A Body Area Network-Based Detection of Sleep Apnea

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ABSTRACT
Presented in this paper are the analysis and the results of our body area network (BAN) for the detection and classification of obstructive sleep apnea. Our algorithm is based on a low-order Daubechies D4 and D6 hybrid filter. Feature extractions are taken from the QT intervals of the Electrocardiography (ECG) waveform. These features include a QT-ECG-derived respiratory rate (QT-EDR) and the instantaneous heart rate. A determination of the existence of sleep apnea is based on the variability of these features.

Categories and Subject Descriptors
D.2 [SOFTWARE ENGINEERING]: Miscellaneous; D.2.6 [Programming Environments]: Integrated environments; D.3.2 [PROGRAMMING LANGUAGES]: C.

General Terms
Algorithms, Experimentation, Human Factors

Keywords
Linear Regression Classifier (LRC), Obstructive Sleep Apnea (OSA), Oxygen Saturation Level (SpO_2), Wavelet Transform Hybrid Filter, Body Area Network (BAN).

1. INTRODUCTION
BANs can be given to patients at an affordable cost. The data produced by the BANs then can be accessed by their care givers in real-time. This is absolutely possible because of the advancements and achievements in wireless and mobile communication. BANs have simple components and functionality such that, each node "works" as an independent communicator. Their components and functionality include monitoring, processing, sampling and recording patients' vital signs.

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We focus our work on the use of a BAN to detect and classify sleep apnea. Our focus is on sleep apnea, because of its wide effect on the American population and enormous cost on health care. Consequently, what is sleep apnea?

According to the U.S. Department of Health & Human Services, sleep apnea is a chronic condition that disrupts a patient's sleep. It is also a type of sleep disorder and is referred to as sleep-disordered breathing (SDB). An indication of this chronic condition is that the patient's breathing pauses or becomes shallow. Therefore, these disruptions in breathing cause a patient to move out of deep sleep into light sleep. These pauses can occur 30 times or more an hour. This results in very poor quality of sleep thus, leading to other more serious disorders in patients. "Obstructive sleep apnea" is the most severe form of sleep apnea. It is often times life threatening. We will broaden the focus of our work on this more severe form of sleep apnea OSA.

The variability of the following features: the instantaneous heart rate, the amplitude and timing of QRS complex, and an ECG-derived respiratory rate, have been used as indicators in the detection and classification of OSA. These researchers have also used the dip in the oxygen saturation levels (SpO_2) together with these features as indicators of having OSA. In a PSG the SpO_2 is the second important indicator of having OSA. Therefore, it has been used as a standalone indicator by some of these researchers in their detection and classification schemes.

Most recent studies have suggested that an accurate recording of the respiratory rate has shown to be very important in predicting severe medical events. The respiratory rate is the number of breaths a person takes during a one-minute period of time while at rest. It is often an ignored vital sign because it is not measured as often as it should be. An ECG waveform offers useful information that can be used in the screening of OSA. This information is gathered by placing the ECG electrodes on the body. Once in place a recording can be made, showing a history of the changes in thoracic electrical impedance (the filling and emptying of the lungs) and the functions of the heart. This history can then be observed and studied. These changes in the thoracic electrical impedance can be measured within the electrical axis of the ECG waveform. They have a very close connection to the respiration [4]. Our decision to use a QT-EDR is based on the knowledge that the respiratory rate is very important in the detection and classification of a patient's medical condition.

Section 2 presents the related work. Section 3 provides an overview of our BAN. Our proposed detection and classification scheme is in Section 4. Section 5 is the data analysis and results. In Section 6 are our conclusions and projected future works.

2. RELATED WORK

In this section we present some of the recent work done in the detection and classification of sleep apnea using BANs.

In [6] a system called Apnea MedAssist for monitoring OSA consists of a single lead ECG sensor and an Android based smartphone. Also, a low-order Daubechies D4 wavelet for filtering process was used. This system examines the heart's electrical system and categorizes the apnea and non-apnea based on an ECG-derived respiratory rate signal.

We proposed in our previous work [1] a BAN as a surrogate to the Existing Polysomnography that would afford physicians with a low-cost, universal, remote, flexible, and real time monitoring access system into their patients' current state of heath for diagnostic and classification purposes. Our BAN is based on detection and classification for the detection of OSA with respect to the underlying long QT syndrome. The inconsistencies in the beat-to-beat QT intervals are known to be visible during sleep in the most severe cases of OSA. In this paper we present the results of our BAN's detection and classification algorithm. Our algorithm consists of a Daubechies Hybrid Filter and a Linear Regression Classifier.

