Heart Rate Tracking using Wrist-Type Photoplethysmographic (PPG) Signals during Physical Exercise with Simultaneous Accelerometry

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Abstract—This paper considers the problem of heart rate tracking during intensive physical exercise using simultaneous 2 channel photoplethysmographic (PPG) and 3 dimensional (3D) acceleration signals recorded from wrist. This is a challenging problem because the PPG signals recorded from wrist during exercise are contaminated by strong Motion Artifacts (MAs). In this work, a novel algorithm is proposed which consists of two main steps of MA Cancellation and Spectral Analysis. The MA cancellation step cleanses the MA-contaminated PPG signals utilizing the acceleration data and the spectral analysis step estimates a higher resolution spectrum of the signal and selects the spectral peaks corresponding to HR. Experimental results on datasets recorded from 12 subjects during fast running at the peak speed of 15 km/hour showed that the proposed algorithm achieves an average absolute error of 1.25 beat per minute (BPM). These experimental results also confirm that the proposed algorithm keeps high estimation accuracies even in strong MA conditions.

Index Terms—Causal Heart Rate Monitoring, Photoplethysmograph (PPG), Singular Value Decomposition (SVD), Adaptive Motion Artifact Cancellation, Sparse Spectrum Estimation, Iterative Method with Adaptive Thresholding (IMAT).

I. INTRODUCTION

Pulse oximeters facilitate noninvasive continuous monitoring of heart rate (HR) by recording Photoplethysmographic (PPG) signals from skin [1]. A PPG signal is obtained by illuminating skin using a light-emitting diode and detecting the intensity changes in the reflected light. Hence the periodicity of the PPG signal represents HR [2].

However, PPG signals are highly contaminated by artifacts caused by movements of the subject. Such motion artifacts (MAs) strongly interfere with HR especially in fitness applications when the PPG signal is recorded during physical exercise of the subject [3]. The situation gets worse in the case considered in this paper when the PPG signals are recorded from wrist. Such PPG signals experience severe MA due to the loose interface between the pulse oximeter and skin [4]. The periodic movement of arm during high speed running leads to periodic motion artifacts with fundamental frequencies close to that of HR or its harmonics. Such kind of motion artifacts even cannot be considered statistically independent of the clean PPG signal [5]. Hence exact HR extraction from wrist-type PPG signals recorded during intensive physical exercise remains a challenging problem.

The signal processing algorithms proposed so far for MA reduction from PPG signals mostly consider weak MA scenarios in which subjects perform small motions such as finger movements [6], [7], [8] and walking [8]. Only a few prior works considered the scenario of HR monitoring from PPG signals in fitness and they consider low MA PPG signals recorded from fingertip [8], [9] or ear [10]. Although HR monitoring from wrist-type PPG signals during intensive physical exercise is extremely challenging, but it is of great interest to wearable smart devices such as smart-watches [4].

In order to overcome this challenge, we consider that simultaneous acceleration data is also recorded and available for processing. By using this extra information, we propose an efficient algorithm that accurately tracks HR during high speed (12-15 km/hour) running of the subject by simultaneous processing of the PPG signals taken from two different sensors and the acceleration data along the three axes. The proposed algorithm consists of two main steps of MA cancellation and spectral analysis.

The MA cancellation step decomposes the acceleration signals into periodic MA components using Singular Value Decomposition (SVD). These MA components are then suppressed in the PPG signals by adaptive filtering leaving 2 channel cleansed PPG signals with sparse spectrum.
The Spectral Analysis step applies a few iterations of the IMAT (Iterative Method with Adaptive Thresholding) sparse reconstruction algorithm to achieve a higher resolution spectrum of the cleansed signals and selects the spectral peaks corresponding to HR. These blocks are further explained in section II. Experimental results on datasets recorded from 12 subjects during fast running at the peak speed of 15 km/hour showed high estimation accuracy of the proposed algorithm achieving an average absolute error of 1.25 BPM. These datasets are provided by [4], [11] as benchmark for comparisons. The simulation results show that our proposed algorithm achieves an improvement of 1.09 BPM in terms of the average absolute error compared to the latest research [4]. This improvement is a result of the proposed Peak Selection algorithm that efficiently tracks HR by simultaneous processing of the two channel PPG signals in comparison with [4], [11] that consider single channel PPG signals available.

The rest of this paper is organized as follows. Section II explains the proposed method. Section III presents and discusses the simulation results achieved by the proposed method on the 12 benchmark datasets. And finally section IV concludes this paper. For further reproduction of the reported results, MATLAB codes of the proposed algorithm have been made available online at: ee.sharif.edu/~imat/

II. THE PROPOSED ALGORITHM

As mentioned earlier, the proposed algorithm consists of two main steps of MA cancellation and spectral analysis. Fig. 1 shows a block diagram of the proposed HR tracking algorithm. The blocks used in the proposed algorithm are explained in the following subsections.

