Computationally Efficient Heart Rate Estimation During Physical Exercise Using Photoplethysmographic Signals

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***Abstract*—Wearable devices that acquire photoplethysmographic (PPG) signals are becoming increasingly popular to monitor the heart rate during physical exercise. However, high accuracy and low computational complexity are conflicting requirements. We propose a method that provides highly accurate heart rate estimates at a very low computational cost in order to be implementable on wearables. To achieve the lowest possible complexity, only basic signal processing operations, i.e., correlation-based fundamental frequency estimation and spectral combination, harmonic noise damping and frequency domain tracking, are used. The proposed approach outperforms state-of-the-art methods on current benchmark data considerably in terms of computation time, while achieving a similar accuracy.**

***Index Terms*—Photoplethysmography (PPG), Heart Rate Estimation, Motion Artifacts (MA)**

I. Introduction

On the emerging market of wearable devices for healthcare and fitness, it is becoming common practice to monitor the user's heart rate with the help of photoplethysmography (PPG). In contrast to traditional ECG belts, PPG only requires low-cost hardware and can easily be recorded with wrist worn devices. However, PPG-based heart rate estimation is challenging, especially during intense physical exercise. Motion artifacts (MA) can strongly deteriorate the quality of a PPG signal, e.g., the arm movements while running can cause strong periodic components that overlap with the desired heartbeat-related PPG component. Moreover, environmental light leaking into the gap between the photo diode and the skin causes additional MA.

In recent years, numerous techniques have been proposed to estimate the heart rate from PPG signals [1]–[14]. However, some of these methods [1]–[6] do not consider strong motion and are, thus, not suited for heart rate estimation during physical exercise.

The work of M. Muma was supported by the project HANDiCAMS which acknowledges the financial support of the Future and Emerging Technologies (FET) programme within the Seventh Framework Programme for Research of the European Commission (HANDiCAMS), under FET-Open grant number: 323944.

In 2015, Zhang *et al.* [8] proposed a framework for this use-case, which consists of signal decomposiTion for denoising, sparse signal RecOnstructIon for high-resolution spectrum estimation, and spectral peaK trAcking with verification (TROIKA), and, at the same time, provided a data set that is commonly used as a performance benchmark and also served as training data set for the IEEE Signal Processing Cup 2015 [15], [16]. However, TROIKA is very computationally demanding and not suitable for wearable devices. The subsequent publication by Zhang [10] is based on joint sparse spectrum reconstruction (JOSS). It jointly estimates the spectra of the PPG and acceleration signals, utilizing the multiple measurement vector model in sparse signal recovery. JOSS achieves highly accurate results but is still computationally complex [12]. Both TROIKA and JOSS rely on large matrices which cannot be stored on embedded systems with constrained internal memory.

In this work, we present a new method that provides highly accurate heart rate estimates during physical exercise using extremely low computational cost and memory requirements. To achieve this, only fundamental signal processing functions that are easily implementable on hardware and allow for very rapid execution, are used. Numerical results based on current benchmark data are provided, which show that our proposed approach outperforms state-of-the-art methods on current benchmark data sets considerably in terms of computation time (e.g., about 80 times faster than JOSS), while achieving similar accuracy.

The remainder of the paper is organized as follows: First, Section 2 introduces the signal model, while the method is presented in Section 3. The description of the benchmark data set and the real-data results, as well as computational complexity are given in Section 4. Finally, Section 5 concludes the paper.

II. System Model

As in [9], we use the following measurement model:

$$p(n) = s(n) + m(n) + v(n) \tag{1}$$

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Here, $p(n)$ is the measured PPG signal, $s(n)$ is the unobservable noise-free PPG signal, $m(n)$ are the motion induced artifacts, and $v(n) \sim \mathcal{N}(0, \sigma^2)$ represents the sensor and amplifier noise.

III. Proposed Method

As the aim of the paper is to present a fast algorithm, we keep the computational complexity as low as possible. We apply correlation functions to enhance periodic components and suppress wideband noise that is caused by motion-induced artifacts or sensor and amplifier noise. The results in this paper are based on using two PPG and three acceleration channels. However, the method is also applicable to other configurations. The summation of the squared spectra further enhances common components between the PPG channels and suppresses remaining artifacts and noise. Motion artifacts are reduced by taking into account the estimated periodic components from the acceleration spectra. The heart rate estimation picks the maximal value in a weighted spectrum using a linear prediction. All steps are detailed in the subsequent sections.

