A Variational Mode Decomposition-Based Approach for Heart Rate Monitoring using Wrist-Type Photoplethysmographic Signals during Intensive Physical Exercise

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Abstract

Heart rate monitoring using photoplethysmographic (PPG) signals recorded from wrist during intensive physical exercise is challenging because the PPG signals are contaminated by strong motion artifact. In this paper, we present a new approach for PPG based heart rate monitoring. We first perform the variational mode decomposition to decompose the PPG signal into multiple modes then eliminate the modes whose frequencies coincides with those from accelerator signals. Finally, the spectral analysis step is applied to estimate the spectrum of the signal and selects the spectral peaks corresponding to heart rate. Experimental results on a public available dataset recorded from 12 subjects during fast running validate the performance of the proposed algorithm.

Keywords: Adaptive motion artifact cancellation, Photoplethysmographic (PPG), Heart rate monitoring Variational mode decomposition, Spectral analysis

1. Introduction

Heart rate (HR) monitoring is necessary in detection of heart diseases, health monitoring for the elderly, and in other applications. Heart rates traditionally were estimated by using electrocardiography (ECG) signals with sensors attached to the chest, hand and reference ground [1]. As an alternative to ECG signal, PPG signal is preferred for heart rate measurement in many applications due to its low cost and convenience [2]. Recently, with the emergence of wearable devices such as smartwatches and wristbands, the HR monitoring has attached much attention.

PPG signals can be recorded by illuminating the skin with a light emitting diode and detecting changes in the reflected light, so the periodicity of the PPG signal represents heart rate. The PPG signals can be acquired from different body parts like fingertip, wrist and earlobe [3]. Thus, the embedded pulse oximeters in smartwatches and wristbands can facilitate noninvasive monitoring of heart rate. However, PPG signals can be easily contaminated by motion artifact (MA) due to the loose interface between the pulse oximeter and skin surface [1]. Especially, when the signals are measured in subjects during their intensive physical exercise like fast running or cycling. Therefore, accurate heart rate estimation from wrist-type PPG signals during intensive physical exercise is challenging [2, 4, 5].

There have many signal processing algorithms for motion artifact reduction from PPG signals using the simultaneously recorded accelerometer signals i.e., adaptive filtering [4, 6, 7], independent component analysis [8], spectral subtraction [9] models. More recently, the empirical mode decomposition (EMD) [10] has been proposed for MA reduction for PPG signals [3, 11]. Though having advantages in motion artifact cancellation, EMD have shortcomings. In the EMD, the mode-mixing problem should be handled, and the number of modes vary with different signals. As an alternative to the EMD approach, variational mode decomposition (VMD) [12] has been proposed to address shortcomings of EMD. Since introduced in 2014, VMD has attracted a lot of interests from many researchers in various signal processing applications such as detecting rub-impact fault of the rotor system, and power quality events. However, to the best of our knowledge, the VMD has not been studied in PPG signals for heart rate monitoring.

In this paper, inspired by the VMD, we present an automatic method to reduce motion artifact from the PPG signals. The PPG signal that is contaminated with motion artifact, is first decomposed into different modes by the VMD. After decomposition of the PPG signal, the instantaneous frequencies of the modes are calculated and compared with the fundamental frequency of the accelerator signals. The mode whose frequency coincides with accelerator frequency will be assigned as the motion artifact component, then the remaining modes are combined to obtain a cleansed PPG signal. Based on the

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cleansed PPG signal, the spectral analysis is implemented, and the heart rate monitoring is performed. The proposed algorithm has been applied for the IEEE Signal Processing Cup 2015 dataset and obtained comparative results.