A. MA Cancellation

In this step, prior to further processing, we filter both PPG signals in [0.4-5] Hz band to reject the MAs outside the natural HR range. Once the out-of-band MAs are cancelled, we apply adaptive filters to suppress in-band MAs. The reference MA signal components needed for the adaptive filter are extracted from the simultaneous acceleration data by Singular Value Decomposition (SVD). These two substeps are further explained in the following:

Reference MA Generation using SVD: As expected, the simultaneous acceleration data along the three axes include footprints of the MAs. However, the acceleration data are complicated noisy signals composed of different periodic components themselves. This will strongly hamper convergence of the applied adaptive filter. Hence, we propose to generate the reference MA signals by decomposing the three acceleration signals by SVD prior to adaptive filtering as depicted in Fig. 1. In this technique, each acceleration signal goes through embedding, SVD and grouping steps [4]. During embedding, a so called L-trajectory matrix is formed from each acceleration signal. Subsequently, these L-trajectory matrices are decomposed to linearly independent rank-one matrices. These $d$ matrices are classified into $g$ groups with the same or harmonically related oscillatory components. Finally, $n$ groups with frequency components inside [0.4-5] Hz band are utilized as the MA reference signal components for adaptive cancellation.

Adaptive MA Cancellation: During this procedure, all the reference MA components derived by SVD are removed from both PPG signals by successive application of adaptive filters [8] as depicted in Fig. 2. Each adaptive filter stage receives the residual signal resulting from its prior stage and a reference signal component as input. Fig. 3 also depicts the structure of one stage Adaptive MA Cancellation block. The effects of the adaptive filter types and orders are well investigated in the following section. These adaptive filters remove both periodic and random MA components. By using this technique, we remove the footprints of all reference MA signal components from the PPG signal. Finally, the resulting cleansed signal is input to the spectral analysis step for HR tracking.
B. Spectral Analysis

Spectral Analysis is a key step in the proposed HR tracking algorithm. As observed in Fig. 1, this step consists of two substeps of High Resolution Spectrum Estimation using the Iterative Method with Adaptive Thresholding (IMAT) and Peak Selection. IMAT is a fast and efficient algorithm for sparse signal reconstruction [12], [13] that proved to outperform other sparse spectrum estimation techniques regarding reconstruction performance and complexity [14]. This algorithm is used to provide a higher resolution and denoised spectrum of the input signal prior to Peak Selection. In Peak Selection, we apply some decision mechanisms to accurately estimate the frequency location index of HR in each time window. These decision mechanisms are thoroughly explained below.

Peak Selection: The decision mechanisms used in Peak Selection exploit the frequency harmonic relation of HR along with the assumption that HR varies smoothly along time and does not experience jumps between successive time windows. In fact, our experiments showed that in many cases the spectral peak associated with HR keeps its location unchanged in two successive time windows.

To initialize our system, we estimate HR by considering the highest peak in the spectrum of the first 8 second window. This initialization technique is valid as the subjects are required to reduce hand motions during the first few seconds of recording and hence the first PPG window is considered artifact-free.

In the proceeding windows, we track HR by the following algorithm. Denote the estimated HR frequency locations in the current and previous windows by $N_{\text{cur}}$ and $N_{\text{prev}}$ respectively. Now, consider the three frequency ranges $R_1, R_2, R_3$ in the current time window as in (1):

$$
R_1 = [N_{\text{prev}} - \varepsilon_1, N_{\text{prev}} + \varepsilon_1]
$$

$$
R_2 = [2 \times N_{\text{prev}} - \varepsilon_2, 2 \times N_{\text{prev}} + \varepsilon_2]
$$

$$
R_3 = [3 \times N_{\text{prev}} - \varepsilon_3, 3 \times N_{\text{prev}} + \varepsilon_3]
$$

Case1: If one of $S_{11}, S_{21}, S_{31}, S_{12}, S_{22}, S_{32}$ is significantly greater than others (dominant peak) as defined by equation (2), we select the HR frequency index in the current time window as its corresponding fundamental frequency. Note that in (2), $0 < T < 1$ is a predefined threshold optimized by simulations for the best performance.

$$
N_{\text{cur}} = \frac{P_{ij}}{l} \Leftrightarrow \forall (k,l) \neq (i,j): S_{ij} \times T > S_{kl}
$$

Case2: If there is no dominant peak as defined in case 1 in either PPG channels, we search among $P_{11}, P_{21}, P_{31}, P_{12}, P_{22}, P_{32}$ to find a peak pair with a harmonic relation and choose the corresponding fundamental frequency as the HR frequency index in the current time window according to equation (3).

$$
N_{\text{cur}} = \frac{P_{ij} + P_{kt}}{2} \Leftrightarrow \left| \frac{P_{ij}}{l} - \frac{P_{kt}}{k} \right| < \delta
$$

