# Extraction of Respiratory Activity from PPG and BP signals using Principal Component Analysis

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*Abstract*— **In high risk situations such as cardiac arrhythmias, ambulatory monitoring, stress tests, sleep disorder investigations and post-operative hypoxemia situations, monitoring of respiratory activity would be mandatory. Electrocardiogram (ECG), blood pressure (BP) and photoplethysmographic (PPG) signals can be used for extraction of respiratory activity, and will eventually eliminate the use of additional respiratory sensor. Using a simple and standard non-parametric mathematical technique, Principal Component Analysis (PCA), the respiratory related information is extracted from complex data sets such as PPG and BP signals. The respiratory induced variations (RIV) of PPG and BP signals are described by coefficients of computed principal components. Singular value ratio (SVR) trend is used to find the periodicity, which is one of the crucial parameters in forming the data sets for PCA. Test results on MIMIC data base clearly indicated a strong correlation between the extracted and actual respiratory signals. Statistical measures in both time and frequency domains such as Relative Correlation Coefficient (RCC) and Magnitude Squared Coherence (MSC) respectively and Accuracy Rate (AR) are calculated to demonstrate the fact, that respiratory signal is present in the form of first principal components.**

***Keywords-Respiratory activity, PPG signal, Principal Component Analysis (PCA).***

## I. INTRODUCTION

Photoplethysmography is a non-invasive electro-optic method developed by Hertzman, which provides information on the blood volume flowing at a particular test site on the body close to the skin. A photoplethysmogram (PPG) is obtained by illuminating a part of the body of interest with either red or infrared light and acquiring either the reflected or transmitted light [1]-[2]. PPG waveform contains two components; one, attributable to the pulsatile component in the vessels, i.e. the arterial pulse, which is caused by the heartbeat, and gives a rapidly alternating signal (AC component). The second one is due to the blood volume and its change in the skin which gives a steady signal that changes very slowly (DC component). PPG signal consists of not only the heart-beat information but also a respiratory signal [3]. It is also evident from the literature that, the intra-aortic blood pressure (ABP) signals are also modulated by respiratory activity [4]. Different signal processing techniques like filtering, wavelets and other statistical methods, which work by extraction of respiratory trend embedded into BP signals, as an additive component, or an amplitude modulated (AM) component or frequency modulated (FM) component. Extraction of respiration activity from PPG and BP signals would be an alternative approach for obtaining information related to respiration.

### *A. Respiratory induced modulation of PPG and BP signals*

In addition to heart-synchronous variations, the PPG signal contains respiratory-induced intensity variations (RIIV) [5]-[7]. This modulation arises from respiratory-induced variations in venous return to the heart, caused by the alterations in intrathoracic pressure. A part of the respiratory-related fluctuations in perfusion also originates from the autonomous control of the peripheral vessels and is also synchronous with respiration.

Pulses Paradoxus (PP) is the inspiratory reduction in systolic blood pressure and is proportional to changes in intrathoracic pressure during inspiration and expiration [8]. Blood Pressure Variability (BPV) is due to the sudden increase in volume when, the heart contracts and the blood is pumped through the aorta in to arteries. Each time interval of systolic blood pressure has been shown to have a cyclic variation related to respiration.

### *B. PPG and BP derived respiration algorithms*

A bivariate AR spectral estimation method [9] demonstrated that there exist high coherence between spectrum of respiratory and PPG signals. An adaptive FIR filter [10], designed in frequency sampling method with suitable specifications drawn automatically from the PSD, efficiently estimates heart and respiratory related signals.

The blood pressure induced respiration is also extensively studied by different researchers. Various signal processing methods [11] were proposed for extracting BDR activity. These algorithms mainly utilize the amplitude and temporal variations of systolic blood pressure. In this paper, our work is also extended to estimate the breathing rates from the ABP signals.

### *C. Principal Component Analysis*

PCA identifies patterns in data, and expresses the data in such a way as to highlight their similarities and differences. Since patterns in data can be hard to find in data of high dimension, where the luxury of graphical representation is not available, PCA is a powerful tool for analyzing such data. PCA is a technique which is generally used for reducing the dimensionality of multivariate datasets i.e. reducing the number of dimensions, without much loss of information.

