Both studies claim around 2-8% improvement over other benchmark studies.

A study by Diykh et al. [23] proposed a two-stage network classification method that used hand-crafted network features in a sequential learning model to classify sleep stages. That training and testing approach achieved an average accuracy of 78.6%.

Meanwhile, Aboalayon et al. [24] proposed a U-network architecture to generate a spontaneous temporal scale based on interval classifications, which achieved an average accuracy of 72.8% for the St. Vincent's University Hospital database and 67.8% for the CAP's Sleep database.

Table 1: Sleep EEG Stages Databases

SLEEP STAGES DATA (FROM 3 DATABASES AFTER PRE-PROCESSED):

Database	Total Subjects	Epoch Size	Awake Epochs	Stage 1 (S1) Epochs	Stage 2 (S2) Epochs	Stage 3 & 4 (S3) Epochs	REM Epochs	Total Seep Time (Hours)
St. Vinc. DB	25	30sec.	4729	3387	6985	2668	3005	173.24
Dream's DB	26	5sec.	38276	6764	67708	6196	16328	187.88
CAP's DB	16	30sec.	1380	580	6350	3360	3120	123.25

A study by Zapata et al. [14] used two different methods for sleep stage classification with an average accuracy of 85%. The first method was based on the definitions and the characteristics of the sleep stages according to the R&K rules, and the second method applied a support vector machine. The features used in those two methods were obtained using time-frequency signal analysis.

3. Experimental Data

This study employs three open-access databases that come with expert sleep stages labels, as shown in Table 1. The three databases used are the St. Vincent's University Hospital and the University College Dublin Sleep Apnea Database (St. Vincent's Database) published by Heneghan [25], the Dream's Database published on ZENODO by Devuyst [26,27], and the Cyclic Alternating Pattern (CAP) database published on Physionet by Terzano *et al.* [28].

3.1. St. Vincent's Database

The St. Vincent's database contains the overnight polysomnogram EEG data from 25 adult subjects with suspected sleep disorders. The selection of such subjects claimed to be randomly from individuals over the age of 18 that did not present symptoms of cardiovascular diseases or dysautonomia. Sleep experts manually labelled the sleep stages using the R&R rules [25].

3.2. Dream's Database

The Dream's database contains two datasets of importance for this study. The first dataset (subjects DS) contains overnight sleep polysomnographic recordings from 20 healthy subjects. The second dataset (patients DS) contains overnight sleep polysomnographic recordings from 27 subjects with various pathologies. Both datasets contain two hypnograms labelled by experts using the R&K rules and the AASM standards [26].

3.3. CAP's Sleep Database

The CAP's database contains eight datasets, including healthy subjects and subjects with different pathologies. This research will use the n1-n16 (CAP_n1-16) data from no-pathology subjects. The CAP_n1-16 contains whole-night sleep polysomnographic recordings from 16 subjects without medications or presenting neurological conditions. The hypnograms were scored using the R&K rules [29].

4. Methodology

The methodology of this research encompasses four essential parts: pre-processing, preliminary and secondary feature extraction, and the implementation of the classification method, as shown in Figure 1.

In the pre-processing stage, the EEG data are checked and filtered out various noises. The EEG segments with too much noise are removed using an independent component analysis method.

In the preliminary feature extraction phase, the primary method is designed based on our existing studies [14,30]. This technique applies time-frequency signal analysis, employing multitapers and convolution methods for signal decomposition.

Moving on to the secondary feature extraction, the approach centres on convolutional neural networks (CNN) within a visual geometric group network (VGGNet). This integration incorporates squeeze-and-excitation (SE) blocks to optimise feature representation. Moreover, the method includes the utilisation of a scaled exponential linear unit (SELU) and batch normalisation (BN) techniques, illustrated in Figure 2.

A multi-layer perceptron is employed to accomplish the task for the classification method. This classifier effectively integrates the SELU and BN techniques into its architecture, which were earlier discussed in the secondary feature extraction section.

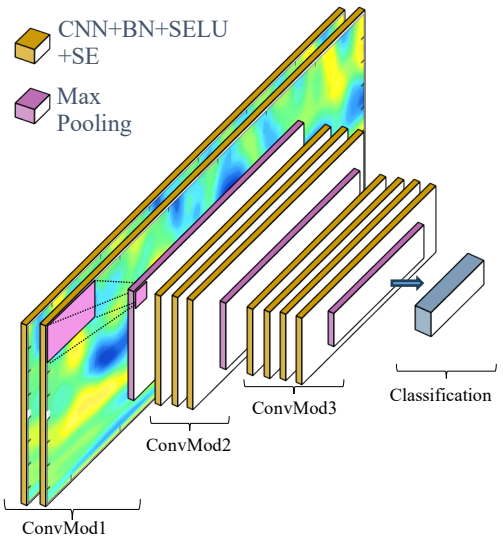


Figure 2: SE-VGGNet-S-BN architecture. ConvMod refers to the module of the CNN or internal layer. In the orange blocks are contained the CNN+BN+SELU+SE.

Subsequent subsections will delve into comprehensive explanations of each individual building block within the methodology.

4.1. Data processing

All the sleep EEG data are pre-processed using the MNE Python library [31]. Firstly, the EEG data is filtered with a bandpass between 0.2 Hz and 200 Hz, followed by a denoising procedure using an independent component analysis (ICA) estimation method. The ICA is implemented by computing the covariance of the picks of each channel and selecting the 0.99 component with a maximum iteration of 3000. Subsequently, a notch filter is applied to the identified picks [32–34]. Finally, the data segments identified by muscle movement are excluded from the databases [32–34].

4.2. Feature Extraction: MT&C

The multitapers and convolution (MT&C) method is the first feature extraction method, as shown in Figure 3. It is based on time-frequency analysis, proposed by Zapata et al. [14,30].

The MT&C method generates a spectral density estimation (SDE) from the input EEG data using tapers that simulate the characteristic of the frequency found in sleep stages. The tapers or wavelets are created using a Gabor kernel (Eq. (1)) with the parameters of the sleep waves to highlight the spectra density in each sleep stage from EEG data [14,30,35].

$$g_k(t)=e^{\left(\frac{(-t^2)}{(2S^2)}\right)} e^{(i\,2\pi\,f_k\,t)} \qquad (1)$$

The Gabor function $g_k(t)$ comprises two parts, the Gaussian window and an imaginary sine wave. k in $g_k(t)$ refers to the frequency of the wave, and t refers to its time duration.

The out-product section in each convolution from the MT&C method can be represented as follows:

$$(l * g_k)(t) = \int_b^a l(\tau) * g_k(t) \qquad (2)$$

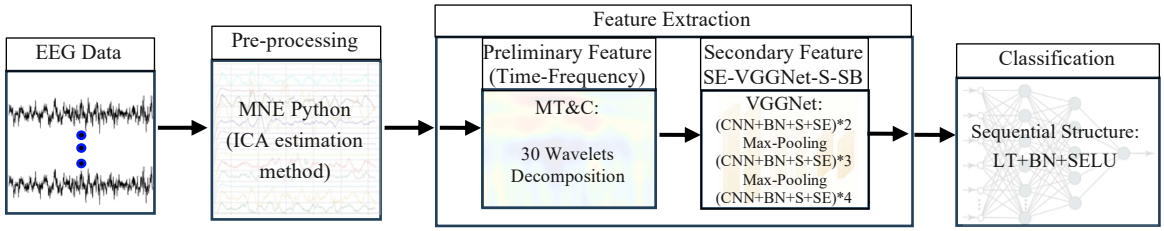


Figure 1: Methodology workflow diagram.

