Chapter 6
Conclusion and Scope of Future Work

6.1 Conclusions

In this study we have focused on the wearable ambulatory electrocardiogram (A-ECG) recorders and A-ECG signals used for long-term, ambulatory monitoring and recording of ECG signals. The A-ECG recorders although have countless advantages, do have several drawbacks as well associated with them. The most prominent drawback is the introduction of motion artifacts in the recorded A-ECG signals due to routine physical activities (PAs) or body movement activities (BMAs) of the wearer. We have investigated the impact analysis and its implications on the A-ECG signal in this study. The A-ECG signals have been recorded by Biopac MP 36 acquisition system and wearable ECG recorder involving ten healthy subjects of age between 22 to 37 years with following body movements: left arm up-down, right arm up-down, waist-twisting, sitting down standing up/ walking.

The motion artifacts contained in the recorded A-ECG signals with these movements have been extracted. For extracting motion artifacts, principal component analysis (PCA) and Wavelet transform based approaches have been applied. The classification of above mentioned body movement activities (BMAs) has been performed using machine learning techniques: artificial neural networks (ANN), neuro-fuzzy classifiers (NFC) and support vector machines (SVM). The time/frequency domain features of the motion artifacts have been extracted using Gabor transform and the ANN, NFC and SVM have been training using these features for classifying the BMAs of an individual subject. Following are the general conclusions observed during this study:

1. Wearable electrocardiogram signal used for ambulatory cardiac monitoring always contains the motion artifacts due to the physical activities (PA) or body movement activities (BMAs) performed by the wearer. The impact analysis of these BMAs on A-ECG and classification of BMAs has been carried out by extracting the motion artifacts from the A-ECG signal.

2. Recursive principal component analysis (RPCA) has been applied to analyze and quantify the motion artifact episodes in ECG signals. The ECG signals available from MIT-BIH arrhythmia database have been artificially contaminated by noise-like motion artifacts episodes. The RPCA algorithm has been quantified by performing 36 simulations on 25 input ECG signals.
The RPCA algorithm, by means of output RPC'A error, not only detects the noise like motion artifact episodes but also identifies the false beats/VPBs occurring in the ECG signals.

3. The spectral characteristics of motion artifacts occurring in A-ECG signals have been studied by analyzing the power spectrums of the PCA and Wavelet residual errors. The PSD plots of the extracted motion artifacts indicate that the motion artifacts have considerable spectral overlap with the ECG signal portion. The spectral study of motion artifacts proves handful in deciding the frequency features to be applied to the classifier like ANN or SVM.

4. The A-ECG signals have been acquired by Biopac MP-36 system and the indigenous wearable ECG (A-ECG) recorder. The A-ECG recorder consists of wireless transmitter and receiver modules along with a 3-axes accelerometer. The A-ECG signals of ten healthy subjects (aged between 23 and 37 years) with four body movement activities (BMAs)—left arm up-down movement, right arm up-down movement, waist-twisting and walking—have been recorded in lead II configurations.

5. The classification of four body movement activities (BMAs) viz. left-arm updown, right-arm updown, waist-twist and walking has been performed by three machine learning techniques: the artificial neural network (ANN), the neuro-fuzzy classifier (NFC) and the support vector machines (SVM).

6. The ANN, NFC and SVM classifiers have been trained by the time/frequency feature vectors obtained by taking the Gabor transform of the motion artifact signals. The frequency domain features of motion artifacts have been extracted by four Gabor sub-bands. The spatial or time-domain features of motion artifacts have been extracted by taking fixed windowed moving average Gabor energy signals.

7. The single-fold and ten-fold validation experiments for BMA classification using ANN, NFC and SVM have been performed. The overall BMA classification rate achieved by all the three classifiers is over 95%; however it the time in which this classification is performed distinguishes these classifiers among them.

8. It is observed that the SVM classifier performs BMA classification exceptionally fast, as the average classification time elapsed for SVM is only 0.1859 second against 1.2495 seconds for ANN and 38.1072 seconds for NFC. The NFC classifier requires higher classification time due to its more complex architecture.
6.2 Limitations of Study and Scope for Future Work

1. In this study the A-ECG signals have been recorded with four types BMAs. This work can further be extended for more types of BMAs under various physiological conditions like stress and exercise.

2. Wavelet transform based approach applied for separating/extracting motion artifacts from A-ECG signals may be combined with other technique like adaptive filtering. Further, other transforms KL-transform or Hilbert transform may be used separately or combined with the Gabor transform for extracting features of motion artifacts contained in A-ECG signals.

3. In order to increase the classification accuracy, along with Gabor energy feature vectors more features like heart rates, accelerometer data and other statistical parameters like mean, median and variance of these features may be used for training the classifiers.

4. The BMA classification performance of ANN, SVM, NFC classifiers used in this study may be compared with previously implemented classifiers like HMM [10], nearest neighbor or naive Bayes [121].

5. Only healthy subjects of age group 22 to 37 years have been asked to participate in A-ECG signal acquisition process. The subjects of age groups 40 to 50 years or 50 to 60 years may be involved for experimentation, which are more prone to cardiac abnormalities. Hence, in addition to the impact of body movements on normal ECGs how and in what manner the BMAs affect the abnormal ECGs can also be observed.