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Heart Rate Monitoring During Physical Exercise Using Wrist-Type Photoplethysmographic (PPG) Signals

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Abstract – Heart rate monitoring using wrist-type using photoplethysmographic (PPG) signals during subjects' intensive exercises is a challenging problem, since signals are strongly affected by motion artifacts caused by unexpected movements. This paper presents a method that uses both time and frequency characteristics of signals; using sparse signal reconstruction for high-resolution spectrum estimation. Experimental results on type data sets recorded from 12 subjects during fast running at peak speed of 15 km/hour. The results have a performance with the average absolute error being 1.80 beat per minute.

Index Terms - Photoplethysmographic (PPG), Sparse Signal Reconstruction, Regression, Heart rate.

I. INTRODUCTION

Heart rate (HR) monitoring is a significant criterion for measuring training load. Nowadays, by developing wearable objects, real-time HR monitoring during fitness with noninvasive devices, gets high concentrations [1, 2].

Estimating HR using photoplethysmographic (PPG) signals is a useful method. PPG signals are optically obtained by pulse oximeters [3]. A pulse oximeter evaluates the oxygen saturation by comparing how much light is absorbed by the blood. This changing in density forms the PPG signal. As the PPG signal's periodicity is similar to the heart beats, HR can be estimated using PPG signals.

During exercises, spacing between sensors on the device from the subject skin, is one the effects of motion artifacts (MA) [4]. So, PPG signals can be hardly affected by MA and various signal processing methods have to be used for denoising PPG signals [5]. Some techniques have been implemented for this purpose, such as Lasso method for solving sparse matrix. Although these methods can be helpful, but in high physical movements that motion artifacts cause extremely serious PPG distortions, more efficient methods have to be used.

In this paper, we describe an algorithm that detects HR using wrist-type PPG signals while wearers are performing high physical movements. The algorithm is based on peak detection in frequency domain after denoising PPG by using accelerometers signal. The key point is to find appropriate coefficient for accelerometers signal which the raw PPG signal carries [6].

Estimating HR in time domain is extremely hard due to strong MA because the signal has a component with close period to HR due to rhythmic hand swings and thus it's

difficult to separate HR and MA in frequency domain. Fig. 1 shows this fact.

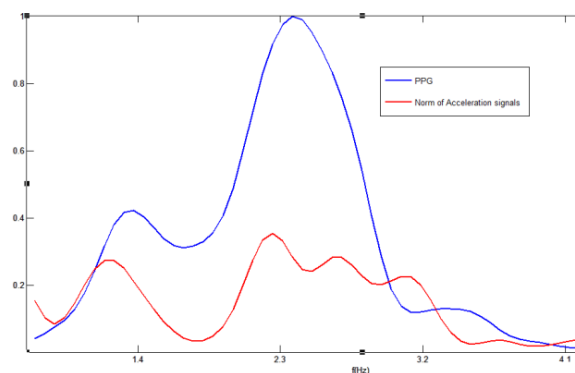


Fig. 1. PPG and motion spectrum

This paper is organized as follows: in the next section, the details of proposed method are described in several steps. Following these methodological aspects, the results of the proposed method is reported on wrist-type PPG data sets were recorded from 12 subjects during fast running.

II. METHODS

The proposed algorithm consists of several steps. Details are shown below.

A. Removing irrelevant frequency component

According to the fact that HR frequency ranges from 0.8 to 4, denoising can be done with a bandpass filter. In order to more caution, the authors prefer to set the low frequency and high frequency to be 0.5 and 5 Hz respectively.

B. Linear estimating of MA in PPG using accelerometer signals

As 3-axis acceleration is given, we try to find how these signals are proportional to the noise that PPG carries. Our first attempt was to use the signal which had more power than the others. This idea led us to nowhere. So we decide to use three signals simultaneously. For this purpose a 1000×63 matrix is associated to every 42 consecutive samples in order to make a vector equation between 3-axis vectors and PPG. Each row contains 21 samples of every three axis acceleration signals.

As sampling frequency is 125 Hz, number of columns is $125 \times 8 = 1000$ due to our standard window length.

Lasso method has been used here to solve $\mathbf{Ax} = \mathbf{b}$ in order to obtain following sparse estimation

$$\hat{\mathbf{M}} = \mathbf{Ax}. \quad (1)$$

where \mathbf{A}, \mathbf{b} are acceleration and PPG signals matrices respectively. The motivation behind this is to find the significant harmonics and avoid over fitting.

