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Sleep Apnea Identification using HRV Features of ECG Signals

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Article Info	ABSTRACT
	Sleep apnea is a common sleep disorder that interferes with the breathing of a person. During sleep, people can stop breathing for a moment that causes the body lack of oxygen that lasts for several seconds to minutes even until the range of hours. If it happens for a long period, it can result in more serious diseases, e.g. high blood pressure, heart failure, stroke, diabetes, etc. Sleep apnea can be prevented by identifying the indication of sleep apnea itself from ECG, EEG, or other signals to perform early prevention. The purpose of this study is to build a classification model to identify sleep disorders from the Heart Rate Variability (HRV) features that can be obtained with Electrocardiogram (ECG) signals. In this study, HRV features were processed using several classification methods, i.e. ANN, KNN, N-Bayes and SVM linear Methods. The classification is performed using subject-specific scheme and subject-independent scheme. The simulation results show that the SVM method achieves higher accuracy other than three other methods in identifying sleep apnea. While, time domain features shows the most dominant performance among the HRV features.

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1. INTRODUCTION

Sleep is very important for the human body to perform optimally. During sleep, the body will form and regenerate cells, support brain function, and recharge the body's energy. For children and adolescents, sleep is required to help the growth process. Sleep can be divided into two phases, i.e. rapid eye movement (REM) and non-Rapid Eye Movement (NREM) where both are always repeated in sleep [1]. When a person does not experience normal REM and non-REM cycles, the body will experience various adverse effects such as fatigue, decreasing ability to concentrate, disrupted body metabolism, and so on [2] .

There are various types of sleeping disorder, e.g. insomnia, narcolepsy, sleep apnea, parasomnia, hypersomnia, restless leg syndrome, etc [3]. Sleep apnea is a disturbance to the breathing process because the wall of the throat is relaxed and narrowed while sleeping [4]. While sleeping, the muscles of the throat become relaxed and weak. When the muscles are too weak and not treated immediately, it may cause constriction or even block the airways that potentially cause health problems, accidents, and premature death. There are 3 types of sleep apnea, i.e. obstructive sleep apnea caused by obstruction of the respiratory tract, central sleep apnea caused by the unstable respiratory control centers that result in the brain failing to signal the breathing muscles [4],[5], and mixed complex which is a combination of obstructive and central apnea Sleep apnea is very common, usually found more in men than in women. This condition can occur in patients of any age, but more common in middle-aged adults. Sleep apnea can be treated by knowing the symptoms or signs of sleep apnea, reducing risk factors and being discussed with the doctor for further action. Common

symptoms are snoring, others notice some breathing interruptions during sleep, sudden wake with shortness of breath, headache in the morning, insomnia, attention problems, irritability, and hypersomnia. Sleep apnea disorder can cause hypertension, high blood pressure, stroke, obesity, and diabetes. Sleep apnea could not be treated, but can be diminished by doing treatments such as behavioral therapy, positive pressure therapy, installation of oral breathing apparatus, and operation [6], [7].

There are some researches have been performed in sleep apnea identification. Almazaydeh, *et al.*, performs obstructive sleep apnea detection using support vector machine (SVM) method [8]. The feature used in the paper are mean epoch, standard deviation epoch, NN50 (variant 1), NN50 (variant 2), pNN50, etc. They used ECG signal database from physionet.org as their data set. On the other hand, Yilmaz, et.al. have proposed sleep stage and obstructive apneaic epoch classification using single-lead ECG in order to classify sleep stage and sleep apnea automatically using single-lead ECG [9]. In this research, Yilmaz perform data preprocessing and feature extraction before the classification. Another paper from Carolina Varon, *et al.*, performs sleep apnea classification using four easily computable features, three generally known ones and a newly proposed feature [10]. They perform classification using least squares support vector machines (LS-SVM) with RBF kernel. Finally, Sani M. Isa, *et al* proposed the implementation of the principal component analysis (PCA) in sleep apnea identification in order to improve the the accuracy of classification process [11].

