Low Complexity Heart Rate Measurement from Wearable Wrist-Type Photoplethysmographic Sensors Robust to Motion Artifacts

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LOW COMPLEXITY HEART RATE MEASUREMENT FROM WEARABLE WRIST-TYPE PHOTOPLETHYSMOGRAPHIC SENSORS ROBUST TO MOTION ARTIFACTS

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ABSTRACT

This paper presents a low complexity while accurate Heart Rate (HR) estimation technique from signals captured by Photoplethysmographic (PPG) sensors worn on the wrist during intensive physical exercise. Wrist-type PPG signals experience severe Motion Artifacts (MA) that hinder efficient HR estimation especially during intensive physical exercises. To suppress the motion artifacts efficiently, simultaneous 3 dimensional acceleration signals are used as reference MAs. The proposed method achieves an Average Absolute Error (AAE) of 1.19 Beats Per Minute (BPM) on the 12 benchmark PPG recordings in which subjects run at speeds of up to 15 km/h. This method also achieves an AAE of 2.17 BPM on the whole benchmark database of 23 recordings that include both running and arm movement activities. This performance is comparable with state-of-the-art algorithms while at a significantly reduced computational cost which makes its standalone implementation on wearable devices feasible. The proposed algorithm achieves an average processing time of 32 milliseconds per input frames of length 8 seconds (2 channel PPG and 3D ACC signals) on a 3.2 GHz processor.

Index Terms— Realtime Heart Rate Monitoring, Wearable Photoplethysmography (PPG) Technology, Wristbands and Smartwatches

1. INTRODUCTION

The increased functionality of wearable technologies has made them a significant part of everyday life nowadays. Heart rate (HR) monitoring from wrist-type Photoplethysmography (PPG) signals captured by wristbands and smartwatches during physical exercise is one of these functionalities. This helps exercisers to adapt their training load to better meet their goals.

The PPG sensors embedded in wearables emit light to the skin and measure the changes of intensity in the reflected portion. The periodicity of these measurements in an artifact-free condition correspond to the cardiac rhythm and hence HR can be estimated from the PPG signal [1]. However, wrist-type PPG signals captured during physical exercises are significantly affected by relative movements of the skin tissue and the PPG sensor. This causes Motion Artifacts (MA) that significantly hinder efficient HR estimation from the PPG signal. An effective technique to cleans MA-contaminated PPG signals is to utilize simultaneously recorded accelerometer (ACC) signals as MA reference [2].

This problem was posed in the initial work of Zhang et. al. [2] which also provided the benchmark database and performance metrics for subsequent researches. This database was made public for the IEEE Signal Processing Cup 2015 (http://zhilinzhang.com/spcup2015/data.html) and includes 23 wrist-type 2 channel PPG and simultaneous 3D ACC recordings of subjects running on treadmill or doing intensive physical exercises. Since [2] that achieved an AAE of 2.34 BPM on the first 12 recordings (running activities), several HR monitoring algorithms have been proposed and tested [3–16]. Although some recent studies achieved AAEs as small as 1 BPM on the first 12 and 2 BPM on the whole 23 database recordings [3], the computational complexity of the proposed signal processing algorithms still needs to be reduced. For example, a couple of the prior works [2],[4],[5] propose sparse reconstruction techniques for high resolution estimation of the PPG spectrum which impose a large computational burden to wearable processors. Moreover, the advanced signal processing techniques proposed so far for MA suppression such as Independent Component Analysis (ICA) [6], Adaptive Noise Cancellation (ANC) [5], [7], asymmetric least squares [8], Ensemble Empirical Mode Decomposition (EEMD) [15], Multi-Channel Spectral Matrix Decomposition (MC-SMD) [16] and wiener filtering [3] could also be avoided by a concise study of intrinsic PPG signal properties.

The HR estimation technique proposed in this letter is based on several observations on the intrinsic PPG signal properties. It consists of 4 main steps of Auto Regressive (AR) spectrum estimation, MA suppression by spectral division, HR amplification by Cumulative Spectrum (CUM-SPEC) and HR tracking by a lazy tracker algorithm. Fig.

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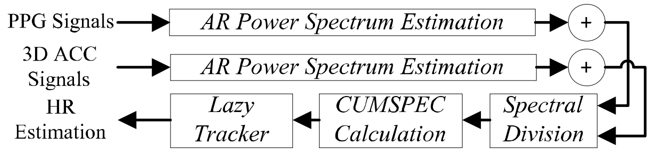

Fig. 1. Overall block diagram for the proposed method

1 gives the overall block diagram for the proposed method. Each block is based on an observation on a basic PPG property. In the following, we explain each block and the corresponding observation on PPG properties.

