A New Framework to Extract Heart Rate Information from Photoplethysmographic (PPG) Signals with Strong Motion Artifacts

Zi-Hao Zhang, Jian Liu, Xiao-Yue Wu, Chao-Ying Wang and Ran Yang
School of Mobile Information Engineering, Sun Yat-sen University, Zhuhai, P. R. China, 519082
Email: yangran@mail.sysu.edu.cn

***Abstract*—Photoplethysmography (PPG) is a kind of physiological information that can be easily disturbed by motion artifacts. Therefore,this paper paid attention to the extraction of information from PPG with motion artifacts. In the paper, a new framework that can extract heart rate(HR) information from PPG signals with severe motion artifacts is proposed, using Singular Spectrum Analysis, Real-time Clustering, Frequency Points Selection and Prediction and Multiple-way Selection as the key points.**

***Index Terms*—Photoplethysmograph (PPG); Heart Rate Extraction; Motion Artifacts;**

I. Introduction

Physiological data are used in clinical treatment widely.The Heart rate (HR) information extracted from PPG data can be used to control the strength of exercises and monitor heart diseases. So we can draw a safe conclusion that real time HR information is of great use.

The Photoplethysmography (PPG) technique can meet the requirement. On one way, it can provide multiple cardiovascular and respiratory information. On the other, it can be accessed in real-time using wearable devices. However, the PPG signal would be interfered by motion artifacts and lost its information while severe exercises. In order to apply PPG on clinical issues, the motion artifacts must be removed.

II. Related work

Up to now,there already existed several signal processing techniques that deal with the motion artifacts in PPG signal. Three categories can be classified form them: techniques that construct model for ideal PPG signals or for the noise only [1] [2]; techniques that separate motion artifacts from the corrupted signal,techniques that independently measure motion artifacts.

For the first kind of techniques,the raw PPG signal can be reconstructed since the motion artifacts are supposed to be lineared [3] [4] [5]. However, the assumption may not be correct because it contradicted with the experiment result [6]. Moreover, it is not reliable to construct model for motion artifacts to remove them because the model cannot fit every situation [2].

The second kind of techniques, it is more capable. Under specific condition, the raw PPG signal could be separated from the noise [7]. The demerit is that,if the frequency of corrupt and uncorrupt part are similar to each other, these techniques will lose available information.

For the third kind of techniques, motion artifacts are recorded by sensors. For instance, a 2-D active noise cancellation was tried using accelerator data. [8]. However, the extra sensors increase the volume of hardware, and the correlation between acceleration data and the motion artifacts are not verified [9].

Moreover, most of the techniques can only work under motionless environment, where motion artifacts are not strong, which indicates that it may not work correctly under severe exercises.

Months ago, a new framework named TROIKA was proposed in order to separate PPG signal under intensive exercises.The method extract HR from PPG signals with strong motion artifacts in frequency domain. The signals are collected form the wrist. Despite the traditional techniques mentioned before, the TROIKA replaced Fast Fourier Transform by sparse signal reconstruction, to get the high-resolution spectrum information, and the performance is hopeful [10]. Our framework is inspired by TROIKA, and we improve the framework with new idea.

A. Our Work

In this paper, our work focuses on the HR extraction from Wrist-Tpye Photoplethysmographic (PPG) Signals with strong motion artifacts. There are four key procedures in the framework: Singular Spectrum Analysis, Real-time Clustering, Frequency Points Selection and Prediction, Multiple-way Selection. These four procedures will be introduced detailly in later parts.

The datasets used in this work are from 12 subjects [10], in which two-channel PPG signals, three-axis acceleration signals, and one-channel ECG are recorded.

There are 4 following sections. Section 2 shows the problems the motivation. The details of the proposed framework are showed in Section 3. In section 4 the experiment and result of the proposed framework in contrast with TROIKA Algorithm [10] are carried out. In section 5, the conclusion and future expectations are illustrated.

III. Problems and motivations

The constitution of PPG waveform are as follow: an AC component, the pulsatile physiological waveform ('AC');the

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motion artifacts component;a DC component in low frequency caused by respiration and other noise [11].The HR information are in pulsatile physiological waveform, and we analyze the waveform in frequency domain since it is periodic.

