Applied Intelligence (2022) 52:1325–1337
https://doi.org/10.1007/s10489-021-02422-2

Automated Sleep apnea detection using optimal duration-frequency concentrated wavelet-based features of pulse oximetry signals

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Accepted: 3 March 2021 / Published online: 20 May 2021

Abstract

Sleep apnea is a potential sleep disorder, which deteriorates the quality of sleep. It is characterized by the obstruction in nasal airflow, which results in a low concentration of oxygen in the blood. Though polysomnography (PSG) is considered as a gold standard for diagnosing sleep apnea, it is arduous, demanding, expensive and inconvenient to the patients. This study presents an effective, efficient and sustainable sleep apnea automated detection system using pulse oximetry signals (SpO_2), which indicate the percentage of oxygen content in the blood. The conventional methods, which employ PSG recordings are computationally intensive and costly. Nowadays, the focus is on non-invasive and portable devices for higher convenience and cost-effective diagnosis. In this work, we have used optimal duration-bandwidth concentrated wavelet transform to decompose the SpO_2 signals into various sub-bands (SBs). The Shannon entropy features are extracted from various SBs coefficients. These features are then fed to various supervised machine learning algorithms, including decision trees and ensemble algorithms for automated detection of sleep apnea. The proposed model has attained the highest accuracy of 95.97%, and area under the receivers operating characteristics curve (AUC) of 0.98 for optimal wavelet-based Shannon entropy features when an ensemble boosting technique called random under-sampling boosting (RUSBoost) is employed with ten-fold cross-validation strategy. Thus, the proposed model is portable, economical, and accurate which can be used even at homes.

Keywords Classification · SpO_2 · Wavelets · Sleep apnea · Filter banks

1 Introduction

Sleep is considered an essential research topic for many decades. Good sleep has an enormous impact on our emotions and health. Sleep apnea is a potential sleep disorder delineated by obstructed breathing during sleep-time. The person's breathing stops and starts many times during sleep resulting in less oxygen supply to the brain. Apnea is one of the notable types of sleep disorder which results in the intrusion of breathing. Its severity is measured on the scale of apnea/hypopnea index (AHI). An index of < 5 is considered normal, and an AHI > 5 shows sleep apnea disorder. An AHI in between 5 to 15 denotes mild apnea, an AHI in between 15 to 30 is regarded moderate, and greater than 30 is rated as severe sleep apnea disorder [4]. The sleep apneic patient has cessation in his breathing or phases of shallow breathing during sleep. These cessations lasts for a few seconds to minutes and may occur several times during the sleep. As the breathing resumes, the cessations may be followed by snorting or loud snoring sound [16]. The people may encounter sleepiness or may feel tired during the day time due to lack of sleep. It can cause hyperactivity

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induced problems in children [35]. It is estimated that 2% of adult women and 4% of adult men are affected by sleep apnea. Sleep apnea is curable, but most of the patients are unidentified and, therefore, untreated [52]. Untreated sleep apnea-hypopnea syndrome (SAHS) can cause various heart diseases such as chlorosis, cardiovascular dis-function, and stroke-related problems [44].

Obstructive sleep apnea (OSA) is one of the most prevalent types of sleep apnea. Across the world, there are more than 1 billion cases of undiagnosed OSA [3, 38]. Chronic OSA requires treatment to avert hypoxemia, sleep depletion, and various other sleep-related complexities. The elders and men are more prone to have OSA than youngsters and women. The risk of OSA in individuals also rises with aging, increase in body weight and smoking [52]. Diabetic patients are three times more prone to have OSA than healthy individuals. The diagnosis methods include polysomnography or oximetry during sleep.

Polysomnography (PSG) is the conventional method used for sleep disorder detection including OSA. The typical PSG contains recording of electroencephalogram (EEG), electrooculography (EOG), electromyography (EMG), electrocardiography (ECG), oronasal airflow, respiratory effort, and oxygen saturation (SpO_2) [32]. The analysis of PSG is cumbersome, expensive and tedious as it requires the data collection during overnight sleep in sophisticated clinics. Hence, it is desired to have a substitute for PSG-based system which is simple, inexpensive and portable which can be used in homes and clinics. Several apnea detection systems have been developed based on snoring [29], questionnaires [28], ECG [14, 38, 45], and pulse oximetry [18, 21, 23]. Pulse oximeter ($SpO2$) signal has attracted the attention of several researchers [2, 13, 25] as an alternative for PSG.

SpO_2 signals measure the percentage (%) of oxygen saturated hemoglobin present in the blood. It is widely accepted for both pediatric and adult occupants. The pulse oximeter is one of the well-known sensors used to evaluate the saturation of oxygen (SpO_2) in the blood and pulse rate [53]. These sensors can report the results within seconds with high accuracy and are inexpensive. The presence and severity of OSA can be determined by calculating the desaturation index of the patient's blood, and after that patient can be sent for further diagnostic confirmation. [9]. A normal pulse oximeter (SpO_2) reading is between 95% to 100%, and it is considered low if it is below 95%. Some frequently used SpO_2 features are, oxygen desaturation index [21], saturation variability index and total time spent below a specific saturation level [23].