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Considering a vector of n random variables $x$ for which the covariance matrix is $\Sigma$, the principal components (PCs) can be defined by

$$z = Ax \quad (1)$$

where $z$ is the vector of $n$ PCs and $\mathbf{A}$ is the $n$ by $n$ orthogonal matrix with rows that are the eigenvectors of $\Sigma$ [12]. The eigenvalues of $\Sigma$ are proportional to the fraction of the total variance accounted for by the corresponding eigenvectors, so the PCs explaining most of the variance in the original variables can be identified. If, as is usually the case, some of the original variables are correlated, a small subset of the PCs describes a large proportion of the variance of the original data. PCA has found widespread application in ECG signal processing [13].

## II. Materials And Methods

MIMIC database of the Physiobank archive [14] contains multi-parameter data records of the ICU admitted patients. These records all contain simultaneously recorded PPG, Aortic Blood Pressure (ABP) and also respiratory waveforms for use as ready reference. Eight such identified records were used in assessing the accuracy of the algorithms for extraction of breathing rates. All these signals were recorded at a sampling rate of 125Hz. Five neat portions, each of one minute from eight different records are taken which did not have missing data in any of the three signals. An extrema detection algorithm is used for detection of time stamps for individual breaths in the reference respiratory signal, with results checked visually so that all of the respiratory cycles are compared with that of the derived ones.

### *A. Identifying the periodicity:*

SVD is applied to the aligned PPG data matrix and the ratio of first two singular values, called singular value ratio (SVR) is computed, in each case length of signal to be considered as a period for expected range of heart rates. The ratios are then plotted against the period to obtain graph called SVR spectrum of the signal. From SVR spectrum, the particular value of period for which the SVR is maximum, is considered as the period of PPG or BP signal as shown in Fig. 1 Then the data is aligned according to the period of the signal.

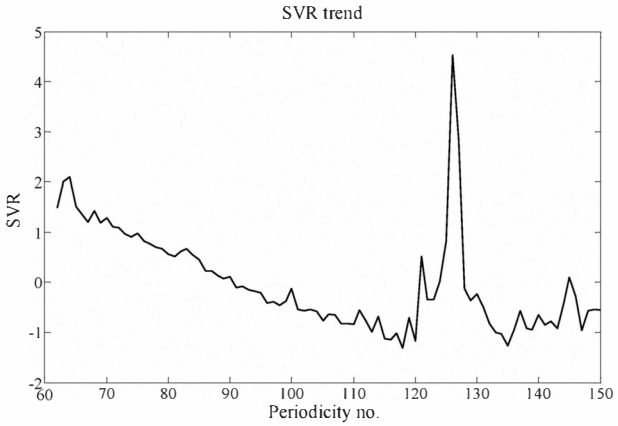


Figure 1. SVR profile for a typical PPG signal

### *B. Applying PCA*

The two methods by which PCA can be solved are covariance matrix method and the other singular value decomposition (SVD) method. The steps involved in covariance method are discussed below.

Form a data set by using the periodicity of the PPG signal. Periodicity will be found using SVR profile i.e. the ratio of first principal component to the second principal component. The data matrix $X$ is size of $m$ x $n$, where $n$ is the SVR computed periodicity and $m$ is the number of periods considered.

$$X(t)=[x_1(t), x_2(t), x_3(t),\ldots\ldots x_m(t)] \quad (2)$$

is the time ordered collection of the feature at all beats into a single matrix to which PCA can be applied. The means of the $x_i$ are removed and the covariance matrix computed. The covariance is defined as

$$\Sigma = \frac{1}{n}\left[X X^T\right] \quad (3)$$

$\Sigma$ is an $m$ x $m$ square symmetric matrix, eigenvalues ($a_j$) and corresponding eigenvectors ($\lambda_j$) will be calculated, In general, once eigenvectors are found from the covariance matrix, the next step is to order them by eigenvalue, highest to lowest. This gives you the components in order of significance. The lesser eigenvalues can be ignored; this will form the basis for compression. Principal components are ordered eigenvectors of the covariance matrix. The PCs were obtained using

$$z_j = a_j x \qquad j=1,2, \ldots\ldots n \quad (4)$$

The PCs are a linear transformation of the beats with transformation coefficients given by the eigenvectors $\alpha_j$. It is the eigenvectors which provide the surrogate respiratory signal in our analysis.

