Comparative Analysis of PCA and Wavelet based Motion Artifact Detection and Spectral Characterization in W-ECG

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Abstract: - The use of wearable ECG recorders is becoming common nowadays for the people suffering from cardiac disorders. Although it is a convenient option for hospitalization, it has an inherent drawback of recorded ECG being contaminated by motion artifacts due to various body movement activities of the wearer. In this paper, the spectral characteristics of motion artifacts occurring in wearable ECG (W-ECG) signals have been studied using principal component analysis (PCA) and wavelet transform. The residuals of PCA and wavelet transform characterize the spectral behaviour of the motion artifacts occurring in W- ECG signals. The ECG signals have been acquired from Biopac MP-36 system and a self-developed wearable ECG recorder. The performance is evaluated by power spectral density (PSD) plots of PCA residual errors as well as statistical parameters like mean, median and variance of PCA and wavelet residuals. The PSD plots indicate that the peak frequency of the motion artifacts occurring due to various body movements (like left arm up-down, right arm up-down, left and right legs up-down, waist twist, walking and sitting up-down) is located around 5-15 Hz, coinciding with the ECG spectrum.

Key-Words: - Wearable ECG (W-ECG), PCA, Wavelet transform, Motion artifacts, PSD

1 Introduction

There has been a huge increase in the number of people suffering from cardiac disorders over a last decade. Hence the use of various wearable devices (WD) such as wearable ECG recorder has also been increasing. These compact and light weighted devices give freedom to the person from frequent hospitalization; however it has some inherent drawbacks. The major disadvantage being the recorded ECG gets contaminated by the motion artifacts due to various body movements like walking, standing up-sitting down, climbing stairs, left-right arms up-down etc. However, the “unwanted” motion artifacts contain useful information related to BMA and various types of BMA classes can be recognized from the collected ECG signal itself. Thus recognition of BMA is useful for continuous monitoring of heart in ambulatory conditions [1] - [5]. For ambulatory ECG recorders the impact of body movement activity (BMA) on motion artifacts has not been fully investigated. Hence, a comprehensive study of motion artifacts in the ECG signal is a prime requirement, yet, in order to improve the accuracy of the commercially available wearable and similar ambulatory ECG recorders. The possibility of artifact detection and filtering was initially explored in [6]. In [7], the ECG signals were analyzed using wavelet transform and a neural network.

In other works related to BMA analysis from non-ambulatory ECG, body position changes are detected for ischemia monitoring in [8]-[10]. [11] have proposed a physical activity (PA) recognition algorithm for a wearable wireless sensor network using both ambulatory electrocardiogram (ECG) and accelerometer signals using support vector machine (SVM) and Gaussian mixture models (GMM). In [12]-[16] authors have classified the daily and sports activities using classifiers like artificial neural network (ANN) and K-nearest neighbours (KNN). However, the behaviour of motion artifacts resulting from these physical/body movement activities has still not fully discovered. In this paper, the spectral characteristics of motion artifacts contained in W-ECG signals have been studied. The motion artifacts have been extracted from the W-ECG signals by principal component analysis (PCA) and wavelet transform and then the comparative analysis of both the approaches has been made by PSD plots and other statistical parameters. Section II describes the W-ECG data acquisition, section III gives insight to PCA and wavelet based algorithms for extracting motion artifacts, section IV discusses the simulation results and section V concludes the paper.

2 W-ECG Data Acquisition

The ECG signals for this work have been acquired using two different recorders. The *first*, shown in fig. 1 (a), is a Biopac MP-36 4-channel data acquisition system. The ECG signals were acquired in lead I configuration while performing following *four* types of body movement activities:

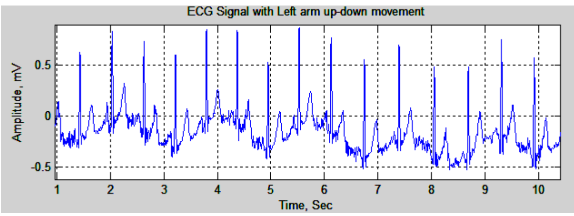
1) left arm up and down movements,

2) right arm up and down movements,

3) twisting of waist left-right-left while standing,

4) change from sitting on a chair to standing up and vice versa.