1.1 Related work

Some of the works, which have employed SpO_2 signals for apnea detection are discussed in this section. Burgos et al. [5] have employed a bagged tree classifier using statistical features extracted from SpO_2 signals of sleep apnea ECG database (SAE) database and obtained a classification accuracy of 93%. A seminal work by Xie et al. [51] used SpO_2 signals for the identification of sleep apnea. They have used 150 statistical and frequency domain features extracted from SpO_2 signals and achieved classification accuracy (CAC) of 82% using SVM and decision tree classifiers on the UCD database with 25 records. They showed that SpO_2 signals could perform better than ECG signals in identifying sleep apnea. Mostafa et al. [25] employed 61 time and frequency domain features along with a neural network (NN) and got maximum sensitivity of 96.5% with the SAE database. Similarly, Almazaydeh and Faezipour [1] used statical features, delta index, and a multi-layer NN for sleep apnea detection. They obtained an accuracy of 93.3% and sensitivity of 87.5% by taking 17% of the SAE database as test data. Zhang et al. [53] designed a smart pillow with an SVM classifier to detect apnea using a private database and obtained a CAC of 90%. Similarly, Oliver and Flores-Mangas [30] have used features based on power spectral density (PSD) and SpO_2 signals for developing a wearable device to detect apnea using a personal database. They did not mention classification performance. Garde et al. [12] used five-time and spectral-domain features with linear discriminant for sleep apnea detection and achieved CACs of 92.1% using the data acquired from British Columbia children's hospital. Ravelo-Garci et al. [33] combined ECG based features with 19 SpO_2 based frequency domain features and reported CAC of 86.5% using the SAE database. Haoyu et al. [13] achieved good performance using SpO_2 signals coupled with SVM classifier for private and UCD databases. However, they used features obtained from SpO_2 and heart rate variability (HRV) signals. Further, Mostafa et al. [26] used a deep belief network (DBN) formed using stacked restricted Boltzmann machines (RBM) to detect the sleep apnea. They used SpO_2 signals extracted from the UCD database. The DBN is trained and tested using 10-fold CV and achieved CACs of 85.26%. Recently, Cen et al. [6] used Convolutional Neural Network (CNN) using UCD database with 1s-SpO_2 epochs instead of 1 min epochs and achieved CAC of 79.61%. Several above-mentioned previous works [13, 13, 25, 51] required the overnight recordings of SpO_2 signals and analysis required a large feature set.

1.2 Proposed work

This study proposed an automated system using optimal duration-frequency concentrated (ODFC) wavelet filter bank (WFB) and SpO_2 signals. We aim to design a simplified, economic, and portable OSA detection system using SpO_2 signals to be used even at homes. The salient features of the proposed study are mentioned below:

1. The SpO_2 can be easily recorded using a pulse-oximeter sensor even when a subject is sleeping. The SpO_2 based apnea detection system overcomes the drawbacks of PSG-based systems, which require laborious visual inspection of multi-channel signals. Hence, an automated apnea detection system is proposed using SpO_2 instead of conventional PSG or ECG signals.
2. The proposed system is simple, portable, inexpensive, fast, comfortable, and accurate.
3. To extract features from SpO_2 signals, a new class ODFC of WFB has been employed.
4. Wavelet-based Shannon entropy features have been used to train and test the model.
5. The model is trained and tested using two independent databases obtained from two different sources.
6. The performance of the developed method has surpassed all other techniques.
7. In order to address the inherent data imbalance problem, a random under-sampling is boosting (RUSBoost) algorithm has been built for the classification, which is exceptionally useful in classifying imbalanced data.
8. We have shown that SpO_2 based systems outperformed ECG based sleep apnea detection systems.
9. The SpO_2 sensors are economical, simple to use, and convenient to place on subjects' bodies.

2 Methods and materials

2.1 Database

In this work, we have used St. Vincents University Hospital/ University College Dublin Sleep Apnea Database (UCD) [17]. The database contains records of 25 subjects with 21 males and four females. The database contains full overnight PSG recordings of patients with a suspected sleep disorder. Each record is nearly about 5.9 to 7.7 hours long with annotation files. In each annotation file, the details of sleep apneic/hypopnic events are indicated. The PSG recording also contains EOG, EEG, EMG, oro-nasal airflow, ribcage movements, abdomen movements (uncalibrated strain gauges), snoring (tracheal microphone) and body position [7].

These PSG recordings were recorded using JaegerToennies system. Recording of an ECG and SpO_2 signal was done via a modified V2 lead and a finger pulse oximeter, respectively. An experienced sleep technologist performed the staging of sleep using the full polysomnography record along with sleep apnea types namely: obstructive, mixed, central apnea and hypopnea during the entire sleep duration of patients [51]. Table 1 shows the general physiological details of subjects used in two databases [49].

Our second database is Sleep Apnea ECG database (SAE). This database contains 70 records with 35 records for training and 35 records for testing. Each recording may vary from 7 hours to 10 hours. The database contains a continuous digitized ECG signal with machine generated QRS notes along with apnea annotations. These apnea annotations are assigned to each one minute non-overlapping segments of signal. In this database, 8 recordings also consists 4 additional signals which are chest and abdominal respiratory signals, Resp N, oronasal airflow and oxygen saturation (SpO_2). In this work, we have used only SpO_2 signals. Table 1 shows the general physiological properties of patients and further information can be found in [50]. It is very important to note that SpO_2 signals are sampled at frequency of 100Hz in SAE database, whereas in UCD database they are sampled at 8 Hz only. The minimum desirable sampling frequency for SpO_2 signals is 25 Hz [4].

2.2 Proposed method

The proposed approach is shown in Fig. 1. The SpO_2 signal is acquired from the whole night PSG recordings and then segmented. These signals are subjected to pre-processing followed by wavelet decomposition, feature extraction and classification.

