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Technical Note

A portable respiratory rate estimation system with a passive single-lead electrocardiogram acquisition module

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Abstract.
BACKGROUND: Among vital signs of acutely ill hospital patients, respiratory rate (RR) is a highly accurate predictor of health deterioration.
OBJECTIVE: This study proposes a system that consists of a passive and non-invasive single-lead electrocardiogram (ECG) acquisition module and an ECG-derived respiratory (EDR) algorithm in the working prototype of a mobile application.
METHOD: Before estimating RR that produces the EDR rate, ECG signals were evaluated based on the signal quality index (SQI). The SQI algorithm was validated quantitatively using the PhysioNet/Computing in Cardiology Challenge 2011 training data set. The RR extraction algorithm was validated by adopting 40 MIT PhysioNet Multiparameter Intelligent Monitoring in Intensive Care II data set.
RESULTS: The estimated RR showed a mean absolute error (MAE) of 1.4 compared with the "gold standard" RR. The proposed system was used to record 20 ECGs of healthy subjects and obtained the estimated RR with MAE of 0.7 bpm.
CONCLUSION: Results indicate that the proposed hardware and algorithm could replace the manual counting method, uncomfortable nasal airflow sensor, chest band, and impedance pneumotachography often used in hospitals. The system also takes advantage of the prevalence of smartphone usage and increase the monitoring frequency of the current ECG of patients with critical illnesses.

Keywords: Respiratory rate, single-lead ECG, algorithm, e-health system, mobile applications

1. Introduction

Critical illnesses incorporate various variables that deviate from normal values, such as systolic blood pressure, heart rate (HR), and respiratory rate (RR) [1]. Abnormalities in these vital signs often predict a serious condition that may occur within 24 h [2]. Congestive heart failure may result in tachyarrhythmia

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and tachypnea [3]. Many studies showed that, among vital signs measured in acutely ill hospital patients, RR provides a highly accurate prediction of deterioration [4,5].

Traditional methods of detecting respiratory conditions involve directly measuring airflow in or out of the lungs or indirectly measuring changes in body volume. These techniques, such as spirometry, require the use of cumbersome devices that may interfere with normal respiration. Respiratory inductance plethysmography devices, which patients strap on their chest, are considered highly accurate RR measurement gadgets. The respiratory system is assumed to move with two degrees of freedom; thus, changes in inductance are proportional to the changes in ribcage and abdominal volume [6]. However, adopting the devices mentioned earlier may cause users to feel distressed when their RR is recorded.

Another non-invasive RR estimation technique used in hospitals is impedance pneumography (IP). The drawback of using IP, which measures impedance at the electrocardiogram (ECG) electrodes, is the injection of high-frequency AC current into the tissue through drive electrodes [7]; thus, IP becomes an active electronic device. IP is also not as robust and accurate as inductance plethysmography. Furthermore, most of the devices currently adopted in hospitals are bulky and extremely expensive.

Changes in ECG have the same rhythm as respiratory movements, and RR may affect ECG by inducing (1) R-peak amplitude [8], (2) respiratory-sinus arrhythmia (RSA) [9], and (3) baseline wander (BW) [10]. ECG is routinely monitored in many situations, and researchers have developed methods to extract respiratory signals directly from the acquired ECG [11]. In this study, we propose a passive and non-invasive single-lead ECG acquisition module and an ECG-derived respiratory (EDR) algorithm in the working prototype of a mobile application. This technique employs a passive device that is portable and affordable.

2. Methodology

The proposed system consists of a single-lead ECG recorder (three-electrode contacts) connected to an Arduino microcontroller. The e-health board is attached to the microcontroller. The ECG electrodes, microcontroller, and e-health are used as the ECG signal acquisition module. The raw ECG data is transmitted using RN-XV WiFly protocol wirelessly to smartphones. Unlike wired communication techniques, this wireless communication approach provides comfort to patients. The fully functional prototype smartphone application detects and analyzes the data using a specific EDR algorithm tool.

