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Diagnosis of Obstructive Sleep Apnea Using ECG Sensor Computer-Aided Diagnosis with Portable ECG Recorder and Acceleration Sensors for Detecting Obstructive Sleep Apnea

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Abstract: Obstructive sleep apnea (OSA) is defined as a sleep disorder caused by periodic obstruction or stricture of the upper airway. It was recently discovered that OSA is associated with cardiovascular diseases. Since polysomnography, which was previously used to evaluate OSA, requires high-cost and has time/spatial restrictions, HRV analysis and acceleration sensors are being investigated as new parameters of OSA. In this study, ECG electrodes were attached to the acceleration sensors to simultaneously measure 2 different types of biomarkers: acceleration of thoracic motion and ECG. HRV was measured using the ECG and it was analyzed to obtain LF/HF ratios, indicators of autonomic nervous systems, at different times. Also, ECG Fourier coefficient was used. A filter was used to remove the noise from the acceleration data and 6 characteristic points of OSA were detected. The 6 characteristic points of OSA were analyzed using the Weka program. Adaboost, one of the boosting algorithms, was used. 10-folds cross validation method was used to evaluate the model, which showed a sensitivity of 90 %, specificity of 80 %, accuracy of 85 % in diagnosing OSA

Keywords: Computer-aided Diagnosis, Sleep Apnea, Adaboost, Machine learning.

1. Introduction

A person is awake 2/3 of their lifetime, including daily activities, and the remaining 1/3 is spent by sleeping. In case of neonates, 16 out of the 24 hours in a day are spent to sleep while the elderly only require 5~6 hours of sleep a day. Sleep is a big part of our lives and sleep is used to recover our fatigued bodies, intestines and minds. Above all, sleep is the most basic and necessary part of our lives [1].

The Obstructive sleep apnea (OSA) is a sleep disease where the flow of air through the airway is impaired during sleep, which causes repetitive awakening and decreased blood oxygen levels. OSA is a common disease with a prevalence of 4.5 % in males and 3.2 % in females. In the past, OSA was considered to be a sleeping habit which encompassed snoring. However, the association of OSA with hypertension, cardiovascular diseases and chronic metabolic diseases such as diabetes in adults and growth impairments, facial skeletal anomalies, behavioral diseases and enuresis in children has increased clinical awareness on OSA. Furthermore, OSA is more common in the elderly. Since the birth rate is dramatically decreasing and mortality is increasing in Korea, it is expected that the number of OSA patients will increase drastically [2].

50 % of OSA patients have hypertension since repetitive sleep apnea causes fall in blood oxygen levels, which causes awakenings that lead to cardiac stress through increased pulse and blood pressure. Repeated increase in nighttime blood pressure causes

increase in the baseline blood pressure, which ultimately leads to hypertension. Excluding hypertension, OSA patients experience bradycardia followed by tachycardia with the end of apneic period due to activation of sympathetic nervous system. Repeated exposure to this cycle leads to arrhythmia and patients experience abnormal heart rate. OSA can also lead to narrowing of the coronary artery or even obstruction. The sudden decrease or halt in blood flow to the heart causes hypoxia in cardiac cells and this could lead to ischemic cardiac diseases [3].

Apnea can cause a significant effect on the human heart. Awakening and sleep are largely affected by the central nervous system and autonomic nervous system. Central nervous system regulates all organs that contribute to homeostasis. On the other hand, autonomic nervous sys-tem corrects body function imbalance, regulates acute emergencies and emotions. Cardiac activity is regulated by the autonomic nervous system's sympathetic and parasympathetic nerves. Sympathetic nerves have catalytic effects while parasympathetic nerves have inhibitory effects. Parasympathetic nerves have the following actions:

1) Slow down the cardiac rhythm originating from the sinoatrial node;

2) Decrease contractility of cardiac muscle cells;

3) Decrease speed of cardiac excitation conduction;

4) Decrease blood flow in the coronary arteries.

On the contrary, sympathetic nerves have the following effects:

1) Increase heart rate;

2) Increase speed of cardiac excitation conduction;

3) Increase cardiac muscle contractility and blood pressure,

4) increase blood flow in coronary arteries that facilitate oxygenation.