PCA provides as many PCs as there are analyzed beats however, because these beats are highly correlated and the respiratory related PPG changes are large, most of the variability was expressed by the first few PCs. Therefore the assessed eigenvectors of the first three PCs as surrogates for the respiratory signal for all PPG features.

The SVD based method for solving PCA problem is discussed here. Let X is an arbitrary $n \times m$ matrix and $X^TX$ be a rank r, square, symmetric $m \times m$ matrix. $\{\hat{v}_1, \hat{v}_2, \hat{v}_3 \ldots\ldots \hat{v}_r\}$ is the set of orthonormal m×1 eigenvectors with associated eigenvalues for $\{\lambda_1, \lambda_2, \lambda_3, \ldots\ldots \lambda_r\}$ the symmetric matrix $X^TX$.

$$(X^T X)\hat{v}_i = \lambda_i \hat{v}_i \quad (5)$$

$\sigma_i = \sqrt{\lambda_i}$ are positive real and termed the singular values $\{\hat{u}_1, \hat{u}_2, \hat{u}_3 \ldots\ldots \hat{u}_r\}$ is the set of n×1 vectors defined by

$$\hat{u}_i = \frac{1}{\sigma_i}\left[X \hat{v}_i\right] \quad (6)$$

$$\hat{u}_i \hat{u}_j = \begin{cases} 1 & i = j \\ 0 & i \neq j \end{cases}$$ Eigenvectors are orthonormal.

$$\left\| X \hat{v}_i \right\| = \sigma_i \quad (7)$$

The scalar version of singular value decomposition is

$$X\hat{v}_i = \sigma_i \hat{u}_i \tag{8}$$

$X$ multiplied by an eigenvector of $X^TX$ is equal to a scalar times another vector. The set of eigenvectors $\{\hat{v}_1, \hat{v}_2, \hat{v}_3 \ldots\ldots \hat{v}_r\}$ and the set of vectors are $\{\hat{u}_1, \hat{u}_2, \hat{u}_3 \ldots\ldots \hat{u}_r\}$ both orthonormal sets and bases in $r$ dimensional space.

$$\sum = \begin{pmatrix} \sigma_1 & \cdots & 0 \\ \vdots & \ddots & \vdots \\ 0 & \cdots & \sigma_{\tilde{\gamma}} \end{pmatrix} \tag{9}$$

$\sigma_1 \geq \sigma_2 \geq \sigma_3 \ldots \geq \sigma_{\tilde{\gamma}}$ are the rank-ordered set of singular values. Likewise we construct accompanying orthogonal matrices,

$$V = [\hat{v}_1, \hat{v}_2, \hat{v}_3 \ldots\ldots \hat{v}_r] \tag{10}$$

$$U = [\hat{u}_1, \hat{u}_2, \hat{u}_3 \ldots\ldots \hat{u}_r] \tag{11}$$

Matrix version of SVD

$$XV = U\sum \tag{12}$$

where each column of $V$ and $U$ perform the scalar version of the decomposition (Equation 3). Because $V$ is orthogonal, we can multiply both sides by $V^{-1} = V^T$ to arrive at the final form of the decomposition.

$$XV = U\sum V^T \tag{13}$$

## III. Results and Discussion

The respiratory signals derived using the PCA on PPG and BP signals of the different records of MIMIC database are compared with the reference respiratory signal present in the records. Fig 2 shows a PPG signal, original respiratory signal, first three principal components and their corresponding spectra, for two different data sets. Similarly Fig 3 shows BP signal, original respiratory signal, first three principlal components and their corresponding spectra for two different data sets. It can be clearly seen from the figures that the first principal component is exactly carrying the respiraoty information. Fig 4 shows original respiratoy, PPG, respiratory signal extracted from PPG signal, BP and respiratory signal extracted from BP signal. The results clearly indicated that the extracted respiratory signal is having a strong correlation with that of the actual respiratory signal. Though the visual inspection of the derived respiratory signals indicates a close match with those of reference respiratory signals, a degree of similarity in time domain is quantified in terms of relative correlation co-efficient *(RCC)* defined as

$$RCC = \frac{R_{XY}(0)}{R_{XX}(0)} \tag{14}$$

where $R_{XY}(0)$ is maximum value of cross correlation between derived and original respiratory signal,

