Comparison of EMD, VMD and EEMD Methods in Respiration Wave Extraction Based on PPG Waves

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Abstract. Plethysmographic (PPG) wave analysis can provide interesting information including heart rate and oxygen saturation. Since PPG signals are modulated by breathing waves, further analysis can provide additional information that is the respiration rate (RR). This is a way to simplify sensor devices. This paper discusses a respiration wave extraction mechanism to calculate RR using the signal decomposition approach. Decomposition methods which are applied in this study include empirical mode decomposition (EMD), variational mode decomposition (VMD) and ensemble empirical mode decomposition (EEMD). This paper specifically addresses the performance of EEMD to EMD and VMD. This proposed method has been tested on an open PPG dataset (containing PPG and RR wave signals). Test results on 20 PPG signals, each of which had a duration of 1 minute showed that the EEMD was able to estimate the RR with an accuracy of more than 90% with an average error rate of 1 rate/minute.

1. INTRODUCTION

Vital parameters of the patient's body that are routinely or continuously monitored include heart rate (HR), body temperature, oxygen saturation and respiration rate. These parameters are measured by placing sensors in several parts of the body. For example a pulse oximeter sensor is used to measure HR and oxygen saturation. Temperature sensors are used to measure body temperature. This can cause patient discomfort if many sensors are placed on the body. One technique for the efficient use of sensors is the extraction of information for the measurement of other parameters. An example that can be done is the extraction of respiratory rate through a pulse oximeter by analyzing the PPG signal. Thus the number of sensors can be reduced.

Photoplethysmography or people know it as PPG is a traditional optical technique that long time ago has been used in the measurement of blood oxygen saturation and heart rate. Its working principle is to monitor changes in dynamics of blood flow [1]. This dynamic occurs because of changes in blood volume due to pumping by the heart. Observation of PPG waves in a certain duration shows the existence of respiratory modulation both in amplitude and frequency [2] (illustrated in Figure 1). This is a potential for developing methods or algorithms for extracting respiration waves so that they can be applied to conventional pulse
oximeters. Thus providing medical devices which are cheap, easy, simple and integrated can be realized.

The main challenge in developing methods for extracting RR from PPG is noise sensitive. PPG signals are very susceptible to noise contamination, especially low frequency noise due to motion artefacts so that it can obscure RR waves. Research continues to find the most optimal method in both complexity and accuracy. Some research on RR detection from PPG uses time, frequency, time-frequency or wavelet domain approaches. Time series analysis method based on signal decomposition has been reported in research [3]–[7]. Frequency analysis for RR extraction was reported in the study by Maldav et.al. [8]. Analysis of the time-frequency domain has also been applied to the RR estimation of the PPG signal [9]. Analysis of the wavelet domain can also be used for RR estimation as reported in the study [10]. Various methods have been proposed for the estimation or extraction of RR from PPG signals, however time series analysis-based methods will be more desirable because it will be easier if implemented in a system that has limited resources.

![Figure 1 Respiratory modulation in PPG signal](image)

Time domain methods such as empirical mode decomposition (EMD), variational mode decomposition (VMD) and ensemble empirical mode decomposition (EEMD) are thought to be able to extract intrinsic respiratory modulation signals that are contained in PPG waves. Respiratory wave extraction studies from PPG using EMD, VMD or EEMD have been proposed several years ago, however a comparative study of these methods has not been conducted. This is important because to know the performance of each method so that the best method can be determined so that it can be implemented on a conventional pulse oximeter device. Therefore, this paper discusses the EMD, VMD and EEMD methods for the extraction of respiration waves from PPG. This study is a series of previous studies in which EMD and VMD have been compared [12].

2. MATERIAL AND METHOD

2.1 Dataset

The dataset used in this study including PPG signal and respiration rate is sourced from an open dataset which can be accessed for free via https://physionet.org [13], [14]. The duration of all recorded PPG signals is 8 minutes and the total number of records is 53 time series data. This PPG signal is digitized with 125 Hz sampling frequency. This dataset also includes respiration waves taken using impedance breathing techniques. In this work, the signal which is observed is the PPG signal and the signal used for performance testing is the respiratory impedance. Figure 2 below is one of the series PPG signal which is analyzed in this study. In this preliminary research, 20 series PPG signals with a duration of 60 seconds were analyzed.
2.2 Ensemble Empirical Mode Decomposition (EEMD)