A. Preprocessing

First, PPG and acceleration signals ($f_s = 125$ Hz) are bandpass filtered with a finite impulse response (FIR) filter ($f_{c1} = 0.5$ Hz, $f_{c2} = 6$ Hz), and downsampled to 25 Hz.

In contrast to our preceding method [9], this method does not require the use of adaptive normalized least mean squares (NLMS) filters, which greatly reduces the computational complexity.

B. Correlation Based Fundamental Frequency Indicating Function

To enhance periodic components, we next calculate the sample correlation functions of the two measured PPG signals $p_i(n)$, $i = 1, 2$,

$$r_{p_i p_j}(\kappa) = \frac{1}{2N-1} \sum_{n=-N+1}^{N-1} p_i(n+\kappa) p_j(n), \quad i,j = 1,2 \tag{2}$$

and normalize them

$$r^{\text{norm}}_{p_i p_j}(\kappa) = \frac{r_{p_i p_j}(\kappa) - \mu_{p_i p_j}}{\sigma_{p_i p_j}}, \quad i,j = 1,2. \tag{3}$$

Here,

$$\mu_{p_i p_j} = \frac{1}{2N-1} \sum_{\nu=1}^{2N-1} r_{p_i p_j}(\nu), \quad i,j = 1,2 \tag{4}$$

and

$$\sigma_{p_i p_j} = \sqrt{\frac{1}{2N-1} \sum_{\nu=1}^{2N-1} \left(r_{p_i p_j}(\nu) - \mu_{p_i p_j} \right)^2}, \quad i,j = 1,2. \tag{5}$$

Collecting the elements of (3) into vectors $\mathbf{r}^{\text{norm}}_{p_i p_j}(n)$ results in three unique vectors $\mathbf{r}^{\text{norm}}_{p_1 p_1}(n)$, $\mathbf{r}^{\text{norm}}_{p_1 p_2}(n)$ and $\mathbf{r}^{\text{norm}}_{p_2 p_2}(n)$.

C. Fourier Transformation

Finally, the fast Fourier transform (FFT) is applied to all three unique vectors. Each spectrum with 2048 bins and a resolution of 0.37 beats per minutes (BPM) is again normalized by subtracting its mean and dividing by the standard deviation, resulting in estimates of the spectra of the noise-free PPG signals $\hat{S}_{11}(n, f)$, $\hat{S}_{12}(n, f)$ and $\hat{S}_{22}(n, f)$, respectively.

Next, we compute

$$\hat{S}^{\text{sum}}(n, f) = \hat{S}^2_{11}(n, f) + \hat{S}^2_{12}(n, f) + \hat{S}^2_{22}(n, f), \tag{6}$$

to further enhance common components between the channels and suppress uncorrelated background noise in the spectrum.

D. Harmonic Noise Damping

The resulting spectrum from (6) is multiplied element-wise with a Gaussian bandstop filter defined by the window function

$$w_{\text{acc}}(n, f) = 1 - \sum_{q=1}^{2} e^{-\frac{1}{2}\left(\frac{f - \hat{f}_q(n)}{\sigma_{\text{win,acc}}}\right)^2}, \quad f = 1, \ldots, F, \tag{7}$$

whose parameters $\hat{f}_1(n)$ and $\hat{f}_2(n) = \hat{f}_1(n)/2$ are estimated by tracking the frequencies $\hat{f}_q(n)$ that are associated with the maximal energy values of the accelerometer spectrum. Here, F is the number of frequency bins and the value of $\sigma_{\text{win,acc}} = 0.31$ Hz, which is about 19 BPM, is determined empirically.

E. Heart Rate Tracking

The heart rate is recursively obtained by evaluating

$$\hat{f}_{\text{HR}}(n) = \arg\max_f \hat{S}^{\text{sum}}(n, f) \cdot e^{-\frac{1}{2}\left(\frac{f - \hat{f}^{\text{pred}}_{\text{HR}}(n)}{\sigma_{\text{win,HR}}}\right)^2}, \tag{8}$$

where $\sigma_{\text{win,HR}} = 4$ BPM is the physiologically motivated width of the Gaussian window and $\hat{f}^{\text{pred}}_{\text{HR}}(n)$ is the predicted heart rate, which is the estimate of a linear least squares fit of the preceding three heart rate estimates

$$\hat{f}^{\text{pred}}_{\text{HR}}(n) = \alpha(n) + 2 \cdot \beta(n) \tag{9}$$

with

$$\beta(n) = \frac{\hat{f}_{\text{HR}}(n-1) - \hat{f}_{\text{HR}}(n-3)}{2} \tag{10}$$

and

$$\alpha(n) = \frac{1}{3} \sum_{i=1}^{3} \hat{f}_{\text{HR}}(n-i). \tag{11}$$

If the frequency of the maximal energy in the accelerometer spectrum overlaps with the predicted heart rate, the heart rate is tracked either based on $\hat{S}_{11}(n, f)$ or $\hat{S}_{22}(n, f)$. The choice is made based on the maximal energy in the frequency bins of the last 5 estimated heart rates $\hat{f}_{\text{HR}}(n-i)$ with $i = 1, \ldots, 5$. Finally, to smooth the heart rate estimate sequence, we restrict the tracker to maximally jump ± 4 BPM in relation to the last estimate.