2.2.1 Segmentation and preprocessing

The SpO_2 signals in UCD and SAE database are sampled at 8 Hz and 100 Hz, respectively. For our experiment, we segmented both database signals into 1-min events (epochs) for further analysis. Then consequently, the annotations are altered to give minute-based details. The particular epoch is labeled as "apneic" if it has apnea/hypopnea events for at least five consecutive seconds; otherwise, the particular epoch is annotated as "normal." The distribution of 1 min segments for the apneic and non-apneic condition is given in Table 1. The segments are passed through Butter-worth filters of order six [4]. Although, pulse oximetry is highly stable if the patient is stationary and well- perfused. However, the motion artifacts may lead to loss of data, inaccurate readings, and false alarms. The movements during transportation, tapping, rubbing, scratching, waving, and shivering are few common patient motion sources. In order to remove the motion artifacts, we have used a duration-bandwidth localized length-12 orthogonal wavelet filter with four vanishing moments for six levels of the wavelet decomposition. Then soft thresholding has been applied to the obtained wavelet coefficients. Subsequently, inverse wavelet transform is taken using the same wavelet filter to

Table 1 Physiological details of subjects used in two databases

	DATABASE			
	UCD		SAE	
	Mean Value	Range	Mean Value	Range
Age (years)	50 ± 10	28 - 68	43.25 ± 8.35	31 - 54
BMI (kg/m^2)	31.6 ± 4.0	25.1 - 42.5	25.12 - 42.54	19.2 - 40.4
AHI	21.4 ± 20.3	1.7 - 90.9	32.0 ± 35.9	0 - 77.4
Total subjects	25		8	
Normal subjects	2		2	
Apneic subjects	23		6	
Sampling frequency	8 Hz (SpO_2)		100 Hz (SpO_2)	
Epoch size	1 minute		1 minute	
Apneic epoches	222		1609	
Normal epoches	9359		2338	
Total epoches	9581		3947	

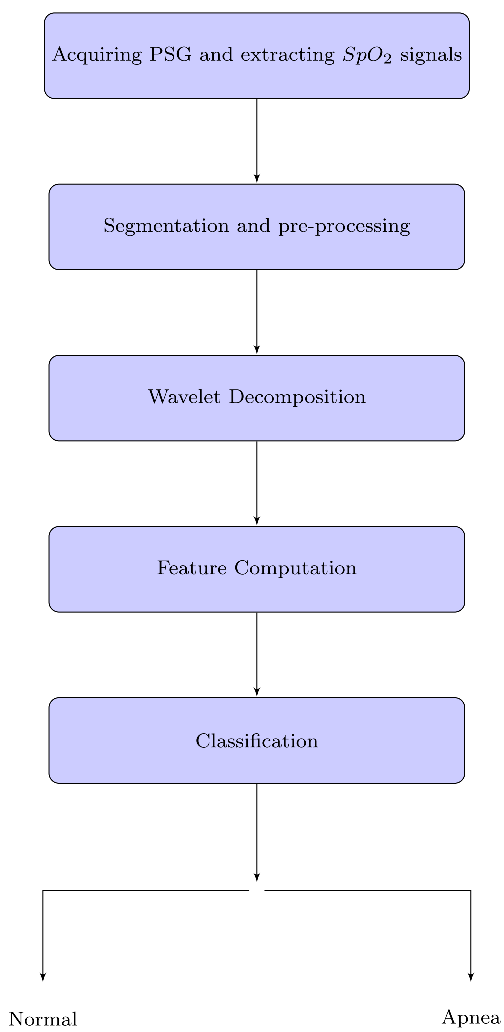


Fig. 1 Schematic diagram of the proposed method

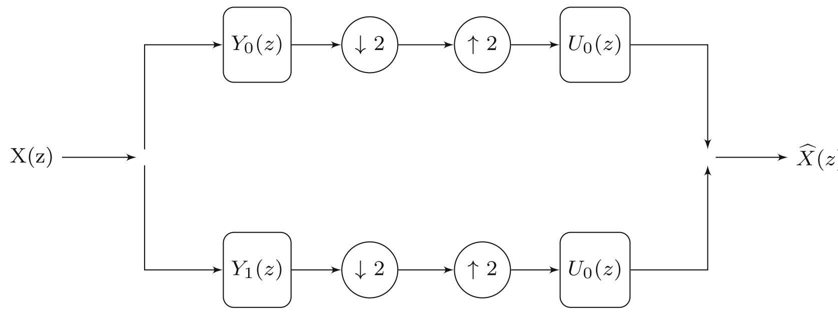
obtain clean epochs. Then these clean epochs are used for further processing.

2.2.2 Design of wavelet based filter banks

The decomposition of signals using Fourier transform fails to extract time localization information [48]. Wavelets are widely used to provide good duration-frequency localization to decompose the signal [19, 42]. This section presents the eigen-filter design to design of linear-phase, time frequency optimized dual band, bi-orthogonal filter banks. We have used eigen-filter technique as it is computationally efficient and provides a global solution [41]. The properties of filter bank depends largely on decay rate of frequency response, flatness of frequency response curve at particular frequency, size of pass band, transition band and stop band, ripples in frequency response in pass band and stop band, duration-frequency concentration, linearity of phase and length of individual filters [43]. According to the Gabor's uncertainty principle, it is not possible to localize a signal simultaneously in both time and frequency domain arbitrarily [39]. Thus, designing filters with minimum time-frequency product is a challenging and interesting problem. In this study, we have used duration-frequency optimized biorthogonal linear phase wavelet filter banks [41].

A conventional dual channel perfect reconstruction bi-orthogonal FB consists of an analysis bank and a synthesis bank [41]. Let us assume $Y_0(z)$ and $Y_1(z)$ represents analysis low pass and high pass filter, respectively of the filter bank (Fig. 2). The output of analysis filter is down-sampled by scale of 2. Similarly, for synthesis bank $U_0(z)$ and $U_1(z)$ represents low pass and high pass filter where input to filter is up-sampled by scale of 2. To ensure alias,

Fig. 2 Design of dual channel biorthogonal FB



amplitude and phase distortion cancellation [47], the choice of high-pass filter must follow (1) and (2) [46]

$$Y_1(z) = z^{-1}U_0(-z), U_1(z) = zY_0(-z) \tag{1}$$

$$Y_0(z)U_0(z) + Y_1(z)U_1(z) = 2 \tag{2}$$

Let product filter is defined as $P_0(z) = Y_0(z)U_0(z)$, then phase reconstruction condition is expressed as [40]

$$S(z) + S(-z) = 2 \tag{3}$$

Equation (3) denotes that product filter is symmetric which means coefficients regarding even powers of z are 0 except for z^0 which is 1. This reduces the design of dual channel filter bank to half band filter $S(z)$ [37]. In this work, we have used complementary eigenfilter based approach to design time-frequency localized filter bank. First an optimal analysis lowpass filter is designed via formulation an eigenfilter based optimization problem. In this optimization problem, we minimized the time-frequency product of analysis filter subject to the constraints of regularity. Having obtained the analysis filter, we proceeded to design synthesis lowpass filter by formulating another eigenfilter problem wherein the objective is to minimize the time-frequency product of the synthesis filter subject to the constraints of bi-orthogonality and regularity.

