Identification of Individuals using Electrocardiogram

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Abstract
Protection anxiety is to be increased as the technology for forgery grows. Reliable personal Identification and prevention of forged identities is one of the major tasks. Currently, Biometrics is being used extensively for the purpose of security measures. Biometric recognition provides strong security by identifying an individual based on the feature vector(s) derived from their physiological and/or behavioral characteristics. It has been proved that the human Electrocardiogram (ECG) shows adequately unique patterns for biometric recognition. Individual can be identified once ECG signature is formulated. This paper presents a systematic Template matching for Identification of individuals from ECG data. This work establishes that ECG signal is a signature like fingerprint, retinal signature for any individual Identification. Samples of individuals from the MIT/BIH database were taken. The matching decisions are evaluated on the basis of correlation coefficient between features. Preliminary experimental results indicate that the system is accurate (99%), robust, error rate is smaller than 0.9 and achieves a good result for Identification process.

Keywords
Biometric, Electrocardiogram (ECG), QRS complex, Amplitude Features, Template Matching.

1. INTRODUCTION

Conventional methods of identity verification based on strategies such as ID cards, Social security numbers and passwords provide less security. There are many applications for a more secure, easily-applied, low-cost method to identify (or to verify) the individuals. Human Identification plays an important role in many applications, especially in security systems through Biometric. Recent advancements have made Identification of people based on their biological, physiological, or behavioral qualities a reasonable approach for access control [1]. Establishing human identity reliably and conveniently has become a major challenge for a modern-day society.
Biometric is an “automatic”, “real-time”, “non-forensic” for human Identification. Biometric Identification or verification shows great potential in bridging some of the existing security gaps. To reach a higher security level, specific features from the human must be selected to recognize a person. Biometrics use anatomical, physiological or behavioral characteristics that are significantly different from person to person and are difficult to forge. This is useful in security applications and authentication devices, offering an alternative to conventional methods.
A number of biometrics modalities have been investigated in the past, examples of which include physiological traits such as face, fingerprint, iris, and behavioral characteristics like gait and keystroke. Human Identification through ECG is feasible and highly effective [2-3]. The way the heart beats is a unique & private feature of an individual. People have similar but different ECG. Figure - 1 shows an example of two persons with exactly the same age, sex, weight and height who have completely different ECG patterns

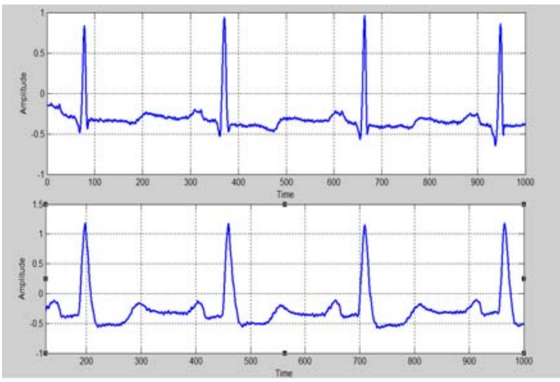

Figure - 1 Two persons having different ECG patterns

There is strong evidence that heart’s electrical activity embeds highly unique characteristics, suitable for applications such as the recognition of humans [4-6]. The validity of using ECG for biometric recognition is supported by the fact that the physiological and geometrical differences of the heart in different individuals display certain uniqueness in their ECG signals [7-9].
The advantage of ECGs in biometric systems is their robust nature against the application of falsified credentials. Further, ECG signal is a life indicator, and

Manuscript received December 5, 2010
Manuscript revised December 20, 2010

can be used as a tool for liveness detection increasing system reliability. ECG person Identification relies on the *all-or-nothing* phenomena of action potentials and assumes that the PQRST waveform shape remains relatively constant over a reasonable time period.

2. BIOMETRICS

The term "biometrics" is derived from the function of measuring biological characteristics. It refers to any and all of a variety of Identification techniques which are based on some physical and difficult-to-estrange characteristic. Biometrics is also referred to as 'positive Identification', because it provides greater confidence that the Identification is accurate. Since it uses individual personal characteristics to verify or recover identity, it becomes a successor to the personal Identification token. The technique of using biometric methods for Identification can be widely applied to forensics, ATM banking, communication security, time and attendance, and access control. It also plays an important role in enhancing homeland security.

Biometric techniques involve 'metrics' or measurements of some kind, rather than depending merely on familiar or hidden methods. Taxonomy of Biometric Techniques is given below.

- **appearance** - the familiar passport descriptions of height, weight, colour of skin, hair and eyes, visible physical markings; Gender; race; facial hair, wearing of glasses; supported by photograph

- **social behaviour** - habituated body-signals; general voice characteristics; style of speech; visible handicaps; supported by video-film

- **bio-dynamics** - the manner in which one's signature is written; statistically - analysed voice characteristics; keystroke dynamics, particularly in relation to login-id and password

- **natural physiography** - skull measurements; teeth and skeletal injuries; thumbprint, fingerprint sets and handprints; retinal scans; earlobe capillary patterns; hand geometry; DNA-patterns

- **Imposed physical characteristics** dog-tags, collars, bracelets and anklets; brands and bar-codes; embedded micro-chips and transponders

Behavioral traits often reveal personalized patterns which can be coupled with recognition systems. This class of biometric attributes has great prospective in surveillance applications, as it is easy and non invasive to monitor someone's gait, keystroke or signature. However, factors such as stress, drug usage, age and illness can lead to significant variability among multiple recordings of the same person. In addition, behavioral-based Identification methods are rather exposed to interruption, as they can be easily mimicked. Biometric traits are features highly correlated to a particular person [10].