3. OVERVIEW OF OUR BAN

Our proposed BAN is presented in this section. The proposed network's system architecture consists of three levels, the Physiological Sensors, the Central Communication Access Point, and Data Routing. A star topology design is configured for the overall system infrastructure. Within level one we have our physiological sensors. We use two physiological sensors, Alive Technologies' Alive Heart and Activity Monitor (ECG sensor) and the WristOx2™, Model 3150 Wrist-worn Pulse Oximeter (SpO2 sensor). All sensors at this level have their own Bluetooth component. At the second level is the Central Communication Access Point. It is comprised of a personal computer using Microsoft ActiveSync® 4.2 synchronization software. Each sensor sends data to the Internet through their Wi-Fi (IEEE 802.11) component. In layer 3 the sensors' data is routed to the Internet, a personal computer running on Windows 7.

4. PROPOSED DETECTION AND CLASSIFICATION SCHEME

The QT interval of the ECG represents the duration of ventricular depolarization and subsequent repolarization, and is measured from the beginning of the QRS complex to the end of the T wave. Measuring from the Q-wave to the end of the T-wave will give the timing of the QT interval. If the heart rate is normal (60 beats per minute), a normal QT interval will last less than 0.42 seconds, less than half the time between heart beats. A long QT interval is said to be greater than 0.44 seconds.

Similar to the RR interval, the QT interval is dependent on the heart rate. If the heart rate is fast, the QT interval will be shorter. It needs to be adjusted to improve the detection of ventricular arrhythmia. Bazett's formula in Equation 1 is given and is one of the most common correction methods being used where RR Interval = 60/HR and HR is the heart rate.

$$QT_B \frac{QT}{\sqrt{RR}} \quad (1)$$

The corrected QT interval can vary from 400 ms to 440 ms. An abnormal QT corrected in adult males is above 450ms, and in females above 470 ms.

It is very important when using wavelet transforms in the detection of changes seen in an ECG waveform to select the one that best resembles its shape. The D4 transform has proven to have better results than D6 in the detection and the removal of unwanted artifacts. Even though D4 was shown to have better results based on their algorithm, it was also stated that D6 is similar to the QRS complex. Work in [7] showed that using the wavelet family Daubechies 6 gives better results than Daubechies 4. We present the use of a low order Daubechies hybrid filtering, consisting of the Daubechies 4 (D4) and Daubechies 6 (D6). In our previous work we proposed the use of a single filter consisting of D4 transform [1]. Our Daubechies hybrid filter was incorporated into the Alive Heart and Activity Monitor's existing software.

Figure 1 demonstrates an overview of our detection and classification scheme. The scheme is organized in three phases. Phase one is the pre-processing of the SpO_2 sensor data and the hybrid filter. Our hybrid filter is part of the ECG sensor software. In phase two we perform the removal of artifacts from the SpO_2 data. Once that process is completed the feature extraction takes place. Next the calculation of the corrected QT interval is produced. Then the QT-ECG-derived respiratory signal is produced [3]. The information from phases one and two are transferred to phase three. In phase three we have a Linear Regression Classifier (LRC). The LRC is comparable to a black box pattern recognition system.

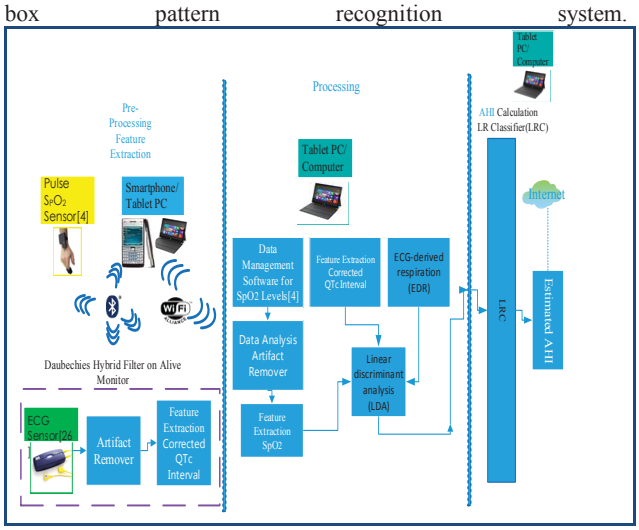

Figure 1. The Detection and Classification Scheme.

The LRC is a union of the first two modules. All the modules work in processing either the ECG signal or the pulse oximetry signal, thus generating the two outputs, the ECG signal and the SpO_2 levels. Then in turn, the outputs from these two modules produce an apnea-hypopnea index (AHI). We reserve the reporting of the pulse oximetry for our future work. We used the LRC, analysis process as a discriminant in the classification of an AHI. Linear discriminant function analysis performs a multivariate test of differences between signals. We ran each sample signal through our hybrid filter before creating the QT-EDR signal. The QT-EDR can be seen to be useful in ECG based research. Its units are given in in breaths per minute.

