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Improved Method for Motion Artifact Reduction from Finger Photoplethysmogram Signal

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Abstract: Finger pulse signal, popularly known as Photoplethysmogram (PPG), can provide important information on circulatory functions in the human body. PPG signal is prone to motion artifact (MA) due to peripheral body movement. In this paper, a new method of motion artifact reduction is proposed. Here, the accelerometer signal is utilized for its frequency domain analysis for detecting the presence of MA in the PPG signal. From the frequency peak analysis of both the PPG signal and the accelerometer signal, the heart rate (HR) is estimated. Once the HRs are calculated in the 8-sec moving time window, the calculated time series-based HRs are sent to the HR updation unit, where the HRs are analyzed and modified using the LSTM algorithm to further reduce the effect of motion artifacts. The result showed a significant improvement in the Average Absolute Error (AAE) calculated with respect to the ground truth HR given. The mean AAE was 2.05, whereas the popular literature demonstrated an AAE of 2.42(TROIKA) and 1.285(JOSS). Although the algorithm didn't give the best result among the literature, the fact that it didn't require any reference clean signal for its functioning and the presence of the LSTM algorithm also makes the algorithm adaptive person to person, case to case, making this work significant. Since the algorithm is not trained once but is constantly getting trained on the consecutive input HRs, it will be very adaptive and can provide good results for critical care unit patients, whose cardiac vitalities vary to a larger extent.

Keywords: *Biomedical signal processing; Motion artefact; Photoplethysmogram; LSTM; Frequency domain*

1. Introduction

Photoplethysmography (PPG) is a non-invasive optical technique for the measurement of blood volume changes in the superficial vessels with respect to the cardiac cycle in the human body [1-2]. Owing to the low cost, instrumentation, and ease of collection, PPG has become a popular choice as a diagnostic monitoring tool in many physiological measurements [3-4]. A PPG sensor, placed at a peripheral body parts like fingers, ear lobes, or toes, consists of a light source operating in the infrared (IR) wavelength and a photodetector. The sensing is based on the difference in absorbance of infrared light by the blood and the remaining skin tissues [5]. As shown in Fig. 1, the pulsatile component of a typical PPG wave consist of two parts, viz., a rising part or anacrotic phase due to ventricular systole (represented by AFB contour containing PPG foot A and systolic peak B) and, the second, a falling part or catacrotic phase due to ventricular diastole (represented by BCDEH contour containing dicrotic notch C and Diastolic Peak D). Over the last two decades, the various clinical features associated with PPG have been utilized to indirectly infer many cardiovascular parameters, like heart rate variability [6]-[7], blood pressure [8], respiratory rate [9]-[10], cardiac output (CO) and systemic vascular resistance (SVR) [11]. Heart rate turbulence can be can be found from the PPG signal which was used for classifying patients as being either resistant or prone to hypotension [12]. Because the peripheral body portion where the sensor is attached can move freely during ambulatory monitoring, the PPG signal becomes distorted with motion artefact (MA). In order to reduce artefacts in the PPG data for computerised analysis and classification applications, pre-treatment is a crucial prerequisite. Baseline drift, interference from power lines, and interference from biological and electromagnetic signals are some more examples of artefacts. The pre-processing or noise reduction of the finger pulse signal from MA is the main topic of this research.