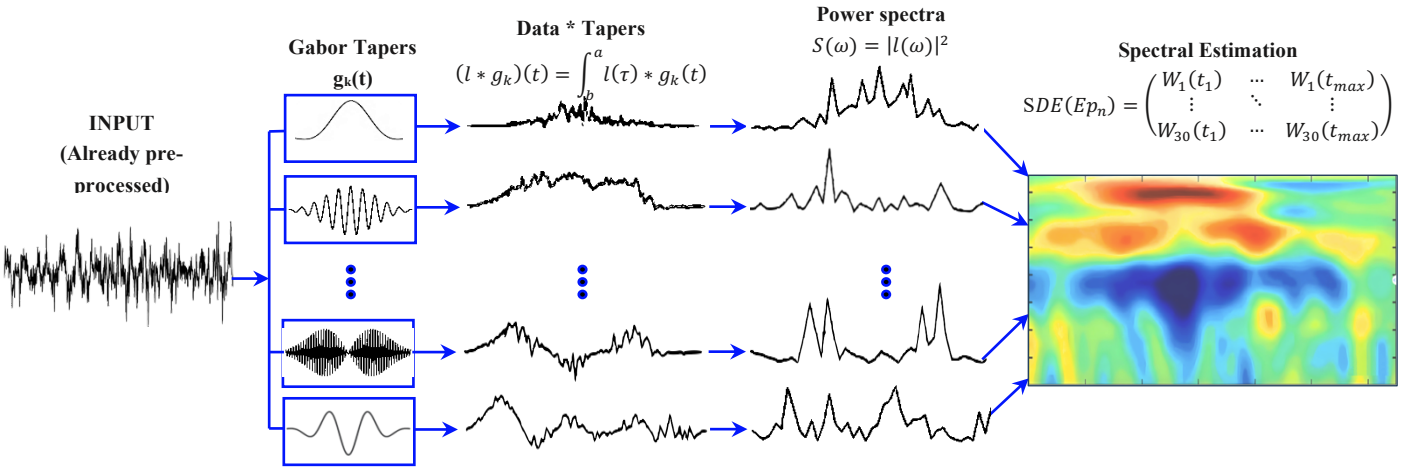


Figure 3: MT&C workflow, from the convolution of the signal to the SDE. $S(\omega)$ is the power spectra also known as the square magnitude of the Fourier transform.

where the integral symbol $\int$ denotes the integration over the entire domain presided by *a* and *b*, the asterisk symbol represents the convolution between the input signal *l(t)* and the Gabor taper $g_k(t)$ at the taper window *k* [14,30].

The total output of the MT&C method ($SDE(Ep)_k$) is given by Eq. (3):

$$SDE(Ep)_k = F(g_k(t) * l(Ep)) \quad (3)$$

where *F* refers to the frequency domain. The SDE for each epoch in the signal is the computation of all sliding window *k* across the whole sleep stage. The resulting product is a two-dimensional matrix array that contains the power content of the frequencies (from 0.2Hz to 30Hz) at each instance of time for the signal. Eq. (4) represents the structure of the array:

$$SDE(Ep_n) = \begin{pmatrix} W_1(t_1) & \cdots & W_1(t_{max}) \\ \vdots & \ddots & \vdots \\ W_n(t_1) & \cdots & W_{30}(t_{max}) \end{pmatrix} \quad (4)$$

where $W_n(t_1)$ is the convolution at the time instance t_1 of the kernel $g_k(t)$, and with the frequency *n* with the signal epoch Ep_n. The level of *W* (1 to *n*) indicates the convoluted frequency in Hz (1 to 30 in this specific case). The level of *t* (1 to max) refers to each one of the points in the signal that will go from 1 to the last (max).

4.3. Feature Extraction: SE-VGGNet-S-BN

The SE-VGGNet with SELU and BN (SE-VGGNet-S-BN) from Figures 4 and 5 is a unified visual geometric group analysis framework with enhanced feature extraction. The main component of this method is the CNN module in a fully connected layer structure. It is implemented in conjunction with batch normalisation, scaled exponential linear units and squeeze-and-excitation in each CNN layer, followed by a max pooling module.

The SE-VGGNet-S-BN architecture in Figure 5 comprises three fully connected layers, each with multiple CNNs that increment its size on each main layer.

4.3.1. CNN in a VGGNet structure

The role of the CNN in a VGG structure is to identify deep-relevant features or patterns in the SDE data obtained from the previous section. The CNN comprises multiple filters that slide over the input data to extract features. The input data of the SE-VGGNet-S-BN is a two-dimensional matrix (frequency, $Epoch_{size}$) that starts with a size 30x$Epoch_{size}$. The filters in the CNN are small matrices with a defined size that slides over the input data and produces a singular output. The parameters refer to the learnable weights that are updated during the training process using gradient descent. The stride, which defines how the filters move over the input data, specifies the number of steps the filter takes at each iteration. The padding is an optional parameter that adds an extra set of zeros around the input matrix. It is used to avoid the loss of information at the boundaries of the data. The current VGGNet structure comprises a 3x3 series of convolutional layers and a 2x2 max polling in three fully connected layers [36–38].

4.3.2. Batch Normalisation

The next module after the CNN is the batch normalisation (BN) unit. It is used to improve the training and performance of the CNN by normalising the activation of each layer across every batch of training data. During the training process, the BN operates on batches of training data. There, it computes the activation's mean and variance on each feature dimension. Then, the activation is normalised by deducting the mean and dividing it by the square root of the variance to ensure uniform distribution, as seen in Eq. (5). Next, a learnable parameter known as *gamma* and *beta* are applied to scale and shift the normalised activations as seen in Eq. (6). Finally, it passes into the activation function the scaled and shifted activations [39–41].

$$\hat{A}_i = \frac{A_i - \mu_{mov_i}}{\sqrt[2]{Var(A)}} \quad (5)$$

Figure 4: SE-VGGNet-S-BN structure

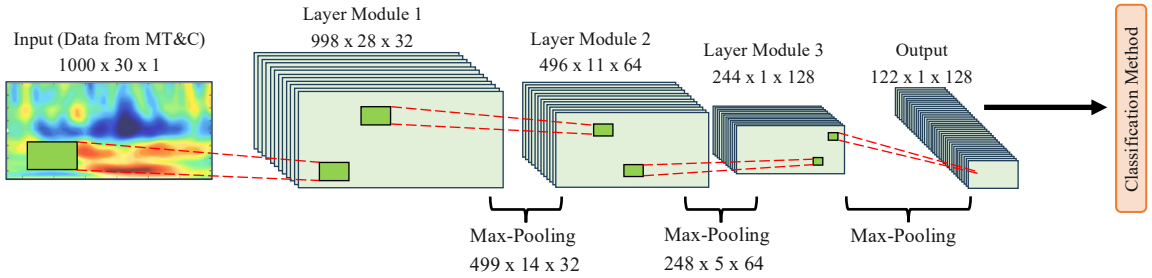


Figure 5: Architecture of SE-VGGNet-S-BN highlighting the Max-pooling module.

where $\hat{A}_i$ is the value of a single input, μ_{mov_i} is the mean within the batch and $Var(A)$ is the variance within the batch.

$$B\tilde{N}_i = \gamma\Theta\hat{A}_i + \beta \tag{6}$$

where $B\tilde{N}_i$ is the final normalised value. γ is gamma, and β is beta, values learned by the layers [39,40].

4.3.3. *Activation Function: SELU*

The activation function used in this study in Eq. (7) is the scale exponential linear unit (SELU), which contributes to the self-normalisation of the network. The primary attribute of the SELU is to help to maintain a mean activation close to zero and a standard deviation close to 1, stabilising the training process and improving the performance of the network.

$$if\ x > 0 \longrightarrow\ f(x) = \lambda * x$$
$$if\ x \leq 0 \longrightarrow\ f(x) = \lambda * \alpha(e^x - 1) \tag{7}$$

where $f(x)$ represents the SELU function, λ and α are constant with approximated values of 1.051 and 1.673, respectively. The SELU functions have two possible outcomes, when the input is larger than zero and when the input is smaller.

