MICROST: A Mixed Approach for Heart Rate Monitoring During Intensive Physical Exercise Using Wrist-Type PPG Signals

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***Abstract*— The performance of heart rate (HR) monitoring using wrist-type photoplethysmographic (PPG) signals is strongly influenced by motion artifacts (MAs), since the intensive physical exercises are common in real world. Few works focus on this study so far because of unsatisfying quality of corrupted PPG signals. In this paper, we propose an accurate and efficient strategy, named MICROST, which estimates heart rate based on a mixed approach. The MICROST framework is designed as a MIxed algorithm which consists of acceleration Classification (AC), fiRst-frame prOcessing and heuriStic Tracking. Experimental results using recordings from 12 subjects during fast running and intensive movement showed the average absolute error of heart rate estimation was 2.58 beat per minute (BPM), and the Pearson correlation between the estimates and the ground-truth of heart rate was 0.988. We discuss our approach in real time to face the applications of wearable devices such as smart-watches in reality.**

I. INTRODUCTION

Heart rate monitoring during physical exercise is a brand new demand which provides exercisers with the information of training since wearable devices become more popular than before. An efficient estimation method is the fundamental of these smart wearable devices such as Samsung Gear Fit which records photoplethysmographic (PPG) signals obtained by pulse oximeters. Compared with electrocardiogram (ECG) obtained from chest without the body movement, PPG signals acquired at red and infrared (IR) wavelengths with suitable sensors attached easily to body parts such as finger, wrist, earlobe or forehead have showed a great advantage.

When people use wearable devices to monitor the condition of the body, intensive physical movement is unavoidable. Moreover, motion artifact (MA) can produce a hard barrier to compute HR from PPG signals accurately. In general, PPG signal is fragile and easily corrupted. For reliable estimation, several techniques to reduce MA have been proposed in recent years. One common attempt suggested by Ram *et al.* [2] is Adaptive Noise Cancelation (ANC). Adaptive filter, in some studies, is placed to optimize parameters in [3], [4], [5]. Kim *et al.* [6] and Krishnan *et al.* [7] proposed another frequently-used method – Independent Component Analysis (ICA). Fukushima *et al.* [8] led acceleration data into MA reduction. Some new processing methods include Singular Value Decomposition (SVD), Time-Frequency Analysis, Wavelet Denoising, Artificial Neural Network, Ensemble Empirical Mode Decomposition (EMD) and higher order statistics. Moreover, other approaches focus on mechanical and electronic design have also been proposed. An impressive approach to estimate HR using heuristic peak tracking is proposed in [1]. But the algorithm has a high complexity and may not be suitable for real time applications.

However, most of approaches described above are not satisfactory with vigorous exercise due to their applying with slight movement. These techniques cannot work well while facing strong MA. We propose an accurate and efficient strategy, named MICROST, which estimates heart rate based on a mixed approach. Experimental results using recordings from 12 subjects during fast running and intensive motion artifacts showed a satisfying performance as we expected.

The rest of the paper is organized as follows. In Section II, we illustrate the design of MICROST approach. The experimental results are presented in Section III. Finally, we conclude the paper in the last section.

II. THE MICROST APPROACH

The MICROST mixed approach consists of three main components: acceleration classification (AC), first-frame processing and heuristic peak tracking. The first-frame processing combines both wavelet and time-domain methods in the first frame. The architecture of MICROST is shown in Figure 1. It is noticed that practical applications of PPG like smart-watch highly require real-time measurement, thus the MICROST is designed for on-line use.

A. Wavelet Estimation

The estimation on the first window is extremely crucial for a memory-based heuristic frequency tracking algorithm. Here a wavelet method is implemented to handle the first window estimation.

A 7-order Haar wavelet transform is applied on the PPG signal, and all the zeroth order is set to zero because they are in very low frequency. Furthermore, a threshold of each order is set to the mean value of the $order \times r$ to suppress motion artifact, where r is a parameter we should configure.

One channel of PPG signals is utilized and we choose $r = 0.1, 0.8, 1.5$ to get six windows of processed signal. Then scores for each peak are assigned based on its magnitude rank in each processed window. The peak with the highest score will be selected as the estimation.

B. Time-domain Estimation

A simple method is developed from time-domain using PeakFinder. The heart rate is computed as

$$BPM_{T-D} = \frac{(length(Peak_{loc}) - 1) \times SampleRate}{Peak_{loc}(end) - Peak_{loc}(first)} \quad (1)$$

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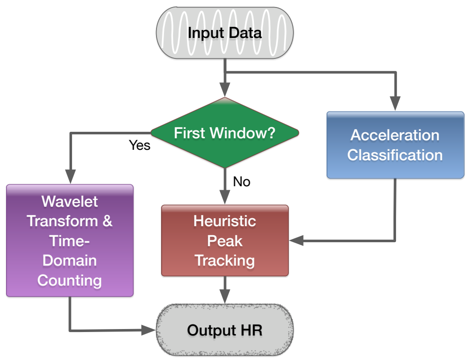

Fig. 1. Framework of the MICROST approach.

where $Peak_{loc}$ is the location of the detected peaks and $SampleRate$ is set to 125 Hz.

