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Analysis of Ambulatory ECG Signal

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Abstract— **Ambulatory electrocardiogram (ECG) recorders are increasingly in use by people suffering from cardiac abnormalities. However, the ECG signal acquired by the ambulatory recorder is influenced by motion artifacts induced by any body movement activity (BMA). The goal of the paper is to demonstrate that it is possible to determine the BMA from the motion artifacts in the ECG signal itself. The ECG signal during a specific BMA is presumed to be an additive mix of signals due to cardiac activities, motion artifacts induced due to the BMA and sensor noise. We propose to characterize and determine the BMA from the corresponding motion artifact data in the ECG signal itself. The proposed technique is useful for removal of motion artifacts from the ECG signals for ambulatory cardiac monitoring.**

I. Introduction

We are focused on developing low cost ambulatory ECG solutions. In the situation where dynamic monitoring of heart is required, a light-weight, wearable ECG recorder may prove to be a more convenient option compared to the standard Holter monitor which often restricts free movement of the person. The goal of this study is to determine the impact of body movement activity (BMA) on motion artifacts in the ECG signal in order to improve accuracy of ambulatory ECG recorders. For this purpose we have used a device called *locket* with an inbuilt ECG data acquisition system developed by Lal *et al.* [1]. Currently, we have restricted our studies to only people with no known cardiac abnormalities but at multiple settings (laboratory and outdoors). Subsequently, we plan to test on actual patients at all locations.

Arbitrary BMA during ECG signal collection causes motion of electrodes and hence induces noise in the signal also known as motion artifacts. It is challenging to handle the motion artifacts since they have a significant overlap in frequency spectrum with the cardiac signal [2]. Since it is not possible to filter the motion artifacts in spectral domain due to spectral overlap, we propose a principal component analysis (PCA) based class-specific approach of filtering of motion artifacts. We characterize and then classify some specific BMAs like sitting still, movement of hand(s), walking, climbing up/down the stairs, etc. from the ambulatory ECG signal. We use the proposed class-specific filtering of the ECG signal for removal of motion artifacts for subsequent detection of P and T waves in ECG signals captured during BMA.

The possibility of BMA classification from ECG signals was initially explored in [3] where the motion artifacts in ECG are characterized using a neural network trained with wavelet coefficients of the ECG signal. However, the reported performance is not very satisfactory as the wavelet based representation does not separate the in-band BMA signal from the ECG. In other works related to BMA analysis from non-ambulatory ECG, body position changes are detected for ischemia monitoring in [4], [5]. However, the existing methods have not fully explored the usefulness of BMAs and their impact on motion artifacts in ECG signals in the ambulatory monitoring.

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II. Data Acquisition and Mathematical Model

The *locket* specifications are as follows: single lead, bandwidth- 0.28 to 106 Hz, sampling frequency- 256 Hz, A/D conversion- 12 bits/sample [1]. The ECG signal from lead-II configuration is acquired during the specific commonplace BMAs as follows: (1) sitting still on a chair, (2) up-down movement of left, right or both arm(s) at a rate of approximately 25 cycles/min, (3) walking with a speed of about 3 km/hour on a level floor or climbing down stairs, and (4) climbing up stairs at an average rate of 85 steps/min. The BMAs are performed over a short duration followed by sufficient rest so that the effect of a particular BMA subsides before the next data is collected. The BMAs are performed at a relaxed physical state of the subject to avoid any stress on the heart.

The collected ECG signal has three components: cardiac signal due to involuntary cardiac activity, motion artifacts induced due to the BMA and sensor noise introduced by the *locket* electronics. Following [3] we hypothesize that each class of BMA induces a particular type of motion artifacts in the ECG signal. Hence the ECG signal r_i during the i^{th} class of BMA is modeled as $r_i(n) = q_i(n) + s_i(n) + \eta(n)$, where q_i, s_i and η are the three components as stated above, respectively. Let the vector representations of the corresponding signals during a single period of the j^{th} heart beat be $\underline{r}_{ij}$, $\underline{q}_i$, $\underline{s}_{ij}$ and $\underline{\eta}_j$, respectively then $\underline{r}_{ij} = \underline{q}_i + \underline{s}_{ij} + \underline{\eta}_j$, where the cardiac component $\underline{q}_i$ is the same for all j. The dimension M_0 of these vectors depend on the beat period and the sampling frequency. For example, for a normal heart beating 72 times a minute and sampled at 256 Hz, the dimension $M_0 = 256 \times 60/72 \approx 213$. If one considers N consecutive heartbeats together as a signal then the dimension of the signal would be NM_0. Following assumptions are further made while developing a classifier.

