EAST WEST UNIVERSITY

Measurement of Heart Rate in Intense Motion Using Photoplethysmographic Signals

By

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and

Golam Kibria

In partial fulfillment of the requirements for the degree of Bachelor of Science in Electrical and Electronic Engineering

Spring, 2018

Department of Electrical and Electronic Engineering

Faculty of Science and Engineering

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Dhaka, Bangladesh

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Approved By

Thesis Advisor	Chairperson
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Abstract

Photoplethysmographic signal is one of the most convenient approaches to measure heart rate (HR) when subject is not in motion. But in intense motion, HR estimation becomes difficult as the peaks of motion artifacts are mingled with the peaks of heart rate in photoplethysmographic (PPG) signal. In this work, a data independent algorithm is proposed to measure heart rate from the contaminated PPG signal. The method is verified using the 12 data sets provided by IEEE signal processing cup 2015 [13]. Using this method, an average absolute error of 10.60 beat per minute (BPM) and standard deviation of 8.42 BPM are obtained while subjects are running at an average velocity of 15 km/h. Though the results are not highly satisfactory yet, the algorithm may be considered as a potential candidate for data independent PPG-based HR estimation approach.

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1. Introduction

1. 1. Background

Heart is the most important organ of human body. The heart circulates oxygen and nutrient rich blood throughout the body. If heart does not work properly, other organs get affected. Therefore, measuring heart rate is a very important task. Patient's heart rate has been monitored using electrocardiogram (ECG) signal at hospitals with accuracy. Very recently another method named as Photoplethysmographic (PPG) has been replacing ECG for measuring HR due to convenience of measurement. PPG signals are acquired using pulse oximeters and a fingertip device is used for acquisition of this signal [1]. Though the process of signal acquisition is very convenient, the HR estimation may not be accurate enough in presence of motion artifacts [1]. It has been observed that PPG signals get distorted even in slight movement of the finger of the subject [1]. Accordingly, electrocardiogram still remains the gold standard for heart rate measurement.

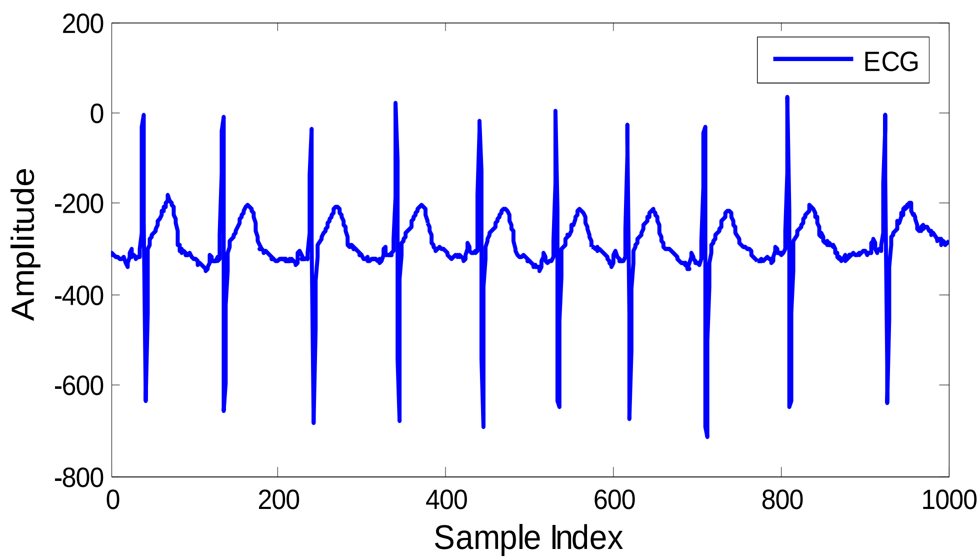


Figure 1.1. Segment of an ECG signal

Many sportsmen, physical exerciser want to monitor their heart rate using pulse oximeters in intense motion so that they can stop themselves from doing intense exercises that may result in serious heart seizures. Therefore, the problem of monitoring heart rate from PPG signals, its future importance and the development of HR measurement using motion artifact contaminated PPG signal is still in research [1-12]. The significant aspect of signal processing in this regard was highlighted in IEEE Signal Processing Cup 2015 [13].

1.2. Literature Review

PPG signals are becoming popular for measuring heart rate because it can be obtained conveniently using a small wearable device which is called pulse oximeters. Using light emitting diode (LED) and photo diode (PD), pulse oximeters determine the intensity changes of transmitted or reflected light which depends on the amount of blood in the arteries under the skin. The amount of blood depends on cardiac rhythm. Therefore, HR can be estimated from PPG signal [1].

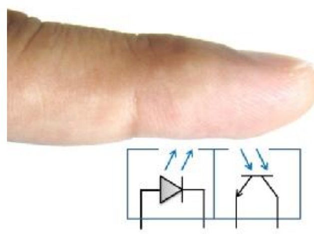


Figure 1.2. Acquiring PPG signal [15].

A PPG signal is a volumetric measurement of blood that detects the changes of blood volume in microvascular bed of tissue. It has two components, these are AC component and DC component. The AC component comes from arterial blood pulsation. It occurs between the systolic and diastolic phase of cardiac cycle. The DC component comes from venous blood, non pulsating arterial blood and other tissues. Different absorbing substances of human body absorbed the transmitted light. Skin pigmentation, bones, arterial and venous blood are the primary absorbers. The transmitted light is emitted by LED and the reflected light is detected by PD. This reflected light generates the PPG signal [17].

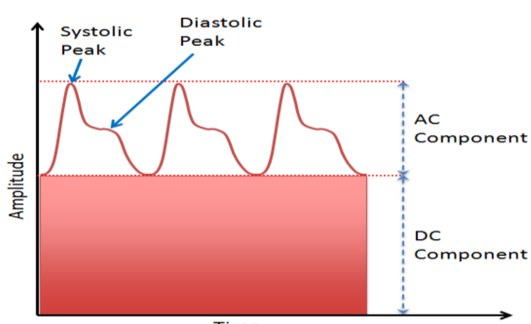


Figure 1.3. The AC and DC components of PPG signal [18]