According to the study that have been performed in this area, it is interesting to conduct performance evaluation among well known classification method in the similar simulation condition. In this research we evaluate the performance of ANN, KNN, N-bayes, and support vector machine in classifying sleep apnea. Then, mostly in previous study, they perform classication for 2 class of sleep apnea. In this study, we perform classification of 2, 3, and 4 class of sleep apnea. In this research we also perform feature extraction with four techniques, i.e. time domain, geometrical with histogram, poincare and frequency domain. We evaluate which feature achieve the best performance for sleep apnea identification. In the end of study we expect to achieve the best accuracy of sleep apnea identification with machine learning method. We also perform two methods of classification, i.e. subject-specific scheme and subject-independent scheme. This is paper is organized as follow. Research methodology is explained in Section 2. The simulation results and discussion are explained in section 3, while the result of the paper is concluded in Section 4.

2. RESEARCH METHOD

This research focuses on HRV Features of ECG signaling to identify sleep apnea. We create classification model based on the data obtained from ECG signal. In this research, we identify the sleep apnea until 4 classes, i.e. non-sleep apnea, hypoapnea, obstructive apnea, and central apnea. Figure 1 shows the methodology flowchart of the research. The next subsection presents about the detail of every step in the flow chart, started from data collection, data pre-processing, feature extraction, classification model development and performance evaluation.
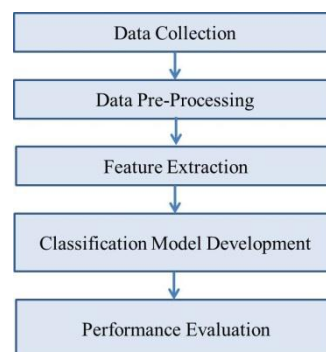

Figure 1. Research methodology

2.1. Data collection

At this stage the data collected where the data used is MIT-BIH Polysomnographic Database (slpdb) [12] obtained from https://physionet.org. This data contains a collection of recordings of several physiological signals of objects during sleep, ie ECG, EEG, blood pressure and respiratory signals, and calibration constants, the length of the recording, age, gender, and weight. The data used comes from male

sleep records, aged 32-56 years old (average 43 years old), weight 89-152 kg (average 119 kg). The data consists of 18 recordings of 16 people who have different durations of measurement. Then, every 30 seconds of duration, it was made into 1 sample data that will proceed to the pre-processing phase of the data. The data is about the RR interval and Sleep apnea annotations. Table 1 show samples of data which had been divided into 30 seconds and as data used to obtain HRV features. Figure 2 shows one of the signals from the MIT-BIH Polysomnographic Database (slp01a) data to be separated every 30 seconds.

Table 1. Sleep Apnea Datasets

Data	Duration (hour-minutes)	Number of samples
slp01a	2 H	240
slp01b	3 H	360
slp02a	3 H	360
slp02b	2 H 15 M	270
slp03	6 H	720
slp04	6 H	720
slp14	6 H	720
slp16	6 H	720
slp32	5 H 20 M	640
slp37	5 H 50 M	700
slp41	6 H 30 M	780
slp45	6 H 20 M	760
slp48	6 H 20 M	760
slp59	4 H	480
slp60	5 H 55 M	710
slp61	6 H 10 M	740
slp66	3 H 40 M	440
slp67x	1 H 17 M	154
Total of Sample		10274

Figure 2. Sample of ECG signal used for sleep apnea identification

2.2. Data pre-processing

The pre-processing stage is the disposal stage of ECG recording data (RR intervals and sleep apnea annotations) that are out of sync in order to obtain the valid data. In this stage, we remove data slp03 and slp60 because the data are out of sync. Then all data from the pre-processing results is entered into the formulas to get the HRV features.

2.3. Feature extraction

In this process, data from pre-processing result is processed to obtain HRV features. We employ four techniques in this paper, i.e. time domain, geometrical, poincare, and frequency domain [13], [14]. The features contain SDNN, RMSDD, NN50, pNN50, Mean RR, HRV Index, SD1, SD2, SD1 / SD2, TP, VLF, LF, HF, LF / HF, LFnorm, HFnorm. Time Domain is derived from ECG Signal Data in the form of RR interval, frequency Domain of total spectrum of each beat separated in index to generate PSD. There are 18 features used in this research as shown by Table 2. We perform feature extraction using matlab. Figure 3 shows the value of feature extraction with time domain method. Figure 4 shows the results of feature extraction with frequency domain techniques, while Figure 5 shows the feature extraction results with poincare techniques.

