A Personal Body Area Network as a Pre-Screening Surrogate to the Polysomnography

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ABSTRACT
In this paper we introduce a Personal Body Area Network (PBAN) as a pre-screening surrogate to the sleep study known as polysomnography (PSG). The network consists of an automated algorithm for detecting the presence of the Long QT Syndrome (LQTS) which is associated with Obstructive Sleep Apnea (OSA). Our LQTS detection algorithm uses the Daubechies D4 wavelet filter transform to further enhance the results of our detection process. We incorporated the LQTS detection algorithm into Alive Technologies' Heart and Activity Monitor. The ECG signal and the SpO2 data are correlated through our proposed Correlation Classifier resulting in a hypopnea index, or AHI.

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
Polysomnography (PSG), Long QT Syndrome (LQTS), Obstructive Sleep Apnea (OSA), Oxygen Saturation Level (SpO_2, Discrete Wavelet Transform (DWT), Personal Body Area Network (PBAN).

1. INTRODUCTION
A polysomnography (PSG) is an all-night sleep study used to diagnose sleep disorders and sleep disordered-breathing (SDB). The most common SDB is known as sleep apnea - a disorder of interrupted breathing during sleep [1]. If left untreated an undiagnosed OSA can have the following effects: raise heart rate and increase the risk of high blood pressure, heart attack, stroke, arrhythmias (irregular heartbeat), diabetes, and obesity. The Long QT Syndrome (LQTS) has been linked to patients with OSA. With patients who experience Long QT the heart takes longer to reset for the next heartbeat. [4]. Long QT can be potentially life threatening [5]. The cost for an overnight sleep study is estimated to be between $900 and $3,000. The proposed Surrogate to the PSG is intended to provide physicians with a cost-effective, pervasive, remote, flexible, and real time monitoring access system into their patients' current state of health for diagnostic and classification purposes.

The remainder of the paper is organized as follows, Section 2 presents Related Work. Section 3 gives an overview of the PSG study. Our proposed scheme is described in Section 4. In Sections 4.1, 4.2.and 4.3 we introduce the main modules, the QT Interval Detection Module, the SpO2 Signal Module, and the Logical Correlation Classifier Module. Finally results and future work are outlined in Section 5.

2. RELATED WORK
The most recent use of the PBAN technology is in the detection and classification of sleep apnea. Its portability help deflate the cost of an overnight study. A general architecture [10] [11] of sensors and detection schemes send recorded data to a smart phone, a home computer, and clinic or physician secure website. Communication between PBAN and the medical server is done with either Bluetooth® wireless technology, ZigBee, or IEEE 802.16 [12]. Bluetooth wireless technology [13] has become the standard for exchanging data over short distances from fixed and mobile devices, creating personal area networks (PANs) with high levels of security. We will use it in our proposed scheme.

In earlier studies classification markers used from the oximetry sensors where the number of dips in oxygen saturation per hour, and frequency based features such as the spectral peak in the SpO2 spectrum and pulse rate periodogram in the range 30-70 seconds [12][15]. Our proposed scheme will use temporal SpO2 markers for example the percentage time below a certain level, and the sum of the differences between successive readings.

Previous studies have used the timing of the QRS complexes and amplitude height as indicators for the classification of OSA. We use the abnormalities of the LQTS. LQTS is a rare inherited heart condition in which delayed repolarization of the heart occurs and is more often seen in patients with OSA [16] [17].

The ECG monitor chosen for these PBANs was the Holter monitor. Our proposed scheme will use the heart monitor in [18]. Its features are: real-time transmission to PC, Smartphone or PDA continuous wireless transmission up to 48 hours, and internal SD memory card. It takes recordings of the heart rate, activity, body position, and falls. This monitor can be worn comfortably during

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normal daily activities. The sampling rate is 300 samples/sec. It also has a dynamic range of 5.3mV peak to peak and Bandwidth 0.5Hz – 90Hz.

The linear discriminant classifier introduced in [19]. The proposed scheme will use. A classifier performance using cross-validation of both the ECG and oximetry data is presented in the above studies. Our classifier method like that in the above works will include the ECG data and the SpO2 data.

In the previous work mentioned the filtering process consists of a 2nd order- band pass filter (0.5-40Hz) [11] [23]. Just in the past ten years the use of wavelets in the filtering process of medical sensors has gain significant respect because of their accurateness in detection and removal algorithms. The Daubechies D4 discrete wavelet transform filter [22] is chosen as an enhancement to the filtering process that is done by the Alive Heart Monitor.