2.1. Single-lead ECG acquisition module

We propose the e-health sensor system, which processes the biosensor using the Arduino Uno (ATMega328) embedded with a 16 MHz crystal oscillator and a 5 V linear regulator, and can be powered using a USB connector or a 12 V and 2 A external power supply. The power supply is isolated and not designed to power up the ECG electrodes. For future implementation, Arduino Nano will be used, which is similar to a match box in size. The nasal airflow sensor device consists of a flexible thread that fits behind the ears and a set of two prongs placed in the nostrils. The prongs measure the "gold standard" RR. In this study we use Lead II ECG and the ECG and the RR gold standard signals were recorded simultaneously.

2.2. RR extraction algorithm

The algorithm that was developed to extract RR from ECG was performed in a MATLAB environment. The RR extraction was conducted using the RSA method due to its 75% more accurate and covers an extensive age range of patients. The data obtained from mobile patients are generally noisier and more difficult to interpret than those obtained from a system where the patient is immobile [12]. The algorithm starts with signal quality indices (SQI) to identify invalid data containing the undesired artefact and to determine the best raw ECG data for extraction.

To obtain SQI, we first identified the QRS annotations from two QRS peak detectors. The present study utilized the functions developed by Behar, 'qrs_detect2' [13] and Zhang, 'rpeak' [14]. The two sets of annotations (i.e., from the two QRS detectors) are used as input to the 'Bxb_compare' [15] function. The window size used is 10 s with shifts of 1 s. If the two peak detectors are consistent with the annotated values, the SQI value is 1; otherwise, the value is below 1. A threshold is set to decide whether a segment has good or bad quality. A value of 0.8 is the threshold used in the present study. The developed SQI algorithm is validated by employing 40 MIT PhysioNet Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II) data sets for the qualitative approach.

The quantitative approach is validated using set A of the PhysioNet Challenge 2011 training data consisting of two records, namely, RECORDS-acceptable and RECORDS-unacceptable, which represent two classes (i.e., good and bad quality). These data are in wfdb format; thus, they were imported and converted in.mat files. The window size is 1.5 s with shifts of 1 s. The two sets of annotations given by 'gqrs' and 'wqrs' functions are used as input to the 'Bxb_compare' function with the same threshold SQI of 0.8. In this scenario, only the ECG signals with a median SQI of 1 and interquartile range (IQR) below 0.05 are used as the input ECG signal for RR estimation.

The noise spectrum can be randomly spread throughout the entire ECG spectrum [16]. Preprocessing, which aims to improve the signal-to-noise ratio and enhance the accuracy of the analysis and measurement, includes the removal of BW, high-frequency noise, and high-frequency random noise caused by power line interference (50 Hz, 60 Hz). Savitzky-Golay filtering is used to remove the high-frequency component of the signal. The filter coefficients can be derived by performing unweighted linear least squares fit using a polynomial of an appropriate degree. For this reason, a Savitzky-Golay filter is also called a digital smoothing polynomial filter or a least-squares smoothing filter [17].

The next process is the removal of BW using a high-pass linear-phase digital filter with a cut-off frequency of 5 Hz. This process aims to prevent considerably low-frequency components instead of respiratory signals from being detected. The infinite impulse response filter is employed to eliminate the 50+/0.2 Hz power line interference. The QRS peak or beat detection is identified by adopting the ECG demo peak detection function developed by Sergey Chernenko. The RR peak interval versus time data, which is the RSA method, is used in the current study.

The next step is the respiratory quality index (RQI) detection. This process is implemented by first accessing the order of an autoregressive (AR) model using partial autocorrelation sequence for the RSA waveforms. The sample autocorrelation sequence of the time series is examined. The AR peak with the highest autocorrelation scores compared with the ideal sinusoidal waveforms is selected. We obtained the RR signals based on the number of ideal sinusoidal waveform peaks using a 32 s overlapped window. The highest correlation scores of a 32 s window is selected, and the respiratory signal quality, which represents RQI, is determined.