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	S 1	S 2	S 3	S 4	S 5	S 6	S 7	S 8	S 9	S 10	S 11	S 12	Mean AAE ± STD
TROIKA [8]*	2.87	2.75	1.91	2.25	1.69	3.16	1.72	1.83	1.58	4.00	1.96	3.33	**2.42 ± 2.47 BPM**
JOSS [10]*	1.33	1.75	1.47	1.48	0.69	1.32	0.71	0.56	0.49	3.81	0.78	1.04	**1.28 ± 2.61 BPM**
AF-Combine [9]	2.52	1.42	2.22	1.18	1.08	1.49	1.32	0.90	0.74	3.91	1.73	1.34	**1.66 ± 0.88 BPM**
Proposed Approach	1.45	1.29	0.58	1.52	0.78	0.86	1.02	0.65	0.39	5.07	0.79	1.46	**1.32 ± 1.24 BPM**

* The results for this method are obtained from [10].

TABLE I
AVERAGE ABSOLUTE ERROR (AAE) OVER ALL 12 DATA SETS FROM THE TRAINING DATA [8] IN BPM.

	Total Duration (12 Data Sets)
TROIKA [8]†	3.5 hours
JOSS [10]†	300 seconds
AF-Combine [9]	51.46 seconds
Proposed Approach	3.73 seconds

† The computation times for this method are obtained from [12] using the M-FOCUSS algorithm [17], which is by far the most complex operation in TROIKA and JOSS. Our own implementation of JOSS using [18] achieved similar computation times.

TABLE II
TOTAL COMPUTATION TIMES FOR THE TRAINING DATA [8].

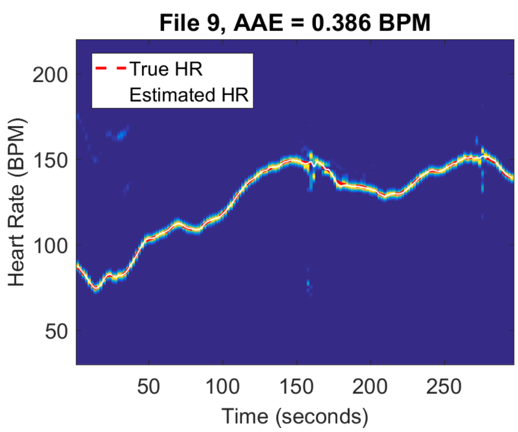

Fig. 1. Spectrogram of the best result with superimposed true heart rate in red and estimate of the proposed method in white.

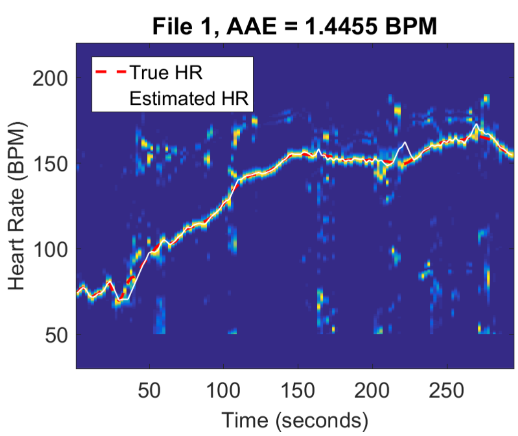

Fig. 2. Spectrogram of a medium result with superimposed true heart rate in red and estimate of the proposed method in white.