The central cardiac nerve, which originates in the medulla oblongata, detects signals from different parts of the body and regulates the heart rate accordingly. These signals gather in the central root and travels to the heart. Therefore, it is referred to as the cardiac reflex. Furthermore, the respiratory reflex determines the heart rate based on the expiration or inspiration. The change in heart rate based on respiratory rate is called respiratory sinus arrhythmia (RSA). Centers responsible for HRV cardiovascular regulation are cardiac center, respiratory center and vascular center. These centers respond to the afferent nerves of the baroreceptors, chemoreceptors and mechanical nociceptors. RSA is being investigated as an important component for the diagnosis of cardiovascular diseases and is also used to diagnose sleep apnea.

Polysomnography is commonly and widely used to diagnose obstructive sleep apnea. Polysomnography is the most accurate diagnostic tool for different types of sleep respiratory dis-eases. It uses different body signals and vital signs such as electroencephalogram (EEG), electrocardiogram (ECG), electrooculogram (EOG) and electromyogram (EMG). Furthermore, it detects heart rate, blood pressure and respiratory rate, which are analyzed by a medical specialist to diagnose obstructive sleep apnea. Other diagnostic methods include cephalometry, computed tomogram, MRI and fibro-optic endoscopes. Double cephalogram diagnoses sleep apnea based on the changes in facial hard tissues, tongue and soft tissues such as hypopharynx [4].

However, polysomnography requires attachment of electrodes and measurement equipment in order to detect biosignals. Patients could experience discomfort during the attachment of these electrodes and equipment. Furthermore, polysomnography is a high-cost procedure and the test can only be carried out in institutions of labs where the equipment is available. Current researches are focusing on improving these disadvantages of polysomnography. For example, some researches are focusing on decreasing the number of required biosignals to reduce the number of equipment attachment while other studies are working on automation of the biosignal detection. The ultimate goal of these studies is to develop an automated OSA diagnostic device that can be used at home. The biosignals used for the diagnosis of OSA include airflow, bronchial sound, snoring, oxygen saturation and blood pressure. However, these markers have relatively low detection rates [5].

Submit Heart rate variability (HRV) is recently being suggested as a new parameter for the detection of obstructive apnea. In 1984, HRV was first studied by Guilleminaualt as a characteristic of obstructive sleep apnea and it is now widely studied for the diagnosis of obstructive sleep apnea. Cardiac signals and its consequential changes in HRV can be detected accurately and the ease of data measurement lead to widespread use for detecting obstructive sleep apnea [6].

Furthermore, other techniques without cost-restrictions and with easier measurements are being developed for diagnosis of sleep apnea. For example, changes in the abdomen detected using ultrasound sensors, pressure sensors and PVDF films can detect changes in respiration. However, these methods have low accuracy, high cost and low durability [7]. In order to improve these disadvantages and to allow easy detection at home, 3-axis acceleration sensors are used to measure the user's respiration in sleep. Acceleration sensors directly measure abdominal movements without being influenced by external stimuli. The sensors are durable, al-low long-term usage and the measured respiratory data is saved and easily viewable by the user.

In this study, HRV and 3-axis acceleration sensors were used to measure biosignals and the collected data was analyzed using an automated system to investigate computer-assisted diagnostic algorithm for diagnosing OSA. Data on apnea is currently viewed as a single parameter. This raises concern for errors but there is a lack of studies on its improvement. Therefore, ECG electrodes were attached to the 3-axis acceleration sensors to simultaneously detect ECG signals and respiration through abdominal movements. Simultaneous detection of 2 signals allow a more accurate detection of OSA compared to 1 signal.

Furthermore, the two signals are passed through the data processing algorithm, which could determine characteristic points that could help computer-assisted diagnostic algorithm.

2. Biosignal Detection

2.1. Acquisition of Biosignals

In this study, acceleration sensors were attached on the participants' thorax. Changes in respiratory muscle movements in z-axis are converted to voltage, which does not require electrode attachment, and no tension bands were attached on the chest to avoid unnecessary pressure. As shown in Fig. 1, ECG electrodes were attached to the acceleration sensors to simultaneously measure thoracic movements and ECG signals. A dipole model was used to measure ECG signals and lead one was used to measure the difference in voltage between the right and the left hand. MATLAB was used for the acquisition and saving acceleration and ECG data. A serial port was opened using MATLAB's serial communication and the data bit was set to 8 bits. As shown in Fig. 2, the acquired data was expressed in graphs based on ECG signals and acceleration sensor's X, Y and Z axis using MATLAB's GUI. Also, the data was saved in text format.