4.3.4. *Squeeze-and-Excitation Blocks Module*

The squeeze-and-excitation blocks (SE) module is introduced into the proposed method to enhance the representational power of the CNN layer and improve its performance. This module dynamically adjusts the channel-wise feature response by capturing the relationships and independencies among different channels. Eq. (8) is the function of SE:

$$Z_c = \frac{1}{h-w}\sum_{i=1}^{h}\sum_{j=1}^{w} X_{[c,i,j]} \tag{8}$$

where $X_{[c,i,j]}$ denotes the values at channel c and spatial position *(i, j)* in the input feature map. The final product of the squeeze operation (SO) is a vector of channel-wise statistics.

Given the squeezed feature vector Z_c, generated from the SO, the excitation operation (EO) learns the scaling factors weighing from the importance of every channel so that:

$$Excitation(Z) = S \tag{9}$$

where S is a size of a vector representing the learning scaling factor.

$$S_c = \sigma\left(\Psi_2\left(f(x)(\Psi_1(Z_c))\right)\right) \tag{10}$$

where Ψ_1 and Ψ_2 are fully connected layers (CNN in this case), *f(x)* is the activation function (SELU), and σ is the sigmoid module.

4.3.5. *Max Pooling Module*

The max pooling (MP) module is introduced into the proposed method at the end of each internal CNN layer, as seen in Figures 2, 4 and 5. This module aims to down-sample the feature maps generated by the CNN internal layers and to reduce the spatial dimensions maintaining the essential characteristics of the features. The MP output *Y(c, i, j)* from Eq. (11) is derived from the convolution of a non-overlapping square-like region, and the input feature map *X* of size *(c, h, w)*, where it selects only the most outstanding value from each region. So, given a specific pooling window *(i, j)*, it can be expressed as Eq. (11):

$$Y(c,i,j) = Max(X[c(a):(a_r),(b):(b_r)]) \tag{11}$$

where a is defined as *(i*sh)*, a_r is defined as *(i*sh+ph)*, b is defined as *(j*sw), and* b_r is defined as *(j*sw+pw)*. The *sh* and *sw* are the stride along the height and the width dimensions [42,43].

4.4. *Classification Method*

The classification method in Figure 6 is based on a custom sequential structure of one flattened layer followed by three sets of layers. Each set of layers contains a linear transformation (LT), BN, and the activation function SELU. The classification method includes reducing the dimensionality of the features and evaluating the most predominant characteristics embedded in the resulting features from the SE-VGGNet-S-BN method.

The combination of the SELU and BN helps to moderate the issues of vanishing and exploding gradients and reduce sensitivity to weight initialisation. Leading to more stable and efficient training as the BN reduces internal covariance shifting and enables higher learning rates while reducing the need for extensive hyperparameter turning.

4.4.1. *Flatten Layer*

The flattening layer converts the data received from the SE-VGGNet-S-BN method (multidimensional data with a size of 122 x 1 x 128 into a flattened vector (one dimension) of the size of 15616. The flattening of the data improves the subsequent layer performance and helps extract relevant features from the input data.

4.4.2. *Transformation Layer and Activation Function*

The linear transformation (LT) layer in Eq. (12), aims to learn a linear mapping between the receiving and out features by adjusting the learnable values associated with the weight and bias vector during training. Considering that the

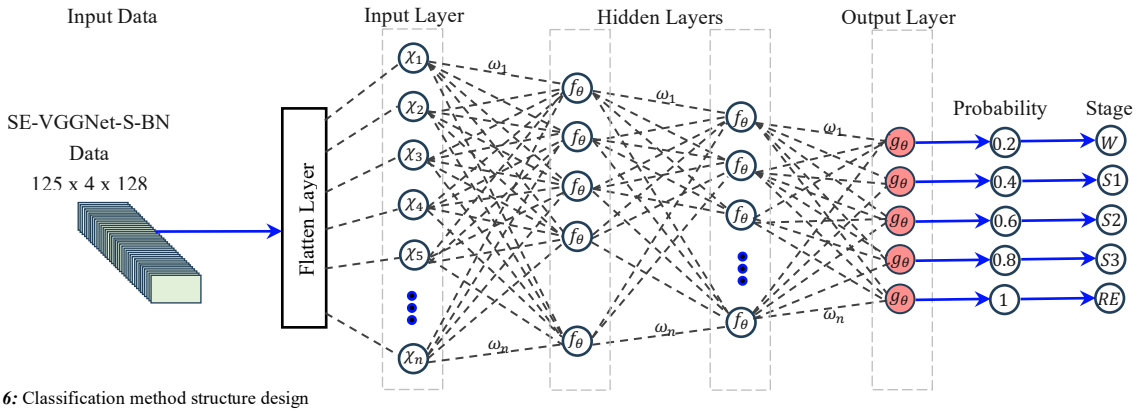


Figure 6: Classification method structure design

LT does not introduce non-linearity by itself, it requires an activation function, discussed in the next section.

$$x_i = x * w^T + b \quad (12)$$

where x_i is the output of the LT layer, x is the input, w is the learnable weight matrix of size (in-features, out-features), b is the learnable bias vector of shape (out-features), and T denotes the transpose of the weight matrix.

The activation function used in the classification method was introduced in section 4.3.3. It leads to non-linearity in the classification by transforming the input signal into values that vary from 0 and 1.

The output of each neuron in the LT is represented by the function in Eq. (13).

$$a_q = f\left(\sum_i w_{iq}\, x_i + b_q\right) \quad (13)$$

where a_q is the output of the neuron q, f_θ represents the activation function to the weighted sum, $\sum_i$ denoted the summation over the index, i, that represents the inputs from the previous layer, w_{iq} is the weight associated with the connection between the input i and neuron q, x_i is the input or activation from the previous layer connected to neuron q, and b_q is the bias expression that determines which node becomes activated at a specific input level. In other words, Eq. (13) calculates the weighted sum of the inputs or activations from the previous layer, adds the bias term, and applies the activation function f_θ to generate the output or activation of neuron q.

4.4.3. Loss Function Optimisation and Learning Rate

Cross entropy is the loss function (LF) implemented for the classification. The cross-entropy measures the dissimilarity between the prediction distribution and each class's true values [44,45].

The cross-entropy function is presented in Eq. (14):

$$LF = \frac{-1}{N} * \sum (y * \log(\hat{y})) \quad (14)$$

where N is the number of the training samples on each batch, y is the true label in the training set, and $\hat{y}$ is the predicted probability distribution over the five labels of the corresponding training example. $(y * \log(\hat{y}))$ computes the element-wise multiplication of the true values and the logarithmical provability of the prediction. The LF is then averaged over the batch size (N) to get the total loss value [44,45].

The optimiser is the stochastic gradient descent (SGD), which helps to optimise the model by minimising the loss. The SGD optimisation is presided by Eq. (17).

$$\vartheta_1 = \vartheta_{-1} - \alpha * \nabla R(\vartheta_{-1}) \quad (17)$$

where ϑ_1 is the updated optimisation value, ϑ_{-1} is the current optimisation, α is the learning rate, and $\nabla R(\vartheta_{-1})$ is the gradient of the cost function R with respect to the current optimization[46,47].

The classification uses the learning rate decay model, which is adjusted during the training. It allows the learning rate to fluctuate based on the training process, improving the overall performance and convergence of the classification method.

The learning rate is presided by Eq. (18).

$$lr_1 = \frac{lr_{-1}}{(1 + dr * Ep)} \quad (18)$$

where lr_1 is the updated learning rate at a given epoch (Ep), lr_{-1} is the initial learning rate, and dr is the decay rate, which controls the learning rate [46,48].

4.5. Performance Measurement Metrics

The performance of the proposed method is assessed using six measurement metrics: Lin's concordance correlation coefficient (CCC), agreement rate (AR), sensitivity (SE), specificity (SP), positive predicted value (PPV), and F-measure (F).

