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# An Improved Algorithm for Heart Rate Tracking during Physical Exercise Using Simultaneous Wrist-Type Photoplethysmographic (PPG) and Acceleration Signals

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***Abstract*— Causal Heart Rate (HR) monitoring using photoplethysmographic (PPG) signals recorded from wrist during physical exercise is a challenging task because the PPG signals in this scenario are highly contaminated by artifacts caused by hand movements of the subject. This paper proposes a novel algorithm for this problem, which consists of two main blocks of Noise Suppression and Peak Selection. The Noise Suppression block removes Motion Artifacts (MAs) from the PPG signals utilizing simultaneously recorded 3D acceleration data. The Peak Selection block applies some decision mechanisms to correctly select the spectral peak corresponding to HR in PPG spectra. Experimental results on benchmark dataset 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 1.50 beats per minute (BPM), which outperforms state of the art.**

***Keywords- Heart Rate Tracking, Wrist-Type Photoplethysmograph (PPG), Singular Spectrum Analysis (SSA), Adaptive Noise Cancellation (ANC), Kurtosis Classification.***

## I. INTRODUCTION

Online processing of Photoplethysmograph (PPG), measured by pulse oximeters, is proposed as a noninvasive framework for continuous monitoring of Heart Rate (HR) [1].

PPG signal is obtained by irradiating a light-emitting diode towards the skin surface and recording the intensity changes of the reflected light by a photo detector [2].

Unfortunately, PPG signals are highly susceptible to disturbances caused by movements of the subject. In the case of heart rate monitoring during physical exercises, the motion artifacts (MAs) are particularly strong and interferes with Heart Beat (HB) fundamental frequency or its harmonics [3]-[5].

Signal processing algorithms proposed so far for MA reduction, range from bandpass filtering [6], wavelet denoising [7], and time-frequency analysis [8] to Independent Component Analysis (ICA) [9] and Adaptive Noise Cancelation (ANC), which mostly cancels in-band MAs [10]. Unfortunately, most of these researches consider weak MA scenarios, in which subjects perform small motions [11], [12]. Hence, they are not applicable for HR monitoring during intensive physical exercise [4].

In this research, the PPG signals are recorded from wrist and experience more severe MAs due to the loose interface between the skin and the sensor [4]. Hence, real-time HR monitoring from wrist-type PPG signals during intensive physical exercise is a challenging problem. To cope with this challenge, we use simultaneous acceleration data as a reference signal for MA estimation [3]. This problem was first posed by [4], which provided the benchmark dataset and made it available for subsequent researches [13]-[16]. In our work, we propose a novel MA reduction algorithm which facilitates accurate HR tracking from wrist-type PPG signals during high speed (12-15 km/hour) running of the subject. The proposed algorithm is of great interest to wearable smart watches, which monitor HR during intensive physical exercise. The experimental results show that the proposed algorithm achieves an improvement of 0.84 BPM on the results reported by [4] using the same dataset and performance measures.

The rest of the paper is organized as follows. Section 2 describes the experimental setup, Section 3 explains the proposed method, Section 4 presents the simulation results achieved by the proposed method, and finally Section 5 concludes this paper.

## II. EXPERIMENTAL SETUP

The data set used in this work was provided by Zhang et al in [4] for Signal Processing Cup 2015. The dataset was recorded from 12 subjects while running on a treadmill at the maximum speed of 15 km/h. The subjects were wearing a two-channel PPG embedded wrist band accompanied with a three-channel acceleration sensor. The subjects were asked to deliberately use the hand with the wristband to pull clothes, wipe sweat on forehead, and push buttons on the tread mill, in addition to freely swing [4]. Simultaneous ECG signal was acquired from wet electrodes pasted on the subjects' chest in order to extract the ground truth of HR estimation. The signals were collected at the sampling rate of 125 Hz and sent to a nearby computer via Bluetooth.