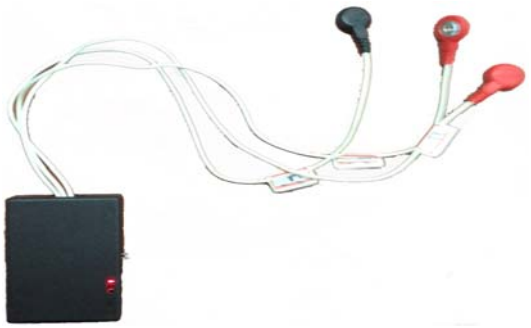


Fig. 1. ECG electrode-attached acceleration sensor.

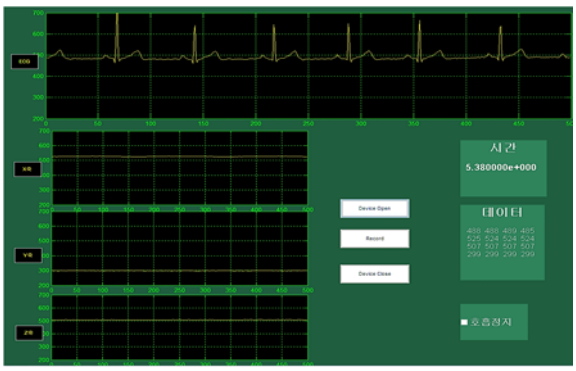


Fig. 2. ECG and x, y, z axis GUI graphing.

2.2. Biosignal Analysis

2.2.1. ECG Data Analysis

To obtain HRV, ECG signals were processed. Among the ECG signal characteristic processing methods, the QRS complex, which has the largest amplitude and most drastic changes, was selected and used.

The acquired data was first processed using a band pass filter composed of 90 Hz and 10 Hz low-pass filters followed by 2 Hz high-pass filter to remove noise. In order to fortify the characteristics of QRS complex, large amplitude and drastic changes, a differential was applied. To positivize high-frequency components, the signals were multiplied by an exponential. The Win-does size was set to 80 ms to smoothen the signals and the moving window's thresh hold was set to determine the R peak (Pan-Tompkins algorithm).

In order to determine the HRV, the distance between R points must be calculated. Assuming the R point in the i position is R(i) and the R in i-1 position is R(i-1), the distance between R(i) and R(i-1), I(i), could be determined [5]. Repeated calculation of time between each heart rate (R-R distance), can be expressed as Equation (1).

$$I(i) = R(i+1) - R(i), \\ I(i+1) = R(i+2) - R(i+1) \quad (1)$$

The calculated heart rates are not equally spaced. Therefore, it cannot be directly applied to a normal frequency analysis method. To analyze HRV frequency, heart rates with equal spacing should be induced. In this study, the R-R spacing series was down sampled at 4Hz equally spaced heart rates. Fig. 3 shows the tachogram of the HRV that was used for frequency analysis.

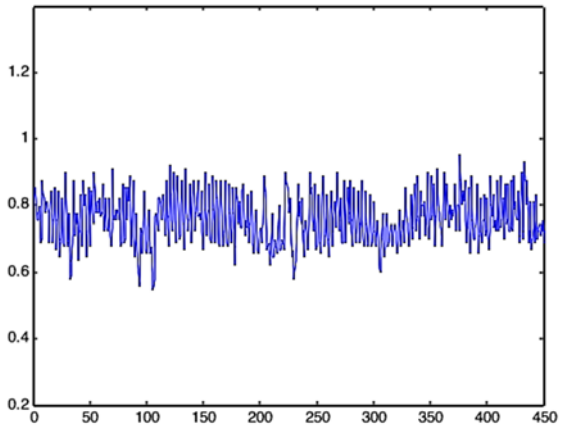


Fig. 3. HRV's Tachogram.