4.5.1. Lin's Concordance Correlation Coefficient

The CCC performance metric is applied to assess the level of agreement between two entities representing the same variable, aiming to demonstrate the concordance between the results obtained from the proposed method and the sleep stages provided by experts. The CCC in Eq. (19) combines the precision and the accuracy metrics to provide a single value representing the overall agreement between two variables [49–5253].

$$\rho_c = \frac{2\rho\, \varphi_x\, \varphi_y}{\varphi_{x^2} + \varphi_{y^2} + (\mu_x - \mu_y)^2} \quad (19)$$

where ρ is the Pearson correlation between two variables, $\varphi_x\, \varphi_y$ are the standard deviations of the variables x and y, and $\mu_x - \mu_y$ are the means of the measurements of the preside variables [14,30,50,52].

4.5.2. Agreement Rate

The AR of sleep stages is based on each stage. It considers all the stages evaluated during testing and verification. The AR is defined as:

$$AR = \frac{(a+b)}{a+b+c+d} \quad (20)$$

where a is the number of positive sleep stages scored by the method, and the expert (TP), b is the number of sleep stages classified as false positives (FP), c is the number of sleep stages classified as false negatives (FN), and d is the number of true negatives TN [14,50,54].

4.5.3. Sensitivity

The sensitivity or recall metric evaluates the correctness of measurements in terms of true positives (TP) and false negatives (FN), as shown in Eq. (21) [14,55].

$$SE = \frac{TP}{TP+FN} \quad (21)$$

4.5.4. Specificity

Specificity is used to evaluate the performance of a binary classification model, which represents the capability of the method to identify (TN) from the actual negative cases, as shown in Eq. (22) [14,55,56].

$$SP = \frac{TN}{TN+FP} \quad (22)$$

4.5.5. Positive Predicted Value

The PPV, or precision, is used to assess the probability of a condition present on a subject. It represents the proportion of TP cases out of all cases predicted as positive by the model, as shown in Eq.(23) [14,55,56]. The false positives refer to the sleep stages identified by the method but not by the expert.

$$PPV = \frac{TP}{TP+FP} \quad (23)$$

4.5.6. F-measure

The F-measure or F1 score evaluates the performance of binary classification of the method by combining the precision (PPV) and recall (SE) of a model, as shown in Eq. (24) [14,30,57].

$$F = \frac{2(SE * PPV)}{SE + PPV} = \frac{2TP}{2TP + FN + FP} \quad (24)$$

5. Experimental Results

This study proposes a robust sleep stage classification method that significantly improves accuracy by utilising the features associated with the sleep stages based on the R&K rules and the AASM standards.

The proposed method is evaluated based on over 480 hours of polysomnography (PSG) data across three databases. The data is pre-processed and filtered using the MNE Python tools, with around 10% of the stages rejected

Table 2: Training and validation data after pre-processing

TRAINING AND VALIDATION DATA AFTER PRE-PROCESSING

Databases	Total Data (Ep)	Training Data (Ep)	Testing Data (Ep)
St. Vinc. DB	18590	14868	3722
Dream's DB	121066	96851	24215
CAP's DB	13236	10587	2649

Table 3: Proposed method accuracy on St. Vincent's Database.

METHOD ACCURACY ON **ST. VINCENT'S DATABASE**:

Metrics \ Stages	W	S1	S2	S3	REM
Total Stages Evaluated	847	607	1251	479	538
Total Stages Identified	689	385	1090	388	454
AR (%)	0.81	0.63	0.87	0.81	0.84
SE	0.81	0.63	0.87	0.81	0.84
SP	0.93	0.96	0.90	0.96	0.95
PPV	0.81	0.78	0.84	0.78	0.77
F-Score	0.81	0.70	0.85	0.79	0.81

due to excessive noise or abnormalities. Training and validation are performed on 152911 epochs, split randomly into 80% training and 20% testing, as shown in Table 2. Features are obtained using the MT&C and SE-VGGNet-S-BN methods. While the MT&C generates the spectral density estimation, which can be directly associated with the visual parameters used to score stages, the SE-VGGNet-S-BN method extracts mathematical characteristics from the MT&C features. The classification employs a sequential structure with a SELU activation and batch normalisation, and it is evaluated using accuracy, recall, precision, and F-measure metrics.

5.1. Method Performance on St. Vincent's Database

Table 3 contains the performance accuracy, recall, precision, and F-measure of the sleep stage classification on the St. Vincent's DB. The overall accuracy on the test set was 80%, with the highest performance for the S2 and REM stages, having 87% and 84% accuracy, respectively.

Figure 7 illustrates the confusion matrix for St. Vincent's DB. The values correctly classified by the method (trues positive) are on the diagonal line, while the values off the diagonal line indicate misclassified ones.

Comparing the results among our proposed method and the previous studies conducted by Zapata [14], Perslev [58], Langkvist [59], Sun [60], and Yilita [61], who also used the St. Vincent's DB, our method demonstrated notable improvements in accuracy, recall, precision, and F-score across all sleep stages.

Comparing to Zapata [14] that introduced the Rules-based and SVM-Q methods for sleep stage classification, the proposed method in this paper shows performance improvements of more than 3% for most stages based on the Rules-based method and over 2% for the case of the SVM-Q.

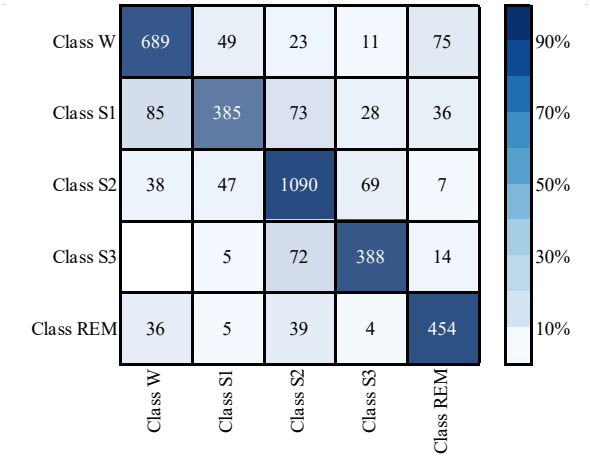


Figure 7: Confusion matrix St. Vincent's Database

Table 4: The accuracy by the proposed method for Dream's Database.

ACCURACY FOR THE **DREAM'S DATABASE**:

Metrics \ Stages	W	S1	S2	S3	REM
Total Stages Evaluated	6852	1211	12120	1109	2923
Total Stages Identified	6310	873	10849	997	2616
AR (%)	0.92	0.74	0.89	0.91	0.89
SE	0.93	0.45	0.97	0.73	0.88
SP	0.96	0.95	0.97	0.98	0.98
PPV	0.92	0.45	0.97	0.73	0.88
F-Score	0.93	0.45	0.97	0.73	0.88

Our proposed method significantly improves the performance in terms of all assessment metrics, achieving an average increase of 10% compared to Perslev's results [58]. Perslev [58] employed a CNN for the sleep stage classification.

With respect to Langkvist [59] who employed an unsupervised feature learning method for sleep stage classification, significant performance improvements are evident with our proposed method, with a 15-30% accuracy increase for classifying the sleep stages.

Sun [60] and Yulita [61] who used Bi-directional long-short memory method with slight modifications between them, our proposed method shows notable advancements in performance with an average of 4% increase for S1 and S2 stages compared to Sun [60], and an average 22% improvement for stages REM, S3, and W.

5.2. Method Performance on Dream's Database

The performance accuracy, recall, precision, and F-measure for sleep stage classification in Dream's DB are summarised in Table 4. The overall testing accuracy was 89%, with exceptionally high accuracy in stages W and S3 at 92% and 91%, respectively. Stage S2 had a precision, recall and F-score of 0.97, while stage S1 had the lowest performance with a precision, recall and F-score of 0.45. Another stage with a relatively low precision, recall and F-score was S3 at 0.73, despite its accuracy being 91%.