The frequency response of designed FB is shown in Fig. 3. The six subbands (SBs) of the sample SpO_2 signals that are obtained from ODFC WFB are shown in Fig. 4.

2.2.3 Feature extraction

After the wavelet decomposition of signal into six subbands(SBs), from each of SB, we have extracted Shannon entropy (SE) to differentiate apneic and normal classes. Entropy is termed as measure of disorder, uncertainty or randomness in the given information. Together ODFC WFB based entropy is found to be very effective to discriminate between apneic and non-apneic signals. The Shannon entropy(SE) is given by [22]

$$SE = -\sum_{k=1}^{n} x_k log_2(x_k) \tag{4}$$

where x_k represents the k_{th}sample pf the wavelet coefficient sequence $x(n)$ of length N.

The extracted vectors using SE are concatenated to form a feature matrix. The generated feature matrix is labeled and fed for classification. Only six features are computed for both UCD and SAE databases to classify apneic/non-apneic segments of data.

2.3 Classification

The labeled feature matrix is fed to various classifiers such as bagged decision trees, logistic regression, and KNN and SVM classifiers. We employed the ten-fold cross-validation scheme to reduce the over-fitting [11]. Cross-validation is used in model selection better to estimate the mis-classification error of a predictive model. In ten-fold cross-validation, ten folds are used for training, and the remaining one is employed for testing. The advantage is that the entire data is used for training and testing. The classification accuracy of the developed model is an average of the accuracy of ten folds.We obtain the optimal performance of decision trees when combined with the ensemble RUSbossted technique. Decision trees are the exemplar of supervised machine learning algorithms. It is a tree-like structure with a node denoting a feature or an attribute, a branch denotes the classification rule and connects to the next node, and a terminal or leaf node denotes the outcome. The uppermost node is also known as the root node in the decision tree [34]. Decision trees are based on a heuristic called recursive partitioning. This is also called “divide and conquer” as it bifurcates the data into subsets within subsets until the algorithm determines the test class label.

For a dataset with N features, selecting the root attribute randomly can yield us bad results with low accuracy [10]. Therefore, there are few methods that need to be used first to determine which attribute should be chosen as a root node. For appropriate attribute, various parameters are used such as entropy, information gain and Chi-Square. These parameters are calculated for every attribute, and accordingly the node attribute is selected.

In this proposed methodology, the ensemble RUSboost decision tree exhibited the best performance. Ensemble

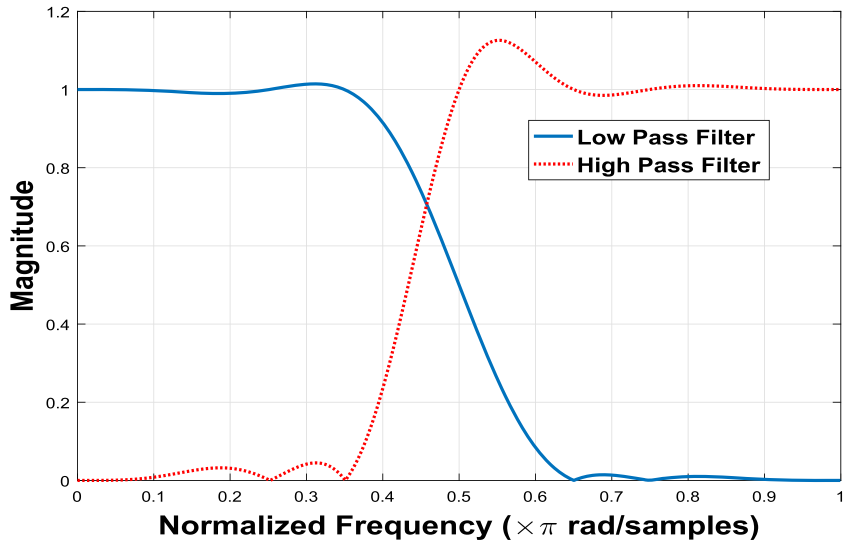


Fig. 3 Frequency response of designed filter pair

techniques combine several decision trees to generate better classification performance. Boosted decision trees are used to avoid over-fitting. Boosting is an ensemble technique used to train a model from many weak learners (decision trees) connected sequentially to each other. RUSBoost is used with skewed data to improve the classification performance of weak learner [15]. It is a hybrid data boosting algorithm. For the balanced class distribution, dropout regularization is used to avoid the over-fitting problem. AdaBoost is an ensemble learning technique that is considered to be more resistant to overfitting than many machine learning algorithms. AdaBoost produces a strong learner by combining weak learners in an iterative manner. In each iteration of training, a new weak learner is appended to the ensemble, followed by the weighting vector's adjustment to focus on examples that are misclassified in previous iterations. This yields a classifier with higher accuracy than the weak learner's classifiers.

