ECG Derived Respiratory Rate Estimation for Wearable Devices

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***Abstract*-We propose a novel method for the estimation of respiratory rate in real-time from the electrocardiogram (ECG) signals catered to the deployment on wearable devices. Continuous data acquisition on wearable devices will lead to predatory battery consumption. We developed a model which learns the respiratory induced inter beat variability representations from a 10 second ECG epoch using the statistical methods of PCA. The coefficients of the principal components describe these learned representations which are generalized to breaths per minute (bpm) using the cubic spline extrapolation technique.**

The proposed method was validated using the physiological recordings from the Physionet – Fantasia Database after the application of preprocessing methods, achieves an overall mean absolute error (MAE) of 0.5. The experimental results of elderly subjects (MAE 0.15) outperformed that of young subjects (MAE 0.85), notably due to the heart rate variability. Consequently, further investigations are recommended.

Keywords- Electrocardiogram; PCA; Respiratory Rate; Extrapolation; Cubic Spline

I. INTRODUCTION

The ability to gauge respiratory rate (RR) remotely and track its trend over time is essential to the development of physiological telemonitoring. An anomalous RR is a subtle precursor of an impending critical illness that often accompanies, and may precede, changes in other non-invasively monitored vital signs including blood pressure (BP), heart rate (HR) or drop in peripheral oxygen saturation (SpO2) [1]. Conventional respiratory signal acquisition methods include pressure sensors, impedance sensors and a thermistor in the nose. However, there are two common disadvantages of using these devices: 1) these complex devices involved might interfere with natural physiological breathing. 2) Such devices cannot be used for certain clinical purposes, for example, ambulatory or long-term monitoring in naturalistic settings [2]. In a number of situations, non-occlusive, non-intrusive and non-invasive methods are highly desirable [3]. In recent times, various methods [4] demonstrated the use of accelerometers, electrocardiography (ECG) and photoplethysmography (PPG) for the estimation of RR using wearable sensors. An array of prevalent wearable devices including smart watches, record the pulse oximeter (PPG) and ECG signals. Thus, RR estimation within the acceptable degree of deviation will help in the realization of a holistic remote healthcare monitoring ecosystem.

The design of wearable sensors is rife with challenges including system size and weight minimization to increase comfort, maximizing battery life and mitigating the corruption of recorded signals by motion artifacts whilst maintaining wearability [5]. Continuous acquisition of signal data will lead to predatory battery consumption. We address this challenge by estimating the RR from a 10 second ECG epoch and extrapolating it to breaths per minute (bpm) units. This will expedite the deployment of RR estimation gainfully in real time applications.

The novel contribution of this research can be summarized as follows:

- RR forecasting from 10 second ECG epoch;
- Reduced prediction error;
- Monitoring in real time - wearable applications.

II. RELATED WORK

Several techniques can be used to obtain a respiration signal from an ECG. The respiratory signal extraction from ECG is known as ECG Derived Respiration (EDR). Yi and Park [6] proposed a method that yielded two sub signals: a detailed and an approximated signal representing the upper half and the lower half of the frequency components respectively. They were obtained at every level of the discrete wavelet transform (DWT) application on the ECG signal. The derived respiratory signal was the reconstruction of the ninth decomposition detail signal in the frequency band of 0.2-0.4 Hz and zero crossing detector in the falling direction was utilized to enumerate the respiration periods. This yielded a correlation with nasal airflow of greater than 90% when monitoring ECG during sleep.

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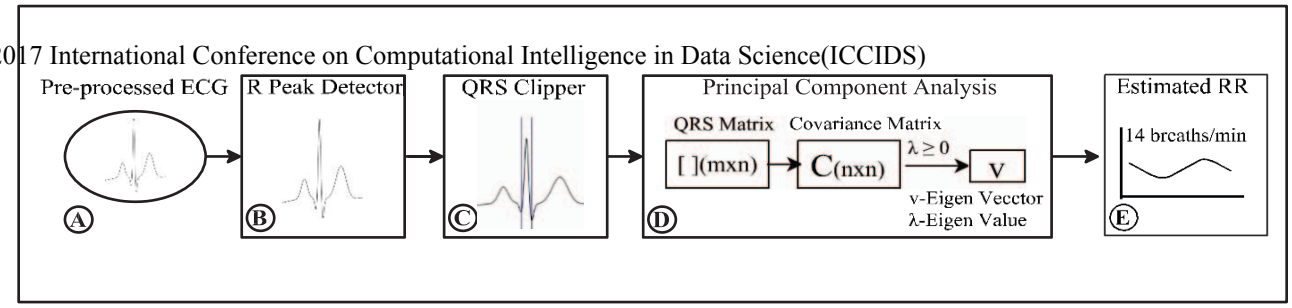

Fig 1: Block Diagram, The ECG is Pre-Processed (A) using wavelet based algorithm, then R-Peaks (B) are detected using Hilbert-Transformation and moving average filtering on the Shannon Energy Envelope. Later, QRS component (C) is clipped using fixed window size of 40 ms around the R- Peaks. QRS complex of each beat is synthesized into a matrix to facilitate the application of PCA (D). The estimated EDR is extrapolated to breaths/minute using Cubic Spline Extrapolation (E) technique.