A hypopnea occurs during abnormally slow or shallow breathing. It is defined as being period of time during which breathing stops or is markedly reduced. The AHI is an index of severity that combines apneas and hypopneas. AHI is determined by using the following formula: AHI = (Apnea + Hypopnea) / (Actual Sleep Time). An AHI of 5 to15 is classified as mild obstructive sleep apnea, 15 to 30 is moderate OSA, 30 or more is severe OSA. The AHI determination is formulated from the feature extractions taken from our physiological sensors. We define a hypopnea-apnea event as following: when the respiratory rate for adults are ≤ 60 breaths per minute and the heart variability is < 60 beats per minute.

The model in Equation 2 is of a simple linear regression that provides a graphical representation and illustrations of the statistical classification models that we used in our analysis process. The goal of linear regression is to find the equation of the straight line that provides a best fit for the data points. The best fit is often the least squares method. A regression equation is written as following:

$$Y = \alpha + \beta X + \epsilon, \quad (2)$$

Y is the value of the Dependent variable (Y), what is being predicted or explained, a or Alpha, a constant; equals the value of Y when the value of X=0, b or Beta, the coefficient of X; the slope of the regression line; how much Y changes for each one-unit change in X. X is the value of the Independent variable (X), what is predicting or explaining the value of Y, Є is the error term; the error in predicting the value of Y, given the value of X [10].

5. DATA ANALYSIS AND RESULTS

5.1 Subject Data

The algorithm ability to detect sleep apnea was evaluated using the data in [9], the Physionet website. This database consists of overnight, single channel ECG recordings (sampled at 100Hz) obtained from 70 patients. There are 35 data recordings designated as training data of one minute annotations (denoting apneic or normal breathing during each minute) are presented with these records. The other remaining records are test data set. Both the test set and the training set have recordings from twenty patients with moderate to severe obstructive sleep apnea, with ten records as a control set, and five diagnosed as borderline.

5.2 Results

5.2.1 The QT-ECG-Derived Respiratory Rate

An automatic template-matching method is applied first to match the QT intervals from our detection algorithm to produce an annotation file. Then this file is used to derive the QT-EDR signal.

A signal processing technique is developed in [4], for measuring the direction of the cardiac electrical axis to form a QRS ECG-derived respiratory signal. This algorithm was designed to correspond to the rapid contraction of the ventricles as blood is expelled from the heart. The algorithm showed poor samples of the respiratory activity. This was mainly due to the low sampling rate paired with the rapid changes in the ECG data during a QRS complex occurrence. Due to these results we chose to use the QT interval and our work in [1] is based on the long QT interval detection.

Again and clearly stating, we have developed our algorithm based on the knowledge that wavelets are known to be better at removing unwanted artifacts and baseline-wandering. These unwanted signals that mass as the real signal can be distinguished according to their specific frequency (low noise) with the use of our hybrid filter. Also the Daubechies' scaling functions are said to be a better filter, because they looks like the ECG signal.

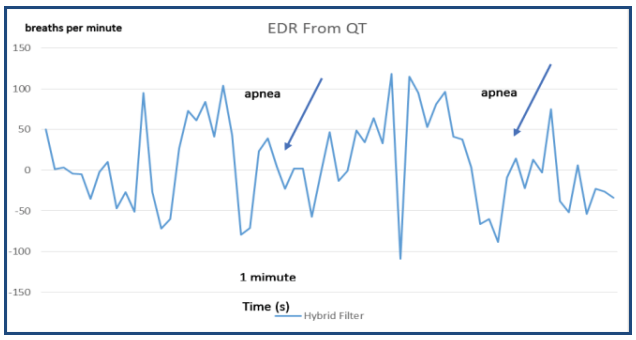

Figure 2 The QT-EDR Using the QT Interval

Figure 2 illustrates the appearance of obstructive sleep apnea within our QT-EDR signal with respect to our hybrid filter. The amplitude of the QT-EDR derived respiratory signal is being altered due to the large baseline shift. Thus, indicating respiratory activity. Within one-minute intervals the amplitude of the signal has low peaks as shown in Figure 2. Our derived respiratory signals produced an apnea index of 12 events per hour. An apnea is defined as cessation of breathing for at least 10 seconds.