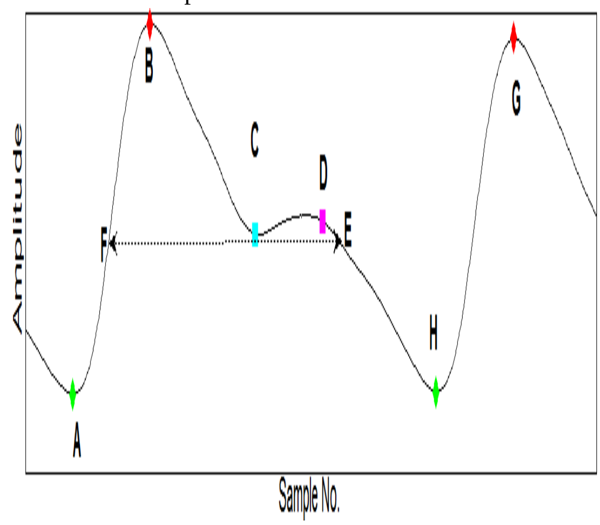

Fig.1: A typical PPG Waveform showing fiducial points

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Techniques for eliminating motion artefacts are crucial for improving the reliability of PPG-based vital parameter estimation. Utilizing adaptive filtering techniques, several motion artefact reduction strategies are developed in the time domain. Other methods, such as wavelet transformation approach [13], IMAT [14], SpaMa [15] used the frequency domain of the signal. Independent Component Analysis (ICA) [16], Window's Adaptive Noise Cancellation (ANC) [17], Empirical Mode Decomposition (EMD) [18], and others are some additional popular pre-processing techniques used for PPG signals. Even yet, the majority of these studies call for the availability of either continuous ECG signal data or accelerometer data. Using an accelerometer signal, Fukushima et al. [19] recommended using a technique called spectrum subtraction to separate the spectrum of acceleration data from that of a PPG signal. In order to recreate the observation model for Kalman filtering [20] to eliminate MA, acceleration data can also be used. However, MA in a PPG signal results from changes in the distance between skin and the surface of a pulse oximeter, whereas the acceleration data (in three axes) indicate hand movement in 3-D space. Because of this, it's possible that simply utilising acceleration data won't yield significant results when there are complex and irregular hand movements present.

In the proposed work, we achieved MA reduction using a straightforward approach, without a separate collection of any clean signal. In this work, the accelerometer signal is used for frequency comparison with the PPG signal and an HR updation unit updates the HR using LSTM algorithm. The structure of this paper is organized as follows: Methodology section describes the data collection protocol and a detailed algorithm overview. Results and Discussion section analyses the performance outcome of the algorithm. The conclusion section summarizes the main outcomes of the work.

2. Methodology

The step adopted to obtain the HRs from an input PPG signal with motion artifact are discussed in this section. The raw PPG signal is extracted from a standard database which contain motion artefact contaminated data. A bandpass digital filter is designed to eliminate frequency components outside the area of interest. The workflow diagram is given in Figure 2.

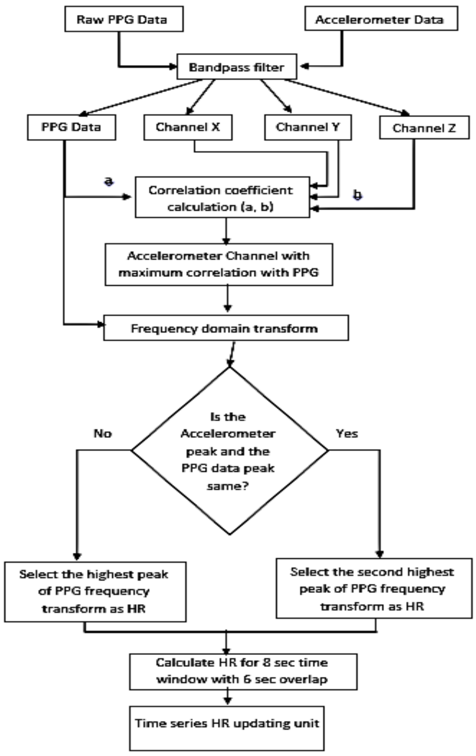

Fig.2: Work flow diagram

2.1. PPG Data Collection

A standard publicly available IEEE Signal Processing Cup 2015 [21] dataset is used in this work. This dataset is divided into two parts: a training dataset and a test dataset. The IEEE training and testing dataset were recorded with a wrist-worn device, which included a PPG sensor (two-channel) with LEDs having a wavelength of 515 nm and a three-axis accelerometer. It also has the record of ECG signal obtained simultaneously, providing the heart rate ground truth. The data from 12 different people with 18-35 age group were recorded while running on a treadmill at varying speeds with a sampling rate of 125 Hz. The IEEE_Test dataset contains the records of 8 different subjects of age group 19–58 years, following the same hardware setup. However, the data collection protocol for the IEEE_Test dataset consists of 10 sessions. In the first 4 sessions, various arm exercises and the last 6 sessions, intensive arm movements were performed by the subjects.

2.2. Bandpass filter

A 2nd order bandpass filter with a passband frequency of 0.4Hz to 5Hz is designed as the first stage of pre-processing the raw signal. The frequency band remains the main band of interest for heart rate. Not much of a difference is being noticed pre and post-filtering as the motion artefact is not only in the filtered frequency range. The frequency of the PPG signal is s 0.5 to 5 Hz, while for motion artefacts it is 0.01 to10 Hz [22].