(a)



(b)

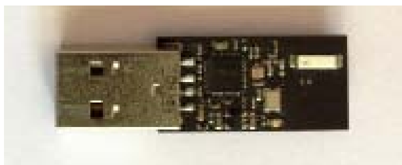
Fig. 1. Biopac MP-36 with electrode lead set (a) and recorder ECG signal with *left arm up-down* movement (b)

The ECG signal with each of the four movements was recorded for 300 Sec with 500 Hz sampling frequency.

The *second* recorder, shown in fig. 2, is a self-developed *wearable ECG acquisition system.* In addition to *wireless* ECG Tx/Rx modules it consists of the *accelerometer* module to provide the motion data corresponding to various movements. The ECG signal were recorded in lead II configuration with *four* body movement activities viz. left arm up-down, right arm up-down, sitting down-standing up and waist twist. Fig. 3 shows the ECG signal and the accelerometer data recorded by the wearable recorder.

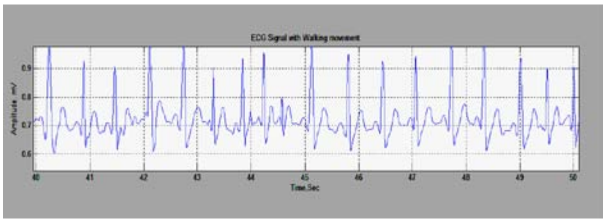
(a)

(b)

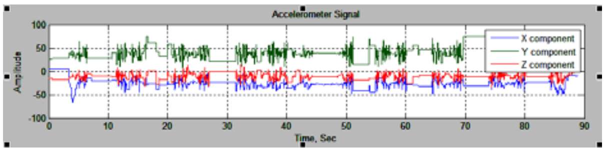


(c)

Fig. 2. Wearable ECG recorder: Transmitter in (a); Receiver in (b) and accelerometer module in (c)



(a)



(b)

Fig. 3. ECG signal with *sit-stand* movement in (a) and accelerometer signal in (b)

3 PCA and Wavelet based Motion Artifact Extraction

In this section the principal component analysis (PCA) and wavelet transform are briefly described.

3.1 Principal Component Analysis

The central idea of principal component analysis (PCA) is to reduce the dimensionality of a data set consisting of a large number of interrelated variables, while retaining as much as possible of the variation present in the data set. This is achieved by transforming to a new set of variables, the principal components (PCs), which are uncorrelated, and which are ordered so that the first few retain most of the variation present in all of the original variables. The PCA has been widely used for varieties of applications like noise reduction, denoising, QRS complex detection, ECG beat and arrhythmia classification, ECG feature extraction, T-wave alternans (TWA) analysis etc. [17]-[21]. The PCA here has been used to separate out the non-homogeneity from the data, i.e. the motion artifacts in ECG signals occurring due to various BMAs. The spectral characteristics of motion artifacts have been investigated by means of the PCA residual errors. Various statistical parameters like mean, median, variance, maximum and minimum value of PCA residual error have been calculated to consolidate the analysis.

In order to perform the PCA, the ECG signal needs to be converted into the aligned beats of size *nxm*. If the input ECG signal has 50000 samples with 500 Hz sampling frequency then there are 100 ECG beats; and if the average width of an ECG beat is selected as 200 samples then the size of aligned ECG beats will be 200x100. Fig. 4 explains the algorithmic steps implemented to derive the PCA residual error, *e*. The PCA residual error, *e* have been calculated by retaining 10 principal components, i.e. $p = 10$. The power spectral density (PSD) plots of PCA residual errors have been shown in fig. 8 and 9, for the W-ECG signals recorded with Biopac MP-36 and wearable ECG recorder, respectively.

