An EEMD-PCA Approach to Extract Heart Rate, Respiratory Rate and Respiratory Activity from PPG Signal

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***Abstract*—The pulse oximeter's photoplethysmographic (PPG) signals, measure the local variations of blood volume in tissues, reflecting the peripheral pulse modulated by cardiac activity, respiration and other physiological effects. Therefore, PPG can be used to extract the vital cardiorespiratory signals like heart rate (HR), respiratory rate (RR) and respiratory activity (RA) and this will reduce the number of sensors connected to the patient's body for recording vital signs. In this paper, we propose an algorithm based on ensemble empirical mode decomposition with principal component analysis (EEMD-PCA) as a novel approach to estimate HR, RR and RA simultaneously from PPG signal. To examine the performance of the proposed algorithm, we used 45 epochs of PPG, electrocardiogram (ECG) and respiratory signal extracted from the MIMIC database (Physionet ATM data bank). The ECG and capnograph based respiratory signal were used as the ground truth and several metrics such as magnitude squared coherence (MSC), correlation coefficients (CC) and root mean square (RMS) error were used to compare the performance of EEMD-PCA algorithm with most of the existing methods in the literature. Results of EEMD-PCA based extraction of HR, RR and RA from PPG signal showed that the median RMS error (quartiles) obtained for RR was 0 (0, 0.89) breaths/min, for HR was 0.62 (0.56, 0.66) beats/min and for RA the average value of MSC and CC was 0.95 and 0.89 respectively. These results illustrated that the proposed EEMD-PCA approach is more accurate in estimating HR, RR and RA than other existing methods.**

I. Introduction

Monitoring of cardiorespiratory signal like heart rate (HR), respiratory rate (RR), respiratory activity (RA), blood oxygen saturation and blood pressure accurately and reliably without disturbing the normal activities of patients is a task of interest for ubiquitous healthcare (u-health). It is also important for patients having long term cardiorespiratory diseases in the intensive care environment. Pulse oximeter based photoplethysmogram (PPG) signal is one of the strongest candidates for promoting the opportunities of ambulatory and tele-monitoring by monitoring the oxygen saturation (SpO_2) reliably and noninvasively. Extraction of HR, RR and RA from this simple, low cost and portable device attracts the researcher, which will be helpful not only for monitoring primary health care but also for detecting cardiorespiratory diseases.

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Respiratory signal can be monitored via direct (spirometric measurements) and indirect (capnograph, impedance pneumograph, nasal thermistor, abdomen belts, inductive photoplethysmograph, magnetometer and physiological signal derived) measurement techniques [1]. The direct measurement of respiratory signal is operable only at hospital settings and it is highly inconvenient for the patient [2]. Although most of the indirect measurement approaches reduce the patient discomfort for short term monitoring, they mostly suffer from requirement of additional devices, affects patient's natural breathing and unsuitable for ambulatory monitoring [2]. To overcome these limitations, researchers pay more attention on physiological signal (electrocardiogram (ECG) and photoplethysmographic (PPG) signal) derived respiratory activity monitoring. However, in the case of pervasive and tele-monitoring, PPG signal is more attractive than ECG signal for its simplicity, portability and small number of sensors.

PPG derived RR was first suggested by Nakajima *et al.* [3, 4] in the early 1990s using simple band pass filter. An automated algorithm based on wavelet transform was proposed by Leonard et al. [5, 6]. In addition to digital filtering [3, 4, 7] and wavelet transform [8], time domain methods [9-11], bivariate auto-regressive modeling [12-14] and time-frequency analysis [15, 16] were proposed to extract RR from the PPG signal. Though, all of these methods were proposed for estimating RR, there were none for estimating RA. Madhav *et al.* [17] first proposed the modified multi scale principal component analysis (MMSPCA) technique for extracting RA from PPG signal.

In this paper, we propose a novel approach based on ensemble empirical mode decomposition with principal component analysis (EEMD-PCA) for simultaneous estimation of HR, RR and RA from PPG signal.

II. Material and Method

A. Data

The MIMIC database contains [18] 121 simultaneous recordings of BP, ECG, PPG and respiratory signals of ICU patients. All signals were sampled at a rate of 125Hz. In this study, we extracted 45 epochs of simultaneous PPG and respiratory signal, each with a length of 30 seconds, to evaluate the performance of proposed EEMD-PCA based technique.