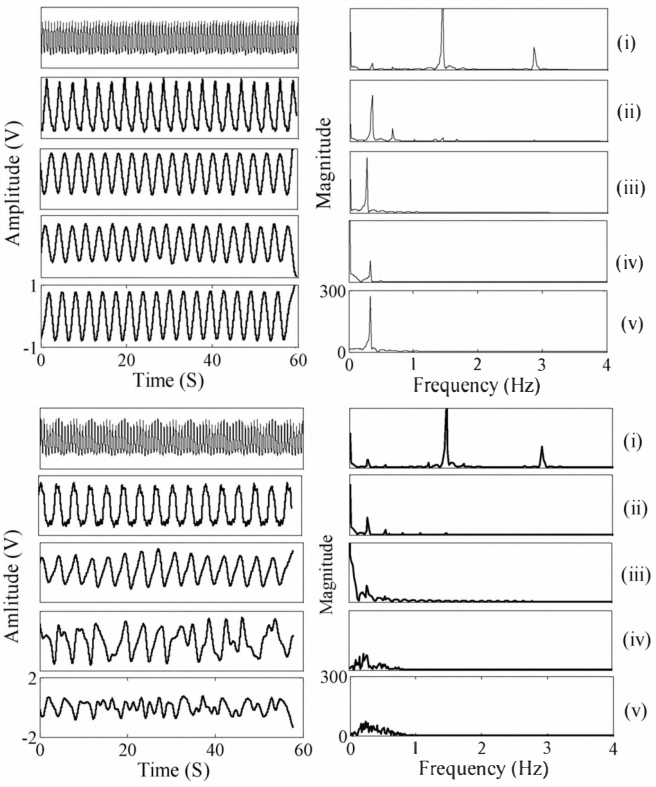


Figure 2. (i) Original PPG (ii) Original respiratory (iii) PC1 (iv) PC2 (v) PC3 along with their corresponding spectra for two different subjects

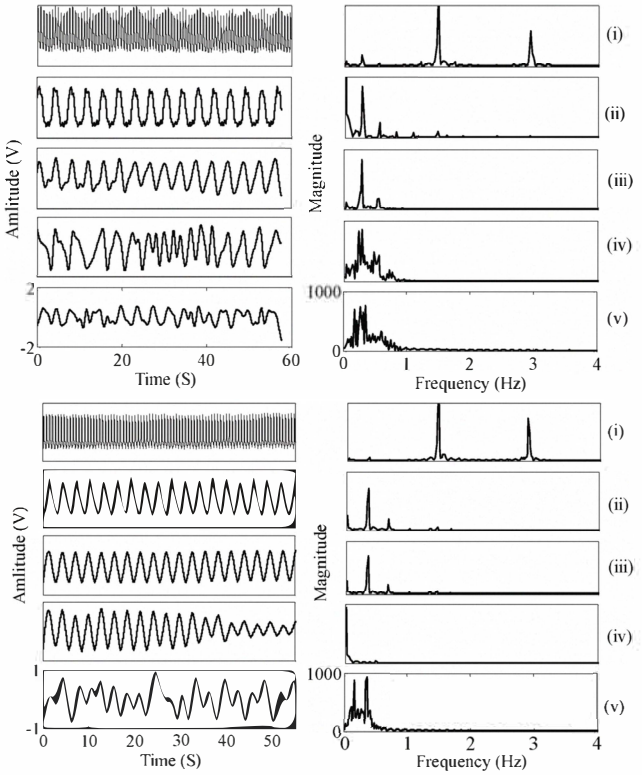


Figure 3. (i) Original BP (ii) Original respiratory (iii) PC1 (iv) PC2 (v) PC3 along with their corresponding spectra for two different subjects

