POSTURE-INVARIANT ECG RECOGNITION WITH POSTURE DETECTION

Saeid Wahabi, Shahrzad Pouryayevali, Dimitrios Hatzinakos

Edward S.Rogers Department of Electrical and Computer Engineering, University of Toronto
10 Kings College Road, Toronto, ON, Canada, M5S 3G4.
{swahabi, shahrzad, dimitris}@ece.utoronto.ca

ABSTRACT

Recently Electrocardiogram (ECG) has been proposed as a biometric modality which offers liveliness detection. The fact that ECG is a vital signal makes it challenging to work with as it is affected by physical and psychological changes. In realistic applications, this type of biometrics still needs to be verified in conditions related to the practical use. In real life our body posture changes frequently, therefore in the context of a biometric system our body posture may be different in enrolment and verification which can potentially decrease the performance of the system. In this paper we first investigate the effect of the body posture on the accuracy of ECG biometric systems. Second, a new method is presented that is able to clearly distinguish the ECG signal of different postures of an individual. Finally, we propose a posture-detection verification system in order to mitigate the effect of body posture by first detecting the posture of a subject and then identifying it.

Index Terms— ECG biometrics, Posture detection

1. INTRODUCTION

Biometrics provide a means of identifying individuals based on anatomical and behavioural characteristics which are unique to each individual. Currently, there are many biometric modalities being used, such as face, voice, fingerprint, signature, iris, etc. All of the mentioned biometrics have been successfully used in many applications but a major weakness of many of them is the lack of liveliness detection which can lead to spoof attacks. The biometric template of a genuine user can be acquired by synthetic reproduction to produce an artifact. The artifact then can be presented to a biometric system to get access as a genuine user and consequently delude the system. Therefore the presence of vitality detection can protect the system from spoof attacks. The Electrocardiogram (ECG) biometric systems inherently have liveliness detection thus can ensure that the individual is present at the time of verification. Also the ECG signal is very difficult to regenerate or mimic. Therefore the ECG signal has strong

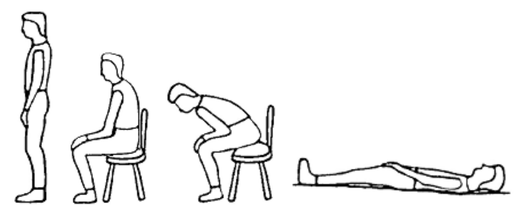

Fig. 1: (a) Stand, (b) sit, (c) tripod, and (d) supine

characteristics that can address the issues of previous biometrics. However unlike most biometrics, ECG is naturally affected by physical and psychological activity of the human body. This unique characteristic of the ECG signal presents a challenge for biometric deployment and measures have to be taken to ensure that ECG biometric systems are robust to such changes.

Among the factors that can affect the ECG signal is body posture. In the medical literature it has been extensively shown that body position can change the ECG signal. Definite changes in the appearance of the QRS and the T-waves were reported with alterations of posture [1, 2], however these changes are not always uniform across all the individuals [1, 4]. Furthermore, Jones *et al.* [3] found that the heart rate varies in different postures, for example the heart rate is higher in standing than in supine and sitting. As a result the amplitude of the R-wave decreases with the increase in heart rate. Also the experimental observations explain that different postures affect the conducting media adjacent to the heart in different ways and therefore the resultant electrocardiograms are different [1]. These observations demonstrate the importance of knowing the body posture under which a recording was taken.

As mentioned before the ECG signal can be affected by physical and psychological activity. For instance, physical activity can be in the form of exercise or different body postures. Although, to our knowledge, there has not been studies on the effect of body posture in biometric research, recently Pathoumvanh *et al.* [5] studied the robustness of ECG biometric systems in heart rate variability conditions caused by exercise. They show that the performance of the system de-

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creases by 17% in such conditions.

The main contributions of this paper are 1) to show how different body postures under which the ECG signals are captured can deteriorate the performance of biometric systems; 2) to propose a method that can differentiate the ECG signals of different postures; 3) to propose a novel posture-detection verification method that can mitigate the influence of body posture on the performance of ECG biometric systems.

The rest of the paper is organized as follows. Section 2 demonstrates the affect of body posture on the performance of biometric systems. Section 3 describes the proposed method for posture detection. The posture-detection verification system is presented in section 4. The preformed experiments and results are shown in Section 5. Finally a conclusion is drawn in section 6.