The EMD method has a disadvantage when oscillations with the same time scale are stored in several IMF or vice versa in one IMF storing oscillations with different time scales. This results in ineffectiveness of the EMD method due to the effect of mixing modes. The EEMD method is used to overcome the weaknesses of EMD [15]. This method has the ability to scale better as evidenced by trials with the addition of white noise to the signal, the resulting IMF does not show links with other IMF. The effectiveness of the EEMD depends on the noise amplitude ($A$) and the choice of ensemble number ($N$) which is seen from the final standard deviation ($\varepsilon$) value between the original signal and the resulting IMF.

$$\varepsilon = \frac{A}{\sqrt{N}}$$

The steps of the EEMD algorithm are as follows:

1. $Y_n(t) = X(t) + u_n(t), \text{for } n = 1, 2, ..., N$
   
   Where the original signal $X(t)$ is added with white noise $u_n(t)$ so that it produces a signal with white noise according to the ensemble number ($N$).

2. $Y_n(t) = \sum_{m=1}^{M-1} IMF_m^{(n)} (t) + r_M^{(n)}(t)$
   
   Signals that have been contaminated with white noise $Y_n(t)$ are decomposed into several IMF with the residue. $M - 1$ is the total amount of IMF decomposed from $Y_n(t)$. $IMF_m^{(n)}$ is the $m$th IMF and $r_M^{(n)}$ is the remainder obtained in the $n$th experiment.

3. Repeating the first and second steps using different white noise added to the original signal.

4. $IMF_{m}^{\text{ave}}(t) = \frac{1}{N} \sum_{n=1}^{N} IMF_m^{(n)}(t)$
   
   The final step is to calculate the average $IMF_{m}^{\text{ave}}$ of several ensembles ($N$).

2.4 Fast Fourier Transform

A time domain signal $x(t)$ can be translated into a frequency domain $X(\omega)$ by using Fourier transform. The transformation is expressed in equation (2).
\[ X(\omega) = \int_{-\infty}^{\infty} x(t)e^{-i\omega t}dt \]  

(2)

With \( i = \sqrt{-1} \) and \( e^{i\theta} = \cos \theta - i \sin \theta \). \( X(\omega) \) is the spectrum of the signals [16].

The fast Fourier transform (FFT) is a fast-computational algorithm for a discrete Fourier transform (DFT). For a discrete and periodic signal \( a_n \) for \( n = 0, 1, ..., N - 1 \), the DFT can be calculated using equation (3).

\[ A_k = \sum_{n=0}^{N-1} e^{-i\frac{2\pi}{N}kn}a_n \]  

(3)

FFT can be said as the fast algorithm for computing DFT. The FFT process has to do with taking an array of time-domain wave form samples processing those to produce an array of frequency-domain spectrum samples [17].

Figure 3 showed the basic concept of FFT. The \( N \) samples of input array in the time domain with \( t \) seconds has the same size with the output samples (bidirectional bandwidth). Note that \( N \) must be a power of 2 for FFT algorithm to be truly “fast”. On the input side, we have real valued samples, while in the output side we have complex valued samples. For this reason, we typically work with magnitude and phase representation of the complex values. To compute DFT with \( N \) point sequence, DFT needs a \( N^2 \) multiplications while FFT only needs \( N \log_2 N \). This multiplications affect the processing time for evaluating the signal. In this study, FFT was used for the analysis of decomposition signal in frequency domain.

2.5 Proposed RR Extraction Method

In this section, the proposed method in the purpose of respiratory wave extraction is explained. Figure 4 shows the proposed method for this study. This method refers to previous research, so EMD and VMD are not discussed in this paper. Pre-processing aims to reject DC noise and signal normalization. Then the signal is decomposed using EEMD. Fourier transform was applied to each decomposition signal for the analysis of respiration wave candidates. Criteria for respiratory wave candidates are signals with dominant spectral power at frequencies below 1 Hz. Signals with a frequency of 1 Hz or more are considered heart rate information or noise signals. The proposed method validation is by comparing the estimated RR with the actual RR.
3. RESULT AND DISCUSSION
In methods are not discussed in detail, but only as a comparison to the proposed method in this paper. Since the observed PPG signal contains very little noise, we set the parameter noise standard deviation EEMD is 0.1. The decomposition results which is called IMF of a 60-second PPG signal are presented in Figure 5.

