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Breathing Rate Estimation from a Single-lead Electrocardiogram Acquisition System

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Abstract- Breathing rate (BR) is highly predictive of health deterioration among vital signs measured in acutely ill hospital patients. This study proposes a single-lead electrocardiogram (ECG) acquisition system and a BR estimation algorithm from ECG. The signal quality index algorithm was validated quantitatively by using the PhysioNet/ Computing in Cardiology Challenge 2011 training data set. The BR extraction algorithm was validated using 40 MIT Physionet Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II) data set. The estimated BR showed a mean absolute error (MAE) of 1.4 compared with the reference BR. Using the proposed acquisition system, 20 ECGs of healthy subjects were recorded, and the estimated BR with MAE of 0.7 bpm was obtained. Results indicate that the proposed hardware and algorithm could replace the manually counted, uncomfortable nasal air flow sensor or chest band often used in hospitals.

Keywords: Critical Illness, Breathing rate, Single-lead ECG, Algorithm, e-Health Sensor System

Introduction

Critical illnesses incorporate various variables, such as systolic blood pressure, heart rate (HR), and breathing rate (BR) [1]. Abnormalities in these vital signs often predict a serious condition within 24 h [2]. Congestive heart failure may result in tachyarrhythmia, an abnormally increased heart rate; and tachypnea, an elevated breathing rate [3]. Many studies have shown that BR is highly predictive of deteriorations among vital signs measured in acutely ill hospital patients [4] [5].

Traditional methods of detecting breathing are performed by directly measuring air flow in or out of the lungs, or indirectly measuring changes in body volume. These techniques require the use of cumbersome devices, such as spirometry, which may interfere with natural breathing. Respiratory inductance plethysmography devices, which patients strap on their chest, may cause users to feel distressed during the recording. Acutely ill patients are not only attached with breathing detection devices but they also have to be hooked up to ECG and pulse oximeter devices, thereby making them highly uncomfortable and inconvenienced. Changes in ECG have the same rhythm as breathing movements, effects of breathing on ECG are (1) R-peak amplitude [7], (2) respiratory sinus arrhythmia (RSA) [8], and (3) baseline wander (BW) [9]. ECG is routinely monitored in many situations; thus, researchers have pursued methods to extract breathing signals directly from the acquired ECG [10]. Therefore, this study proposes a single-lead ECG acquisition system called e-Health and BR estimation algorithm using RSA method from ECG.

Methodology

A. Single-lead ECG acquisition system

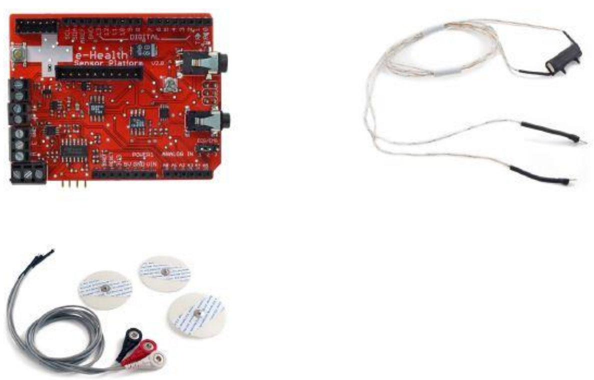

Fig.1. e-Health sensor system consisting of Arduino Uno microcontroller, nasal air flow sensor, and single-lead ECG sensors.

