

# Sleep apnea classification using ECG-signal wavelet-PCA features

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**Abstract.** Sleep apnea is often diagnosed using an overnight sleep test called a polysomnography (PSG). Unfortunately, though it is the gold standard of sleep disorder diagnosis, a PSG is time consuming, inconvenient, and expensive. Many researchers have tried to ameliorate this problem by developing other reliable methods, such as using electrocardiography (ECG) as an observed signal source. Respiratory rate interval, ECG-derived respiration, and heart rate variability analysis have been studied recently as a means of detecting apnea events using ECG during normal sleep, but these methods have performance weaknesses. Thus, the aim of this study is to classify the subject into normal- or apnea-subject based on their single-channel ECG measurement in regular sleep. In this proposed study, ECG is decomposed into five levels using wavelet decomposition for the initial processing to determine the detail coefficients (D3-D5) of the signal. Approximately 15 features were extracted from every minute of ECG. Principal component analysis and a support vector machine are used for feature dimension reduction and classification, respectively. According to classification that been done from a data set consisting of thirty-five patients, the proposed minute-to-minute classifier specificity, sensitivity, and subject-based classification accuracy are 95.20%, 92.65%, and 94.3%, respectively. Furthermore, the proposed system can be used as a basis for future development of sleep apnea screening tools.

Keywords: Apnea, wavelet decomposition, principal component analysis, support vector machine, electrocardiogram

## 1. Introduction

Sleep apnea (SA) is a potentially serious sleep disorder caused by one or more breathing pauses or shallow breaths during sleep. Some symptoms that might be noticed by an individual with SA are daytime sleepiness, morning headaches, and leg swelling. However, SA is often recognized as a problem by another person (bed partner) witnessing the apnea event as a result of its effects on the body. SA typically is divided into three classes, central SA (CSA), obstructive SA (OSA), and mixed SA. OSA is characterized by repetitive episodes of upper airway obstruction that occurs during sleep and is usually associated with a reduction in blood oxygen saturation, whereas CSA is characterized by a cessation or decrease of ventilator effort during sleep and is usually associated with oxygen desaturation [1]. Most adults SA patients, about 84% of cases, are classified as OSA [2]. OSA often goes undiagnosed, because neither blood test nor physical change can help to diagnose the condition. Undiagnosed OSA is known to create a risk of high blood pressure, heart attack, stroke, obesity, diabetes, and arrhythmias, and also to increase the likelihood of driving accidents, because the person driving is fatigued [3].

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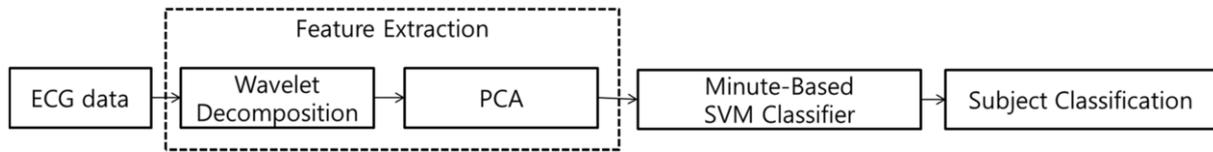


Fig. 1. Schematic Diagram of the System.

Currently, polysomnography (PSG) is considered the gold-standard for sleep disorder diagnosis. A PSG test consists of recording various physiological signals, including oxygen saturation (SaO<sub>2</sub>), ECG, electrooculogram (EOM), electroencephalography (EEG), nasal airflow, and body movement. However even though PSG has become the standard for sleep disorder diagnosis, there are problems with its implementation. For example, it is expensive because it can only be done in a sleep laboratory. PSG also requires patients to sleep in a sleep laboratory for one or two nights, in the presence of technicians. Furthermore, patients must maintain a particular position throughout the night with wires and sensors attached to their bodies during measurement. Given such problems, researchers have sought an efficient alternative method that is more convenient, cheaper, long-term, home-based, and reliable.

