Effect of Number of Modes of EMD in Respiratory Rate Estimation from PPG Signal

***Abstract*—Hertzman invented photoplethysmography, a non-invasive electrooptic technology that delivers information on the blood volume flowing at a specific area on the human body near the skin. Multiple attempts on PPG Derived Respiration have been made; these approaches are based on various signal processing strategies such as wavelets, filtering, and other statistical methods. The principal component analysis is a technique for identifying patterns in the dataset and expressing them in a way that highlights their similarities and contrasts. As the patterns in data might be difficult to discover in high-dimensional data without the benefit of graphical presentation, PCA is a useful technique for evaluating such data. Empirical Mode Decomposition is suitable for extracting key components that are specific to the underlying biological or physiological processes. This paper examines the EMD method and associated algorithms, as well as some examples of applications. The suggested EMD technique successfully retrieved respiratory information from PPG signals when tested on PPG signals from the well-known Capnobase database from the Physio bank archive. Moreover, the method's superiority was demonstrated by the evaluated similarity metrics in both the time and frequency domains for original and predicted respiratory rates.**

Keywords— Respiratory Rate Estimation, PPG Signal, Spectral Analysis, Empirical mode decomposition

I. INTRODUCTION

Einthoven et al. [1] was the first to investigate the effect of respiration-induced cardiac displacement on the ECG. It has been demonstrated experimentally that the mobility of the electrodes relative to the heart is the primary source of electrical rotation throughout the respiratory cycle, with thoracic impedance changes contributing only as a second-order effect [2], [3]. Respiration regulates heart rate (HR) in such a way that it rises during inspiration and falls during expiration, a condition known as respiratory sinus arrhythmia (RSA). It demonstrated that the mechanical process of breathing produces the same frequency content in the ECG as heart rate variability (HRV) [4], [5].

Multiple researchers have established signal processing algorithms to extract respiratory data from the ECG signal, referred to as ECG-derived respiratory (EDR) data [6]. Few of the approaches rely on changes in beat-to-beat morphology caused by breathing, while others try to derive respiratory information from the HR.

Monitoring such signals at home for patients or at the intensive care unit with a long-term illness and accompanying variability in cardiovascular or respiratory function requires reliable and simple procedures. The capacity to monitor respiratory rate (RR) with a low-cost, easy to uses, non-invasive biosensor will encourage and simplify physiological telemonitoring. An irregular RR is frequently a precursor to serious disease. The evaluation of an increased respiratory rate (RR > 40 breathing per min), is an important criterion with recommendations for the diagnosis of pneumonia affected children [7], [8]. Clinical measurements of RR, are unreliable and inconsistent. Pulse oximetry is a popular method of monitoring physiological signals in hospitals. It utilizes an optical method to determine local changes in blood volume in tissues, as well as provide PPG and SpO2. The PPG signal is a complicated signal that is made up of an AC component that is synchronized to each heartbeat and a DC component that fluctuates slowly owing to breathing, vasoconstrictor waves, and vasomotor activity [9], [10]. Several attempts have been made to estimate RR from PPG signals, including morphological analysis of PPG cycles in the time domain, time-frequency analysis, and digital filtering. EMD is another vital approach for reducing motion distortions in PPG signals, extracting RR from ECG, and decomposing respiratory sounds. The EMD approach is an adaptive decomposition strategy whose basis functions are derived from the signal [11]. The EMD is remarkably well suited to non-stationary and non-linear signal analysis.

In this work, we provide various techniques for estimating both RR the PPG signals. The spectral analysis of the EMD utilized to the PPG yields cardiac and respiratory modulation. As a result, the RR is calculated using spectral analysis of these signals.

II. METHODOLOGY

A. PPG Waveform Analysis

The difference between the greatest (systolic) and minimum (end-of-diastolic) values within a cardiac cycle was determined as the pulse amplitude for every PPG wave. The average of total pulses in a single recording was used to compute the mean amplitude. Each measurement site's raw PPG waveform was then normalized as follows: first, the baseline drift was eliminated. Then, once each pulse was detected with the foot, all the pulses within a single recording were normalized beat by beat in both amplitudes (0–100) and width (1000 sample points) and. Finally, each body site's normalized pulses were averaged to provide a single reference normalized waveform.

