Transition Detection in Body Movement Activities for Wearable ECG*

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Abstract

It has been shown in [1] that the motion artifacts induced by body movement activity (BMA) in a single-lead wearable ECG signal recorder, while monitoring an ambulatory patient, can be detected and removed by using a PCA-based classification technique. However, this requires the ECG signal to be temporally segmented so that each segment comprises of artifacts due to a single type of BMA. In this paper we propose a simple, recursively updated PCA-based technique to detect transitions wherever the type of body movement is changed.

Index Terms

Wearable ECG, body movement activity, motion artifacts, principal component analysis, transition detection.

*Partial funding under a *Swarnajayanti* project is gratefully acknowledged.

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I. Introduction

Wearable ECG (W-ECG) recorders are useful for ambulatory monitoring of the heart. However, the body movement activity (BMA) of the wearer may distort the collected ECG signal by inducing motion artifacts. The difficulty in ambulatory monitoring is that the motion artifacts have significant spectral overlap with the ECG signal itself and can mimic a cardiac event. However, it has been shown in [1], [2], [3] that 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. It has also been shown in [1], [2] that the motion artifacts can be suppressed using a principal component analysis (PCA)-based filtering technique specific to the individual subjects and the recognized BMA classes. Thus recognition of BMA is useful for continuous monitoring of heart in ambulatory conditions.

In [1], the BMA classes are recognized from ECG segments (a number of temporally contiguous beats) recorded from different subjects using PCA. The reported classification rates are very good in terms of both accuracy (average 92%) and inter-subject variability. However, the test condition ensured that a single BMA (e.g. left arm movement) will be recorded in each ECG segment. In the event of multiple BMA episodes the segmentation can be done if the transition boundaries between any two different BMA episodes are known. However, it is impractical from user and clinical view points to note and interpret such BMA transitions manually.

In earlier work on automatic detection of body posture changes, effects of heart axis changes on QRS-complex and ST-T levels were considered [4], [5], [6]. These methods are useful for ischemia monitoring in clinical set-up and limited to a few specific body postures. Fancourt and Principe [7] have proposed a method for segmentation of a non-stationary signal into stationary segments using a learnt time-delay neural network. Khalil *et al.* [8] have provided an unsupervised solution to the above problem for the specific problem of analyzing uterine electromyogram (EMG) signal. Very recently, Assaf [9] has proposed a supervised, multi-resolution based method for detecting transitions in muscular activities from the myoelectric signal with an improved accuracy. The purpose for his study is to develop better and intelligent prosthetic aids. However,

our goal is different and we are concentrating on the impact of BMA in W-ECG recorders. The effect we consider here is the change in skin resistance due to stretching and contraction as opposed to changes in heart axis in previous studies mentioned. The primary objective is to show how the *BMA transitions* can be found automatically from the ECG signal itself without any supervised learning.

Since different BMA will affect the skin-electrode interface in a different manner, a transition between any two different BMA will cause abrupt changes in motion artifacts patterns. We use a recursively updating PCA (RPCA) [10] to detect sudden discontinuities in artifacts. To study the feasibility of BMA transition detection using the RPCA technique, continuous ECG signals are recorded while the wearer performs various activities using a W-ECG recorder developed by Baghini *et al.* [11].

II. Data Acquisition

The specifications of the W-ECG recorder used in this study are as follows: single-lead, bandwidth- 0.05 to 106 Hz, sampling frequency- 256 Hz, A/D conversion- 12 bits/sample [11]. The lead-II configuration is chosen for all the recordings in this study for consistency. Here in this experiment, commonplace BMA and body postures such as movement of arm(s), sitting down, standing up, walking, climbing stairs, twisting motion at waist, are recorded. Care has been taken not to unduly stress the heart during the BMA. Since climbing up the stairs may cause stress, this is restricted to only up to three floors and is performed at a relaxed pace, i.e., about 80-100 steps per minute. The ECG signals are collected from normal subjects containing different types of BMA transitions given in Table I.

