Adaptive Frequency Tracking for Robust Heart Rate Estimation Using Wrist-Type Photoplethysmographic Signals During Physical Exercise

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Abstract

In recent years, wearable photoplethysmographic (PPG) biosensors have emerged as promising tools to monitor heart rate (HR) during physical exercise. However, PPG waveforms are easily corrupted by motion artifacts, rendering HR estimation difficult. In this study, HR was estimated using wrist-type PPG signals. A normalized least-mean-squares (NLMS) algorithm was first used to attenuate motion artifacts and reconstruct multiple PPG waveforms from different combinations of corrupted PPG waveforms and accelerometer (ACC) data. An adaptive band-pass filter was then used to track the common instantaneous frequency component (i.e. HR) of the reconstructed PPG waveforms. Our proposed HR estimation method, which is almost real time, resulted in an average absolute error of 1.71 $\pm$ 0.49 beats-per-minute and a Pearson correlation coefficient of 0.994 between the true and the estimated HR values. Importantly, as all ACC-PPG combinations were used for motion artifacts cancellation, no assumption about individual ACC axis contribution was required.

1. Introduction

In recent years, wearable photoplethysmographic (PPG) biosensors have emerged as very promising tools to monitor heart rate (HR) outside of the hospital environment, such as during physical exercise to evaluate the physical condition of athletes and prevent injuries. PPG is an optical technique used to detect blood volume changes in biological tissues. PPG waveforms comprise a pulsatile “AC” component and a slowly varying “DC” baseline. The AC component reflects the cardiac synchronous changes in the blood volume occurring at each heart beat, while the DC component reflects the influence of respiration, sympathetic nervous system activity and thermoregulation [1]. Fourier-based methods are commonly used to extract HR from the AC component of PPG waveforms. However, due to the non-stationary nature of PPG signals, these techniques may not be optimal. Additionally, an important issue is the presence of motion artifacts (MA) which corrupt PPG signals and can make them unusable. Therefore, hardware and software improvements are still required to fully exploit the potential of wearable PPG sensors. Different approaches have been investigated so far to identify and remove MA from PPG signals. Some of these methods involve various types of frequency-domain data processing, including smoothed pseudo Wigner-Ville distribution [2], frequency-domain independent component analysis [3] and Fourier series applied on a cycle-by-cycle basis [4]. Another possible course of action to reduce MA in PPG waveforms is adaptive filtering. Different variants of least mean squares (LMS) filters were tested using either accelerometer signals as noise reference [5] or a synthetic noise [6]. Recently, Zhang *et al.* [7] developed a complete framework for precise HR estimation in case of strong MA, consisting of three main steps: signal decomposition for denoising, sparse signal reconstruction and spectral peak tracking. In a similar study, the difference between the power spectra of PPG and acceleration was used to estimate HR on running subjects [8]. Nevertheless, most of the solutions that have been proposed until now present limitations. These limitations are mostly related to computational complexity or strong dependencies to thresholds/parameters which have to be precisely tuned for each subject. The purpose of this study was to develop a robust approach for HR estimation using wrist-type PPG signals corrupted by strong MA. MA reduction and frequency tracking were achieved by two consecutive adaptive filters.

2. Methods

2.1. Data

The IEEE Signal Processing Cup 2015 database [7] is composed of 12 recordings, of duration of five minutes each, from male subjects aged from 18 to 35. For each subject, the following waveforms were recorded simultaneously: three-axis acceleration (ACC), one channel ECG and two-channel PPG. Each waveform was sampled at 125 Hz. The two pulse oxymeters (using green LEDs) as well as the accelerometer sensor were embedded into a wristband. The ECG signal was recorded from the subject's chest. The subjects were asked to run on a treadmill at different speeds according to the following protocol: 0.5 min at 1-2 km/h, 1 min at 6-8 km/h, 1 min at 12-15 km/h, 1 min at 6-8 km/h, 1 min at 12-15 km/h and 0.5 min at 1-2 km/h. In addition to the raw signals, a ground-truth HR (BPM_{ref}) derived from ECG was also provided. BPM_{ref} was defined as the average HR value in every 8-seconds time window (6-seconds overlap).

2.2. Adaptive MA reduction

In the present study, we hypothesized that the PPG and ACC waveforms were correlated and decided to use an adaptive filter for MA reduction. The normalized least-mean-squares (NLMS) algorithm is widely used in adaptive filtering due to its computational simplicity [9]. In this well known algorithm, an input signal $x(k)$ is provided as well as a desired signal $d(k)$. The filter output $y(k)$ minimizes the least mean squares error and the error signal $e(k)$ is used to update the filter coefficients.