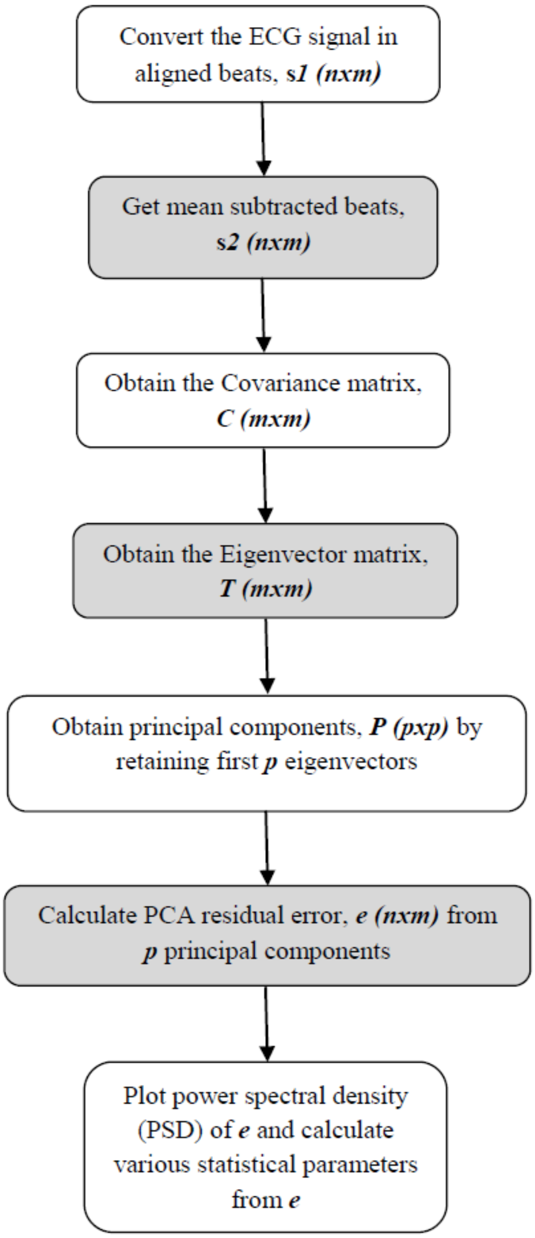


Fig. 4. PCA based algorithm for spectral characteristics of motion artifacts

3.2 Wavelet Transform

The Discrete Wavelet Transform (DWT), which is based on sub-band coding, is found to yield a fast computation of Wavelet Transform. It is easy to implement and reduces the computation time and resources required. The DWT is computed by successive lowpass and highpass filtering of the discrete time-domain signal as shown in fig. 8. This is called the Mallat algorithm or Mallat-tree decomposition. Its significance is in the manner it connects the continuous-time multiresolution to discrete-time filters. In the figure, the signal is denoted by the sequence x[n], where n is an integer. The low pass filter is denoted by G_0 while the high pass filter is denoted by H_0. At each level, the high pass filter produces detail information, d[n], while the low pass filter associated with scaling function produces coarse approximations, a[n]. After decomposing the input ECG signal (with motion artifact) upto fifth level using ‘bior 3.7’ wavelet, the signal is reconstructed by eliminating higher frequency components, which represent the motion artifacts. Fig. 6 (a) and (b) show the reconstructed motion artifact-free ECG signal (top) and the extracted motion artifact signal (bottom) for the W-ECG signals recorded by Biopac Mp-36 and wearable ECG recorder, respectively.