![Figure 5 Decomposition signals](sequentially from top to bottom represents IMF-1 to IMF-10)

The next process is identification of respiration wave candidates by conducting spectral power analysis for each IMF. IMF signals in the frequency domain are presented in Figure 6.
Referring to the typical respiration frequency criteria, IMF-7 is the most powerful candidate which represents RR. The power spectrum of IMF-7 shows one of the most
dominant frequencies, that frequency is close to 0.4 Hz. Validation was done visually by comparing IMF-7 signals with reference respiration waves as shown in Figure 7. Figure 7 contains the IMF-7 signal (red-line) as an estimate of a breathing wave and the other one is a reference signal (blue-line). The whole process was also carried out on nineteen other PPG signals and then a performance test was performed with the RR estimate as a parameter. The results of this test are presented in Table 1.

![Figure 7 IMF-7 signals and reference breathing waves](image)

| Signal | RR Actual/min. | Estimated RR/min. | Delta error (RR/min.) |
|--------|----------------|-------------------|----------------------|
|        | EMD | VMD | EEMD | EMD | VMD | EEMD |
| PPG1   | 23  | 23  | 24   | 24  | 0   | 1    |
| PPG2   | 16  | 17  | 20   | 17  | 1   | 4    |
| PPG3   | 17  | 21  | 20   | 20  | 4   | 3    |
| PPG4   | 17  | 20  | 19   | 16  | 3   | 2    |
| PPG5   | 14  | 14  | 14   | 0   | 0   | 0    |
| PPG6   | 19  | 18  | 19   | 19  | 1   | 0    |
| PPG7   | 20  | 21  | 20   | 19  | 1   | 0    |
| PPG8   | 21  | 21  | 20   | 20  | 0   | 0    |
| PPG9   | 20  | 24  | 19   | 24  | 4   | 1    |
| PPG10  | 18  | 17  | 18   | 18  | 1   | 0    |
| PPG11  | 14  | 16  | 12   | 14  | 2   | 2    |
| PPG12  | 18  | 19  | 18   | 18  | 1   | 0    |
| PPG13  | 18  | 15  | 18   | 18  | 3   | 0    |
| PPG14  | 16  | 20  | 16   | 16  | 4   | 0    |
| PPG15  | 19  | 16  | 18   | 21  | 3   | 1    |
| PPG16  | 23  | 17  | 23   | 23  | 6   | 0    |
| PPG17  | 18  | 18  | 18   | 19  | 0   | 1    |
| PPG18  | 18  | 15  | 18   | 18  | 3   | 0    |
| PPG19  | 19  | 14  | 18   | 18  | 5   | 1    |
| PPG20  | 25  | 26  | 23   | 23  | 1   | 2    |
| Mean   | 2.1 | 0.9 | 1    |
Table 1 presents the EMD, VMD and EEMD results in estimating the RR of the PPG wave. The number of PPG data which was tested in this paper differs from previous studies. In this paper the proposed method was tested on a larger number of PPG data in order to get a better generalization of results. From Table 1, it is known that VMD performance is better than EMD, this is consistent with previous study [12]. An encouraging and interesting result is that EEMD has a competitive performance against the VMD method. The average errors of VMD and EEMD are 0.9 and 1 rate/min. respectively. This error is much less compared to EMD.

From the simulations that have been carried out, the proposed method has better performance compared to EMD. However, it is not better than VMD. But the EEMD method was becoming a competitive method because the breath waves are more easily identified at a fixed IMF. In observing a total of 20 PPG data series with a duration of 60 seconds, the EEMD always estimates breath waves in IMF-7. EEMD was able to provide better accuracy compared to EMD, this is because EEMD has better performance for noise compensation compared to EMD. With these characteristics, EEMD has great potential to be implemented in conventional PPG devices by considering memory resources.

4. CONCLUSION
This study has successfully simulated a method for the extraction of respiration waves from PPG signals. Specifically discuss the EEMD method for estimating RR. Performance and validation tests have been carried out on 20 PPG data series with a duration of 60 seconds. The performance parameter of the proposed method is the estimated number of RR. This research report is used to complement the analysis of previous research [12], the EMD and VMD methods have been compared. The test results show that EEMD has better performance compared to EMD and is also competitive to the VMD method. The average error detection in EEMD, EMD and VMD is 1, 2.1 and 0.9 rate/minute, respectively. The EEMD has the advantage of being able to estimate breath waves at a fixed IMF. In the future, the EEMD method has great potential and opportunity to be applied in low-cost PPG devices.

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