

Detection of Obstructive Sleep Apnea Using Width and Gradient of QRS Complex With Discriminant Analysis

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ABSTRACT

Obstructive Sleep Apnea (OSA) or breathing problems during sleep causes sudden death from heart failure during sleep. Because of the serious effects of OSA, early OSA detection is important. OSA detection can be developed using an electrocardiogram. In this article, OSA detection is designed using an electrocardiogram with a discriminant analysis method. Inputs for discriminant analysis are examined, namely the width and gradient of the electrocardiographic QRS complex. Different approaches to find the width and gradient are investigated. The performance of the proposed method is examined using clinical data of patients with OSA from the MIT-BIH Apnea-ECG database. The performance is found from 5-fold cross validation. The performance of the detection for a patient achieves 99.99% in terms of accuracy.

Keywords: OSA, discriminant analysis, QRS complex, electrocardiographic, gradient.

1. INTRODUCTION

Obstructive Sleep Apnea (OSA) is the occurrence of upper airway obstruction (pharynx) that occurs periodically during sleep. It can cause breathing to stop intermittently either completely (apnea) or partial (hypopnea) but breathing efforts still continue [2,4]. Airway obstruction in OSA patients can be seen in **Figure 1**. The severity of OSA can be assessed based on the value of the Apnea Hypopnea Index (AHI). The severity of OSA can be divided into three stages, called mild OSA ($5 \leq \text{AHI} < 15$ events/ hour), moderate OSA ($15 \leq \text{AHI} < 30$ events/ hour), and severe OSA ($\text{AHI} \geq 30$ events/ hour) [3].

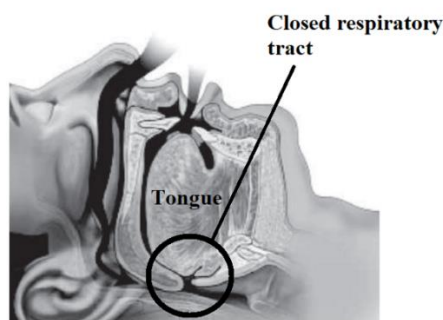


Figure 1. OSA patient's airway obstruction [11]

OSA is often not detected because it occurs while the patient is sleeping. Symptoms of OSA can be characterized by frequent snoring during sleep, shortness of breath during

sleep, gasping during sleep, snoring sounds, headaches when wanting to wake up, and drowsiness during the day [8]. OSA can cause some serious cardiovascular and neurological disorders, such as stroke, insomnia, hypertension, congestive heart failure, acute coronary syndrome, excessive daytime sleep, memory loss, and poor daytime cognitive performance [9]. In the clinical practice the severity of cardiovascular disease and stroke is quite high in OSA patients, including 50% of cases of hypertension, 25% of cases of congestive heart failure, 30% of acute coronary syndromes, and 60% of strokes [9].

Seeing the serious impact of OSA, it is necessary to diagnose OSA early to reduce the negative impact of OSA. For OSA detection can be done using Polysomnography (PSG). PSG is a diagnostic test tool to evaluate sleep disorders. Basically, an examination with PSG uses several tools at once to diagnose OSA. Examination with PSG feels uncomfortable for the patient. It is because of that the patient's body is fitted with many sensors [18].

In order to provide comfort for patients, OSA detection can be carried out using only a single lead electrocardiogram (ECG). An ECG is a medical device used by experts to record the heart's electrical activity by measuring the biopotential differences of the heart measured on the outside of the body. The working principle of ECG is the difference in electricity, when the human body produces electricity even with a very small amount. The existence of an electric current causes a difference in potential or voltage. The voltage can describe the state of the human heartbeat. The characteristics that are evaluated from ECG signals are the amplitude, morphology, duration of the waves, segments, and intervals recorded in a display [14].