Figure 8 shows the confusion matrix for Dream's DB. In this matrix, the squares adjacent to the main diagonal, which correspond to the classifications by our proposed method, exhibit high values shaded in moderated dark blue, indicating that the classifier often encounters confusion among sleep stages that

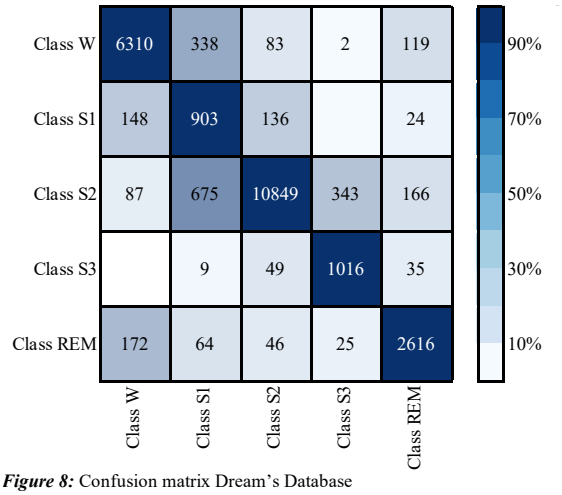


Figure 8: Confusion matrix Dream's Database

Table 5: The accuracy by the proposed method for CAP's Database.

ACCURACY FOR THE CAP'S DATABASE:

Metrics \ Stages	W	S1	S2	S3	REM
Total Stages Evaluated	247	104	1137	602	559
Total Stages Identified	235	88	1023	546	531
AR (%)	0.95	0.84	0.89	0.91	0.95
SE	0.95	0.84	0.90	0.47	0.95
SP	0.98	0.97	0.97	0.99	0.97
PPV	0.81	0.59	0.97	0.95	0.91
F-Score	0.88	0.69	0.93	0.63	0.93

are closely related or have similar characteristics, for example, stage W with stages S1 and REM, and S2 with S1 and S3 stages.

5.3. Method Performance on CAP's Database

Table 5 shows the performance metrics of our proposed method on CAP's Database. The average testing accuracy was 92%, with the highest performance on stages W and REM with a 95% accuracy. The highest recalls were achieved by stages W and REM at 0.95, while the lowest was for the S3 stage at 0.47. As for the precision, stage S2 had the highest performance at 97, whereas stage S1 had the lowest at 0.59. Regarding F-score, the stages of W, S2 and REM achieved the pick performance at 0.88, 0.96 and 0.91, respectively, while stages S3 and S1 were the lowest at 0.63 and 0.69.

Figure 9 presents the confusion matrix for the CAP's DB, revealing that most values located off the main diagonal are remarkably low. Notably, our proposed method reveals misclassifications primarily in the S2 stage, which has the most discrepancies.

When comparing the performance of our proposed method to the results from Zapata [14] and Perslev [58], our method showcased significant improvements in accuracy, recall precision and F-score across all sleep stages, having an average improvement accuracy of 5%. It presented a slight improvement compared to the Rules-based method, which has an average classification rate of 87.6 5 and to the SVM-Q, which was 90%.

Our proposed method demonstrates remarkable performance improvements compared to Perslev [58] for stage classification, ranging from 11% to 50% accuracy.

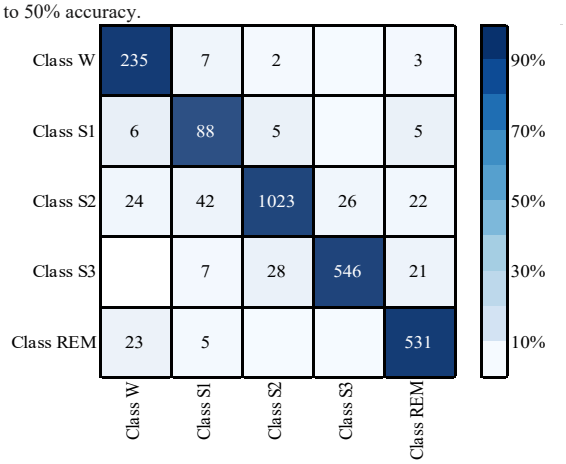


Figure 9: Confusion matrix CAP's Database

6. Discussion & Conclusion

This study develops a deep-learning method that processes preliminary features and extracts, identifies, and classifies sleep stages using EEG signals from three databases that have subjects with and without different neurological conditions. The results demonstrated promising performance in accurately classifying different sleep stages.

The proposed method achieved an impressive overall accuracy of 87% in sleep stage classification, an improvement compared to other state-of-the-art approaches.

In the feature extraction section, two distinct methods are used, each with advantages. The first method (MT&C) is a comprehensive approach that utilises time-frequency analysis following the parameters outlined in the R&K rules and the AASM standards. This method effectively captures essential characteristics and patterns associated with different sleep stages, aligning with the visual scoring criteria.

The second method involves a unified short-visual geometric group analysis framework with enhanced feature extraction. It establishes connections between the characteristics derived from the time-frequency analysis method, generating associations that the system interprets based on their relevance through weights and biases. By incorporating the two methods for feature extraction, our proposed algorithm can effectively extract relevant information embedded in the EEG data.

This study also employed three well-known mid-size databases, incorporating diverse sleep study subjects. This inclusion enhances the relevance of our findings and increases the application of the proposed method in future studies. The arduous validation process, which included independent testing, further supports the consistency and robustness of our results.

Nonetheless, some limitations should be mentioned. Firstly, this study focused exclusively on EEG and EOG signals and did not consider another physiological signal, such as EMG. Additionally, while our method demonstrated outstanding performance in distinguishing between sleep stages, further research is required to address the challenges associated with specific sleep stages, such as S1, W and S2 stages, which exhibit overlapping characteristics in the EEG signals. Moreover, it is essential to note that the performance of the proposed method may vary depending on the type or approach of data pre-processing employed. Likewise, Given the lack of united agreement on the interpretation of certain stages, training the method with labels from a specific expert may lead to decreased performance when testing data from another expert.

This study opens opportunities for several future directions, like the implementation of multi-method approaches to improve accuracy and the incorporation of methods that can create features that are relevant and easy to interpret by medical experts.

By exploring these future directions, we can advance the field of sleep stage classification, enhance the overall comprehension of sleep physiology, and make valuable contributions to developing more effective diagnostic and treatment approaches for sleep disorders.

In conclusion, this study demonstrates the feasibility and effectiveness of integrating and utilising time-frequency analysis and deep learning for sleep stage classification. The outstanding accuracy achieved, along with the inclusive feature selection process and diverse databases, illustrates the capability of our approach in identifying visual characteristics and interpreting them to classify sleep stages. Future research can build upon our findings to develop more sophisticated models to address other challenges and further improve the accuracy and capability of sleep stage classification.

7. Funding

No Funding to report.

8. Data Availability

The datasets used in the current study are open sources and are available in Open Science Framework (OSF) [62], ZENODO [26,27], and Physionet [28].

9. Implementation Details

The data were pre-processed using the MNE Python Library [31], and the methods were created and implemented in Python and MATLAB.

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Chapter 5: EEG-Based sleep stage classification using CNN with squeeze-and-excitation blocks in a short-visual geometric group.

5.2. Chapter Summary

In this chapter, the EEG-based sleep stage classification with a CNN in a short-visual geometric group method is presented to classify the sleep stage with the help of a time-frequency analysis method. The preliminary features are extracted by combining multitapers and convolution, and then a visual geometric group network with SE blocks, SELU, and BN is applied to refine the features. The classification is performed using a multi-layer perceptron with SELU and BN.

The research showcases promising results, achieving an average accuracy and precision of 87% in sleep stage classification across three different EEG databases. The proposed method outperforms several state-of-the-art approaches, demonstrating its efficacy in accurately classifying different sleep stages. This research included diverse healthy and unhealthy subjects and conducted a rigorous validation process that enhanced the relevance and reliability of the findings.