B. Dataset

The dataset can be downloaded from the online database, BIDMIC PPG and Respiration Dataset. The BIDMIC dataset contains simultaneously recorded 53 patients of ECG, PPG, and the respiratory signal recorded from 53 patients during the critical condition. In this research, we utilized the test data sets. Records that are appropriate for the suggested technique for extracting BR are identified. PPG signals are present in the records, along with the RR signals that were collected at the same time. As a reference signal, this RR signal might be employed. A sampling frequency of 300Hz is utilized to

record the signal in the records. There are no missing data segments in the captured data. The signal processing toolbox in MATLAB R2018b is used to process all of the recordings. The following are the experimental results acquired utilizing the proposed approach.

C. Data pre-processing and Decomposition

For removing high-frequency noises and smoothing the fundamental PPG signal pre-processing is required. There are many techniques for decomposing PPG like EMD, EEMD, CEEMD, CEEMDAN, and ICEEMDAN. In this research, we will discuss EMD.

1) EMD: EMD is a signal analysis approach widely utilized to locate bearing faults, analyze seismic signals, analyze power signals, and analyze the biological dataset. To produce the IMF, EMD is employed to the signal. These IMFs are subjected to a variable window-sized median filter, with a smaller window size for high-frequency parameters and larger window size for low-frequency parameters. The signal is then reconstructed by summing the filtered IMFs. The rebuilt signal is subjected to EMD once again, and better IMFs are produced.

Here, s(t) is any signal and IMF means the intrinsic mode function. e_{max} (t) defines upper envelope and e_{min} (t) defines lower envelope, d(t) is the extracted details of the signal, r(t) is the residue of the signal. The whole process is illustrated by a flow chart, which is shown in fig. 1.

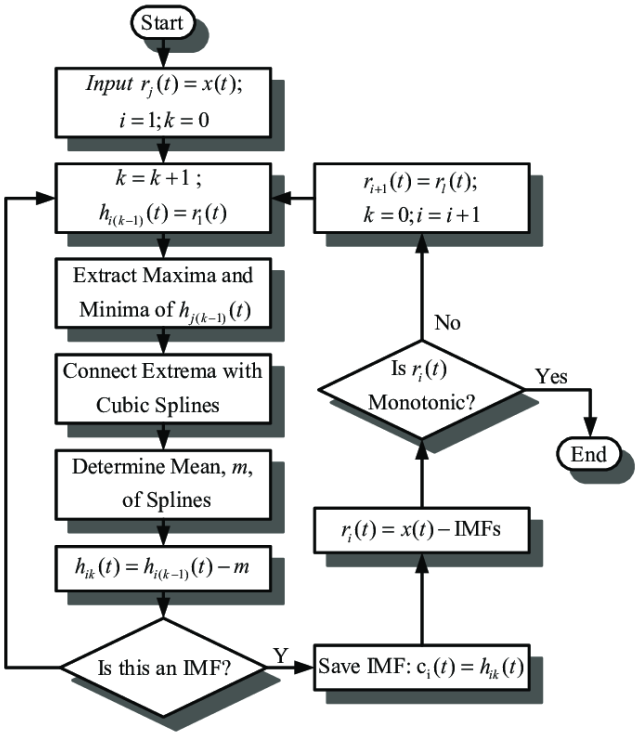


Fig. 1: Flowchart for EMD

2) PCA Theory: Principal component analysis is the entire definition of PCA. From a bigger collection of datasets, PCA is a method for identifying a smaller number of non-correlated variables expressed as the principal component. The approach is extensively utilized in datasets to emphasize variance and capture significant patterns. PCA, invented by Karl Pearson in 1901, is a method utilized in prediction models and exploratory dataset analysis. PCA is a valuable statistical approach that is utilized in computer graphics, neurology, face recognition, and image compression.

