ECG BASED HUMAN AUTHENTICATION USING WAVELETS AND RANDOM FORESTS

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ABSTRACT

The electrocardiogram (ECG) is an emerging novel biometric for human identification. It can be combined in a multi-modal biometric identification system or used alone for authentication of subjects. His primary application can be in health care systems where the ECG is used for health measurements. It does furthermore, better than any other biometrics measures, deliver the proof of subject's being alive as extra information which other biometrics cannot deliver as easily. The main purpose of this study is to present a novel personal authentication approach for human authentication based on their ECG signals. We present a methodology for identity verification that quantifies the minimum number of heartbeats required to authenticate an enrolled individual. The cardiac signals were used to identify a total of 80 individuals obtained from four ECG databases from the Physionet database (MIT-BIH, ST-T, NSR, PTB) and an ECG database collected from 20 student volunteers from Paris Est University. Feature extraction was performed by using Discrete Wavelet Transform (DWT). Wavelets have proved particularly effective for extracting discriminative features in ECG signal classification. The Random Forest was then presented for the ECG signals authentication. Preliminary experimental results indicate that the system is accurate and can achieve a low false negative rate, low false positive rate and a 100% subject recognition rate for healthy subjects with the reduced set of features.

KEYWORDS

ECG; human authentication; wavelet decomposition; random forests.

1. INTRODUCTION

Biometric measures are used in many different areas and industries to provide a relatively high level of security where identification and verification of subjects are required. The National Center for State courts lists 8 physiological biometrics and 3 behavioural characteristics used to allow recognition of individuals [1]. Among the most used biometric traits are the fingerprint, iris, face and voice [2]. Some other complementary biometrics are introduced which can be very helpful in multimodal systems but cannot provide reliable performance in terms of recognition accuracy (e.g., gait, keystroke). The most used ones are not as robust as usually considered against attacks to falsify the identity [3]. It's known that biometric traits can be easily bypassed using different techniques such as artificial disguise, latex, contact lenses and voice recording. Analysis of electrocardiogram (ECG) for clinical diagnosis has been a research topic for a couple of decades, and recent proposals of using ECG as a new biometrics measure for human identity

recognition have been published [4],[5],[6]. The uniqueness of the electrocardiogram signal has encouraged its use in building different biometric identification systems.

ECG signal measures the change in electrical potential over time. The trace of each heartbeat consists of three complexes: P, R, and T. These complexes are defined by the fiducial that is the peak of each complex as shown in Figure. 1.

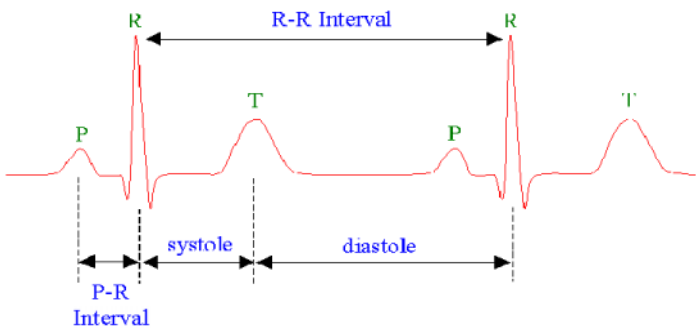


Figure 1. The Standard ECG Waveform.

A biometric application is based on three steps: i) the enrolment, where biometric information from an individual is stored, ii) the connection steps, where an individual tries to connect to a system and biometric information is detected and compared with the information stored at the time of enrolment and iii) the decision step. Then, two contexts exist, the identity verification and the identification. In the context of identity verification [4, 8], an identity is first announced by the subject, his signal is compared to signals owning to him (one-to-one comparison) and the decision consists in accepting or rejecting the claimed identity. In the context of identification [1, 5, 7], the signal is compared to a biometric database (one-to-many comparison) and the first neighbor (or first rank identity) provides the identity of the subject.

In this paper we propose to use the wavlet coefficients of the ECG raw data as features for human authentication. Then the authentication accuracy of the random forest identifier is investigated.