To enable the fast Fourier transform (FFT) process, the RSA signals are regularly resampled at 4 Hz by employing spline interpolation. After the FFT process, the RSA waveforms are filtered using a finite impulse response (FIR) bandpass filter with cut-off frequencies of 0.1 Hz and 0.6 Hz (equivalent to respiratory rates of 6 breaths per min or 36 breaths per min) [18] to eliminate non-respiratory frequencies. Respiratory signals are identified in sinusoidal form. The data set from MIMIC-II [19] is used to validate the RR.

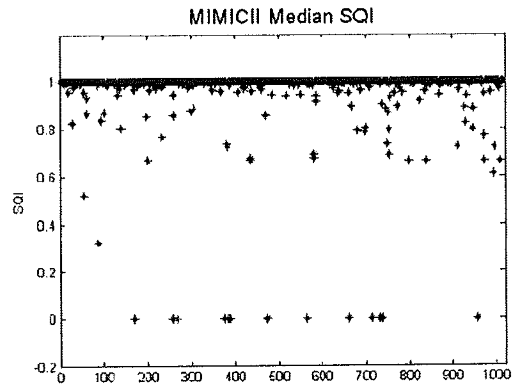

Fig. 1. MIMIC-II Median SQI validation.

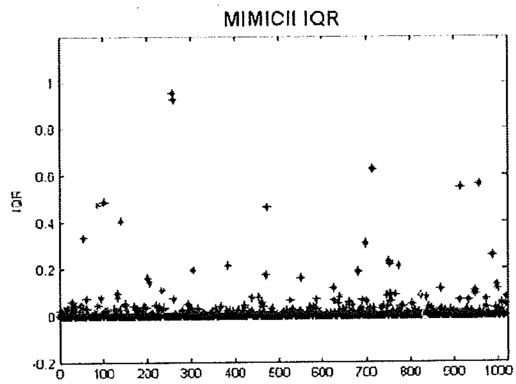

Fig. 2. MIMIC-II interquartile range validation.

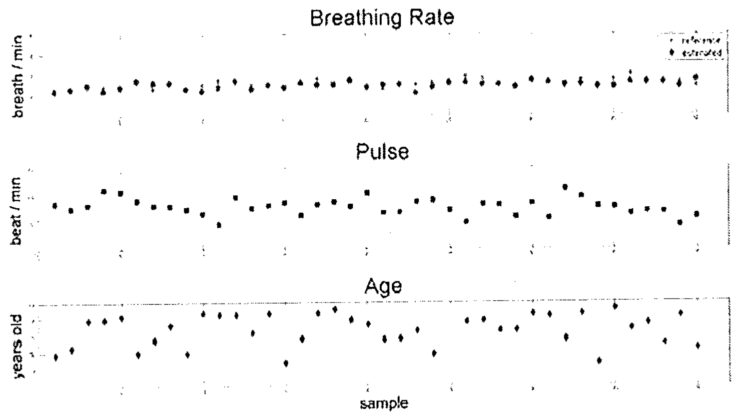

Fig. 3. Comparison of RR estimation with the gold standard of the MIMIC-II data sets.

The ECGs of 20 healthy people were recorded using the proposed signal acquisition system. By adopting the developed algorithm, the estimated RR is compared with the gold standard nasal airflow sensor output. The mean absolute error (MAE) with respect to the reference RR was computed in bpm as

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|bpm_{estim} - bpm_{ref}\right| \tag{1}$$

where N is the length of the window, bpm_{estim} is the estimate RR, and bpm_{ref} is the reference RR.