2.2.2. HRV Data Analysis

HRV signal analysis can largely be divided into time and frequency. HRV is a time-series data of timely R-R spacings. Time analysis method placed the time-series data in time order and analyzed the R-spacing data. The R-R spacings are added together and the mean is calculated. Al-so, another methods calculate the standard deviation of the R-R spacings, average and distribution of adjacent data and filters the time-series data of R-R spacings to determine the changes in the signal outputs [8].

Frequency analysis of HRV analyzes the power spectral density (PSD) of the R-R spaced time-series data to measure the power distribution. Based on the frequency range, the results are divided into very low frequency(VLF), low frequency(LF) and high frequency(HF).

Table 1. HRV frequency classifications.

Changes in HRV	Frequency range
VLF	0.003~0.04
LF	0.04~0.15
HF	0.15~0.4

HF components are known to be affected by the effects of respiratory sinus arrhythmia (RSA) on parasympathetic nerves. Depending on the researcher, LF components are reported to be affected by both sympathetic and parasympathetic nerves or only affected by sympathetic nerves. Hence, LF/HF is used as an indicator of autonomic nerve activity regulation. Increase in LF/HF reflect increased activity of sympathetic nerves and its decrease indicates increased activity in parasympathetic nerves. Although many explanations have been suggested for the effects of VLF components, its effects are not clear and most studies on autonomic nerve evaluation exclude VLF components.

In terms of frequency, HRV analysis is usually done using power spectrum of the R-R spacing time-series data based on Fourier transform. However, Fourier transform results only provides quantitative information on the frequency components of the overall signal and does not provide any visual information. Short Time Fourier transform (STFT) was developed to improve these disadvantages. STFT was used in this study to determine the characteristics of the frequency components of R-R spacing time series data. Furthermore, spectogram, STFT times an exponent, was used to determine power distribution. STFT was first introduced by Gabor. STFT divides the overall signal x(t) into time windows and the intervals in each window are trans-formed using Fourier transform.

The windows are transferred and the overall signal is repeated. Each segment, which are time dependent, go through Fourier transformation as shown in Equation 2.

$$STFT(t', f) = \int_{-\infty}^{\infty} [x(t)w'(t-t')]e^{-2\Pi ft}dt \qquad (2)$$

The spectogram, which is obtained using STFT, can be obtained using Equation (3).

$$Spectrogram(t, f) = |STFT(t, f)|^2 \qquad (3)$$

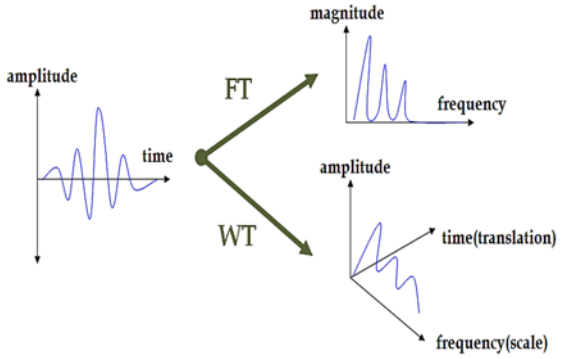


Fig. 4. Difference between Fourier transform (FT) and STFT.

In this study, the size of the FFT used in STFT was 64 and the sampling frequency was set to 4 Hz, which is down-sampled from HRV signals. The window was Hamming window size 64 and the overlap range with the previous window was set to 63. Fourier transformation was done with one sample at a time. The STFT data was used to obtain spectogram and the LF/HF, which rep-resents autonomic nervous system balance, was displayed in different times.

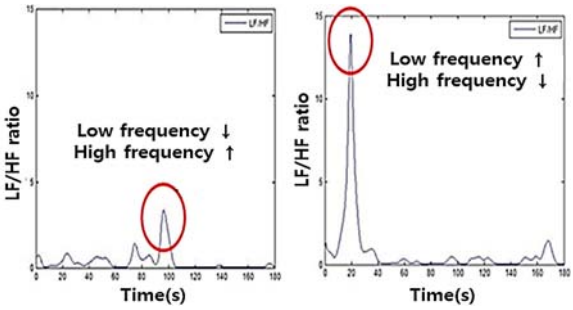


Fig. 5. Timely change sin LF/HF based on respiration(left) and apnea.