However, limitations should be acknowledged, such as excluding other physiological signals and the challenges associated with specific sleep stages exhibiting overlapping characteristics. Future research could explore multi-method approaches to improve accuracy and incorporate features easily interpretable by medical experts.

Overall, this research contributes to the field of sleep stage classification by effectively integrating time-frequency analysis and deep learning techniques. The proposed method can advance our understanding of sleep physiology and facilitate more effective diagnostic and treatment approaches for sleep disorders.

CHAPTER 6

Conclusions and Future Research Directions

6.1. Introduction

Sleep constitutes a vital physiological process essential for upholding overall health and well-being. As humans, we spend a significant portion of our lives in a state of restful slumber, during which crucial bodily functions, such as memory consolidation, immune system regulation, and tissue repair, take place. The quality and quantity of sleep directly impact our cognitive abilities, emotional regulation, and physical health. Therefore, a comprehensive understanding of sleep patterns and stages is of utmost importance in the fields of sleep medicine, neuroscience, and public health.

Sleep EEG analysis has emerged as a powerful tool to investigate and understand the complexities of sleep patterns. EEG data are non-invasive recordings of electrical brain activity, collected using electrodes on the scalp, which capture the dynamic changes in brain wave patterns throughout different stages of sleep. Analysing these EEG signals allows researchers to categorise sleep into distinct stages, such as awake, stage 1 (light sleep), stage 2 (intermediate sleep), stage 3 (deep sleep), and REM sleep. Each stage exhibits unique EEG wave characteristics that provide valuable insights into sleep physiology.

In recent years, advancements in signal analysis techniques, machine learning, and deep learning models have presented exciting opportunities to automate and improve the accuracy of sleep stage classification. The integration of time-frequency analysis, which explores the temporal dynamics of EEG signals, has shown promise in extracting meaningful features that correlate with sleep stages. Additionally, machine learning and deep learning algorithms have demonstrated the ability to learn complex patterns from EEG data, enabling more precise and efficient sleep stage classification.

This thesis delves into the realm of sleep EEG analysis, addressing five fundamental concerns and main objectives to enhance the accuracy and efficiency of sleep stage classification. The research aims to combine various signal analysis methods, such as multitapers and convolution, with machine learning and deep learning models such as rules-based approach, SVM-Q, CNN and VGG to develop innovative multi-method approaches. By integrating these approaches, the research strives to achieve a more

comprehensive understanding of sleep, sleep spindles and their distribution across the scalp, and sleep stages. Exploring advanced time-frequency analysis techniques and deep learning models aims to significantly improve sleep stage classification accuracy and facilitate personalised sleep health involvements.

The thesis presents compelling evidence for the effectiveness of the proposed multi-method approaches through extensive experiments and rigorous evaluations across different EEG databases. The findings enhance the understanding of sleep physiology and offer practical applications in sleep research, clinical diagnosis, and personalised treatment strategies. The visualisations and direct connections between the extracted features by the methods and EEG definitions further contribute to the interpretability of the classification results, providing valuable insights to medical experts and supporting the outcomes of the proposed methods.

As chapters progress, we discuss the main contributions of this research in advancing sleep EEG analysis and sleep stage classification. Furthermore, we analyse and interpret the results of each chapter, addressing the research questions and objectives laid out at the beginning of the study. The investigated approaches, which encompassed the rules-based, SVM-Q, SAMC, and CNN with squeeze-and-excitation blocks, exhibited encouraging outcomes in both features extraction and classification. By integrating time-frequency analysis, multitapers, and convolution, in addition to leveraging deep learning techniques, a substantial enhancement in the accuracy of sleep stage classification was observed across diverse databases.

We conclude this thesis with a discussion of the potential implications and applications of the proposed methods, laying the groundwork for future research directions in this evolving field of study. By comprehensively evaluating the research outcomes, we strive to revolutionise sleep research, improve current deep learning and machine learning methods, expand clinical practice, and ultimately contribute to better sleep health outcomes for individuals.

6.2. Discussions and Conclusions

The research presented in this thesis aimed to enhance the understanding and accuracy of sleep EEG analysis and sleep stage classification using innovative multi-method approaches. The key findings and contributions can be summarised as follows:

1. **Development of Innovative Approaches**: The thesis introduced novel methods for sleep EEG analysis, combining the MT&C method with advanced machine

learning and deep learning techniques. These approaches significantly improved the accuracy of sleep stage classification and provided valuable insights into the characteristics of sleep spindles across the brain.

2. **Enhanced Sleep Stage Classification Accuracy**: Integrating the MT&C, machine learning algorithms, and deep learning models improved sleep stage classification accuracy. The proposed methods demonstrated superior performance, particularly in datasets with normal sleep patterns.
3. **Comprehensive Analysis of Sleep Spindles**: The SAMC method offered a comprehensive analysis of sleep spindles by identifying and categorising them across multiple EEG channels. This approach provided valuable information about the distribution and characteristics of spindles in different cortical areas.
4. **Integration of Advanced Techniques**: The integration of advanced time-frequency analysis and deep learning techniques was proved to be highly effective in sleep EEG analysis and sleep stage classification, surpassing existing methods in accuracy and performance.

Overall, this research contributes significantly to the field of sleep EEG analysis and sleep stage classification. The proposed approaches hold the potential to streamline the sleep stage scoring process, improve diagnostic accuracy, and provide visual support to medical experts, thereby enhancing sleep health outcomes for individuals.

6.2.1. Sleep EEG Analysis and Sleep Stage Classification

Implementing and evaluating the MT&C method for sleep EEG analysis and sleep stage classification showcased promising results. The SVM-Q and rules-based classifiers, in combination with the MT&C, achieved high accuracy and performance, particularly in datasets with normal sleep patterns. However, challenges in classifying stage 1 in subjects with abnormal sleep EEGs were identified, suggesting room for improvement in this aspect. Future research could explore incorporating additional descriptive wavelet methods into the rules-based classifier to enhance identifying specific characteristics in sleep stages.

6.2.2. Sleep Spindles Identification

The SAMC method demonstrated superiority over existing spindles identification methods, achieving higher agreement rates and precision than expert labels. Visualising spindles across multiple channels provides valuable insights into their characteristics and behaviours, enhancing the understanding of sleep dynamics and neural activities. Future research may focus on applying the SAMC method to different types of EEG

data and exploring its capabilities in various mental tasks and clinical applications beyond sleep spindles.

6.2.3. Advanced Time-Frequency Analysis in Combination with Deep Learning Methods for Sleep Stage Classification

Integrating time-frequency analysis techniques and deep learning models for sleep stage classification led to significant improvements in accuracy across different EEG databases. The proposed method outperformed several state-of-the-art approaches, demonstrating its efficacy in accurately classifying different sleep stages. While the results are promising, future research could explore additional multi-method techniques to improve accuracy further and incorporate other features easily interpretable by medical experts.

In summary, this thesis has successfully addressed the research questions and objectives outlined at the beginning of the study. The proposed multi-method approaches have enhanced the accuracy and efficiency of sleep stage classification by combining various signal analysis methods, machine learning algorithms, and deep learning models. The integration of time-frequency analysis and advanced techniques has provided valuable insights into the characteristics of sleep spindles and their distribution, contributing to a deeper understanding of sleep physiology and cognitive processes during rest.

Moreover, the proposed approaches have the potential to streamline the sleep stage scoring process and offer valuable visual support to medical experts, thereby improving the overall sleep stage classification efforts.

6.2.4. Study Limitations

6.2.4.1. Signal Processing Limitations:

Frequency Range: The EEG signal processing focuses on a specific frequency range (0.2 Hz to 30 Hz). This might limit the detection of certain patterns or anomalies that occur outside this range, potentially missing relevant information.