In this study, the OSA classification was performed using discriminant analysis method with QRS complex width and gradient features. Discriminant analysis is one of the statistical dependency analysis techniques that has the purpose of classifying objects into groups. This discriminatory grouping analysis occurs because of the influence of other variables which are independent variables. Discriminant analysis is a multivariate technique that includes the dependence method, i.e. there are dependent and independent variables. Discriminant analysis is used if the dependent variable is categorical (ordinal or nominal) and the independent variable uses a metric scale (interval or ratio) [7].

OSA detection system in general is presented in **Figure 2**.

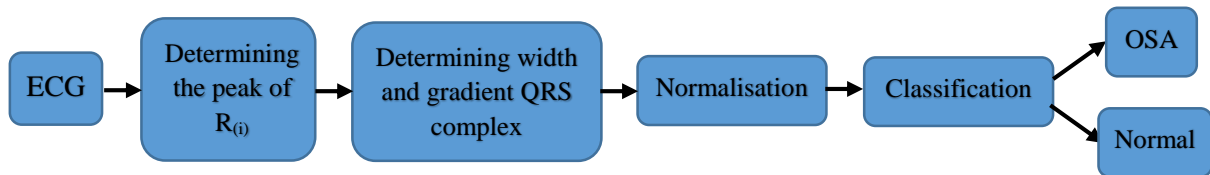


Figure 2. OSA detection system in general

The first stage of study was data collection. The downloaded ECG data has the Apnea-ECG Database (apnea-ecg) basis. Next is the peak determination Apnea-ECG Database (apnea-ecg). Continued by determining the peak of $R_{(i)}$ with $i = 1, 2, 3, \dots, n$. Determining the peak of $R_{(i)}$ can be defined by referring to data provided by PhysioNet [12]. After determining the peak of $R_{(i)}$, Next is feature extraction, normalization, classification using discriminant analysis so that it can distinguish between OSA and normal.

2.2. Feature Extraction

The first feature extraction stage is by grouping the normal waves and OSA waves of each patient. Then determine the peak $R_{(i)}$, so that from the data can be used to determine the value of the width and gradient of the QRS complex. To determine the width and gradient values of complex QRS, we must first look for linear equation for each peak $R_{(i)}$. Look for linear line equations with gradient m and constant b as in Equation (1).

$$y = mx + b$$

(1)

The width of a complex QRS is the interval between the beginning and end of a complex QRS. The width of a complex QRS can be measured through the two points specified on the complex QRS, namely the point on the left side of the complex QRS and the point on the right side of the complex QRS [13]. To make it easier to determine the width of a complex QRS, see **Figure 3**.

2. MATERIALS AND METHODS

2.1.Data Set

The data in this study were taken from an Apnea ECG database from the Massachusetts Institute of Technology at Beth Israel Hospital (MIT-BIH). The data used was based on Apnea-ECG database consisting of 19 patients and each patient had a recording duration of between 7-10 hours.

OSA detection system in general

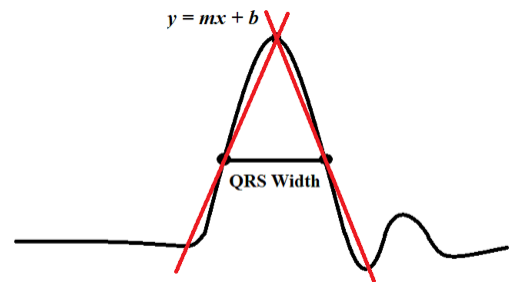


Figure 3. Measuring the width of a complex QRS by calculating the interval between two points on the left side and the right side of the QRS complex [13]

Complex QRS gradients can be measured based on the average value of the gradients at the two points specified in the complex QRS. The gradient is determined at the point on the left side of the QRS complex or the point on the right side of the QRS complex. Mathematically, the gradient of a line can be calculated by finding the ratio of the height change on the vertical axis with the assumption that the horizontal distance is the same in all calculations [13]. To determine the complex QRS gradient, see **Figure 4**.