Table 2. HRV Features List

No	Feature	Method	Description	Equation
1	AVNN	Time Domain	The average of all NN (or RR) intervals,	$AVNN = \dfrac{1}{N}\sum_{j=1}^{N} RR_j$
2	SDNN	Time Domain	The standard deviation of all NN (or RR) intervals	$SDNN = \sqrt{\dfrac{1}{N-1}\sum_{j=1}^{N}\left(RR_j - \overline{RR}\right)^2}$
3	RMSSD	Time Domain	The square root of the average of the sum of the squares of differences between adjacent RR intervals	$RMSSD = \sqrt{\dfrac{1}{N-1}\sum_{j=1}^{N-1}\left(RR_{j+1} - RR_j\right)^2}$
4	SDSD	Time Domain	Standard deviation of differences between adjacent RR intervals	-
5	NN50	Time Domain	The count of adjacent NN (or RR) intervals differences that are more than 50 ms	$Number\ of\ \left(RR_{j+1} - RR_j\right) > 50$
6	pNN50	Time Domain	The division of NN50 by total of all RR intervals minus one one times 100	$pNN50 = \dfrac{NN50}{N-1} \times 100$
7	HRV Triangular Index	Geometrical	The total number of RR intervals divided by the peak of histogram created from RR intervals data with 7.8125 bin size	-
8	SD1	Poincare	The standard deviation of points perpendicular to the axis of line-of-identity	$SD1^2 = \dfrac{1}{2}SDSD^2$
9	SD2	Poincare	The standard deviation of points along the axis of line-of-identity	$SD2^2 = 2SDNN^2 - \dfrac{1}{2}SDSD^2$
10	SD1SD2 Ratio	Poincare	Ratio of SD1 and SD2,	$SD1\ SD2\ Ratio = \dfrac{SD1}{SD2}$
11	S	Poincare	Area of ellipse	$S = \pi \times SD1 \times SD2$
12	TP	Frequency Domain	Total power	-
13	VLF	Frequency Domain	Total power of 0 to 0.04 Hz	-
14	LF	Frequency Domain	Total power of 0.04 to 0.15 Hz	-
15	HF	Frequency Domain	Total power of 0.15 to 0.4 Hz	-
16	LFHF Ratio	Frequency Domain	Ratio of LF and HF	-
17	LFnorm	Frequency Domain	Normalized LF	$LFnorm = \dfrac{LF}{TP - VLF}$
18	HFnorm	Frequency Domain	Normalized HF	$HFnorm = \dfrac{HF}{TP - VLF}$

Time Domain and Geometrical Result

Variable	Units	Value
Mean RR*	(ms)	923.6
STD RR (SDNN)	(ms)	44.1
RMSSD	(ms)	22.5
NN50	(count)	1
pNN50	(%)	3.2
RR triangular index		8.000

Figure 3. Result of time domain & geometrical features
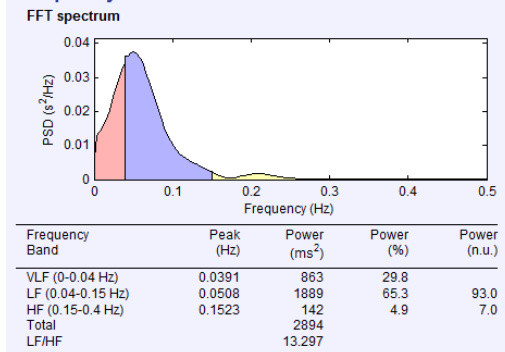
Frequency-Domain Results

FFT spectrum

Frequency Band	Peak (Hz)	Power (ms²)	Power (%)	Power (n.u.)
VLF (0-0.04 Hz)	0.0391	863	29.8	
LF (0.04-0.15 Hz)	0.0508	1889	65.3	93.0
HF (0.15-0.4 Hz)	0.1523	142	4.9	7.0
Total		2894		
LF/HF		13.297		

Figure 4. Result of frequency domain techniques

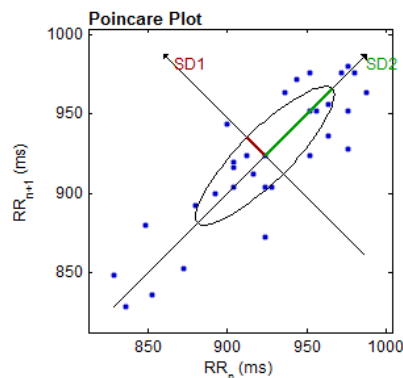| Variable	Units	Value
Poincare plot		
SD1	(ms)	16.2
SD2	(ms)	60.2
SD1/SD2	(ms)	0.269