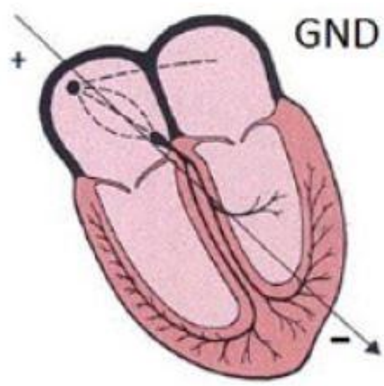

Fig.2. Lead II Connection

We propose an e-Health sensor system for the ECG acquisition (Fig.1). Compared with the existing equipment, the benefits of the proposed system include its portability and affordability. The e-Health sensor system, which process the biosensor using the Arduino Uno (ATMega328) with embedded 16 MHz crystal oscillator and 5 V linear regulator, can be powered using a USB connector or a 12 V and 2 A external power supply. The algorithm running the e-Health system was developed using c++ with Arduino ERW 1.0.5 software as the interface. The nasal airflow sensor device comprises a flexible thread that fits behind the ears and a set of two prongs placed in the nostrils. The prongs measure the "gold standard" BR. Lead II ECG comprises three external electrodes, namely, the positive electrode placed on the right arm, the negative electrode on the left foot, and the N electrode. N electrode serves as a ground to reduce the amount of electrical interference. Fig. 2 shows the placement of the electrodes for the single-lead ECG used in this study. Electrodes are occasionally referred to as leads, which is inaccurate. An electrode is a device attached to the skin that detects and relays information on the electrical activity in the heart to the monitoring equipment; by contrast, lead is a particular arrangement of electrodes that produces a specific pattern on the ECG paper [11]. In this study, ECG and the BR gold standard signals were recorded simultaneously.

B. BR Extraction Algorithm

The algorithm development to extract BR from ECG was performed in a MATLAB environment. The BR extraction was conducted using the RSA method. In our initial analysis, the RSA method is 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]. Fig.3 shows that the algorithm development starts with the signal quality indices (SQIs) to identify invalid data containing the undesired artefact.

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.m* [13] and Zhang, *rpeak.m* [14]. To ensure that QRS is correct, these annotations are plotted alongside ECG across the entire record. Thereafter, the two sets of annotations (i.e., from the two QRS detectors) are used as input to the *Bxb_compare.m* [15] function. The window size used is 10 s with shifts of 1 s. If the two peak detectors agree on the annotated values, then the SQI value is 1; otherwise, the value is below 1. A threshold can be set to decide which segment is of good or bad quality; 0.8 is the threshold used in the present study. The validation of the developed SQI algorithm is performed using 40 MIT PhysioNet Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC-II) data sets for the qualitative approach. For the quantitative approach, validation is performed using set A of the 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, the two peak detectors used *wqrs* [16] and *gqrs* [17] to obtain the QRS annotations. The window size is 1.5 s with shifts of 1 s. The two sets of annotations are also used as input to the *Bxb compare.m* function with the same threshold SQI of 0.8. In this scenario, only the ECG signals with median SQI of 1 and interquartile range (IQR) of below 0.05 are used as the input ECG signal for BR estimation.

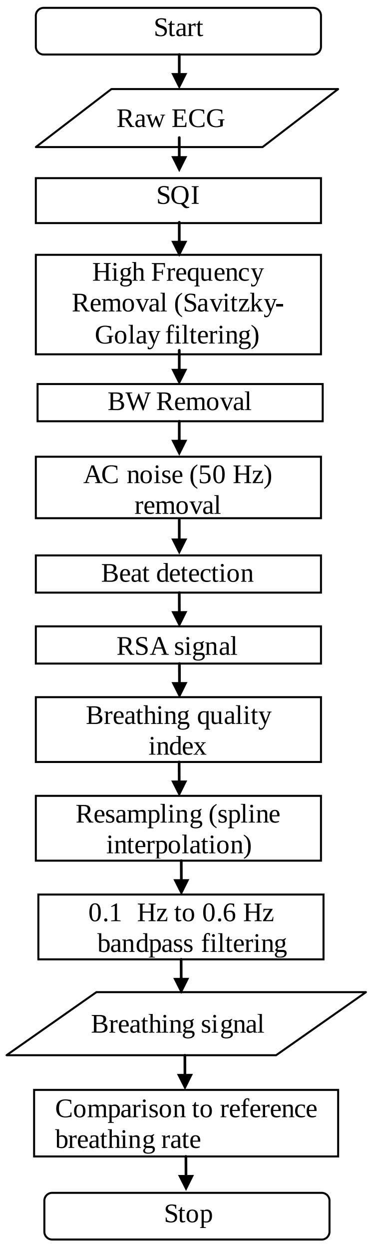

Fig.3. Algorithm Development

The noise spectrum can be randomly spread throughout the entire ECG spectrum [18]. Preprocessing, a process to improve the signal-to-noise ratio to enhance the accuracy of the analysis and measurement, comprises 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 [19].