Lastly, the data collected from the medical sensors are transmitted to an online medical server, using either a cellular network (4G, GPRS, GSM, WiMAX) or a home/commercial internet connection. The smartphone uses Microsoft ActiveSync® 4.2 synchronization software.

3. OVERVIEW OF THE PSG STUDY

In a PSG which is a diagnostic test during which several physiological variables are measured and recorded during sleep. Polysomnography monitoring of obstructive sleep apnea syndrome have to consist of monitoring of sleep by electroencephalography, electrooculography, electromyography, airflow, and respiratory muscle effort, and should also include measures of electrocardiographic rhythm and blood oxygen saturation SpO2 [9]. An extensive amount of data is generated by a sleep study, but the most crucial is the apnea-hypopnea index, or AHI. An apnea is a complete cessation of breathing for 10 seconds or longer. A hypopnea is a constricted breath (more than one-fourth, less than three-fourths) that lasts 10 seconds or longer. The index number is the number of apneas and hypopneas the sleeper experiences each hour.

4. PROPOSED SCHEME

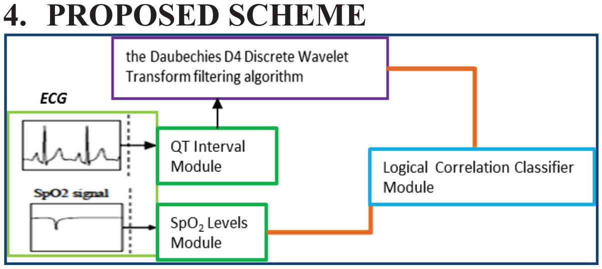

Figure 1. Proposed Scheme.

Figure 1 demonstrates the proposed PBAN scheme In Figure 2 the placement and function of each medical sensor is presented. QT Interval Module preforms the following steps:

Filtering: we introduce the Daubechies D4 discrete wavelet transform filtering algorithm in [22] and we incorporated it into the Alive Technologies' Heart Monitor software.

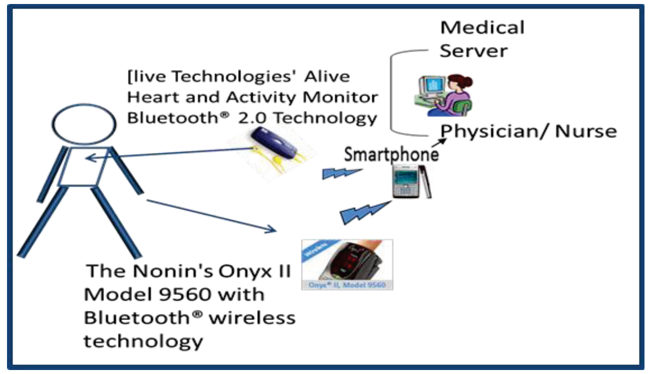

Figure 2. Medical Sensors used in the Proposed Scheme.

The DWT of an ECG signal ***x*** is calculated by passing it through a series of filters. Samples are passed through a low pass filter with response ***h*** resulting in the convolution of the two. The signal is also decomposed using a high-pass filter ***g***. The outputs giving detail coefficients from the high-pass filter ***g[n]*** and approximation coefficients come from the low-pass filter ***h[n]***. These equations and processes can be seen in Figures 3 and 4 the wavelet coefficients are derived by reversing the order of each scaling function, then reversing the sign of every second one. The mathematical representation is the following: $b_k = (-1)^k a_{N-1-k}$ where **k** is the coefficient index, **b** coefficient of the wavelet sequence, **a** coefficient of the scaling sequence and **N** is the wavelet index (4 for D4).

Heartbeat Detection: The scheme is based on [24] and [25]. We made modification to the existing C, C++ code to include D4 DWT filtering algorithm for the QT Interval detection process. Alive Technologies' Heart Monitor uses the detection method in [28]. The performance of other detection algorithm has been validated against the QT Database in [26][27].

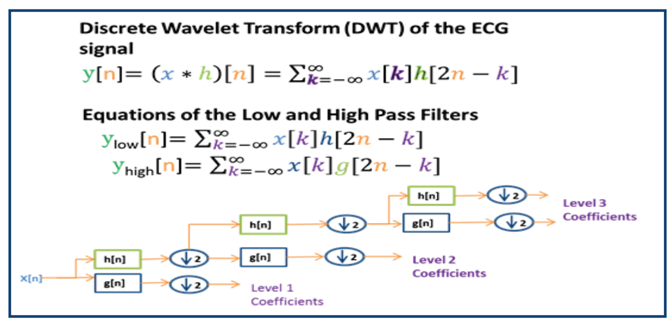

Figure 3. The Daubechies D4 Transform Filters.