2. BODY POSTURE IN ECG BIOMETRICS

The effect of having different body postures at enrolment and verification on the performance of ECG biometric systems is investigated in this section. The ECG recordings are from the UofTDB [6] which has recordings in four different postures, namely sit, stand, supine and tripod (Figure 1). For the sit position the subjects were asked to sit on a chair and rest for 2 minutes before the recording procedure starts. In the standing position, the subjects were standing still during the recording and in the supine position the subjects were asked to lay back and relax. In the tripod posture, the subjects were asked to completely lean forward while sitting on a chair. The recordings were captured from subjects fingertips similar to Lead-I configuration. Furthermore sit and stand postures recordings are from session five while tripod and supine recordings are from session 6. There are 52 subjects considered for this analysis.

The AC/LDA ECG biometric method proposed by Agrafioti *et al.* [7] was employed for this analysis. The method uses the normalized autocorrelation (AC) of windowed ECG signals as the feature space, along with Linear Discriminant Analysis (LDA) method for dimensionality reduction. Since the number of the training AC windows was less than the dimension of each sample, we used Principal Component Analysis (PCA) as a preprocessing step for LDA. Furthermore the method was tested in the authentication mode of operation.

In the first experiment, training and testing data are from same postures and in second experiment they are from different postures. In order to factor out the effect of session of recording, we only considered the posture combinations for training and testing that are from same sessions.

The Receiver operating characteristic (ROC) curves of the two experiments are shown in Figures 2 and 3. In all the cases when the training and testing signals are from different postures the performance of the system is worsened. The average Equal Error Rate (EER) is 1.50% when training and testing ECG are from same posture whereas for the other case this number increases to 8.24%.

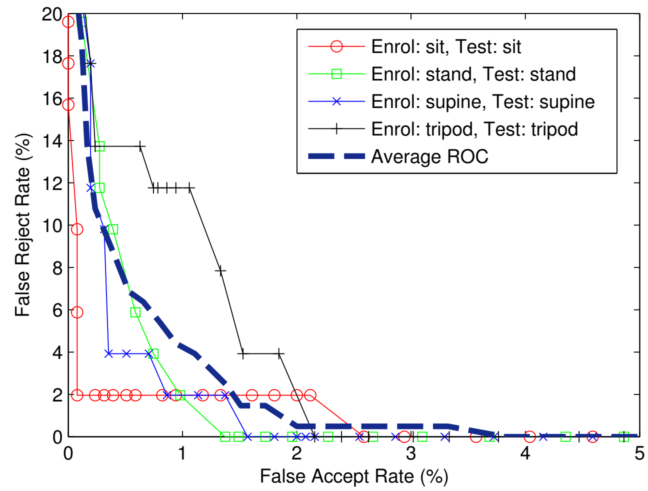

Fig. 2: ROC curves of AC/LDA method when training and testing data are from same posture.

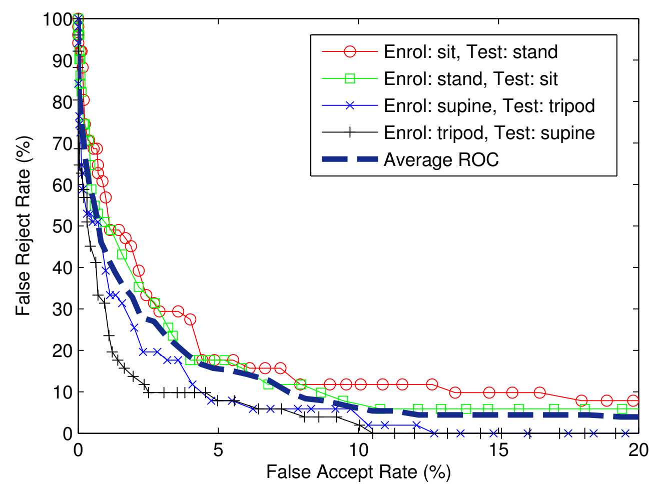

Fig. 3: ROC curves of AC/LDA method when training and testing data are from different posture.

3. POSTURE DETECTION

The experimental results of the previous section show that the performance of the biometric system is decreased when the ECG signals used for training and testing are from different body postures. One solution is to primarily detect the posture and then identify the individual. In this section we first propose a posture detection method and then use it in the following section for our posture-detection verification system.