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 breathing signals, from being detected. Thereafter, the infinite impulse response filter is used to eliminate the 50 +/ 0.2 Hz power line interference. The QRS peak or beat detection is then identified using the *ECG demo* peak detection function developed by Sergey Chernenko. The heart rate in beats per min is equivalent to 60 divided by the length of the R–R peak interval. The R–R peak interval versus time data, which is the RSA method, is used in the current study.

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

To enable the fast Fourier transform (FFT) process, the RSA signals are then regularly resampled at 4 Hz by using 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 breathing rates of 6 breath-per-minute (bpm) or 36 bpm) [20] to eliminate non-breathing frequencies. Breathing signals are identified in sinusoidal form. The data set available from MIMIC-II [21] is used to validate the reference “breathing signal.”

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

$$MAE = \frac{1}{N}\sum_{i=1}^{N} | bpm_{estim} - bpm_{ref} | \qquad (1)$$

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

Result and Discussion

The qualitative validation of the developed SQI algorithm was performed for 1017 MIMIC-II, 8-min patient data sets. This study used a 30 s window with 30 s shift. Fig.4 and Fig.5 show the results of the median SQI and SQI interquartile-range (IQR), respectively. Fig.6 and Fig.7 show two different signal qualities as the result of the validation process. Fig.8 and Fig.9 show the quantitative validation results using PhysioNet Challenge 2011. Fig.10 illustrates the SQI results of randomly taken one signal. Fig.11 shows the BR estimation validation using 40 MIMIC-II data sets. BRs estimated using the developed algorithm and the gold standard value provided by MIMIC-II data sets were compared. In this comparison, HRs of patients range from 47 bpm to 111 bpm, which are considered normal. The ages of the patients are from 20 to 90 years old. The results indicate that MAE gained is 1.4. Fig.12 shows the BR estimation using the acquired data, as well as the peak detection, resampling process, bandpass filtering, respiratory signals, and the gold standard or reference signal. Fig.13 demonstrates the comparison using the reference nasal air flow sensor output, where the calculated MAE for the acquired data is 0.71.

