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Fusion of Induced Variations Using Quality Metrics to Estimate Respiratory Rate from Photoplethysmography Signal

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Abstract: Among the vital signs of acutely ill hospital patients, Respiratory Rate (RR) is a highly accurate predictor of health deterioration. The most common method for measuring RR in hospitals is transthoracic Impedance Pneumography (IP). The drawback of IP which measures impedance at the electrocardiogram electrodes is the injection of high-frequency alternating current into the tissue through drive electrodes. Thus, IP becomes an active electronic device. The usage of IP may also cause natural breathing disturbance in patients and eventually contributes to discomfort. This study aims to evaluate the RR from passive and noninvasive acquisition module, Photoplethysmogram (PPG) signals. Algorithms comprise signal quality indices. The RR estimation method for extracting three respiratory signal-induced variations of PPG was described. The three respiration rates were combined through a weighted average using quality metrics for each signal. The weights were determined using good quality MIMIC II benchmark datasets. PPG signal and reference breathing signal using nasal air flow sensor of 20 healthy subjects have also been recorded and the RR has been combined. The Mean Square Error (MSE) was 0.86 breath/min compared with the reference RR. The proposed methodology could replace the manual counting method of RR, uncomfortable nasal airflow sensor, chest band and IP which are often used in hospitals. Given its simple setup, the future system can increase the efficiency of the RR monitoring frequency for patients with critical illnesses.

Key words: Respiratory rate, photoplethysmogram, algorithm, signal quality indices, estimation, critical illnessess

INTRODUCTION

Obtaining multiple vital signs from a single, simple, low-cost and easy-to-use non-invasive peripheral sensor is desirable to facilitate physiological telemonitoring. Reliable methods for tracking cardiorespiratory activity over time to monitor patients in intensive care environment or patients at home with long-term disease-associated instability in respiratory or cardiovascular function are clearly needed (Garde *et al*., 2014). Respiratory Rate (RR), Heart Rate (HR) and adequacy of oxygenation are the most important vital signs being measured and provide physiological indicators of critically ill ward patients (Goldhill *et al*., 1999). Among the vital signs, RR is the most essential parameter to monitor the condition of a patient's respiratory status and thus, prevent life-threatening complications (Addison *et al*., 2015). RR monitoring is done through many traditional methods including measuring air flow in or out of the lungs directly and measuring body volume changes indirectly.

Spirometry, inductance plethysmography and Impedance Pneumography (IP) are examples of cumbersome devices used to evaluate RR. The usage of those devices is troublesome as they may cause discomfort and are quite expensive. Transthoracic IP is the most common method used in hospitals to measure RR (Drummond *et al*., 1996). The principle of IP device is to measure changes in the electrical impedance of the person's thorax during respiration. The drawback of using IP is the injection of high-frequency alternating current into the tissue through drive electrodes thus, IP becomes an active electronic device (Prutchi and Norris, 2005).

Alternatively, pulse oximetry is widely used in health facilities to monitor physiological vital signs. It is based on the principle of Photoplethysmography (PPG), an optical measurement technique to detect blood volume changes in the microvascular bed of tissues; PPG consists of two light-emitting diodes to illuminate the tissue and a photo detector to detect the light reflected by the tissue.

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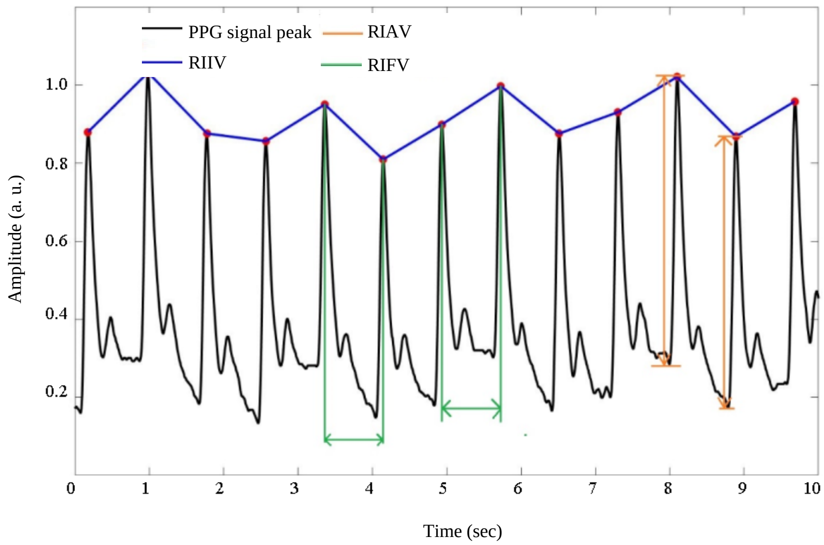

Fig. 1: Graph shows the PPG signal and three different modulation induced by the respiration: RIIV, RIAV and RIFV

The intensity of the detected light varies with each heart beat as the blood volume changes over time (Nilsson *et al*., 2000).