5.2.2 Hybrid Filter

A band-pass filter, with a pass band from (0.5 to 40 Hz) was used to remove unwanted baseline wander and high frequency interference. The moving average filter was chosen by observation such that most of the energy from the QRS complex is captured with a fixed window size. Thus extending the P-QRS interval (such that each cardiac beat extends 350 ms prior to and after the QRS onset) to accommodate for the corrected QT and long QT interval. When considering a normal heart rate of 60 bpm. A corrected QT interval for example that is ≤ 420 ms would be 420 ms, based on Bazett's formula in Equation 1. A detection algorithm based on curve length transform was employed to ensure the end of the T-wave was properly detected. Moving average filter is essentially a finite impulse response (FIR) filter and by nature they can become very noisy. This is why we propose a Daubechies Hybrid Filter to remove unwanted baseline wander and high frequency interference. This will produce a signal with much better edges (boundaries that are visible). We employed the algorithm that was mentioned in our previous work [1]. The original software was based on D4 and we extended it to include the D6 wavelet to form a hybrid filter.

5.2.3 The Heart Rate Variability

Some of today's researchers believe that the heart rate variability (HRV) lends itself as a most valuable marker than just the heart rate alone. The HRV is the measurement of the time variance between each heartbeat. The HRV is measured in beats per minute. Figure 3 presents the frequencies of the heart rate variability as it trends below 60 beats per minute to about 120 beats per minute. This figure also shows the HRV as it swings from a normal rate to an abnormal (irregular) rate. The figure is a representation of the comparison study of our detection algorithm

to that of the manually annotated data in [9]. An average of 62.76 and a standard deviation of 4.43 were found from the comparison study.

The heart rate variability ranges from normal to irregular. A normal adult has a resting heart rate of 60-80 beats per minutes (bpm). If the range goes below 60 bpm it said is to be a bradycardia. When the heart rate is too fast this condition is called tachycardia. It is noted that a low heart rate is sometimes related to sleep apnea [8]. Evaluating the heart rate variability to produce a hypopnea index –AHI, we counted the number of times the instantaneous heart rate dipped below 60 bpm and divided by the total sleep time. Also, we took a running average how many times our QT-EDR dropped below 40 breaths per minute based on the total sleep time. Our AHI is a combination of the instantaneous heart rate and our QT-EDR. We saw an average of 10 hypopnea-apnea event per hour.

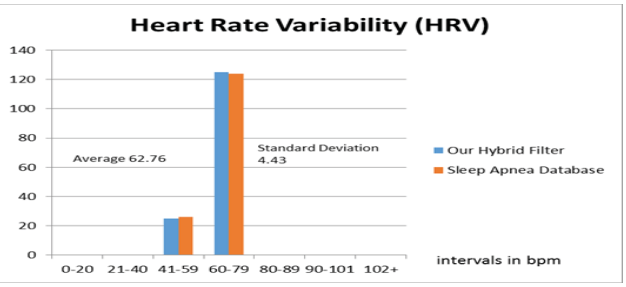

Figure 3. HRV with Respect to the Hybrid Filter

Here we present the results of the feature extraction classifier algorithm based on a linear regression classification methodology. The ECG features we used are a QT-EDR and the instantaneous heart rate (ihr) [4] for determination of the AHI. Here we see that our method did not predict any severe case, but mild: (AHI ≥ 5, but < 15 per hour of OSA) and moderate: (AHI ≥ 15, but < 30 per hour). This may be due to not associating the oxygen saturation levels. The proposed method predicted on average an apnea-hypopnea index -AHI of ≤ 21.

5.2.4 Analysis

After employing the Weka data mining software tool we present the overall performance of our system. A linear regression probabilistic statistical classification model is chosen as a best fit for analyzing ECG data, because of its ability to predict a binary response from a binary predictor. A decision is made to use a several cross-validation - linear regression –algorithms and took the average as to show impartial and just results. The results are as following:

Kappa statistic	0.691733
Mean absolute error	0.03505
Root mean squared error	0.132683

An overall performance of our work shows a Kappa value of .69 without correlation of the oxygen saturation levels. Thus, concluding from these results this algorithm is suitable in the detection and classification of OSA from a QT-EDR signal in the presence of a D4 and D6 hybrid filter. Furthermore a sensitivity of 99.94% and a specificity of 82.04% are presented.

6. CONCLUSION AND FUTURE WORK

We presented the analysis and the results of our body area network (BAN) for the detection and classification of obstructive sleep apnea. Our algorithm is based on a low-order Daubechies D4 and D6 hybrid filter. Feature extractions are taken from the QT intervals of the Electrocardiography (ECG) waveform. These features include a QT-ECG-derived respiratory rate (QT-EDR) and the instantaneous heart rate. A determination of the existence of sleep apnea is based on the variability of these features. We use HVR and QT-EDR as markers in formulating an AHI to predict the existence of OSA; these markers proved to be suitable and reliable. In conclusion our proposed scheme performed well in the detection of mild to moderate sleep apnea without the correlation of the SpO_2 levels.

Our future work will include the correlation of our SpO_2 module and the real-life validation of our proposed classification and detection scheme of OSA for our BAN.

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