Digital Signal Processing

Heart Rate Monitoring during Physical Exercise using PPG Signals

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Abstract

Heart rate monitoring using wrist-type photoplethysmography (PPG) signals during subjects' intensive exercise is a difficult problem, since the signals are contaminated by extremely strong motion artifacts caused by subjects' hand movements. So far few works have studied this problem. Monitoring the HR can give a person insights on their medical condition as well as their fitness level. When performing physical activities, monitoring the HR is useful since it can help the user keeping track of their training load. In this project we use the TROIKA framework which is proposed to have a high estimation accuracy and robust to strong motion artifacts.

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1. OBJECTIVE

The heart rate (HR) is the number of times your heart beats per minute. For the average person this rate is between 60 and 100 beats per minute (BPM) when in rest. Heart rate (HR) monitoring is a key feature in many wearable devices. But measurement of heartrate from PPG signals is a challenge as it is very vulnerable to motion artifacts and easily corrupted. A typical approach in estimating the HR in the presence of MA is to first remove MA from the PPG signal. Removal of these motion artifacts is very important to measure the heart rate accurately. The objective is to develop a matlab code to successfully remove the motion artifacts and reduce the error in measurement of heart rate.

2. MOTIVATION

Fitness tracking is gaining massive popularity due to the advent of wearable devices that can track your vital signs. Thus it is a key feature in many wearable devices, such as Samsung Gear Fit, Atlas Fitness Tracker, and Mio Alpha Heart Rate Sport Watch. The heart rate is estimated in real time and can guide exercises to adjust their workload and training programs, which is especially useful in rehabilitation. The periodicity of the PPG signal corresponds to the cardiac rhythm, and thus HR can be estimated using the PPG signal.

3. INTRODUCTION

Real time heart rate (HR) estimation from the photoplethysmography (PPG) signal is a key step in developing wearable devices that can monitor the Heart rate in a non-invasive way. The PPG signal is optically obtained by pulse oximeters. A pulse oximeter illuminates the wearer's skin using a light emitting diode (LED) and measures intensity changes in the light reflected from skin, forming a PPG signal. The intensity changes are due to the changes in volume of the arteries and veins as the heart pumps blood. The periodicity of the PPG signals obtained from the pulse oximeter corresponds to the cardiac rhythm.

In spite of the heart rate information available in the PPG signal, reliable estimation of the heart rate is not straightforward due to the fact that the PPG signal is vulnerable to motion artifacts, which strongly interfere with the HR. Given that such wearable devices are widely used by field medics and during sports activity, depending on the type of physical activity of the user, the MA component can completely mask the HR information in the PPG signal causing the Heart Rate monitoring from the PPG signal challenging.

A reliable approach to monitor HR using PPG signals is to remove motion artifacts. There are several techniques for removing MA from PPG signal out of which some of them do not require data from an accelerometer while some others

do. Independent Component Analysis (ICA) is one of the technique where motion data is not required, however it requires multiple PPG sensors. On the other hand, when the accelerometer data is available, the MA component is adaptively cancelled using adaptive filter based algorithms including least mean square (LMS), normalized LMS, fast transversal recursive least square (RLS) algorithms as well as spectrum subtraction technique and Laguerre basics function based signal representation. However in case of an intensive physical exercise, most of these techniques do not work well.
Hence, In this project we use the TROIKA framework for removal of MA from the PPG signals proposed by Zhang et al. this method consists of signal decomposition for denoising, sparse signal reconstruction for high resolution spectrum estimation, and spectral peak tracking with verification.

4. TROIKA

The TROIKA framework consists of three key parts: signal decomposition, SSR, and spectral peak tracking. Signal decomposition is used for denoising and sparsifying spectra of PPG signals. SSR yields high-resolution spectrum estimation. The spectral peak tracking part selects correct spectral peaks and deal with the non-existence cases of the peaks. TROIKA is used for a single-channel PPG signal and simultaneously recorded acceleration data. A time window of T seconds is sliding on the signals with incremental step of S seconds. S is kept as small as possible to ensure that the consecutive windows are very similar to each other and overlap almost perfectly.