A total of 27 healthy subjects were chosen in the age group of 22 to 40 years with an average age of 28 years and a standard deviation of 6 years. All subjects were intentionally chosen to be right-handed males in order to preclude variations arising out of possible gender and orientation effects. In addition, there were no instances of dextrocardia.

III. Experimental Method

In [1], the collected ECG signal is modeled as an additive mix of the cardiac signal and the motion artifact signal. It has also been shown that by supervised learning, the motion artifact subspaces for different BMA can be learned using PCA and a set of top few (6-8) eigenvectors

can effectively represent the motion artifact subspace specific to each BMA. Since the artifact subspaces, as represented by the sets of eigenvectors, are separable [1] we should be able to find whether the BMA in the subsequent beat is in the span of the top few eigenvectors of the current BMA signal. The error in the PCA-based reconstruction of the ECG can be used for this purpose. A lower error indicates that similar motion artifacts are present whereas a higher value indicates that the motion artifacts are structurally different. Thus transition detection in BMA should be possible from the ECG signal itself, without any training. The bases for the subspaces of currently ongoing BMA should be learned adaptively from the signal itself.

We propose a RPCA algorithm to detect abrupt changes in motion artifacts due to BMA transition. Since the RPCA algorithm, like any PCA algorithm is sensitive to feature alignment and it requires the data vectors to have the same dimension, the ECG beats are time synchronized with respect to R-peak in each beat and resampled to equalize each beat to a fix length of M_0 samples [1]. The value of M_0 is chosen based on the normal heart-beat duration and the given sampling rate of the ECG recorder. The choice of R-peak for the purpose of heart beat alignment is due to the fact that the R-peak is the most prominent feature of the ECG signal that can be detected easily even in presence of motion artifacts. The R-peaks in the ECG signals are detected using the Pan-Tompkins method [12]. The duration between the current R-peak and the one prior to it is considered as the current ECG beat interval.

In order to account for occasional instances of atrial extra-systoles (AES) and missed R-peaks, the ECG beat interval is robustly estimated from the calculated RR-interval as the median of the five most recent RR-intervals. That is, at the i^{th} beat, the length of current beat period $M(i)$ is estimated as median of $RR(i), RR(i-1), \ldots, RR(i-4)$, where $RR(i)$ is the computed beat period for the i^{th} beat. For length equalization, the i^{th} beat with estimated beat period $M(i)$ is resampled by a fraction of $M_0/M(i)$. The dimension $M(i)$ depends on the beat period and the sampling frequency. For example, for a normal heart rate of 72/min and a sampling rate of 256 Hz, the dimension $M(i) = 256 \times 60/72 \approx 213$. A small variation in heart rate is quite natural during ambulation and hence this requires the lengths of the ECG beats be resampled so that a PCA based technique can be used. The resampling may generate certain artifacts in the QRS complex. The use of dc-padding circumvents this problem. However, since our interest lies in studying the motion artifacts prevailing over the entire beat period and not just in the QRS-complex and since effect of distortion in QRS-complex due to resampling is quite negligible,

we use the resampling technique for length equalization.

The i^{th} length normalized ECG beat $\underline{r}(i)$ is represented as addition of two components in column vector format

$$\underline{r}(i) = \underline{r'}(i) + \underline{\eta}(i), \tag{1}$$

where $\underline{r'}(i)$ is the composite signal component of dimension $M_0 \times 1$ (i.e., BMA artifacts riding on the actual ECG signal) and $\underline{\eta}(i)$ is the noise. We assume that the composite signal for a given BMA can be represented by a few principal components only and that the principal components for different BMAs are different [1].