2. DISCRETE WAVELET TRANSFORM

Wavelets are mathematical functions that satisfy certain criteria, like a zero mean, and are used for analyzing and representing signals or other functions. A set of dilatations and translations, $\psi_{i,j}(t)$ of a chosen mother wavelet $\psi(t)$ is used for signal analysis. In Discrete Wavelet Transform, dilation factors are chosen at a power of 2 and the set of dilation and translation of the mother wavelet is defined as:

$$\psi_{i,j}(t) = 2^{-\frac{j}{2}}\psi(2^j t - k)$$

where j is the scaling factor and k is the translation factor. It is obvious that the dilatation factor is a power of 2. A scaling function $\square(t)$ is defined as:

$$\square(t) = \begin{cases} 1 & if\ t \in [0,1] \\ 0 & otherwise \end{cases}$$

And the set of dilation and translation of the scaling function is:

$$\square_{i,j}(t) = \sqrt{2^j}\ \emptyset(2^j t - k)$$

To span our data domain at different resolutions, the wavelet is represented in a scaling equation:

$$\psi_{i,j}(t) = \sum C_k \square(2^j t - k)$$

where C_k are the wavelet coefficients and they must satisfy linear and quadratic constraints. With scaling basis $\square_{i,k}(t)$ and wavelet basis $\psi_{i,k}(t)$, we can decompose any function $f(t)$ as:

$$f(t) = C_{00}\square(t) + \sum_{j=0}^{n-1} C_{j,k}\psi_{i,k}(t)$$

The coefficients C_{00} and $C_{j,k}$ are selected as features for personal identity verification approach.

3. MATERIALS AND METHODS

3.1. Protocol and Databases

The ECG records were chosen primarily from existing ECG databases, including the MIT-BIH arrhythmia database [11], the European Society of Cardiology ST-T database [12], the Normal Sinus Rhythm Database [13] and the PTB database [14]. The existing databases are an excellent source of varied and well characterized data, and represent a wide variety of QRS and ST-T morphologies to which have been added reference annotations marking the waveform boundary locations.

In addition to those databases, we have created our ECG biometric database. The subjects' ECG signals were measured and collected with an ECG data acquisition unit (Leybold GmbH) that was connected to a computer through an USB National Instrument input/output card (Low Cost Multifunction DAQ 6008) with a sampling frequency of 250Hz, and captured using a LabView software running on the personal computer. A single lead ECG recording was done by following the connections in Figure (2). Participants were required to remain calm and relaxed throughout the recording session.

A total of 20 healthy subjects participated in this study. All were male students and staff at Paris Est University (UPEC - Créteil). The ranges of age, weight and height were 20 to 40 years, 55 to 95 kg and 155 to 190 cm, respectively. For the lead recording, one electrode were placed on the left palm and the other on the right palm. These subjects were in a resting position and sitting upright, and they were asked to relax and resting on their legs.

Figure 2. Connections of single lead ECG recording.

Four ECG recordings were obtained from each participant with duration of two minutes for each recording. The recordings are made on different days and time for every participant. It is then preprocessed using Labview and Matlab code, (Figure 3). First, individual ECG cycles are separated and waveform cycles are interpolated to get the same size. The first minute was taken as our training data to build the ECG verification system database. The second minute was used as the test data for our system. The lead II ECG signals were acquired in this research.

Unlike a clinical ECG database with 12-lead records including limb and thoracic signals, this research focused on palm ECG signals. The ECG recorded from the palms has more noise than the ECG recorded from the torso, but the waveform morphologies are the same as the Lead I ECG. The electromyogram (EMG) interference and baseline wander become more significant when ECGs are recorded from palms; that is, the signal-to-noise ratio (SNR) of the palm ECG signal is lower than of the chest ECG signal. However, the big advantages for palm ECG are easy to access, to combine with fingerprint/palm biometrics, and to use mental/dry electrodes.

3.2. Preprocessing

ECG preprocessing included selection of appropriate beats and removal of various artefacts. Baseline wander, dc shift, power-line noise, and high-frequency interference were removed [15], [16]. Standard ECG machines have a bandwidth of 0.05 to 150 Hz. However, the noise was so severe for a palm ECG that the signal was band limited to the frequency range between 1 and 40 Hz (Figure 4).

Figure 3. ECG system acquisition.