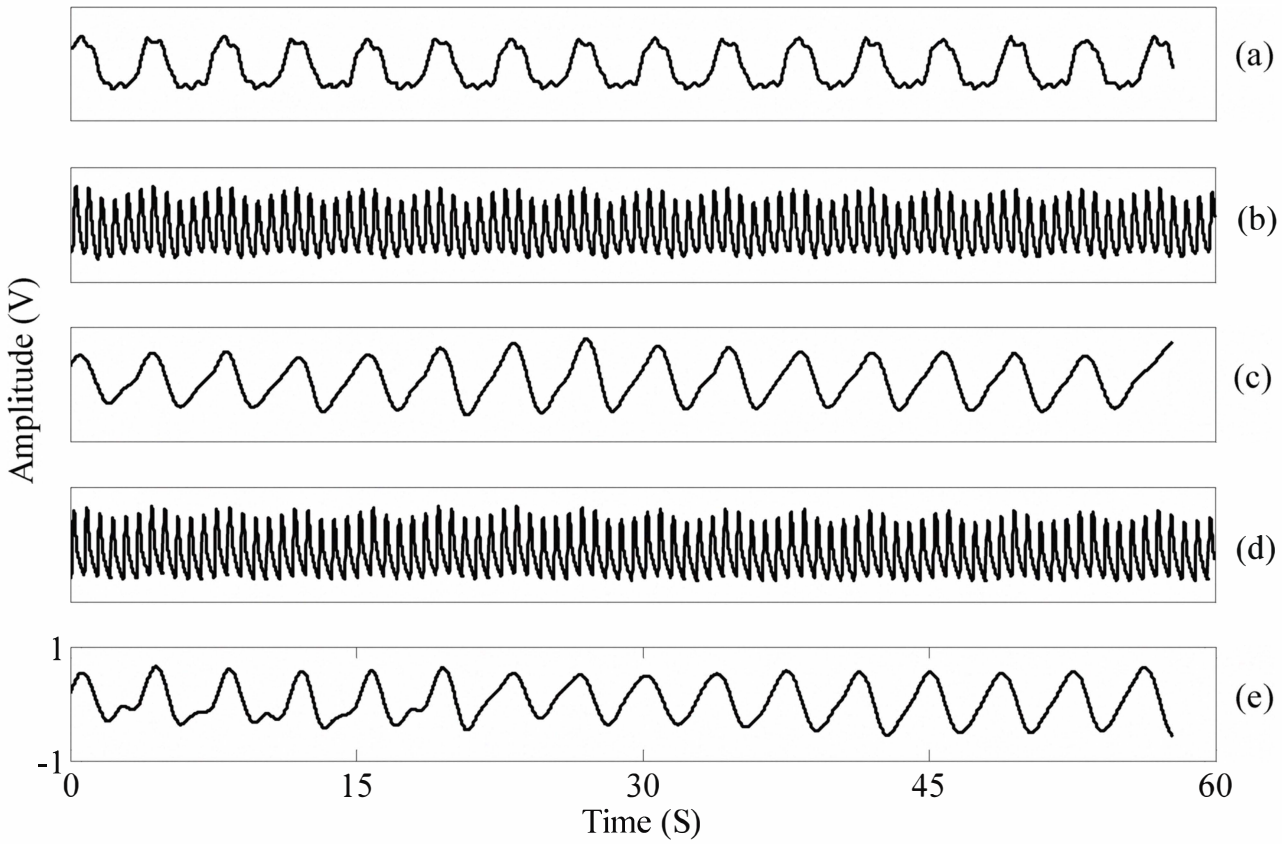


Figure 4. (a) Original respiratory signal (b) Original PPG signal (c) PDR signal (d) Original BP signal (e) BDR signal

$R_{XX}$ *(0)* is the maximum value of auto correlation function of original respiratory signal. In addition, a frequency domain measure of similarity, the magnitude squared coherence *(MSC),* was also estimated for each recording as defined in equation (15).

$$MSC = \frac{|P_{XY}(f)|^2}{P_X(f)\,P_Y(f)} \qquad (15)$$

where $P_{XY}$ *(f)* is cross power spectral density of original and surrogate respiratory signals, $P_X$ *(f),* $P_Y$ *(f)* are auto power spectral density of original and surrogate respiratory signals respectively. These two measures were computed for the surrogate respiratory signal and reference respiratory signal. Table I and III indicates the computed RCC and MSC for the presented method for first three principal components of PPG and BP. Table II and IV presents the accuracy calculations for the same.

