

Conclusions

The work presented in the previous chapters is focused on deriving ambulation information from the motion artifact induced due to physical activities in wearable ECG systems (W-ECG). Various methodologies required to achieve that have been discussed in details. We have also provided hardware and calibration details. The experimental protocol is defined for acquisition of data. Finally we have presented results of different experiments. The conclusions derived from this work and scopes for future work in the same area are now discussed in this chapter.

9.1 Conclusions

In this monograph, we have studied the impact of body movement activities (BMA) on the ambulatory ECG signal. Motion artifact in ECG signal induced due to BMA is considered here as a source of useful information related to the physical activities of the subject. The presented work was initiated in view of increasing demand and popularity of W-ECG for ambulatory cardiac monitoring. One such W-ECG, called *loket* and developed at IIT Bombay, is used for collecting the ECG signals during subject ambulation with some specific types of BMA. The ideas generated and hypothesis like “BMA recognition is possible from ECG signal itself” have been verified from the analysis of the real life ECG signals.

The motivation for BMA recognition from ECG signal comes from the fact that if the motion artifacts can be well understood from BMA point of view then it can help us in better interpretation of automated analysis of ECG signal. Since every BMA is performed in a different manner, BMA specific analysis of motion artifact should be possible. We have shown that it is possible to recognize the motion artifact from BMA specific view point.

In Chapter 6, we have shown that the changes in BMA due to activity transition can be detected from the ECG signal itself. This is useful for temporal segmentation of ECG signal. The method used for this task is an

unsupervised learning approach based on recursive principal component analysis (RPCA) of the ECG beats and hence can be implemented on computer based W-ECG. The BMA segmented ECG signal can be useful for automated analysis of ECG signal.

In Chapter 7, we exploit differences in motion artifacts due to different BMAs for recognition of a particular BMA from the ECG signal itself. The possibility of BMA recognition using motion artifacts is verified with a supervised learning approach based on principal component analysis (PCA) of the ECG beats. Several commonplace BMAs such as movements of arm(s), walking, climbing, etc. are recognized from the ECG signal itself. We have attempted various class combinations for improving the recognition rates and formed five different BMA classifiers based on that. We have searched for the most suitable number of principal components for the BMA recognition in order to achieve a high accuracy in recognition and to reduce the computational complexity and found that 6 to 8 eigenvectors would be a good choice for recognition of the BMAs considered in our studies. We also investigated the impact of inter personal variability on this method and found that the subject specific training gives better performance in terms of accuracy in classification. Since the goal of the study is to develop a pervasive monitoring system for individual cardiac patients, initial study suggests that the training of the system should be individually tuned. We have also discussed a BMA specific PCA-based filtering method for removal of the induced motion artifact due to the particular BMA without affecting the morphologies of P and T waves in the cardiac cycle. The performance of the PCA-based filtering is verified by locating P and T waves using an automated method with and without using the proposed filtering. The improvement due to the filtering is shown using the histograms of detected P and T wave locations.

In Chapter 7, we have also re-validated the concept of BMA recognition from motion artifacts using a parametric, supervised learning technique based on a hidden Markov model (HMM). We have suggested the use of an HMM to represent each BMA class, trained from the Gabor features derived from the motion artifact signals corresponding to that particular BMA class. We have also suggested an adaptive filtering technique for separating the motion artifact signal for that purpose. Separation of the estimated cardiac component of the ECG from the composite signal is required to prevent the HMM classifier from working with the artifact signal under the heavy bias of the cardiac component, thus improving the classification accuracy. We have used a fully connected HMM with a few number of states and Gaussian mixture components. BMA classifiers with various class combinations as we found in the earlier PCA-based method are used for recognition of the specific BMA. The recognition rates are found to be better than that in the PCA-based method. We have also studied the effects of length of the test data and selection of number of states and number of mixture models. We have found a length of 5s for the test data to be sufficient for achieving a high level of accuracy in BMA recognition. A smaller length will result in a decreased accuracy and a

longer length will add to further delay without much improvement. The effects of number of states and the actual number of mixture components have been studied for a limited number of combinations and require a more detailed investigation. However, we have shown that it is possible to achieve a very good performance even with a very few states (3-4) and mixture components (3-4) for all the BMA classes. The effect of increasing these numbers remains to be investigated but it will surely increase the complexity while learning the model parameters.