B. Extraction of PPG derived heart rate (HR), respiratory rate (RR) and respiratory activity (RA) using EEMD-PCA

The overall block diagram of EEMD-PCA technique is illustrated in Fig. 1. The overall process can be divided into four stages: (a) EEMD decomposition of PPG data, (b) Selection of intrinsic mode functions (IMFs) without artifacts, (c) PCA of the selected IMFs, (d) Extraction of HR, RR and RA. In the first stage, EEMD was used to decompose each epoch of a PPG signal into a series of embedded IMFs. In the second stage, the IMF containing artifacts was automatically identified and rejected. In the third stage, PCA was applied on the selected IMFs. Finally, the first and second principal component (PC) was retained for extracting HR, RR and RA. The remainder of this section provides the details of the four stages.

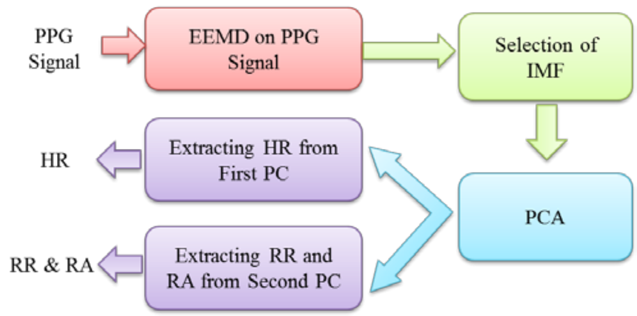

Figure 1. Overall block diagram of EEMD-PCA approach for extracting HR, RR and RA from PPG signal. (Different colors represent different stages).

a) Decomposition of PPG signal using EEMD

EEMD was applied to the PPG signal for decomposing into true IMFs. EEMD, a new noise assisted algorithm, was first proposed by Wu *et al.* [19] that eliminates the mode mixing dilemma of empirical mode decomposition (EMD) by defining the true IMFs of a data as the mean of an ensemble of trials, each consisting of the original signal plus a white noise of finite amplitude. According to the principal of EEMD, the original PPG signal $x(t)$ was added with white noise $n(t)$ with magnitude α to generate a new signal $y(t)$ and decomposed into true IMFs. The data $y(t)$ can be written as

$$y(t) = x(t) + \alpha n(t) \tag{1}$$

$$y(t) = \sum_{i=1}^{N} IMF_i(t) + r_y(t) \tag{2}$$

where, r_y is the residual of signal after N true IMFs are extracted.

b) Selection of IMFs and rejection of artifacts

Once the IMFs were obtained, the noisy IMFs should be identified and rejected. PPG signals are dominantly modulated by cardiac frequency (1-2 Hz) and respiration frequency (0.2-0.4Hz). To identify the artefacts, fast Fourier transform (FFT) was applied on each IMF to determine the dominant frequency, the frequency at which maximum power was obtained. Once all dominant frequencies were obtained, IMFs having frequency greater than or equal to 2.5 Hz were considered as artifacts and IMFs with frequency less than 2.5 Hz were selected for further processing.

c) PCA on the selected IMFs

To separate the cardiac and respiratory information from PPG signal, PCA was applied on the selected IMFs. PCA of the interrelated selected IMFs produced a number of uncorrelated variables which is called the principal components (PCs). PCs are ordered so that the first PC retained most of the variation present in the PPG signal, and so on. Since the artifacts are removed beforehand, we hypothesized that the PC presenting maximum and second maximum variance will represent the cardiac and respiratory activity respectively.

d) Extraction of HR, RR and RA

Since first PC represent the cardiac activity, FFT was applied on the first PC to extract HR frequency (f_{HR}) and then it was converted to HR using eq [3a]. Similarly, breathing frequency (f_{RR}) was extracted by applying FFT on the second PC and then it was converted to RR using eq [3b].

$$HR = f_{HR} * 60 \text{ (beats/min)} \tag{3a}$$

$$RR = f_{RR} * 60 \text{ (breaths/min)} \tag{3b}$$

Reference RR was calculated by applying FFT on the reference respiration signal obtained from capnograph and reference HR was calculated manually from ECG signal.

C. Performance measurement

To measure the performance of PPG derived RA, magnitude squared coherence (MSC), correlation coefficients (CC) and normalized root mean square error ($NRMSE$) of it was measured with reference respiration signal.

MSC is a widely used technique to measure the similarity between two signals in the frequency domain. MSC of the reference respiration signal and PPG derived RA was calculated as follows:

$$MSC = \frac{|P_{od}(f)|^2}{P_o(f)P_d(f)} \tag{4}$$

where, $P_o(f)$ and $P_d(f)$ are the power spectral density of original and PPG derived RA respectively. P_{od} is the cross power spectral density of original and PPG derived RA.

CC is another way of measuring similarity between two signals in time domain method, CC is defined as:

$$CC = \frac{COV(o,d)}{\sigma_o \sigma_d} \tag{5}$$

where, $COV(o,d)$ represent the covariance of reference respiration signal and PPG derived RA; σ_o and σ_d are the standard deviation of original respiration signal and PPG derived RA respectively.