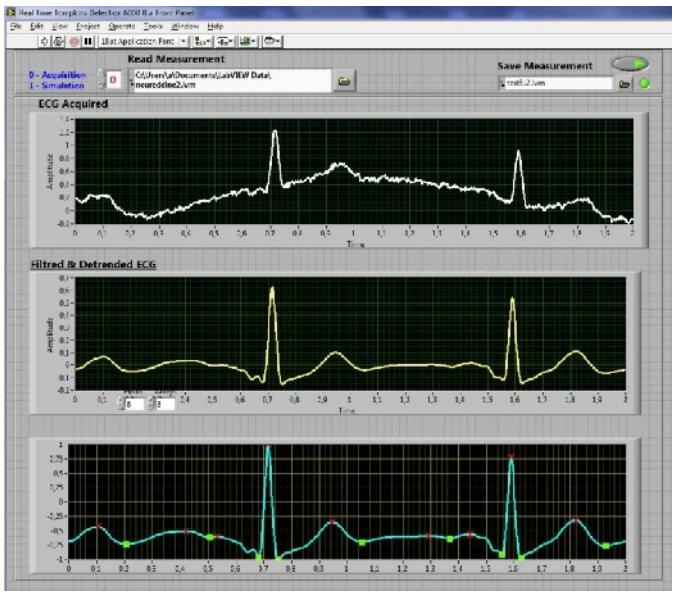


Figure 4. Original ECG, Base line wander removed signal and denoised signal.

3.3. Features Extraction

In the existing literature, the most commonly encountered types of features for human identification are morphological characteristics of single heartbeats. It has been suggested [13], [14], [15], [16], [17], [18] that amplitude and normalized time distances between successive fiducial points constitute unique patterns for different individuals. However, in these applications, it is implied that fiducial points can be successfully detected. The algorithms that perform such a task are built solely for medical applications, where the exact wave boundaries are not needed to diagnose abnormalities. This is not the case for human recognition and authentication systems, where accuracy is crucial in order to facilitate further pattern analysis. Furthermore, there is no universally acknowledged rule about the exact location of wave boundaries, which could constitute the basis of fiducial detectors [19]. Moreover, in ECG monitoring, several kinds of anomalies are met, some of which affect the morphology of the signal significantly, making the boundaries of the waves difficult to localize. To address these problems, nonfiducial points

methods can be adopted for feature extraction. The Discrete Wavelet Transform (DWT) method has been found to be a suitable candidate for this purpose [20], [21].

The Continuous Wavelet Transform decomposes the signal over a set of elementary functions obtained by dilation by a scale factor *a* and translation by a shift parameter *t* of a mother wavelet as shown in:

$$\psi_{t,a}(s) = \frac{1}{\sqrt{a}}\psi\left(\frac{s-t}{a}\right)$$

In the case of Discrete Wavelet Transform, the parameters *t* and *a* are discretized as:

$$a = 2^j, t = k2^j, (j,k) \square Z^2$$

According to Mallat's algorithm [22], the Discrete Wavelet Transform, can be implemented by cascading identical low-pass and high-pass filters as a 2 channel filter bank as shown in Figure 5.

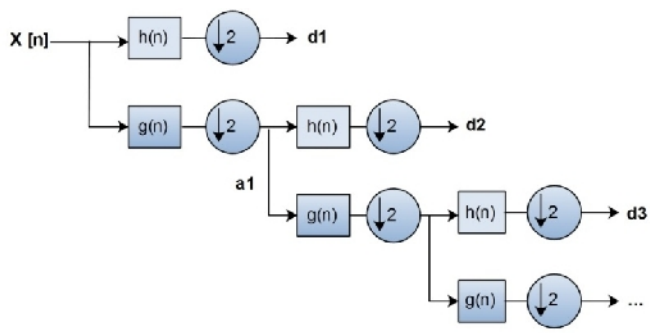


Figure5. Mallat's algorithm for implementation of Discrete Wavelet Transform using 2 channel filter bank for decomposition.

In this study, cycles of each individual were reduced to one cycle by averaging all above cycles in each iterance to reduce the effects of signal variation effects to identification performance. Each cycle contains 192 discrete sampling points. The amplitude of all the ECG signal cycles is normalized in to values in the range of [-1 1].

Each heartbeat of training set was sequentially segmented from the full recording, and then all individual waveforms were aligned by their R peaks as shown in Figure 6.