2. Variational Mode Decomposition

Variational mode decomposition (VMD) proposed by Dragomiretskiy and Zosso [12] is a signal processing technique that decomposes a real-valued signal, $f(t)$, into different levels modes u_k, that have specific sparsity properties. It is assumed that each mode k to be concentrated around a center pulsation ω_k determined during the decomposition process. Thus, the sparsity of each mode is chosen to be its bandwidth in spectral domain. To obtain the mode bandwidth, the following steps should be implemented: (1) applying Hilbert transform to each mode u_k in order to obtain unilateral frequency spectrum. (2) Shifting the mode's frequency spectrum to "baseband", by using an exponential tuned to the respective estimated center frequency. (3) Estimation of the bandwidth through the *H1* Gaussian smoothness of the demodulated signal, i.e. the squared *L2*-norm of the gradient. More detail about VMD approach can be found in [12]

3. The proposed algorithm

The proposed algorithm for heart rate monitoring includes following steps: preprocessing, variational mode decomposition, motion artifact cancellation and heart rate estimation.

3.1. Signal Preprocessing and MA analysis

Input signals including PPG and accelerometer signals are first filtered with a 4th order Butterworth band-pass filter (0.5-4Hz) to remove baseline wander and high frequencies. The PPG signals are then normalized to zero mean for further processing. The accelerometer signals are resampled to 125Hz, the sampling rate of the PPG signals. The data of each subject are divided into multiple epochs with 50% overlapping, each epoch lasts 10 seconds.

Since the PPG signal is corrupted by the motion artifact, the frequency of motion artifact signal measured by accelerometer contribute to the PPG signal. Then the heart rate can be estimated by removing the MA component from the PPG signal. However, with strong motion artifact, it is difficult to estimate the heart rate from frequency distribution of the PPG signal. This is demonstrated in Fig.1. In this figure, two epochs from a recording are extracted, given the true heart rates, denoted with a circle in the frequency distributions of the corresponding epochs. In particular, in epoch (A), with less motion artifact, the maximal value of the spectral envelope is 1.95Hz, coincides with the true heart rate, 1.95Hz (equivalent to 117bpm). However, in epoch (B), in the presence of strong motion artifact, the maximal value of the spectral envelope is 2.81Hz, does not coincide with the true heart rate 2.26Hz (equivalent to 135bpm).

3.2. PPG signal decomposition

As analyzed above, with strong motion artifact, it is difficult to estimate the heart rate from frequency distribution directly from the PPG signal. To separate the heart rate from the motion artifact, we apply the mode decompose approach using VMD. In more detail, after being filtered by bandpass filter, the PPG signals are applied to the VMD method [12]. By the VMD algorithm, the signal can be separated into modes. Figure 2 shows an example of the decomposition step by VMD for a representative epoch B in Fig.1. In this epoch, the VMD decomposes the PPG signal into 5 modes. The frequency distribution obtained by performing Fast Fourier Transform (FFT) for each mode. Along with the time-series plot of each mode, the frequency distribution with spectral envelopes of PPG epoch and decomposed modes are also provided. As can be observed from Fig 2, though not being identified from the PPG epoch, the heart rate is separated from the highest spectral envelope of mode 3. It also can be observed from Fig.2 that the maximal envelope in the input PPG is associated with the motion artifact, and this maximal value coincides with the maximal envelope in mode 4.

3.3. MA cancellation and HR estimation

Based on PPG and MA signals, in this study, we propose a new approach for MA cancellation. Our approach stems from the fact that the acquired PPG signal is contaminated with motion artifact. This can be seen in Fig.3, the two envelopes (peaks denoted by circles) in the input PPG signal coincide with the envelopes in the accelerators. Accordingly, it is reasonable to remove the MA signal from the decomposed PPG's modes.