PPG signal is composite in nature and has 5 different frequency components at intervals of 0.007-1.5 Hz (Varady *et al*., 2002). Sources of these frequency components may be respiration, blood pressure control, thermoregulation, autonomous nervous system and heart-synchronous pulse waveform (Madhav *et al*., 2010). The pulsatile component of the PPG waveform signal is synchronous with cardiac rhythm and thus can be identified as the source of HR information. In addition to heart-synchronous variation, the respiratory activity may lead to three fundamental wave form modulations of PPG as shown in Fig. 1. They are Respiratory-Induced Intensity Variations (RIIV) Respiratory-Induced Amplitude Variations (RIAV) and Respiratory-Induced Frequency Variations (RIFV). RIIV is a baseline DC modulation of the PPG signal. During inspiration, decrease in intrathoracic pressure results in a small decrease in central venous pressure and eventual increase in the venous return. The opposite state occurs during expiration. As more blood is shunted from low-pressure venous system at the probe site and venous bed cyclically fills and drains, the baseline is modulated accordingly (Addison *et al*., 2015). RIAV is caused by the corresponding decrease in cardiac output because of reduced ventricular filling (Saeed *et al*., 2011). Moreover, RIFV is caused by an autonomic response to respiration causing variation of HR to synchronize with the respiratory cycle. RIFV is also referred to as respiratory sinus arrhythmia in which it increases during inspiration and decreases during expiration. Three respiratory-induced variations are present. Thus, combining them to obtain the most accurate RR is necessary.

In this study, we use a quality metric to combine the RR extracted from RIIV, RIAV and RIFV. Thus, we derive the RR of the subject.

MATERIALS AND METHODS

PPG signals and the reference respiratory signals from two different studies were used are MIT Physionet Multiparameter Intelligent Monitoring in Intensive Care II (MIMIC II) (Karlen *et al*., 2013; Orphanidou *et al*., 2015) and clinical study on healthy South-East Asian citizen (denote MH).

MIMIC II dataset is available for public use via MIT/Physionet website and consisting of 1017 patient data and sampling at 125 Hz and collected using patient monitors (component monitoring system intellivue MP-70, Philips healthcare) placed in every ICU bed. The reference respiration signals from IP are employed in this dataset.

MH database is collected as part of a feasibility study to investigate the suitability of the available wearable sensors. The PPG data are measured using blue finger pulse oximeter CMD 50+ and sampled at 75 Hz. The reference respiratory signals for MH are measured using nasal air flow sensor connected to Arduino UNO board at sampling frequency of 125 Hz. The sensor is placed near the nose of the subjects to measure the RR. The air flow sensor uses e-Health with two connections to e-Health board. The recordings were performed by the researcher. The subject population consists of 20 healthy South-East Asians, aged between 13 and 60 years old. The subjects were required to breathe normally. The data from the pulse oximeter and nasal air flow sensor are then synchronized analytically. Mean Squared Error (MSE) for MIMIC II and MH are determined after the analysis.

Signal quality index: Signal Quality Index (SQI) is an evaluation of the quality of PPG signals in two ways. Low-quality signals refer to any segments containing artefacts. Then, the correlation between an averaged beat's morphology and that of each individual beat is quantified using template matching. The signal quality is low if the average correlation coefficient across a segment is below an empirical threshold.

SQI for PPG starts with the PPG pulse-peak detection (Orphanidou *et al*., 2015) by using three-point peak detector. The peaks are as shown in Fig. 1. The PPG pulse and the entire detected peak will be selected for the regularity in a segment for the next template matching searches. First, median beat-beat interval of the detected PPG pulse peak is identified. Then, individual PPG pulses are extracted by taking a 10s-window. The window is centered on each detected PPG pulse peak. Afterward, the mean PPG pulse-wave template is obtained by taking the means of all PPG pulse waves in each sample. The correlation coefficient of each individual PPG pulse wave and the average PPG pulse wave template is calculated and will give a score between 0 and 1 (Orphanidou *et al*., 2015). Finally, the average correlation coefficient is obtained by averaging all correlation coefficients over the whole PPG sample. At this point, the threshold of good and bad segment or window is set as 0.8. This process aims to demonstrate that by restricting the amount of the low-quality signal which may be caused by the motion artefacts from the irregularity artefact presents in a segment of PPG signal, the MSE can be reduced in the RR estimation.

