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Artifact Reduction based on Empirical Mode Decomposition (EMD) in Photoplethysmography for Pulse Rate Detection

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Abstract— **The pulstile components of photoplethysmography (PPG) contain valuable information about a subject's cardiovascular and metabolic systems. Pulse rate is one of the most significant vital signs that can be extracted from PPG signals. However, patient movement, especially movement at the measurement sites, such as fingers, can disturb the PPG's light path significantly, resulting in corrupted measurements. In this paper, a method is proposed for removing motion artifacts from PPG recordings. In this method, the Empirical Mode Decomposition (EMD) and Hilbert transform are used together to decompose PPG recordings into instantaneous frequency series on different scales of resolution. Motion artifacts and physiological signals are separated based on these series. The proposed method was used to recover PPG signals recorded in an experiment, where motion artifacts were intentionally introduced by finger bending. By using our method, the signal-to-noise ratio was increased from 0.078 dB of the contaminated signals to 0.318 dB, and the true detection rate of heartbeats was improved from 59.2% to 96.6%. The results demonstrated that the EMD combined with Hilbert transform has great potential in reducing motion artifacts in PPG signals and can improve the accuracy of heartbeat detection.**

I. INTRODUCTION

Photoplethysmography (PPG) is an optical measurement technique that measures volumetric change of blood at peripheral sites noninvasively. A PPG measurement device typically consists of two LEDs and a photodetector (PD). The light intensity measured at the photodetector reflects changes in the volume of blood in the optical path between the LEDs and PD. As more blood enters the optical path, less light is recorded at the detector [1]. The PPG signal can provide continuous information about a subject's cardiovascular and metabolic systems. For example, pulse rate, one of the most important parameters for cardiovascular evaluation, can be derived from PPG by detecting heartbeats.

Nowadays, more and more PPG sensors are built into wearable devices, to be clipped onto a finger or worn as a ring. These wearable PPG devices can be used for monitoring people's cardiovascular conditions in many situations, ranging from battle-field to excise monitoring. However, since in most of these applications, people perform other tasks while wearing PPG sensors, PPG signals are often affected with various disturbances. Among them, motion artifacts are mostly often seen, mainly resulting from the change of air gaps between the sensors and the skin when subjects bend their fingers or shake hands [2]. Motion artifacts can drive the measurements far from their true physiological values, resulting in false evaluation about a subject's condition.

Generally, the frequency band of PPG is from 0.5 to 4 Hz (see Fig.1(a)); The frequency band of motion artifacts (due to finger movement, tremble, change of probes, etc.) is lower than 0.1 Hz [2]. Since the frequency spectrum of motion artifacts is overlapped with that of the PPG signal (see Fig.1 (b)), traditional band-pass filters are not capable of reducing the noise without causing significant signal distortion. How to remove finger motion artifact and recover PPG signals still remains an open problem.

In this paper, we propose a method based on the Empirical Mode Decomposition (EMD) and Hilbert transform to reduce motion artifacts in PPG, in the hope that after noise reduction, heartbeats can be more accurately detected from PPG. In this study, motion artifacts were generated from finger bending or shivering, and assumed to be additional noise.

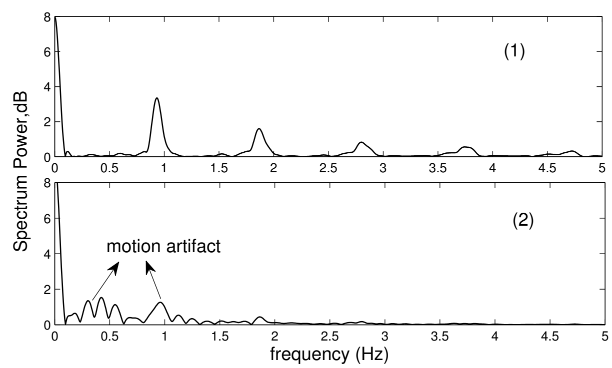

Fig. 1. (a) Frequency spectrum of a PPG signal with no artifact; (b) frequency spectrum of a corrupted PPG signal with motion artifacts

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II. MOTION ARTIFACT REDUCTION

A. Empirical Mode Decomposition

The EMD technique was initially proposed for analyzing fluid mechanics, and soon found its applications in biomedical signal processing [3]. The key idea of this technique is that any complicated time-series can be decomposed into a number of "intrinsic mode functions"(IMF) [4]. With this definition, each cycle in an IMF, defined by zero crossings, involves only one mode of oscillation, no complex riding waves will be presented.