Finally in Chapter 8, we have investigated a different aspect of deriving BMA information from the ECG signal. We derived a measure of motion artifact called impact signal from the ECG signal itself using the RPCA method discussed previously for detection of BMA transitions. The impact signal is validated using acceleration signals acquired from the motion sensors placed on various parts of the body for measurement of the level of BMA. Three different levels of certain commonplace BMAs are considered. The levels are also quantitatively described in terms of acceleration values at different positions on the body. We have shown that the impact signal derived from the ECG signal can be used for measuring the level of a BMA without requiring any extra motion sensors. This is demonstrated by showing the relation between the impact signal and the acceleration signal in terms of their cross-correlation coefficients and the slope of best fitting line. We have also tested the possibility of applying RPCA to ECG signal with different types of QRS morphologies, collected from patients with known cardiac abnormalities. We have found that the method works well irrespective of the QRS morphology provided that the pattern itself is regularly repetitive without serious disturbances in rhythm. The rhythm disturbances or infrequent arrhythmia are manifested as very large values of impact signal and hence can be detected by a simple analysis of RR intervals as well as by using some standard method of arrhythmia classification.

9.2 Scopes for Future Work

In this monograph some of the very preliminary but useful methods for deriving BMA information from ECG signal for wearable ECG monitoring are devised. These methods are found to be suitable even for a single-lead ECG recorder. The lead-II configuration was adopted for the investigation of the feasibility of the BMA recognition from ECG signal. Both the proposed PCA-based and HMM-based methods should work for any lead configuration. However, from the experiments we have observed that the induced motion artifact due to any specific BMA is sensitive to placement of electrodes. For example, the lead-II configuration is more sensitive to right arm movements than that to the similar left arm movements because of the proximity of the electrode to the right arm. This kind of sensitivity of a specific lead to a specific type of BMA can provide more useful information of the BMA in a multiple lead sys-

tem. Therefore, in future we plan to study impact of various types of BMA on different ECG lead configurations. We hope to increase the confidence levels in recognition of BMA using the analysis of multiple ECG leads. It should also be possible to use more sophisticated methods to take advantage of redundant and independent components of information in multiple lead ECG signals.

After achieving a satisfactory level of accuracy in identifying all usual BMAs, it should be possible to conduct some ergonomic studies regarding the routine of physical activities of the cardiac patient wearing ECG recorders without requiring any sophisticated motion sensors. This will help to increase the utility of the W-ECG for personal health monitoring.

Every method discussed here requires detection of R peaks in ECG signal as a preprocessing step. In this work, R peak detection was not a challenging problem and performed in an automated way and accurately even in the presence of motion artifacts due to the various BMAs performed by the subjects. Therefore, it should be possible to use the proposed algorithms as it is for practical applications. However, it is of interest to know how can the R peak detection be made more robust using ECG signals in conjunction with the motion artifact information available from multiple leads. This should be possible because we anticipate that the ECG signal recording in only few of the available ECG leads would be contaminated severely and hence the signals from other less affected ECG leads can be used for detecting the R peaks.

We have discussed an HMM based technique for BMA recognition in Chapter 7 which shows very promising results. However, we need to fully investigate issues related to feature selection, types of HMM and numbers of states and mixture components to further improve in terms of accuracy and computational efficiency. Are the Gabor features the right feature? It requires a thorough investigation to come out with the correct feature set which can capture the distinguishing characteristics of the motion artifacts. Another interesting study would be to relate the hidden states with the dynamics of the body motion. Finally, it is to be recalled that all BMA recognition efforts have been restricted to cases where the heart is not stressed due to activity. With the induced stress, the cardiac component of the signal will also undergo changes. Suitable modifications in the methodology are required to deal with such cases.

In this monograph, the BMA recognition and impact analysis of ECG signal are considered as two separate aspects. It remains to be investigated how both the analyses can be done more efficiently in a unified manner. Moreover, the method of the impact analysis has been tested successfully up to the third level of the Bruce tread-mill test protocol, that is up to approximately a walking speed of 5.5 kmph whereas the BMA recognition is tested at relaxed or normal pace levels of BMA. However, challenges in practical applications of these methods are required to be studied. For example, different types of motorized vehicles have different levels of vibrations and hence can affect the the comfort of the patient as well as W-ECG recordings differently. This kind of motion studies can also be useful and can be done in future work. Similarly,

impact of movement on ECG signals and motion artifact generation during sport activities can also be studied. We have used the reconstruction error after appropriate RPCA updating as the measure of impact. Although this yields quite interesting results, this is quite an ad-hoc measure. Is there a better measure of the impact? A detailed study is required in this regard.

Thus we see that the studies related to motion artifact in ECG signals during ambulatory monitoring have wide scopes for future work. Further investigations in this area will definitely improve the analysis and the utility of wearable ECG recorders.