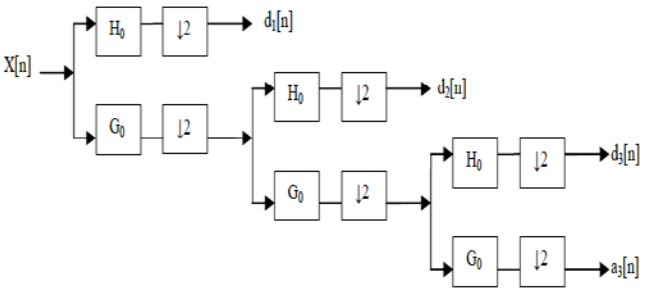
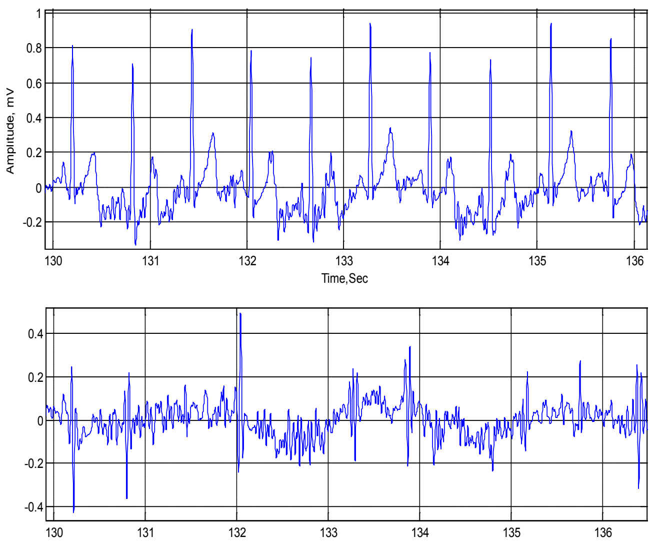
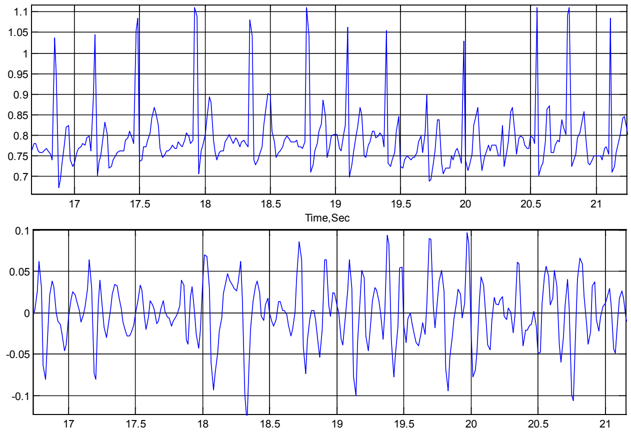


Fig. 5. A three-level Wavelet decomposition.



(a)



(b)

Fig. 6. (a) W-ECG signal recorded with Biopac MP-36 recorder (top) and extracted motion artifact signal (bottom); (b) similar results for W-ECG signal recorded with wearable recorder

After extracting the motion artifacts from W-ECG signal the power spectral density (PSD) plots of these signals are plotted as shown in fig. 10 and 11. Tables I and II describe the maximum, minimum and mean values of the PCA and wavelet residual errors for the W-ECG signals recorded by Biopac Mp-36 and wearable ECG recorder, respectively.

4 Conclusion

The wearable electrocardiogram (W-ECG) inherently contains the motion artifacts due to various body movements made by the wearer. The principal component analysis (PCA) and wavelet transform have been applied to extract these motion artifacts from the W-ECG.

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i.

Table I: PCA and Wavelet residual errors for the W-ECG signals with four BMAs captured using Biopac MP-36

Type of BMA	PCA Residual Error			Wavelet Residual Error		
	Max	**Min.**	**Mean**	**Max**	**Min.**	**Mean**
Left Arm Up-down	0.1811	-0.1811	0.0204	0.5697	-0.4864	0.0569
Right Arm Up-down	0.2480	-0.2138	0.0213	0.4866	-0.4524	0.0517
Waist Twisting	0.1416	-0.1114	0.0176	0.5037	-0.4043	0.0559
Sitting down and Standing up	0.4652	-0.2453	0.0235	0.4467	-0.3549	0.0427

Table II: PCA and Wavelet residual errors for the W-ECG signals with four BMAs captured using wearable recorder

Type of BMA	PCA Residual Error			Wavelet Residual Error		
	Max	**Min.**	**Mean**	**Max**	**Min.**	**Mean**
Left Arm Up-down	0.2126	-0.1021	0.0071	0.1423	-0.1276	0.0275
Right Arm Up-down	0.1998	-0.1179	0.0081	0.0987	-0.0844	0.0208
Waist Twisting	0.1509	-0.1173	0.0104	0.0701	-0.0701	0.0160
Sitting down and Standing up	0.2593	-0.0974	0.0088	0.0618	-0.0618	0.0131