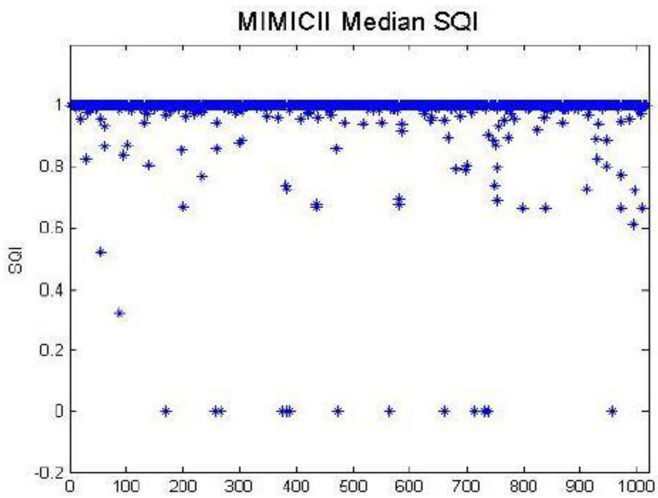

Fig.4. MIMIC-II Median SQI validation

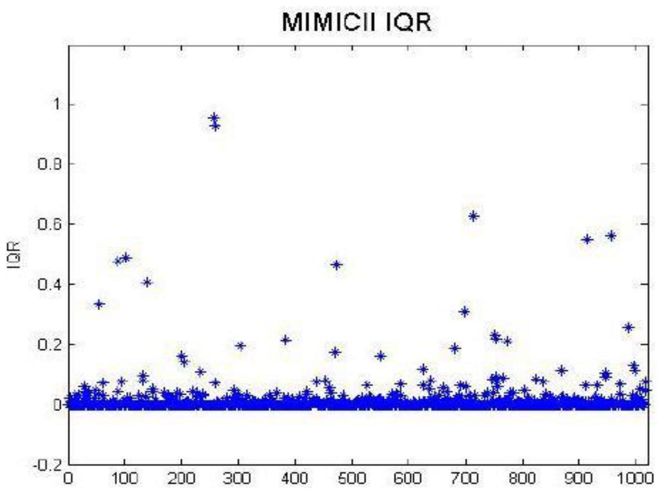

Fig.5. MIMIC-II interquartile range (IQR) validation

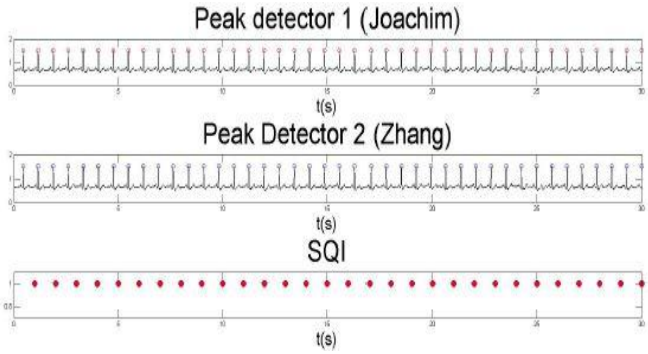

Fig.6. Good quality signal detected

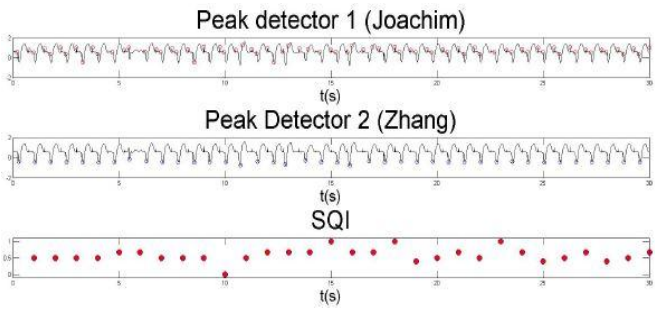

Fig.7. Bad quality signal detected

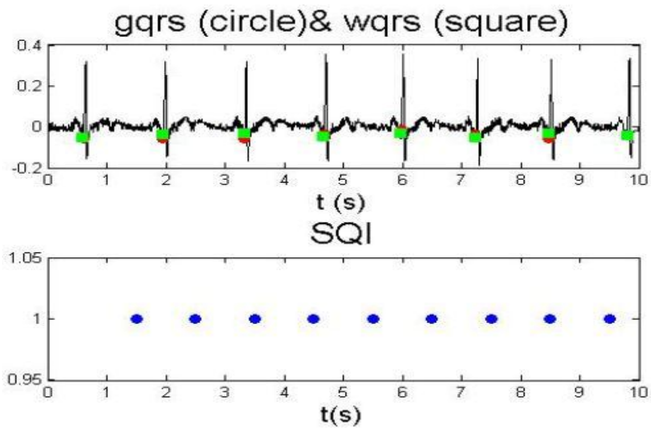

Fig.8. Good quality signal detected using wfdb format

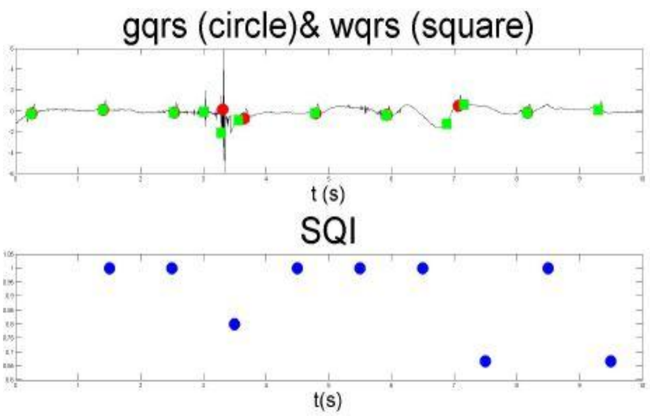

Fig.9. Bad quality signal detected using wfdb format

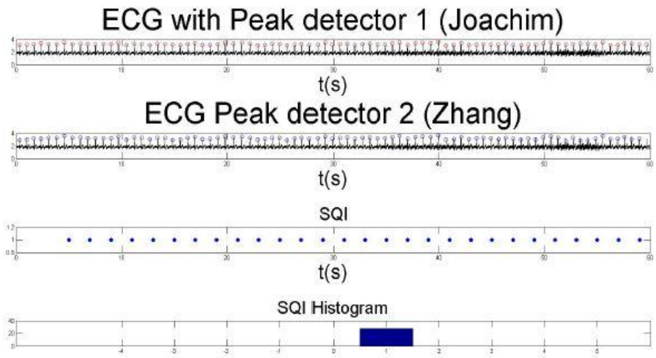

Fig.10. SQI for the acquired data

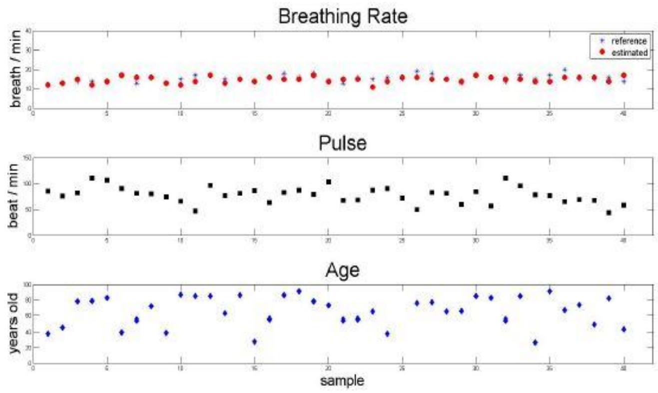

Fig.11. Comparison of BR estimation with the gold standard of the MIMIC-II data sets