The proposed body posture detection method consists of three stages: 1) preprocessing, 2) feature extraction and 3) classification. The preprocessing step is for signal quality enhancement, heartbeat extraction, outlier removal and

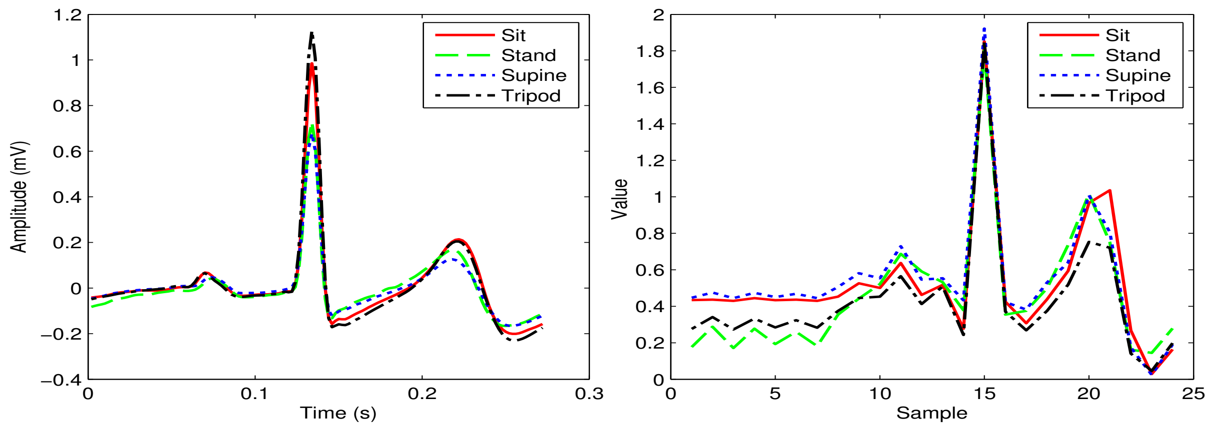

Fig. 4: The heartbeats of a subject under different postures (left) and their corresponding level-3 approximation coefficients (right).

heartbeat normalization. Then features are extracted from the multilevel-discrete wavelet transforms of the preprocessed heartbeats and used to train a Support Vector Machine (SVM) classifier. The rest of the section gives details of each step:

1. **Preprocessing:** the ECG recordings were first filtered using a fourth order bandpass Butterworth filter with cut off frequencies at 0.5 and 40Hz. Below 0.5Hz the signal is corrupted by baseline wander and the frequency contents beyond 40 Hz mainly correspond to noise created by muscle movements, 60Hz power line noise etc. [8].

   In this work the features are extracted from the PQRST complexes (heartbeats). Therefore after filtering, the signals were segmented into heartbeats and were aligned from their respective R peaks. The QRS detection method described in [9] was employed to extract the heartbeats. Since the duration of the heartbeats varies among subjects, all the heartbeats were fixed to have same length. Moreover, the outlier heartbeats were detected and discarded by measuring their Euclidean distance from the time-averaged heartbeat.

   The heartbeats were then normalized to have a dynamic range of one using the following formula:

$$hb_{norm} = \frac{hb - \min(hb)}{\max(hb) - \min(hb)}$$

2. **Feature extraction:** multilevel discrete wavelet transform (DWT) of the heartbeats were considered for feature extraction. The level-3 approximation coefficients were treated as a feature vector which was empirically found to yield optimal results in terms of detection rate. Figure 4 shows the corresponding level-3 approximation coefficients of four different postures.

3. **Classification**: a Support Vector Machine (SVM) was used for classifying each posture feature vectors. SVM is a supervised learning model that constructs hyperplanes with the largest margins between two classes. SVM is used for classes that can not be divided linearly. It maps the data to a higher dimension, using a kernel, where they can be separated linearly. SVMs were originally designed for binary classifications, therefore we used an extended multiclass SVM using one-against-all method [10] with the linear kernel function.