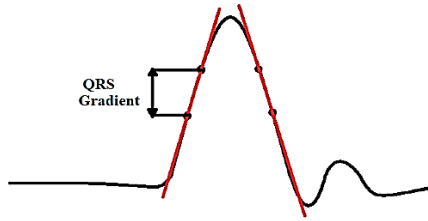


Figure 4. Measure complex QRS gradients by calculating the difference in height from two consecutive points on the left or right side of the complex QRS [13]

In this study, several variations of features are used as input discriminant analysis. The first feature (F1) is the width of the complex QRS obtained from the linear equation with 2 points before and after the peak of R (i) whose width is at a

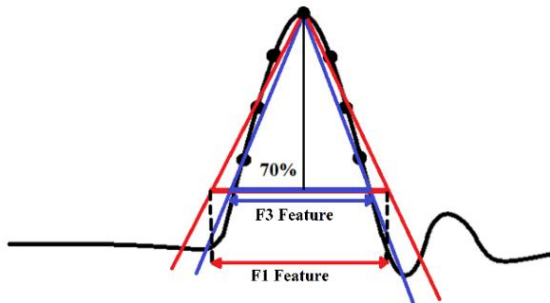


Figure 5. F1 and F3 features

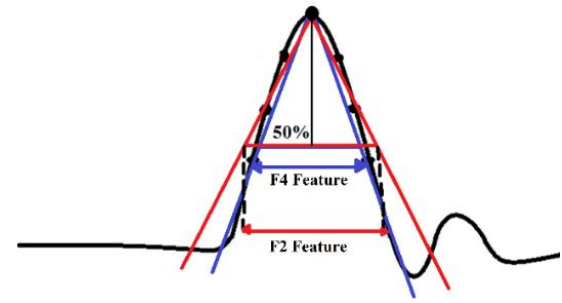


Figure 6. F2 and F4 features

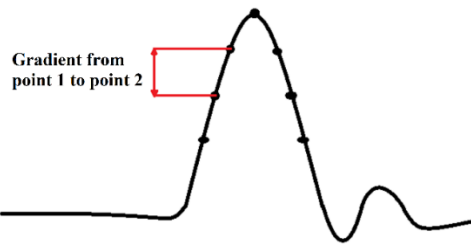


Figure 7. F5 feature

Data generated from feature extraction is irregular data within a certain range, therefore, it must be normalized. Normalization was done to scale the data so that it falls within a predetermined range [6]. In this study, Min-Max normalization and Z-Score normalization are used. In the Min-Max normalization, the range used is 0 to 1. Meanwhile, the Z-Score normalization was normalized based on the average value and standard deviation of the data. [16]. Min-Max (X_m) normalization and Z-Score (X_s) normalization are shown in Equations (2) and (3).

$$X_m = \frac{x - x_{min}}{x_{max} - x_{min}}$$

(2)

Interpretation :

- x = width and gradient of QRS complex
- x_{min} = minimum x
- x_{max} = maximum x [16]

position of 70% from the peak of R (i). The second feature (F2) is the width of the complex QRS obtained from the linear line equation with 2 points before and after the peak of R (i) whose width is at a position 50% from the peak of R (i). The third feature (F3) is the width of the complex QRS obtained from the linear equation with 3 points before and after the peak of R (i) whose width is in the position of 70% from the peak of R (i). The fourth feature (F4) is the width of the complex QRS obtained from a linear line equation with 3 points before and after the peak of R (i) whose width is at a position 50% from the peak of R (i). The fifth feature (F5) is the gradient from point 1 to point 2 before the peak of R (i). F1 and F3 features are shown in **Figure 5**. The F2 and F4 features are shown in **Figure 6**. The F5 feature can be seen in **Figure 7**.

$$X_s = \frac{x - x_{mean}}{x_{std}}$$

(3)

Interpretation :