C. Acceleration Classification (AC)

The grid effect is one of the main difficulties for heuristic tracking due to the low resolution on frequency domain. It is easy to lose right tracking especially when the real heart rate is in a sharp rise. Therefore, in this paper, we implement the regular pattern of acceleration (ACC) signal for each window to partly relieve this problem. Linear predictive analysis on the z-axis ACC signal is considered, assuming that

$$Acc[n] = \sum_{k=1}^{p} a_k \times Acc[n-k] + G \times Acc[n] \qquad (2)$$

$$E = arg \min_{S,\eta} \sum_{i=1}^{2} \sum_{x \subset S_i} \|x - \eta_i\|^2 \qquad (3)$$

where G corresponds to the magnitude of the input signal. $[G, a_1, ..., a_{10}]$ is firstly used as the feature vector for each window of ACC signal. Then a K-means algorithm is implemented to cluster those feature vectors from training data into 2 sets. From the cluster result, we could observe that the change of class from ACC signal usually happens in the beginning of a sharp rise or fall on heart rate. For each incoming window of signal, the Euclidean distance is calculated from the LPC result of this frame to each center η_i of i-th cluster in Eq.(3), where x is the ACC feature vector and S_i denotes the set where $x \in i$-th cluster. Then the class of ACC could be determined and intensity of MA could be evaluated for this window.

D. Heuristic Peak Tracking

Heuristic algorithm technique for heart rate (HR) estimation is the key part of MICROST which consists of initialization, peak detection and selection, verification and estimation, and modification. Due to the frequency relation of HR in two successive time windows with large overlap, we propose a multinomial peak tracking procedure, which utilizes historic information to track the heart rate in the spectrum. The details are shown in Figure 2.

Initialization: In the initialization stage, there is no historic information about heart rate to help estimation. Thus, we combine wavelet estimation and time-domain estimation to handle the first window. When MA is strong, due to the comparation results of the reliability of two methods, we

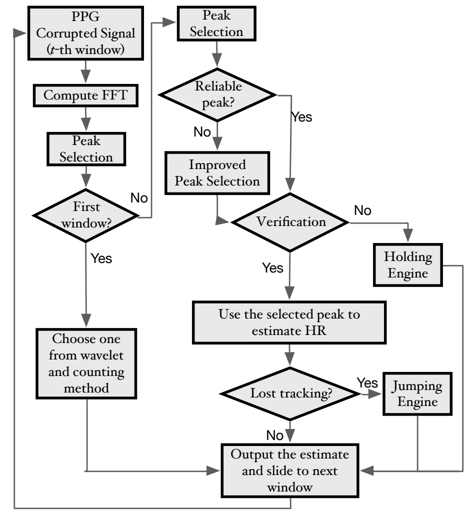

Fig. 2. Flowchart of the MICROST heuristic peak tracking algorithm.

prefer to use time-domain method while its estimation is in a normal range otherwise wavelet method.

Peak Detection and Selection: The spectral peaks of the PPG signals in t-th time window, whose amplitudes are larger than a threshold in the range of possible spectral area (0.6∼3.5Hz), are elected by a raw PeakFinder. When the time window is not the first one, the previous information can be used to track the current HR. If a spectral peak is very close to the previous estimate or its amplitude is higher than other peaks, the peak is a candidate. Generally, there is more than one candidate. Therefore, a strategy for further selection is given based on the similarity D between each candidate and the HR estimation in the previous window. The similarity D is shown as follows

$$D = |PeakX - BPM\,(t-1)| \,/ BPM\,(t-1) \qquad (4)$$

where $PeakX$ is the frequency that corresponds to the current peak and $BPM\,(t-1)$ is the historic HR estimation.

Let $N\,(t)$ be the number of the candidates whose similarity Ds are not larger than the threshold $D_{threshold}$ in the t-th time window. In our experiment, the $D_{threshold}$ is set to 0.25. If $N\,(t)$ is not larger than one, the peak with the smallest D is selected. Otherwise, we consider two cases.

Case 1: If $N\,(t)$ and $N\,(t-1)$ are both equal to 2, and the two candidates' locations in current window are the same as those in previous window, then the candidate with the smallest D is selected.

Case 2: Otherwise, the candidates should be filtered by the following condition, which means that only those candidates whose similarity Ds are close to the smallest D can survive.

$$|D - min\,(D)| < 0.1 \qquad (5)$$

If only one candidate survives, we select it. Otherwise, the changing trend of the HR peak location can be used to help selection. When the trend is rising, the candidate with the largest frequency is selected. Once a peak is selected, it is necessary to judge whether it is reliable according to previous result and some empirical rules. Here, we consider three rules.