2. SMEARED SPECTRAL PEAKS AND THE AUTOREGRESSIVE (AR) MODEL

A first observation on the spectrum of the PPG signals under study is that the spectral peak corresponding to HR is smeared by MAs and hence, it cannot be resolved by the simple periodogram. To cope with this issue, we use the Auto Regressive (AR) parametric model for spectrum estimation. The AR model is known to minimize sidelobes and provide the flattest spectrum by the maximum entropy criteria [17]. This technique is also computationally efficient (second order polynomial time complexity) as it can be realized recursively by the Levinson-Durbin algorithm [17]. More precisely, we model the PPG signal as a periodic excitation due to the Heart Beat which is subsequently filtered by the all-pole transfer function of the overall artery system and the PPG sensors as in (1). In (1), $P(\omega)$ is the estimated PPG spectrum, p is the AR model order and the unknown coefficients a_i are iteratively calculated by the Levinson-Durbin algorithm. The AR model also proved to yield superior results compared with other parametric spectrum estimation methods (ARMA, MUSIC, etc.) in preliminary simulations which further confirms the above model.

$$P(\omega) = \frac{1}{|1 + \sum_{k=1}^{p} a_k \exp(-j\omega k)|^2} \tag{1}$$

It should be noted that to make efficient use of diversity in the spectrum estimation step, the proposed algorithm estimates the AR spectra for both PPG channels, normalizes them to 1 and adds them together to achieve a single PPG spectrum. A similar normalization/addition is also applied to the 3D ACC signals. Note that normalization is required to cope with the effects caused by different PPG and ACC sensor gains.

3. MA SUPRESSION BY SPECTRAL DIVISION

It is observed that the 3D ACC signals include spectral peaks that correspond to MAs. Usually, these peaks also appear in the PPG spectra and interfere with the HR peak. To suppress the MAs, we simply divide the PPG spectrum to the ACC spectrum according to (2). In (2), $P(\omega)$ and $A(\omega)$ denote the PPG and ACC spectra respectively, $D(\omega)$ is the cleansed PPG spectrum and C_d is a constant parameter to avoid division by small values. In other words, (2) attenuates $P(\omega)$ in frequencies for which $A(\omega)$ is large and C_d acts as a soft threshold to avoid division by small spectral fluctuations due to sidelobes or sensor noise. This parameter is later trained on the database in the range $[0, 1]$ to achieve the best performance. Spectral division proved to be a simple but pretty efficient MA suppression method in simulations with an affordable complexity (linear time complexity).

$$D(\omega) = P(\omega) \times \frac{C_d}{A(\omega) + C_d} \tag{2}$$

4. VENUS PULSATION PHENOMENON AND THE CUMULATIVE SPECTRUM (CUMSPEC)

A determinant factor on temporal shape of the PPG signal is the venous pulsation phenomenon which causes a less significant but noticeable second peak in each cardiac cycle [18]. As a result, HR is observed to possess a considerable second harmonic in the PPG spectrum. Considering both harmonics in HR estimation improves the accuracy especially for frames in which one of the harmonics is highly interfered by MA. To consider the intrinsic second harmonic, we propose the heuristic CUMulative SPECtrum (CUMSPEC) measure that scores each frequency in the natural human HR range according to its own and second harmonic amplitudes in the cleansed PPG spectrum as in (3).

$$H(\omega) = \begin{cases} D(\omega) + C_h \times D(2\omega), & \omega \in [\omega_l, \omega_h] \\ 0, & \text{otherwise} \end{cases} \tag{3}$$

In (3), $H(\omega)$ denotes the proposed CUMulative SPECtrum (CUMSPEC) measure, C_h is a constant weight and $[\omega_l, \omega_h]$ covers natural human HR range. The CUMSPEC also amplifies the HR spectral peak in comparison with MAs and further alleviates the need for computationally demanding MA suppression techniques. Note that C_h is trained on the database in the range $[0, 2]$ to achieve the best performance.

5. SPECTRAL FOOTPRINTS OF HR AND MA AND HR TRACKING

It is observed in the spectrogram of the PPG recordings that HR and MA frequencies pose different behaviors with time. HR experiences a smooth and derivative-bounded curve, however, the MA spectral peaks appear and vanish suddenly, but infrequently. This is due to the fact that physical exercises