(II.1) Since cardiac activity is by nature involuntary, it is independent of voluntary muscular activities and motion of electrodes.

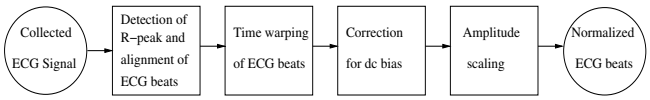

Fig. 1. Preprocessing applied to the collected ECG signal.

(II.2) The sensor noise η is present in the ECG signal due to ambient conditions of recording and therefore it is assumed to be independent of both cardiac signal and the motion artifact.

(II.3) In the pre-processing steps to follow, the dc bias in the ECG signal is set to zero. Therefore, the sensor noise can be assumed to be of zero mean, ie, $E[\underline{\eta}] = 0$.

(II.4) Rank$(E[\underline{r}_i \underline{r}_i{}^T]) \approx M_i$, where $M_i \leq M_0$, signifying that the actual information in the recorded ECG signal can be compactly represented by only top M_i eigenvectors.

(II.5) There is greater correlation between the motion artifacts due to same BMA than that for any two different BMAs. That is, s_i and s_k are highly correlated if $i = k$ (at different time instants) and nearly uncorrelated if $i \neq k$.

(II.6) The signal component due to the motion artifacts is smaller compared to the cardiac signal, but much greater than the sensor noise, i.e., $|\underline{\eta}| \ll |\underline{s}_i| < |\underline{q}_i|$, $\forall i$.

III. Body movement Classification

We propose a supervised learning technique using the derived motion artifacts data from the ECG signal along with a priori knowledge of the types of BMA episodes over the data to classify BMA episode at any ECG beat occurring later. Here considering the pace of the BMAs performed and the heart-rate, a single ECG beat can partly contain a BMA episode if any. The sitting still represents a class where there is no BMA episode. The variability of heart rate and the coupling between skin and electrodes affect the time interval and amplitude (scale) of the ECG beat data, respectively. Since the proposed technique is sensitive to translation and variations in amplitude, it is required to pre-process the data as follows (see Fig. (1)).

A. Pre-processing of ECG data

The data is processed in a batch of ECG beat epochs collected over a one minute duration termed as observation window considering that all the epochs have the same amplitude scale and are of the same duration. The R-peaks in the ECG signals are detected using the Pan-Tompkins method [6]. The ECG signal is segmented into individual ECG beats using the R-peaks and time-synchronized by keeping the R-peak in the exact middle position of each ECG beat. Since the proposed method based on PCA is applicable only to vector observations in a space of fix dimension, the dimensions of all the ECG beats are equalized using a linear time warping. The dc bias in the ECG signal during the observation window is estimated by arithmetic mean of the isoelectric levels of all the ECG beats and then removed from the ECG signal. In order to correct for amplitude variations a scale-factor is estimated by averaging of R-wave amplitudes with respect to the corresponding isoelectric levels from all ECG beats in the observation window. The amplitude of the ECG data is normalized by the scale factor.

B. Characterization of body movement

We wish to derive motion artifact data using the model derived in Section II. Since after the above pre-processing steps the cardiac components of all the ECG beats for a specific BMA are aligned, the arithmetic mean of the ECG beats in the entire training data set of the BMA class estimates the cardiac signal $\underline{q}_i$. We will term $\underline{q}_i$ as the class-mean henceforth. Let $\underline{r'}_{ij}$ be the residual vector derived after the class-mean is subtracted from the ECG beat data, then as per our assumption (II.6), the derived residual vector $\underline{r'}_{ij} = \underline{r}_{ij} - \underline{q}_i$ contains predominantly the motion artifacts with the sensor noise.