A signal can be decomposed into IMFs of different resolution scales, similarly as in the wavelet analysis [5]. However, in the EMD, the basis functions of expansion are directly extracted from the data, while in wavelet decomposition, a pre-designed mother wavelet is selected before the analysis and determines the basis functions for different scales. Compared with wavelet analysis, IMF can better represent the local characteristics of a signal, and adapt to the signal's oscillation patterns over time. Due to this advantage, the EMD is suitable for analyzing nonlinear and nonstationary signals, thus applicable to PPG analysis.

In the EMD decomposition, a signal must satisfy two criteria to be an IMF: (1) in the whole data set, the difference between the number of maxima and the number of zero crossings must be no more than one; and (2) the average of the upper and lower envelopes is zero at any time instant.

Given the definition of IMFs, the problem of interest is how to derive a series from the given signal $x(t)$ to satisfy the two requirements mentioned above. The solution consists of four steps [4]:

Step (1): a cubic spline is used to connect all the local maximum points of signal $x(t)$ to obtain its upper envelope. The local maxima are obtained by comparing the values of neighboring points, if a point's value is larger than both its neighbors, it will be taken as a local peak. In the same way, a cubic spline connects local minimum points of $x(t)$ to form a lower envelope.

Step (2): the averaged trace $m(t)$ of the upper and lower envelopes is subtracted from the data to obtain their difference over time $x_1(t)$:

$$x_1(t) = x(t) - m(t), \tag{1}$$

Step (3): Let $x(t) = x_1(t)$ and repeat step (1) and step (2) until $x_1(t)$ meets the two criteria of an intrinsic mode. This process is called *sifting process* [3]. The resulting $x_1(t)$ of this process is an IMF, represented as $C_j(t)$ in the below, where j is the label of scale.

Step (4): Separate $C_j(t)$ from the initial signal $x(t)$ to obtain the residue signal $r_j(t)$.

$$r_j(t) = x(t) - C_j(t), \tag{2}$$

The residue $r_j(t)$ can be further decomposed by treating $r_j(t)$ as the new data, i.e., $x(t) = r_j(t)$ and processing it using the sifting process described above. This iterative procedure continues until the residue $r_j(t)$ finally becomes a monotonic function from which no more IMF can be extracted [3].

Following this decomposition process, the original signal $x(t)$ is decomposed into N IMFs, each with a different resolution. The original signal $x(t)$ equals to the summation of the extracted IMFs of different scales and the residual signal:

$$x(t) = \sum_{j=1}^{N} C_j(t) + r_N(t), \tag{3}$$

where N is the total number of IMFs, j is the scale label of a IMF, $r_N(t)$ is the final residue, which can be either a monotonic trend or a constant mean value, and function $C_j(t)$ are approximately orthogonal to each other, and all have zero means. Fig. 2 shows the corresponding IMF components of an example PPG signal.

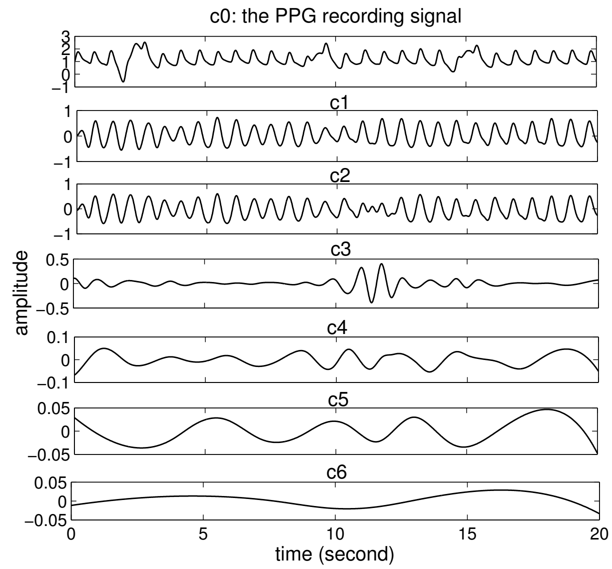

Fig. 2. Intrinsic Mode Function (IMF) components (c1-c6) of an example PPG signal (c0) using the Empirical Mode Decomposition (EMD)

B. Hilbert Transform

Hilbert transform can be used to generate instantaneous frequency for each IMF obtained in EMD. For each IMF component $C(t)$, we first calculate its analytic signal as:

$$z(t) = C(t) + iH[C(t)] = a(t)exp[i\theta(t)], \tag{4}$$

where $H[C(t)]$ is the Hilbert transform of $C(t)$, $a(t)$ and $\theta(t)$ are the instantaneous amplitude and phase of the analytic signal $z(t)$ respectively. The instantaneous frequency of $C(t)$ can be further derived from the instantaneous phase as below:

$$\sigma = \frac{d\theta(t)}{dt}, \tag{5}$$

With the calculated instantaneous amplitude and frequency, we can express the original signal in the following form:

$$x(t) = \sum_{j=1}^{N} a_j(t)exp(i\int \sigma_j(t)dt), \tag{6}$$

where $\sigma_j(t)$ represents the instantaneous frequency of every IMF, and $a_j(t)$ is the instantaneous amplitude of every IMF.