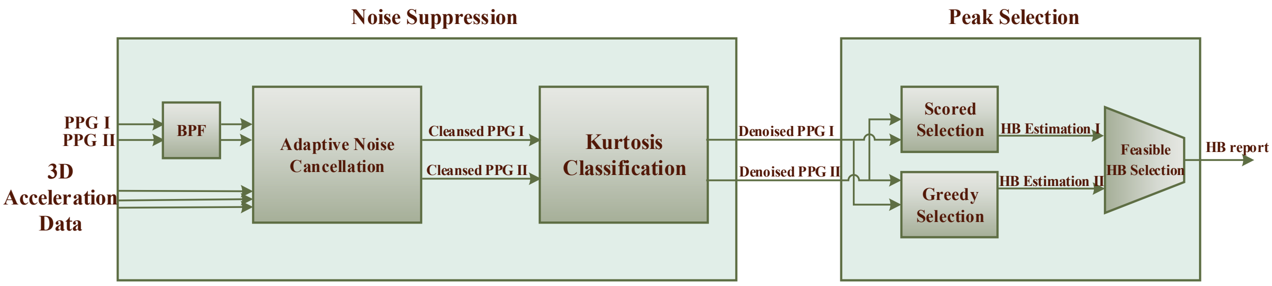


Figure 1. Overall Block Diagram of the Proposed HR Tracking Algorithm

## III. THE PROPOSED METHOD

The proposed algorithm consists of two main stages of Noise Suppression and Peak Selection. Fig. 1 shows a block diagram of the proposed HR tracking algorithm. The blocks used in our approach are explained in the following subsections.

It is noteworthy to state that a temporal frame of 8 seconds is sliding on the PPG signals with incremental step of 2 second in consistence with [4], which makes possible the comparison of results.

### A. *Noise Supression*

In this stage, first we apply band pass filters on both channels of the PPG signal. The band pass filter uses the value of the estimated HR from the previous frame, which is denoted by N_p, and filters the current frame in the frequency range given by (1).

$$[N_p - \epsilon, N_p + \epsilon] \cup [2N_p - \epsilon, 2N_p + \epsilon] \cup [3N_p - \epsilon, 3N_p + \epsilon] \quad (1)$$

This range is chosen in order to include the fundamental frequency and first and second order harmonic frequencies of HB, which are used for correct HR tracking in Section 3.2. Once the out-of-band MAs are cancelled by band pass filtering, we apply the following two blocks of Adaptive Noise Cancellation (ANC) and Kurtosis Classification (KC) to suppress in-band MAs.

*Adaptive Noise Cancellation (ANC):* Due to the fact that hand swings cause severe MAs, simultaneously recorded 3D acceleration data are highly correlated with MAs. Hence, the acceleration data can be used as the reference signals for ANC. However, the acceleration data are composed of different periodic components, which will strongly hamper convergence of the applied adaptive filter. Therefore, we generate the reference noise signals by decomposing the three-channel acceleration signal by Singular Value Decomposition (SVD) prior to adaptive filtering. In this technique, each acceleration signal enters both SVD and grouping steps [4]. Subsequently, all the reference MA components derived by SVD are removed from both PPG signals by successive application of adaptive filters [13]. Each adaptive filter stage receives the residual signal resulting from its prior stage and a reference signal component as input. Using this technique, we cleanse all MA components of the PPG signals, which are present in the acceleration data.

*Kurtosis Classification (KC):* The ANC block may not be able to completely remove the MA components derived from acceleration data. In addition, some motion artifacts caused by the changes of the gap between hand and the PPG sensors leave no footprints on the acceleration data. Hence, in order to perfectly cleanse the PPG signals, we propose a second mechanism called Kurtosis Classification (KC). In this block, the output of the ANC block is decomposed into 100 time series using Singular Spectrum Analysis (SSA) similar to [4]. Then we take an approach to recognize some groups corresponding to MAs. To this end, we estimate the Kurtosis for all the resulting groups, which is defined as follows:

$$Kurt[X] = \frac{\mu_4}{\sigma^4} = \frac{E[(X - \mu[X])^4]}{(E[(X - \mu[X])^2])^2}$$

in which $E[X]$ is the expectation of the random variable $X$ and is replaced by the temporal average of the signals in our scenario.