Respiratory rate estimation: As shown in Fig. 1, RIFV is derived from the PPG pulse peak (beat) intervals by converting it into tachograms. The tachogram is regularly resampled at 4 Hz grid to enable the Fast Fourier Transform (FFT) process. Each data is grouped into shifting windows of 1s and multiplied using Hamming window. After the FFT process, the signal is filtered using a finite impulse response band pass filter with cut-off frequencies of 0.1 and 0.6 Hz (equivalent to RRs of 6-36 breaths/min).

The maximum peak or intensity of the PPG pulses is used to extract RIIV and the amplitude of the PPG pulse is used to extract RIAV. As done in RIFV, the intensity and amplitude trend data are then resampled at 4 Hz by using linear interpolation. Finally, the RR is derived from the respiratory signal.

Quality metric and weighting method is needed to combine the estimated RR of different source of respiratory information from the PPG, depending on the quality. High-quality PPG data from 57 patients of MIMIC II data has been selected. The data have been evaluated through the SQI algorithm and the correlation coefficients of 0.98-1.0 for 8 min PPG recording were gained. A quality Q, ranging from 0-1 is computed for each respiratory-induced variations (intensity (QRIIV), amplitude (QRIAV) and frequency (QRIFV) to denote the reliability of the estimated rate from the signal. The final RR is computed as the weighted mean of the breathing rate of all signals and is defined in Eq. 1:

$$\text{Combined}_{\text{estRR}} = \frac{Q_{\text{RIIV}}\left({}^{\text{estRR}}{}_{\text{RIIV}}\right)+Q_{\text{RIAV}}\left({}^{\text{estRR}}{}_{\text{RIAV}}\right)+Q_{\text{RIFV}}\left({}^{\text{estRR}}{}_{\text{RIFV}}\right)}{Q_{\text{RIIV}}+Q_{\text{RIAV}}+Q_{\text{RIFV}}} \quad (1)$$

We use the combined RR in Eq. 1 to estimate the RR of 20 PPG data from MH and compare with reference RR. The final RR is then assessed using the MSE (breaths/min) and is defined:

$$\text{MSE} = \frac{1}{N}\sum_{i=1}^{N}\left(\text{Combined}_{\text{estRR}^i} - \text{Reference}_{\text{RR}}\right)^2 \quad (2)$$

RESULTS AND DISCUSSION

RR is widely used in hospitals as an indicator of health status. It is useful in diagnosing and determining the prognosis of a patient. Moreover, it is a key element in determination of physiological state and clinical deterioration of a person. RR can be used to monitor and simultaneously improve quality of life. The available devices used to evaluate RR cause quite a discomfort to patients. PPG which is simple, convenient and low cost is widely used in clinical settings to evaluate RR.

Three respiratory-induced variations, namely, RIFV, RIIV and RIAV can be obtained through the PPG. These variations correlate with each other. The heart rate will increase and decrease during inhalation and exhalation to form RIFV. Intrathoracic pressure variation will exchange blood between pulmonary and systemic circulation. RIIV or perfusion baseline variation will be formed. Next, the ventricular filling will be reduced to decrease cardiac output. Hereby, RIAV occurs.

In this study, we used quality metric to fuse the three respiratory-induced PPG modulations. The respiratory signals of 57 high-quality MIMIC II PPG dataset are used

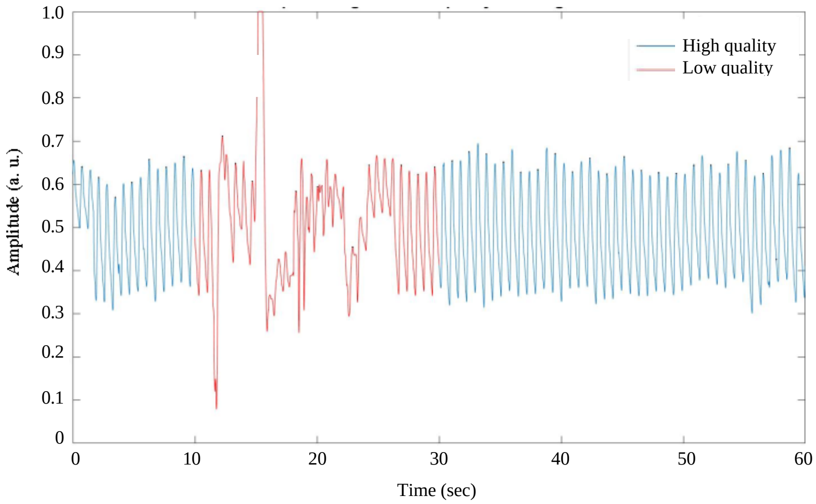

Fig. 2: Graph shows the PPG signal and three different modulation induced by the respiration: RIIV, RIAV and RIFV, a plot of high and low quality PPG segments

