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ECG as a Biometric for Individual's Identification

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Abstract— **In this paper, we investigate a new method to analyze electrocardiogram (ECG) signal, extract the features, for the real time human identification using single lead human electrocardiogram. The proposed system extracts special parts of the ECG signal starting from the P wave, the QRS complex and ending with the T wave for that we used the multiresolution wavelet analysis. Different features are selected and reconstructed from both amplitude and time interval of the ECG signal. The matching decisions are evaluated on the basis of correlation coefficient between the features and the Radial Basis function network classifier is introduced for validation and comparison. The performance evaluation was carried out on four ECG public databases with a total of 149 persons subjected to different physical activities and heart conditions, the preliminary results indicate that the system achieved an accuracy of 90-93%.**

Keywords- Biometrics; Discrete Wavelet transform(DWT); Electrocardiogram(ECG); Feature Extraction; Neural Network; QRS detection; Template Matching.

I. INTRODUCTION

The need for highly reliable security systems is dictated by the modern life style. Starting from airports and crossing through key administration buildings and ending at transportation stations, all of these facilities are frequented by a large crowd. Hence, a need for identity verification by means of automatic biometric systems becomes a must in order to speed up the verification process and prevent criminals from penetration.

This is because identity fraud these days is one of the most common criminal activities and is related to massive costs and serious security issues. Several techniques have been implemented to be able to prevent those issues. Early developed biometric methods, such as fingerprint and face and iris recognition, have been used with their advantages and shortcomings. On the other hand, different types of biometrics are under investigation, such as DNA analysis which is a very costly operation, keystroke, gait, ear shape, hand geometry, iris, retina, written signature, palm print and vein pattern [1]. However, these biometrics modalities either cannot provide reliable performance in terms of recognition accuracy (e.g., gait) or are not robust enough against falsification. For instance, face is sensitive to artificial disguise, fingerprint can be recreated using latex, and iris can be falsified by using contact lenses with copied iris features printed on [2]. New types of biometrics, such as electrocardiography (ECG), are based on physiological signals, rather than more traditional biological traits, means they can be used as biometrics signatures. 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 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 [3]. Perhaps the most important advantage in using ECG as a tool to distinguish between different individuals is that it cannot be forged. Electrocardiograph is the graph of the heart's electric activity. It is recorded through a non-invasive method i.e. it does not involve injecting any kind of surgical equipment into the body; rather it is taken from the outer surface skin, usually by attaching electrodes to the person's skin and is recorded to be displayed [4], ECG electrodes pick up electrical impulses generated by the polarization and depolarization of the cardiac tissue and converts them into waveform.

A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex, and a T wave. The P wave is generated when the right and left atria of the heart are depolarized and it corresponds to low frequency spectral components, 10-15 Hz [5]. The QRS complex reflects the depolarization of the right and left ventricles. It has much steeper slopes and its spectrum is concentrated in the interval of 10-40 Hz. Finally, the T wave occurs during ventricular repolarization and its position depends on the heart rate, appearing closer to the QRS complex when the rate increases, Atrial repolarization is less commonly observed in ECG traces and is labeled as a U wave [6].

For the purpose of human identification, feature extraction, and classification based approach were mostly used. Features can be fiducial or non-fiducial. Fiducial points are marker on ECG wave such as PR interval etc [3]. But marking these points is highly dependent on machine. Non-fiducial approach is often based on discrete cosine transform (DCT) of auto correlated sequence [7].

It is well-known that ECG signal plays a crucial role as a diagnostic tool in the field of pathologies explorations. Likewise, recently it has been introduced as a biometric [5]. Willem Einthoven developed the ECG method in the early 1900s. The origin of the electrical activity measured by ECG is

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in the muscle fibers of different parts of the heart. Biel et al. [3] showed the possibility of identifying individuals based on a ECG signal. Irvine *et al*. [8] developed a system to exploit heart rate variability as a biometric for individual identification. Israel *et al* [9] claimed the uniqueness of an individual's ECG by making use of temporal features. Israel *et al.* [10] developed a system that combines Palm image and ECG signal for biometric identification. Shen *et al.* [11] developed a two-step algorithm for individual verification from ECG signal.