2.3. *Wireless communication system*

In this paper, RN-XV WiFly module is used to establish communication between the microcontroller and the smartphone. The two components are also connected through a cable for signal processing and

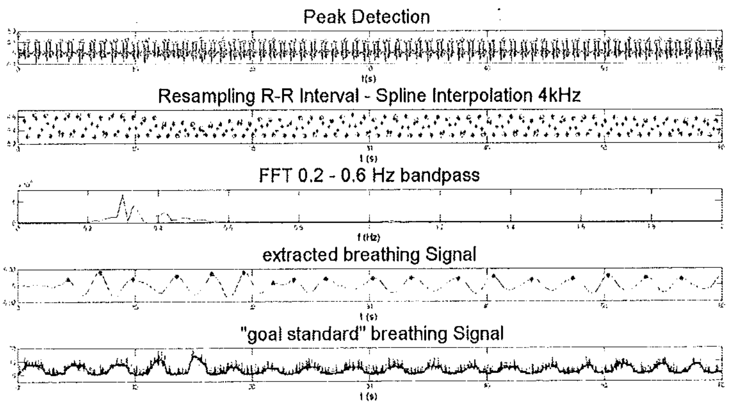

Fig. 4. RR estimation using the proposed ECG acquisition system and RR estimation algorithm.

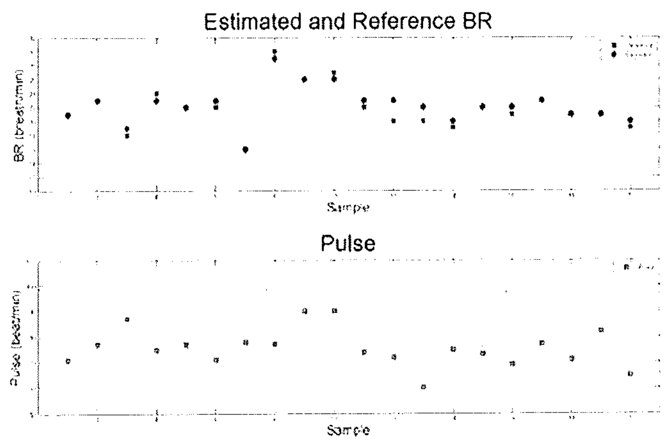

Fig. 5. A total of 20 data sets are compared with the gold standard RR and HR of each recorded datum.

mobile application development in personal computers. In the actual application, this module is wirelessly connected to a smartphone. Tera Term is used to set up the IP address of the module and perform this process. As mentioned, the USB adapter is connected to the RN-XV WiFly module to establish a serial connection during configuration. The configurations for iOS and Android are performed independently. The Wi-Fi antenna of the RN-XV WiFly module transmits data from the Arduino microcontroller to a smartphone.

3. Result and discussion

The qualitative validation of the developed SQI algorithm was performed for 1017 MIMIC-II and eight-min patient data sets. This study used a 30 s window with 30 s shifts. Figures 1 and 2 show the results of the median SQI and interquartile SQI, respectively. The quantitative validation results using

PhysioNet Challenge 2011 data shows a 98% correlation. Figure 3 shows the RR estimation validation using 40 MIMIC-II data sets. The estimated RRs using the developed algorithm and the gold standard value provided by MIMIC-II data sets were compared. In this comparison, the HRs of patients range from 47 bpm to 111 bpm, which are considered normal. The patients are 20 to 90 years old. The results indicate that the obtained MAE is 1.4. Figure 4 presents the RR estimation using the acquired data, as well as the peak detection, resampling process, bandpass filtering, respiratory signals, and the gold standard or reference signal. Figure 5 provides a comparison using the reference nasal airflow sensor output, where the calculated MAE for the acquired data is 0.71.

The working prototype uses iOS mobile applications. The display indicates the real-time ECG signal, heart rate (beat/min), and respiratory rate (breath/min). Furthermore, in the case of abnormal heartbeat, the applications display "arrhythmia" at the bottom portion of the display.

4. Conclusion

In summary, RR estimation integrated with the single-lead ECG acquisition module as part of the portable respiratory rate estimation system was developed. The proposed algorithm with the e-Health sensor platform resulted in an MAE value of 0.7. The results indicate that the proposed hardware and algorithm could replace the manual counting method, uncomfortable nasal airflow sensor, chest band, or IP, which are widely adopted in hospitals.

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