2.2.3. Acceleration Data Analysis

In order to analyze the acceleration sensor's x, y and z axis data, each axis's noise was removed using 1 Hz low-pass filter followed by 0.1 Hz high-pass filter. Each axis's mean was calculated.

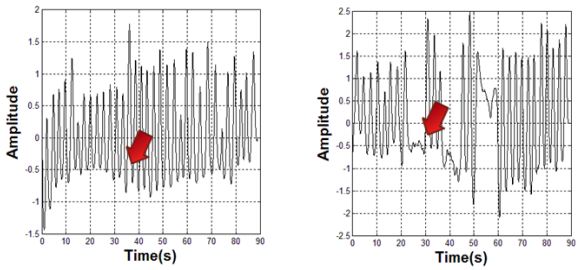


Fig. 6. The acceleration data.

3. Procedure and Results

The portable sleep study device in this study and the obtained ECG signals and acceleration sensor signals were analyzed to determine how accurately the device could discern respiration and apnea. A total of 20 data samples were obtained.

The data was composed of 10 samples from normal respiration and 10 samples from apnea. Each data represented 180 seconds. Out of the 10 apnea data samples, 5 samples showed halted respiration from 5 seconds while the remaining 5 samples showed 10 seconds of halted respiration. 5 apnea data samples included 87 seconds of comfortable and normal respiration followed by 5 seconds of halted respiration and 87 seconds of normal respiration. The remaining 5 apnea samples included 85 seconds of normal respiration followed by 10 seconds of halted respiration and 85 seconds of normal respiration. In order to discern the 10 apnea data samples from the total of 20 samples, 6 characteristics were previously determined and calculated. The characteristics are shown below.

1. f1: Maximum value of LF/HF(max(LF/HF))
2. f2: Minimum value of LF/HF(min(LF/HF))
3. f3: Average value of LF/HF(avg(LF/HF))
4. f4: Average x-axis acceleration sensor value (avg(accel.x))
5. f5: Average y-axis acceleration sensor value (avg(accel.y))
6. f6: Average z-axis acceleration sensor value (avg(accel.z))

In order to evaluate each feature's usefulness, AUC for each characteristic was calculated (Fig. 7~Fig. 12). In ROC curve, which displays a specific diagnostic method's sensitivity and specificity in a graph format, an AUC value, which represents surface area under the curve, closer to 1 and a graph closer to 45° diagonal line indicates high reliability.

When the diagnostic method's AUC surface area is between 0.6 and 0.7, the reliability is average. When the AUC value is 0.8 or higher, the reliability is high and AUC of 0.5 or lower indicates reliability less than that of a random distribution. Using statistics program MedCalc, each characteristic's ROC curve and AUC areas were calculated as shown below. Out of all the diagnostic characteristics, AUC area for f2 was the highest at 0.880 and AUC area for f4 was the lowest at 0.505.

The 6 characteristics were analyzed using Weka program and were used in Adaboost learning, a type of boosting algorithm. In order to evaluate the learning model, 10-folds cross validation method was used. 20 data samples were classified using learning model, which successfully discerned 8 of the 10 respiration data. Furthermore, 9 out of the 10 apnea data samples were correctly discerned. Using a confusion matrix, which displays the relationship between actual values and system discerned values in a matrix, the sensitivity, specificity and accuracy were calculated. Confusion matrix is composed of TP, FP, FN and TN. TP indicates patients with disease who were correctly discerned by the system, FP indicates normal patients who were incorrectly discerned as having the disease by the system, TN indicates normal patients who were correctly discerned by the system and FN indicates diseased patients who were incorrectly discerned as being normal by the system. Accuracy indicates the percentage of correctly discerned patients, which can be calculated using (TP +TN)/(TP+FN+FP+TN)×100. Sensitivity indicates the ability to correctly discern diseased patients while specificity indicates the ability to correctly discern normal patients. Sensitivity and specificity can each be calculated using TP/(TP+FN)×100 and TN/(TN+FP)×100 respectively. Each axis's values are shown in % and this study showed TP=9, FN=1, FP=2 and TN=8. Using these numbers, sensitivity, specificity and accuracy were calculated as shown below.