In order to estimate the principal components, the covariance matrix C_i is recursively computed as

$$C_i \;=\; \sum_{k=1}^{i} \alpha^{(i-k)} \underline{r}(k)\underline{r}^T(k) = \alpha C_{i-1} + \underline{r}(i)\underline{r}^T(i), \tag{2}$$

where $\alpha,\ 0 < \alpha < 1$ is the forgetting factor. A smaller value of α results in a faster forgetting of the past data. The use of the term α, as above, also prevents any possible buffer overflow if one is interested in a hardware implementation of the technique being proposed. A set of top L eigenvectors of the covariance matrix C_i at i^{th} ECG beat is derived using (2). Let $E_i = [\underline{e}_{i1}\ \underline{e}_{i2} \ldots \underline{e}_{iL}]_{M_0 \times L}$ be the set of top L eigenvectors arranged in a non-ascending order of magnitudes of the corresponding eigenvalues, $|\lambda_{i1}| \geq |\lambda_{i2}| \geq \ldots \geq |\lambda_{iL}|$ till the i^{th} beat, where $\underline{e}_{ik}$ and λ_{ik} are k^{th} eigenvector and eigenvalue, respectively.

To detect changes in motion artifacts present in the next ECG beat $\underline{r}(i+1)$, we obtain the component that lies in the span $\{\underline{e}_{i1},\ \underline{e}_{i2}, \ldots, \underline{e}_{iL}\}$. The error in approximation

$$\epsilon(i+1) = |\underline{r}(i+1) - (E_i E_i^T)\underline{r'}(i+1)|^2 \tag{3}$$

provides a measure of departure from the nearest BMA signal of the same class. If the error is large it corresponds to initiation of different BMA by the user. Hence the BMA transition is detected as a binary signal $T(i)$

$$\begin{aligned} T(i) \;&=\; 1,\ \text{if}\ \epsilon(i) \geq \theta \\ &=\; 0,\ \text{if}\ \epsilon(i) < \theta, \end{aligned} \tag{4}$$

where θ is an appropriate threshold, chosen empirically to be 2.5 times the error magnitude $\epsilon(i)$ averaged over a running window of 15 beats. This introduces a delay of 15 beats in detecting the

transition which corresponds to about 12s delay in detection which is quite acceptable from the health monitoring point of view. One may instead select a fixed threshold θ when there would be no delay. But the choice of θ would then be subjective as the generated motion artifacts are often person specific, due to the nature of skin in contact with the electrode. It may be noted that the proposed method is quite different from the two-step adaptive PCA based method [13] as we are not explicitly, solving the time-series segmentation problem.

IV. RESULTS

Continuous single-lead ECG signals are recorded with various types of BMA transitions as described in Section II. The ground truth regarding all BMA transitions are obtained by a passive observer and reinforced through simultaneously video recording. The RPCA algorithm as given in the previous section is applied to all the available ECG signals. The ECG beats are time-aligned and length equalized to a uniform length of 160 sample point duration as explained in Section III. The complete ECG signal is marked beat-by-beat for the BMA transitions in terms of the binary transition signal $T(i)$.

Initially, we consider four different types of BMA episodes: movement of right arm, twisting motion at waist, standing up and walking. A rest period of 1.5 min was kept after each episode so that artifacts may subside before the next episode is performed. The duration of each of the ECG signals thus collected is around 7.5 min. There are overall 36 (9×4) BMA episodes for a duration of 67.5 (9×7.5) min. Fig. 1(a) and 1(b) depict RR-interval and transition detection of the four BMA episodes in a single ECG signal. A significant correlation between the variation in RR-interval and the BMA transition can be seen in Fig. 1. However, some deviations are also noted, and hence the RR-interval itself cannot be fully indicative of a BMA transition (see Fig. 2). The ECG beats near a detected BMA transition are shown in Fig. 1(c).

Next, walking transitions are performed as single step of walking, allowing a rest period of 1-1.5 min. There were 9-12 transitions in each ECG signal of 12 min duration. Three ECG signals were collected under this protocol, thus there are a total of 27 walking transitions over a duration of 36 (3×12) min. Fig. 2(a) and 2(b) show the corresponding RR-interval and detection of the walking transitions. Here the correlation between RR-intervals and the BMA transitions is not at all apparent. However, all the transitions are detected correctly by the proposed method. A marked portion of the ECG signal corresponding to one of the walking transitions is depicted

in the Fig. 2(c). In all our experiments we have chosen the number of eigenvectors $L = 8$ and value of $\alpha = 0.8$ for the forgetting factor. This allows rapid learning of the subspace of the new BMA artifacts (4-8 heart-beats).

