Human Identification Using QT Signal and QRS Complex of the ECG

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Abstract-In this paper the possibility of using the ECG signal as a Biometric feature for human identification is investigated. A test set of 550 lead I ECG traces recorded from 22 healthy people at different times are used to validate the system. The proposed system extracts special parts of the ECG signal starting from the QRS complex to the end of the T wave. Two different approaches were used to compensate for the change in the signal shape with the change in Heart Rate, By the first approach time domain normalization according to Framingham correction formula[1] is used. By the second approach the QT signal to a fixed length is applied. Finally the ability to use only the QRS complex for identification without any time domain manipulation has been investigated. Selected DCT coefficients obtained from the normalized signal were introduced to a Neural Network based classifier. Experiments show a very promising possibility of using ECG as a biometric feature.

Keywords-Human Identification, ECG, Neural Network

I. INTRODUCTION

Successful Biometrics provides the way to identify individuals based on a unique physiological or behavioral characteristic of the individual person. For many years external physiological biometrics like fingerprint, Iris recognition and face recognition [2-3] were used. The problem with such biometrics is that they are considered external physiological Biometrics which are easy to mimic and face by Fake finger, Iris and Face photos. All of these raise a need to a new internal physiological biometric like ECG and EEG signals. ECG was used for many years ago as a medical diagnostic data, in the last few years it was introduced as a new Biometric feature [4-8] as the ECG reflects the way the Heart functions and its geometry which are believed to be unique and different form one person to another. In previous studies temporal and amplitude features “fiducial points” were extracted from the ECG signal and then used for classification process. The problem with the previously mentioned methods is that, they depend on the accuracy of signal delineation techniques to extract the temporal features as there is no universal[9] standard way to define the boundaries of the signal [4-6]. Other studies depended on the use of the appearance shape after applying a time normalization to a fixed number of samples to treat the Heart Rate variability then the resulting signal was used for classification[7-8], the problem with these studies is that they treat all the ECG components as they change with the change of Heart Rate in the same way which doesn’t comply with observations.

In our work a selected portion of the ECG signal “starting from Q wave to the end of the T wave” is used for classification after adapting it to compensate for its change with the change of Heart Rate [10].

II. THE HEART AND THE ECG

The In order to correctly use the ECG signal as a Biometric we need to know how exactly the heart works and what is the relation between its function and the produced ECG signal. The cardiac cycle starts with the Action Potential (AP), AP occurs when the cell membrane potential suddenly depolarizes and then repolarizes back to its resting state. There are two general kinds of AP, Pacemaker AP generated spontaneously like that of the Sinus Atria (SA) node and non pacemaker AP generated by depolarization current from adjacent cell like that of Ventricle muscles[11-12]. The cardiac cycle starts from the SA node the prime pacemaker of the heart by spontaneous generation of an AP, the AP firing rate is controlled by the Automatic nerve system, the self excited AP generated from the SA node propagates through the Atrium muscles by the cell to cell conduction causing its cells to depolarize and the atrium to contract producing the P wave in the ECG signal, the excitation pulse then reaches the Atrioventricular (A-V) node where it is delayed to allow the atrium to complete its contraction before the start of the Ventricle contraction. As the excitation pulse leaves the A-V node it rapidly spreads through the ventricle muscles via Purkinje fibers which transmit AP very fast in a velocity 6 times greater than that of the ventricle muscles, The AP
reaches the ventricle muscles causing them to depolarize producing the QRS complex of the ECG and the ventricle to contract. In the ventricle the AP propagate through Purkinje fibers to the endocardium then travels through the Ventricle muscles to reach epicardium, then after a time related to the plateau period of the AP the ventricle muscles cells start to repolarize producing the T wave, the epicardium cells start to repolarize before the endocardium ones. The Automatic nerve system ”ANS” controls the Heart Rate and the RR interval by changing the firing rate of the SA node and the time interval of the Plateau period of the AP as well as the conduction velocity of the muscles. The QRS complex is considered to be fairly constant and doesn’t change with the change of heart rate as it reflects the time that passes between the depolarization of first ventricle muscle and the last one and because the AP is carried on the ventricle through the high speed Purkinje fibers and travels only a short distance in the ventricle between the endocardium and the epicardium. The QT period is closely related to the Plateau Period of the Ventricle AP, Which is controlled by the ANS ”Automatic nerve system” and changes with the Heart Rate. Several formulas were developed to link between the QT interval and the Heart Rate. The recent and the most accurate one is the Framingham correction formula [1], The formula linearly normalize the QT interval to 60 BPM Heart Rate according to the relation.

\[ QT_{LC} = QT + 0.154 \times (1 - RR) \]  

Where \( QT_{LC} \) is the linearly corrected QT interval duration in seconds, \( QT \) is the original QT intervals in seconds, and RR is the original interval between two successive R waves in seconds.