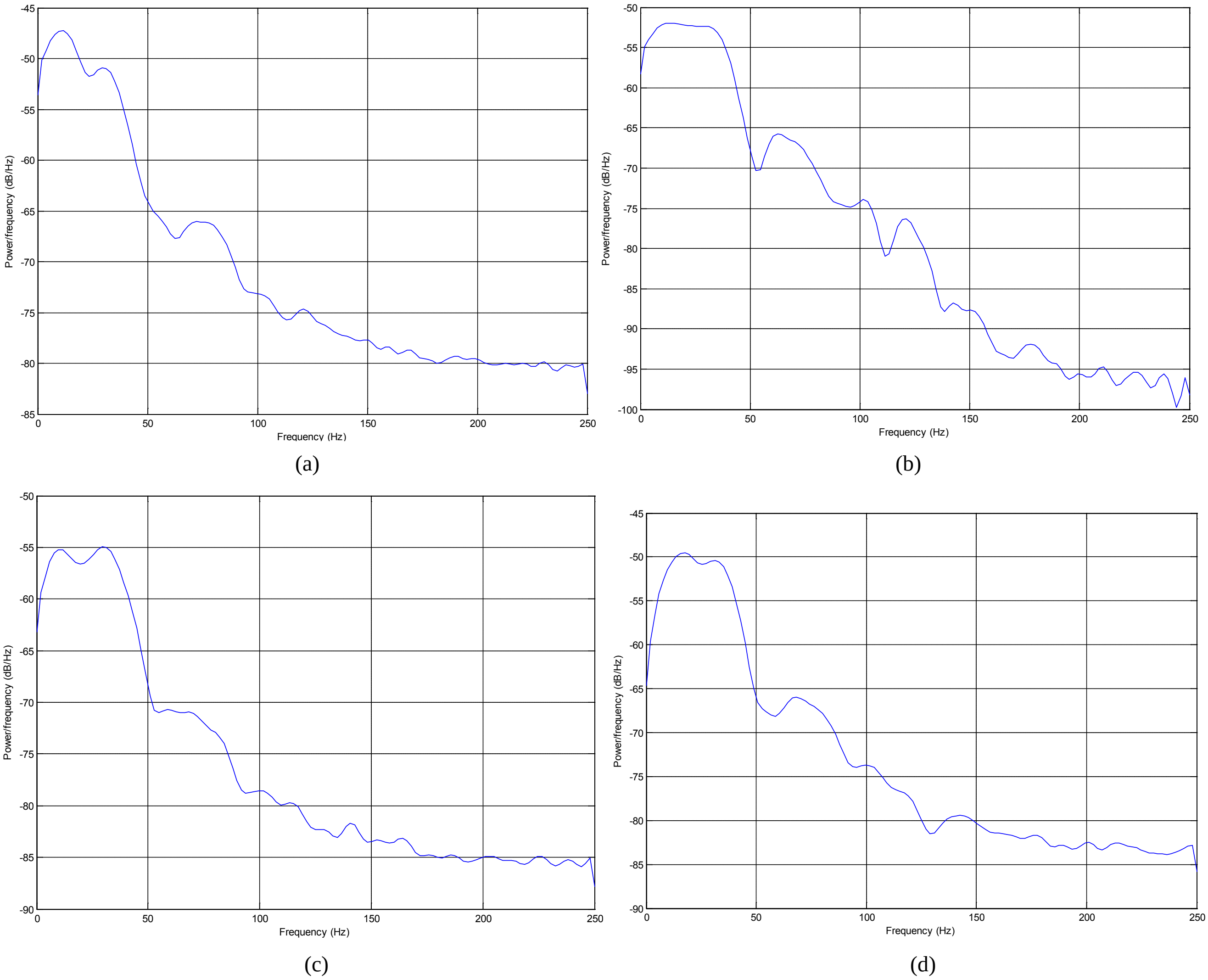
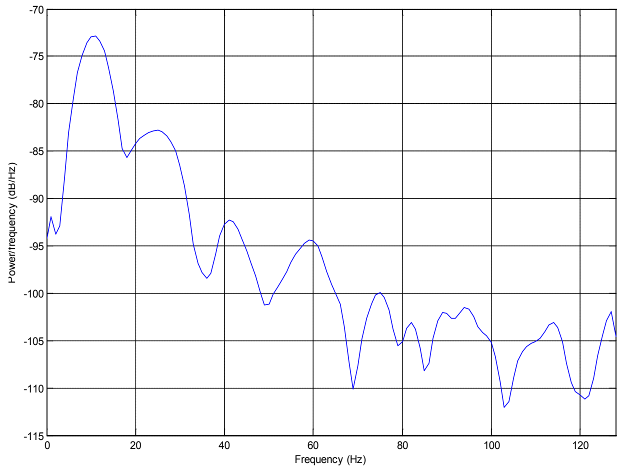


Fig. 8. PSD plot of PCA residual error for *left arm up-down movement* in (a); similar plots for *right arm up-down, waist twist and sit-stand movements* in (b), (c) and (d). All plots are for W-ECG signals recorded with with Biopac MP-36.



