Respiratory rate extraction based on plethysmographic wave analysis

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Abstract. Respiratory rate (RR) is one of the vital parameters of a person's health. In certain conditions such as patients with respiratory problems or heart who are in the treatment room, respiratory rate monitoring is carried out continuously. In health care centers such as hospitals, RR measurements use a bedside monitor. However, this device is not yet widely available in small scale health services such as Community Health Centers (Puskesmas) because this device is expensive. One alternative for RR extraction is through plethysmographic wave analysis measured using a photopletismograph (PPG) device. This is based on the hypothesis that breathing affects the dynamics of PPG wave amplitude modulation so that by extracting this information we can know the respiratory rate. PPG devices are widely available in small health services because of their low prices. Meanwhile, PPG is only used to measure heart rate and oxygen saturation. In this study, a method for extracting RR information is proposed by analyzing PPG waves. Two methods, namely empirical mode decomposition (EMD) and variational mode decomposition (VMD), are applied to obtain respiratory oscillation information. The aim is to get the most optimum method for RR extraction. The performance test of the two proposed methods was carried out through time-frequency domain transformation using Fast Fourier Transform. The method used in this study is expected to be applied to conventional PPG devices.

1. Introduction
Respiratory rate (RR) is an important physiological parameter which is used in determining the patient's health condition. Respiratory rate can provide information related to the condition of the lungs, heart and even nerves. Intensive and continuous respiratory rate monitoring is performed on premature infants and patients who are in critical condition \cite{1,2}. In hospitals, RR monitoring can use a bedside monitor through impedance measurements or plethysmographic wave modulation analysis. However, this device is not yet widely available in small scale health service centers (Puskesmas) because this device is expensive and quite complex. Therefore, an alternative technique is needed to calculate RR, one of which is by extracting plethysmographic wave information measured using a photopletismograph (PPG).

Photoplethysmograph is a simple, non-invasive and cost effective method to assess variations in light modulation by the cardiac cycle \cite{3}. Typically, PPG signals carry respiratory information, this is a modulation which is induced by respiration \cite{4}. This phenomenon is due to changes in tissue blood
The respiratory rate measurement provides some information about the patient’s health by diagnosing various respiratory diseases.

Respiratory rate measurement through analysis of PPG signal are based on respiratory-induced intensity variations (RIIVs) contained in the baseline of the PPG signal [5]. Qualitative RIIV signals may be used for monitoring purposes regardless of age, gender, anesthesia, and mode of ventilation [5]. The PPG signal has different frequencies and can all be characterized according to their sinusoidal components. Sources of signal interference comes from movement artefacts and also physiologic variations such as yawn, vasoconstriction and a deep gasp. Therefore, extracting the PPG signal is the most important process identify the real respiratory waveforms [6]. Some research related to RR extraction or estimation through PPG wave analysis has been carried out to find the method with the best accuracy. Breathing wave extraction on PPG through time, frequency or wavelet domain analysis has been applied. Research by Ye et.al., simulating respiration signal estimation based on PPG using variational mode decomposition combined with principal component analysis [7]. Other research by Prasetiyo et.al., implemented a system for measuring respiration rates on an Embedded Device based on PPG signal using fast Fourier transform (FFT) method to determine the state of RIIV [8]. The FFT method which is implemented on this system may require quite complex computing. PPG wave analysis to estimate respiration rates was also carried out by Jaafar and Rozali in the wavelet domain [6]. There are already many studies on respiratory rate estimation through PPG wave analysis, however there are very few references which study and compare methods to determine the most appropriate if these methods will be implemented on a system.

In this research, a method for extracting RR on PPG waves has been proposed using two signal decomposition approaches. These methods are empirical mode decomposition (EMD) and variational mode decomposition (VMD). The application of these two methods aims to compare the best method in RR extraction so that this method is expected to be applied efficiently with high accuracy on a low cost system. Respiration rate extraction simulations are performed on PPG waves sourced from open datasets where actual RR information is also contained in the dataset so that performance tests can be performed. All simulations in this study were conducted using Matlab.

