Internet-of-Things Based Respiratory Rate Monitoring for Early Detection of Cardiovascular and Pulmonary Diseases

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1 Introduction

Cardiovascular and pulmonary diseases are the leading causes of death in many developed and developing parts of the world, with a total of 21% and 19% of annual deaths attributed to these, respectively, in the age group of 25–69 years [1]. It is widely acknowledged that the problem of increasing risk factors for cardiovascular and pulmonary diseases is the lack of surveillance system for timely diagnosis [2]. These challenges are acutely amplified in rural and remote regions, where there is a startling lack of accessibility to healthcare facilities due to which villagers do not generally go for regular health checkups. Apart from the lack of accessibility, many villagers cannot afford to visit far away specialty hospitals to see a physician, unless critically ill.

One of the promising technological solutions that can potentially bring about a marked change in this situation is the use of Internet-of-Things (IoT) based remote health monitoring (RHM). Our research group at Amrita University in collaboration

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with our large University hospital, Amrita Institute of Medical Sciences (AIMS), India, has developed an IoT based RHM system in which patients use a body worn IoT device that includes ECG and photoplethysmograph (PPG) sensors that continuously monitor their electrocardiograph (ECG), pulse rate (PR), respiratory rate (RR), blood pressure (BP), and blood oxygen (SpO2) [3]. A patient wears this device all day long on his/her wrist and the vital parameters are sent to physicians in specialty hospitals over the cloud or directly to their smartphones as and when required. The parameters sent from this device are used to monitor and detect, early on, many cardiovascular, pulmonary, and neurological disorders such as cardiac arrest, cardiac arrhythmias, sleep apnea, hypertension and stroke, pneumonia, chronic obstructive pulmonary disease, etc.

Along with the other vital parameters, respiratory rate (RR) is one of the most clinically relevant parameters that can diagnose and monitor the severity of many pulmonary, metabolic, neurological, and cardiovascular diseases. Moreover, the possibility of monitoring RR along with other vitals using small wearables increases the prospects of extending critical care to peripheral centers and subcritical care to homes. Some of the diseases that warrant such monitoring include metabolic acidosis (a complication of diabetes), acute respiratory distress syndrome, pneumothorax, acute asthma, pneumonia, chronic obstructive pulmonary disease (COPD), etc. These conditions can result in a type of respiratory failure wherein there is hypoxia (low PaO2) and Tachypnea. Some of the chronic lung diseases, including sleep apnea, could result in hypertrophy and failure of the right ventricle of the heart. Another very pragmatic application is the use of RR for identification and classification of pneumonia in children, according to the WHO clinical classification criteria: (a) 2–12 months: RR > =50/min, (b) 1–5 years: RR > =40/min, and (c) 6 years and above: RR > =20/min. The role of RR estimates in early detection of many critical diseases as well as the ease with which wearable sensors can be used to obtain PPG signals (which are modulated by respiratory signals), makes it even more important to have robust algorithms for automated RR estimation from PPG signals. Hence, in this paper, we particularly focus on such algorithms that automatically estimate RR from PPG signals.

Our paper contributes the following:

- A review of existing reported work on RR measurement from PPG signals and their performances.
- A real-world validation of a PPG based IoT sensor on 25 subjects, for computation of RR.
- A comparison of 15 different processing algorithms for RR derivation from PPG signals.

The rest of this paper is organized as follows: In Sect. 2, we begin with a review of related work. In Sect. 3, we describe our system architecture. We detail the experimentation design, the sensor device, algorithms used, and data collection procedure in Sect. 4. We present our validation study results in Sect. 5, and finally we conclude this paper in Sect. 6.

2 Related Work

Addison et al. [4] estimated the respiratory rate using an algorithm based on continuous wavelet transform technology within an infrastructure incorporating weighted averaging and logical decision-making processes. The correlation coefficient between this method and an end-tidal CO_2 reference rate is reported as 0.93. Garde et al. [5] employed an algorithm based on the correntropy spectral density (CSD) to estimate the respiratory rate. They tested the algorithm against the CapnoBase benchmark dataset [6]. It gave them an unnormalized root mean square error of 0.95 breaths/min and a median error of 4.2 breaths/min when using 60 s windows and 1.9 breaths/min when using 120 s windows. The median error significantly decreased ($p < 0.05$) with longer time windows when CSD (from 1.77 to 0.95 breaths/min) approach was employed.

Madhav et al. [7] created an algorithm called modified multiscale principal component analysis to estimate the respiratory rate from PPG signals. The number of data set used in this paper is 15 healthy subjects and the reported accuracy was 98%. Lin et al. [8] estimated the respiratory rate from the PPG signal using a wavelet-based algorithm (the complex Morlet wavelet). They conducted an experiment with five healthy subjects. The correlation coefficient between the respiratory rate derived from PPG signal and respiratory signal is 0.9678. Nilsson et al. [9] used a third order Butterworth Band-pass filter with a pass-band from 0.1 to 0.3 Hz. The obtained average error is <0.5 breaths/min when compared to the reference rate, with a correlation of 0.93. These works present a representative set of the broad research literature that is available in the area [10, 11]. We summarize and compare these techniques in Table 1.