2.3. Adaptive frequency tracking

HR estimation was achieved using a time-varying band-pass filter, constantly updated to track the instantaneous frequency. This algorithm, described in [10, 11], was derived from the discrete oscillator based adaptive notch filter (OSC-ANF) proposed in [12]. The transfer function of the time-varying single pole band-pass filter is expressed as follow:

$$G(z;n) = \frac{1-\beta}{1-\beta e^{jw(n)}z^{-1}} \tag{1}$$

with $w(n)$, the normalized instantaneous frequency estimate and β ($0 \ll \beta < 1$), a factor related to the bandwidth of the filter. The adaptive mechanism used to update the central frequency of the band-pass filter in (1) at each time step requires the minimization of a cost function, which is derived from the complex oscillator equation:

$$c(n) = e^{jw_0}c(n-1) \tag{2}$$

By considering an input signal that is a complex sinusoid corrupted by a complex interference, from (2), the output signal $y(n)$ can be written as:

$$y(n) = \theta(n)y(n-1) + e(n) \tag{3}$$

with $e(n)$, the error term and $\theta(n) = e^{jw(n)}$. A minimization of the mean square error leads to the following expression for $\theta(n)$:

$$\theta(n) = \frac{E[y(n)\overline{y}(n-1)]}{E[|y(n-1)|^2]} \tag{4}$$

Which can be approximated in practice by:

$$\hat{\theta}(n) = \frac{Q(n)}{P(n)} = \frac{\delta Q(n-1) + (1-\delta)y(n)\overline{y}(n-1)}{\delta P(n-1) + (1-\delta)|y(n-1)|^2} \tag{5}$$

where the convergence rate can be adjusted with a forgetting factor δ. And finally, the instantaneous frequency $w(n)$ is defined as:

$$w(n) = arg\left(\frac{\hat{\theta}(n)}{|\hat{\theta}(n)|}\right) \tag{6}$$

This single frequency tracker can be extended to the multivariate case [13] in order to track the common frequency component present in L input signals. In a first step, all inputs are individually filtered by the same band-pass filter and the instantaneous frequency of each sinusoid is estimated using the method previously described. The instantaneous frequency estimates are then weighted to obtain a global estimate. The computation of the weights A_l is based on the minimization of the variance of the linear combination of the individual instantaneous frequency estimates. The global instantaneous frequency estimate is finally defined as:

$$w(n) = \sum_{l=1}^{L} A_l(n)w_l(n) \tag{7}$$

Since our algorithm, referred to as OSC-ANFc-W, operates in the complex domain and the signals of interest were real-valued, the Hilbert transform was used to obtain the analytic representation whose real part is the original signal. More specifically, the Hilbert transform was computed using a sliding centered window of 31 samples.

2.4. HR estimation framework

The ACC and PPG waveforms were first re-sampled at 35 Hz. Then, adaptive MA reduction was performed using the NLMS algorithm. Since the contribution of each ACC-axis to the deterioration of the PPG waveforms was not known, adaptive noise reduction was performed for the six ACC-PPG channel pairs. For this purpose, the corrupted PPG signals were defined as reference input signals $d(n)$ and ACC signals were defined as input signals $x(n)$ of the NLMS algorithm. The clean reconstructed PPG signals with minimized MA were approximated by the error outputs $e(n)$ of the NLMS filter. In order to make real-time implementation possible, the filter was chosen to be causal. The filter length was 70 samples and an adaptation coefficient of 0.1 was used. Finally, all reconstructed PPG signals, as well as the original PPG signals, were fed to the OSC-ANFc-W algorithm in order to estimate HR. We chose $\beta = 0.98$ and $\delta = 0.98$.

2.5. Performance measurement

In order to assess the performance of our HR estimation scheme, two classical error measures were used. The first one is the average absolute error:

$$error1 = \frac{1}{N}\sum_{i=1}^{N}|BPM_{est}(i) - BPM_{ref}(i)| \quad (8)$$

with *N*, the total number of time windows (see section 2.1). The second one is the average absolute error percentage:

$$error2 = \frac{1}{N}\sum_{i=1}^{N}\frac{|BPM_{est}(i) - BPM_{ref}(i)|}{BPM_{ref}(i)} \quad (9)$$

In addition, the Pearson correlation coefficient between the true and estimated HR values across all subjects was computed.

3. Results

Figure 1 illustrates an example of MA reduction using the NLMS algorithm. In this example, the original PPG waveform (dashed line) exhibits supplementary pulses while the reconstructed PPG waveform (red) is well synchronized with the ECG waveform displayed below.