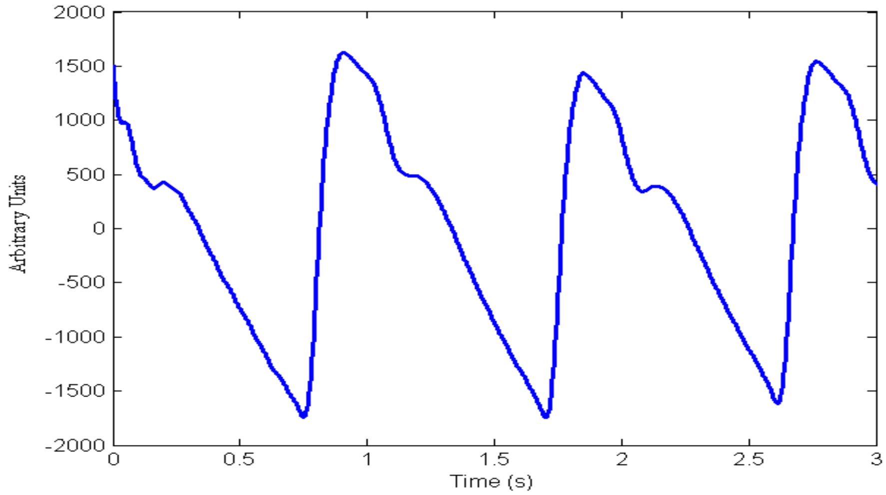


Figure 1.4. A PPG signal acquired in laboratory [17]

It is observed that distorted PPG signals made heart rate monitoring difficult in presence of any kind of physical motion which is named as motion artifacts (MA). Accordingly, reputed works suggests numerous methods to reduce error by removing MA.

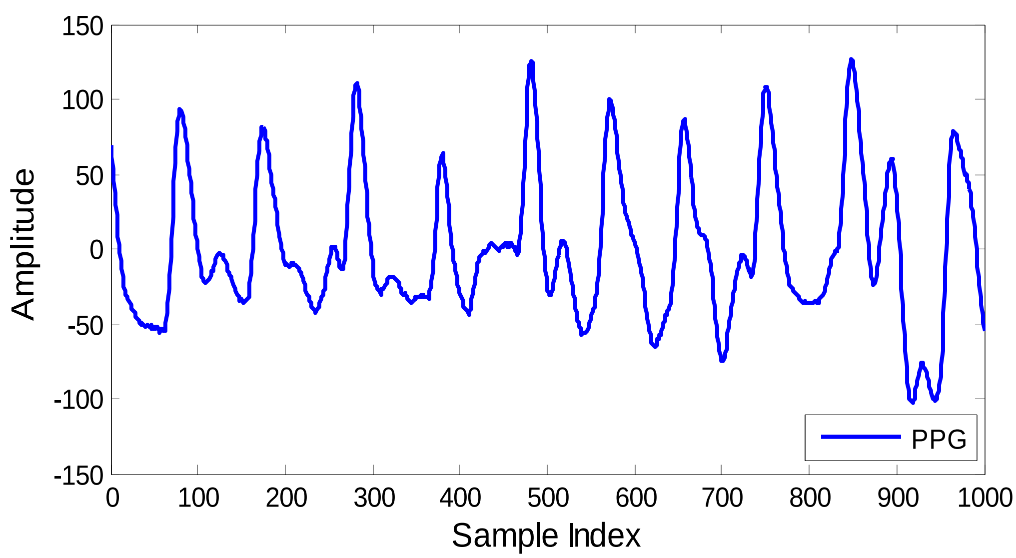


Figure 1.5. Segment of a PPG signal with motion artifacts

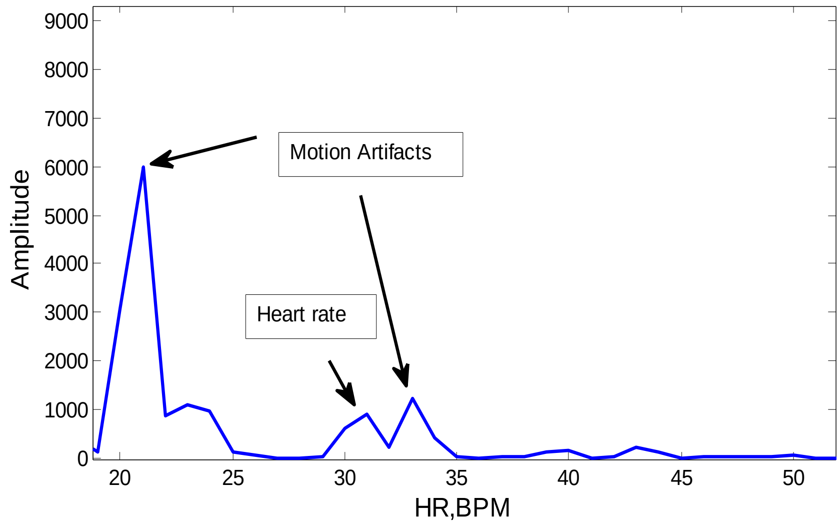


Figure 1.6. Periodogram of a PPG signal to show the existence of MA with HR

A well known technique, named as TROIKA [2] consists of three major parts. These are signal decomposition for denoising, sparse signal reconstruction for high resolution spectrum estimation and spectral peak tracking with verification mechanisms. In this method, error is drastically reduced compared to the previous research works even in presence of high speed motion [2].

Another recent heart rate monitoring scheme [1] has shown better result than TROIKA at the same high speed motion. In this novel technique, initial resting phase or previously calculated HR value is not needed. Here, absolute criterion condition is introduced based on ensemble empirical mode decomposition (EMD). Because of using two channel PPG signals, the algorithm became stable. Moreover, RLS filtering and time-domain extraction reduced off track errors which have increased the robustness of this algorithm [1].

A very recent algorithm is proposed in [3] to estimate instantaneous frequency of Hilbert transformed PPG signal during intense motion from PPG signal. Although error estimated from this algorithm is not better than those reported in [1] and [2], but instantaneous heart rate can provide more information on human body which is very important significance. Instantaneous heart rate provides a direct measure of vagal nerve and sympathetic nervous system of activity [3].

A method is proposed in [14] estimates spectra of PPG signals jointly utilizing multiple measurement vector modeled in sparse signal recovery. This can easily identify and remove spectral peaks of motion artifacts due to common sparsity constraint in spectral coefficients. It is reported to perform well at low sampling rates [14].

Another algorithm is proposed in [4] named by Particle filter-based heart rate estimation (PARHELIA) from photoplethysmographic signals during physical exercise which shortened the estimation time of heart rate and showed better result compared to [14]. It is a particle filter based algorithm which estimates heart rate within a small range of data where the time period is short. As HR variation is low in a small range of data, it shows better result [4].