Table 1 Comparative analysis of different methods to estimate respiratory rate from PPG

Work	Methods	Sample characteristics	Results
Addison et al. [4]	Continuous wavelet transform	139 healthy adults (58 M, 81 F)	Correlation = 0.93
Garde et al. [5]	Correntropy spectral density	59 children (median age: 8.7) and 35 adults (median age: 52.4)	Error = 1.77–0.95 breaths/min
Madhav et al. [7]	Modified multiscale principal component analysis	15 healthy subjects, age group of 32.5 ± 3.8 (nine male and six female)	Accuracy = 98%
Lin et al. [8]	Wavelet	5 healthy subjects (male, aged 24 ± 1 years)	Error = 0.2534 breaths/min
Nilsson et al. [9]	Third order Butterworth band-pass filter	16 healthy subjects	Error = <0.5 breaths/min Correlation = 0.93

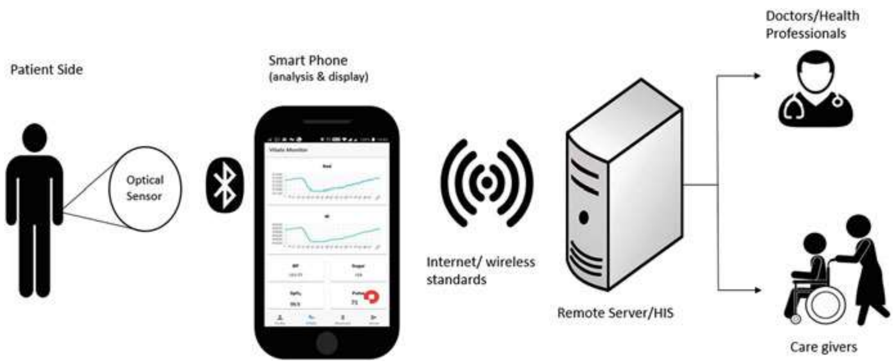

Fig. 1 System architecture showing the transmission of PPG signal from the patient's body to the doctors via mobile app interfaced with the Hospital Information System (HIS) cloud server

3 System Architecture

Our system architecture (see Fig. 1) incorporates different sections, namely sensors and visualization application on the patient side, wireless transmission from the smartphones to the remote server, and the applications running on this remote server. On the patient side, an optical sensor collects PPG signals from a patient's finger-tip, which is used as the primary signal for respiratory rate estimation. The PPG signals are transmitted from the sensor to the patient's smartphone using the Bluetooth Low Energy (BLE) module equipped in the sensor platform. An Android application receives the PPG data, and derives three different vital parameters: pulse rate (PR), blood oxygen (SpO2), and respiratory rate (RR). The values of these parameters are displayed on the smartphone for user assessment, and it is also send to remote hospital information system (HIS) over the internet. Later, a medical expert or caregiver can make use of this information for analysis of a patient, who can then be given advice or prescription remotely. In this paper, we particularly focus on RR estimation from the PPG signals.

4 Experimental Evaluation

4.1 Sensor Device

We used a commercially available off-the-shelf IoT PPG sensor device from Maxim [12] to collect the PPG signals from volunteers. This sensor platform, called Maxim MAXREFDES100#, has multiple health and environment monitoring sensors, including one pulse oximeter that we use in our application. This device uses photoplethysmogram (PPG) based sensor to obtain reflected PPG signal. By using a pulse oximeter which illuminates the skin, it can measure the light reflected by

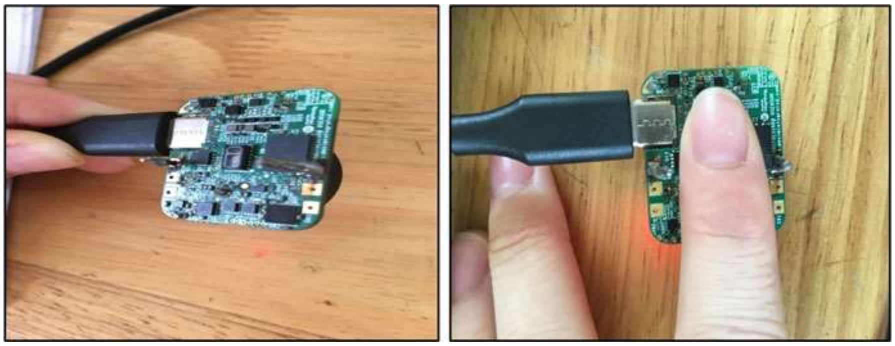

Fig. 2 The Maxim PPG sensor platform that was used for experimentation and data collection

the blood, and generate PPG waveforms in infrared and red regions of the spectrum. Using these signals, we derive RR.