In this paper, we present a real-time system for individual's verification and identification with the electrocardiogram (ECG) based on fiducial points extraction. The system is evaluated using four public databases with persons subjected to different physical and heart conditions.

The remaining of the paper is organized as follows. In section II we give a brief description of the wavelets and multiresolution analysis followed by the proposed scheme to analyze the signal and extract the features in section III. The results will be discussed in section IV followed by a conclusion in the last section.

II. WAVELET AND MULTIRESOLUTION ANALYSIS

Wavelets are finite support duration waveforms that have an average value of zero. Whereas Fourier series analysis exploits sinusoids as bases functions, wavelet analysis decomposes signals using an orthonormal family of basis functions. Sinusoids are useful in analyzing periodic and time-invariant phenomena, while wavelets are well suited for the analysis of transient, time-varying signals, thus well suited for ECG signals. Generally, wavelet transform is computed by convolving the signal under processing f(t) and the wavelet function $\boldsymbol{\psi}(t)$. The discrete wavelet transform (DWT) is given by equation (1):

$$X_{j,k} = \int_{-\infty}^{\infty} f(t)\, \psi_{j,k}(t)\, dt \quad (1)$$

The approximation coefficient of the signal f(t) is represented as

$$A_{j,k} = \int_{-\infty}^{\infty} f(t)\, \varphi_{j,k}(t)\, dt \quad (2)$$

Where $\varphi(t)$ is scaling function, j and k are scale and location respectively. For a range of scale n, the original signal f(t) under discrete wavelet transform can be represented as:

$$f(t) = f_n(t) + \sum_{j=1}^{n} d_j(t). \quad (3)$$

Where $f_n(t)$ is mean signal approximation and is given by:

$$f_n(t) = A_{n,k}\varphi_{n,k}(t) \quad (4)$$

And $d_j(t)$ is detail signal approximation in scale j. Thus, given an approximation of a signal using translations of a mother wavelet up to some chosen scale. The wavelet transform as such decomposes a signal into two sub signals – detail signal and approximation signal. Detail signal contains the upper half of the frequency components and approximation signal contains the lower half. The decomposition can be further repeated on the approximation signal in order to get the second detail and approximation signal. Thus, in discrete wavelet domain, multiresolution analysis can be performed.

The proposed multiresolution wavelet based approach for ECG feature extraction is performed with Daubechies 8 (Db8) wavelet. There is no predefined rule to select a wavelet for a particular application, rather the selection is application oriented. It is a common practice to select a wavelet function which is having similar physical properties as the subject signal [12]. Daubechies wavelets have structural similarity with QRS complex and their energy spectrums are concentrated around low frequencies. Thus, it is expected that some detail coefficients from multiresolution decomposition will show better resemblance with QRS complex of the ECG wave in time scale domain [13]. Decomposition of the signal is done up to level eight. Level of decomposition is taken to be a high value to ensure the presence of some low frequency components of original signal.

III. THE PROPOSED SCHEME

A biometric system is essentially a pattern recognition system that operates by acquiring biometric data from an individual, extracting a feature set from the acquired data, and comparing this feature set against the template set in the database. Fig. 1 shows the general block diagram of a biometric identification system using ECG Signal.

In order to extract information from the ECG signal, the raw ECG signal should be processed. In the ECG processing stage, the noise is removed from the raw ECG signal and the different ECG waves are detected. In the next stage, the features extraction is performed to form distinctive personalized signatures for every person. The purpose of the features extraction process is to choose the most discriminative information that allows the system to distinguish between persons.

A. ECG Waves' Detection

The most important wave in the ECG signal is R wave. Therefore, maximizing the detection accuracy of this cornerstone wave is a perquisite for the entire extraction accuracy. After the detection of the R wave, all other waves of the ECG signal including T, P, Q and S waves can be easily located with reference to R-peak.

