Poster: A Robust Method for Heart Rate Estimation Using Wrist-type PPG Signals

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Abstract

Heart rate is a critical index of well-being. However, estimating it accurately in a non-invasive way is a challenge. Photoplethysmography(PPG)-based estimation enables the non-invasive tracking of heart rate, but it is vulnerable to motion-induced noise, which consequently degrades the accuracy of heart rate estimation. In this poster, we present FitHR - a robust method for accurate heart rate estimation on wrist-type wearables. Experimental results show that the average error of FitHR is around 1.65 beats per minute.

1 Introduction

The proliferation of wrist-type wearables enables the non-invasive PPG-based heart rate tracking. Specifically, a PPG sensor consists of a LED and a phtoto detector. The light emitted from LED is absorbed by blood flow when traveling through the tissue. Then the intensity of reflected light is measured by phto detector to sense periodic blood flow variation caused by cardiac cycle, which can be used to estimate heart rate[1].

However, the PPG signal is extremely vulnerable to motion-induced noise. To improve the accuracy, many researches have been proposed to achieve a noise-free result. One direction is to utilize adaptive filters by referring acceleration signals. However, when the motion is too severe or irregular, the result might be not very accurate. Another is based on frequency analysis by using parametric model like AR model. The problem is that the choice of these parameters is not very easy in a specific situation, since the data is quite different crossing devices and users.

In this poster, we propose FitHR, a method for accurate heart rate measurement on wrist-type wearables. The framework is based on some previous works and our observation that, motion artifact can be suppressed by utilizing some other sensors like acceleration sensor. Besides, the information about heart rate is all hidden in the spectrum of PPG signals, and we can locate them by some mechanisms. Based on these considerations, we designed this framework and got a good solution in test.

2 Design and Implementation

As show in Figure 1, the sensor signals are firstly preprocessed, which involves the removal of the base line drift and signal standardization. Then FitHR denoises the comtaminated PPG signals using the decomposition algorithm called singular spectrum analysis(SSA). Finally, we use a robust verification algorithm to check each frame of spectrum of PPG signals to make sure that the result won't vary too much.

Preprocessing: To facilitate the motion artifact reduction, the pulsatility of sensor signals is extracted and standardized during the preprocessing. The raw PPG signals always contain a large direct current(DC) and low frequency(LF) trend components which distort PPG signals both in time and frequency domain intensely, and thus needed to be removed. Here we choose wavelet decomposition for it's low distortion after processing. Specifically, FitHR exploits wavelet decomposition to break down the signals into approximation components and detail components, which represent low- and high-frequency parts in signals respectively. The approximation components are then removed to eliminate the baseline drift.

Signal Decomposition: To remove the motion artifact out of the PPG signal, we have to make an assumption that the noise is additive to the signal. Specifically, the comtaminated PPG signals can be decomposed into several components as a form of cumulation:

$$y = \sum_{i=1}^{n} x_i + \sum_{j=1}^{m} n_j \tag{1}$$

where y, x and n denote raw signals, PPG signals and noise, respectively. Notice that the signal parts and noise parts are separable. FitHR adopts singular spectrum analysis(SSA) to decompose the original signal into multiple components[2]. For each component we calculate its power spectral density(PSD) and compare it to the acceleration signals. The

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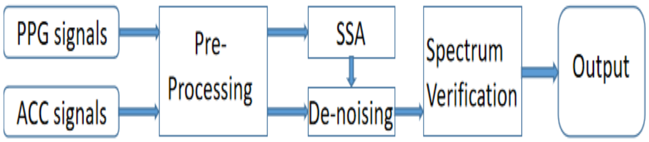

Figure 1. The flowchart of the method.