Algorithm 1 Lazy Tracker

Input: $H(\omega)$: CUMSPEC measure
ω_r: Most recent HR estimate
ω_p: Average 5 previous HR estimates
Output: ω_c: Current HR estimate
1: **if** Initializing the Track **then**
2: $\quad \omega_c \leftarrow \arg\max_{\omega} H(\omega)$
3: **else**
4: $\quad \omega_c \leftarrow \arg\max_{\omega \in [\omega_p - C^-,\ \omega_p + C^+]} H(\omega)$
5: $\quad \omega_c \leftarrow \min(\omega_c,\ \omega_r + C_j)$
6: $\quad \omega_c \leftarrow \max(\omega_c,\ \omega_r - C_j)$

usually consist of periodic body movements each being performed for a limited duration (e.g. running on a treadmill at different speeds, each speed for a limited interval). We use this observation to propose an HR tracking algorithm that uses previous estimates of the HR value to improve the estimation accuracy in frames severely corrupted by MAs. The proposed Lazy Tracker algorithm searches for the highest spectral peak in CUMSPEC $H(\omega)$ in a wide frequency range around the average 5 previous HR estimates. Yet to avoid misleading jumps due to MAs, it takes a step bounded by a constant parameter (denoted by C_j) towards that frequency. The Lazy Tracker is formally presented in Algorithm 1. Note that the parameters $C_j < 10$ BPM, $C^+, C^- > 15$ BPM are trained on the database for the best performance.

6. PERFORMANCE COMPARISONS

As mentioned previously, we use the benchmark database provided for the IEEE SP CUP 2015 [2] for simulations. This database contains 23 recordings of 2 channel PPG and simultaneous 3D ACC signals. The first 12 recordings involve subjects' running on treadmill and the rest include arm movement activities (e.g. boxing, etc.). The signals are recorded at 125 Hz sampling rate. Ground truth HR values are available for each 8 sec frame and the consecutive frames overlap 6 secs together. Also note that for a fair comparison of the results with the literature, we use the Average Absolute Error (AAE) value proposed in [2] as the performance measure.

Utilizing this database, we pick one recording of the database at a time and train the algorithm parameters on it for minimized AAE using a Genetic Algorithm (GA). Then we use the optimized parameters for all the other recordings. We repeat this procedure for all recordings in a leave-one-out cross-validation scheme. The parameter vector $(C_d, C_h, C^-, C^+, C_j, p)$ is modeled as a gene and optimized by GA on a population of size 30 for 50 generations, while holding the range constraints stated in the previous sections. Utilizing this strategy, we set $(C_d, C_h, C^-, C^+, C_j, p) = (0.031, 0.34, 25, 37, 5.1, 510)$ and report the AAE values for all 23 database recordings in Table 1. Table 1 also compares the AAE values achieved by the proposed method with several state-of-the-art techniques in the field. However, to provide a fair comparison with previous studies, we also need to compare the computational complexity/runtime of the algorithms.

Table 1. Average Absolute Error (AAE) Comparisons

Rec. #	[2]	[4]	[5]	[15]	[3]	This Study
1	2.29	1.33	1.72	1.70	1.25	1.81
2	2.19	1.75	1.33	0.84	1.41	1.44
3	2.00	1.47	0.90	0.56	0.71	0.63
4	2.15	1.48	1.28	1.15	0.97	1.16
5	2.01	0.69	0.93	0.77	0.75	0.83
6	2.76	1.32	1.41	1.06	0.92	1.40
7	1.67	0.71	0.61	0.63	0.65	1.02
8	1.93	0.56	0.88	0.53	0.97	0.63
9	1.86	0.49	0.59	0.52	0.55	0.68
10	4.70	3.81	3.78	2.56	2.06	2.77
11	1.72	0.78	0.85	1.05	1.03	1.03
12	2.84	1.04	0.71	0.91	0.99	0.90
AAE-12	2.34	1.28	1.25	1.02	1.02	**1.19**
13	–	–	–	–	3.54	6.58
14	–	–	–	–	9.59	7.13
15	–	–	–	–	2.57	1.35
16	–	–	–	–	2.25	2.41
17	–	–	–	–	3.01	4.42
18	–	–	–	–	2.73	2.04
19	–	–	–	–	1.57	3.25
20	–	–	–	–	2.10	2.20
21	–	–	–	–	3.44	3.52
22	–	–	–	–	1.61	1.45
23	–	–	–	–	0.75	0.71
AAE-23	–	–	–	–	1.97	**2.17**

As mentioned previously, the overall complexity of our proposed algorithm is bounded by the AR spectrum estimation step which is asymptotically quadratic $O(n^2)$ in frame length [17]. Simulations show that the proposed algorithm processes each 8 sec input frame in $28ms$ on average using MATLAB™ on a 3.2 *GHz* processor. This figure for [2], [5], [4], and [15] is $7.4sec$, $6.05sec$, $853ms$, and $583ms$, respectively. Hence, the proposed method achieves feasible estimation accuracy at a reduced computational complexity. Considering the fact that modern smart watches are equipped with processors operating at clock rates higher than 0.5 GHz, the proposed algorithm seems suitable for real-time stand-alone operation on wearable devices.

7. CONCLUSION

In this paper we proposed a low complexity technique for realtime heart rate monitoring using simultaneous wrist-type PPG and 3D acceleration signals, when the subjects are performing intensive physical exercises. In comparison with state-of-the-art algorithms in the field, our proposed framework shows acceptable estimation accuracy at a considerably reduced computational cost.

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