Rule 1: $|PeakX_{selected} - BPM(t-1)| > 0.3$ Hz.

Rule 2: 2 Hz $< BPM(t-1) <$ 2.5 Hz, but no peaks of current frame are in this range.

Rule 3: 2 Hz $< BPM(t-1) <$ 2.5 Hz, and the number of peaks > 1, but the highest peak is equal to or more than two times than all other peaks.

If the selected peak satisfies any of the rules above, it is regarded as a suspicious peak. Then an improved PeakFinder is used which is able to detect more possible peaks than the old one to re-detect and reselect a peak.

Verification and Estimation: In order to estimate HR more safely, a further verification for the selected peak is necessary. According to the verification, we may have two choices: abandon the selected peak and hold the previous estimation $BPM(t) = BPM(t-1)$ or adopt the selected peak and use it to estimate HR:

$$\begin{aligned} BPM(t) =& w1 \times PeakX_{selected} + w2 \times Memory(t-1) \\ &+ (1 - w1 - w2) \times BPM(t-1) \end{aligned} \tag{6}$$

where $Memory(t-1)$ is defined as the selected peak in $(t-1)$-th frame. If the current selected peak is far from the previous estimation but acceleration changes very little, it is supposed to be wrong. An abnormal frequency range is also considered to help verification. Generally, the current HR can be neither too large nor too small, especially when the previous estimation is in a normal range. Thus, the selected peak is abandoned in these situations.

Additionally, our experiments showed that in many cases the spectral peak associated with HR could be submerged by large MA, while locations of other peaks remain unchanged in two successive time windows. Or sometimes there is only one spectral peak in the current window because of large MA. Thus, it is necessary to abandon the selected peak in such situation. A holding operation is defined as $BPM(t) = BPM(t-1), Memory(t) = Memory(t-1)$. If not, Eq.(6) is used to estimate the current HR using the selected peak.

Modification: With the intensity of exercise increasing, the exerciser's heart rate is rising and ACC class may change by larger MA. Due to vulnerability to strong fluctuation of HR and the low resolution of the spectrum, the ideal peak might drown in the spectrum and error could be accumulated, so that the spectral peak associated with HR may lost and could not be found back. A modification module is quite necessary when the holding operation is not executed.

Our experiments showed that many spectral peaks are submerged when MA is very large, which means only very few useful peaks can be detected in a normal range. In this situation, the selected peak is always just a suboptimal and lower one and it is unassociated with HR. Then we fix the HR estimation and memory with an empirical increment by $BPM(t) = BPM(t) + increment$ and $Memory(t) = Memory(t) + increment$.

III. Experimental Results

A. Experimental Setting

The PPG datasets are recorded from 12 subjects provided by [1], including two-channel PPG signals, a three-axis acceleration signal and an ECG signal recorded by pulse oximeter (Green LED: 515 nm), an accelerometer from wrist and chest sensors, respectively. We estimate HR in every 8-second time window and two successive time windows overlap by 6 seconds. All signals were sampled at 125 Hz. The running speed is from 6 km/h to 15 km/h, including rest period. In the wavelet method of the first frame, parameter p is set to 10. The parameters of heuristic tracking is implemented in our experiment: $D_{threshold}$ = 0.25, $increment$ = 0.3, w_1 = 0.4 and w_2 = 0.3. The ground-truth of HR was calculated by $60H/D$ from the simultaneously ECG signal, where H is the number of cardiac cycles and D is the duration. In order to evaluate the performance of MICROST, two measuring objects, the average absolute error (ABE) and the average absolute error percentage (ABEP) are computed

TABLE I

Average Absolute Error (BPM) and Average Absolute Error Percentage of 12 subjects.

	1st	2nd	3rd	4th	5th	6th
ABE	2.93	3.06	2.03	2.29	2.64	2.58
ABEP	2.55%	2.94%	1.60%	1.89%	1.80%	2.03%
	7th	**8th**	**9th**	**10th**	**11th**	**12th**
ABE	1.97	1.77	1.87	3.81	1.91	4.07
ABEP	1.49%	1.50%	1.64%	2.39%	1.31%	2.76%

TABLE II

Average Run Time per Frame of 12 subjects.