The paradigm for the proposed approach to estimate the PPG signal is described as follows. For each signal epoch, we decompose the PPG into modes, then compute the instantaneous frequency of each mode. The mode whose instantaneous frequency outside the range [0.5-3.5] Hz is excluded. Besides, we calculate a set of spectral envelopes from frequency distributions of the accelerometer signals, denoted as F_{acc} of that epoch. Then, we compare the frequency of the modes (f_1, f_2,.., f_N) with the MA frequency set, F_{acc}. If the frequency of one mode coincides with F_{acc} with a tolerance of 0.15Hz, it is eliminated. The remaining modes are then combined to get a cleansed PPG signal. After the motion artifact cancellation step, we estimated the heart rate from the cleansed PPG signals adapting the spectral peak tracking algorithms by Zhang et al. [5].

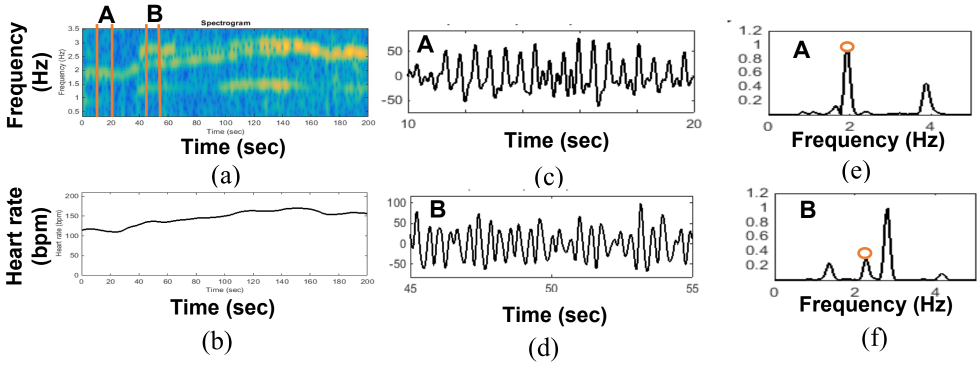

Fig. 1. Representative illustration for the challenge of HR estimation during physical exercise: Plots (a) and (b) shows the spectrogram of a PPG data of a subject and the true heart rate in beat per minute (bpm). Plots (c) and (d) show examples of two epoch (A) and (B) from the PPG subject. Plots (e) and (f) show the spectral envelopes of the examples. The true HR is denoted with a circle.