For the best representation of the motion artifacts of the i^{th} BMA class for the given data model we compute some of the significant eigenvectors (with the highest eigenvalues) of the training residual data $\underline{r'}_{ij}$. This technique is known as PCA in the literature. The proposed PCA of the training data will represent the motion artifacts by neglecting components due to the sensor noise. For i^{th} BMA class, the eigenvectors and eigenvalues are computed by eigen decomposition of a covariance matrix of the training data $\underline{r'}_{ij}$ given by $C_i = \frac{1}{N_i}\sum_{j=1}^{N_i}(\underline{r'}_{ij})(\underline{r'}_{ij})^T$, where C_i is the covariance matrix for the i^{th} BMA class and $(\cdot)^T$ is matrix transpose. If the data is in an M dimensional space then the eigen decomposition gives a total M eigenvectors $[e_{i1}, e_{i2}, \ldots, e_{iM}]$, arranged in non-ascending order of the corresponding eigenvalues denoted by $\lambda_{i1} \geq \lambda_{i2} \geq \ldots \geq \lambda_{iM}$. Let $E_i = [e_{i1}, e_{i2}, \ldots, e_{iK_i}]$, $K_i \ll M$ be a set of first K_i eigenvectors that represent the motion artifacts of i^{th} BMA class. As per our assumption (II.5), the eigen functions for any two different motion artifacts are also expected to be nearly uncorrelated. Thus a BMA class is characterized by the corresponding class-mean and the corresponding set of eigenvectors.

C. Body movement classification

Let c be a total number of BMA classes characterized as above, $\underline{p}_u$ be a test ECG beat extracted after the pre-processing steps given earlier, where u denotes the unknown class label and it can be any of the possible class labels $i = 1, 2, \ldots, c$. We wish to determine the class label u based on the previous characterization of the BMA classes i.e. the class-means $\underline{q}_i$ and the sets of eigenvectors E_i as computed above for all $i = 1, 2, \ldots, c$.

First, the class-mean is subtracted from the test beat to derive the corresponding residual motion artifact vector as $\underline{p'}_i = \underline{p}_u - \underline{q}_i$ for all i. The derived motion artifact vector $\underline{p'}_i$ is reconstructed from projections on the corresponding set of eigenvectors E_i to capture its contents in the motion artifact subspace defined by E_i as

$$\widetilde{\underline{p'}_i} = E_i {E_i}^T(\underline{p'}_i), \ \forall i, \tag{1}$$

where $\widetilde{\underline{p'}_i}$ is the captured i^{th} motion artifact. A measure of error in the reconstruction is denoted by $error(i)$ and defined

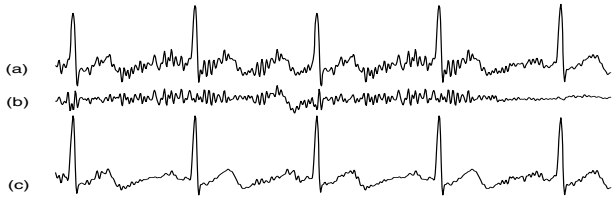

Fig. 2. (a) Original ECG signal before any artifact removal, (b) artifact signal derived by the proposed method, and (c) reconstructed ECG signal after subtracting the artifact signal.

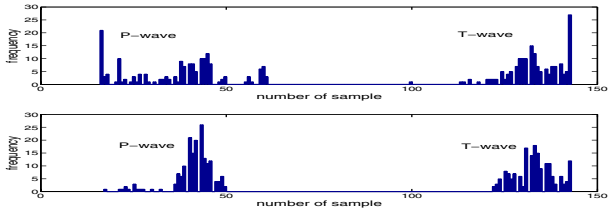

Fig. 3. Histograms for P and T wave detections are shown (top): when motion artifacts were not removed and (bottom): after artifact removal.

as

$$error(i) = \|\underline{\widetilde{p'}}_i - \underline{p'}_i\|. \quad (2)$$

The unknown class label u is determined from the possible labels $i = 1, 2, \ldots, c$ for which the $error(i)$ is the minimum.