2.3. Correlation coefficient calculation

The COF between each channel of the accelerometer signal channel X,Y,Z taken one at a time (b) and the PPG signal

(a) is calculated by the formula:

$$COF(a,b)=\frac{1}{M-1}\sum_{i=1}^{M}\left(\frac{a-\mu_a}{\sigma_a}\right)\left(\frac{b-\mu_b}{\sigma_b}\right) \quad (1)$$

Where, M is the total number of samples recorded for both the PPG and accelerometer data, here represented as a and b, μ_a and μ_b are the respective means of the PPG signal and accelerometer data and σ_a and σ_b are the respective standard deviation of the signals. The accelerometer channel which gives the maximum correlation is taken for further evaluation.

2.4. Frequency domain transform

Using Fast Fourier Transform (FFT), signals from the time domain are transformed to the frequency domain. FFT analysis can help in investigating numerous signal characteristics to a much greater extent. In the frequency domain, the signal characteristics are described by independent frequency components, wherein in the time domain it is described by one waveform, containing the sum of all characteristics.

The length of FFT signal is taken larger (4 times) than the input signal size for higher spectral resolution. An array of frequency bins of width 0.122 is created. Frequency bins are intervals between samples in the frequency domain. For example, if your sample rate is 100 Hz and your FFT size is 100, then you have 100 points between [0 and 100) Hz. Therefore, you divide the entire 100 Hz range into 100 intervals, like 0-1 Hz, 1-2 Hz, and so on. Each such small interval, say 0-1 Hz, is a frequency bin.

2.5. Frequency domain analysis and heart rate calculation

From the FFT frequency bins, the frequency peaks in order of peak magnitude are sorted from the highest to lowest frequency. This is done for both the PPG and accelerometer selected channel frequency spectrum.

The frequency peak with the highest magnitude, unless the peak is also present in the accelerometer peaks is taken as the Heart Rate (HR). If the peak is also present in accelerometer frequency spectrum, the peak can be considered created due to the motion artifact. Hence, the next highest peak of the PPG spectrum is taken as the HR.

2.6. Time window-based HR verification and updating unit

The PPG signal and the corresponding accelerometer signal are passed through an 8 sec time window frame with 2 sec overlap in each consecutive window. The HR for each time window are calculated as per the method described in Section 2.5. The HR derived from consecutive time windows are compared and if a sudden abrupt change is detected from the previous time windows, the HR is analyzed and updated. The updation is done following the method described below:

The first derivative of the time series HR value is calculated using the formula:

$HR\_derivative_i = HR_{i+1} - HR_i$

If $HR\_derivative_i$ > (Threshold),

$HR_i = LSTM\_model\,(HR_{i-1}, HR_{i-2}, \ldots HR_{i-5})$

Else, $HR_i = HR_i$

Where i denotes the current time window. The threshold can be varied and the extent of MA reduction can be controlled.

2.7. Calculation of threshold

The derivatives of the ground truth HR are calculated and compared. The mean derivative is calculated for all 24 user data which rounded off to be 0.98. The mean derivative indicates the mean variation of the heart rate over consecutive time windows. The maximum change in consecutive heart rate observed is 1.02. The threshold is selected as the maximum derivative value which is 1.02.

2.8. LSTM Model

Long Short-Term Memory networks, or LSTMs for short, can be applied to time series forecasting.

The LSTM model will learn a function that maps a sequence of past observations as input to an output observation. The number of features is one, since it is a univariate series. The shape of the input for each sample is specified in the input_shape argument on the definition of first hidden layer. In this case, we define a model with 40 LSTM units in the hidden layer and an output layer that predicts a single numerical value. The model is fit using the efficient Adam version of stochastic gradient descent and optimized using the mean squared error, or 'mse' loss function. Once the model is defined, we can fit it on the training dataset i.e. the last five HR. After the model is fit, we can use it to make a prediction. The next value can be predicted in the sequence by providing the input.

3. Results and Discussion

In this paper, we presented a new method for HR detection from motion artifact corrupted PPG signal involving frequency domain peak analysis and LSTM algorithm. To show the efficacy of the method, we verified with the ground truth BPM given in the dataset that is measured from ECG. The Average Absolute Error (AAE) was calculated using the given formula:

$$AAE = \frac{1}{W}\sum_{i=1}^{W}|BPM_{est}(i) - BPM_{true}(i)|. \quad (2)$$

Where W is the total number of time window, BPMest is the BPM calculated and BPM_{true} is the ground truth BPM. The calculated AAE of the 12 data IDs is compared with two existing literatures. The mean AAE was found to be 2.05 whereas the popular literature demonstrated an AAE of 2.42(TROIKA) and 1.285(JOSS).