6.2.4.2. Feature Extraction Challenges:

Data Quality: The efficacy of feature extraction methods, such as the MT&C technique, heavily relies on the quality of the input data. Noisy or artifact-ridden EEG data can affect the accuracy of feature extraction and methods classification.

6.2.4.3. Algorithmic Constraints:

Generalization: The paper mentions the use of a CNN with a specific architecture (SE-VGGNet-S-BN). The effectiveness of this architecture might vary across different

datasets, and its ability to generalize to diverse populations or conditions might be limited.

6.2.4.4. Pre-processing Assumptions:

Assumed Noise Characteristics: The pre-processing steps involve filtering and denoising based on assumed characteristics of noise in EEG signals. If these assumptions don't hold true for all scenarios, it might lead to inadequate noise removal or even loss of relevant information.

6.2.4.5. Diversity in Databases:

Representativeness: The research uses several databases for classification, training and validation. Limitations may arise if these databases are not fully representative of the broader population, leading to potential biases in the algorithm's performance.

6.2.4.6. Interpretability of Features:

Clinical Correlation: While the presented studies discuss the association of features with sleep stages and sleep spindles based on medical definitions (R&K rules or AASM standards), the interpretability of features in a clinical context might be challenging, and certain nuances in sleep stage characteristics may be missed.

6.2.4.7. Lack of Multimodal Integration:

Single-Modality Data: The study exclusively focuses on EEG data. Integrating data from other modalities like EMG or EOG could potentially enhance the robustness of sleep stage classification.

6.2.4.8. Subjectivity in Sleep Stage Labelling:

Inter-Expert Variability: The research assumes accurate sleep stage labels in the training datasets. However, there might be variability in the interpretation of sleep stages among experts, potentially introducing inconsistencies.

6.2.4.9. Performance Metrics:

Comprehensiveness: While the studies use several performance metrics (CCC, AR, SE, SP, PPV, F-measure), the comprehensiveness of these metrics might be discussed. They offer specific insights, but a holistic view of the algorithm's performance might require additional evaluation criteria.

6.2.4.10. Ethical Considerations:

Data Privacy: The papers are limited to the databases ethical considerations, and most do not explicitly mention considerations regarding data privacy or ethical guidelines in using EEG data, which is crucial, especially when dealing with sensitive health information.

6.3. Future Work

While this research has made significant strides in advancing sleep EEG analysis and sleep stage classification, several aspects for future work can be explored to enhance the field further:

Incorporation of Other Physiological Signals: Future research could explore the integration of other physiological signals, such as heart rate variability and body movement data, to improve the accuracy and depth of sleep stage classification.

Exploration of Collaborative Score Validation: To improve manual and automatic scoring accuracy, collaborative efforts between experts and modern algorithms could be explored. This could involve combining the strengths of different experts' scoring with the objectivity and efficiency of the advanced methods.

Real-Time Sleep Stage Classification: Developing real-time sleep stage classification algorithms could have practical applications in sleep monitoring devices and sleep health interventions, enabling immediate feedback and personalised sleep recommendations for individuals.

Transfer Learning and Generalisation: Investigating transfer learning techniques to generalise the proposed methods across different EEG databases and diverse populations could further enhance the robustness and adaptability of the classification models.

Integrating Semi-Supervised Learning Models: Incorporating semi-supervised learning models offers the advantage of adjusting or refining the model using expert feedback. The performance of various models can be fine-tuned and improved by utilising the initially labelled training model and subsequently incorporating additional observations from experts. This way, an expert's input facilitates the ability of a model to adapt and learn from new information or challenges.

Explainable Artificial Intelligence (AI) for Sleep Stage Classification: Research in explainable AI techniques could be integrated into the proposed methods to provide medical experts with interpretable insights into the

classification results, fostering trust and acceptance in automated sleep stage scoring systems.

Clinical Validation and Applications: Further validation of the proposed methods in clinical settings with a more extensive and diverse patient population would strengthen the practical applications of the research in diagnosing sleep disorders and improving patient care.

Longitudinal Sleep Studies: Conducting longitudinal sleep studies with the proposed methods could provide valuable information on sleep patterns and changes over time, facilitating better understanding and personalised sleep health interventions.

In conclusion, the research conducted in this thesis has laid a strong foundation for advancing sleep EEG analysis and sleep stage classification. The innovative multi-method approaches, and the integration of advanced signal analysis and deep learning techniques have shown promising results in enhancing accuracy and understanding sleep physiology. With continued efforts in exploring the suggested future directions, this research has the potential to revolutionise sleep research, improve clinical practice, and contribute to better sleep health outcomes for individuals.

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APPENDICIES

A

Size of Gabor Dictionary

The size of the Gabor dictionary is determined by the number of atoms generated across frequencies. This number is equal to the sample rate (Fs) divided by two, plus one ((Fs/2) + 1). The "two" represents the vanishing point between one wavelet and the next. The first wavelet is generated at 0, and the last at the final point. Therefore, for each frequency iteration in the Gabor dictionary, ((Fs/2) + 1) atoms are spread across the time duration of the signal.

The Gabor dictionary created for this research includes frequencies from 1Hz to 40Hz. If the sample rate Fs is an odd number, the division by two results in a float number approximated to the nearest preceding integer. As a result, the size of the Gabor dictionary is given by Fs x (((Fs/2) + 1) * 40).

Appendix.

B

Gabor Dictionaries in MP

According to Mallat and Zhang (1993), a Gabor dictionary for time-frequency atomic decomposition is constructed by scaling (*s*), translating (*u*), and modulating (*ξ*) a window function. This window function corresponds to the Gaussian element of the equation, depending on the three parameters (*s, u, ξ*). It is assumed that the integral of *g(t)* is a continuous variable and real while ensuring that the essential of $g(t) \neq 0$ and the norm of *g* is equal to 1 ($\|g\| = 1$). For any $s > 0$, *ξ*, and *u*, denoted as $\gamma = (s, u, \xi)$, it is defined as shown in Eq.1.

$$g_\gamma(t) = \frac{1}{\sqrt{s}} g\left(\frac{t-u}{s}\right) e^{i\xi t} \tag{1}$$

where $\gamma \in \Gamma$ and $\Gamma = R^2 \times R^+$, the normalisation factor $\frac{1}{\sqrt{s}} g$ is employed to ensure that $\|g_\gamma(t)\|$ is normalised to 1 (for a more comprehensive understanding of the window function generation, kindly refer to Mallat and Zhang, 1993).

The initial Gaussian window generates a highly redundant dictionary, necessitating the inclusion of time-frequency atoms of different scales, as shown in Eq.2, to ensure the presence of efficient functions.

The functional application of MP, as presented by Mallat and Zhang (1993), has been utilised by Malinowska (2009) and Kus (2013). Both studies followed the same principle of γ = (s, u, ξ) in a Gabor atom, with slight variations. For further details on their methodologies, please refer to Malinowska et al. (2009) and Kus et al. (2013).

$$x \approx \sum_{n=0}^{M-1} \langle R^n x, g_{\gamma_n} \rangle \, g_{\gamma_n} \tag{2}$$

In Eq.2, *M* represents the number of iterations, g_{γ_n} denotes the Matching Pursuit (MP) of the signal *x* at the n^{th} iteration, and $R^n x$ represents the n^{th} residuals of the signal. A Gabor function was then formulated as shown in Eq.3.

Appendix.