A technique proposed in [5] for HR measurement is claimed to be suitable for excessive occurrence of motion artifacts in PPG signal. Three axis acceleration data are used here as reference signals and multi stage X-LMS filter is used for motion artifacts reduction. Multi stage X-LMS filter refers that the output of the adaptive filter is back to the input several times to reduce error. For tracking the heart rate peaks, Slope Sum Method (SSM) is used in this algorithm [5].

An algorithm is proposed in [6] for HR estimation based on motion artifact removal (MAR) and adaptive tracking (AT). Singular value decomposition (SVD) is applied for separation of the PPG in two subspace. FFT peak finder is used in this algorithm to get dominant frequencies. This algorithm is simpler compared to the other algorithm, but the estimated error is high [6].

Another algorithm is proposed in [7] to remove MA by two stage data analysis. At first stage, data is analyzed by higher order statistical analysis which finds the presence of MA with HR and in the second stage MA is reduced [7].

An algorithm is developed in [8] based on linear filtering, frequency domain and heuristic analysis. In this algorithm heuristic approach first developed observing the PPG signal. This algorithm first identifies three frequencies from PPG signals where two MA can be identified using simple logics, and the remaining frequency corresponds to HR peak. This algorithm does not work well in presence of exercising activities [8].

Another research work [9] first included the tissue effects on HR measurement employing pulse oximeters. Adaptive noise canceler is used in two stages for removing MA and noise reduction in this algorithm [9].

An algorithm is proposed in [10] for estimating heart rate using wrist-type photoplethysmography and acceleration sensor while running. In this method, Motion artifacts (MA) are rejected from the power spectrum difference between PPG and acceleration data. The heart rate estimation is defined with reliability in conjunction with acceleration signal [10].

In our proposed algorithm, bandpassed and windowed data is given to the input of RLS filter. Six combinations of PPG signals and acceleration signals are passed through the RLS filter. It estimates motion artifacts from the PPG signals. FFT is then performed on six sets of RLS filter's output. By taking geometric mean of six sets of FFT, heart rate in BPM is determined. Our proposed algorithm is data independent. Therefore, heart rate computation from this algorithm may be improved in future work.

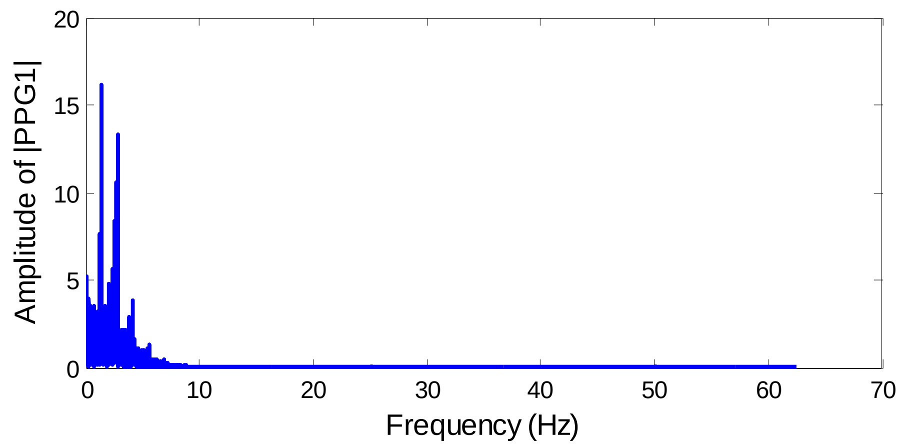
1.3. Thesis outline

Our objective is to measure heart rate using photoplethysmographic (PPG) signal acquired during intense motion. An algorithm in this thesis is proposed to measure heart rate from MA contaminated PPG signal. In order to do so, we will implement the proposed technique on twelve data sets from twelve different subjects during running at a peak speed of 15 km/hour. The results will be compared with the HR estimation from ECG of the same data set.

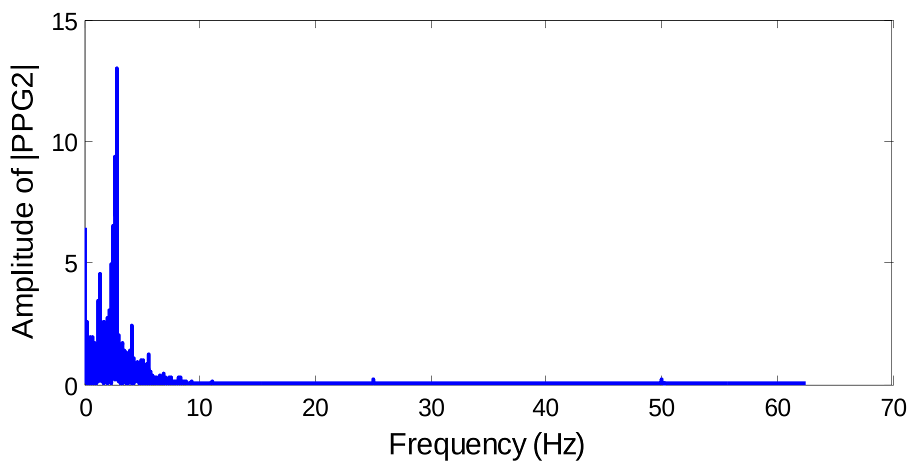
2. Method

2.1. Data acquisition

A dataset of two PPG signals and three acceleration signals are taken from 12 healthy people (age range: 19 to 58 years). The PPG signals were recorded from the wrist by two pulse oximeters. The acceleration signals were also recorded from the wrist by a tri-axis accelerometer. Both the pulse oximeters and the accelerometer are inserted into a wrist band. Simultaneously an ECG signal is recorded from the chest by an ECG sensor. All of these signals are sampled at 125Hz.



(a)



(b)

Figure 2.1. Single sided frequency spectrum of raw (a) PPG signal of channel-1. (b) PPG signal of channel-2.

2.2. Bandpass filter on raw data

A bandpass filter is a device that passes frequencies of a particular range and rejects frequencies outside that range. Here all PPG and acceleration signals are passed through an infinite impulse response (IIR) bandpass filter. The lower and upper cut off frequencies of the passband are 40 BPM, and 200 BPM, respectively. The lower and upper cut off frequencies of the stopband are 35 BPM, and 205 BPM, respectively. Passband ripple is 1 dB, and stopband attenuation is 80 dB. All the frequencies between lower cut off frequency (i. e., 40 BPM) and upper cut off frequency (i. e., 200 BPM) are allowed to pass through the bandpass filter.