PCA facilitates data exploration and visualization. It's a straightforward non-parametric strategy for extracting data from large, jumbled data sets. The PCA focuses on obtaining the greatest amount of variation with the fewest number of main components. One of the main benefits of PCA is that once patterns are discovered in the data, data compression is also supported. PCA is used to reduce the number of parameters in a model or to avoid multicollinearity when there are too many predictors compared to the number of observations.

It uses an orthogonal transformation to turn a set of observations including correlated variables into a set of values known as fundamental parameters. It is closely connected to canonical correlational analysis. In PCA, the number of principal components employed is less than or equal to the number of observations. The PCA is responsive to the relative scaling of the variables that were originally employed.

PCA is broadly utilized in a variety of fields, including biomedicine, social sciences, market research, and other industries that deal with huge datasets [12], [13]. The method can also be used to create a low-dimensional representation of the original dataset. In the case of PCA, only a small amount of effort is required to convert a complicated and confusing data set into a simple and valuable dataset [14].

3) Steps Associated in PCA

- Normalize the dataset by considering mean as zero and variance as one.
- Then, the covariance dimension matrix is calculated.
- Based on the covariance matrix, Eigenvalues and Eigenvectors are measured.
- Select the top Eigenvectors that correspond to the biggest eigenvalues by sorting eigenvalues in ascending order.
- Then the projection matrix is constructed by utilizing the chosen Eigenvectors.
- To obtain the new dimensions feature subspace, transform the original dataset using projection matrices.

4) Graphical Representation: Fig. 2 represents the graphical presentation of PCA. The points are dispersed diagonally to highlight the relationship between the X and Y-axis factors. These points reflect the factors and characteristics of a specific dataset.

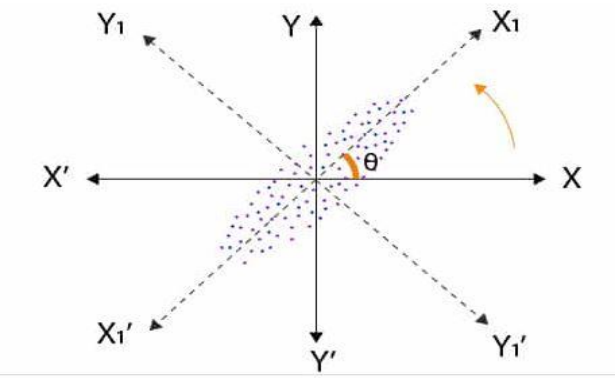


Fig. 2 graphical representation of PCA

We can now use a strategy to minimize the graph's dimensions and complexity. PCA is a way for reducing the complexity of the dataset through dimensionality reduction. As a result, we'll rotate the graph's axis anticlockwise by angle theta. The graph looks like fig. 3 after rotating the axis.

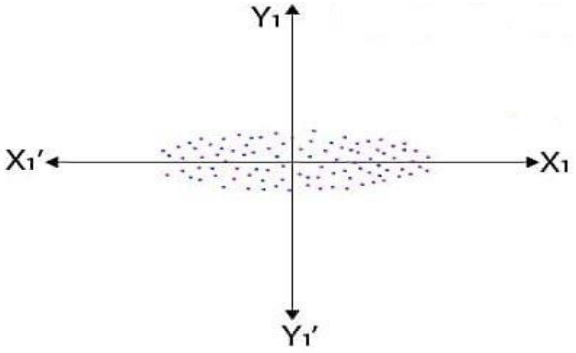


Fig. 3 graphical PCA after rotating the axis.

5) PCA Equation

The covariance matrix of X is called,

S € $R^{m\times m}$, and defined by,

$$S = \frac{1}{n}\sum_{i=1}^{m}(\vec{x}_i - \bar{x})(\vec{x}_i - \bar{x})^T \quad (1)$$

Here,

$\vec{x}$ is nonzero vector and $\overrightarrow{x}$ € R^n

$\vec{x}$ is also called an eigenvalue of a specific matrix.