Several alternative methods have been proposed for identification of sleep apnea over the decade as a PSG alternative. Methods have been developed based on a single signal such as pulse oximetry [4], snoring [5], EEG [6], or ECG [7–9]. Among them, ECG is the most extensively studied signal. In terms of feature extraction, ECG-based features have been extracted using various analysis methods. For example, Yilmaz et al. [7] used feature extraction from a respiratory rate (RR) interval as a classifier input, and introduced such features as inter-quartile range, mean absolute deviation, and median value. Bsoul et al. [8] combined RR interval and ECG-derived respiration signal (EDR) [9] for real time SA monitoring using a support vector machine (SVM) classification, extracting approximately 111 features in each minute of an ECG segment. Heart Rate Variability (HRV) and wavelet analysis have also been used for ECG initial processing [10,11]. The classification techniques used by researchers include, k-nearest neighbor [12], SVM [4,13,14], and artificial neural network (ATNs) [10,15].

In this paper, alternative SA screening using a new type of wavelet feature with principal component analysis (PCA) as features of an extraction algorithm is introduced. Figure 1 shows the schematic diagram of the whole system. The ECG is initially broken down into five levels using wavelet decomposition to determine the detail coefficient on each level. A total of 15 features from every 1-min epoch have been extracted. We apply the PCA algorithm to transform and reduce the dimension of the extracted features, then use the principle components (PCs), output of PCA, to become the input of the SVM classifier.

## 2. Methodology

### 2.1. Database

Thirty-five subjects with annotation are tested in this study, each subject having an approximately eight-hour single ECG signal digitized at 100 Hz with 12-bit resolution [16]. Each annotation describes one minute containing an apnea event and was created by human experts on the basis of simultaneously recorded related signals [17]. Each minute of recording is labeled with A or N, indicating the presence or absence of an apnea event during that minute. The observed subjects can be placed in

one of three classes: A, B, or C. Recordings in class A (apnea patient class) contain at least 100 apnea minutes or have an apnea-hypopnea index (AHI)  $\geq 15$ . Recordings in class B are in the borderline class, meanings that patients included in this class can be considered as apnea patients or normal patients. Patients that are categorized in class B have between five and 99 apnea minutes or have  $5 \leq \text{AHI} < 15$ . Class C contains fewer than five apnea minutes ( $\text{AHI} < 5$ ); this class is categorized as a normal patient class.

## 2.2. Feature extraction

In this proposed algorithm, two steps of processing are used to gather the features from ECG data. In the initial step, wavelet decomposition is used to divide ECG signals into some levels at particular frequencies. The relative power of an ECG wave is between two and 30 Hz [18], so decomposing ECGs into five levels of signal is enough (A1 to A5 and D1 to D5), including detail and approximation coefficients. Debauches 4 (db4) is chosen as the mother wavelet for wavelet decomposition. The first step of feature extraction is combining the proven features from [17] such as Shannon entropy and new parameter extracted from the wavelet. The extracted features include Shannon entropy, Interquartile range (IQR, the difference between the 75th percentiles) of detail coefficient, Variance of detail coefficient, Standard deviation (square root of an unbiased estimator of the variance of the population from which detail coefficient), and Mean Absolute Deviation (MAD) of a detail coefficient.

$$\text{MAD} = \text{mean}(\text{abs}(\text{detail}_{\text{coeff}} - \text{mean}(\text{detail}_{\text{coeff}}))) \quad (1)$$

The second step of feature extraction is using PCA. PCA is a data compression and classification method, whose purpose is to identify a new set of underlying linearly uncorrelated variables and principal components (PCs). There are several equivalent ways of deriving PCs, the simplest of which is to find projections that maximize the variance. Mathematically, the PCA transformation is defined by a set of  $p$ -dimensional vectors with weights that map each vector of the data matrix  $X$  into a new vector with principal component.

$$T = XW \quad (2)$$

where  $W$  is  $p \times p$  matrix whose columns are the eigenvectors of  $X^T X$ , with  $T$  as the PC score. However, keeping only the first  $L$  principal components is sufficient, because not all of the PC are required. This method is called dimensional reduction in PCA.

$$T_L = XW_L \quad (3)$$

where the matrix  $T_L$  now has  $n$  rows but only  $L$  columns.