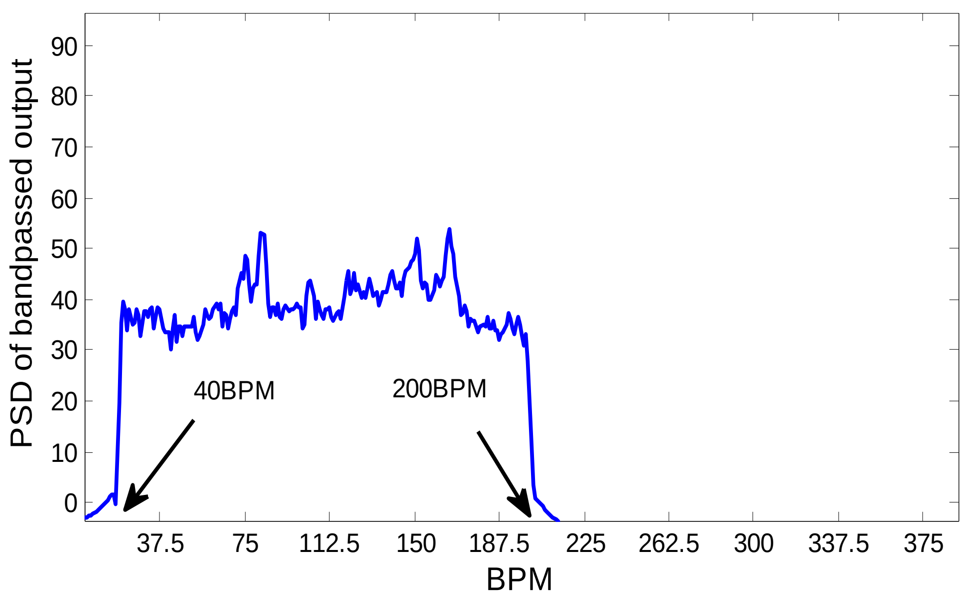


Figure 2.2. Power spectral density estimation of the output of bandpass filter.

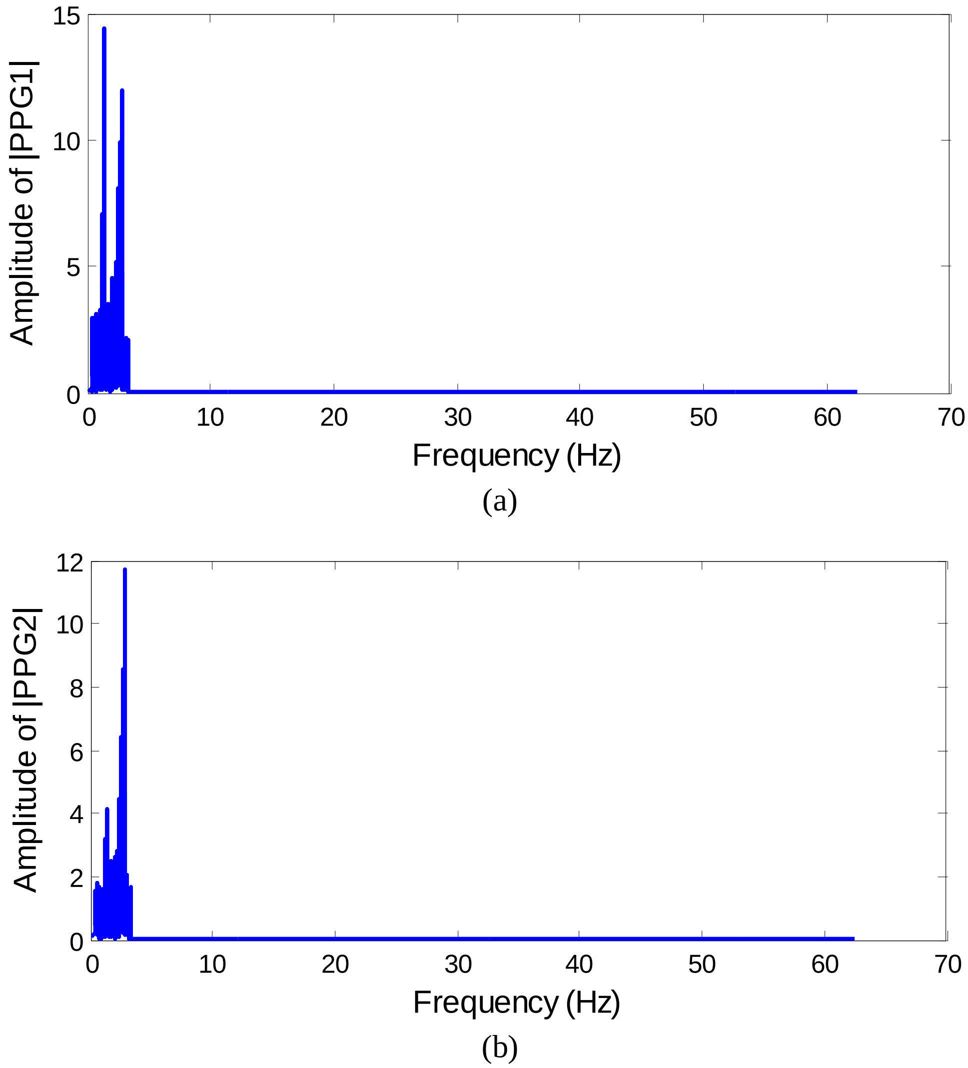


Figure 2.3. Single sided frequency spectrum of the output of (a) filtered PPG signal of channel-1. (b) filtered PPG signal of channel-2.

It is evident from Fig. 2.3 that identifying heart rate from this spectrum is quite difficult.

2.3. Windowing on bandpass filtered data

All the output signals of bandpass filter are segmented into several windows. Time duration of T seconds is set for each window which corresponds to N samples. Two consecutive windows are overlapped by $T/4$ seconds corresponds to $N/4$samples. In our work we have used T = 8 seconds and $N = 1000$ samples. Therefore, the first estimated HR is calculated from 1000 samples and the next estimated HR is calculated from the 750 to 1750 samples and so on.