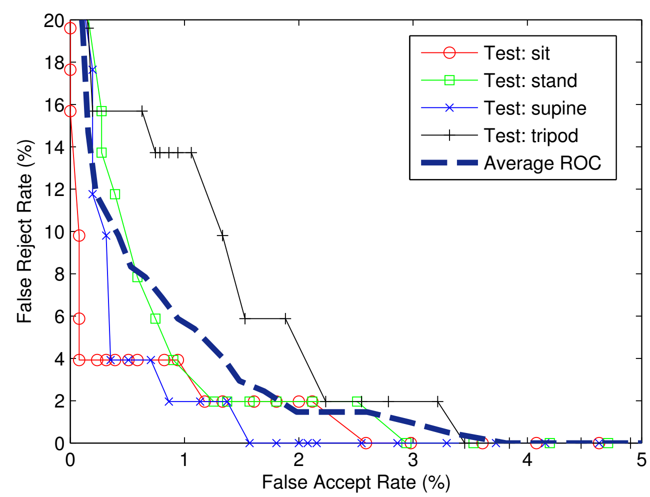

Fig. 6: ROC curves of posture-detection verification system under different test postures.

4. POSTURE-DETECTION VERIFICATION

Consider an enrolment protocol in which the user's ECG signal is collected under sit, stand, supine and tripod postures. In real-world settings when the system is in normal verification operation the underlying posture of the user may be random and unknown to the system.

In the posture-detection verification method, the biomet-

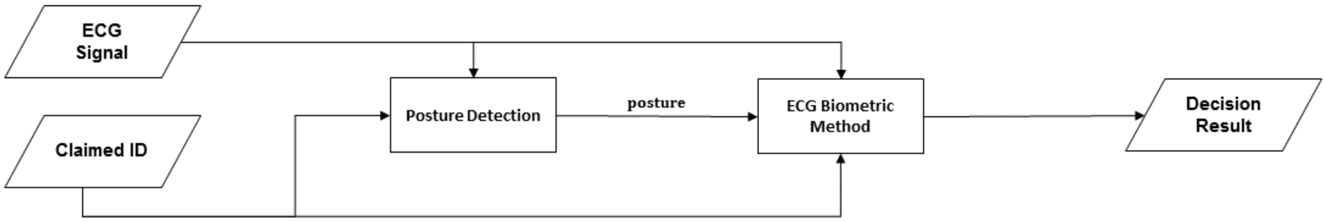

Fig. 5: System block diagram of posture-detection verification system.

ric template is composed of ECG signals under all postures but the biometric algorithm is trained individually for each posture. Using the UofTDB database, for instance, four different AC/LDAs are trained, each corresponding to a different underlying posture. In addition, the system is trained per subject for posture detection by using the proposed method explained in section 3. The projection matrices and the projected feature vectors collectively form a subject's biometric template. During verification, as shown in Figure 5, the posture of the user is first classified prior to biometric matching. Then the system compares the test biometric signal with the detected posture template of the claimed identity.

5. RESULTS AND DISCUSSIONS

From the UofTDB we used 52 subjects for whom recordings under all postures (sit, stand, supine and tripod) are available. The system was trained and tested as follows: for each subject, the first half of the signal for each posture was used for training and the second half was used for testing.

For posture detection, the time-averaged heartbeat was used for testing. The posture detection rates for sit, stand and supine were 98.04% and 94.12% for tripod. Figure 6 shows the ROC curves for posture-detection verification. The average EER of the system reduced to 1.86% which is very close to the case where the test and enrol ECG are from same posture (1.50%). This great improvement can be explained by the high classification rates of the posture detection method.

6. CONCLUSION

One of the main challenges of working with the ECG signal as a biometric is susceptibility to physical activity. This paper investigated the robustness of ECG biometric authentication with different body posture. There are no articles in the ECG biometric research devoted to studying the impact of being in different body postures, which may occur frequently in practical applications. As shown in this paper when the posture at enrolment and verification are not identical, on average there is a 6.74% decrease in the performance of the system. We proposed a novel posture-detection verification system to reduce this drop in performance. This system first detects the posture of the test signal and then verifies the identity of the test signal. In this research, the features extracted from the multilevel-discrete wavelet coefficients of the heartbeats are used in conjunction with SVM as a posture detection method. Further, this posture detection method is used in the first step of the posture-detection verification system. In the second step, the system is trained four times to distinguish the subjects in the different postures. In conclusion our study verified that enrolling and testing in different postures can significantly decrease the functioning of an ECG biometric system. Our proposed method can reduce the performance drop from 6.74% to 0.36% which is a major improvement.

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