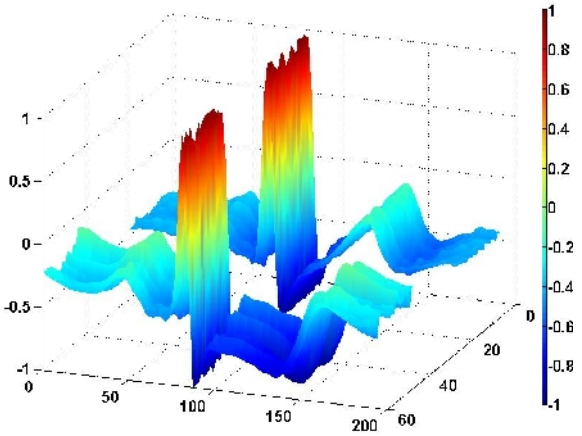
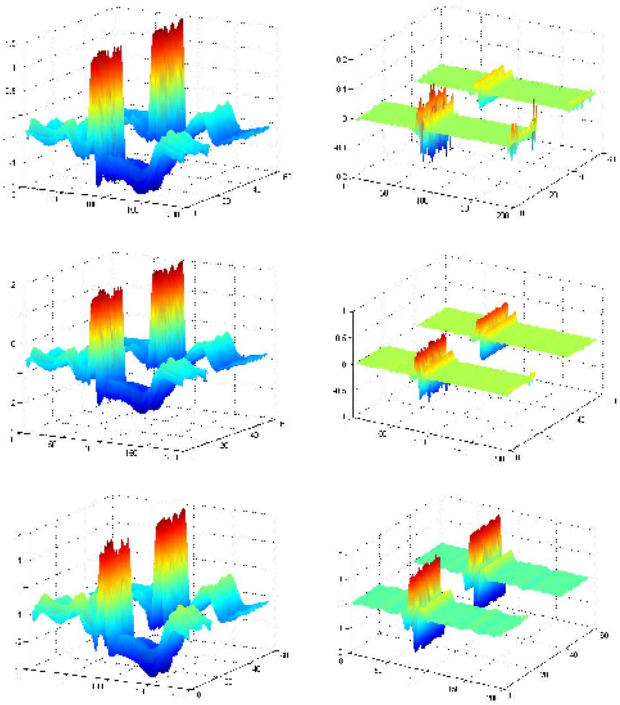


Figure6. 40 Heartbeats synchronized at the R peak from two different individuals.

Afterwards the first 100 heartbeats of any data have been averaged and the coefficients of Discrete Wavelet Transform of this averaged beats are considered as features. In this paper, the Daubechies wavelet (db3) was chosen with five levels of decomposition, which were empirically found to be the optimal value for ECG compression using wavelets [23]. The wavelet transform coefficients of two different individuals in different scales are shown in Figure 7.



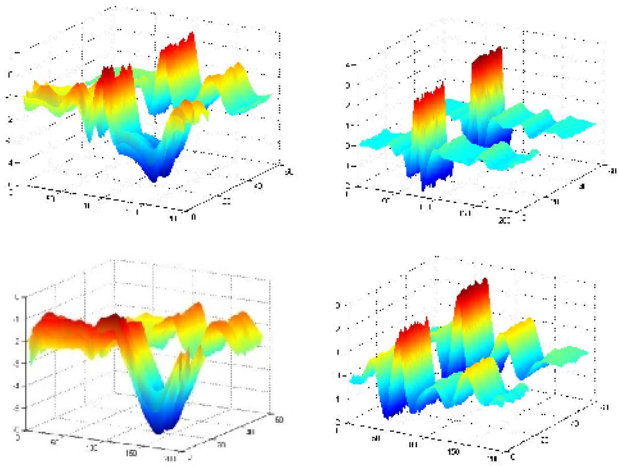


Figure 7. Two heartbeats from two different individuals and their wavelet transform (db3) in five scales.

3.4. Authentication Process

Authentication represents the last step of the proposed system. For this step, every input feature vector is compared to the ones stored in the gallery set in order to find the best match. Growing an ensemble of random trees for classification using a probabilistic scheme is called random forest of trees. Classification accuracy is high as the trees vote for the most popular class. Trees drawn at random from a set of possible trees is called random tree. Random tree is a decision tree that considers K randomly chosen attributes at each node. The class probabilities on each node are based on back fitting with no pruning [24]. The steps involved in growing a random tree are:

- The training set for growing the tree is obtained by selecting N cases at random but with replacement from the original dataset.
- A random number of attributes m are chosen for each tree. These attributes form the nodes and leafs using standard tree building algorithms. The best split on m is used to split the nodes and m is held constant.
- Each tree is grown to the fullest extent possible without pruning.

A new object is classified using its input vector down each of the trees in the forest. The forest chooses the class with most votes, and new object input vector is classified. The advantages of random forests are that it is easy to calculate a measure of “variable importance” and out of bag data can be used to estimate the classification error. The error rate of the random forest depends upon the correlation between the trees in the forest and the strength of the trees. Higher the correlation between two trees, higher is the error rate. A tree is a strong classifier if it has lower error rate, increasing the strength of each tree decreases the error rate of the random forest.