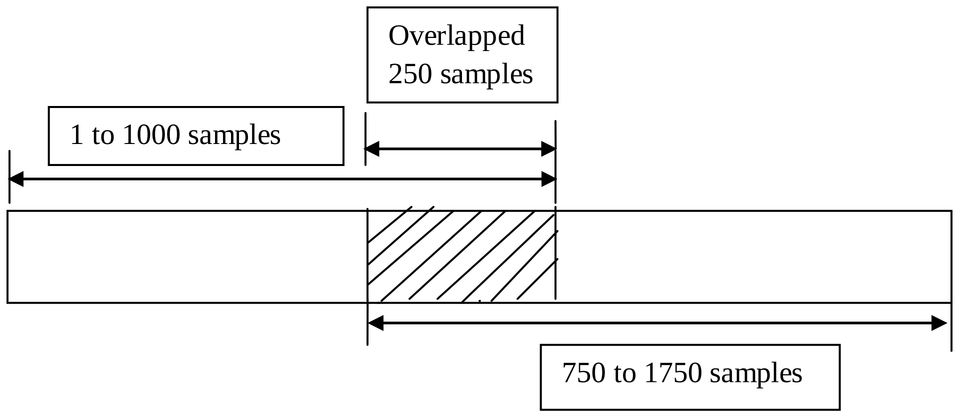


Figure 2.4. Windowing of raw data

2.4. RLS filter on windowed data

Two PPG and three acceleration signals are acquired using two pulse oximeters and a tri-axis accelerometer and denoted as $y_{(i),raw}(n)$, and $a_{j,raw}(n)$, respectively; where $i = \{1,2\}$ and $j = \{x, y, z\}$.The motion artifacts present in the PPG signal may be considered as random noises $(u_{(i,j)}(n))$. In the reported works this is assumed to be related with the acceleration signals ($a_{j,raw}(n)$). The adaptive RLS filter estimates the noise component ($\hat{u}_{(i,j)}(n)$) for the actual noise component ($u_{(i,j)}(n)$) using the acceleration signals ($a_{j,raw}(n)$), and finally denoise the raw PPG signals as,

$$Y_{(i,j)}(n) = y_{(i),raw}(n) - \hat{u}_{(i,j)}(n) \dots\dots\dots (2.1)$$

Where, $j = \{x, y, z\}$. Here the aforementioned equation is the cost function of RLS filter. The square of this cost function is minimized by the RLS filter which can be denoted as,

$$\xi(n) = \sum_{q=0}^{n} \lambda^{n-q} |Y_{(i,j)}(q)|^2 \dots\dots\dots (2.2)$$

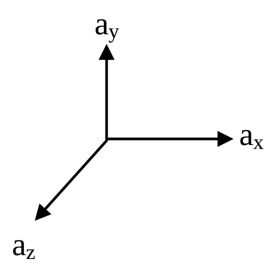


Figure 2.5. Representation of three-axis acceleration signal

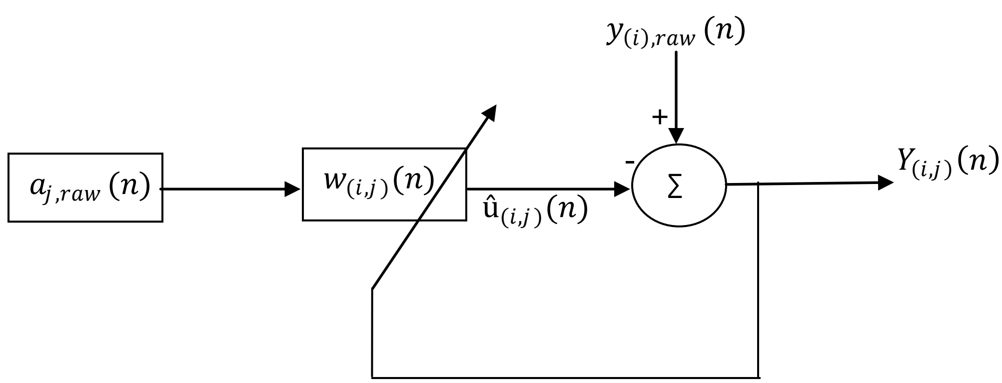


Figure 2.6. Block diagram of RLS filter to eliminate motion artifacts (MA).

Where λ is the forgetting factor (for our work λ=1) and $Y_{(i,j)}(n)$ is the error signal. Here $w_{(i,j)}(n)$ is the RLS filter coefficients which are found in an adaptive way. Six different combinations of PPG and acceleration signals are used separately as input of the RLS filter. Each pair of PPG and acceleration signals, i. e., $\{y_1, a_x\}$, $\{y_1, a_y\}$, $\{y_1, a_z\}$, $\{y_2, a_x\}$, $\{y_2, a_y\}$, and $\{y_2, a_z\}$ are passed through the RLS filter.

For six combinations of two PPG and three acceleration signals the denoised output can be expressed as,

$$Y_{(i,j)}(n) = y_{(i),raw}(n) - a_{j,raw}(n) * w_{(i,j)}(n) \ldots \ldots \ldots (2.3)$$

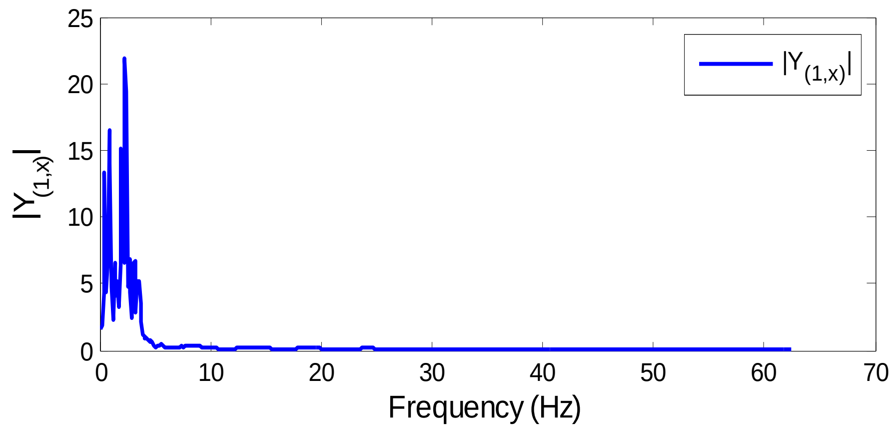
Where, $Y_{(i,j)}(n)$ is the output of RLS filter for the six combinations of two PPG signals (i. e., $y_{(i,),raw}(n)$) and three motion artifacts (i. e., $a_{j,raw}(n)$), and $w_{(i,j)}(n)$ indicates filter coefficients for this six combinations, and '*' indicates convolution operation.