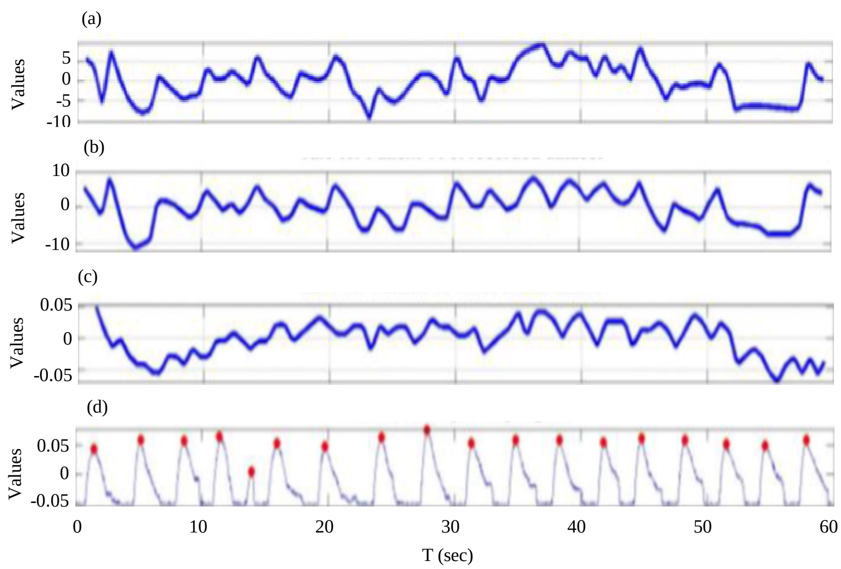

Fig. 3: RIIV, RIAV and RIFV of 11th subject from PPG data and its reference respiratory signal: a) RIAV for patient 11 of recorded dataset; b) RIIV for patient 11 of recorded dataset; c) RIFV for patient 11 of recorded dataset and d) Refrences respiratory signal

to determine the weights. The high-quality data of PPG signal are determined through the score of the signal quality index. The low-quality data of PPG signal, as shown in Fig. 2 are excluded because they contain only noisy PPG signals. This contributes to difficulty in RR estimation.

Figure 3 shows the example of the extracted respiratory signal from the 11th patient of MIMIC-II. After all the 57 subjects with good-quality PPG signal have been examined, the quality metric, i.e., QRIIV is 0.94, QRIAV is 0.92 and QRIFV is 0.88.

In this study, the quality signals for RIIV are highest, followed by RIAV. RIFV shows the lowest quality signals. The combined RR method has been used to estimate the RR for MH dataset and the result is shown in Fig. 4 and Table 1. The average RR from the 20 subjects is 21 breaths/min.

The obtained PPG signal is compared with the standard RR from nasal air flow sensor as the PPG signal is easily affected by poor blood perfusion, ambient light and patient motion (Karlen *et al*., 2013). The interpretation of PPG signals may result in errors caused by such

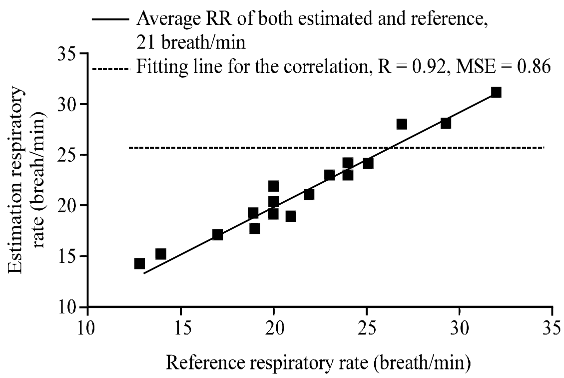

Fig. 4: Correlation between estimated and reference RR for our 20 samples

Table 1: The result of the estimated RR and the reference RR

Variables	Values
Number of subjects	20
MSE	0.86 breaths/min
p-value	1.63×10^{11}
R^2	0.92

artefacts (Elgendi., 2016). As shown in the graph of the estimated RR vs. reference RR, the method is useful with MSE of 0.86 breaths/min and $p<0.01$.

CONCLUSION

The method is reliable because an Mean Squared Error (MSE) of 0.86 breaths/min of the combined RR estimation using quality metrics for respiratory rate estimation is achieved. The proposed methodology could replace the manual counting method, uncomfortable nasal airflow sensor, chest band and IP. Given its simple setup it can increase the frequency of RR monitoring for patients with critical illnesses in the future.

This analysis is limited in terms of management of low-quality data. SQI was used to detect and exclude low-quality data. A complex technique that combines the results of multiple SQI is suggested to evaluate the signal quality. Such a technique should strengthen the RR algorithm performance in clinical practice (Charlton *et al*., 2016). An alternative method is needed to ensure that the data are accurate even when low-quality data are used.

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