## 2.3. Classifier

An SVM [19] with a Gaussian radial basis function kernel is used in this study to classify apnea and non-apnea minute of ECG automatically. During the classification phase, a 10-fold cross-validation

(CV) scheme is adopted to check the performance of SVM. The overall set of samples is randomly divided into 10 approximately equal and balanced parts. Then, each time one of these subsets is excluded from the overall set of samples and used as the test set and remaining samples set as training set. 10-fold CV accuracy is the percentage of correctly classified data. 10-fold CV was also used to optimize two Gaussian kernel parameters during the learning phase:  $\sigma$ , which controls the trade-off between minimizing training errors and model complexity and  $\gamma$ , the width of the Gaussian kernel. In this proposed system, SVM classifier performance is evaluated on the test set using accuracy, sensitivity, and specificity defined as follows.

$$\text{Sensitivity} = \frac{TP}{TP+FN} \quad (4)$$

$$\text{Specificity} = \frac{TN}{TN+FP} \quad (5)$$

$$\text{Accuracy} = \frac{TP+TN}{P+N} \quad (6)$$

with TN, TP, FP, and FN, corresponding to true negative, true positive, false positive, and false negative event, respectively.

### 3. Results

All evaluation and computations are conducted using the MATLAB toolset. An apnea-ECG database is used to evaluate the effectiveness of the proposed model on 35 recordings data. The subjects of these recordings are men and women between 27 and 63 years of age, with weights between 53 and 135 kg (BMI between 20.3 and 42.1), and AHI ranges from 0 to 93.5 in these recordings.

#### 3.1. Feature extraction

The mean of extracted features from the first step of processing is shown in Figure 2(i). It shows that an apnea subject and a normal subject tend to have different value in detail coefficient 3, 4, and 5

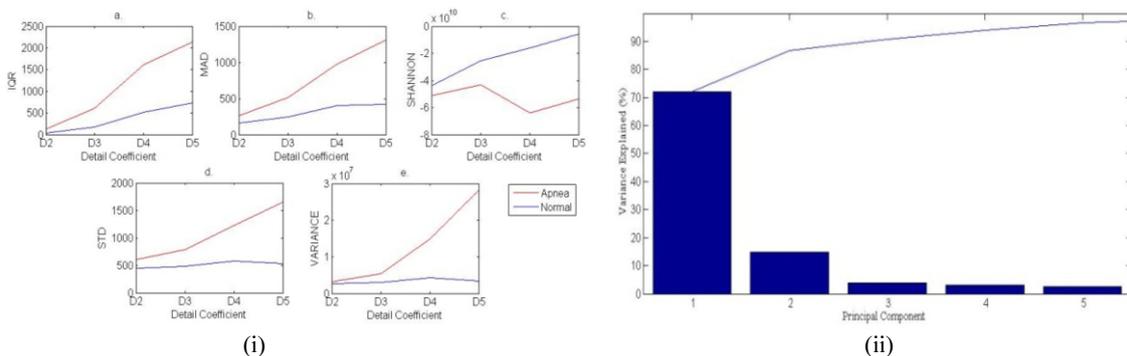


Fig. 2. Feature extraction from (i) wavelet-ECG; Mean of (a) IQR (b) MAD (c) Shannon entropy (d) Standard deviation (e) Variance in 5-levels detail coefficient for Apnea Subject and Normal Subject; (ii) Principal Component Score.

for each feature. Thus features of d3, d4, and d5 can be used as discriminative features exposing the minute-based sleep apneas. There are 15 features extracted from the first processing step.

The second step of processing is using PCA. PCA reduces the dimension of features from 15 into a lower dimension. Figure 2(ii) shows a one case example of features dimension reduction. The screen plot results shown in Figure 2(ii) only show the first five components instead of the total 15; these five components explain 95% of the total variance. The clear break in the amount of variance accounted for by each component is between the first and second component. However, the first component itself explains around 73% of the variance, so more components might be needed. In this case, the 15 features reduced into five features, and it became the input of SVM.