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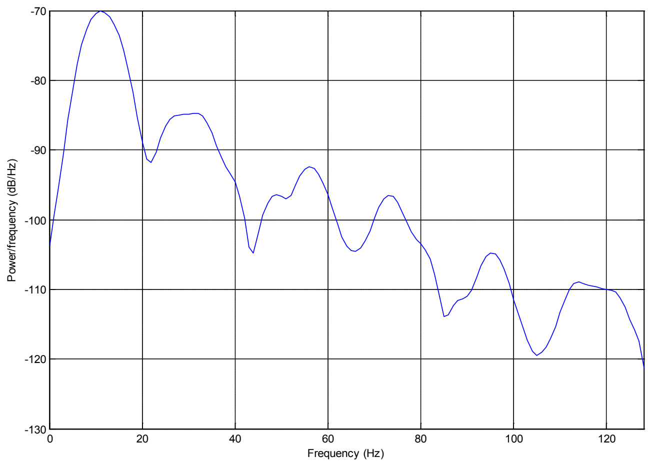

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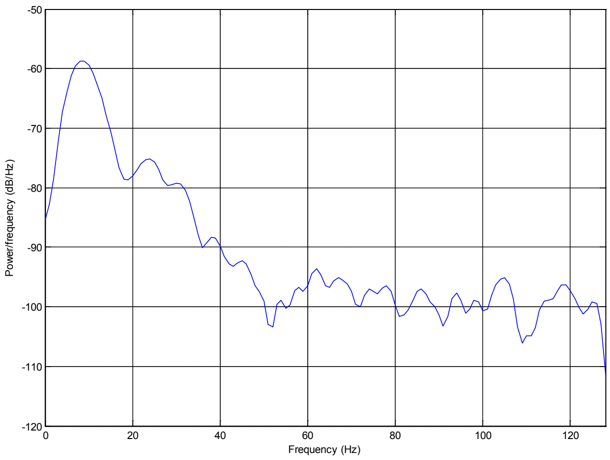

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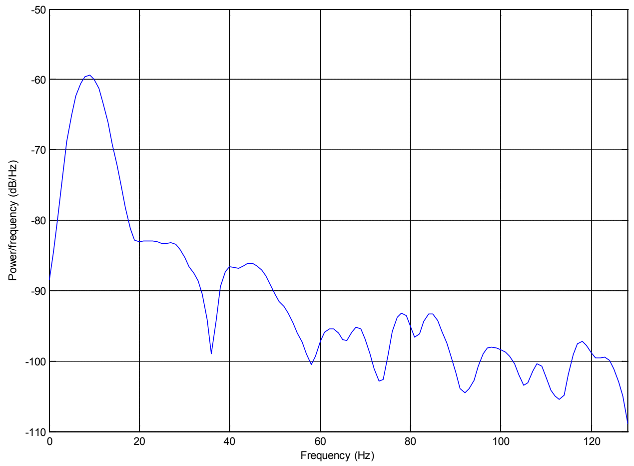
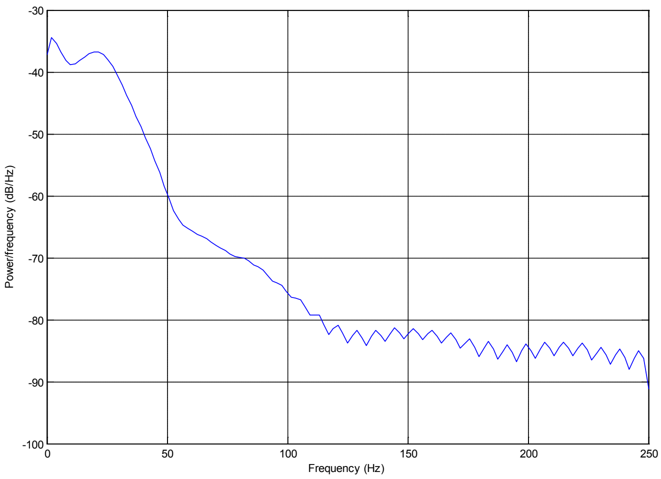