Case3: If none of the above two cases occur, we make a 10 second time window by concatenating the current and the previous windows and similarly define the three harmonic ranges as above. We also denote the frequency location index of the highest peaks in these ranges by $Q_{11}, Q_{21}, Q_{31}, Q_{12}, Q_{22}, Q_{32}$. Finally, we set $N_{\text{cur}}$ as the average of all the available fundamental frequencies as given by equation (4).

$$
N_{\text{cur}} = \frac{1}{12} (P_{11} + P_{21} + P_{31} + P_{12} + P_{22} + P_{32} + Q_{11} + Q_{21} + Q_{31} + Q_{22} + Q_{32})
$$

III. SIMULATION RESULTS

A. Parameter Setting

When using SSA, we choose $d = 100$ for the SVD algorithm. An adaptive LMS filter of order 10 was used for MA cancellation with an optimized $\mu = 0.005$. It was also observed that 5 iterations of the IMAT algorithm with optimized parameters $\alpha = 0.1$ yields a high resolution and sufficiently accurate spectrum of the cleansed PPG signals. Finally, the parameters $T$, $\delta$ and $\varepsilon$ are set to 0.6, 9 and 100 respectively. The simulation parameters $\varepsilon_1$ and $\varepsilon_2$ are optimized on each training data for best results. These optimized parameters are reported along with the corresponding results in Tables 1 and 2.

B. Results

To observe the effects of motion on the recorded PPG signals of subject 1, the frequency content of a single window of the original and cleansed PPG signals are shown in Fig. 4 (a) and (c), respectively. Fig. 4 (b) also shows the 3D acceleration signals used as the reference for Adaptive MA Cancellation. This figure shows that the MA cancellation step successfully removes motion artifacts from the PPG signals.
and makes the spectral peak associated with HR more significant.

Fig. 4. Frequency Content of a) The Original PPG Signal b) 3D Acceleration Data c) Cleansed PPG Signal

Fig. 5 gives the estimation results on recordings of subject 1. The estimated HR is very close to the ground-truth resulting in a Pearson correlation of 0.9998 with the ground-truth of HR, an average absolute error of 1.72 BPM and an estimation variance of 7.63.

Table 1 lists the achieved average absolute error, average error percentage, estimation variance, Pearson correlation and total simulation time on all 12 subjects’ recordings. This results yield an average absolute error of 1.25 BPM. Table 2 also lists the values of the parameters $\varepsilon_1$ and $\varepsilon_2$ used to achieve the results in Table 1.

IV. CONCLUSION

In this paper we proposed a novel algorithm for real-time heart rate estimation using wrist-type PPG signals when subjects are performing intensive physical exercise. In order to deal with the strong MAs caused by subjects’ fast running, we recorded and utilized simultaneous acceleration data as the MA reference signals. The proposed algorithm consists of two key steps of MA Cancellation and Spectral Analysis and shows high robustness against strong motion artifacts caused by intensive physical exercise.

| Subj1 | Subj2 | Subj3 | Subj4 | Subj5 | Subj6 | Subj7 | Subj8 | Subj9 | Subj10 | Subj11 | Subj12 |
|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|--------|--------|
| Average absolute error | 1.72  | 1.33  | 0.90  | 1.28  | 0.93  | 1.41  | 0.61  | 0.88  | 0.59   | 3.78   | 0.85   | 0.71   |
| Average error percentage | 1.5   | 1.3   | 0.75  | 1.2   | 0.69  | 1.2   | 0.5   | 0.8   | 0.5    | 2.4    | 0.6    | 0.5    |
| Estimation variance | 7.63  | 6.23  | 1.88  | 6.21  | 2.06  | 9.67  | 0.66  | 1.99  | 0.71   | 28.40  | 1.42   | 0.79   |
| Pearson correlation | 0.9998| 0.9998| 0.9998| 0.9998| 1.0000| 0.9997| 1.0000| 0.9999| 1.0000 | 0.9994 | 1.0000 | 1.0000 |

Table 2. The Algorithm Parameters used to Achieve the Results in Table 1

| $\varepsilon_1$ | Subj1 | Subj2 | Subj3 | Subj4 | Subj5 | Subj6 | Subj7 | Subj8 | Subj9 | Subj10 | Subj11 | Subj12 |
|----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|--------|--------|
| 90             | 70    | 80    | 65    | 70    | 125   | 30    | 70    | 50    | 120    | 30     | 55     |

| $\varepsilon_2$ | Subj1 | Subj2 | Subj3 | Subj4 | Subj5 | Subj6 | Subj7 | Subj8 | Subj9 | Subj10 | Subj11 | Subj12 |
|-----------------|-------|-------|-------|-------|-------|-------|-------|-------|-------|--------|--------|--------|
| 70              | 70    | 55    | 60    | 95    | 65    | 110   | 75    | 60    | 50     | 80     | 65     |
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