C. High-Resolution spectrum estimation

After MA estimation has been obtained, new PPG approximation is defined as below:

$$\hat{\mathbf{P}}_1 = \mathbf{P}_{\text{raw}} - \hat{\mathbf{M}}_1. \quad (2)$$

To reach a high-resolution spectrum estimation, we form a matrix of \sin, \cos in frequencies ranged from 0.5 to 5 Hz, length of steps assumed to be $1/60\text{Hz}$ that is equivalent to one beat per minute precision.

$$D = \begin{pmatrix} \sin(2\pi \frac{0.5}{f_s} \times 1) & \cos(2\pi \frac{0.5}{f_s} \times 1) & \dots & \cos(2\pi \frac{0.5}{f_s} \times 1000) \\ \sin(2\pi \frac{0.5}{f_s} \times 2) & \cos(2\pi \frac{0.5}{f_s} \times 2) & \dots & \cos(2\pi \frac{0.5}{f_s} \times 1000) \\ \vdots & \ddots & \ddots & \vdots \\ \sin(2\pi \frac{0.5}{f_s} \times 1000) & \cos(2\pi \frac{0.5}{f_s} \times 1000) & \dots & \cos(2\pi \frac{0.5}{f_s} \times 1000) \end{pmatrix}_{1000 \times 542}$$

After solving equation with Lasso method, power of each harmonics has been calculated. With examining \mathbf{x} for different λ parameter of Lasso, the one that redounded to at most 20 nonzero components has been chosen. These 20 components are due to the most significant harmonics in denoised PPG.

D. Post processing

HR can be calculated through the previous steps, using the fact that the largest harmonic in magnitude is corresponded to cardiac rhythm. There are some technical details as follows.

There are cases in which algorithm detects second harmonic of the desirable frequency instead. Note that larger harmonic had been removed via bandpass filter. To eliminate this type of error, difference of signal has been calculated and whenever difference is not appropriate frequency have halved.

In order to remove remaining inconsequent spikes, a *bad point* is defined as a point in HR which has considerable difference with its neighbors. This type of simple regression reduced error and results in a quite acceptable estimation. Roughly speaking, no rise by more than 11 and no decrease by more than 6 is acceptable.

The intuition behind of these bounds on oscillation of HR comes from our everyday experiment in exercising. When you get tired of a few minutes running, you will not be in your

neutral position as soon as stop your exercise and need minutes to cool down.

There are some disorders for heart which has been widely studied in arrhythmias that can make a heart unpredictable. For instance *tachycardia* can cause significant growth of HR just in second. In these cases, changing the parameters is needed to modify algorithm.

In order to replace a bad point with a better estimation, we use the 2 last samples difference as our differential magnitude. If the bad point was greater than its previous sample, we replace it with a value higher than the latter sample by the differential magnitude. Otherwise we use the differential magnitude allocated with a minus sign. In order not to lose correct tracking in a case of receiving poor signal for a long time, a variable named \mathbf{K} is defined. \mathbf{K} is the number of bad points in a row that are all above or below the last good sample. This variable can somehow indicates that we had loosed track because of receiving poor signals and not good time domain enhancements in a long period of time, and leads us to rely on the raw estimation without considering bad points.

III. RESULT

A single-channel PPG signal, a three-axis acceleration signal, and an ECG signal simultaneously were recorded from 12 male subjects [2]. For each subject, the PPG signal was recorded from wrist using a pulse oximeter with green LED (wavelength 609nm).

The proposed method was applied to these data set. Fig. 2 shows one of the most challenging subject which had been affected by MA in almost every points. Algorithm fails at points in which interval of strong movement and consequently MA is too long.

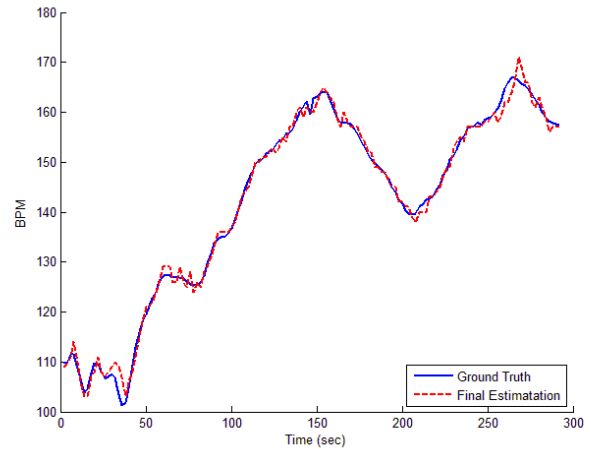


Fig. 2. Subject 5

In order to quantitative evaluation of performance the average absolute error is used that is defined as:

$$Error = \frac{1}{W} \sum_{i=1}^W |BPM_{est}(i) - BPM_{true}(i)|$$

Table 1. The average absolute error of all subject for various K

	Subj. 1	Subj. 2	Subj. 3	Subj. 4	Subj. 5	Subj. 6	Subj. 7	Subj. 8	Subj. 9	Subj. 10	Subj. 11	Subj. 12	Average Error
$K = 3$	1.68	2.56	1.10	1.76	1.08	2.38	2.23	1.01	0.85	4.7	1.69	1.31	1.86
$K = 4$	1.68	2.71	1.11	1.84	1.08	2.49	2.35	1.05	0.85	3.42	1.78	1.31	1.80
$K = 5$	1.68	2.86	1.11	1.93	1.08	2.52	2.44	1.05	0.85	3.60	1.87	1.31	1.86

In Table. 1 the average absolute error of each subject is shown for various K . according to this results the best K , in the sense of mean error of all subjects, is due to $K = 4$.