2. Material and method

2.1. Dataset

The dataset used in this research simulation is sourced from the open source BIDMC PPG and Respiratory dataset which can be accessed via https://physionet.org [9,10]. All data was recorded from patients undergoing treatment at the hospital at Beth Israel Deaconess Medical Center (Boston, MA, USA). This dataset contains 53 signal recordings of 8 minutes each and a frequency sampling at 125 Hz. Respiratory information is manually annotated in each recording using the impedance respiratory signal. Detailed information in this dataset is as follows:

- Physiological signals, such as PPG, electrocardiogram (ECG) and impedance breathing signals.
- Physiological parameters, such as heart rate (HR), respiratory rate (RR), and oxygen saturation (SpO2) at a 1 Hz frequency sampling
- Age and sex
- Manual breath annotation.

In this work, physiological signals and physiological parameters which are used are PPG signals, respiratory impedance and respiratory rate. PPG signals are the main information for the extraction of respiratory rate information and the actual RR parameters used to test the performance of the proposed method. Figure 1 below is an example of the PPG signal which was analyzed in this research.
2.2. Pre-processing the signal

Pre-processing was applied to eliminate DC noise that contaminates typical PPG signals. The purpose of this pre-processing is also to normalize the data so that the minimum value of the signal becomes zero ‘0’. This stage was done by applying the mathematical equation as follows:

\[ X_{\text{norm}}[n] = X_{\text{raw}}[n] - \min(X_{\text{raw}}), \quad n = 1, 2, \ldots, \text{Number of sample} \]  

Where

- \( X_{\text{norm}} \) = Normalized signal
- \( X_{\text{raw}} \) = Raw data

2.3. Empirical Mode Decomposition (EMD)

Empirical mode decomposition or called EMD is a method for decomposing a signal into a number of constituent signal components. EMD decomposes the signal based on frequency and amplitude in a certain time. In its application, EMD can be used to decompose stationary and non-stationary signals into several Intrinsic Mode Functions (IMFs) [11]. The decomposition process in EMD also produces residue signals, but this was not used in this study. Only the IMF component is the focus of analysis. In a mathematical equation, the relationship of the original \( x(t) \) signal to the IMF and its residue is expressed as follows:

\[ x(t) = \sum_{i=1}^{N} \text{IMF}_i(t) + r(t) \]  

Then the algorithm to get the IMF is as follows [12]:

- Determining local maxima and minima of signals \( x(t) \).
- Determining envelope of the signal by interpolating all local maxima to get the upper envelope and do the same to all local minima to get the lower envelope.
- Compute the average for local maxima and minima so will get the mid value called \( m(t) \).
- Compute candidates of IMF, \( \text{IMF}_i(t) = x(t) - m(t) \).
- The IMF is obtained if have two criteria: 1) The number of zero crossings and extrema points must be the same or different at least one. 2 The average envelope must be zero at all points.
- Repeat steps 1-5 to get other IMF and finally produce a residue with monotonous values.

2.4. Variational Mode Decomposition (VMD)

The variational mode decomposition (VMD) is a fully intrinsic and non-recursive method to process the non-stationary signals [13]. In EMD, there was a failure to deal with noise, hard band restrictions, and the selection of filter bank limits that have been determined due to the missing ad-hoc algorithmic nature.
Then the VMD was formulated to overcome the noise in the input signal by selecting the appropriate mode and performing error balancing correctly through adaptive band calculations. The updating of modes in the Fourier domain directly to the VMD method makes optimization fast and easy. VMD shows certain sparsity properties on the multiplication of input signals by decompose non-stationary signals into modes at central frequencies with limited bandwidth so that the extraction of components in a composite signal can be obtained precisely. 

In VMD method, some parameters in VMD need to initialization including quadratic penalty factor ($\alpha$), the modes number (K), the time-step in dual ascent (tau), the frequency center of mode ($\mu_k$), the convergence tolerance (tol), and the part of DC imposed (dc). The initialization of these parameters depends on the application. For the initialization of parameters from VMD first note its use to capture the center frequency mode accurately. Large values in the VMD technique are not appropriate, on the contrary small values will cause a trade-off of extracted modes for noise [13]. In a simple explanation, the VMD algorithm decomposes the original signal into a limited-band IMFs [7]. Thus the intrinsic signal which is not the main component of the signal can be determined at the first IMF as shown in this research simulation.