- x = width and gradient of QRS complex
- x_{mean} = average x
- x_{std} = standard deviation x [16]

2.3. Classification

After the data was normalized, the sample data is divided into several parts by the N-fold cross validation method, where the value of $N = 5$. In the 5-fold cross validation method, the data set is divided into five random partitions. Next, a total of five experiments were carried out with each experiment using the fifth partition data as testing data and the remaining partitions as training data [10]. After sharing the data into training data and testing data, the next step is to classify between OSA and normal with discriminant analysis methods. Discriminant analysis is generally used to solve classification problems and the type used in this study is Linear Discriminant Analysis (LDA) [5].

LDA performs based on the deployment matrix analysis. LDA works by finding an optimal projection so that it can project the input data in spaces with very small dimensions, where all patterns can be separated as much as possible.

Because for the purpose of separation, the LDA will maximize the spread of input data between different classes and minimize the spread of input in the same class [15,17].

The discriminant function which is usually used in LDA, is shown in Equation (4).

$$f_i = \mu_i C^{-1} x_k^T - \frac{1}{2} \mu_i C^{-1} \mu_i^T + \ln(P_i)$$

(4)

Interpretation :

- f_i = function of discriminant class to-i
- μ_i = the average value of each class from each matrix
- C^{-1} = inverse of the covariance matrix group
- x_k^T = transpose of the test data matrix
- μ_i^T = average grade transpose to -i
- P_i = the opportunity of class to appear to-i

The purpose of LDA is to classify objects into one group based on a set of features that describe the class or group. In general, in determining the object based on observations made on the object [1].

2.4. Performance

After classifying by the LDA method, the next is determining performance. In this study the determination of performance by calculating the value of accuracy. Accuracy is the ability to correctly identify positive and negative results. The results of these parameters are used to find

out the best performance results. Equation to find the accuracy value can be seen in Equation (5).

$$\text{Accuracy} = \frac{TP+TN}{TP+TN+FP+FN} \times 100\%$$

(5)

Interpretation:

- TP (True Positive) = the number of OSA pulses detected correctly
- FP (False Positive) = the number of OSA pulses detected incorrectly
- FN (False Negative) = the number of normal pulses detected incorrectly
- TN (True Negative) = the number of normal pulses detected correctly [19]

3. RESULTS AND DISCUSSION

In this study, the performance results of the LDA process are accuracy values. Accuracy is the ability to correctly identify OSA and normal. If the accuracy value is high, then a program is able to recognize OSA patterns and normal patterns well. In this study OSA detection was performed for each patient and a combined total of patients (19 patients).

For more detail data, it can be seen in Table 1 which is the accuracy of each patient's data from the five features (F1, F2, F3, F4, and F5) with Min-Max normalization.

Table 1. The accuracy of OSA detection uses all features with Min-Max normalization

Patients	Accuracy (%)	Patients	Accuracy (%)
A1	78.52	A11	69.34
A2	70.52	A12	92.20
A3	61.79	A13	81.51
A4	83.29	A14	82.35
A5	72.52	A15	77.72
A6	77.80	A16	66.99
A7	72.30	A17	71.59
A8	63.07	A18	62.93
A9	91.63	A19	58.80
A10	71.42		

It can be seen in Table 1, the patient who has the greatest accuracy is the A12 patient with an accuracy of 92.20%. While the smallest accuracy results are in A19 patients with an accuracy of 58.80%. If the accuracy value is high, then a program is able to recognize normal patterns and OSA well, while the smaller the accuracy, a program is not able to recognize normal patterns and OSA well. There are so many

factors that affect the small accuracy, one of which is due to the noise that might occur in ECG recordings Besides, using Min-Max nomination, Z-Score normalization is also used. It can be seen in Table 2 which is the accuracy of each patient's data from the five features (F1, F2, F3, F4, and F5) with Z-Score normalization.