$NRMSE$ was used for measuring the deviation of PPG derived RA from original RA. The equation for estimating $NRMSE$ is given below:

$$NRMSE = \left[\sqrt{\frac{\sum_{n=1}^{N}[o(n) - d(n)]^2}{\sum_{n=1}^{N}[o(n)]^2}} \right] \tag{6}$$

where, $o(n)$ and $d(n)$ represent the reference respiration signal and PPG derived RA respectively for n^{th} epoch and $N(= 45)$ is the total number of epochs.

Box-Whiskers plot, Pearson correlation measurement, un-normalized root mean square (RMS) error and Bland-

Altman plot were used for analyzing the robustness of EEMD-PCA based PPG derived RR and HR.

III. Results and Discussion

An example of the reference respiration signal and PPG derived respiratory activity is shown in Fig. 2. It is obvious that the PPG derived RA is visually analogous to the reference capnograph based respiration signal.

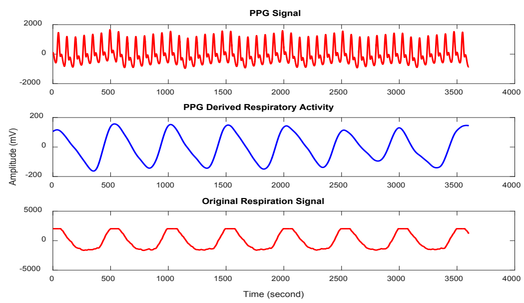

Figure 2. PPG signal, PPG derived respiratory activity and original respiration signal.

A. Respiratory Activity (RA)

MSC, CC and $NRMSE$ between PPG derived RA and reference respiration signal are shown in Fig. 3. The mean value of MSC and CC for 45 epochs was 0.95 and 0.89 respectively that is close to unity. In addition, the average value of $NRMSE$ was -1.24 dB. Since the MSC and CC value close to unity and lower value of $NRMSE$ represent more accurate or exact extraction of RA from PPG signal, we can summarize that EEMD-PCA approach provides nearly accurate estimation of RA from PPG signal.

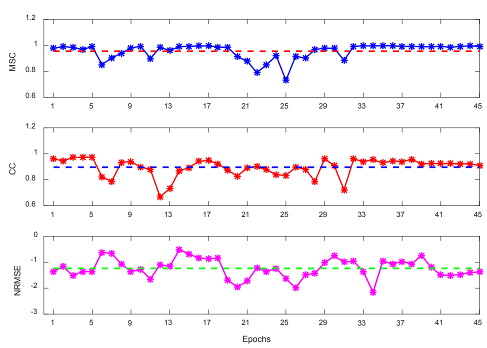

Figure 3. MSC, CC and $NRMSE$ measurement for different epochs between EEMD-PCA derived RA and reference respiratory signal.

B. Respiratory rates (RR) and heart rates (HR)

Box-whiskers plot of RR and HR rate extracted from reference signal and PPG derived signal are demonstrated in Fig. 4, where RR_R, RR_D, HR_R and HR_D represents reference RR, PPG derived RR, reference HR and PPG derived HR respectively. From the box-whiskers plot (Fig. 5), it was found that the derived rates were coincidental with their reference rates. Additionally, the median ($\text{median}(RR_R) = 16$, $\text{median}(RR_D)=16$) and inter quartile range (IQR) ($\text{IQR}(RR_R) = 4.01$, $\text{IQR}(RR_D)=4.50$) for RR_R and RR_D was nearly same. Similarly, the median ($\text{median}(HR_R) = 100.49$, $\text{median}(HR_D)=100.05$) and IQR ($\text{IQR}(HR_R) = 7.18$, $\text{IQR}(HR_D)=6.51$) for HR_R and HR_D was also nearly similar. These results indicated that the RR_D and HR_D were analogous to the RR_R and HR_R respectively.

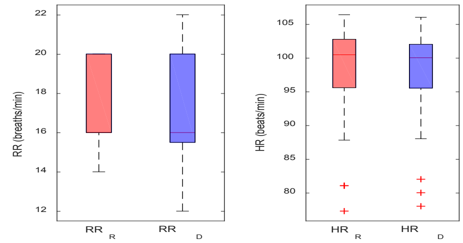

Figure 4. Box-Whiskers plot of reference and EEMD-PCA based PPG derived RR and HR.