If, $\overline{x}$ € R^m is the mean of each row in X and defined by,

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} \vec{x}_i \quad (2)$$

Now,

$$S = U \sum V^T \quad (3)$$

Here,

S = co-variance vector.

U, V are orthogonal matrices and U € $R^{n\times n}$, $\sum$ € $R^{n\times m}$, V € $R^{m\times m}$ (4)

Here,

$\sum$ is a diagonal matrix and consists of non-negative singular values.

The data matrix X can be projected into a new matrix, Y € $R^{k\times m}$, by multiplying a matrix P^T.

Where,

P = [U_1 U_2 …….U_k], k ≤ m

K = proper number of the principal component.

m = data dimension.

6) Artifacts rejection and IMFs Selection: IMFs related to cardiac activity and artifacts should be recognized and discarded once the IMFs have been gathered. The PPG is greatly influenced by cardiac and breathing frequency. To detect cardiac and artifacts activity, FFT is used to determine the dominant frequency of the IMFs. After obtaining all prominent frequencies, IMFs with frequencies ranging from 0.05 to 0.75Hz are used for estimating BR, as shown. The range is sufficient to capture practically all BR, as the average BR for children over the age of two and young adults is between 8 and 45 breaths per minute. As a result, IMFs with frequencies less than 0.05Hz are classified as low-frequency artifacts, whereas those with frequencies greater than 0.75Hz are classified as cardiac data and high-frequency noise and are disregarded.

III. Result and Discussion

A. HR & RR Calculation

The PPG signal is separated into the segment, dissected into IMFs, and examined in the spectral domain using a sliding window of 1 minute with 30 seconds overlap. The frequency peak with the maximum power is assessed for every IMFs. By summing the IMFs whose peak frequency falls within the cardiac frequency ranges, the cardiac modulation is then calculated. The RR modulation is calculated similarly by summing the IMFs whose peak frequency falls within the RR frequency ranges. Following that, spectral analysis is used to measure the frequency peak of these signals, which reflect both RR and HR [15].

An analysis of observational studies using HR information from 53 patients yielded reference respiratory and cardiac frequency ranges. Although the range is significantly more limited, it would be included in this category. The suggested hybrid technique has a sensitivity issue that develops during the automatic selection of IMFs due to the usage of a bandpass filter (0.05-0.75Hz). Because the minimum frequency range in this study is 0.05Hz, the minimum BR is limited to 3 breaths per minute. Because the maximum frequency range was set to 0.75Hz, the maximum measurable BR was 45 breaths per minute. Here fig. 4 represents the normal patient's cardiac information and fig. 5 represents the critical patient's cardiac information.