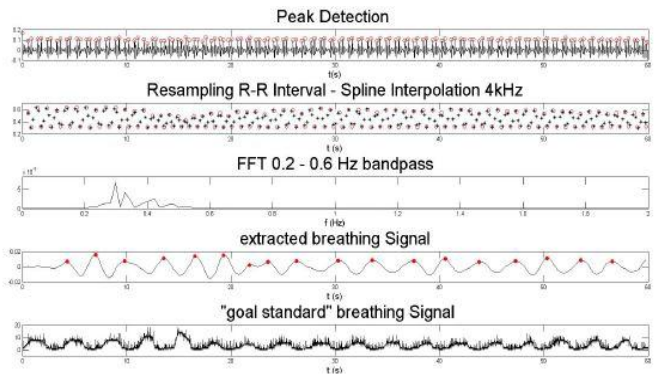

Fig.12. BR estimation using the proposed ECG acquisition system and BR estimation algorithm

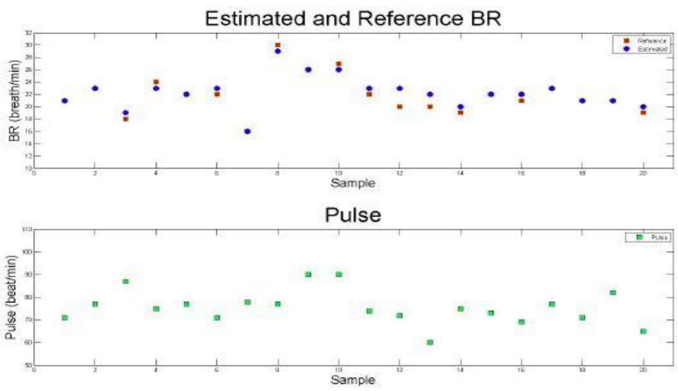

Fig.13. 20 data comparison to gold standard BR and HR of each recorded data

Conclusion

In summary, BR estimation integrated with the single-lead ECG acquisition system was developed. The proposed algorithm with working e-Health sensor platform yielded an MAE value of 0.7. The results indicate that the proposed hardware and the algorithm could replace the manually counted, uncomfortable nasal air flow sensor or chest band often used in hospitals.

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