Table 2. The accuracy of OSA detection uses all features with Z-Score normalization

Patients	Accuracy (%)	Patients	Accuracy (%)
A1	85.76	A11	83.39
A2	88.06	A12	99.87

A3	74.32		A13	99.99
A4	99.49		A14	90.04
A5	95.13		A15	97.79
A6	97.65		A16	81.44
A7	90.02		A17	92.55
A8	75.34		A18	72.12
A9	99.99		A19	68.29
A10	83.83			

It can be seen in Table 2, the patients with the highest accuracy are A9 and A13 patients with an accuracy of 99.99%. Meanwhile, the smallest accuracy results are in A19 patients with an accuracy of 68.29%. It can be seen in Table 1 and 2 that the average accuracy in Table 2 is greater than that in Table 1. This indicates that, in this study the Z-Score normalization has a better performance than the Min-Max normalization to distinguish OSA and normal in each patient.

Data were merged with all patients (19 patients) to determine the performance of each feature and all features in distinguishing between OSA and normal. It can be seen in Table 3, which is the accuracy data for the combined patients (19 patients) of each feature (F1, F2, F3, F4, and F5) and all features with Min-Max normalization.

Table 3. Accuracy for patients combined with a single feature and all features using Min-Max normalization

Feature	Accuracy (%)
F1	64.76
F2	64.72
F3	58.40
F4	58.47
F5	52.26
F1, F2, F3, F4, and F5	67.80

From the results of accuracy in Table 3, it was found that the best feature in distinguishing OSA and normal is the F1 feature, the two F2 features, the three F4 features, the four F3 features, and the five F5 features. The best feature in distinguishing OSA and normal is the F1 feature with an accuracy of 64.76%, while the feature with the least accuracy is the F5 feature with an accuracy of 52.26%. Obtained accuracy for combined patients (19 patients) with all features using Min-Max normalization of 67.80%. This shows that the combination with all features has better accuracy than a single feature. If the high accuracy value, a program is able to recognize normal patterns and OSA well, while the smaller the accuracy, a program is not able to recognize normal patterns and OSA well.

Accuracy data can be seen for the combined patients (19 patients) of each feature (F1, F2, F3, F4, and F5) by normalizing the Z-Score in Table 4.

Table 4. Accuracy for patients combined with a single feature and all features using Z-Score normalization

Feature	Accuracy (%)
F1	62.70
F2	62.79
F3	57.56
F4	57.50
F5	52.28
F1, F2, F3, F4, and F5	63.37

From the results of the accuracy in Table 4, it was found that the best features in distinguishing OSA and normal are the F2 feature, the two F1 features, the three F3 features, the four F4 features, and the five F5 features. The best feature in distinguishing OSA and normal is the F2 feature with an accuracy of 62.79%, while the feature with the least accuracy is the F5 feature with an accuracy of 52.28%. Accuracy for combined patients (19 patients) with all features using Z-Score normalization of 63.37%. This shows that the combination with all features has better accuracy than a single feature.

It can be seen in Tables 3 and 4, that each feature has almost the same accuracy for a combined patient with Min-Max normalization and Z-Score normalization. While accuracy for combined patients (19 patients) with a combination of the five features using Min-Max normalization is greater than using Z-Score normalization. This indicates that in this study, Min-Max normalization had better performance compared to Z-Score normalization to distinguish OSA and normal in a combined patient (19 patients).

4. CONCLUSION

In this study, an OSA detection system design was made using discriminant analysis method. In this research, features and normalization variations were carried out. For variations in features, namely with a single feature and all features. As for the normalization variations, namely the Min-Max normalization and the Z-Score normalization. The best accuracy results from the OSA detection system design for each patient, namely in patients A9 and A13 with an accuracy of 99.99% using normalization Z-Score. For testing all patients, normalization using Min Max resulted in a higher accuracy of 67.80%, compared to the Z-Score normalization of 63.37%.

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