2.5. Fourier transform

Fourier transform (FT) is a mathematical method for transforming time domain signals into frequency domains to obtain signal power information at certain frequencies. For discrete signals, the Fourier transform is applied by the Discrete Fourier Transform (DFT) formulation which is defined as:

$$X[m] = \sum_{n=0}^{N-1} X[n] e^{-\frac{2j\pi nm}{N}}$$

where $n = \text{index in the time domain. } n = 0, 1, ..., N-1$

$m = \text{index in the frequency domain. } m = 0, 1, ..., N-1$

DFT is a Fourier representation for periodic discrete signals. DFT computing requires many complex operations. To reduce this complexity, an algorithm called Fast Fourier Transform (FFT) was developed. In principle, the FFT algorithm breaks N points into (N/2) points and then splits (N/2) points to (N / 4) points and so on up to 1 point. In this research, the use of FFT is as a tool to verify the results of signal decomposition in the frequency domain. From this analysis, it can be determined whether the signal from the decomposition is a candidate which can provide respiration rate information. Figure 2 shows an example of a raw PPG signal in the time domain and frequency domain. In the frequency domain it can be seen that the PPG signal contains RR candidate information, heart rate and noise.

![Figure 2. Raw PPG signal (left) and Fourier transform results (right).](image)
2.6. Proposed RR extraction method

The proposed RR extraction method is shown in Figure 3. The first process, raw PPG signal with a length of 60 seconds was normalized to reject DC noise by applying equation 1. Then this normalized signal is decomposed using EMD and VMD. Next, an FFT analysis is performed on the decomposition signal to determine which signal mode is the candidate for respiration rate information. The criterion is a signal which has a spectral power dominance at frequencies below 1 Hz. Signals with a frequency of 1 Hz or more are thought to not be RR information but heart rate noise. The final step is the calculation of the RR for each method proposed to be compared with the actual RR.

![Proposed respiratory rate extraction method.](image)

3. Results and discussion

In this section will be explained comprehensively, the proposed RR extraction stages in accordance with Figure 3. Simulations are carried out on 10 data records, each with a duration of 60 seconds. The results of signal normalization on one of the observed data are shown in Figure 4. Figure 4 shows a normalized signal which is free of DC frequencies and the lowest value is zero.

![Normalized PPG signal with 60 seconds duration.](image)

Respiration rate extraction was done by two method approaches which are proposed. The results of the decomposition signal using the EMD method are shown in Figure 6. These are the IMFs of one of the observed PPG signals. Each of these signal modes was transformed into the frequency domain to choose a mode that provides respiration rate information. The results of the IMF’s Fourier transform are shown in figure 5.
Figure 5. EMD results from one observed PPG signal (sequentially from top to bottom represents IMF-1 to IMF-10).
Figure 6. The results of each IMF's Fourier transform (a) FT-IMF1 (b) FT-IMF2 (c) FT-IMF3 (d) FT-IMF4 (e) FT-IMF5 (f) FT-IMF6 (g) FT-IMF7 (h) FT-IMF8.

The results of Fourier transform in each decomposition mode showed differences in the power spectral at different frequency ranges. Fourier transforms on IMF-9 and IMF-10 are not shown because they have very low frequencies (below 0.2 Hz) and this is not a typical respiratory frequency. From these results, an IMF candidate which can provide RR information, i.e. IMF-6, has a breathing frequency characteristic. Validation was done by comparing the IMF-6 signal to the measurement of actual respiratory impedance as shown in Figure 7. Figure 7 contains two signals namely IMF-6 as an estimate of a breathing wave (red) and the other one is an actual breathing signal (blue). These two waves show the corresponding rhythm, thus the hypothesis that the PPG wave can provide RR information can be proven.

Figure 7. Comparison of IMF signals with actual respiratory signals.
The next analysis is observing the results of VMD method-based decomposition. In this first simulation, we set the parameter alpha = 2000, tau = 0, the decomposition mode (K) = 5 and DC = 0. The results of the decomposition of the signal are shown in figure 8.