### 3.2. Minute-based SVM

Minute-based classification of the thirty-five subjects gives the best accuracy of 93.91%; these results are obtained from SVM classifier using RBF kernel with the kernel parameter  $\sigma = 0.05$  and the regularization parameter  $\gamma = 4.7$ . Ten-fold CV is used to find the optimum value of those two parameters. Table 1 shows the percent variance explained by the corresponding principal component from two subjects. Through this table, it shows that there may be differences in the number of optimal PCs in each subject. Subject one shows that the first five components explain the total 95% variance, while in the case of subject two, the first four components explain the total 95% variance. Based on this fact, the relationship between the number of PC and the system performance needs to be sought out. Table 2 shows the result of an experiment about the relationship of the number of PC and system performance; the best classification performance comes from the five PCs features. This is not unexpected because in many subjects five PCs become the majority that explains the 95% of data variance.

Table 1

Percent variance explained by the corresponding principal component

	Principal Component	Variance (%)	Sum of Variance (%)		Principal Component	Variance (%)	Sum of Variance (%)
Subject 1	1	73.55	73.55	Subject 2	1	56.53	56.53
	2	11.29	84.84		2	26.49	83.02
	3	6.92	91.76		3	8.44	91.46
	4	2.83	94.59		<b>4</b>	<b>4.13</b>	<b>95.59</b>
	<b>5</b>	<b>2.30</b>	<b>96.89</b>		5	1.98	97.57
	15	0.01	100		15	0.01	100

Table 2

Classification based on PCA features

Number of PC	Sensitivity	Specificity	Accuracy
3	86.28	85.92	86.10
4	90.8	88.05	90.90
5	95.20	92.65	93.91

Table 3

Comparison w-PCA features with w-features and another previous method

Approach	Performance		
	Sensitivity	Specificity	Accuracy
SpO <sub>2</sub> and ECG [4]	79.75	85.89	84.4
EEG signal [6]	69.64	44.44	NA
RR-interval based classification [7]	NA	NA	89
RI waveform [12]	88.1	65.7	91.2
Nasal Pressure + ECG [20]	75	100	87.5
W-ECG with features [17]	81.37	79.09	80.14
<i>Proposed System</i> (W-ECG features + PCA)	95.20	92.65	93.91

Table 4

Accuracy of proposed system in term of apnea subject classification

Subject	Annotated	Classified
Apnea	22	20
Normal	13	13
	<i>Accuracy</i>	94.3%

As can be seen in Table 3, the proposed classification system based on wavelet and PCA outperforms the system that uses only regular wavelet features [18], proving that using PCs as a classifier feature can improve the classification accuracy. The proposed system's sensitivity, specificity, and accuracy are 95.53%, 91.98%, and 93.73%, respectively. Comparisons with other methods using RR interval, EEG, SpO<sub>2</sub>, and RI waveform are also shown in Table 3. Some of these use complicated processing steps and more input features for the classifier, in contrast to the proposed method using reduced set data obtained from PCs for the classifier.

### 3.3. Subject classification

Subject-based classification is also conducted in this study, with the results shown in Table 4. The output of this classification is whether each person in the study was a normal subject or an apnea subject. If the subjects' AHI is more than five, that subject is identified as suffering from apnea, thus, an apnea subject. If less than five, the subject was identified as a normal subject. Unfortunately, the database does not provide the information about hypopnea, so the proposed classification uses the number of apnea minutes as a ground truth. The problem arises when the classifier tries to classify data from subjects in class B (the borderline class). Two subjects, b01 and b04, have apnea minutes 19 and 10, respectively. So the proposed algorithm categorizes these subjects as apnea subjects. But based on AHI, these two subject have 0.24 and 0.7, respectively. Those numbers indicate that these two subjects should be categorized as normal subjects. The limitation of database annotation could be the reason of this issue.

#### 4. Conclusion

This study proposed a system that uses wavelet-PCA features with SVM as the classifier. Features that are extracted from wavelet ECG are reduced into lower dimension using PCA. The classification technique that uses five PCs proved to get the best performance in classifying minute-based apnea problems. There are two types of classification that are shown in this study, minute-based classification and subject classification. The accuracy of minute-based classification and apnea subject classification reached 93.91% and 94.3, respectively. In future work, the algorithm and system introduced in this study can be used as a basis for future development of sleep apnea screening tool.

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