Though the major part of denoising has been done in spectrum analyzing, without post processing result would not be adequate. For instance, Fig. 3 and Fig. 4 show how post processing eliminate a rock in HR path.

As it can be seen the difference and enhancement are significant and post processing cannot be avoided.

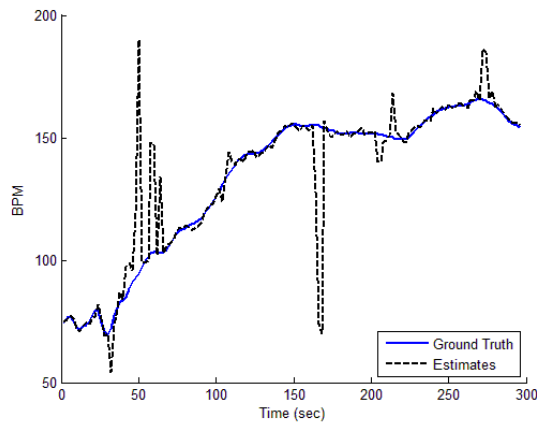


Fig. 3. Before post processing

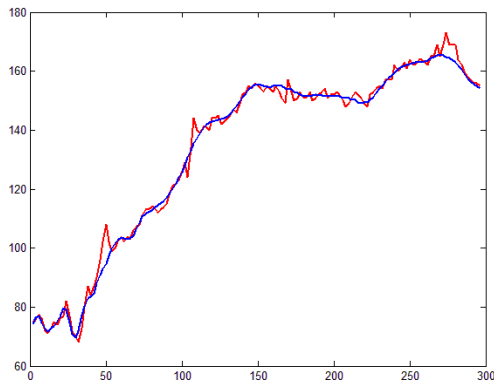


Fig. 4. After post processing

A Bland–Altman plot (Difference plot) in analytical chemistry and biostatics is a method of data plotting used in analysing the agreement between two different assays [7]. This plot is shown in Fig. 5 for proposed method absolute errors.

Finally, to have a statistical estimation of how algorithm performances, two popular correlation meter has been calculated. The scatter plot of true and estimated heart rate value is shown in Fig. 6.

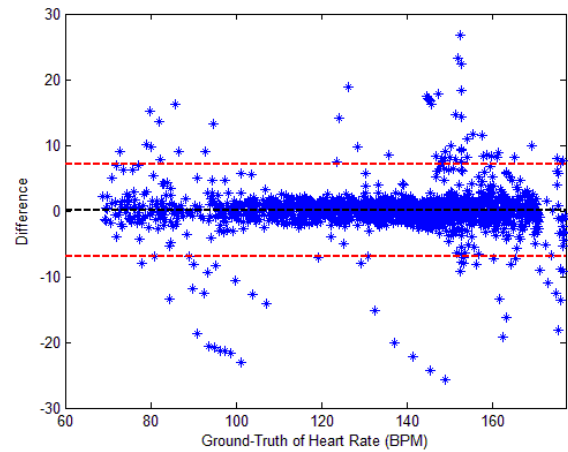


Fig. 5. Bland-Altman plot of the estimation results on the 12 datasets

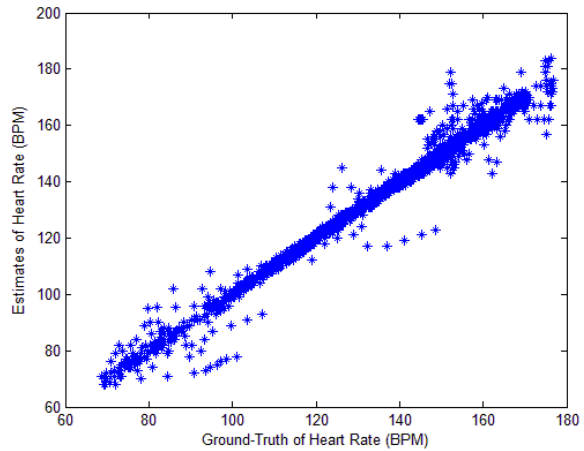


Fig. 6. The Pearson correlation of the estimation results on the 12 data sets
Pearson correlation $r = 0.985$

IV. CONCLUSION

PPG signals are very sensitive to MA and hardly effected by small changes in sensors position. Thus studying raw PPG signal in Time-Domain is too complicated and result is not accurate enough. On the other hand, as HR is periodic with almost constant frequency in small time intervals, working in Frequency-Domain seems to be logical.

Our first attempt to remove MA was physical analyzing of movement such as calculating displacement or velocity of subject's hand thanks to given acceleration. Although reaching good result in some cases, overall was not admissible. Intuitively, according to repeatedly hand motions in every direction it was predictable using three axis simultaneously would perform much better and it did so.

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