It is observed by simulations that in our scenario, groups with absolute Kurtosis values greater than 5 correspond to MAs. Hence, we remove them from the PPG signal prior to SSA reconstruction. Following this procedure, the resulting cleansed signal is input to the Peak Selection stage for HR tracking.

### B. *Peak Selection*

In this stage, we apply some decision mechanisms to accurately estimate the frequency location index of HR in the $2^{12}$ FFT point Periodogram of each frame. These decision mechanisms exploit the frequency harmonic relation of HR along with the assumption that HR varies smoothly along time and does not experience jumps between successive frames.

Peak Selection stage applies two different methods of “Scored Selection” and “Greedy Selection” to derive two estimates of the HR in the current frame. The final decision among these two estimates of HR is made by the “Feasible HB Selection” block. This block chooses the estimate closer to the HR value estimated in the previous frame. We explain these alternative peak selection algorithms as follows.

TABLE I. THE RESULTS ACHIEVED BY THE PROPOSED METHOD ON 12 SUBJECTS' RECORDINGS

| Data No | 01 | 02 | 03 | 04 | 05 | 06 | 07 | 08 | 09 | 10 | 11 | 12 | Mean-12 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MAE(Proposed) | 1.29 | 2.44 | 0.77 | 1.70 | 0.85 | 1.55 | 1.30 | 1.03 | 0.61 | 4.21 | 1.18 | 1.07 | 1.50 |
| MAE(TROIKA[1]) | 2.29 | 2.19 | 2.00 | 2.15 | 2.01 | 2.76 | 1.67 | 1.93 | 1.86 | 4.70 | 1.72 | 2.84 | 2.34 |
| SD (Proposed) | 1.89 | 5.31 | 1.0 | 3.56 | 1.44 | 2.16 | 2.38 | 2.14 | 0.77 | 6.20 | 1.64 | 1.73 | 2.51 |
| PC (Proposed) | 0.9993 | 0.9990 | 1.0000 | 0.9996 | 0.9999 | 0.9999 | 0.9998 | 0.9999 | 1.0000 | 0.9993 | 0.9999 | 0.9999 | 0.9997 |

*Scored Selection:* This algorithm considers three frequency ranges of $R_0, R_1$ and $R_2$ as in (2). Then it chooses three, four and three highest candidate peaks in these ranges, respectively.

$$\begin{aligned} R_0 &= [N_p - \epsilon, N_p + \epsilon] \\ R_1 &= [2N_p - \epsilon, 2\,N_p + \epsilon] \\ R_2 &= [3N_p - \epsilon, 3N_p + \epsilon] \end{aligned} \qquad (2)$$

In which $\epsilon$ is a positive small integer, which is set to 4 in our work.

In both PPG channels, the above mentioned ten peaks are selected and a score is assigned to each of these candidate peaks and finally the corresponding fundamental frequency of the peak with the maximum score is selected as the estimated HR of the frame. These scores are assigned based on the following criteria.

1) Each peak is scored proportional to its amplitude i.e. a higher peak receives a higher score.
2) Each peak receives a score inversely proportional to its distance from corresponding harmonic frequency of HR estimated frequency in the previous frame.
3) Both peaks satisfying a harmonic relation either in one or both PPG channels receive a predefined score.

Note that the amount of the score assigned to each criteria is optimized by Genetic Algorithm (GA) on the benchmark dataset.

*Greedy Selection:* This algorithm computes the "Cumulative Spectrum (CS)" of the cleansed PPG signals and greedily selects the index with the maximum amplitude in the cumulative spectrum as the index corresponding to HR. The CS is computed in $[N_p - \epsilon, N_p + \epsilon]$ frequency range. The CS value for a specific frequency index is computed as a weighted sum of that frequency index and its first-order and second-order harmonics in the cleansed PPG spectrum, as formulated in (3).

$$S_{CS}(i) = w_1 S(i) + w_2 S(2i) + w_3 S(3i) \qquad (3)$$

In which $S_{CS}(i)$ and $S(i)$ denote the cumulative and denoised PPG spectrum at frequency index $i$, respectively.The weights $w_1, w_2$ and $w_3$ are optimized by simulations for the best performance.