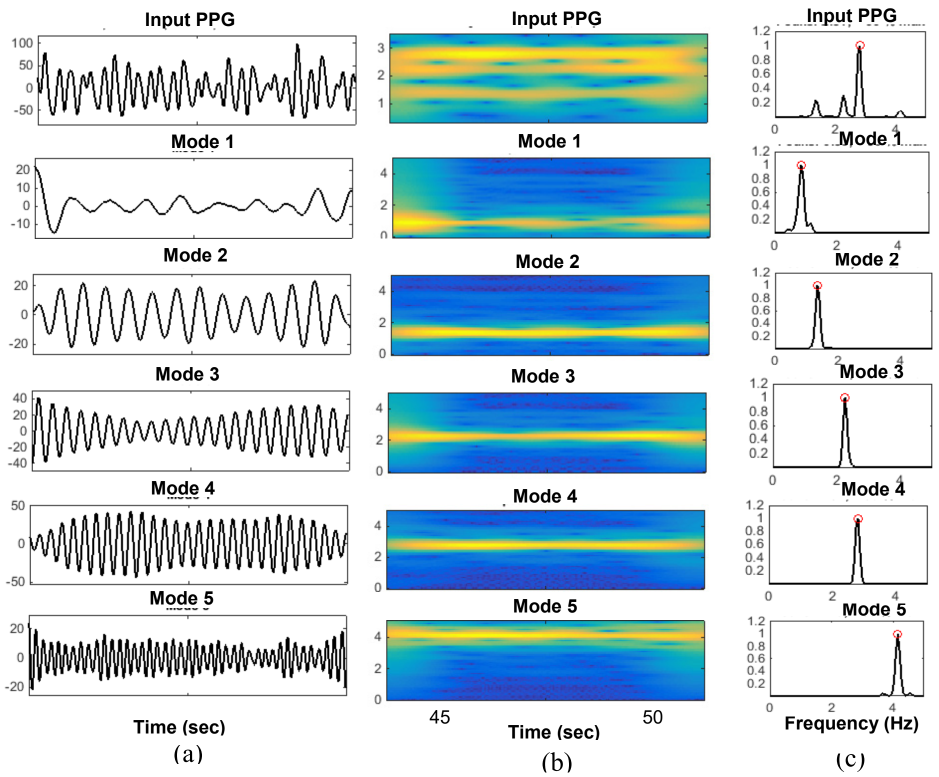

Fig. 2. PPG signal and its decomposed modes: (a) signals in time domain, (b) spectrograms, and (c) frequency distributions. Red circle denoted the highest spectral envelope.

Table 1. The performance of the proposed algorithm for HR estimation from 12 subjects

Subjects	1	2	3	4	5	6	7	8	9	10	11	12
avAE (bpm)	3.60	2.44	1.45	1.90	1.38	1.54	1.28	1.87	1.28	5.53	1.98	3.31
sdAE (bpm)	3.20	2.55	1.32	1.79	1.26	1.72	1.04	1.59	1.03	7.19	1.91	5.37
avRE (%)	2.87	2.39	1.18	1.64	1.06	1.34	1.04	1.64	1.16	3.76	1.29	2.79

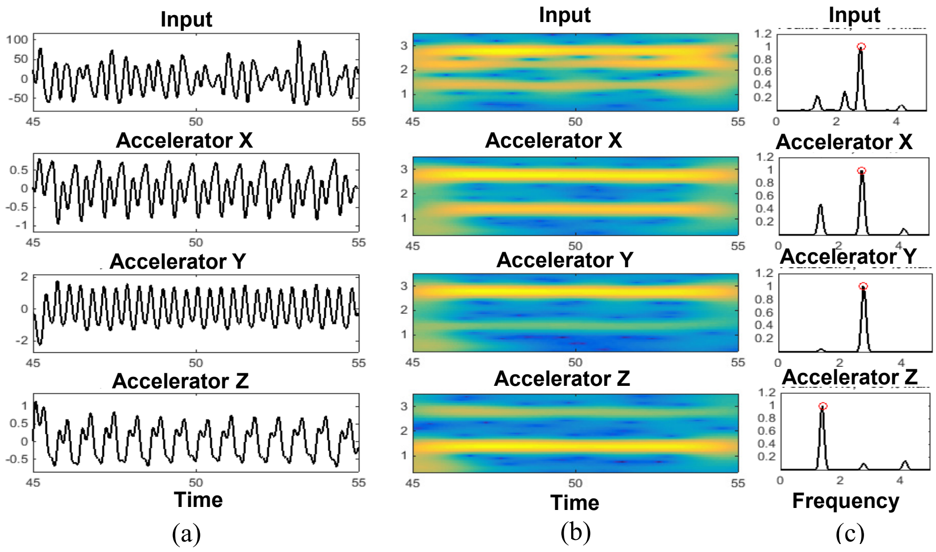

Fig. 3. Signals, corresponding frequency distributions, and spectrograms of a PPG, accelerometer signals (X, Y, and Z axes). (a) Signals in time domain; (b) Gabor Spectrograms; and (c) Frequency distributions. Red circle denoted the highest spectral envelope.

4. Evaluation Results

4.1. Database and Evaluation metrics

We apply the proposed method for 12 subjects during intensive physical exercises from the dataset provided for the IEEE Signal Processing Cup 2015, For each subject, the PPG sensors and three-axis accelerometer were embedded in a comfortable wristband. The ECG signal was recorded simultaneously for computing reference heart rate, then the heart rates from ECG are used as ground truth for heart rate estimation by PPG and accelerator signal. The data including PPG, ECG, and accelerators signals lasts from 300 to 350 seconds.