Figure 5. Feature Extraction with poincare techniques

2.4. Classification process

In this paper, we evaluate following four classification methods in classifying sleep apnea. All of these method are the most well-known classification method [15], i.e.:

a. Artificial Neural Network (ANN) is an algorithm where there is a network of small process units that are modeled or constructed based on the behavior of human neural networks [16]. The function of the neural network is the classification of patterns, pattern mapping obtained from inputs into new patterns of output, mapping of similar patterns, and problem solvers [17]. This ANN is commonly applied for noise identification, wave analysis, speed analysis, reservoir characterization and etc.

b. The Naive Bayes Classifier is a simple probability classification which uses Bayes's theorem with high independency assumptions [18]. Since variables are assumed to be independent so that the variance of a variable in a class is required to determine the classification. The advantage of using this method is that it requires only a few amount of training data to determine the required estimation parameters in the classification process.

c. K-Nearest Neighbor (K-NN) is one of a supervised algorithm where grouping of an object is classified by the majority of the nearest category. The goal is to classify new objects based on the attributes and samples of the data[19]. The K-NN algorithm works based on the minimum distance from the new data to the samples data to determine the K number of nearest neighbors. From here we obtain the majority value used as the predicted result of the new data.

d. Support Vector Machine (SVM) is a technique for making predictions in both classification and regression cases. The intention of SVM is to find an optimal separating hyperplane (OSH), which is the largest margin between the two datasets. It can be found by maximizing the margin between the classes. Firstly, SVM transforms input data into a higher dimensional space by using a kernel function. Then, SVM constructs a linear OSH between the two classes in the transformed space. The nearest data vectors to the constructed line in the transformed space are called as the support vectors [10].

2.5. Performance evaluation

The data is divided into 2: 70% training data and 30% data testing to build the model of the classification to be tested. The result data of the extract feature will be randomized to classify the ANN, KNN, N-Bayes and linear SVM classification methods. We perform the classification with rapidminer. The experiments are conducted several times for each of the following classes:

a. 2 classes: Sleep apnea and non-sleep apnea
b. 3 classes: non-sleep apnea/hypo-apnea/obstructive-apnea
c. 4 classes: non-sleep apnea/hypo-apnea/obstructive-apnea/central-apnea

We perform classification using subject-specific scheme and subject-independent scheme [20]. The difference between them is about the selection of training and testing sets. In subject-specific scheme, the training and testing sets are selected from the same record before being inputted to classifier model. On the other hand, in subject-independent scheme, the training and testing sets are combined from all records. The

subject independent scheme is more practical [20]. However subject specific scheme more useful for multi-night investigations and evaluating the importance of each feature for sleep staging.

3. RESULTS AND DISCUSSION

Firstly, we perform classification of sleep apnea for 2 classes of classification. As mentioned in Section 2, we evaluate the performance of 4 classification method, i.e. ANN, KNN, N-Bayes, linear SVM. Table 3 shows the result of 2 classes of classification with subject-specific scheme. Firstly, we calculate the accuracy for every subject (total 16 subjects used in this experiment) and perform mean operation at the end to compute the average accuracy. Table 3 shows that the SVM linear shows the most superior performance among them. SVM linear achieves 75.8% accuracy, almost 3% more than the second one, i.e. ANN.

Table 3. Accuracy for 2 Classes Classification with Subject-specific Scheme

Data	Method			
	ANN	*KNN*	*N-Bayes*	*SVM(linear)*
Slp01a	77.78%	77,78%	76,39%	83,33%
Slp01b	86,11%	79,63%	87,96%	86,11%
Slp02a	82,41%	69,44%	64,81%	82,41%
Slp02b	85,00%	80,00%	72,50%	91,25%
Slp03	80,00%	64,29%	81,90%	76,67%
Slp04	81,94%	71,30%	84,72%	85,65%
Slp14	71,03%	61,21%	67,29%	72,90%
Slp16	62,02%	53,37%	66,35%	64,90%
Slp32	82,81%	73,96%	72,40%	83,33%
Slp37	84,69%	79,90%	77,99%	85,17%
Slp48	73,25%	62,72%	71,05%	73,68%
Slp59	56,72%	49,64%	47,45%	48,18%
Slp60	65,24%	56,67%	60,48%	63,33%
Slp61	60,19%	60,65%	73,15%	68,52%
Slp66	68,94%	64,39%	75,76%	81,06%
Slp67x	65,22%	47,83%	73,91%	67,39%
Mean	73,96%	65,80%	72,13%	75,87%