The Daubechies D4 Coefficients for the Scaling Functions

$$h_0 = \frac{1+\sqrt{3}}{4\sqrt{2}} \quad h_1 = \frac{3+\sqrt{3}}{4\sqrt{2}}$$

$$h_2 = \frac{3-\sqrt{3}}{4\sqrt{2}} \quad h_3 = \frac{1-\sqrt{3}}{4\sqrt{2}}$$

Daubechies D4 Wavelet Coefficients

$$g_0 = h_3 \quad g_1 = -h_2$$

$$g_2 = h_1 \quad g_3 = -h_0$$

Figure 4. Daubechies D4 Scaling Functions and Coefficients, and Wavelet Coefficients.

SpO2 Levels Module: Step one of the process would be to remove obvious artefacts. The software provided by the Nonin's Onyx II Model 9560 with Bluetooth® wireless technology sensor [34] will be used. It also provides a fast and accurate snapshot of the patient's SpO2 and pulse rate.

The proposed algorithm will use an automated classification method that will correlate the ECG and SpO2 data. A consideration of one minute epochs will be used in the determination of an apneic or a normal respiration.

4.1 QT Interval Detection Module

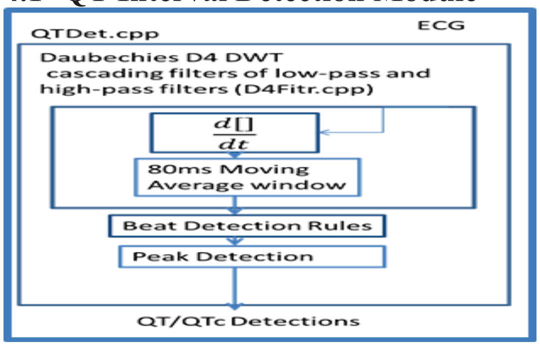

Figure 5. QT Beat Detection Operations.

The software in [34] was originally designed for detecting the QRS detection. We redesigned it to include Daubechies D4 DWT detection algorithm. We also made other design adjustments such as setting a peak threshold to allow for smaller peaks, and setting the Moving Average Window procedure to allow for LQTS. QTc is the corrected QTc interval [4][5][17]. Figure 5 illustrates a visual overview of the QT detection operations.

4.2 SpO_2 Signal Module

Eliminating obvious artefact is step one. We proposed to do this by marking all changes of oxygen saturation between consecutive sampling intervals greater than 4% per second as artefact. Also all SpO2 values of less than 65% or greater than 100% saturation will be marked as artefact. Next produce an estimate of the running 5-minute average of the Spo2 signal. The last step would be to resample both the original Spo2 signal and estimated baseline threshold. The response time of the SpO2 to be based on an exponential averaging every 4 to 8 beats which depends on the actual heart rate. Data Analysis will consist on an independent observer of the PSG along with the oximetry internal software nVISION pulse oximetry data management software from Nonin Medical [35].

4.3 Logical Correlation Classifier Module

This proposed scheme will adopt the discriminant analysis classification algorithm. Linear discriminant function analysis performs a multivariate test of differences between signals. The proposed classifier method will be based on linear discriminants [39] and our selected signal representations. Hypoxemia during sleep, sometimes with an oxygen saturation of less than 50%, is a typical feature of the disorder OSA [17]. Apneas and hypopneas will be scored according to standard definitions based on pulse oximeter readings. Hypopneas scoring will be based on the following criteria: Decrease in SpO2 below 92% from a baseline of at least94% or a drop in SpO2 of at least 3% if baseline was less than 90%. AHI is determined by using the following formula: AHI = (Apnea + Hypopnea)/(Actual Sleep Time) [28]. An AHI of 5 to15 is classified as mild obstructive sleep apnea, 15 to 30 is moderate OSA, 30 or more is severe OSA [14].

5. Results and Future Work

The performance of the algorithm was tested against the PhysioBank QT Database in [27]. All of the computed formulas for Sensitivity and Predictivity are derived in [11]. All records were manually annotated at 5 minutes intervals and sampled at 250 Hz. These are only preliminary results of the proposed scheme's QT detection method being presented. A Sensitivity of 99.74% and a Positive Predictivity of 99.80% was obtained by the proposed scheme. Currently, we are working to complete the SpO2 signal module and the logical correlation classifier module and we will report results from the complete scheme in the future.

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