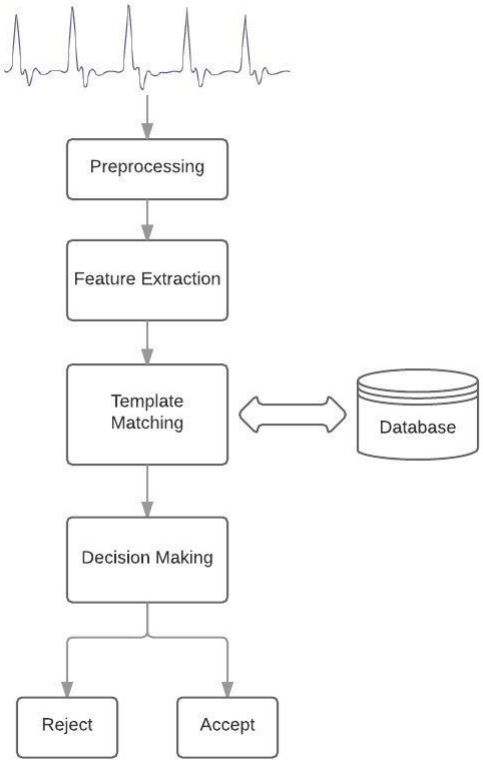

Figure 1. Typical Architecture of a biometric identification system

1) QRS Peaks

Displaying wavelet decomposition coefficients on Fig. 2 and Fig. 3 for scales 1 to 4 and 5 to 8, respectively, suggests that small scales represent the high frequency components and the large scales represent the low frequency components of the signal. The first and eighth level reconstruction coefficient represent high frequency and low frequency contents of the ECG waveform, respectively, which in most of the cases represent noise. From the decomposition results, it is clear that the QRS complex is concentrated at level 3, 4 and 5 and it shows better resemblance. Thus, d3, d4 and d5 coefficients are exploited for the detection of QRS complex. The coefficients are reconstructed using equations (5) and (6) and using adaptive thresholding, the R peaks are identified as the maximum amplitude points.

$$f = d3 + d4 + d5. \quad (5)$$

$$g = f * f. \quad (6)$$

Once the R peak is detected, the Q and S points are identified. Both waves have high frequency and low amplitude for that the decomposition coefficients from d2 to d5 are reconstructed using equation (7)