IV. REAL DATA RESULTS

For evaluation, we consider the training data set recorded by Zhang *et al.* [8] for the IEEE SP Cup 2015. Each data set

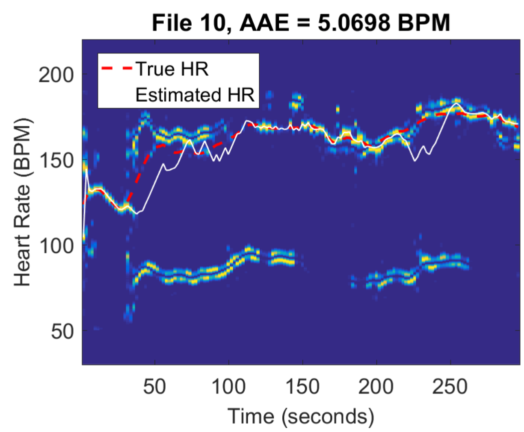

Fig. 3. Spectrogram of the worst result with superimposed true heart rate in red and estimate of the proposed method in white.

includes a two-channel PPG signal, a three-axis acceleration signal, and a reference heart rate for evaluation, obtained from a simultaneously recorded electrocardiogram (ECG). The sampling rate of all signals is $f_s = 125$ Hz. The PPG signals were recorded from the subject's wrist using a pulse oximeter with green LEDs (wavelength: 515 nm). The acceleration signals were recorded at the same position. We adapt the framework of the IEEE SP Cup [16] and estimate the heart rate every two seconds based on overlapping time windows of 8 seconds length.

The performance of the proposed method is measured by the average absolute error (AEE), which is defined as

$$\mathrm{AAE} = \frac{1}{L}\sum_{l=1}^{L} |\mathrm{BPM}_{\mathrm{est}}(l) - \mathrm{BPM}_{\mathrm{true}}(l)|, \tag{12}$$

where L is the total number of estimates, $\mathrm{BPM}_{\mathrm{true}}(l)$ denotes the true BPM value in the lth time window, and $\mathrm{BPM}_{\mathrm{est}}(l)$ is the corresponding estimate in BPM.

ISBN 978-0-9928626-7-1

The results are compared with our preceding algorithm "AF-Combine" [9], TROIKA [8], and JOSS [10]. The best, the worst and a medium estimation result of the proposed method is exemplarily shown in Fig. 1-3, respectively, superimposed on the spectrogram $\hat{S}^{\text{sum}}(n, f)$ that is weighted by the Gaussian bandstop filter. The white line shows the estimate of the proposed method, while the dashed red line shows the true heart rate (HR) that is provided by a reliable, simultaneously recorded ECG. In Fig. 2, motion artifacts are visible as wide-band noise in the spectrum and in Fig. 3, the motion artifacts are present as harmonic disturbances at about 80 BPM, which can be contributed to harmonic movements that are performed while running. The associated first harmonic lies at approximately 160 BPM and overlaps with the heart rate.

As described in Section III, for the time instances, when the maximal energy in the accelerometer spectrum overlaps with the predicted heart rate, the heart rate tracking is performed either on $\hat{S}_{11}(n, f)$ or $\hat{S}_{22}(n, f)$. This effect can be seen for example in Fig. 1, when the spectral track is interrupted at around 160 seconds and 280 seconds.

Table I provides the AAE for the training data set. The last column contains the overall mean and standard deviation for each method. The proposed approach achieves an average AAE of 1.32 $\pm$ 1.24 BPM (mean $\pm$ standard deviation). While all methods achieve a comparable and sufficiently high accuracy for the considered use-case, they strongly differ in their computational complexity.

The total duration of the computation times is shown in Table II. As reported in [12], the heart rate estimation of the training set takes several hours for TROIKA [8] and 300 seconds for JOSS [10], which is of a similar magnitude (402 seconds) as for our own implementation of JOSS. Our preceding method [9] needs about 51 seconds. In comparison, the proposed approach spends only 3.73 seconds to run the complete training set, which is roughly 80 times faster than JOSS and almost 14 times faster than our previously proposed algorithm. The computation time for the proposed approach was evaluated on a 2.8 GHz Intel® Core™ i5-760 CPU with 8 GB RAM and Matlab R2016a. Please note that the most complex operation is the FFT, which is an $\mathcal{O}(N \log N)$ operation. For each time window of 8 seconds, the FFT is executed six times to transform the two time-domain PPG signals, their cross-correlation as well as three accelerometer signals into the frequency domain. Those six vectors with 2048 bins are the biggest variables in the storage.

V. Conclusion

A very computationally efficient algorithm based on PPG and acceleration signals has been proposed to accurately monitor a subject's heart rate in real-time during physical exercise. The approach combines correlation-based fundamental frequency indicating functions, spectral combination, harmonic noise damping and frequency domain tracking. The low computational complexity allows for running the algorithm in real time on a wearable device while keeping the battery consumption as low as possible. Despite its low computational complexity and memory requirements, the proposed method is comparable in terms of accuracy to computationally intensive state-of-the-art methods on a benchmark data set.

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