In order to control the depth of growing tree, we have chosen spit sizes of 10, 20, and 30. In a decision tree, the maximum number split may go up to the number of observations-1 that can lead to a deep and complex tree. The

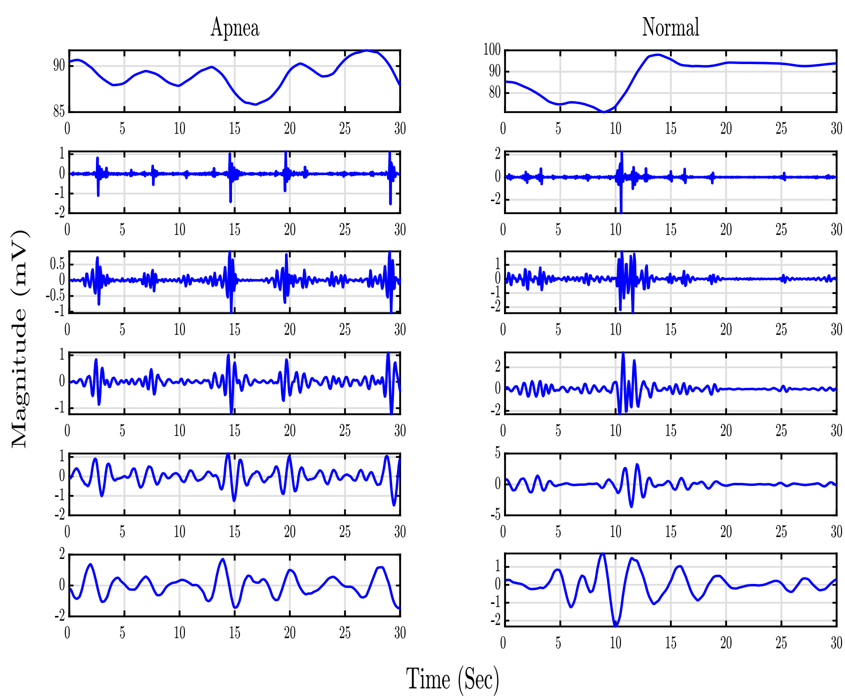


Fig. 4 Waveforms of 6 SBs for the sample UCD SpO_2 signal : Apnea(left) and Normal(right)

tree is built with the objective of minimizing cross-validated misclassification error. The RUSboost decision tree corresponding to the smallest error is chosen for the model. To search for the optimal ensemble of boosted classification trees, the following steps are performed:

- An ensemble of 150 boosted classification trees is cross-validated using 10-fold cross-validation.
- We vary the maximum number of splits to 10, 20, and 30.
- For each split, we varied the learning rate to 0.1, 0.2, and 1.
- Estimated the misclassification rate for each ensemble corresponding to the chosen splits and learning rate.
- Then we have plotted the misclassification rate with respect to the number of trees up to 150 in the ensemble for both UCD and SAE databases. Figures 5 and 6 illustrates the tuning of the parameters corresponding to number of splits 10 & 20 and learning rate 0.1 & 0.2.
- We then identified the number of splits, number of trees, and learning rate that produced the minimum misclassification rate and selected that ensemble as our model. identify
- The optimal parameters thus obtained using the RUSboost technique are given in Table 2 for both databases.

3 Classification results

The performance of a system depends on the appropriate selection of features, number of SBs, and choice of classifier. To achieve the optimum classification performance using the proposed method, we have computed ODFC wavelet-based SE and conducted classification using two datasets (SAE and UCD), as discussed in Section 2.1 and decision tree classifier. The statistical analysis (mean ± standard deviation) of the Shannon entropy features are presented in Table 3 for both databases. The p-values computed using student's t-test for each of six features are found to be less than the threshold .001 indicating that each feature is statistically significant. These features when fed to the classifier are likely to obtain the highest classification performance.

Table 3 shows the summary of the statistical analysis of extracted features from six SBs for our proposed work. It can be observed from the table that mean values of entropy features for apnea is higher than mean values for healthy except in SB-1. The SB-1 consists of higher frequency waves which are not predominant during sleep. Hence, normal class signals will have a higher value in SB-1.

Table 4 shows classification performance in terms of average classification accuracy(CAC), sensitivity and specificity. The confusion matrices for both databases corresponding to the best classifier with ten-fold cross-validation is shown in Table 5. We have attained the highest CAC > 95% for SAE database and more than 89% for UCD database. We also computed the area under the receivers operating characteristics (AUC) of .98 and .94 for SAE and UCD databases, respectively. The values of AUCs are close to unity indicating higher classification performance. Figure 7 depicts the variation of accuracy, sensitivity, specificity with respect to various folds of ten-fold cross-validation.