$$h = d2 + d3 + d4 + d5. \quad (7)$$

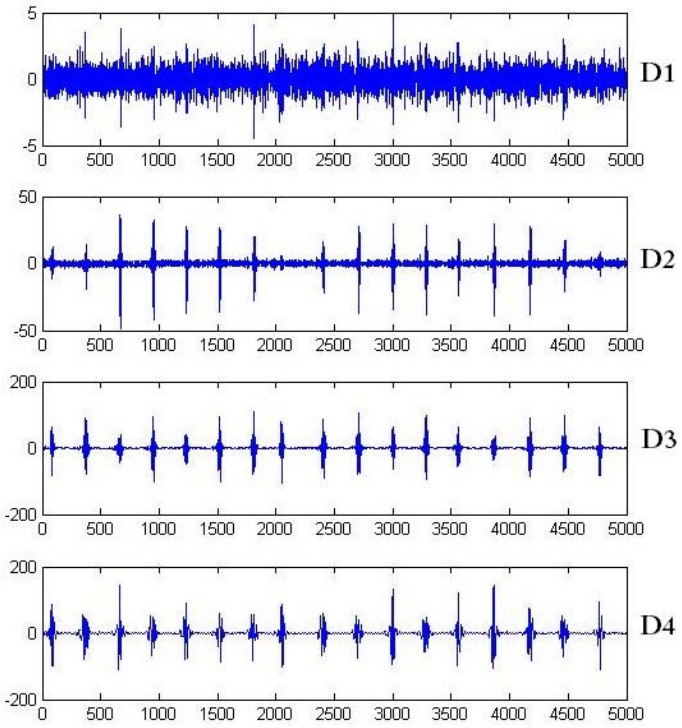

Figure 2. Wavelet coefficients for scale levels 1-4

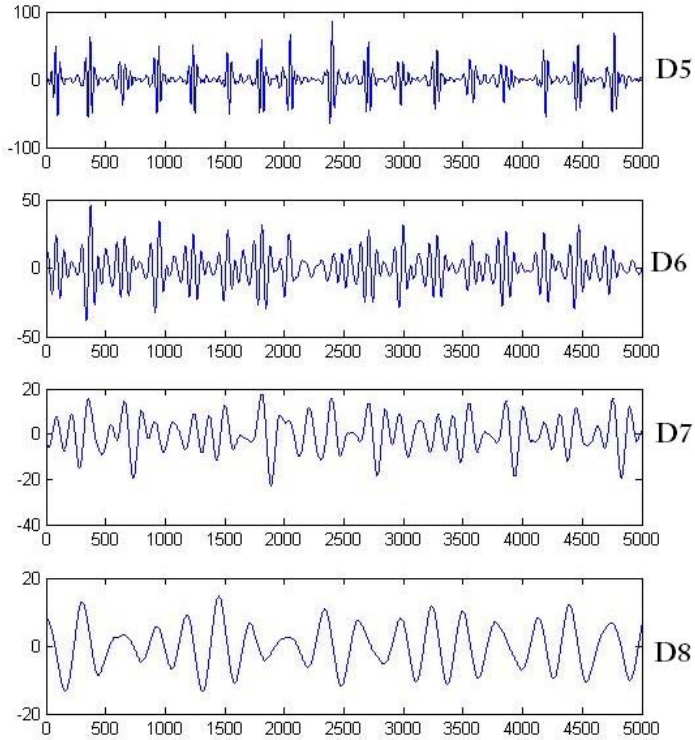

Figure 3. Wavelet coefficients for scale levels 5-8

Q and S points are found in either side of the R wave. So, the first zero slope points on either side of the R peak will represent Q and S point. Using five-point differentiation on "h" described by equation (8), the Q and S points are identified as the maximum amplitude points before and after the zero crossing.

$$h'(x) = \frac{-h(x+2)+8h(x+1)-8h(x-1)+h(x-2)}{12}. \quad (8)$$

2) P and T peaks

Both the T and P waves are mainly at scale levels 6, 7 and 8. But, baseline drift is serious at scale 8, so reconstruction coefficients d6 and d7 are selected to detect T and P waves. Hence the reconstructed wave is formed as

$$k = d6 + d7. \quad (9)$$

Then the T peak is identified as the maxima after the detected S point within a predefined interval. As the T peak is pointed out. P wave is detected by the similar method as T before the Q point.

B. Features Selection

ECG varies among individuals' due to their different anatomy and physiology of the heart. There is a change in normal limits of ECG parameters with age and sex. The internal features of ECG may vary if a person does any physical work and also changes with time (age). These changes are not consistent and vary from one individual to another. These effects are particularly reflected in P wave duration and PR interval. Amplitude of the waves refers to the actual measurement of the electrical activity within the heart. The amplitude of P wave in ECG does not change with time. Similarly, other amplitude features change on small scale including the QRS Complex. For that we selected the maximum amplitude among different peaks for individual's identification. Also, interval durations are added to get more information about the person. Some selected features for our work are PR, PQ, RS, PS, RQ, RT, TS, TQ, QS, PT amplitude as well as the interval durations: QS, PS, PR, PQ, PT, RT, ST, QT.