	1st	2nd	3rd	4th	5th	6th
Time/(ms)	1.643	1.573	1.599	3.620	5.512	2.941
	7th	**8th**	**9th**	**10th**	**11th**	**12th**
Time/(ms)	4.132	6.122	3.933	2.197	6.192	11.994

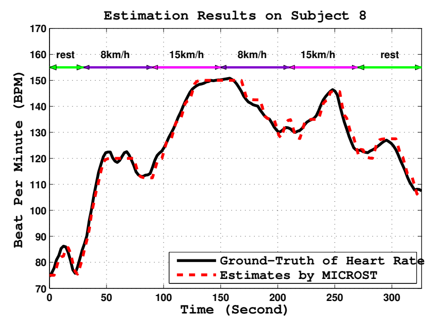

Fig. 3. Estimation results on subject 8 using MICROST framework. The exercise information is provided on the top of the figure.

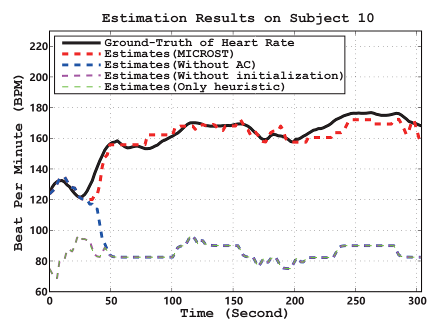

Fig. 4. Estimation results on subject 10. We consider all combinations of parts compared to ground-truth HR estimated from ECG.

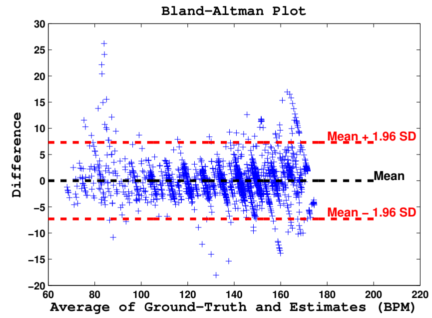

Fig. 5. The Bland-Altman plot of the estimation of 12 subjects.

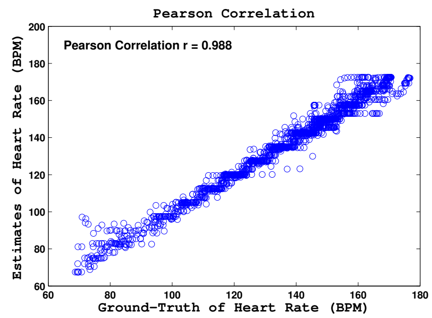

Fig. 6. The Pearson correlation of the estimation of 12 subjects.

as

$$ABE = \frac{1}{W} \sum_{i=1}^{W} |BPM_{est}(i) - BPM_{truth}(i)| \quad (7)$$

$$ABEP = \frac{1}{W} \sum_{i=1}^{W} \frac{|BPM_{est}(i) - BPM_{truth}(i)|}{BPM_{truth}(i)} \quad (8)$$

respectively where $BPM_{truth}(i)$ represents the ground-truth HR (i-th window), $BPM_{est}(i)$ represents the estimated HR (i-th window) and W is the total number of slide windows.

B. Results and Discussion

Experimental Results are shown in Table I, which presents the average absolute error and average absolute error percentage of recordings of 12 subjects, respectively. The results show that the whole MICROST framework can get the satisfying performance with all of its key parts. When implementing MICROST framework, the ABE and ABEP are 2.58 $\pm$ 2.70 BPM (mean $\pm$ standard deviation) and 1.85% (mean). The Bland-Altman plot is shown in Figure 5. The LOA is [-7.31, 7.31] BPM with the standard deviation 3.73 BPM. The Pearson correlation which is shown in Figure 6 is 0.988.

To further emphasize the importance of every module implemented in our framework, we use one subject to illustrate. Figure 4 shows that performance may decrease sometimes when missing any part of the framework. Therefore, MICROST framework is robust anytime only with all of its key parts. Figure 3 presents an example of estimate of MICROST framework. We can see that the estimate HR is quite close to the standard HR as we expected.

The MICROST framework can achieve robust performance due to satisfying cooperation of its key parts. Furthermore, we calculate the average run time per window of 12 subjects which is shown in Table II. The results show the average run time of MICROST takes only a few milliseconds so that it is small enough to face the real-time applications. Compared with the result in [1], [8] and [9], the MICROST framework can obtain the satisfying trade-off between accuracy and time. Furthermore, it is obvious that MICROST has some empirical rules and parameters that may cause partly overfitting when implemented on other types of exercise. However, we believe the novel framework is enlightening and the problem could be solved by machine learning and further analysis in our future works.

IV. Conclusion

In this paper, we proposed a mixed approach, named MICROST, for monitoring HR using wrist-type PPG signals. The proposed approach is mixed of three main components: acceleration classification, first-frame processing and heuristic spectral peak tracking. This new framework was tested on datasets with 12-subjects and ECG was used to validate the derived HRs. The experimental results showed a desirable accuracy and time cost of MICROST. Overall, the MICROST is of great value to development of biomedical signal processing since PPG technology provides a huge potential to wearable devices.

V. Acknowledgement

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