2.5. FFT on RLS filtered data

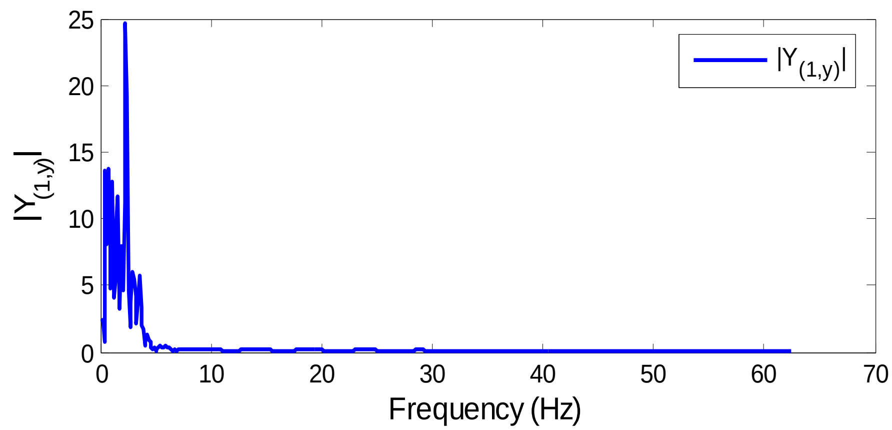
The Fast Fourier transformation (FFT) is a process which samples a signal over a time and estimates the frequency present in the signal. If a signal is a sum of different signals of different frequencies, FFT distinguishes those frequencies. The output of FFT is denoted as,

$$F_{(i,j)}(n) = FFT[Y_{(i,j)}(n)] \dots \dots \dots (2.4)$$

Here, $i = \{1,2\}$ and $j = \{x, y, z\}$. The six set of frequency spectrums are shown in Figure 2.7.



(a)



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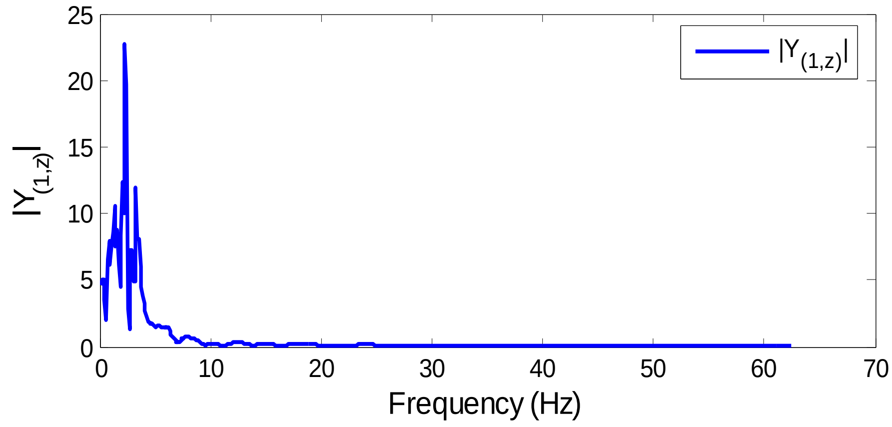
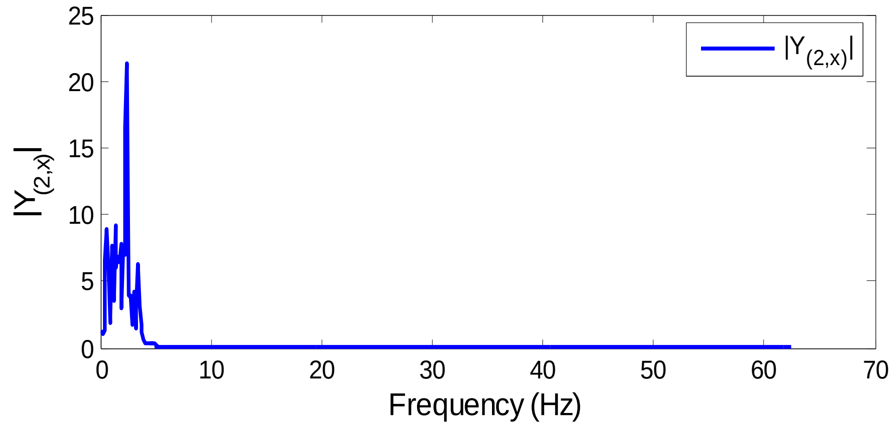

25
20
15
10
5
0
0
10
20
30
40
50
60
70
$|Y_{(1,z)}|$
Frequency (Hz)
$|Y_{(1,z)}|$

(c)


25
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15
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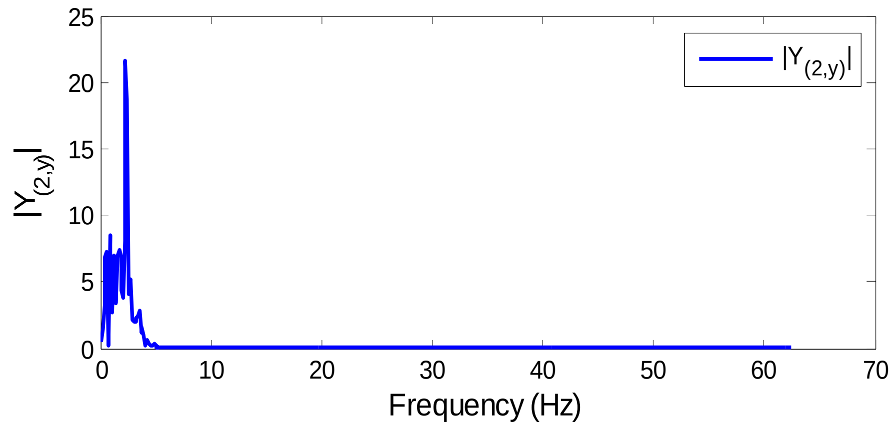
$|Y_{(2,x)}|$
Frequency (Hz)
$|Y_{(2,x)}|$

(d)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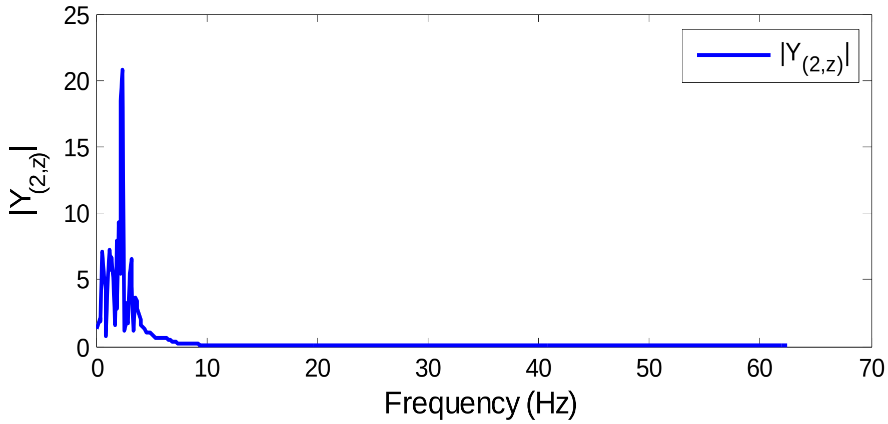
$|Y_{(2,y)}|$
Frequency (Hz)
$|Y_{(2,y)}|$