Next, we have applied this technique to detect BMA transitions when all the BMA listed in [1] are performed in sequence to see the BMA transition detections by the proposed method. There were 10-12 transitions in each ECG signal of 7-8 min duration. A total of five ECG signals were collected for this purpose. An example of detection of turning while walking is shown in Fig. 3. Except for the case of continuous right arm movement, the method worked very well with all other BMA transitions. The difficulty with the right arm motion is due to close proximity of the electrode to the moving limb, when the EMG signal dominates the ECG making the approximation of the BMA subspace of the ECG inaccurate. However, changes in various other body postures like sitting, standing, resting supine, resting left-lateral and resting right-lateral have been successfully detected using the proposed method (Fig. 4). The method is also able to detect transitions due to yawning very accurately, as yawning leads to large movement of the diaphragm. The details of number of BMA transitions in the available ECG data and true detections by the proposed method are given in Table I. The accuracy of the proposed technique is found to be $100 \times \frac{374}{374+16} = 95.9\%$ with false-detection rate of $100 \times \frac{45}{374+45} = 10.7\%$. If we increase the threshold θ in (4), the false detection rate comes down at the cost of increased missed detections.

In the collected data there were quite a few instances of atrial extra-systole (AES). Since the AES represents an abrupt change in ECG beat patten, it is also detected by the proposed method. To identify the AES from the BMA transitions we have applied an autocorrelation based detection technique on the detected ECG beats. We detected 70 AESs in the entire recorded data, presented in I, using the proposed technique. All these detections (for example, see Fig. 4) match the ground truth. Similarly, ventricular extra-systoles (VES), or in general, any ectopic beat patterns also exhibit abrupt changes in the ECG signal and are also detected by the proposed method. To separate ectopic beats correctly from BMA transitions, suitable detection methods available in the literature [14], [15] can be applied. However, these cases are rare in our data sets. We detected only two such instances of VES in the processed data. But there are some other factors that affect the performance of the algorithm like, EMG noise due to muscular activities, 50Hz power noise and very loud oral activities of the subject like shouting.

V. CONCLUSIONS

In this paper we have proposed a PCA-based technique to detect transitions of various BMA such as movement of arms, walking, twisting motion at waist and changes in different body postures using the motion artifacts present in ECG signals. The method was found to be able to adapt to gradual changes in the ECG signal due to sustained activities (resulting in slow variations in respiration and heart-rate, as we use recursively updating of the PCA). Notwithstanding above we found the proposed method to handle an increased heart rate to the extent of being nearly double of the heart rate at rest without any difficulty. However, some spurious ECG-beats like AES or ectopicity may also cause false detections, which can be rectified using suitable post processing techniques. Our future work will involve quantifying the effects of kinematics in BMA induced artifacts in ECG signal.

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LIST OF FIGURES

LIST OF TABLES

TABLE I

SUMMARY OF PERFORMANCE FOR TRANSITION DETECTION.

BMA	True	Missed	False
Still→Twisting	21	0	6
Twisting→Still	10	0	3
Still→Walking	50	0	0
Walking→Still	5	0	0
Still→Climb up	23	0	0
Climb up→Still	9	0	0
Still→Climb down	18	0	0
Climb down→Still	8	0	0
Still→Arm movement	72	1	22
Arm movement→Still	18	0	9
Arm movement→Walking	6	0	2
Walking→Arm movement	11	2	1
Turning while walking	54	8	1
Sit→Stand	20	2	0
Stand→Sit	20	2	1
Supine→Left-lateral	6	0	0
Left-lateral→Supine	6	1	0
Supine→Right-lateral	6	0	0
Right-lateral→Supine	6	0	0
Yawning	5	0	0
Total	374	16	45