III. RELATED WORK

Biel et al. [4] are the first who used ECG signal for human identification, in their work the researchers used a diagnostic ECG device, that automatically extracts the medical features, both chest and limbs leads were used where 360 features were automatically extracted from 12 leads rest ECG for 20 persons, the number of features were further reduced till the best results were obtained by using 10 features from lead I with identification rate of 100% using PCA as a classifier and a test set equal to 50 samples. The problem with Biel work that rest ECG signals were used that do not incorporate significant change in the heart rate along with the small number of test data used for system validation. T.W.Shen et al[5] used ECG signals from 20 normal individuals, taken from the MIT-BIH database. In this research two methods were used for the classification process. The first one is template matching and the second one is Decision Based Neural Network (DBNN) whose input is a group of temporal and amplitude features. The results show that template matching gives an identification rate of 95% and the DBNN algorithm gives an identification rate of 80%. Combining the previous two methods first by template matching then by analyzing only the candidate beats by using DBNN an identification rate of 100% was achieved. The problem associated with this work is that the standard MIT-BIH database was used where each normal person has one record where parts from it was used for learning and other parts were used for testing, and it doesn’t contain a change in the heart rate for each person as it includes only rest ECG signals. Israel et al. [6] showed the uniqueness of an individual’s ECG by investigating temporal features. 15 temporal features were extracted from lead I ECG; some features were considered constant with the change of the heart rate others were normalized by dividing them by the distance from the start of the P wave to the end of the T wave. This system was tested on a database of 29 subjects at different anxiety conditions with 100% human identification rate and around 81% heartbeat recognition rate. In the work of K. N. Plataniotis et al[8] an extensive study of different approaches for using ECG as a biometric feature was done. In this research two standard ECG databases were used the first one is the PTB Diagnostic ECG Database and the other one is the MIT-BIH Database, best results were obtained by using a hierarchal schema, by the first stage an LDA classifier was used and by the second stage a PCA was used, The proposed schema produced heartbeat recognition rates of 98.9% and 99.43% for PTB and MIT-BIH databases respectively. Another method was introduced by the same researcher named AC/DCT that doesn’t depend on extraction of fiducial points from the ECG waveform but instead of that autocorrelation function of an averaged ECG waveform was computed then DCT coefficient for the resulting ACF. Computed recognition rates of 94.47% and 97.8% for PTB and MIT-BIH database were achieved respectively.

The problem with this work that the databases used were from the PTB database and MIT-BIH database, which are not convenient for testing the ECG signal as a Biometric feature as they were recorded at rest for the 12 lead ECG and there is no sufficient data samples for learning and testing as PTB database contains only two records for most of healthy persons where one record was divided to be used for training and the other was divided to be used for testing, and by the MIT-BIH only one long time record for each person was available which was divided into parts for learning and testing.

Kyeong et al[7] used an ECG database collected from lead I at normal and physical active states. In this study a time domain normalization process was applied to each heartbeat to a constant number of samples N = 256 which show an enhancement of similarity for the same features at different heart rates. The problem that the study treated the whole ECG signal the same, where all of its components were changed linearly with the change of the Heart Rate which is not correct from physiology point of view as discussed previously.
IV. ECG DATA

The ECG data used in this work is collected from 22 healthy persons males and females between the age of 22 and 61 by using Philips Pagewriter Trim II device with 500 Hz sampling rate and 5 V resolution, each person has 25 ten seconds records collected within a four months period. Each candidate was asked to set down on a chair connecting only the limb electrodes as ECG records from lead I is only used in this study, after that the test starts immediately to gain different conditions with different heart rates for each session. The collected ECG records contain a range of Heart Rates for the same person as shown in figure 2.

![Figure 2: changes of Heart Rate for each candidate](image)

V. ECG PREPROCESSING

The ECG signal contains high and low frequency noise components that must be filtered from the ECG signal before the rest of experiment takes place.