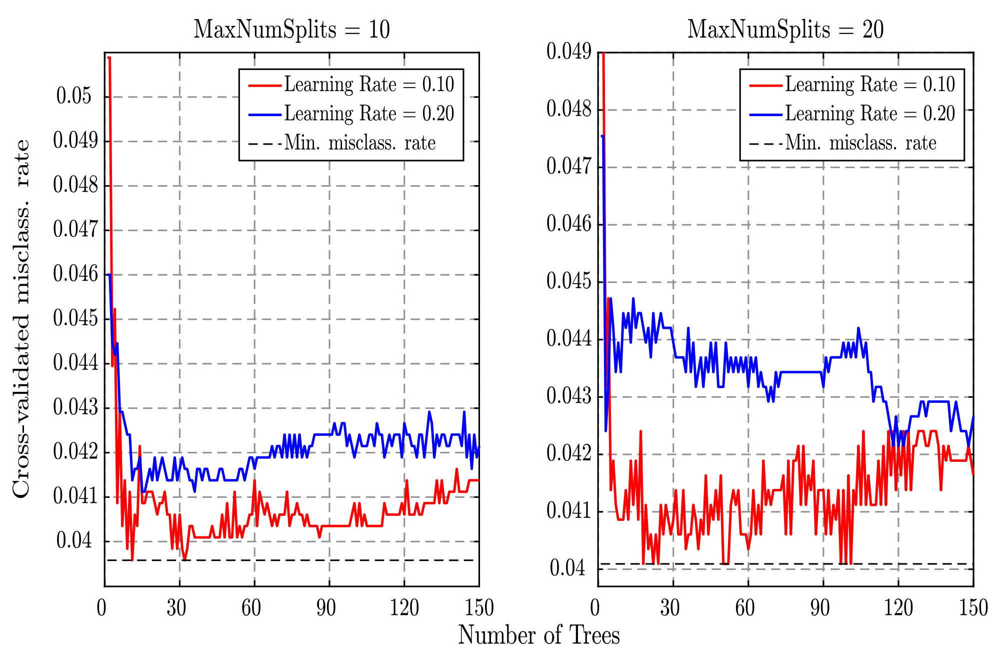


Fig. 5 Optimization of ensemble decision tree models using RUSBoosting for SAE

Fig. 6 Optimization of ensemble decision tree models using RUSBoosting for UCD

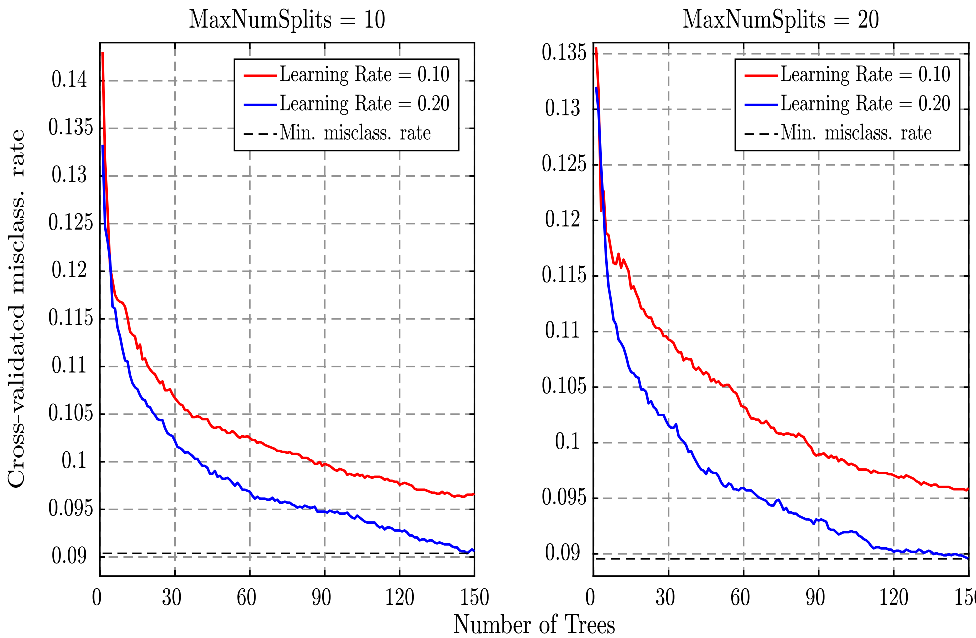


Table 2 Tuning parameters used for the optimal ensemble decision tree classifier

Data Base	UCD	SAE
Classifier	Ensemble RUSboosted tree	Ensemble RUSboosted tree
No. of Observations	9581	3947
Method	RUSBoost	RUSBoost
No. of Learner	140	100
Max no. of Splits	10	20
Learning Rate	0.1	0.1

Table 3 Summary of statistical analysis (mean ± SD) of extracted features from 6 sub-bands for our proposed work

Database			SB 1	SB 2	SB 3	SB 4	SB 5	SB 6
UCD	A	Mean	-2.67E-01	2.44E-01	2.67E-01	3.51E-01	2.60E-01	3.47E-01
		SD	1.12	1.36	1.40	1.62	1.21	2.31
	N	Mean	6.32E-03	-5.80E-03	-6.34E-03	-8.32E-03	-6.18E-03	-8.22E-03
		SD	9.96E-01	9.89E-01	9.88E-01	9.79E-01	9.94E-01	9.45E-01
SAE	A	Mean	-8.26E-01	4.64E-01	7.30E-01	9.29E-01	8.03E-01	2.99E-01
		SD	1.03	1.38	1.16	9.05E-01	1.06	1.45
	N	Mean	5.69E-01	-3.19E-01	-5.03E-01	-6.40E-01	-5.53E-01	-2.06E-01
		SD	4.12E-01	3.59E-01	3.71E-01	3.48E-01	3.98E-01	3.76E-01

**** A: Apnea; N: Normal

Table 4 Performance metrics obtained for our proposed system using two databases

	Accuracy(%)	Sensitivity(%)	Specificity(%)	AUC
UCD	89.21	92.34	89.13	0.96
SAE	95.97	95.78	96.09	0.98

Table 5 Confusion matrix for our proposed system obtained using DT classifier with two databases

		UCD		SAE	
		A	N	A	N
Actual	A	205	17	1520	67
	N	1017	8342	90	2214
		Predicted		Predicted	