C. Noise Reduction

As mentioned above, by using the EMD and Hilbert transform we can derive the instantaneous frequency of a signal at different resolution scales. For example, a PPG signal can be decomposed into 6 scales as shown in Fig.3. The mean frequencies of scale from 1 to scale 6 are 1.5 Hz, 1.5 Hz, 0.85 Hz, 0.45 Hz, 0.25 Hz and 0.10 Hz respectively. According the mean frequency, the components of scale 1-3 mostly likely correspond to the PPG signal and its harmonics; while the components of scale 4-6 mostly likely correspond to artifacts. Therefore, IMFs of scale 4-6 were discarded and only IMFs of scale 1-3 are used for reconstructing PPG signals, in this way, the motion artifact is reduced in the reconstructed PPG signal.

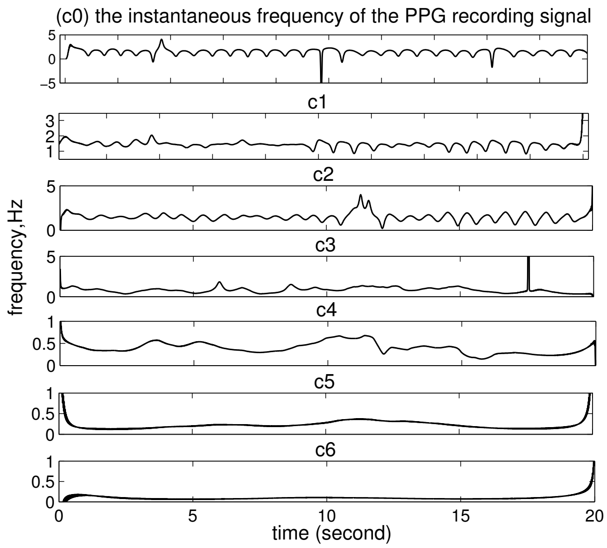

Fig. 3. An example PPG signal and the instantaneous frequency of its IMF components of different scales

III. RESULTS

To evaluate the performance of the proposed method, an experiment was conducted in our institution on 4 voluntary healthy human subjects. From each subject, two PPG signals were collected simultaneously, one from the forefinger of the right hand using the TSD200 transducer, the other from the forefinger of the left hand using the TSD123 transducer. The PPG signals from both transducers were input to the Biopac System MP150 (BIOPAC, Goleta, CA) at a sampling rate of 100 Hz. The subjects were asked to bend their forefingers of the right hand to induce motion artifacts, while keeping the left hand stable. We assume for the same subject the physiological components in the PPG signals acquired from different hands are identical even when hand movements are involved. Therefore the stable PPG signals from their left hands can be used as the reference signal. Twenty seconds of signals were collected from each subject. In total, 80 seconds of PPG signals were used for performance evaluation.

The corrupted PPG signals were processed using the proposed method and the performance of noise reduction was evaluated by comparing the recovered signal with the reference signal. For comparison, a band-pass filter with low and high cut-off frequencies being 1 and 3.5 Hz was also used to process the contaminated signal. As shown in Fig. 4, finger bending caused significant distortion in PPG (see Fig.4 (a)). After using our method, noise contamination was significantly reduced (see Fig. 4 (b)), and the peaks due to heartbeats can be better detected. In contrast, band-pass filter did not perform as well, especially for the motion artifacts at location (1).

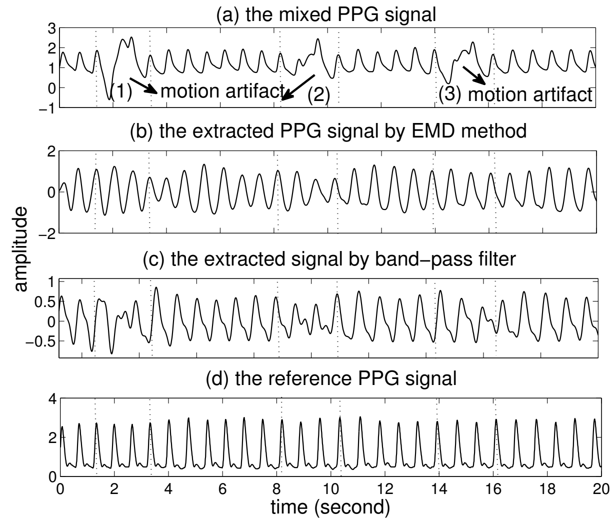

Fig. 4. Comparison of the corrupted PPG signal (a), the recovered PPG signals by the EMD method (b) and band-pass filter (c), and the reference PPG signal (d)