R peak detection from the ECG signal is another technique which turns out to be computationally less complex making it more suitable for wearable applications. The derivation of respiratory signals based on the source statistics [7] was reported to be robust against noise. In this work, the higher order statistics of signals were invoked and reported an accuracy rate on the upward of 93%. However, the conventional methods that made use of lower-order statistics and the geometric characteristics of feature waves reported lower metrics.

Other approaches include the detection of both R and S amplitudes. A cutoff frequency of 5 Hz and 40 Hz for high-pass and low-pass filter respectively, followed by QRS detection was applied by Dobrev and Daskalov [8]. The derived respiratory signal was the result of second order low pass Butterworth filter smoothing over the sum of the absolute values of R and S wave amplitudes. Mason and Tarassenko [9] determined the R wave (R-EDR) and S-wave amplitude (RS-EDR) after preprocessing methods (high pass filtering and baseline wander removal). The S-wave was defined as the minimum value in the 0.1s window after the R-peak. Validation was carried out on a polysomnography database, RS-EDR method exhibited better performance with 77% sensitivity in comparison with 68% of R-EDR method.

Respiratory Sinus Arrhythmia (RSA) is a widely studied and well-known phenomenon, Schafer and Kratky [10] investigated RSA for the evaluation of respiratory signals. Peaks and troughs were detected on the detrended ECG signal, peak values above a threshold limit set as 0.2 times the 75th percentile of all peak values were preserved while others remain ignored. Valid breaths were identified as consecutive peaks separated by only one trough with amplitude less than zero. The mean respiratory rate results of young supine subjects yielded good approximations while elderly subjects recorded less accuracy.

In recent studies, RR estimation via the application of statistical methods of the principal component analysis (PCA) on the heartbeats has exhibited encouraging results. One study [11] applied PCA for the derivation of surrogate respiratory signals from one-lead ECG signals. Correlation and coherence coefficients were found to be high ($p<0.0001$ and $p<0.05$ respectively). Another study [12] demonstrated an enhanced EDR algorithm modelled on kernel PCA (KPCA). KPCA is a generalization of PCA where nonlinear mapping is carried out on the nonlinearities in the data. The results observed in this method outperformed the other methods with better coherence and correlation coefficients ($p < 0.0001$). However, since the processing complexity of algorithm plays a significant role with deployment on wearable devices, we adopted the PCA approach [11].

III. PROPOSED APPROACH

A. *Preprocessing*

The ECG signals obtained from the PhysioNet - Fantasia database [13, 14] required the application of preprocessing techniques as it was contaminated with multiple noise components including high frequency noise and baseline wander. The baseline wander removal was carried out by implementing the wavelet transformation method over the ECG signals [15] and a filtering mechanism to capture the respiratory signal frequency spectrum (0.2 Hz – 0.4 Hz).

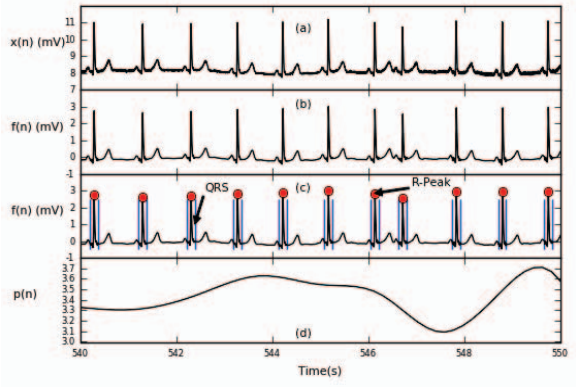

Fig 2: Graphical Representation of results at each step for f1o07 between 540 to 550s. (a) Raw ECG signal (x(n)), (b) ECG signal post preprocessing (f(n)), (c) R-peaks and QRS windows at each beat, (d) EDR for the epoch under consideration (p(n)).

Table-I Validation of results with Reference RR signals from Fantasia Database.

ECG Sample ID	Signal Interval (ms)	Reference RR R(n)/bpm	RR (Proposed method) E(n)/bpm	Absolute Difference Error	Mean Absolute Error
f1o01	180-240	17	17	0	0.15
f1o02	180-240	17	17	0	
f1o05	540-600	12	12	0	
f1o06	240-300	17	17	0	
f1o07	540-600	14	14	0	
f2o06	240-300	12	12	0	
f2o07	180-240	15	14	1	
f1y02	240-300	15	13	2	0.85
f1y04	600-660	19	20	1	
f1y05	120-180	21	20	1	
f1y06	240-300	15	14	1	
f1y07	180-240	15	14	1	
f1y08	180-240	14	14	0	
f1y09	180-240	21	21	0	

B. R peak detection

The implementation of Hilbert-transformation (HT) and moving average filtering in unison on the Shannon energy envelope (SEE) [16] was followed due to its simplicity and robustness. The Shannon energy envelope, s[n], is computed as

$$s[n] = -\tilde{d}^2[n]\, log(\tilde{d}^2[n]) \quad (1)$$

where $\tilde{d}[n]$ denotes the differentiated ECG (dECG) signal after normalization. The major advantage of SEE approach is its R-peak detection supremacy in the presence of small and wider QRS complexes, and non-stationary noise.