The Bland–Altman plot is the preferred method for assessing the agreement between reference and new measurement. It shows the paired difference between the two observations on each event against the mean of these two observations. Bland-Altman plots of RR and HR derived from reference and PPG signal are shown in Fig 5. RR_R and RR_D showed a good agreement with very small bias (0.05) and 95% limit of agreement (-1.23, 1.33), which contain 95% of the difference scores (42/45). Similarly, HR_R and HR_D showed a very good agreement with a bias of 0.17 and 95% limits of agreement (-1.70, 2.04), which contain 100% (45/45) of the difference scores.

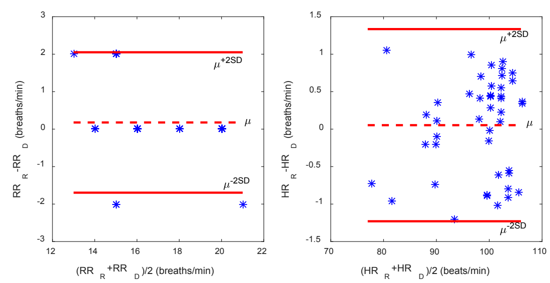

Figure 5. Bland-Altman plot for EEMD-PCA based PPG derived RR and HR with reference RR and HR. $\mathbf{LOA_{RR}}$ is -1.23 to 1.33 and $\mathbf{LOA_{HR}}$ is -1.70 to 2.04 (μ, SD and LOA represent the mean, standard deviation and limits of agreement respectively of the data).

Additionally, the accuracy of the EEMD-PCA based algorithm per epoch is illustrated in Fig. 6, where the estimated rates (RR_D and HR_D) and their reference values (RR_R and HR_R) for each epoch are represented. The Pearson correlation for RR and HR was 0.935 and 0.996 respectively as well as the goodness of fit for RR and HR was 0.875 and 0.992 respectively.

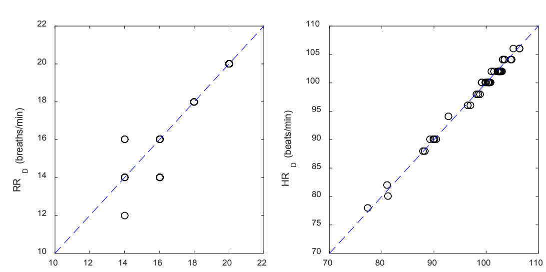

Figure 6. Pearson correlation between ground truth and EEMD-PCA based PPG derived RR and HR for each epoch (The dotted line represents the optimal performance).

The comparison of mostly available methods for extracting PPG derived HR, RR and RA is shown in Table I. The existing methods are mostly used to estimate either one or two parameters out of the three presented in this study. Although, studies were performed on different data sets EEMD-PCA based method provided the lowest median (=0) and IQR (0.89) among existing methods for RR estimation. Similarly, low median (=0.62) and the lowest IQR (=0.10) were also obtained using the proposed EEMD-PCA approach for HR estimation. Although, the median HR-RMS error obtained using proposed algorithm is not the lowest among existing methods, the lowest IQR of it shows higher stability in accurate estimating the HR than other existing methods. In addition, the CC value of respiratory activity of our proposed method (0.89) is considerably higher than MMSPCA based approach (0.68). All these results indicate that EEMD-PCA method performed better than existing methods in estimating HR, RR and RA from PPG signal.

TABLE I. COMPARISON FOR PPG DERIVED HR, RR AND RA WITH OTHER EXISTING METHODS

Methods	RR-RMS error (breaths/min)	HR-RMS error (beats/min)	RA
EEMD-PCA (Proposed)	0(0, 0.89)	0.62(0.56,0.66)	CC(0.89), MSC(0.95)
CSD [20]	0.95(0.27, 6.20)	0.76 (0.34, 1.45)	n/a
MMSPCA [17]	n/a	n/a	CC(0.68), MSC(0.96)
PSD [20]	3.18(1.20, 11.3)	0.58 (0.21, 1.17)	n/a
Smart Fusion [9]	1.56 (0.60,3.15)	0.48 (0.37, 0.77)	n/a
EMD [21]	3.5 (1.1, 11)	0.35 (0.2, 0.59)	n/a
T-F Analysis [22]	1.91 (0.41,7.01)	n/a	n/a
Digital Filtering [4]	7.47(0.59, 10.6)	n/a	n/a

IV. CONCLUSION

In this paper, we have proposed a unique algorithm for simultaneous estimation of three vital physiological parameters (HR, RR and RA) from PPG signal. Most of the previous researches reported the derivation of only one or two of the above parameters from PPG signal. In addition, the proposed novel EEMD-PCA approach showed more accurate results in estimating HR, RR and RA than other existing methods. In the future, we aim to verify this algorithm using large cohorts as well as subjects having different type of cardiovascular or cardiorespiratory diseases.

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