C. Classification and Identification

Classification represents the last step of the identification procedure. For this step, every input feature vector is compared to the ones stored in the database in order to find the best match. Template Matching (TM) can be used to achieve this objective. TM is based on the correlation coefficient, which is estimated between every input and the corresponding ones stored in the system. The correlation coefficient is a normalized statistic that reveals the degree of similarity of signals. The range of values is [-1, 1], with 1 indicating a perfect match, 0 indicating nonrelated signals, and -1 indicating an inverse relationship. When the average correlation coefficient is less than 95% then there is no match between the template and the subject. If the average correlation coefficient is greater than 95% then there is match between the template and the subject. For the correlation coefficient measure, the person associated with the enrolled data with the highest correlation coefficient is selected as a match. The Correlation coefficient is:

$$r_{xy} = \frac{\sum_{n=1}^{N}(x_n-\bar{x})(y_n-\bar{y})}{\sqrt{\sum_{n=1}^{N}(x_n-\bar{x})^2\sum_{n=1}^{N}(y_n-\bar{y})^2}}. \quad (10)$$

Where r_{xy} is the correlation coefficient between the template y_n and the stored data x_n .In the stored data x_n (n=1, 2,3...N), n denotes the number of the samples and N is the length of the ECG template. Here, N is the total number of ECG samples needed to contain full heart beats, where each beat contains a QRS complex, a T wave and a P wave.

The goal is to locate those subjects in the database, which can be regarded as possible candidates for a given input signal. This measure can't be exclusively sufficient to perform identification, for that we use another classifier which is the Radial Basis Function network (RBFN). A Radial Basis Function Network performs classification by measuring the input's similarity to examples from the training set. Each RBFN neuron stores a "prototype", which is just one of the examples from the training set. When we want to classify a new input, each neuron computes the Euclidean distance between the input and its prototype. If the input more closely resembles the class A prototypes than the class B prototypes, it is classified as class A. A typical architecture of an RBF Network consists of an input vector, a layer of RBF neurons, and an output layer with one node per category or class of data. The neuron stores a vector which is just one of the vectors from the training set. Each RBF neuron compares the input vector to its prototype, and outputs a value between 0 and 1 which is a measure of similarity. If the input is equal to the prototype, then the output of that RBF neuron will be 1. As the distance between the input and prototype increases, the response falls off exponentially towards 0. Each RBF neuron has an activation function which measures the similarity between the input and its prototype vector (taken from the training set). Input vectors which are more similar to the prototype return a result closer to 1. There are different possible choices of similarity functions, but the most popular is based on the Gaussian. Below is the equation for a Gaussian function:

$$\varphi(x) = e^{-\beta\|x-\mu\|^2}. \quad (11)$$

In the Gaussian distribution, μ refers to the mean of the distribution. Here, it is the prototype vector which is at the center of the curve. The parameter β controls the width of the curve and it is equal to $1/(2\sigma^2)$, σ is the standard deviation .

The network output consists of a set of nodes, one per category that we are trying to classify. Each output node computes a sort of score for the associated category. Typically, a classification decision is made by assigning the input to the category with the highest score. The score is computed by taking a weighted sum of the activation values from every RBF neuron. By weighted sum we mean that an output node associates a weight value with each of the RBF neurons, and multiplies the neuron's activation by this weight before adding it to the total response. Because each output node is computing the score for a different category, every output node has its own set of weights. The output node will typically give a positive weight to the RBF neurons that belong to its category, and a negative weight to the others.

During the training process, the parameters of the prototype which are the mean and the standard deviation are learned using the K-means clustering algorithm and the output weights are calculated, we use a label 1 for the samples that belong to the same category and 0 for the others. When evaluating the input vector, the maximum output from the RBF network is considered as the identity of the person. [14]

IV. RESULTS AND DISCUSSION

In this part, we are going to assess the performance of the individual's identification using the selected features mentioned before. The algorithm was developed under the MATLAB software and it was tested on four ECG public databases available at the PhysioNet website: The ECG-ID Database [15], The MIT-BIH Arrhythmia Database [16], The MIT-BIH Normal Sinus [17], and The STAFF III Database [18].