(e)



(f)

Figure 2.7. Single sided frequency spectrum (FS) of (a) $Y_{1,x}(n)$ which is the first output of RLS filter (b) $Y_{1,y}(n)$ which is the 2^{nd} output of RLS filter (c) $Y_{1,z}(n)$ which is the 3^{rd} output of RLS filter (d) $Y_{2,x}(n)$ which is the 4^{th} output of RLS filter (e) $Y_{2,y}(n)$ which is the 5^{th} output of RLS filter (f) $Y_{2,z}(n)$ which is the 6^{th} output of RLS filter, out of Six combinations.

2.6. Geometric mean of frequency components

The geometric mean refers to the geometric average of a data set. The geometric mean has an advantage over the arithmetic mean. It is less affected by very small or large data. The six different frequency spectrums are estimated from FFT. Six sets of frequency spectrum are used to estimate GM. Therefore, GM of the FFT spectrum estimation can be defined as,

$$GM(n) = \left(\prod F_{(i,j)}(n)\right)^{\frac{1}{p \times q}} \ldots \ldots \ldots (2.5)$$

Here, $p = 2$ and $q = 3$ refer to two channel PPG signals, and three acceleration signals, respectively.

2.7. BPM calculation from geometric mean

From the geometric mean, the frequency corresponds to heart rate is estimated. The data set is divided into several windows. Each window contains one thousand data and that window corresponds to eight second. From the Fourier transformation of that window, a frequency spectrum is found. Accordingly, the highest peak of the GM in frequency domain is selected as f_{HR} (beats per second). And the heart rate in minute is calculated as,

$$BPM_{estimated} = f_{HR} * 60 \ldots \ldots \ldots (2.6)$$

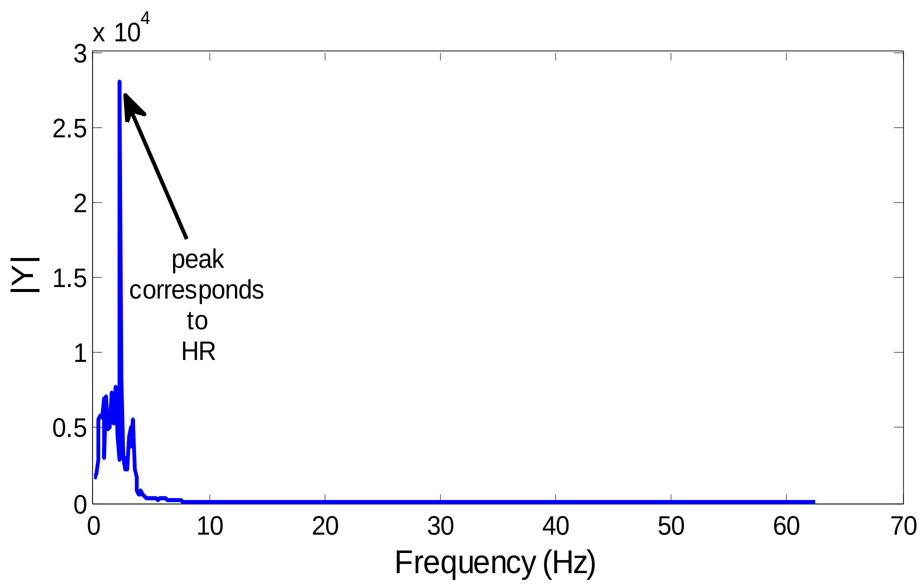


Figure 2.8. Single sided frequency spectrum of geometric mean.