We also used Maxim's Health Sensor Platform for visualization and storage of the PPG signal in a PC. This platform also allows the PPG sensor signal to be stored in a csv file format, which enabled us to use the data for further processing. Figure 2 shows the Maxim PPG sensor device as well how the volunteers used it during our experimentation. Figure 3 shows the screenshot of the user interface that visualizes the PPG signal as well as provides options to tweak the sensor device parameters.

4.2 Algorithms for Computing RR

Once the PPG signals are collected, it needs to be processed in three steps: (a) extraction of the respiratory signal from the PPG signal, (b) calculation of RR from the extracted respiratory signal, and (c) refining RR estimates. These three steps to compute respiratory rates are described below:

Extraction of Respiratory Signal The respiratory activity causes the PPG signal to be modulated in three fundamental ways: through baseline wandering, amplitude modulation, and/or frequency modulation. For the first step, i.e., extraction of the respiratory signal from the PPG signal, we employed two broad approaches: (a) feature based (see Table 2) and (b) filter based (see Table 3) techniques. These techniques are described by Charlton et al. [13]. They had tested these techniques on 57 healthy young subjects aged between 18 and 40 years and elderly subjects aged over 70 years. The correlation coefficient of the respiratory rate measured using gold-standard device and the one calculated using PPG was found to be 0.86 in their experiments. We used a publicly available toolkit [20] that provides a Matlab program to compare these different techniques, and adapted it to make it suitable for our data.

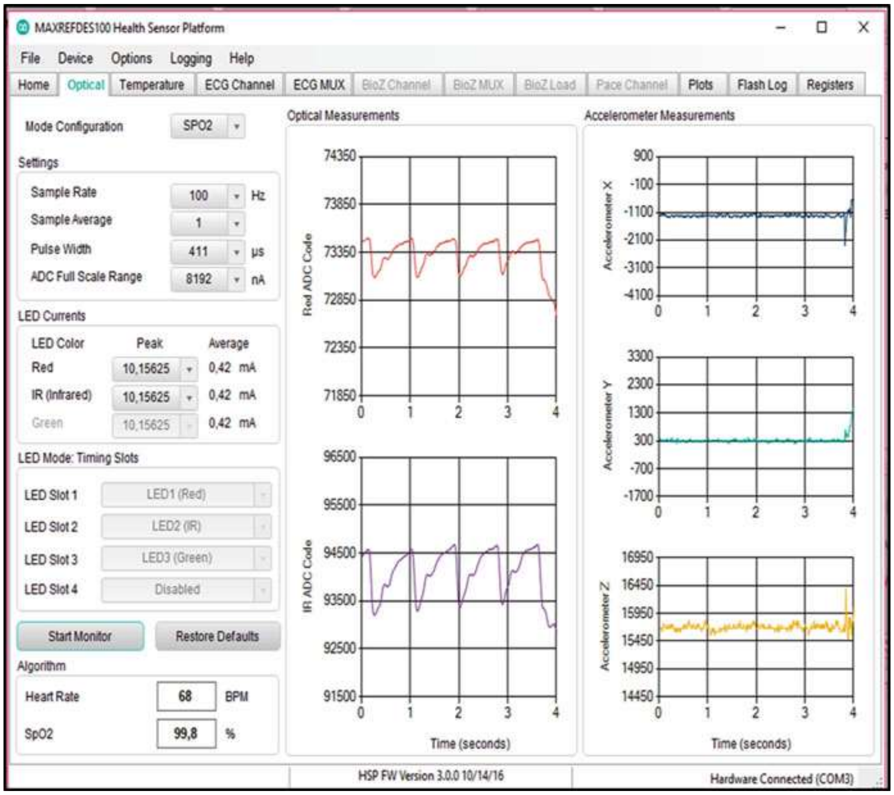

Fig. 3 Screenshot of the front-end software used for visualization of the PPG signals

Table 2 The feature based techniques used for extraction of respiratory signal from PPG signal (adapted from Charlton et al. [13])

Feature based processing	
XB1 (BW)	Mean amplitude of troughs and proceeding peaks (Charlton et al. [13])
XB2 (AM)	Difference between the amplitudes of troughs and proceeding peaks (Karlen et al. [14])
XB3 (FM)	Time interval between consecutive peaks (Karlen et al. [14])
XB4 (BW)	Mean signal value between consecutive troughs (Ruangsuwana et al. [15])
XB5 (BW, AM)	Peak amplitude (Karlen et al. [14])
XB6 (BW, AM)	Trough amplitude (Ruangsuwana et al. [15])
XB9 (BW)	Kernel principal component analysis using a radial basis function, with the variance of the Gaussian kernel determined by maximizing the difference between the first eigenvalue and sum of the remainder (Widjaja et al. [16])
XB10 (FM)	PPG pulse width estimated using a wave boundary detection algorithm (Lázaro et al. [17])