The Correlation Coefficient was used in the identification task after selecting the possible candidates using the template-matching method. Eighteen features were used for Correlation Coefficient classification. The class of an input template can be found by calculating the minimum distances between the feature vectors in an input template and all pre-selected candidates. The experimental results summarized in the Table I and Table II show that ECG data is unique to an individual and that the features extracted are convenient for biometric systems.

The Identification based on correlation coefficient is an effective way. It achieves good Identification performance due to the fact that only one template is compared against every subject stored. As we can see, the correct identification is 135 out of 149 giving average identification rate of 90.3%. When trying to cross-identify persons from another database which doesn't belong to the system, the algorithm misclassified only4 out from 123, achieving a false acceptance rate of 3.25%.

TABLE I. RESULTS OF CALSSIFICATION USING CC

Database	Total Nbr of Subject	Nbr of Subjects misidentified	Nbr of Subjects identified	Accuracy
MIT-BIT Normal Rhythm	18	2	16	88.88%
ECG-ID	40	3	37	92.5%
ECG STAFF III	43	5	38	88.37%
MIT-BIT Arrhythmia	48	4	44	91.66%
Total	149	14	135	90.60%

TABLE II. RESULTS OF CROSS-IDENTIFICATION DIFFERENT SUBJECTS

Database	Subjects to be Identified	Nbr of Subjects	Nbr of Subjects misidentified	False Acceptance rate
ECG-ID	ECG STAFF III	40	1	2.5%
ECG-ID	MIT-BIT Normal Rhythm	40	3	7.5%
ECG STAFF III	MIT-BIT Normal Rhythm	43	0	0%
Total		123	4	3.25%

TABLE III. RESULTS OF CLASSIFICATION USING RBFN

Database	Nbr of Train/Test	Nbr of identified Subjects	Nbr of Subjects	Accuracy
MIT-Normal	20/30	860	900	95.5%
ECG-ID	5/7	442	480	92%
ECG STAFF III	20/80	3959	4300	92%

MIT-Arrhythm	20/30	2240	2400	93.3%
TOTAL	65/147	7501	8080	92.8%

TABLE IV. COMPARISION OF DIFFERENT METHODS

Methods	Accuracy
Our Method	90-92%
Features extraction with Euclidean distance Classifier	82%
Wavelet distance based classification	89%
Wavelet coefficient based algorithm	93%
Template matching and distance classification	98%
Discrete cosine transform/QT normalization	100%

For the sake of comparison, the Radial Basis Function Classifier is used as a second classifier. The RBF Classifier is more complex and more computations are needed. The results of the RBF are shown in Table III. Clearly, the RBF outperforms the correlation coefficient method; the achieved identification accuracy is 92.8%.

Table IV. showcase the results from our method and other existing methods. The method followed in this paper is based on fiducial point extraction and so does the three first methods: Features extraction with Euclidean distance classifier (82%), wavelet distance based classification (89%) and wavelet coefficient based algorithm (93%). Both, template matching and distance classification (98%) and discrete cosine transform/ QT normalization (100%) are non-fiducial method, which doesn't require to detect the different waves from the signal. Unlike, the methods highlighted in Table IV, our method was tested on different conditions including physical activities and heart conditions.

As mentioned before this work is based on fiducial point extraction and it is crucial to accurately detect these points. Marking these points and features is not just important in human identification but also can help detect the different heart pathologies and whether the person have a heart disease or not, so we can make a 2-in-1 system to both identify the person and detect any heart pathologies for that person. Also compared to the other methods, the one we proposed is very simple and have much more space for improvements in the future.

V. CONCLUSION

This work concentrates on using a single lead ECG signal for human identification based on the feature extraction using multiresolution wavelet analysis and classifier technique using Correlation Coefficient and Radial Basis Function network. The proposed scheme has been validated over four public databases and substantially achieved promising results in the presence of different conditions such as physical activities and heart arrhythmias. One way to improve the system is by normalizing time-domain ECG signal to eliminate the time variability of the signal as a further work. Also, a hybrid system which fuses two biometric systems or more may considerably improve the identification rate.

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