Table 1 shows the detail comparison of the AAE. The figure 3 and 4 shows the visual comparison of the BPM derived from this proposed method with the ground truth BPM. Though the algorithm didn't give the best result among the literature, the fact that it didn't require any reference clean signal for its functioning and the presence of LSTM algorithm as well which makes the algorithm adaptive person to person, case to case, makes this work significant.

Table 1: Comparison of AAE of proposed work with literature

Sample ID	**Proposed work**	**TROIKA[21]**	**JOSS[23]**
Data_01_Type _01	2.99	2.87	1.33
Data_02_Type _02	2.58	2.75	1.75
Data_03_Type _02	**1.29**	1.91	1.47
Data_04_Type _02	**1.32**	2.25	1.48
Data_05_Type _02	1.89	1.69	0.69
Data_06_Type _02	2.47	3.16	1.32
Data_07_Type _02	1.96	1.72	0.71
Data_08_Type _02	1.56	1.83	0.56
Data_09_Type _02	1.87	1.58	0.49
Data_10_Type _02	**2.87**	4.00	3.81
Data_11_Type _02	1.06	1.96	0.78
Data_12_Type _02	2.75	3.33	1.04

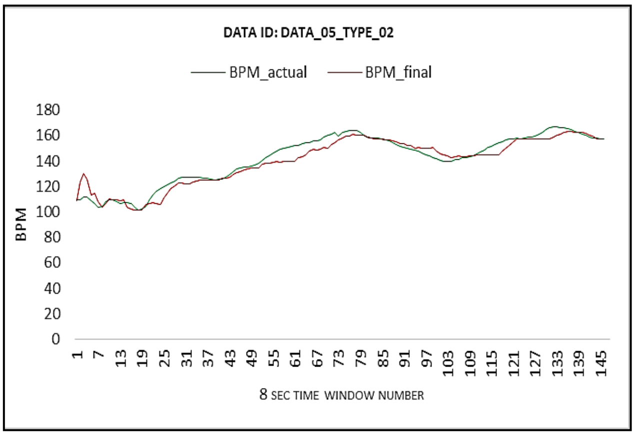

Fig.3: Visual comparison of the BPM of Data ID: DATA_03_TYPE_02

4. Conclusion

In this paper, a new method of motion artifact reduction is proposed. The correlation coefficient of the signal and each accelerometer channel X, Y, Z is calculated. The channel which is more correlated is considered for further evaluation. The signals are converted to frequency domain. If the highest frequency of the PPG signal matches with the accelerometer signal peak, the second highest peak of the PPG frequency spectrum is selected as the HR. Otherwise, the highest peak of the PPG frequency spectrum is selected as the HR for that time window. Once all the HRs are calculated in the 8 sec moving time window, the calculated time series based HRs are sent to the HR updation unit where the HRs are analyzed and modified to further reduce the effect of motion artifact. In the HR updation unit, the consecutive HRs of each time window are compared and based on the threshold explained in this paper the HR is modified using LSTM algorithm. The result showed significant improvement in Average Absolute Error (AAE) calculated with respect to the ground truth HR given. The mean AAE was found to be 2.05 whereas the popular literature demonstrated an AAE of 2.42(TROIKA) and 1.285(JOSS).

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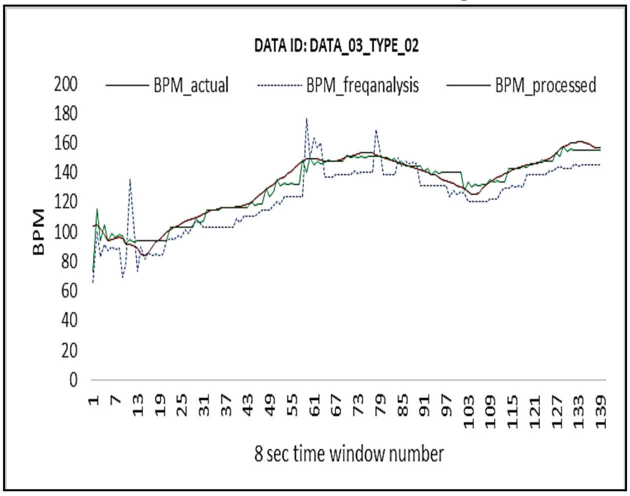

Fig.4: Visual comparison of the BPM of Data ID: DATA_05_TYPE_02

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Conflicts of interest

The authors declare no conflicts of interest.

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