C. QRS segmentation

For a normal adult, the QRS complex duration exhibits variation between 75 to 85 ms, In order to extract the QRS complex from each beat, a discrete window of 80 ms duration (median variability) was applied around the detected R-peaks (40 ms prior to and 40 ms post each peak) [17].

D. PCA

To estimate the principal components, extracted QRS segments were fed as separate columns to the input matrix (X). If there exists n-beats, and each segment is of size m, then we will have a matrix of order m × n. Using linear PCA on the input matrix X, we can compute C (covariance matrix) using the following equation:

$$C = \frac{1}{m} \sum_{j=1}^{m} x_j x_j^T \quad (2)$$

which will be of order n × n. Subsequently, the eigenvalue problem $\lambda v = Cv$ is solved resulting in eigenvalues $\lambda \geq 0$ and eigenvectors:

$$v \in Rn \setminus \{0\} \quad (3)$$

The EDR signal is then derived from the first eigenvector v^1 [12].

E. Extrapolation

The estimated EDR characterizes the 10 second ECG epoch. To deduce the respiratory rate in breaths/minute, cubic spline extrapolation (piecewise cubic polynomial which is twice continuously differentiable) is performed [18]. The input signal for this cubic spline function is the estimated EDR signal. The boundary condition for this function is set to be periodic, where the first and last value of both first order and second order derivatives are equal. The resultant signal from this function is the extrapolated EDR signal in breaths/minute.

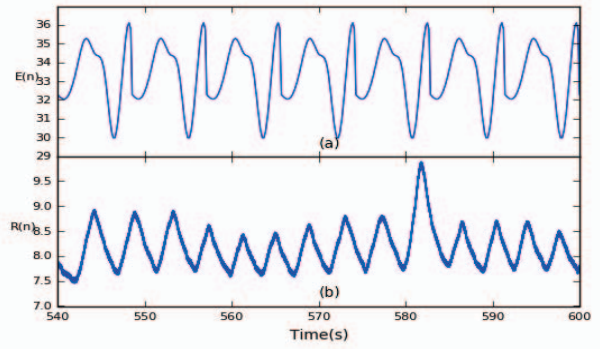

Fig 3: Graphical Representation of result: (a) Extrapolated EDR (E(n)), (b) Reference signal (R(n)) for f1o07 in interval 540 to 600s.

IV. RESULTS AND CONCLUSION

The proposed EDR model is modeled and evaluated using the recorded ECG and respiratory signals available in the Fantasia database. It comprises of recordings sampled at 250 Hz with beat annotations, from 40 subjects (20 elderly and 20 young) healthy subjects who underwent 120 minutes of resting state data recording. ECG recording data from 14 subjects selected randomly with elderly and young subjects considered in equal proportion. From each subject's dataset, 10 second signal epoch was extracted at random for the analysis.

The extrapolated ECG derived respiration signal (Figure 3) was derived from the 10 second ECG epoch (Figure 2). The R-R interval and the magnitude of R peak exhibit variations in accordance with its corresponding respiratory signal. With the implementation of PCA, the variance is preserved in the first principal component, presented in Figure (3) in the interval 540 to 550s.

From Table I, we can observe that with just 1/6th of the recorded ECG data requirement of other approaches, the overall mean absolute error (MAE) is 0.5, MAE is defined as

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |R(n)_i - E(n)_i| \quad (4)$$

Where n, $E(n)$ and $R(n)$ denote the number of observations, the EDR and the reference respiratory rate respectively. The performance of the algorithm is noteworthy for elderly subjects with a MAE metrics of 0.15 while it is 0.85 for young subjects. This disparity is due to increased heart rate variability for young subjects [19].

Our proposed EDR model is catered to wearable physiological monitoring systems. The effectiveness of the developed model is pronounced as it requires only one-sixth of the existing systems' data requirements whilst conforming to the reference respiratory rate standards. This facilitates the dual benefits of reduced battery power consumption and negates the possibility of reduced signal quality indices due to human fatigue on prolonged signal acquisition procedures. Thus, the model is well suited for deployment on wearable devices for use by ambulatory patients.

A limitation of our developed model in its existing form is that the generalized RR in breaths/min is characterized by the data acquired in the 10 second epoch. The predicted respiratory signal variability is thus limited to the variability exhibited by the recorded signal. Implementation of superior forecasting algorithms to mitigate this shortcoming is beyond the scope of this work. In future, we invite supplementary work along these lines.

Not withstanding this limitation, the proposed model, in its ability to forecast respiratory rate with a mean absolute error of 0.15 for the elderly subjects, increased standby time due to reduced battery consumption and demonstrated comparable results with significantly reduced recording time makes this a strong contender for deployment on wearable devices facilitating quality ambulatory patient monitoring and wider clinical practice integration.

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