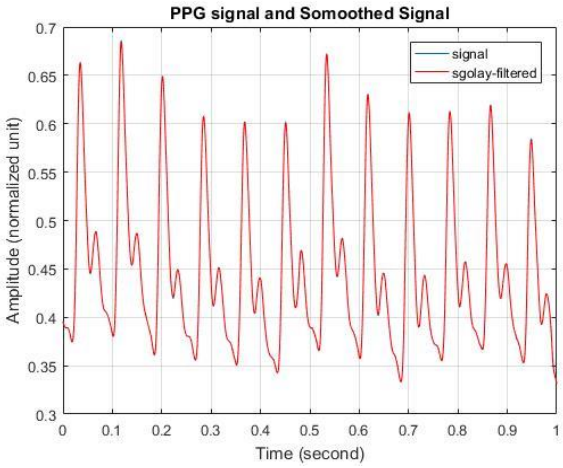


Fig. 4 PPG signal for normal patient

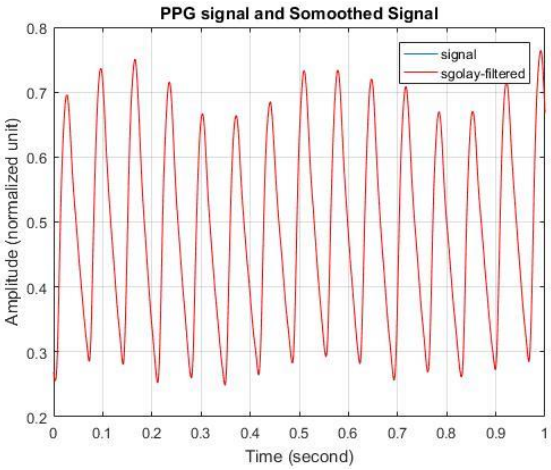


Fig. 5 PPG signal for critical patient

B. *Subject and Data Acquisition*

The appropriate hardware for sensing, software for obtaining, and processing PPG signals have been built to verify the feasibility of the proposed model for extracting RR information from the PPG signals. The sensor was a clip-on kind with two light-emitting diodes (LEDs) on one side and a photo-diode (PD) on the other side of a soft plastic clip [16].

The plastic clip is made in such a way that it fits tightly on a subject's finger. The LED drivers were time-divided, and the PD output was appropriately demultiplexed to separate the IR PPG and red signal. The IR PPG and analog red signals are then captured using a 16-bit resolution dataset acquisition board from National Instruments, the NIDAQ Pad-6015. The data were collected at a sampling rate of 300Hz, with the captured samples being processed in the LabVIEW environment. After gaining informed consent, experiments were conducted on ten volunteers between the ages of 22 and 35.

C. *Signals drawn from Physio Net archive*

The accuracy of the processes for extracting BR was assessed using eight records from the database in the Physio bank archive. These recordings all include PPG signal as well as RR waveforms recorded at the same time as a reference. Fig. 7 All of these signals were captured at a 125Hz sampling rate. Five one-minute segments are picked from eight distinct records that did not contain any missing information in any of the three signals. The detection of timestamps for individual breathings in the reference RR signal is done using an extrema detection method, with the results visually examined to ensure that all the breathing cycles are contrasted to the derived ones.

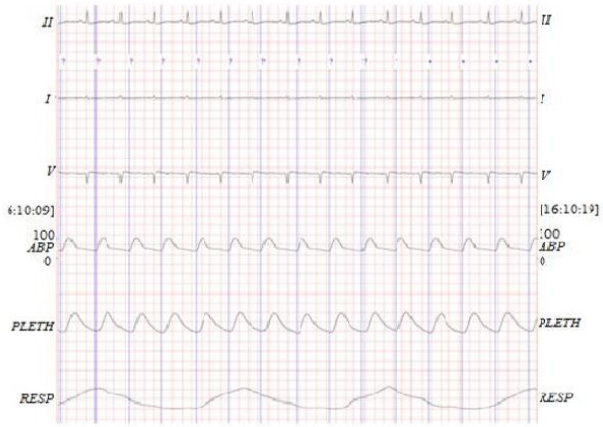


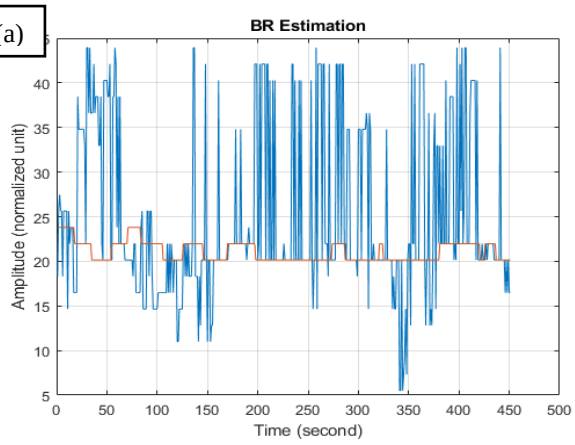
Fig. 6 represents the RESP, PPG, BP, and ECG (lead II, I, V) records from the typical database.

D. *Evaluation of RR induced modulation of BP, ECG signal*

The ECG fluctuations in a single respiratory cycle can be attributed to three main causes, according to experiments.