**** A: Apnea; N: Normal

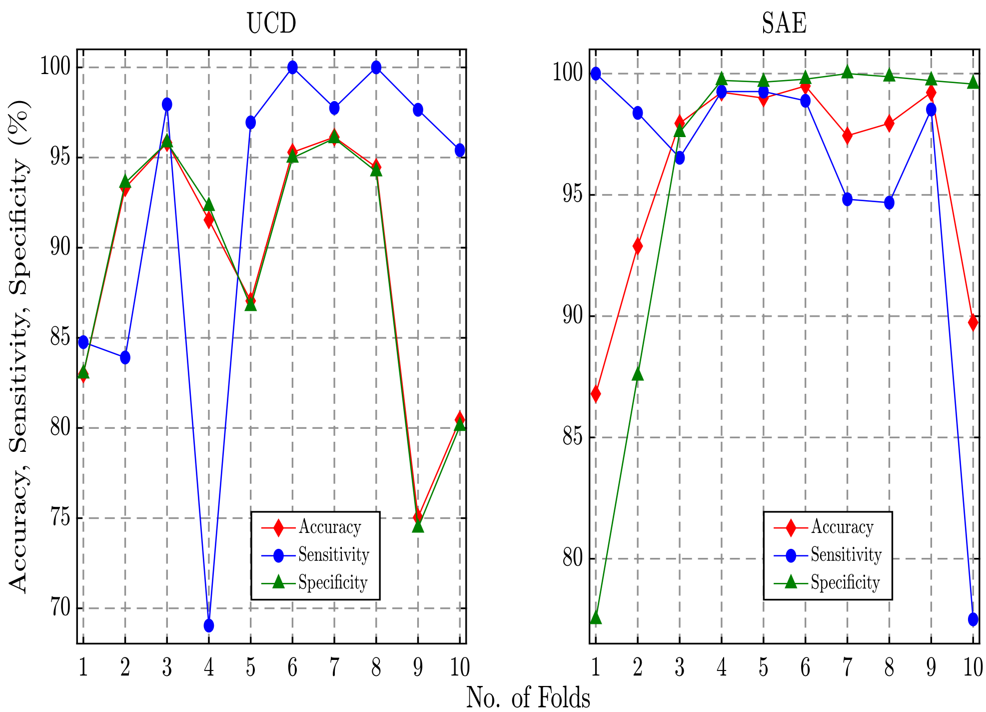


Fig. 7 Graphs of performance metrics vs. number(No.) of folds for SAE and UCD database

4 Discussion

Table 6 compares the various state of the art methods that used SpO_2 signals for automated apnea identification using UCD or SAE databases. From the table it is clear that the classification performance exhibited by the proposed model has surpassed all other methods for both databases. It can be noted from the table that, our model has attained 89.21%, 92.34%, and 89.13% classification accuracy (CAC), classification sensitivity (CSE) and classification specificity (CSP), respectively, using only six features using UCD database. It has achieved more than 95% CAC, CSE and CSP using SAE database. Hence, our model outperformed all other methods.

It is evident from the table that the classification performance yielded by all methods, including our proposed method for the UCD database, is lower than the SAE database. The possible reason may be UCD data is highly imbalanced

Table 6 Summary of various automated state-of-the-art apnea detection systems using SpO_2 signals with UCD / SAE databases (Studies are arranged in the ascending order of CAC)

Study	Methodology	Performance
Cen et al. [6], 2018	Employed multi-layer CNN with `UCD database` using 1s SpO_2 epochs	CAC=79.61%
Xie et al. [51], 2012	Used decision trees on 39 linear and non linear statistical and frequency domain features of SpO_2 signals obtained from `UCD database`.	CAC=82.79% CSE=78.23%, CSP=84.25%
Mostafa et al. [26]	Used a deep belief network (DBN) formed by using stacked restricted Boltzmann machines (RBM) on `UCD database` using ten-fold cross validation.	CAC=85.26% CSE=60.36%, CSP=91.71%
Almazaydeh et al. [1], 2012	Used NN on three Statistical features utilizes `SAE database` with 17% testing data	CAC=90.3% CSE=87.5%
Burgos et al. [5], 2009	Used bagged tree on basic statistical features extracted from `SAE database`	CAC=93%
Pathinarupothi et al. [31], 2017	Used long short-term memory recurrent neural networks on `SAE database`	CAC=95%
`Proposed work`	Used Ensemble RUSBoosted trees by extracting ODFC WFB based SE on `SAE database` with 10 fold CV	**CAC=95.97%, CSE=95.78%, CSP=96.09%**

Bold entries are the results of our proposed work

Table 7 Details of time taken for various databases

	Prediction Speed	Training Time
UCD	22000 obs/sec	7.4254 secs
SAE	10000 obs/sec	8.9134 secs

compared to the SAE database. Also, the UCD database is sampled at 8 Hz, whereas the SAE database is sampled at 100 Hz. The minimum desirable sampling frequency for SpO_2 signals is 25 Hz [4].

It is to be noted that Haoyu et al. [13] achieved the CAC of 98.54%, which is higher than our model. However, they used combined features obtained from SpO2 and HRV signals. They have used a private database consisting of 10 subjects. But, we have used only SpO2 signals and two public databases.

The proposed method is a real-time sleep apnea detection system developed using SpO_2 signal. The method is simple and fast fast (training time is: 7.4254 sec and testing time is 22000/sec). Table 7 denotes the prediction speed and trai ning time for both datasets. Further, the wavelet decomposition has been performed using a new class of WFB called ODFC, in which filter has minimal joint time-frequency localization. It is to be noted that, we have used one feature set containing only six entropy features to obtain the highest performance.

This work focuses on implementation of real-time automated detection of sleep apnea. Figure 8 shows the proposed cloud-based architecture for using wavelet-based features and machine learning model developed using $SpO2$ signal. The system comprises of two parts: (i) SpO_2 signal extraction with a smart device and (ii) cloud-based apnea detection service.

A pulse oximeter can be attached to the patient's finger, which gathers the overnight data throughout the patient's sleep. During online mode, the data extracted is sent to the cloud using a smart device and then to the classifier model for classification. The outcome of the diagnosis is sent to the smart device. The patient is alerted using the alarm if apnea is detected to put continuous positive airway pressure mask or any other oral device to continue the normal sleep. In the cloud, the model is developed by us using a supervised learning model and SpO_2. The apnea identification model which has been trained using UCD and SAE databases can be placed in the cloud for automated immediate diagnosis using SpO2 signals. It also can be re-trained using the patient's test data which is used to detect the unknown class using our developed model.