Finally, it should be noted that to initialize our system, we utilize a similar procedure as defined above. The only difference is that since we have no previous estimate of HR, we set three ranges of $R_0, R_1$ and $R_2$ to [0.9-2.4] Hz, [1.6-5] Hz and [2.5-7.6] Hz, respectively.

## IV. SIMULATION RESULTS

To compare results of our proposed method to the previous works we have used the same performance measure as in [4], consists of Mean Absolute Error (MAE), Standard Deviation (SD) and Pearson Correlation (PC), MAE and SD are defined as follows:

$$MAE = \frac{1}{\omega} \sum_{i=1}^{\omega} |HR_{est}(i) - HR_T(i)|$$

$$SD = \sqrt{\frac{1}{\omega} \sum_{i=1}^{\omega} \left(HR_{est}(i) - HR_T(i)\right)^2}$$

in which $(i)$ denotes the $i^{th}$ frame and $\omega$ is the total number of frames.

Table 1 lists the achieved MAE, estimation variance, Pearson correlation and total simulation time on all 12 subjects' recordings. This table shows that the proposed algorithm achieves an average MAE improvement of 0.84 BPM on the results reported by [4]. We also achieved an average simulation time of 1034 seconds on a 16G RAM, Intel ® Core (TM) i7-4770 CPU @ 3.40GHz PC for each recording.

Fig. 2 shows the simulation result on recordings of subject 8. The estimated HR is very close to the ground-truth resulting in a Pearson correlation of 0.9999 with the ground-truth of HR, an MAE of 1.03 and an estimation standard deviation of 2.14.

## V. COCLUSION

In this paper, we consider the problem of heart rate tracking using simultaneous wrist-type PPG and acceleration signals during intensive physical exercise. This is a challenging problem due to the strong MAs caused by hand movements of the subject during fast running. The proposed algorithm uses Adaptive Noise Cancellation (ANC) to suppress the MAs and cleanse the PPG signals. The MA signals are either achieved by Singular Value Decomposition (SVD) of the acceleration signals or kurtosis classification of the SVD decomposed PPG signal itself. Subsequently, some decision mechanisms are applied on the MA recovered PPG signals to select the spectral peaks corresponding to HR.

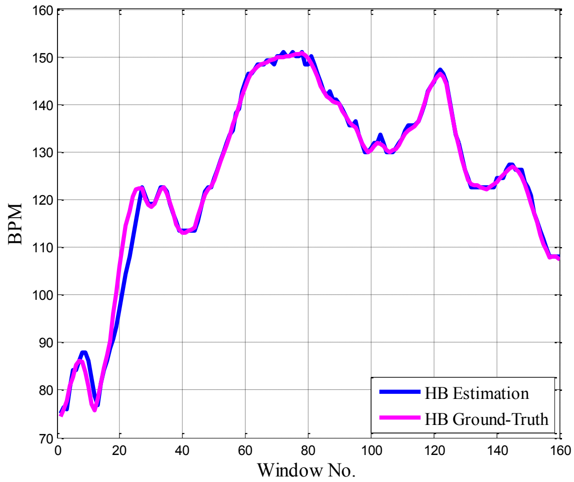


Figure 2. The Estimation Results on Recordings of Subject 8

# REFERENCES

[1] John, A., "Photoplethysmography and its application in clinical physiological measurement", *Physiological Measurement*, vol. 28, no. 3, pp. Rl, 2007.

[2] A. Kamal, J. Harness, G. Irving, and A. Mearns, "Skin photoplethysmographya review," *Computer methods and programs in biomedicine*, vol. 28, no. 4, pp. 257–269, 1989.