IV. Artifact Removal for Wave Detection

We wish to remove the motion artifacts from the ECG signal after determining the BMA class. Let $\underline{p}_i$ be an ECG beat for which i is the determined BMA class following the previous classification procedure. We propose a PCA-filtering of $\underline{p}_i$ as defined below to remove the motion artifacts from the ECG beat

$$\underline{\widetilde{p}}_i = \underline{p}_i - E_i E_i^T (\underline{p}_i - \underline{q}_i), \quad (3)$$

where $\underline{\widetilde{p}}_i$ is artifact-removed ECG signal.

One of the ECG beat sequences collected by the *locket* is shown in Fig. 2(a) before any artifact removal. In Fig. 2(b) the component due to motion artifacts as derived by the proposed method is shown. In Fig. 2(c) the reconstructed ECG signal after subtracting the artifact signal is shown. The ECG signal after the removal of motion is quite clean even though this has been acquired with a very low cost device meant for in-situ data capturing.

The proposed PCA-filtering is useful in automatic analysis of ECG data as demonstrated here by detecting P and T waves in the collected ECG beat data during BMAs. In order to detect the P and T waves, we use a combination of two existing techniques in the literatures [7], [8]. First, the ECG signal is smoothed by a low-pass filter with a 3dB cut-off at 12Hz for P and T wave detection [7]. Then a morphological based method for detecting P and T waves is applied which is inspired by the method of QRS detection in [8].

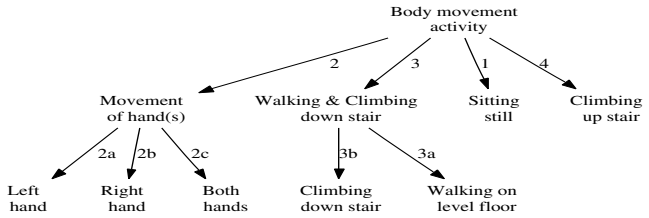

Fig. 4. Various BMAs and possible class formation by combining two or more BMAs into a single class.

The histograms of the location of P and T waves detected from ECG beats, before and after artifact removal by the PCA-filtering are shown in Fig. 3. The histograms in the top are broadly spread out, showing improvement in the detection of P and T waves after the proposed PCA based filtering.

V. Results

In the presented work on BMA recognition in ECG signals, the ECG beats are extracted from the collected ECG signals in Section II using the pre-processing steps explained in Section III-A with a chosen fixed length of 160 sample point duration. The BMA label (ground truth) is known for each of the ECG beats. The data set is divided into two parts: one third of the number of ECG beats corresponding to each BMA are used for training the BMA classifiers, and the remaining part of the data are used for performance testing.

The performance is evaluated by two measures: accuracy (P_T) and false detection rates (P_F) defined as $P_T = N_{true}/(N_{true} + N_{missed})$, $P_F = N_{false}/(N_{true} + N_{false})$, respectively, where N_{true} is number of true detections, N_{missed} is number of missed detections and N_{false} is number of false detections.

Here the problem of classification is explored for various numbers and combinations of BMA classes to determine if it is possible to recognize each of the performed BMAs as a separate class and what are the chances of confusion between any two different BMAs. Fig. 4 shows all different types of BMA studied and how they are combined to form four different classifiers.

The complete performances of the above BMA classifiers: I, II, III and IV are presented in Fig. 5-7. Here six eigenvectors are used for the classification of the data collected from a single subject.

In BMA classifier I there are four BMA classes: 1, 2, 3, and 4 as shown in Fig. 4. The confusion matrix for the corresponding classifier is given in Fig. 5 and one can see that the overall accuracy is very high, justifying our claim that BMAs are indeed, identifiable from the ambulatory ECG itself. In BMA classifier II, there are five BMA classes: 1, 2, 3a, 3b, and 4 as shown in Fig. 4. Here the subclasses (3a) walking and (3b) climbing down stairs are recognized as separate BMA classes. However, there is significant confusion between these two subclasses as shown in Fig. 6, 18% of total known labels of climbing down stairs are recognized as walking. This suggests that climbing down the stairs being

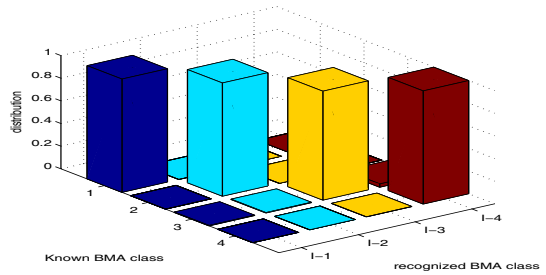

Fig. 5. Confusion matrix for BMA detection for classifier I.