ECG signal contains three sources of noise

1- Low frequency noise: Baseline wondering due to perspiration, respiration, body movements, and poor electrode contact with spectral content usually below 1 Hz
2- Power line interference (50 Hz) due to poor grounding of the ECG equipments.
3- High frequency noise: appears within individual Heart Beats.

The recorded ECG signal is filtered by using a cascaded High pass low pass FIR filters to form Band pass filter between 1 and 40 Hz containing the useful spectral of the ECG signal[14]

![Figure 3: ECG record before and after filtering](image)

After filtering, The R waves are detected and individual complete ECG signals are extracted from the trace. The resulting ECG signals are aligned by the R waves and averaged to produce one complete ECG signal.

Signal Delineation and Adaptation:

As shown in figure 5 the QRS wave shows great stability with the change of the Heart Rate in the contrary to both the T and P waves which show a variation with the change of the Heart Rate. The end of the T wave point and the boundaries of the QRS complex are delineated by using minimum radius of curvature method [6]. For identification process the P wave is not considered as it changes with the Heart Rate and it is difficult to detect and delineate specially in the presence of noise and by the fast Heart Rate [7, 15]. Different approaches are used to compensate the change in the heart rate namely:

![Figure 4: 10 complete ECG signals for the same person at different Heart Rates showing the great stability of the QRS against Heart Rate change and the variation of both T and P wave interval with the change in the Heart Rate.](image)
Framingham Study Formula adaptation:

In this method the rest of the Signal from the start of Q wave to the end of the T wave was adapted by using Framingham study formula as shown in equation 1. Within the QT wave the QRS complex is considered as constant and the change applies only to the rest of the signal starting from the J point “end of QRS” to the end of T wave, the new signal is constructed to its new length by two steps of interpolation and decimation to produce a normalized time signal, also amplitude normalization is done by dividing the signal by the maximum of the R wave as shown in figure 5.

\[ y(k) = w(k) \sum_{n=1}^{N} x(n) \cos \left( \frac{\pi(2n-1)(k-1)}{2N} \right) \]  

(2)

as \( k = 1,2,\ldots,N \)

Where

\[ w(k) = \frac{1}{\sqrt{N}} \quad \text{for} \quad k=1 \quad \text{and} \quad \sqrt{\frac{2}{N}} \quad \text{for} \quad 2 \leq k \leq N \]

The benefit of using the DCT transformation is that the useful information is concentrated in few coefficients.

VII. NEURAL NETWORK CLASSIFIER

For each method a neural network is used with input layer having a number of inputs equal to the number of selected DCT coefficients, one hidden layer and one output layer with the number of nodes equal to the number of candidates. The Neural Networks are trained using back propagation learning algorithm. Each neural network is trained to accept the user coefficients vector and clamp the user’s output node at one and to reject other people’s coefficient vector by clamping there output nodes to zero. The Neural Networks are trained by 15 data sets per person and 10 data sets are used for testing.

VIII. RESULTS

Framingham study adapted QT interval:

For this method we chose selected number of DCT coefficients from 1 to 20. These coefficients are introduced to a neural network with 20 nodes in the input layer, 15 nodes in the hidden layer and 22 nodes in the output layer. The correct identification is 215 out from 220 giving identification rate of 97.727 %.

Constant length QT interval:

DCT Coefficients from coefficient number 1 to number 25 were chosen in addition to the value of \( QT_{LC} \) evaluated by using Framingham study formula. The neural network has 26 node in the input layer, 20 in the hidden layer and 22 in the output layer. The correct identification is 216 out from 220 with an identification rate = 98.18 %.

QRS Complex:

DCT Coefficients are the first 20 coefficients, the neural network has 20 node in the input layer, 20 in the hidden layer and 22 in the output layer. The correct identification is 218 out from 220 Coefficients giving identification rate equal to 99.09%.

The selected DCT coefficients were computed according to equation 2.

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IX DISCUSSION

In this paper a feasibility study has been done on the success of using ECG as interior Biometric feature. A database consisting of 22 healthy persons was constructed containing a wide range of heart rate values and three methods were developed for validation, the study shows that the heart rate variability has the major effect on the stability of the ECG signal as a biometric feature which was treated by two methods. Also the QRS complex of the ECG signal is proven to be stable against Heart rate variability and convenient to be used alone as a Biometric feature. The proposed methods show outstanding performance. Compared to other methods achieving higher recognition rate, it was shown that these methods were validated using resting ECG databases that don’t face the challenge of the change of ECG characteristics due to the change in the heart rate as in our proposed methods.

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References