On the other hand, Kus, Różański, and Durka (2013) introduced a neutral variable (K(γ)) in the Gabor equation mentioned in Eq.3. This neutral variable can be interpreted as the amplitude of the Gaussian window, where γ= (s, u, ξ). The neutral variable was defined in such a way that ‖g‖=1 based on the expansion function presented in Eq.2.

$$g_\gamma(t) = K(\gamma)\, e^{-\pi\left(\frac{t-u}{s}\right)^2} \cos(\omega(t-u)+\phi) \quad (3)$$

In contrast, Malinowska (Malinowska et al., 2009) introduced an additional parameter, the offset or phase of the sine/cosine wave (ϕ), into the definition of γ, resulting in the extended form $\gamma = (s, u, \xi, \phi)$. Consequently, the Gabor function was reformulated as shown in Eq.4:

$$g_\gamma(t) = e^{-\pi\left(\frac{t-u}{w}\right)^2} \cos(2\pi f(t-u)+\phi) \quad (4)$$

In both Eq.3 and Eq.4, the first part ($e^{-\pi\left(\frac{t-u}{w}\right)^2}$ or $K(\gamma)\, e^{-\pi\left(\frac{t-u}{s}\right)^2}$) represents the Gaussian window, and the second part $\cos(\omega(t-u)+\phi)$ or $\cos(2\pi f(t-u)+\phi)$ represents the sine or cosine element of a Gabor wavelet.

As previously mentioned in Eq.3, $K(\gamma)$ is a neutral value ($K(\gamma)=1$), indicating that it does not significantly affect the outcome of the Gabor wavelet. It can also be noted that ω in Eq.3 can be represented as 2πf, as defined in Eq.4.

Although there is no substantial difference in the conceptual interpretation of the functions presented in Eq.3 and Eq.4, their practical applications and manipulation of parameters vary. Eq.4 provides a more versatile and robust dictionary for the Gabor function, as ϕ becomes an essential parameter of the sine/cosine wave. Thus, ϕ is no longer fixed at a nominal value but adapts to the phase of each structure detected in the signal. For a Gabor function g_{γ_n} with a $\gamma_n = (u_n, f_n, \omega_n, \phi_n)$, where u_n represents the time position at the n^{th} iteration, f_n is the frequency at the n^{th} iteration, ω_n is the time width at the n^{th} iteration, and ϕ_n is the phase at the n^{th} iteration (Kuś et al., 2013).

C

Periodogram

In EEG data analysis, the periodogram (Fig. 1A) is a straightforward method to perform spectral density estimation (SDE) using a fast Fourier transform (FFT). However, many scientists consider it a suboptimal application of the SDE due to its composition. The periodogram consists of a large main lobe representing the peak oscillation frequency and fragmented peaks (side lobes) on both sides of the main lobe, exhibiting a decreasing power. This power distribution on the side lobes renders the periodogram a biased estimator spectrum for non-stationary data, as it introduces noise data into the estimation of surrounding frequencies. Consequently, the real spectral content of the signal is misrepresented, leading to reduced accuracy in spectral estimation. Ideally, the power should be concentrated on the main lobe, which is the source of power (M. X. Cohen, 2014; Gribonval, 2001; Lafta et al., 2017).

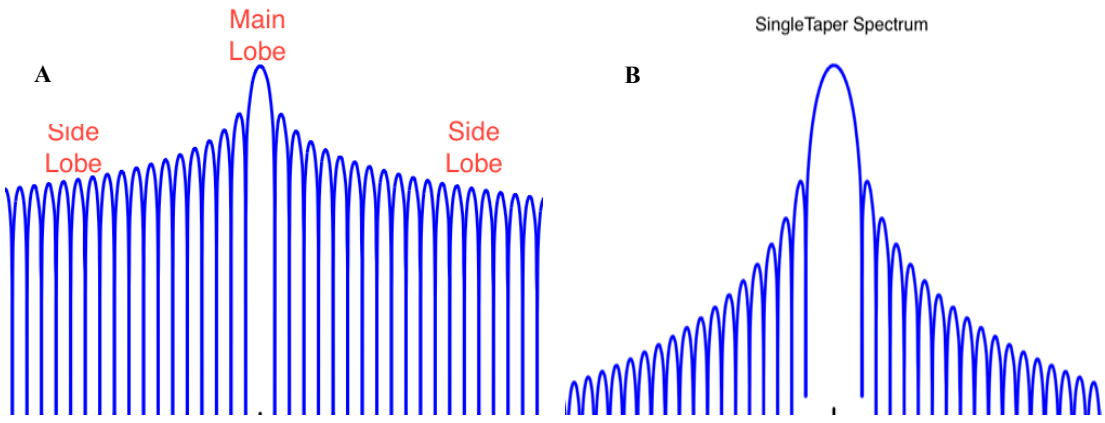

Fig. 1: (A) Periodogram Spectrum, (B) Single-Taper Spectrum.

To reduce the power distribution across the side lobes, improve the SDE, and minimise the periodogram bias, it is recommended to apply a window function, commonly known as a taper function or Gaussian window, to the data before computing the SDE function. This process, called single taper estimation spectrum (STE) (Figure 2.2.5 (B)), smooths out the abrupt transition between the main lobe and

the side lobes. The single taper estimation approach exhibits less bias than the periodogram, as it significantly reduces the power spectrum of the side lobes. However, it should be noted that this method may increase the estimation variance (Babadi & Brown, 2014; Lindberg & Park, 1987; Park, Lindberg, & Thomson, 1987; Park, Lindberg, & Vernon, 1987).

D

Dot-product and Convolution

The dot product between a wavelet and a signal is computed as the sum of all points of the wavelet multiplied by the corresponding points of the signal (indicated by the red mark in Figure 2.2.5 (A)). This computation involves convolving every point of a wavelet kernel with the raw signal. During the convolution process, if no additional points are added to the original signal, the resulting signal will be shorter in size than the raw signal due to the size of the kernel. To address this issue, a zero-padding of half the size of the kernel is applied at the beginning and the end of the raw signal, effectively enlarging the original signal. The added zero values cancel any potential biased values and noise in the resulting signal.

Consequently, the rightmost point of the kernel aligns with the leftmost point of the raw signal at the start and end of a convolution. The resulting size of the signal will equal the original size of the signal and the kernel minus one point. One subtraction is necessary because the kernel overlaps the raw signal by one point (Figure 2.2.5 (B)).

E

Code Repository for Chapter 3

The code used in the experiments and analysis presented in Chapter 3 of this thesis is available on GitHub. You can access the code repository at the following URL:

GitHub Repository: https://github.com/ZapataIgnacio/Chapter-3-Rules-Based-and-SVM-Q.git

Please refer to this repository for detailed code implementation, data pre-processing, and any additional materials related to the experiments conducted in Chapter 3. If you encounter any issues or have questions regarding the code, please feel free to contact the author at Ignacio.zapata@usq.edu.au.

Please note that due to the size of the databases used in this research, they are provided on an external drive. For access to the databases, please contact the author at Ignacio.zapata@usq.edu.au.

Please note that the code may be subject to updates or revisions beyond the completion of this thesis.

F

Code Repository for Chapter 4

The code used in the experiments and analysis presented in Chapter 4 of this thesis is available on GitHub. You can access the code repository at the following URL:

GitHub Repository: https://github.com/ZapataIgnacio/Chapter-4-Sleep-Spindles.git

Please refer to this repository for detailed code implementation, data pre-processing, and any additional materials related to the experiments conducted in Chapter 3. If you encounter any issues or have questions regarding the code, please feel free to contact the author at Ignacio.zapata@usq.edu.au.

Please note that due to the size of the databases used in this research, they are provided on an external drive. For access to the databases, please contact the author at Ignacio.zapata@usq.edu.au.

Please note that the code may be subject to updates or revisions beyond the completion of this thesis.

G

Code Repository for Chapter 5

The code used in the experiments and analysis presented in Chapter 5 of this thesis is available on GitHub. You can access the code repository at the following URL:

GitHub Repository: https://github.com/ZapataIgnacio/Chapter-5-EEG-Based-Sleep-Stage-Classification-Using-CNN-with-SE-B-in-a-SVGG.git

Please refer to this repository for detailed code implementation, data pre-processing, and any additional materials related to the experiments conducted in Chapter 3. If you encounter any issues or have questions regarding the code, please feel free to contact the author at Ignacio.zapata@usq.edu.au.

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