4.1. Flowchart

4.2. Algorithm

Bandpass Filtering

A Butterworth filter of order 32 was used in this case for filtering. A bandpass filter with lower frequency 1.2Hz and higher frequency 2.5Hz was used. This stage all the Motion Artifacts and noise of high frequency are filtered out. This sparsifies the signal.

Signal Decomposition

Signal decomposition is an effective denoising methodology. Generally speaking, it decomposes a signal y into a number of components as follows:

$$y = \sum_{i=1}^{Q} yi$$

In this project we are using Singular Spectrum Analysis (SSA) method to decompose the signal. SSA decomposes a time series into oscillatory components and noise. It includes four steps: Embedding, Singular Value Decomposition (SVD), Grouping, and Reconstruction.

Temporal Difference Operation

To further improve robustness of the framework, we suggest temporally differentiating the cleansed PPG signal output by SSA and then performing SSR-based spectrum estimation. The second-order difference of h, i.e. the first-order difference of h', also maintains the fundamental frequency and the harmonic frequencies. As long as k is not large, the spectrum of the kth-order difference of the time series significantly presents the fundamental frequency and its harmonic frequencies.the PPG component associated with HR is approximately periodic in a short time window, while MA is generally aperiodic. Therefore, the temporal difference operation can make the heartbeat fundamental and harmonic spectral peaks more prominent, while suppressing random spectrum fluctuations.

Sparse Signal Reconstruction

SSR is an emerging signal processing technique, showing great potentials in many application fields. The basic SSR model can be expressed as follows,

$$y = \Phi x + v$$

Here Φ is a known basis matrix of the size $M \times N$. The vector y is an observed signal of the size $M \times 1$. x is an unknown solution vector which is assumed to be sparse or compressive.The goal is to find the sparsest vector x based on y and Φ.

Spectral Peak Tracking

Spectral peak tracking is another key part in TROIKA. It exploits the frequency harmonic relation of HR, and the observation that HR values in two successive time windows are very close if the two time windows overlap largely. In fact, our experiments showed that in many cases the spectral peak associated with HR keeps its location unchanged in two successive time windows. This is achieved by taking fast fourier transform of the reconstructed signal which is free from Motion Artifacts. Now in the frequency domain the power spectral density estimation is done to track the peaks. The peaks correspond to Heart Rate.

5. RESULTS

Final mean error for the data set obtained online:

Test File	Absolute Error
DATA_01_TYPE01.mat	53.9999
DATA_02_TYPE02.mat	30.3872
DATA_03_TYPE02.mat	30.1566
DATA_04_TYPE02.mat	2.9924
DATA_05_TYPE02.mat	6.3668
DATA_06_TYPE02.mat	44.66
DATA_07_TYPE02.mat	1.6353
DATA_08_TYPE02.mat	26.3259
DATA_09_TYPE02.mat	4.4039
DATA_10_TYPE02.mat	25.8249
DATA_11_TYPE02.mat	32.4049
DATA_12_TYPE02.mat	41.1485

Error Plot for Data Set 7

Error Plot for Data Set 8

6. CONCLUSION

We did achieve quite good result in some cases while poor in other cases. The mean error is calculated by dividing the obtained absolute error by the total time the data is recorded for. If the wrist-band was worn quite firmly, then our method gives the output with a mean error of about **2.5 BPM**, which is quite good.

7. FUTURE SCOPE

Currently I have used only signal processing methods. Machine Learning techniques can be used too to determine the Heart Rate and noise reduction. Assumed that Heart Rate for initial value is correct which might not be the case many times. Also window size could be adaptively changed using acceleration data and weights could be adjusted accordingly too.

8. REFERENCES

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