1. Sensitivity = TP/(TP+FN)×100=9/(9+1)×100 = 90 (%)
2. Specificity = TN/(TN+FP)×100=8/(8+2)×100 = 80 (%)
3. Accuracy = (TP+TN)/(TP+FN+FP+TN)×100 = (9+8)/(9+1+2+8)×100= 85 (%)

The tested algorithm, which simultaneously takes into account thoracic movement and ECG, had a sensitivity of 90 %, specificity of 80 % and accuracy of 85 % for the diagnosis of sleep apnea. As shown in Fig. 13, The ROC curve, which was drawn using the learning algorithm of the 6 characteristics, showed a AUC of 0.84, which indicates that this diagnostic method's reliability is higher than average.

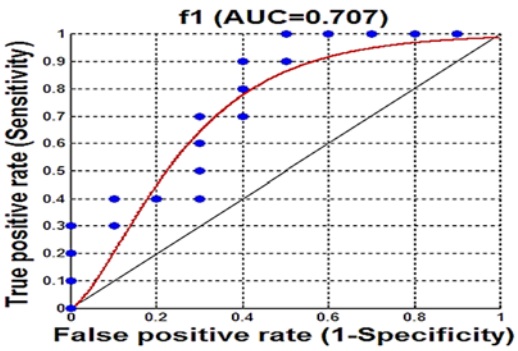


Fig. 7. f1's ROC curve.

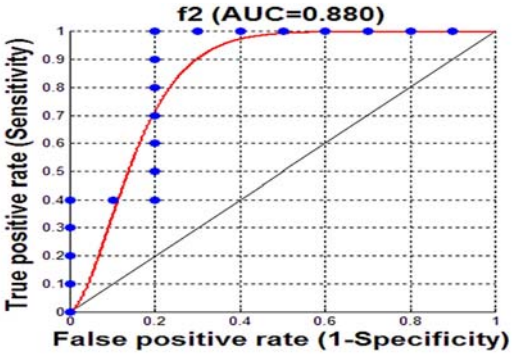


Fig. 8. f2's ROC curve.

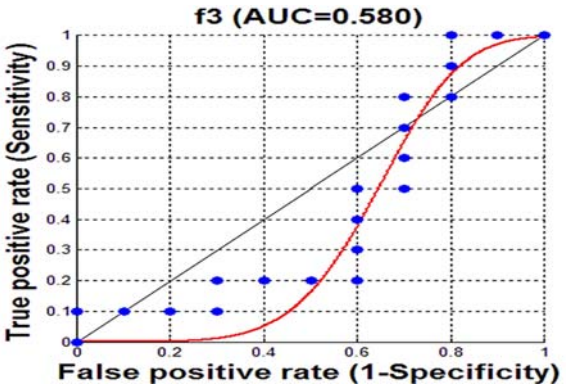


Fig. 9. f3's ROC curve.

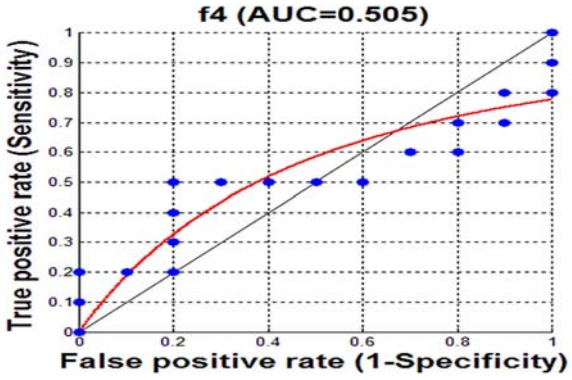


Fig. 10. f4's ROC curve.

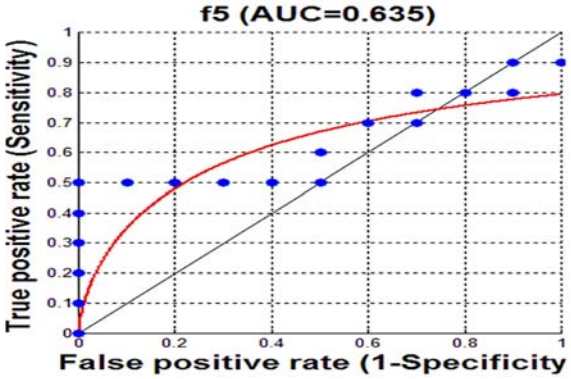


Fig. 11. f5's ROC curve.