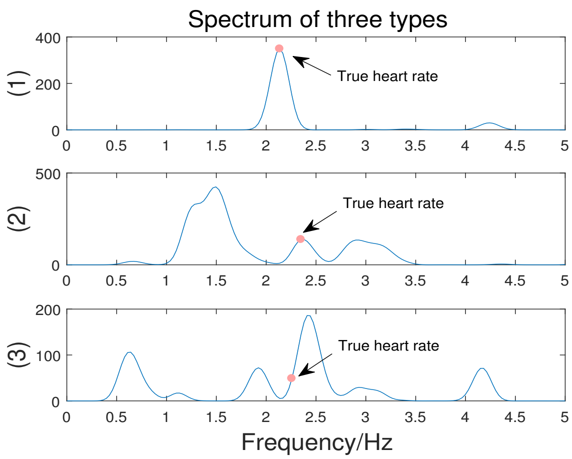

Figure 2. Three types of spectra.

component with a spectral pattern, i.e locations of peaks, similar to acceleration should be removed. Finally, the sum of remaining components, which could be deemed to be clean, depicts the PPG signals induced by heart rate.

Spectrum Verification: Spectrum verification is necessary since the noise can not be removed completely and the signal is not reliably. The final target of this stage and the whole framework is to output a series of time-related heart rate values, so we cut the signal frame by frame and thus one frame is an estimation of a time point. Then we can analyze the spectrum of each frame and identify whether a peak corresponds to a heart rate. Basically, we can distinguish spectrum into three types according to their features as shown in figure 2. Type (1) has a very clear and sparse spectrum, so it could be regarded as a benchmark. Type (2) has much more peaks than (1) but the peak corresponding to the heart rate is still distinguishable. Type (3) offers a totally contaminated spectrum which has no information about heart rate. For type (1), the highest peak can be corresponded to a heart rate, and for (2), we need some extra information to verify those peaks. There is an important assumption that the heart rate won't make a huge change within two adjacent frames. So if the benchmark is nearby and meanwhile the current peak location is in a small range around previous one, then accept the current frequency point as a result. For (3), we simply discard them. Finally, we use linear interpolation to fill the missing data.

3 Experimental Results

We use the real dataset from [3] to verify our methods. In this dataset, there are signals collected simultaneously from a wrist type device and a chest type ECG sensing device, where the wrist type device contains a two channel PPG sensor and a three axis acceleration sensor. All signals are sampled at a sample rate fs of 125 Hz, and from subjects with age from 18 to 35 who are asked to do exercise according to a certain rule. The highly accurate ECG signals were recorded as ground truth.

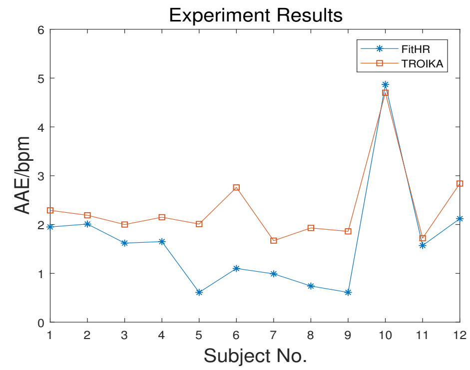

Figure 3. The average absolute error (AAE) of heart rate for different subjects.

With the signals, we set a frame length of 1000 which means a 8 seconds duration, and a sliding interval of 250. Thus two successive frames has a 2 seconds time span. To estimate the spectrum, we use the Welch's PSD method with Balckman window function. The $nfft$ is set to be 4096, so we can get a granularity of 1.83bpm(60*125/4096) in heart rate. We compare FitHR with TROIKA[3] in absolute average error(AAE). The experimental result is shown in figure 3, where we have an AAE of 1.65 in bpm compared to 2.34 of TROIKA.

4 Conclusions

In this poster, we present a new method FitHR for heart rate estimation. Since the PPG signals are contaminated by motion artifact, in FitHR, we process PPG signals and acceleration signals together for accurately counting the heart rate. The framework consists of three steps which are preprocessing, signal decomposition and spectrum verification of FitHR. The first two steps offer a best-effort cleansed signal and the last step makes the whole algorithm more robust and reliable. From experimental results, we can see that FitHR has a high accuracy and it is robust to interference.

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