(d)

Fig. 9. PSD plot of PCA residual error for *left arm up-down movement* in (a); similar plots for *right arm up-down, waist twist and sit-stand movements* in (b), (c) and (d). All plots are for W-ECG signals recorded with wearable ECG recorder of fig. 2.



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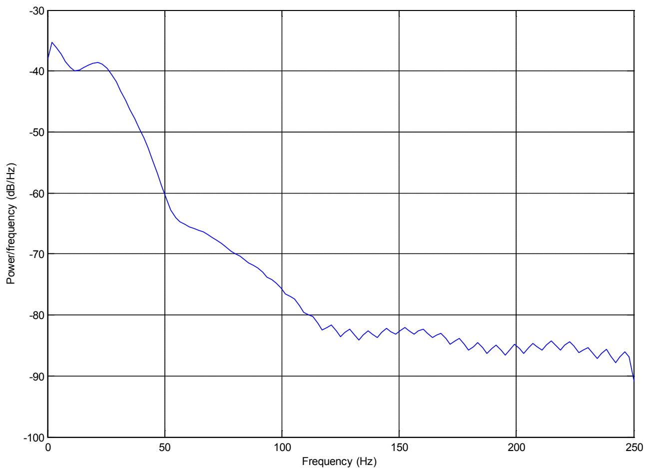

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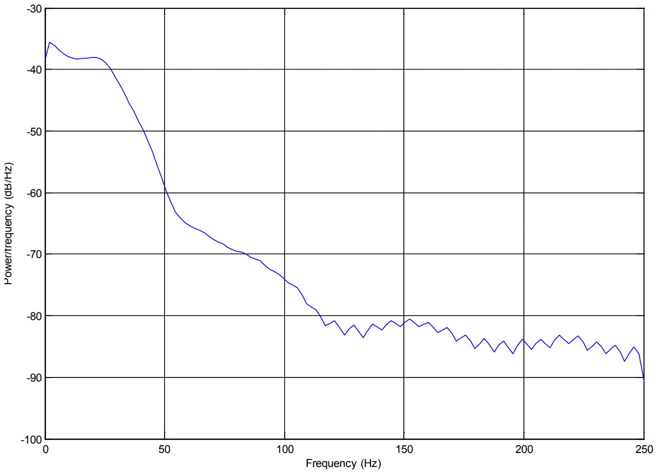

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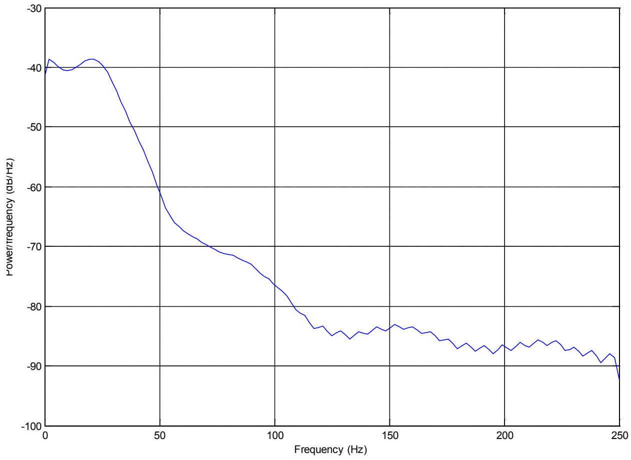