Table 3 The filter based techniques used for extraction of respiratory signal from PPG signal (adapted from Charlton et al. [13])

Filter based processing	
XA1 (BW)	Band-pass filter between plausible respiratory frequencies (Lindberg et al. [18])
XA2 (AM)	The maximum amplitude of the continuous wavelet transform (CWT) within plausible cardiac frequencies (30–220 beats/min) (Addison [19])
XA3 (FM)	The frequency corresponding to the maximum amplitude of the CWT within plausible cardiac frequencies (Addison [19])

Estimation of Respiratory Rate After the respiratory signal is extracted, we employed either one of the two techniques for computation of the respiratory rates: (a) Count Orig—estimates the RR using an implementation of Count Orig [21], and (b) FTS—calculates the frequency spectrum of a signal using FFT (Fast Fourier Transform).

Fusion Techniques for Better Respiratory Rate Estimates Two data fusion techniques, namely Smart Fusion [14] and temporal fusion, were used to further improve the quality of the extracted RR signals.

5 Result and Analysis

We conducted the validation of the wearable IoT device and the above described algorithms with the help of 25 volunteers (12 female and 13 male) in the age group of 23–30 years. First, the volunteers had to sit on a chair and rest for 2 min. Then they have to place their right index finger on the PPG sensor device for 2 min. We did not use any external device to measure the reference respiratory rate, and hence, each subject was asked to mentally count the number of breathing cycles that they took during these 2 min. This count was then entered into the program as the reference rate.

Once all the data was collected, we used a Matlab program [20] to analyze the performance of different algorithms in deriving RR from the PPG signals. The performance of algorithms was compared against the reference RR, and we report the mean absolute error (MAE) as the evaluation parameter.

5.1 Modulation

The algorithms based on frequency modulation (FM) suited best for 8 subjects (MAE $=$ 0.29 breaths/min) as against for six based on amplitude modulation (AM) (MAE $=$ 0.37 breaths/min), five on baseline wandering (BW) (MAE $=$ 0.70 breaths/min), and six on combination of the modulations (MAE $=$ 0.9 breaths/min).

5.2 Feature Based Vs. Filter Based

In general, the least MAE was observed for algorithms which used feature based techniques for respiratory signal extraction. Of the 25 volunteers, 22 gave the best results for feature based techniques, whereas three had the best results using filter based techniques. However, we observed that for different subjects, different feature based algorithms gave the best performance. In 22 subjects in whom the feature based techniques performed the best, the average MAE was 0.54 breaths/min. While for three subjects in whom the filter based technique performed the best, the MAE was 1.3 breaths/min.

5.3 Respiratory Rate Estimation

In the second step, i.e., estimation of the respiratory rate, Count Orig [21] gave best performance on 14 volunteers (with average MAE = 0.58 breaths/min), whereas FFT based technique showed least errors in the rest of 11 subjects (with average MAE = 0.69 breath/min).

In the third step, i.e., fusion of different respiratory signals for further refinement of the results, we observed that out of the 25 subjects, 18 showed improved results using Smart Fusion ($N = 5$) and temporal fusion ($N = 13$).

5.4 Discussion

From these results, we observe that feature based techniques are comparatively better in the extraction of RR signals from the PPG signals, and Count Orig algorithm performs marginally better RR estimation in the subsequent step. These observations are largely corroborated in other studies as well, and our real-world validation using an IoT device provides stronger support to the already existing evidence in this domain.

Since the subjects had to count themselves the number of breath they took during the 2 min of experimentation, it is highly probable that some of the subjects might have made errors in counting. They may also have moved their fingers during the experiment, which might have caused some noise in the PPG signal. The first problem could be solved by using gold-standard devices for measuring RR. The second problem could be solved using a finger-clip that keeps the sensor tightly fixed to the index finger, giving little chance for any movement noise to creep into the PPG signal.

6 Conclusion and Future Work

In this work, we set out to use a single PPG sensor device to derive respiratory rate of patients. We report that the best methods for extraction of respiratory signal from PPG signal are based on feature based techniques, and Count Orig algorithm performed best in respiratory rate estimation. We believe that this is one of the first steps of estimating respiratory rate precisely, using PPG signals. With this single sensor and corresponding software algorithms, people in remote villages will be able to monitor their respiration rate which could be sent to their doctors remotely. This device and the algorithms have far reaching impact in detecting and potentially preventing many NCDs like pneumonia, sleep apnea, or chronic respiratory diseases. This could also drastically improve the early diagnosis and health monitoring of children in remote areas, thereby reducing the child morbidity and mortality rates.

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