4.2. Metrics

To evaluate the performance of the proposed heart rate estimate, we compare the heart rates computed by the proposed approach with those by reference heart rates. The metric includes: Average Absolute Error, Standard Deviation of Absolute Error, and Average Relative Error (avRA) are which are usually computed in other studies [1, 5]. The Average Absolute Error (avAE), Standard Deviation of Absolute Error (stAE), and Average Relative Error (avRE) are defined as:

$$avAE = \frac{1}{N}\sum_{i=1}^{N} AE_i \tag{1}$$

$$sdAE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}\left(AE_i - avAE\right)^2} \tag{2}$$

$$avRE = \frac{1}{N}\sum_{i=1}^{N}\frac{AE_i}{f_{true}(i)}\cdot 100 \tag{3}$$

where $AE_i = \left|f_{est}(i) - f_{true}(i)\right|$ is the Absolute error (AE) used to evaluate the accuracy of each HR estimate, with $f_{est}(i)$ and $f_{true}(i)$ respectively denote the estimated and true heart rate values in the i-th epoch, in beats per minute (bpm).

4.3. Performance assessment of Heart rate estimation

The performance of the proposed algorithm for HR estimation for 12 subjects is summarized in Table 1. The reported results included following parameters: Average Absolute Error, Standard Deviation of Absolute Error, and Average Relative Error (avRA), as computed in Eqs. 1-3. The reported results by the proposed method for 12 subjects of the dataset achieves an average absolute error (avAE) of 2.29 bpm, that is smaller than avAE value reported by the TROIKA method, 2.34 bpm, in [5]. The average absolute value in this study, though larger than that commonly obtained by using gel electrodes, it is adequate since the acquisition is peformed during intensive physical exercises, with large heart rate variabilty. From this table, we can see that subject 9 gives the best performance achieved by the proposed HR estimation algorithm. The agreement between the estimated HR for subject 9 by the proposed method and the true heart rate is interpreted in Fig.4.

To further demonstrate the correlation and agreement between the estimated and true heart rates, we provided the Pearson correlation plots and Bland-Altman plots of heart rates in Fig.5. The figure shows high correlation coefficient (R=0.99) and a good agreement between the estimated heart rates by the proposed algorithm and the true heart rates.

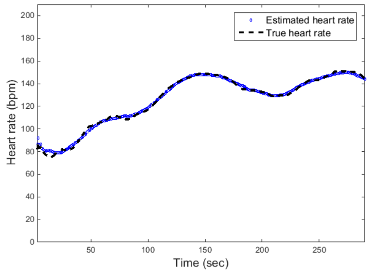

Fig. 4. An example of the heart rate estimation results on subject 9 using the proposed algorithm

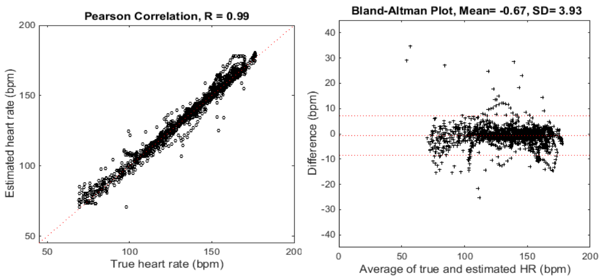

Fig. 5. The Pearson correlation (a) and Bland-Altman plot (b) of the heart rate estimation of 12 subjects in the dataset. R denotes the correlation coefficient.

5. Conclusion

The study has proposed a new approach for heart rate monitoring from the PPG signals during physical exercise. The PPG contaminated with motion artifact is decomposed in to modes via VMD. The frequency of each mode is computed and compared with fundamental frequency of the motion artifact related signal. Then, the cleansed PPG signal is estimated by eliminating the modes whose instantaneous frequencies coincided with the frequency of MA related signal. The assessment of heart rates estimated by proposed algorithm shows a good agreement with those reference heart rate, that demonstrates the performance of the proposed method.

Acknowledgments

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