![Figure 8. VMD results on one of the observed PPG signals (sequentially from top to bottom represents Mode-1 to Mode-5).](image1)

The next decomposition scenario is to change the parameters K (K = 2, K = 3 and K = 4). Decomposition mode K = 1 is not simulated because it will produce a decomposition signal with the same value as the original signal. Observations from all scenarios, it was concluded that mode-1 decomposition results are respiration signal candidates. So that the respiration signal extraction can be done with the minimum decomposition mode that is K = 2. However, the decomposition mode with K = 2 produces a respiration signal candidate with a large amount of noise (Figure 10) so that it is possible to produce an RR estimation error. Therefore, mode K=2 is not recommended to be applied.

![Figure 9. VMD results (mode-1 with K = 2).](image2)

The next step is validation by comparing the mode-1 signal to the measurement of actual respiratory impedance as shown in Figure 11. These two waves show a harmonious oscillation rhythm as in the previous EMD-based test shown in Figure 8.
The performance test of the proposed methods was carried out by estimating the amount of respiration rate of the selected decomposition signal as a respiratory signal. The estimated RR amount was compared with the actual RR so that it can be known the error rate of each proposed approach. The results of RR calculation tests on 10 PPG data with a duration of 60 seconds are shown in table 1.

### Table 1. Estimated and actual respiration rate.

| Signal | RR Actual/min. | Estimated RR/min. | Delta error (RR/min.) |
|--------|----------------|-------------------|----------------------|
|        | EMD          | VMD               | EMD                  | VMD            |
| PPG1   | 23           | 23                | 24                   | 0              | 1              |
| PPG2   | 16           | 17                | 20                   | 1              | 4              |
| PPG3   | 17           | 21                | 20                   | 4              | 3              |
| PPG4   | 17           | 20                | 19                   | 3              | 2              |
| PPG5   | 14           | 14                | 14                   | 0              | 0              |
| PPG6   | 19           | 18                | 19                   | 1              | 0              |
| PPG7   | 20           | 21                | 20                   | 1              | 0              |
| PPG8   | 21           | 21                | 21                   | 0              | 0              |
| PPG9   | 20           | 24                | 19                   | 4              | 1              |
| PPG10  | 18           | 17                | 18                   | 1              | 0              |

| Mean Error | 1.5 | 1.1 |

Two proposed methods produce up to 100% accuracy in estimating respiration rates. In testing 10 PPG data, both methods produce an average delta error of 1.5 rate/min. and 1.1 rate/min. respectively for EMD and VMD. It might be very early to conclude that VMD has better performance in extracting respiratory signal modulation compared to EMD. But in this initial study, VMD showed better accuracy. From 10 series PPG data which have been simulated, EMD more often produces more breathing waves compared to VMD. This can occur because the result of EMD decomposition is more contaminated with large amounts of noise. Error estimation of respiratory waves can also occur due to typical PPG itself when there is body movement causing excessive changes in the baseline signal. Although in some PPG data samples both of the proposed methods provide estimation errors, we can minimize this error by measuring PPG in conditions where the patient does not make body movements that can produce a large amount of noise especially from the arms.
4. Conclusion

In this research, a respiratory wave extraction algorithm based on EMD and VMD methods has been simulated. The entire simulation process was carried out on Matlab. This simulation was carried out on 10 PPG data, each with a data length of 60 seconds. In the EMD method, candidate breathing waves from the decomposition signal are obtained by analysis in the frequency domain. This was done because the candidate breathing waves cannot be determined at a fixed IMF level. Meanwhile, the extraction of respiratory information using VMD can be done with a minimum of K = 2 and the breath wave candidate is always in mode-1 or level 1 decomposition. Thus, to choose a breath wave does not require more complex analysis.

The validation test of the proposed method has been carried out by comparing the actual RR and RR estimated by EMD and VMD. From testing, both of these methods are able to provide accuracy up to 100%. Nevertheless, there are still errors in detection of some PPG data, the average delta error for EMD and VMD was 1.5 rate/min. and 1.1 rate/min respectively. VMD shows smaller estimation errors compared to EMD so it can provide more accurate RR calculations. Error in EMD due to over estimation of RR due to a large number of noise waves. To reduce errors in estimating RR, it can be done by minimizing body movement noise which can disrupt baseline PPG signals. In the end, this research can be the basis in determining the most appropriate method for extracting respiration rates based on PPG signals. If in the future the proposed method will be applied to low cost systems or simple processors in conventional PPG devices, the VMD method will be more appropriate to be applied.

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