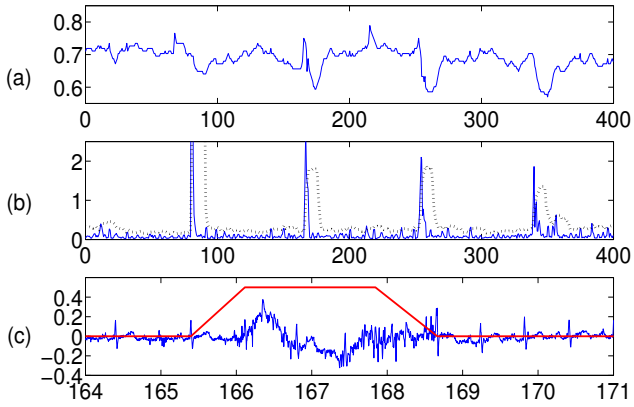

Fig. 1. Illustration of four different BMA transition detection from an ambulatory ECG signal using the proposed RPCA based method. (a) Estimated RR-interval in seconds, (b) threshold detection of BMA transitions from the computed errors (dotted line corresponds to threshold θ), and (c) corresponding ECG signal for one of the detected BMA transitions. The horizontal axes are time in seconds in all plots shown.

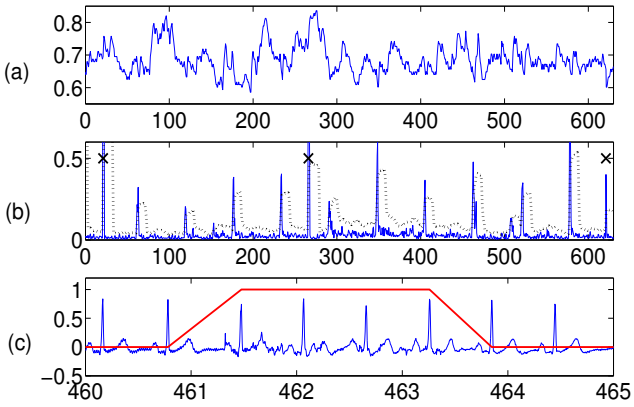

Fig. 2. Illustration of transition detection from ambulatory ECG during walking stride changes using the RPCA based method. (a) Estimated RR-interval in seconds, (b) threshold detection of BMA transitions from the computed errors (dotted line corresponds to threshold θ and '$\times$' signs indicate three detected AES), and (c) corresponding ECG signal for one of the detected BMA transitions.

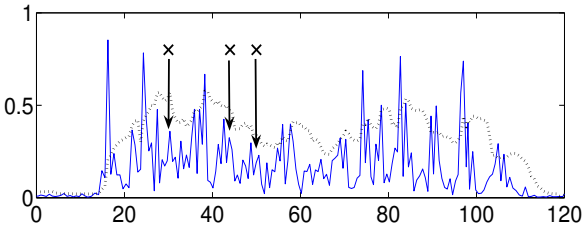

Fig. 3. Illustration of detection of turning transitions while walking. '×' signs indicate the locations of three missed detections.

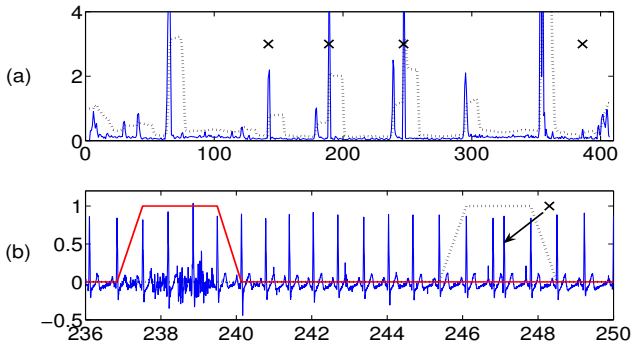

Fig. 4. Illustration of transition detection from ambulatory ECG during various posture changes. (a) Threshold detection of BMA transitions from the computed errors ('×' signs indicate four detected AES), and (b) corresponding ECG signal for one of the detected BMA transitions and one of the detected AES (indicated by '×').