4. RESULT AND DISCUSSION

The signal averaging method successfully increased the signal-to-noise ratio thereby improving system performance.

The verification rate is defined below:

$$\boldsymbol{verification\ rate}(\%) = \frac{Total\ number\ of\ correctly\ samples\ N_C}{Total\ number\ of\ testing\ samples\ N_T}$$

The average training and test data verification rate was 100%. Furthermore, the false acceptance (FAR) and false rejection rates (FRR) were calculated to estimate the performance of the proposed ECG verification system.

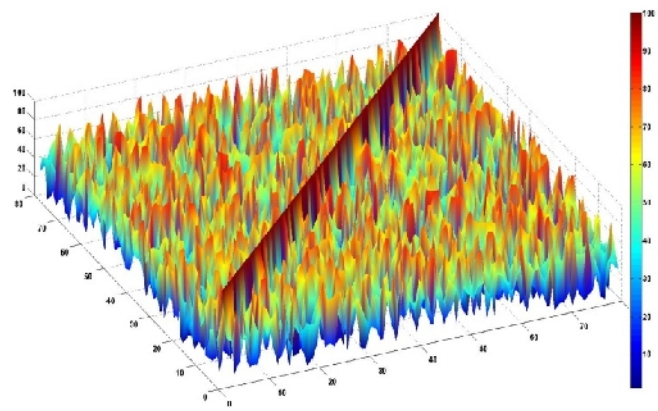


Figure8. Distance matrix between enrolment and test templates.

The false acceptance (FAR) and false rejection rates (FRR) were 0.60% and 0.58%. Figure 8, presents the distance matrices obtained with the proposed methodology between enrolment and test templates. The element *i, j* of the matrix represents the distance from the subject *i* to the subject *j* according to the selected set of features. In the presented color scheme, red is attributed to values close to one, representing subjects with very similar features, and blue is attributed to values close to zero, representing subjects very dissimilar.

In the matrix of Figure 8 we see that there are very few entries with red color, except in the diagonal, which represents the distance from the subject to himself. This characteristic is important in order to have a high true positive rate (TPR).

We increased the number of trees to obtain the best classification rate. 1,5,10 and 20 trees were constructed. The classification accuracy is shown in figure 9. From this figure, it is seen that as the number of trees used in the computation crosses 20, the classification accuracy remains constant with no further increase. The optimal number of trees to get the best classification accuracy can be in the range of 15 to 20 trees based on the time within which the data needs to be computed.

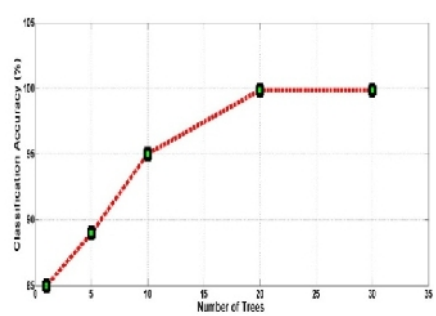


Figure 9. Classification accuracy of random forest with different number of trees.

3. CONCLUSIONS

We presented a novel personal identity verification approach that used one-lead ECG signal. The features were extracted by applying the discrete wavelet transform. The random forests method was used as a measure for the verification mechanism. ECG data for this investigation was obtained from two sources Physiobank website (four databases) and our ECG database. Using this approach, 100% verification rate was achieved for 80 healthy subjects. The results demonstrated the validity of our proposed method and the feasibility of using the ECG as a biometric measure for human identity verification. The advantages of our ECG verification system are as follows. (1) Only living persons have this biometric. The heart beats exist only in living individuals and stop working when then die. The system cannot be cheated using an artefact. (2) The ECG signal is difficult to imitate. The ECG varies from person to person due to many factors and is not an exterior feature. Therefore, this biometric is difficult to learn or imitate by others. (3) It is suitable in combination with other biometrics. Multimodal biometrics are a trend for future biometric identification systems. The ECG is an interior feature and easy to combine with other exterior biometric features. (4) It has a reasonable training time. (5) Good verification rate for verifying normal people is obtained. An investigation of how the ECG will vary over a long time period which may affect the verification rate should also be studied. Moreover, the ECG hardware recorder should be designed to be convenient for low cost, easy application ambulatory measurement as security tool in daily life.

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