We adopted periodogram for frequency domain analyzing. To get rid of leakage effect,the PPG signal are decomposed into several subcomponents using Singular Spectrum Analysis (SSA). Then FFT is applied to every subcomponent to get its periodogram. Then we get the peaks of these periodogram,he main frequency points of the PPG signals can be fetched.

The frequency of HR and motion artifacts are represented in the frequency points of the subcomponents after SSA. Although most of the previous work remove the frequency points close to motion artifacts directly using the information from accelerators, we keep them all to prevent losing useful statistics.

Then we used Frequency Point Selection and Prediction to figure out the frequency of HR. In this section, clustering [12] is introduced. The skeleton of the HR frequency points can be figured out using clustering, and the skeleton will gives guidance to later prediction. Moreover, the the aperiodic noise will be thrown away through clustering. Our clustering is a real-time method, so we use a method called Multiple Way to correct errors of clustering to make it more reliable.

IV. The proposed framework

To sum up, there are six procedures in the proposed framework: Bandpass Filtering, Singular Spectrum Analysis, Frequency Points Extraction, Real-time Clustering, Frequency Points Selection and Prediction, Multiple Way Selection. The detail of each procedures are explained in later parts.

A. Bandpass Filtering

Each channel of PPG signals and three-axis acceleration signals will be band-filtered to extract the noise out of the range of the bands in which HR may located. Since we already knew that the HR of human is ranged from from 40bpm to 190bpm [13], we use Butterworth IIR Filter [11] provided by MATLAB to reserve the band of signals which we focus on.

B. SSA

SSA is widely used in signal analysis [14] [15] since it can decompose a signal into several components. There, we use SSA to extract the HR component from the raw PPG signal excluding the motion artifacts.

SSA has four steps which are discussed below:

At first, embedding transforms the origin signal series $s = [s_1, \ldots, s_N]$ into a Hankel matrix performed below:

$$S = \begin{bmatrix} s_1 & s_2 & \cdots & s_w \\ s_2 & s_3 & \cdots & s_{w+1} \\ s_3 & s_4 & \cdots & s_{w+2} \\ \vdots & \vdots & \ddots & \vdots \\ s_L & s_{L+1} & \cdots & s_N \end{bmatrix} \tag{1}$$

Next, SVD will decompose the matrix S like below:

$$S = \sum_{l=1}^{N} \sqrt{\lambda_l} L_l R_l, \tag{2}$$

where $\sqrt{\lambda_i}$ is the singular value calculated from the matrix $X = SS^T$. The singular value determine how much the related subcomponent contributes to the raw signal.

Grouping combines several subcomponents into one group, there we regard single subcomponent as a group.

After grouping, diagonal averaging reconstructs the signals from the groups obtained before.

C. Frequency Extraction

The key is to find HR, so we perform FFT on signals reconstructed from SSA. For each signal, we select no more than three peaks which amplitude $> 2/3 * P_{max}$ on the periodogram and throw away the signals which have more than three peaks.

D. Real-time Clustering

As we all known, our heart rate change smoothly during the time. Thus we can cluster the frequency points which locate closely to each other into one group [16]. When there is no other frequency points close to current point, current point will be put into a new cluster. Furthermore, we also take the accelerometer into account, any frequency point near the accelerometer frequency will be excluded.

Real-time Clustering's performance is shown in Figure 1. Compare to Figure 1(a), Figure 1(b)(clustering's result) shows a clearer skeleton of real HR.

E. Frequency Point Selection and Prediction

This part contains two steps: initialization, subcomponents selection and prediction.

1) Initialization I: Initialization means get the first three HRs when the subjects are required to keep stationary in order to reduce the influence of motion artifacts. As the motion artifacts can be ignored at beginning, we simply choose the frequency point which has the highest priority and satisfied our constrain as the calculated HR.

2) Subcomponents selection and prediction I: In this step, we use the previous two calculated HR combined with the current frequency point to derive the current calculated HR. First, we denote the previous calculated HR index by N_{prev} and the one before the previous one by N_{bprev}. The difference between these two is denoted by $\Delta = N_{bprev} - N_{prev}$.