[3] H. Fukushima, H. Kawanaka, M. S. Bhuiyan, and K. Oguri, "Estimating heart rate using wrist-type photoplethysmography and acceleration sensor while running," *Engineering in Medicine and Biology Conference (EMBC)*, 2012.

[4] Z. Zhang, Z. Pi, B. Liu, "TROIKA: A General Framework for Heart Rate Monitoring Using Wrist-Type Photoplethysmographic Signals During Intensive Physical Exercise," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 2, pp. 522-531, Feb. 2015.

[5] Z. Zhang, "Heart rate monitoring from wrist-type photoplethysmographic (PPG) signals during intensive physical exercise," *The 2nd IEEE Global Conference on Signal and Information Processing (GlobalSIP)*, 2014.

[6] Johansson, A. and P.A Oberg., "Estimation of respiratory volumes from the photoplethysmographic signal Part I: experimental results", *Medical and Biological Engineering and Computing*, vol. 37, no. 1, pp 42-47, 1999.

[7] M. Raghuram, K. V. Madhav, E. H. Krishna, and K. A. Reddy, "Evaluation of wavelets for reduction of motion artifacts in photoplethysmographic signals," *10th International Conference on Information Sciences Signal Processing and their Applications (ISSPA 2010)*, pp. 460–463.

[8] Y. sheng Yan, C. C. Poon, and Y. ting Zhang, "Reduction of motion artifact in pulse oximetry by smoothed pseudo wigner-ville distribution," *Journal of NeuroEngineering and Rehabilitation*, vol. 2, no. 3, 2005.

[9] Kim, B. S. and S. K. Yoo, "Motion artifact reduction in photoplethysmography using independent component analysis", *IEEE Trans. Biomedical Engineering*, vol. 53, no. 3, pp 566-568, 2006.

[10] Wood, L. B. and H. H. Asada, "Low Variance Adaptive Filter for Cancelling Motion Artifact in Wearable Photoplethysmogram Sensor Signals", *29th IEEE Annual International Conference Engineering in Medicine and Biology Society*, 2007.

[11] R. Krishnan, B. Natarajan, and S. Warren, "Two-stage approach for detection and reduction of motion artifacts in photoplethysmographic data," *IEEE Transactions on Biomedical Engineering*, vol. 57, no. 8, pp. 1867–1876, 2010.

[12] R. Yousefi, M. Nourani, S. Ostadabbas, and I. Panahi, "A motion-tolerant adaptive algorithm for wearable photoplethysmographic biosensors," *IEEE Journal of Biomedical and Health Informatics*, vol. 18, no. 2, pp. 670–681, 2014.

[13] M. Boloursaz Mashhadi, E. Asadi, M. Eskandari, S. Kiani, and F. Marvasti, "Heart rate tracking using wrist-type photoplethysmographic (ppg) signals during physical exercise with simultaneous accelerometry," *IEEE Signal Processing Letters*, vol. 23, no. 2, pp. 227–231, 2015.

[14] E. Khan, F. Al Hossain, S. Z. Uddin, S. K. Alam and M. K. Hasan, "A Robust Heart Rate Monitoring Scheme Using Photoplethysmographic Signals Corrupted by Intense Motion Artifacts," *IEEE Transactions on Biomedical Engineering*, vol. 63, no. 3, pp. 550-562, March 2016.

[15] Z. Zhang, "Photoplethysmography-Based Heart Rate Monitoring in Physical Activities via Joint Sparse Spectrum Reconstruction," *IEEE Transactions on Biomedical Engineering*, vol. 62, no. 8, pp. 1902-1910, Aug. 2015.

[16] M. Essalat, M. Boloursaz Mashhadi, F. Marvasti," Supervised Heart Rate Tracking using Wrist-Type Photoplethysmographic (PPG) Signals during Physical Exercise without Simultaneous Acceleration Signals*," IEEE Global Conference on Signal and Information Processing (GlobalSIP 2016)*, USA, Dec. 2016.