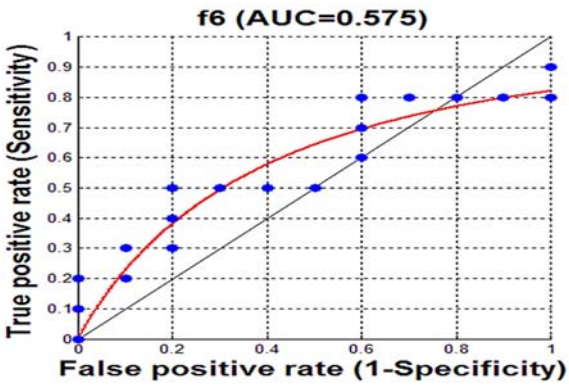


Fig. 12. f6's ROC curve.

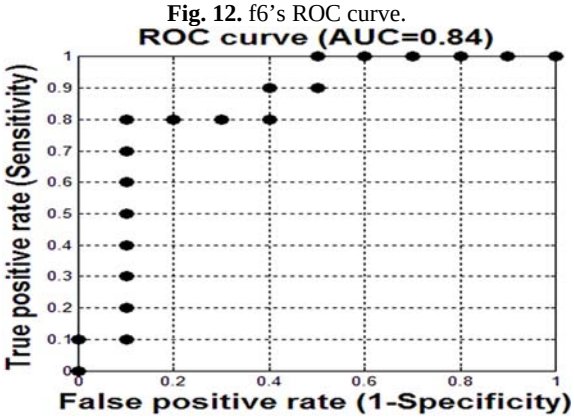


Fig. 13. ROC curve drawn using all 6 characteristics.

4. Conclusion

In this study, the signs of respiration and apnea were analyzed using different methods including changes in thoracic movement measured by acceleration sensors. Studies on sleep apnea have recently reported its association with chronic diseases such as hypertension and diabetes. Based on these findings, sleep apnea is increasingly included in cardiovascular-related risk guidelines. However, awareness in the severity of sleep apnea is low and there is a lack of studies on the relationship between sleep apnea and cardiovascular diseases. When sleep apnea occurs, the brain is repetitively awakened, which leads to insufficient rest, daytime sleepiness and lowered cognitive functions. It could even lead to learning disabilities and patients with sleep apnea are easily fatigued by using excessive energy to straighten the airway and inhale forcefully. Sleep apnea is suggested as an important risk factor of diabetes, hypertension and chronic diseases. However, the availability of diagnostic equipment for sleep apnea is low compared to its high severity. In this study, a more accurate method of diagnosing sleep apnea was proposed.

In HRV analysis, LF/HF ratio was analyzed to discern apnea. The ratio was observed to increase in apnea periods, which indicates activation of sympathetic nervous system. However, analysis of HRV itself showed increased LF/HF despite being an

active respiration period. This observation is inferred to be due to stress. HRV analysis is highly sensitive to stress. Stress decreases HF and leads to increased LF/HF. During the study, environmental obstacles and body positions were perceived as stress and could have increased the LF/HF ratio. Hence, HRV is restricted to stressless environments. It was inferred that determining apnea using HRV would be difficult.

When the apnea data is determined solely by using acceleration sensor, short apnea periods do not exhibit a clear change. Furthermore, the body position could influence the respiration and the acceleration sensor would have difficulty if the respiration is at low-flow as opposed to complete halt in respiration.

Currently, it is not clear how high the LF/HF ratio has go increase in order to indicate activation of autonomic nervous system. The respiration is largely influenced by the body position. Hence, a study that takes into account these factors should be conducted. A tool that automatically relays apnea data during apnea periods should be developed.

Additionally, a method for determining Fourier coefficient was investigated. A relatively high accuracy was observed and it was inferred it could even replace HRV analysis. However, since this method also requires ECG signals, positional alterations in the data should be taken into account when processing the data. In terms of R-peak discerning algorithm developed in this study, it should be compared with other commercial R-peak algorithms to determine its accuracy. The algorithm developed in this study was analyzed using the measured signals. Therefore, a real time measurement should be performed and simultaneous analysis methods should also be investigated.

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