- During ECG recording, the position of electrodes on the chest surface shifts relative to the heart, causing transthoracic impedance to change as the lungs fill and empty.
- During respiration, the cardiac vector's mean electrical axis alters direction, causing amplitude modulation of the pulmonary feature, which is the inverse of the RR signal.
- Respiratory Sinus Arrhythmia (RSA) is characterized by a change in HR throughout the respiratory cycles, which is a normal event that occurs during each respiratory cycle and leads to frequency modulation of respiratory signals with cardiac factors.
- The inspiratory reduction in systolic blood pressure, which is proportionate to variations in intrathoracic pressure during inspiration and expiration, is known as Pulses paradoxus (PP).
- The abrupt rise in volume when the heart contracts and blood is pushed down the aorta into arteries causes Blood Pressure Variability (BPV). Every systolic BP period has been found to exhibit a cyclic variation linked to respiration.

(a)



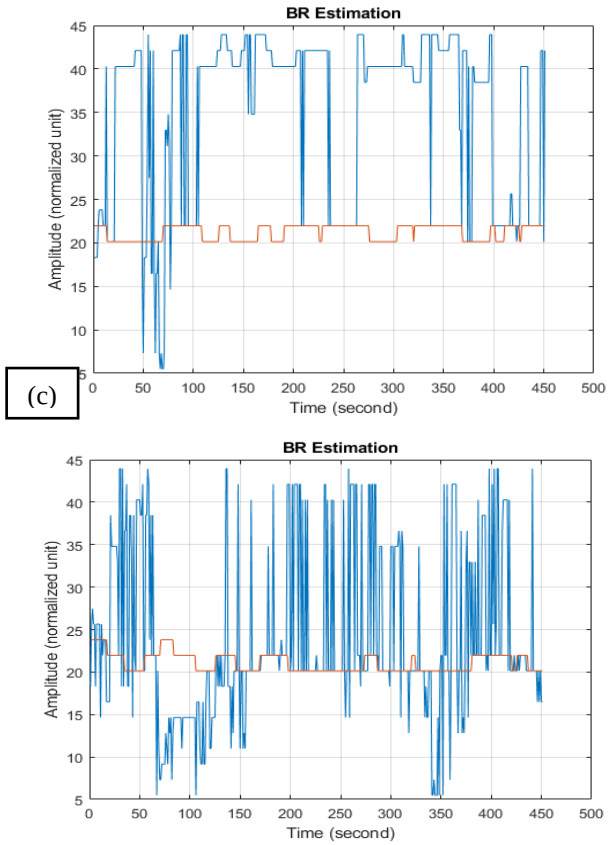


Fig. 7 BR Estimation for different mode (a) mode 5, (b) mode 6, and (c) mode 7

E. Data pre-processing

The raw PPG is first smoothed with a Savitzky-Golay FIR smoothing filter of third-order polynomial and ninth samples in every frame, which offers the least square error in fitting noise-contaminated dataset [14]. This pre-processing approach smoothest the raw PPG signal and removes high-frequency noises.

EMD is used to decompose a signal into several intrinsic mode functions. An IMFs is an oscillatory function with time-varying frequencies that can represent the local characteristics of nonstationary signals. EMD is a signal decomposition technique that divides a signal into numerous intrinsic mode functions. IMFs are time-varying oscillatory functions that can be used to characterize the local properties of nonstationary signals. In this study, we utilized EMD to decompose the actual signal into 3 individual mode functions. We used mode 5, mode 6, and mode 7.

For modes 5,6 and 7 we got 53 different BR estimations for each mode. Fig. 8 shown mode 5, Breathing rate measured to amplitude and time. We extract different MATLAB files from different components. By using those MATLAB files, we can measure the absolute error. We compare the recitation value with the true value and get the absolute error.