Table I. Statistical measures for PDR

| | PPG Derived Respiratory | | | | | |
|---|---|---|---|---|---|---|
| | PC1 | | PC2 | | PC3 | |
| | MSC | RCC | MSC | RCC | MSC | RCC |
| Data 1 | 0.97 | 0.70 | 0.44 | 0.42 | 0.31 | 0.21 |
| Data 2 | 0.95 | 0.63 | 0.48 | 0.30 | 0.25 | 0.14 |
| Data 3 | 0.98 | 0.69 | 0.39 | 0.37 | 0.27 | 0.16 |
| Data 4 | 0.92 | 0.65 | 0.42 | 0.31 | 0.32 | 0.22 |

Table II. Accuracy calculation for PDR

| | ORR | PC1 | | PC2 | | PC3 | |
|---|---|---|---|---|---|---|---|
| | | ERR | AR (%) | ERR | AR (%) | ERR | AR (%) |
| Data 1 | 14.17 | 14.16 | 99.86 | 13.8 | 97.32 | 12.4 | 89.85 |
| Data 2 | 10.38 | 10.38 | 100.0 | 10.2 | 98.27 | 9.12 | 89.41 |
| Data 3 | 12.36 | 12.06 | 97.57 | 12.0 | 97.09 | 11.2 | 92.86 |
| Data 4 | 15.72 | 15.71 | 99.94 | 15.2 | 96.69 | 13.8 | 87.85 |

Table III. Statistical measures for BDR

| | PPG Derived Respiratory | | | | | |
|---|---|---|---|---|---|---|
| | PC1 | | PC2 | | PC3 | |
| | MSC | RCC | MSC | RCC | MSC | RCC |
| Data 1 | 0.94 | 0.73 | 0.34 | 0.44 | 0.33 | 0.23 |
| Data 2 | 0.96 | 0.66 | 0.49 | 0.28 | 0.26 | 0.14 |
| Data 3 | 0.97 | 0.71 | 0.42 | 0.35 | 0.29 | 0.18 |
| Data 4 | 0.94 | 0.62 | 0.38 | 0.30 | 0.33 | 0.25 |

Table IV. Accuracy calculation for BDR

| | ORR | PC1 | | PC2 | | PC3 | |
|---|---|---|---|---|---|---|---|
| | | ERR | AR (%) | ERR | AR (%) | ERR | AR (%) |
| Data 1 | 14.17 | 14.17 | 100.0 | 13.6 | 95.97 | 12.2 | 86.09 |
| Data 2 | 10.38 | 10.36 | 99.80 | 10.0 | 96.33 | 9.19 | 88.53 |
| Data 3 | 12.36 | 12.16 | 98.38 | 11.9 | 96.27 | 11.6 | 93.85 |
| Data 4 | 15.72 | 15.70 | 99.87 | 15.0 | 95.41 | 13.9 | 88.42 |

ORR: Original Respiratory Rate, ERR: Estimated Respiratory Rate, AR: Accuracy Rate

## IV. CONCLUSION

Monitoring the respiratory activity would be mandatory in high risk situations such as cardiac arrhythmias, ambulatory monitoring, stress tests, sleep disorder investigations and post-operative hypoxemia situations. Extraction of respiratory activity from ECG, BP and PPG recordings will potentially eliminate the use of exclusive respiratory sensor intended to record respiratory activity. In this paper, a novel PCA based technique is presented and applied to extract respiratory signals from PPG and BP signals. Test results on MIMIC data base clearly indicated a strong correlation between the extracted and actual respiratory signals. Calculated statistical measures, in both time and frequency domains, demonstrated that respiratory signal is present in the form of first principal components of the data.

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