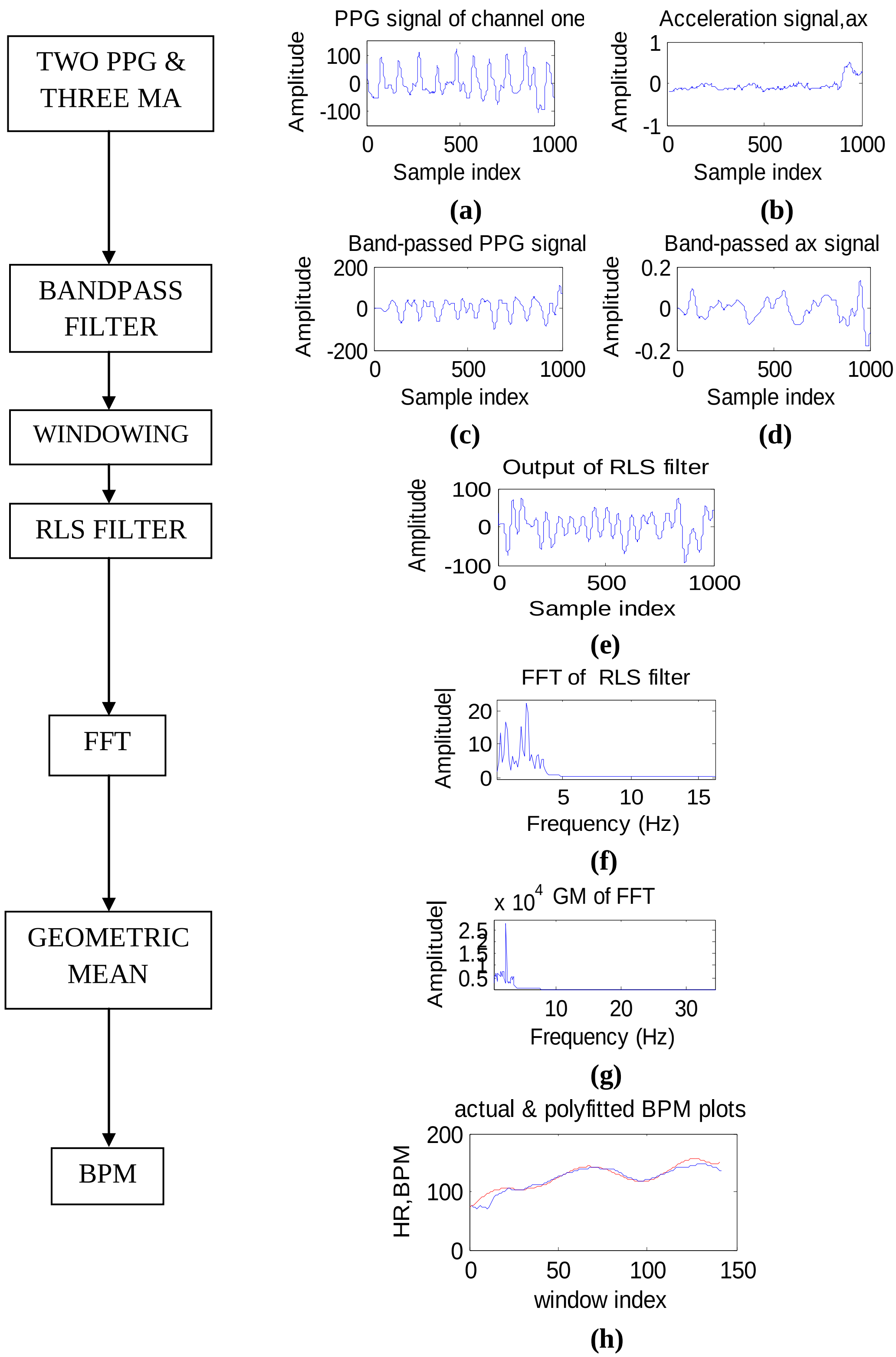


Figure 2.9. Flow chart of the proposed algorithom showing an example of (a) PPG signal (b) acceleration signal (c) band-passed PPG signal (d) bandpassed acceleration signal (e) output of RLS filter (f) FFT of RLS filter's output. (g) GM of FFT (h) comparison of actual and polyfitted BPM.

3. Experimental results

To verify the performance of proposed algorithm, a dual channel PPG signal and three axis acceleration signals are taken from the 12 dataset of 12 different subjects. These data are recorded using 125 Hz sampling frequency. The performance of this algorithm is measured by the average absolute error which is defined as,

$$Error_1 = \frac{1}{w}\sum_{1}^{w} |BPM_{est}(i) - BPM_{true}(i)| \dots\dots\dots (3.1)$$

Here, w is the total number of windows and BPM_{est} is the estimated heart rate expressed as beat per minute. BPM_{true} is considered as the ground truth of HR which is measured using ECG signal. Similarly, the relative average absolute error is defined as,

$$Error_2 = \frac{1}{w}\sum_{1}^{w} \left|\frac{BPM_{est}(i) - BPM_{true}(i)}{BPM_{true}(i)}\right| \dots\dots\dots (3.2)$$

For this proposed algorithm $Error_1$ varies from 4.5 BPM to 35.9 BPM with mean of 10.60 BPM and standard deviation of 8.42 BPM.

Table 3.1

Table 3.1 represents the average absolute $Error_1$ and the relative average absolute $Error_2$ of twelve subjects.

Subject	$Error_1$	$Error_2$
1	15.3312	0.0994
2	4.5279	0.0335
3	5.3160	0.0340
4	10.3939	0.0711
5	8.5497	0.0543
6	6.7079	0.0438
7	8.7695	0.0578
8	8.3149	0.0774
9	8.1736	0.0598
10	35.9524	0.2139
11	7.3670	0.0447
12	7.8652	0.0511

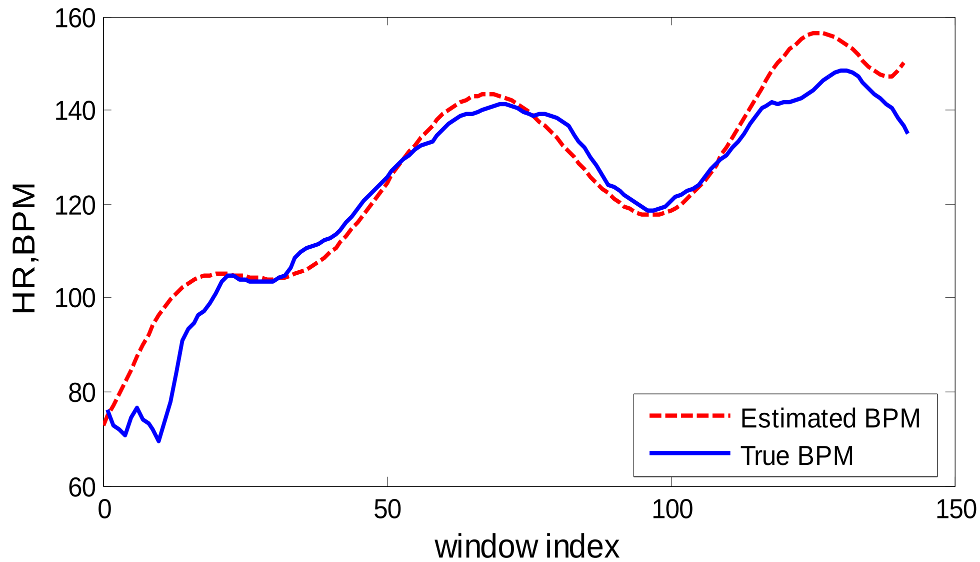


Figure 3.1. Comparison between the estimated and true BPM.

Figure 3.1 shows performance of the proposed algorithm for HR measurement with respect to the true BPM signal recorded from ECG. It is clearly evident from Figure 3.1 that though our algorithm misses actual HR peak initially but eventually it follows the actual HR. The estimated BPM curve is polyfitted by eight degree polynomial.

4. Discussion

In intense motion, presence of motion artifacts (MA) make HR measurement challenging using PPG signal. It is observed that the error found performing this algorithm is not optimal. The results also suggest that this algorithm cannot pick initial value of HR when subject is in motion, but this drawback is common in most of the reported techniques. The average error (i. e., 10.60 BPM) and standard deviation (i. e., 8.42 BPM) obtained using this algorithm on 12 data sets is acceptable as this is a data independent approach. Further processing of this result may attain better accuracy in measuring HR.

5. Conclusion

In this work, a new algorithm is proposed for measuring heart rate in intense motion using two channel PPG signals recorded from pulse oximeters. PPG signals along with three acceleration signals are used to denoise the corrupted signal. Then RLS filter is used to estimate the noise artifacts adaptively and produce robust estimation of PPG. This filtered PPG signal transformed into frequency domain using FFT. Geometric average of six different combinations of filtered PPG and acceleration signals produce a robust frequency spectrum for HR estimation. Though error found performing this algorithm on 12 different data sets from 12 different subjects is not yet satisfactory, the algorithm may be considered as a potential candidate for data independent PPG-based HR estimation approach.

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