Algorithm 1 discribes the method in detail.

F. Multiple-way Selection

The Multiple-way Selection develops several ways to keep track of all possible HRs previously. When there occurs a fatal error, which means the current calculated frequency differs a lot from the real one, it can use Multiple-way Selection to recover from the error.

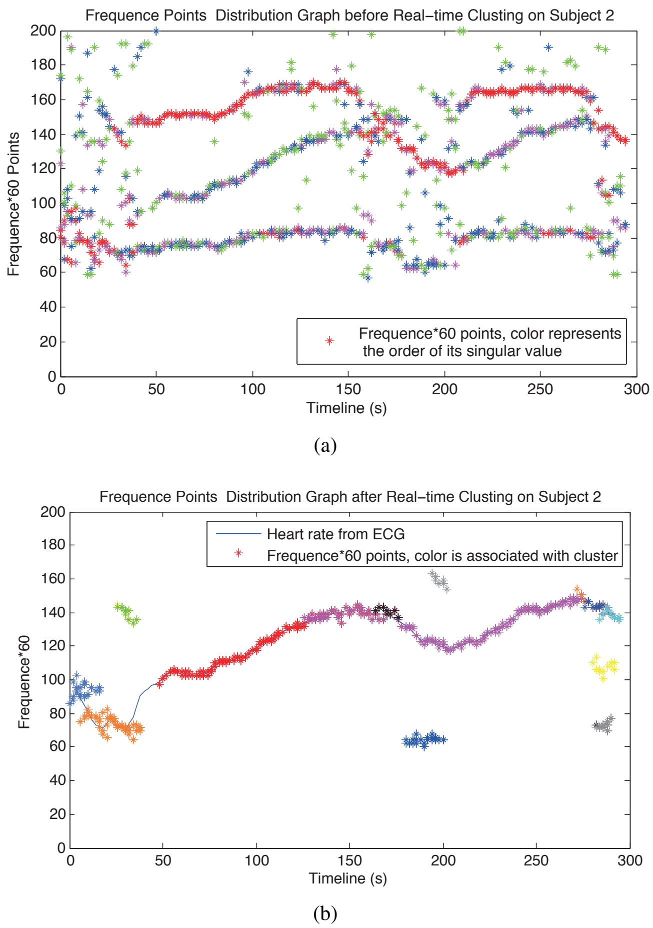

Fig. 1. The Result of Real-time Clustering

Algorithm 1 Subcomponents Selection and Prediction

Input: M_{pos},M_{neg}, M_{cwa}, M_{cwnp}, $M_{cluster\_info}$
$record = [is\_empty(pos1); is\_empty(pos2); is\_empty(neg1); is\_empty(neg2)]$
for index=1:4 **do**
  if $record(i) == 0$ **then**
    $HR = calculate.average(i)$
    $return$
  end if
end for
$addr = min(abs(cluster\_info - N_{prev}))$
if $abs(cluster\_info(addr) - N_{prev}) < \Delta d1$ **then**
  if $HR = cluster\_info(addr) - N_{prev} > 0$ **then**
    $HR = N_{prev} + \Delta d2$
  else
    $HR = N_{prev} - \Delta d2$
  end if
else if $length(M_{cwa}) >= 2$ && $M_{cwa}(1,2) <= 3$ **then**
  $HR = M_{cwa}(1,1)$
else if $is\_empty(M_{cwnp})$ **then**
  $HR = N_{prev}$
else
  if $\sum_{\forall V_x(i) > N_{prev}} weight(i) > \sum_{\forall V_x(i) > N_{prev}} weight(i)$ **then**
    $HR = N_{prev} + \Delta step$
  else
    $HR = N_{prev} - \Delta step$
  end if
end if
Output: HR

1) Calculate current trajectory's frequency I: We use the Frequency Point Selection and Prediction to calculate the current frequency of each trajectory.

2) Split into several trajectories I: If current trajectory generates several possible frequencies, this trajectory will be split into several new trajectories. What's more, trajectories whose frequencies locate closely will be combined as one trajectories, in order to reduce the computation complexity.

3) Choose the most reliable frequency I: Each trajectory is assigned to a priority value, and the trajectory with lower value is considered closer to the real HR.