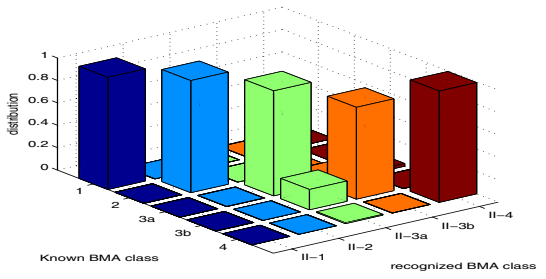

Fig. 6. Confusion matrix for BMA detection for classifier II.

as effortless (or stressful) as walking on a plain is not very well differentiable from the walking BMA.

In BMA classifier III there are six BMA classes: 1, 2a, 2b, 2c, 3, and 4. Here the subclasses (2a) left hand, (2b) right hand and (2c) both hands movement are recognized as separate BMA classes. However, there are significant confusions among these three subclasses as shown in Fig. 7. On average 25% of total known labels of both the subclasses: right hand and both hands movement are recognized as left hand movement and 12% of total known labels of the right hand movement are recognized as both hands movement. Since we are using the lead-II position for collection of ECG data, any movement of the hands (be it left or right) does affect the lead contact with skin. This reduces the differentiability of the corresponding BMAs.

In BMA classifier IV, there are seven BMA classes: 1, 2a, 2b, 2c, 3a, 3b, and 4. Here the subclasses (2a) left hand, (2b) right hand and (2c) both hands movement, (3a) walking

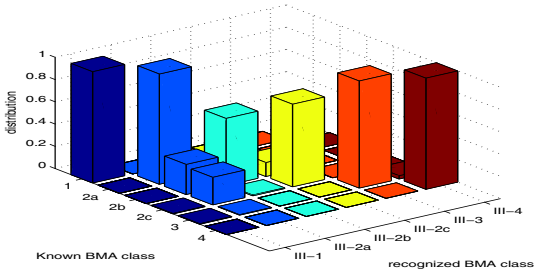

Fig. 7. Confusion matrix for BMA detection for classifier III.

and (3b) climbing down stairs are recognized as separate BMA classes. The advantage in the classifier IV is that the seven different BMA classes can be recognized by a single classifier. It seems to have combined the previous two BMA classifiers II for subclasses of BMA class 3 and III for sub classification of BMA class 2 into this single classifier with all these subclassifications. The significant confusions are still the same as that in the classifier III for subclasses of hand movements and that in the classifier II for subclasses of walking and climbing down stairs.

The overall performances of the classifiers I, II, III and IV in terms of (P_T, P_F) are (0.985, 0.014), (0.96, 0.04), (0.91, 0.07) and (0.88, 0.10), respectively. The accuracy gradually goes down as one is required to identify more and more subclasses due to overlapping in the BMA subclasses.

VI. Conclusions

In this paper we have studied classifiability of some specific yet commonplace BMAs using the motion artifacts induced in ECG signals. Each BMA class has different rate of performance in terms of accuracy of classification and false detection based on the ability of the corresponding PCAs to represent the specific artifacts. For example, the sitting still and the climbing up stairs classes have better performances than the other BMA classes. Here we observe that the movement of either or both of upper limbs have not much differentiability for the lead-II configuration. Similarly, for walking and climbing down being as effortless as each other, there is not much separation between them.

The performances reported here are for individual training. However, for the *locket* (a wearable system), this poses no difficulty as it can be trained for the specific subject. We are currently investigating the suitability of the proposed method for handling subjects with cardiac abnormalities.

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