The pulse rates were detected in the reference PPG signal and also in the recovered PPG signal using the differential peak detection method [6] (see Fig.5). There is a very short period of time delay, which is tolerable in the practice. The true heartbeat detection rate was 59.2% in the contaminated PPG recordings. By using our method, the true detection rate was increased to 96.6%.

We tested the proposed method on all the data collected from the subjects. The performance of noise reduction was evaluated by calculating the signal-to-noise ratio, as defined below:

$$SNRatio = 10\log_{10}\frac{\sum_{N}(s^2(n))}{\sum_{N}(x(n)-s(n))^2}, \quad (7)$$

where s is the reference signal, x is the signal to be evaluated. The averaged signal-to-noise ratio of the original PPG signals was 0.078 dB. After using our method, the ratio was increased to 0.318 dB.

IV. CONCLUSION

The artifacts due to finger motion often corrupt measurements in wearable PPG devices. The occurrence of these

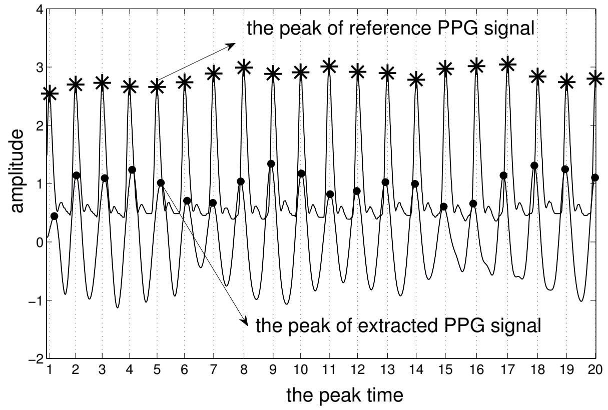

Fig. 5. The peak points detected in the reference PPG signal and the recovered PPG signal

artifacts is often random and hardly predictable. Considering that the amplitude and frequency of PPG signals may change over time in the monitoring process, linear filters are not effective in reducing motion artifacts in PPG recordings [7]. The proposed method based on the EMD and Hilbert transform demonstrated great potential for reducing artifacts in PPG signals for heartbeat detection. The reason is the IMF components are extracted from the signal itself, which adapts the basis function of the multiscale decomposition to the signal's intrinsic oscillation patterns.

There is much room for improvement. In the experiment, the transducers used for measuring the testing PPG signal and the reference PPG signal were different, resulting slight difference in the recordings from two hands even when no artifacts are presented. In the future, it is desirable to use transducers of the same model at the two different measurement sites.

In this study, we focused on artifact reduction. In the future, we will analyze the instantaneous frequency generated by the EMD and Hilbert transform to detect and locate the occurrence of artifacts.

REFERENCES

[1] P. Gibbs and H. H. Asada, "Reducing motion artifact in wearable biosensor using MEMS accelerometers for active noise cancellation", *in American Control Conference*, Portland, 2005, pp: 1581-1586.

[2] J. Lee and W. Jung. "Design the filter to reject motion artifact of pulse oximetry", *Elsevier computer science*, vol. 26, pp: 241-249. July, 2003.

[3] H. Liang and Z. Lin, "Artifact reduction in electrogastrogram based on empirical mode decomposition method", *Medical Biological Engineering and Computing*, vol.38, pp: 35-41. January. 2000.

[4] N. E. Huang, Z. Shen and S. R. Long. "The empirical mode decomposition and the Hilbert spectrum for non-stationary time series analysis", *Proceedings of the Royal Society*, vol. 454. pp: 454-459. November. 1998.

[5] C.M.Lee and Y.T.Zhang. "Reduction of motion artifacts from photoplethysmogrphic recording using a wavelet denosing approach", *IEEE EMBS Asian-Pacific Conference*, 2003, pp: 194-195.

[6] T. H. Fu and S. H. Liu, "Heart rate extraction from photoplethysmogram waveform using wavelet multi-resolution analysis", *Medical and Biological Engineering*, vol. 28, pp: 229-232. June. 2008.

[7] B. Widrow and S. D. Stearns, *Adaptive Signal Processing*, Prentice-Hal, New Jersey, 1985, pp: 119-133.