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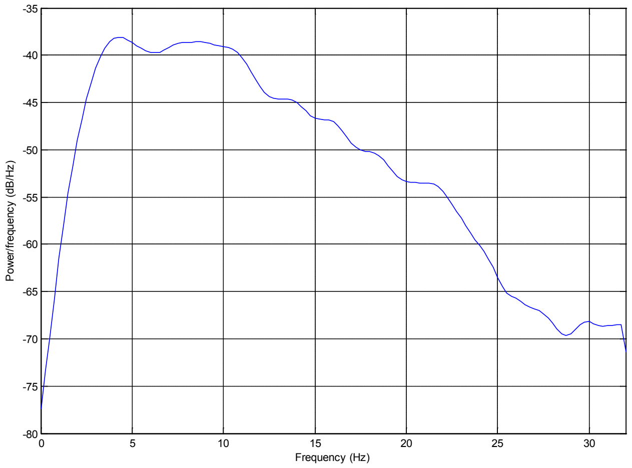
Fig. 10. PSD plot of wavelet residual error for *left arm up-down movement* in (a); similar plots for *right arm up-down, waist twist and sit-stand movements* in (b), (c) and (d). All plots are for W-ECG signals recorded with with Biopac MP-36.



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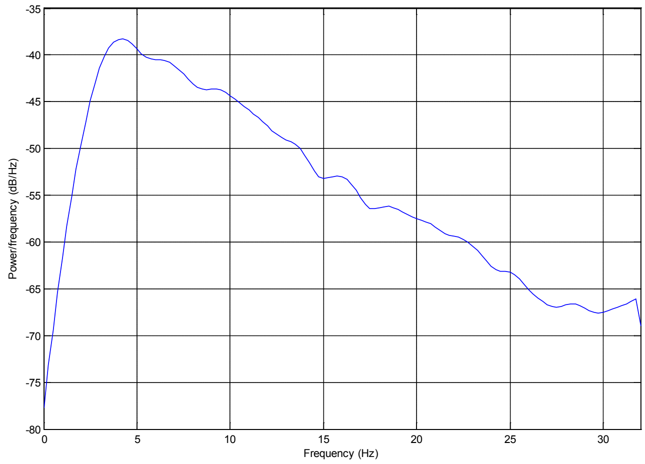

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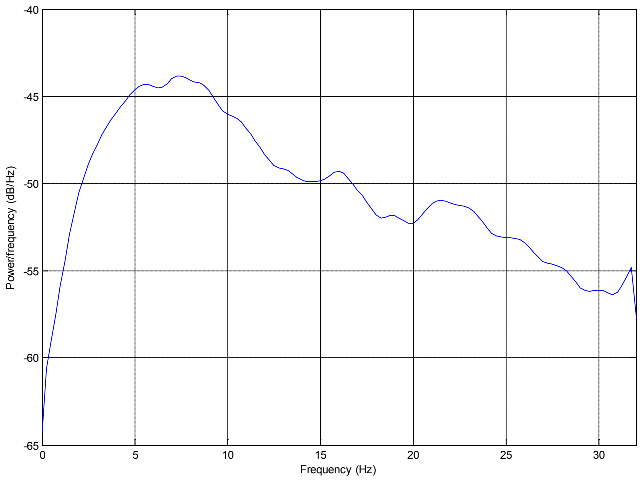

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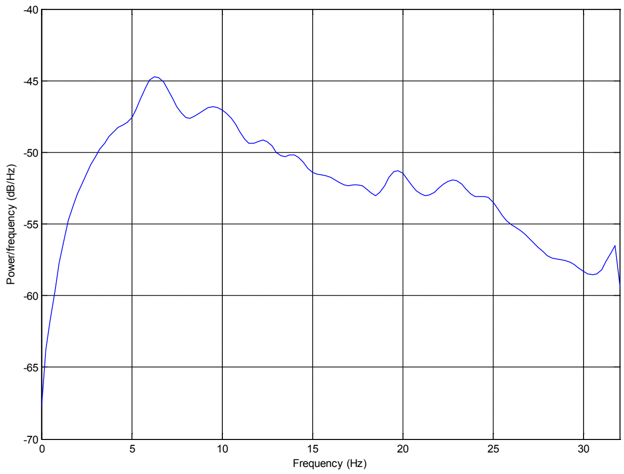

(d)

Fig. 11. PSD plot of wavelet residual error for *left arm up-down movement* in (a); similar plots for *right arm up-down, waist twist and sit-stand movements* in (b), (c) and (d). All plots are for W-ECG signals recorded with wearable ECG recorder of fig. 2.