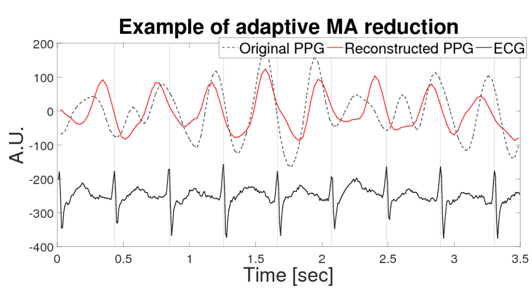

Figure 1. Example of adaptive MA reduction using NLMS for one PPG-ACC channel pair.

Tables 1 and 2 present the two error measures for each subject and for the different methods. Using the whole HR estimation framework (NLMS + OSC-ANFc-W), an overall average absolute error of 1.71 $\pm$ 0.49 beats-per-minute and an average error percentage of 1.41% were achieved. In order to highlight the importance of the adaptive MA reduction step, the two error measures were also computed when HR was estimated only from the two original PPG waveforms, using the OSC-ANFc-W algorithm. In this case, the overall average absolute error was 6.41 $\pm$ 6.13 beats-per-minute and the average error percentage was 5%. The performance of our method was compared with the results reported by Zhang *et al.* [7], who achieved an overall average absolute error of 2.34 $\pm$ 0.83 beats-per-minute and an average error percentage of 1.79%. An additional measure is presented in Table 1 (Best channel), to assess the effect of using all the possible PPG-ACC channel combinations. For each subject, HR was estimated on the different reconstructed and original PPG channels separately and the one resulting in the lowest average absolute error is displayed. The numbers into brackets correspond to the following channel combinations: 1: ACC(1) & PPG(1), 2: ACC(2) & PPG(1), 3: ACC(3) & PPG(1), 4: ACC(1) & PPG(2) , 5: ACC(2) & PPG(2), 6: ACC(3) & PPG(2), 7: PPG(1) only, 8: PPG(2) only.

Subject	Zhang *et al.* [7]	NLMS + OSC-ANFc-W	OSC-ANFc-W	Best channel
1	2.29	1.95	17.37	3.78 (3)
2	2.19	1.89	18.54	2.21 (4)
3	2.00	1.64	6.16	1.37 (6)
4	2.15	2.10	2.49	2.01 (3)
5	2.01	1.25	1.42	1.34 (7)
6	2.76	1.62	2.22	1.79 (2)
7	1.67	1.23	1.34	0.90 (7)
8	1.93	1.72	2.06	1.53 (3)
9	1.86	1.27	1.58	1.16 (6)
10	4.70	2.98	5.15	3.80 (4)
11	1.72	1.49	8.14	1.27 (2,3)
12	2.84	1.37	10.42	1.41 (6)
Av. $\pm$ std	**2.34 $\pm$ 0.83**	**1.71 $\pm$ 0.49**	**6.41 $\pm$ 6.13**	**1.88 $\pm$ 0.96**

Table 1. Average absolute error (error-1).

Subject	Zhang *et al.* [7]	NLMS + OSC-ANFc-W	OSC-ANFc-W
1	1.90%	1.78%	13.87%
2	1.87%	1.82%	15.35%
3	1.66%	1.44%	5.12%
4	1.82%	1.88%	2.30%
5	1.49%	0.96%	1.14%
6	2.25%	1.46%	1.93%
7	1.26%	0.96%	1.06%
8	1.62%	1.51%	1.76%
9	1.59%	1.11%	1.30%
10	2.93%	1.92%	3.23%
11	1.15%	1.04%	5.58%
12	1.99%	1.05%	7.42%
Average	**1.79%**	**1.41%**	**5.00%**

Table 2. Average absolute error percentage (error-2)

Figure 2 shows the HR estimation for the first subject. The ground-truth HR, in black, as well as the HR estimates are displayed. The Pearson correlation coefficient between the true and estimated HR values across all subjects was 0.994 using our method (NLMS + OSC-ANFc-W).