V. Experiment

We have done several experiments on our proposed framework, the details are described below.

A. Experiment Design

We apply our proposed framework on 12 datasets, which are obtained from TROIKA [10] and compare the result with the real HR. We also remove some parts of our framework to show each parts distribution. At last, we compara our result with TROIKA which is regarded has good performance in the PPG signal processing.

The performance is evaluated by the average absolute error $Error_{as}$ and the average relative error $Error_{rl}$. Following has given the definition:

$$Error_{as} = \frac{1}{N}\sum_{l=1}^{N}|bpm(l) - bpm_{real}(l)|. \tag{3}$$

$$Error_{rl} = \frac{1}{N}\sum_{l=1}^{N}\frac{|bpm(l) - bpm_{real}(l)|}{bpm_{real}(l)}. \tag{4}$$

B. Datasets Description

Datasets have six channels, one ECG signal, two PPG signals and three accelerometer signals which are all sampled at 125Hz. Subjects begin at a stationary state and gradually raise the speed to about 15km/h.

C. Results

The results in the tables show that our framework can control all the datasets' error within 5 bpm. What's more, our framework performs better on several subject than TROIKA.

TABLE I

THE RESULT OF COMPARISON TESTS ON 12 DATASETS IN SEVERAL CONDITIONS: THE COMPLETE PROPOSED FRAMEWORK, FRAMEWORK WITHOUT MULTI-WAY (MW), FRAMEWORK WITHOUT REAL-TIME CLUSTERING (RC), AND FRAMEWORK WITHOUT EITHER MULTI-WAY (MW) OR REAL-TIME CLUSTERING (RC).

Algorithm Item	Subj 1	Subj 2	Subj 3	Subj 4	Subj 5	Subj 6	Subj 7	Subj 8	Subj 9	Subj 10	Subj 11	Subj 12
The porposed Framework	1.58	2.25	0.99	1.91	1.47	2.21	1.07	0.97	0.94	4.91	1.71	1.94
Framework without MW	1.70	2.36	1.00	2.14	0.87	1.96	1.01	0.73	0.86	<u>8.93</u>	1.15	1.88
Framework without RC	1.66	2.66	0.97	2.03	0.88	2.65	0.99	1.24	0.96	<u>36.55</u>	<u>21.15</u>	2.04
Framework without MW&RC	<u>6.07</u>	3.17	1.46	1.98	1.12	<u>54.60</u>	1.28	0.73	0.69	<u>44.65</u>	<u>41.15</u>	2.67

TABLE II

ABSOLUTELY ERROR RESULT IN COMPARISON TO TROIKA

Algorithm Item	Subj 1	Subj 2	Subj 3	Subj 4	Subj 5	Subj 6	Subj 7	Subj 8	Subj 9	Subj 10	Subj 11	Subj 12
The porposed Framework	1.58	2.25	0.99	1.91	1.47	2.21	1.07	0.97	0.94	4.91	1.71	1.94
TROIKA	2.29	2.19	2.00	2.15	2.01	2.76	1.67	1.93	1.86	4.70	1.72	2.84

TABLE III

RESULT COMPARISON WITH ERROR PERCENTAGE

Algorithm Item	Subj 1	Subj 2	Subj 3	Subj 4	Subj 5	Subj 6	Subj 7	Subj 8	Subj 9	Subj 10	Subj 11	Subj 12
The porposed Framework	1.39%	2.41%	0.82%	1.77%	1.06%	1.83%	0.79%	0.83%	0.75%	3.18%	1.12%	1.38%
TROIKA	1.90%	1.87%	1.66%	1.82%	1.49%	2.25%	1.26%	1.62%	1.59%	2.93%	1.15%	1.99%

VI. CONCLUSION AND FUTURE WORK

In general, our framework have four steps, including: Singular Spectrum Analysis, Real-time Clustering, Frequency Seletion and Prediction, Multiple-way Selection. We compare the results generated from 12 datasets with TROIKA and our framework is proved to be better at some subjects.

In the future, the computational complexity will be our main focuse since the resources is quite limited in the imbedded system. This research will still value a lot in the wearable devices and mobile telemedicine.

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