TABLE I. BR ESTIMATION PERFORMANCE OF EMD-PCA HYBRID TECHNIQUE: ABSOLUTE ERROR

	Mode 5	**Mode 6**	**Mode 7**
Mean value	6.3092	6.3782	6.4308
Mode value	1.7417	4.3117	4.5472
Standard deviation	3.4952	3.4346	3.4218

Here we can see the mean value, mode value, and standard deviation value for 3 modes. The usage of 100 percent windows for BR estimate is to blame for the poor result. Mean value for different mode like 63.09%,63.78% and 64.31%. Mode value for different mode like 17.41%,43.11% and 45.47%. The standard deviation for a different mode like 34.95%,34.34%, and 34.21%.

This research presents an EMD-based hybrid model, EMD-PCA, for estimating BR from PPG. The box-whiskers plot depicts the distribution of the AE (absolute Error) of these hybrid models in BR estimation for different modes in fig. 8.

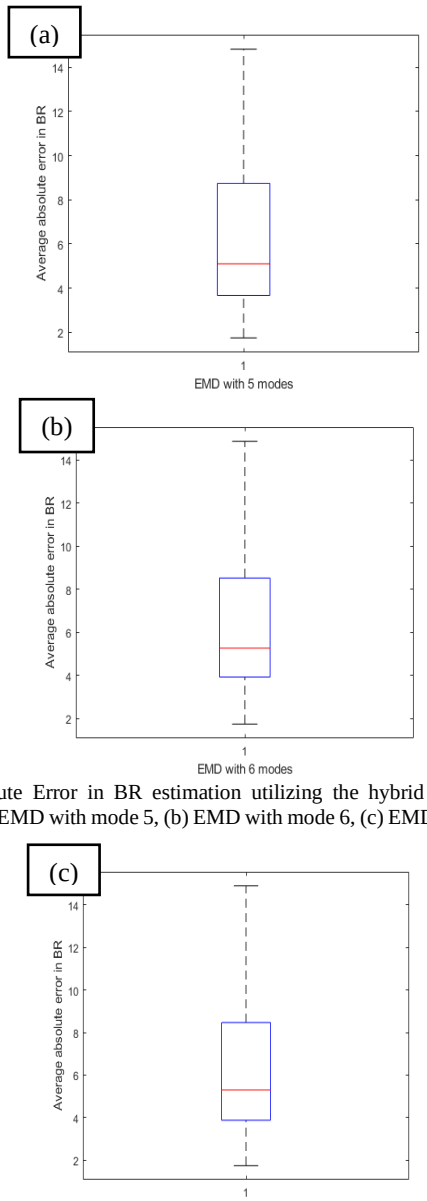


Fig. 8 Absolute Error in BR estimation utilizing the hybrid EMD-PCA algorithm (a) EMD with mode 5, (b) EMD with mode 6, (c) EMD with mode 7.

The distribution of AE of PPG-derived BR to real Breathing Rate is depicted in the box-whiskers graphic.

IV. CONCLUSION

Due to the motion artifacts, the PPG signal is non-stationary and exceedingly noisy. As a result, the EMD approach is introduced in this study to extract required respiratory information from the PPG signal. Non-stationary signals can be processed with this technique. The EMD approach extracts respiratory information from PPG signals while also separating IMFs without mode mixing. MATLAB

R2018b was used to implement the algorithm. Future research will focus on extracting features from PPG signals that can be utilized to identify abnormal respiratory diseases. We proposed a unique device to efficiently measure respiratory rate and blood pressure. Given the great practical interest in these two vital signs, the proposed device opens the way to provide a cost-effective and non-invasive way of measuring the said vital signs. In addition, the device provides us the option to interface with computers and is accurate to a great extent. We were also able to successfully transmit PPG signals over wireless communication. As a future enhancement, the device can be set up at each bed of a hospital ward, where the data will be fed to a central computer for mass patient monitoring. The device is still under experiment for blood pressure estimation. We need to collect a bulk amount of data to verify its performance. We assumed linear regression for blood pressure measurement. Depending on the power consumption, we might or might not need an external power supply. Current studies show that PPG can be used to measure respiratory rate, which is another vital sign. If this can be incorporated into the device, we will be able to measure three of the four vital signals with a single device.

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