4. Discussion and conclusion

This study proposes a novel approach for estimating HR using PPG signals corrupted by strong MA. Our results have shown a strong agreement between the estimated and the ground-truth HR values, which was confirmed by the high Pearson correlation coefficient and the small overall average absolute error. A comparison with the results reported by Zhang *et al.* [7] on the same database indicates

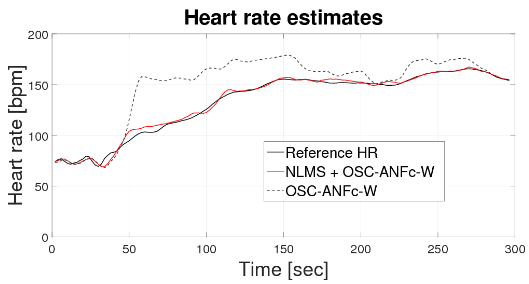

Figure 2. Estimated and reference HR values for the first subject

that our HR estimation framework led to lower error-1 values for all subjects and lower error-2 values for 11 subjects out of 12. Furthermore, our method resulted in an overall error-1 reduction of 27%. It should be noticed that we obtained larger error values when adaptive MA reduction was not performed, confirming the relevance of this step. In addition, our results have emphasized the importance of combining ACC and PPG channels. It must be noted that for six subjects out of 12 the error was lower when only one input signal was fed to the OSC-ANFc-W. However, as indicated by the numbers in brackets, the most accurate HR values were not always obtained from the same input signal. For this reason, it is advantageous to avoid any channel selection process and combine the available information as much as possible. Moreover, if we consider the error-1 averaged across all subjects, the best performance was achieved when all the combinations were used together. Importantly, the HR estimation framework presented in this study could be used for almost real-time applications. The average estimation delay of about 1.5 seconds is caused by the adaptation time of the filter and the computation of the Hilbert transform.

HR estimation from MA corrupted PPG signal during physical exercise is particularly challenging because the arm portion is strongly affected by MA when the subjects are running. Here, we propose a novel two-stage approach based on an adaptive filtering scheme. Our method achieves a very low estimation error. Importantly, it does not require any a priori knowledge about the contribution of each signal. Therefore, it could be easily implemented in wearable PPG devices. Extraneous ACC signals were used for adaptive MA reduction. Yet this should not be considered as a weakness of the method, because ACC sensors are embedded in most of the modern wearable devices. Finally, it would be interesting to further extend this study to subjects performing different kind of physical activities.

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References

[1] Allen J. Photoplethysmography and its application in clinical physiological measurement. Physiol Meas 2007; 28(3):R1–39.

[2] Yong-sheng Y, Poon Carmen CY, Yuan-ting Z. Reduction of motion artifact in pulse oximetry by smoothed pseudo wigner-ville distribution. J Neuroengineering Rehabil 2005;2:3.

[3] Krishnan R, Natarajan B, Warren S. Two-stage approach for detection and reduction of motion artifacts in photoplethysmographic data. IEEE Trans Biomed Eng 2010; 57(8):1867–1876.

[4] Reddy KA, George B, Kumar VJ. Use of fourier series analysis for motion artifact reduction and data compression of photoplethysmographic signals. IEEE Trans Instrum Meas 2009;58(5):1706–1711.

[5] Comtois G, Mendelson Y. A noise reference input to an adaptive filter algorithm for signal processing in a wearable pulse oximeter. In Bioengineering Conference IEEE 33rd Annual Northeast. 2007; 106–107.

[6] Ram MR, Madhav KV, Krishna EH, Komalla NR, Reddy KA. A novel approach for motion artifact reduction in PPG signals based on AS-LMS adaptive filter. IEEE Trans Instrum Meas 2012;61(5):1445–1457.

[7] Zhang Z, Pi Z, Liu B. TROIKA: A General Framework for Heart Rate Monitoring Using Wrist-Type Photoplethysmographic Signals During Intensive Physical Exercise. IEEE Trans Biomed Eng 2015;62:522–531.

[8] Fukushima H, Kawanaka H, Bhuiyan MS, Oguri K. Estimating heart rate using wrist-type Photoplethysmography and acceleration sensor while running. In 2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC). 2012; 2901–2904.

[9] Diniz PSR. Adaptive Filtering. Springer US, 2013.

[10] Van Zaen J, Uldry L, Duchêne C, Prudat Y, Meuli RA, Murray MM, Vesin JM. Adaptive tracking of EEG oscillations. J Neurosci Methods 2010;186(1):97–106.

[11] Uldry L, Duchêne C, Prudat Y, Murray MM, Vesin JM. Adaptive tracking of EEG frequency components. In Advanced Biosignal Processing. Springer, 2009; 123–144.

[12] Liao HE. Two discrete oscillator based adaptive notch filters (OSC ANFs) for noisy sinusoids. IEEE Trans Signal Process 2005;53(2):528–538.

[13] Prudat Y, Vesin JM. Multi-signal extension of adaptive frequency tracking algorithms. Signal Process 2009; 89(6):963–973.

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