Figure 6 and Figure 7 shows the result of classification for 2, 3, and 4 classes with subject-specific scheme and subject-independent scheme, respectively. We can observe in Figure 6 that SVM achieves the best performance among all method with 75.87%, 73.58%, and 71.58% for 2, 3, and 4 classses, respectively. While ANN becomes the second best with performance lower about 1-2% compared to the SVM. Interestingly, as shown by Figure 7, it shows that the performance of ANN slightly better than SVM for 3 and 4 classes classification. Based on this result it shows that in overall, for subject-independent scheme and subject-specific scheme, SVM shows the best performance among them. The reason maybe due to the nature of SVM that performs data selection before doing classification. There it results in better accuracy performance. However, the anomaly in subject independent scheme with 3 and 4 classes classification shows the accuracy result sometimes also influenced by the distribution of data training and testing.

From Figure 6 and Figure 7, we can also evaluate how good the generalization capability of each method is. For example, these results shows that ANN algorithm has good generalization capability because the decrease of accuracy between subject-specific and subject independent scheme is the lowest and most constant among all method, i.e. around 4% for 2, 3, 4 classes of classification. SVM eventhough shows the best performance in overall as explained in the previous paragraph, it suffers 8% decrease of accuracy in 3 and 4 classes of classification. While N-Bayes shows the worst generalization capability by suffers almost 20% of decrease in 4 classes of classification accuracy.

On the other experiments, we evaluate which features extraction techniques has better performance for classification in every classification method. The result is shown by Figure 8. The time domain features shows dominant performance with ANN and SVM method. While, poin care techniques and frequency-domain techniques shows the best performance with N-bayes method and KNN method, respectively. This results means every feature extraction method has different performance in every classification method. Howevery, for sleep apnea case, The time domain features shows the best performances in overall.

Figure 6. Accuracy performance evaluation with subject-specific scheme

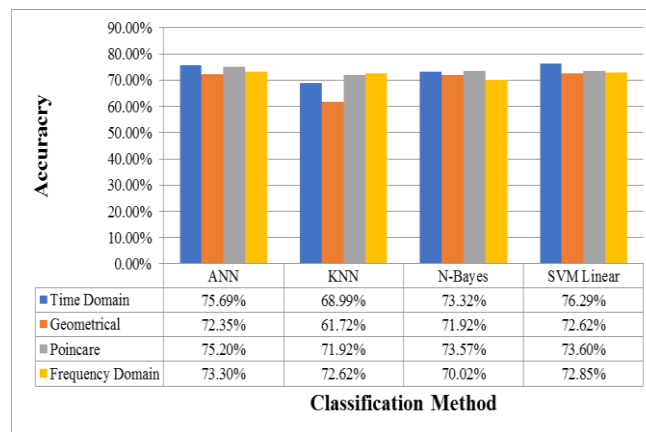Figure 7. Accuracy performance evaluation with subject-independent scheme

Figure 8. Feature extraction method comparison

Finally, we perform a comparison with the existing paper and can be seen through Table 4. The comparison is performed for classification with 2 classes. Table 4 shows that our results outperforms the result of other work by Tilmaz and Erazo with an accuracy of 75.89%. For the future, the sleep apnea classification model that uses the HRV feature of ECG signal for time domain, poincare, geometrical, and frequency domain can produce better accuracy. Then it can produce real-time sleep aids from the ECG signal results when a person sleeps.

Table 4. Comparison with other Works

Author	Year	Approach	Accuracy Result
Yilmaz [21]	2010	kNN, QDA, SVM	74.4%
Erazo [22]	2014	ANN & SVM	55.94%
Proposed	2017	ANN & SVM Linear	74.85%

4.   CONCLUSION

In this paper, we have performed evaluation of sleep apnea identification using HRV features of ECG signal. We have performed comparison of which classification method performs better and what HRV features shows the best performance for sleep apnea identification. We perform the classification for 2, 3, and 4 classes of sleep apnea. Our simulation results shows that the linear SVM achieves the best accuracy compared to the three other methods. While, the ANN method shows the best generalization capability among all method. On the other results, the time domain features shows the most dominant performance among the HRV features. At the end, we shows how our works shows slightly better performance compared to the other references. For the future research, we are going to employ classification method developed in

this paper into sleep apnea monitoring prototype. We are going to build the portable and contactless prototype that we hope can help people to do self monitoring of sleep apnea symptoms at home.

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