The performance of the system can be improved further by developing an accurate and robust deep learning (DL) model with a large SpO_2 database. Various DL architectures namely; convolution neural network (CNN) [8], long short term memory (LSTM) networks, restricted boltzmann machines (RBM) and autoencoders have been used for healthcare applications. Recently Mostafa et al. [27] have summarized several DL-based methods that have been used for apnea detection. The DL algorithms do not have feature extraction, selection and classification steps, separately. Hence, DL algorithms have been preferred by many researchers [24], nowadays. However, DL algorithms are computationally intensive and require more computational power. Further, it cannot be predicted apriori that a particular DL-based method is suitable for a real-time applications. In this regard, it is worth noting that recently, Cen et al. [6] have used CNN based model using UCD database with SpO_2 and achieved CAC of 79.61% which is 10% lower than our model. We attained CAC of 89.21% using UCD database with only six features. Also, Mostafa et al.

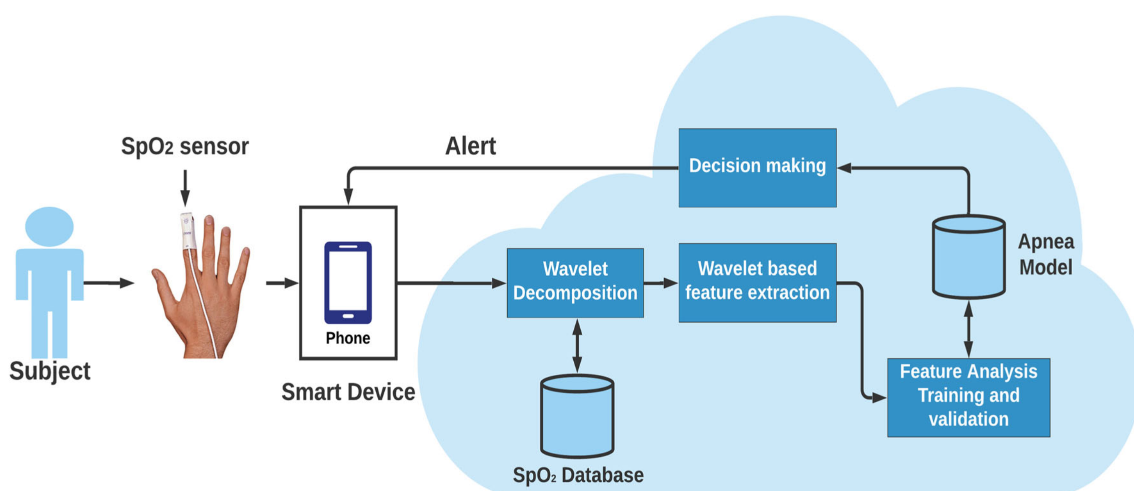


Fig. 8 Illustration of cloud-based sleep apnea detection system

[26] used RBM based DL method and obtained CAC of 85.26% using UCD data which is around 4% lesser than our proposed model.

The advantages of our proposed system are as follows:

1. The ODFC wavelets are considered to be the best tools for non-stationary signals including SpO_2. The use of a novel class of optimized wavelet-based Shannon entropy features yielded high classification performance. It has already been established in the literature that the wavelets have good time-frequency localization and, therefore, they can analyze non-stationary signals well [36]. Moreover, the wavelets designed to have minimal joint duration-bandwidth localization in the proposed study have performed well in the classification of SpO_2 signals.
2. Developed model is economical, and diagnosis is accurate and faster.
3. System is simple and portable due to the use of SpO_2 signals, and fewer features are extracted from them for classification.
4. Though we have proposed a simple and accurate method with a fewer number of features for the classification, we have not used generally used simple classifiers. We have used RobustBoost and RUSBoost ensemble techniques to obtain a high classification performance. Hence, we hypothesize that the proposed combination of optimal ODFC wavelet-based features and the RUSBoost tree algorithm yielded high classification accuracy for the identification of apnea using SpO_2 signals.
5. In order to eliminate probable motion artifacts caused due to voluntary and involuntary movements, we have used time-frequency localized orthogonal wavelets and soft thresholding to remove the artifacts.
6. Result of diagnosis can be obtained from anywhere.
7. Developed a real-time automated detection system that can be used in both primary centers/homes as well at specialized clinics due to its highest classification performance, reduced costs, and most importantly, optimal comfort for patients.

The limitation of the wavelet-based method is that we cannot predict apriori an optimal number of decomposition levels. Further, there may be the possibility of poor contact between SpO_2 sensor and the finger due to body movements, which may lead to capturing of false signals. Also, we have used only 32 subjects. Further study is needed to examine our method's performance when SpO_2 recordings are collected from portable monitoring a patient's home in the absence of technicians. In addition, despite the high classification performance of our model, one must consider that a definitive diagnosis must be made on the basis of additional information (based on comprehensive sleep evaluation).

Hornero et al. [20], developed a apnea detection system using approximate entropy features extracted from arterial oxygen saturation SaO_2 signals (NOT SpO_2) and observed CAC of 85.3%. In future, we plan to explore the performance of our model using SpO_2 signals for automated sleep apnea identification.

5 Conclusion

We have developed a real-time automated sleep apnea detection system using pulse oximetry (SpO_2) signals, which can be used instead of PSG/ECG signals. We have extracted entropy features from wavelet coefficients of SpO_2 signals. We used optimal duration-frequency localized wavelet filter bank in order to decompose SpO_2 signals into subbands. We have achieved the highest CACs of 95.97% and 89.21% for SAE and UCD databases, respectively, using a decision tree classifier with a ten-fold cross-validation strategy. The proposed methodology used only six optimal wavelet-based features for the classification. The proposed method is simple, fast, inexpensive, portable, and accurate. In the future, we intend to test our method with more data and propose using it in hospitals and homes by implementing the algorithm in a small portal device. Hence, sleep apnea can be detected in real-time accurately. Nowadays, specialized sleep laboratories are required to acquire PSG signals and detect sleep apnea accurately. This is expensive, time-consuming, and uncomfortable for the patients. In order to overcome these limitations, our proposed SpO_2 based real-time system can be used.

Declarations

Conflict of Interests The authors declare that they have no conflict of interest.

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