Biometric technology involves the capture and storage of a distinctive, measurable characteristic, feature, or trait of an individual for subsequently recognizing that individual by automated means. A biometric system is essentially a pattern recognition system that recognizes a person by comparing the uniquely specific biological or physical characteristic to the stored characteristic. Samples are taken from individuals to see if there is similarity to biometric references previously taken from known individuals. The system applies a specialized algorithm to the sample and then compares it to the template sample to determine if the individual can be recognized [1].

Figure - 2 shows the Enrolment and verification process of Biometric system. In the case of access control, a person requesting access is asked to submit a sample and claim an "identity" or "oneness of source" with a template already stored. If the acquired sample is adequately similar to the claimed stored template, the access authorizations for the template can be checked and applied to the live person now seeking access. A reference model or reference containing the biometric properties of a person is stored in the system by recording his/her characteristics. These characteristics may be acquired several times during enrolment in order to get a reference profile that corresponds most with reality.

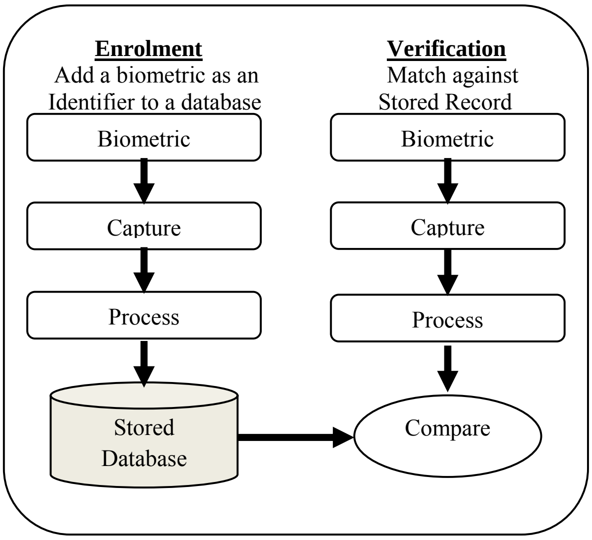

Figure -2 Biometric-based system

3. ELECTROCARDIOGRAM(ECG)

The Electrocardiogram is a biological (Biomedical) signal. It is a quasi-periodical, rhythmically repeating signal, synchronized by the function of the heart, which acts as the generator of bioelectrical events. It is the electrical manifestation of the contractile activity of the heart. The Electrocardiogram is a graphic record of the direction and magnitude of the electrical activity that is generated by depolarization and repolarization of the atria and ventricles. It provides information about the heart rate, rhythm, and morphology. Normally, ECG is recorded by attaching a set of electrodes on the body surface such as chest, neck, arms, and legs. The normal value of heart beat lies in the range of 60 to100 beats/minute.

The ECG is characterized by a recurrent wave sequence of P, QRS and T- wave associated with each beat. A typical ECG wave of a normal heartbeat consists of a P wave, a QRS complex, and a T wave. Figure - 3 depicts ECG waveform with P, Q, R, S, T and U characteristics and standard ECG intervals. The performance of ECG analyzing depends mainly on the accurate and reliable detection of the QRS complex, T and P waves. Both duration and amplitude of each wave (P and T), complex (QRS) are clinically important

The P-wave represents the activation of the upper chambers of the heart, the atria, while the QRS complex and T-wave represent the excitation of the ventricles or the lower chamber of the heart. The detection of the QRS complex is the most important task in automatic ECG signal analysis. The QRS complex consists of three characteristic points within one cardiac cycle denoted as Q, R and S.

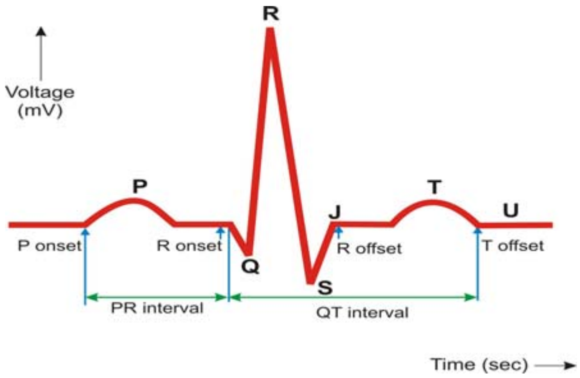

Figure - 3 An ECG waveform with standard ECG intervals

4. METHODOLOGY

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. Figure - 4 shows the Architecture of a Biometric Identification System using ECG Signal.

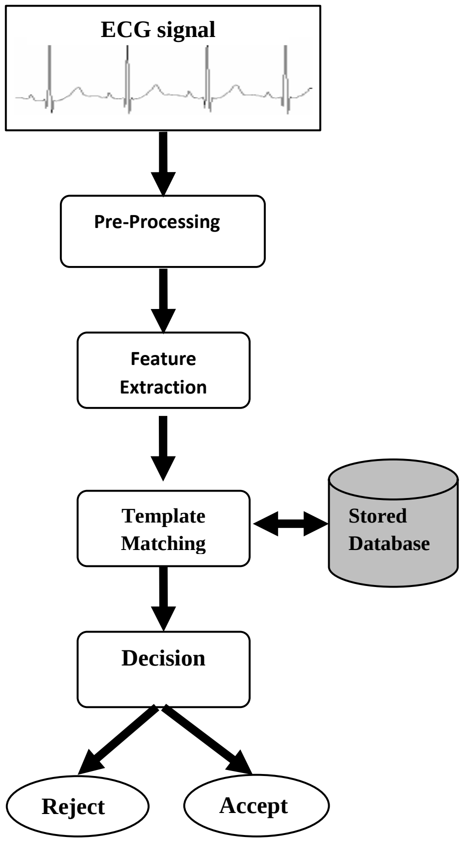

Figure - 4 Biometric Identification System

In order to extract information from the ECG signal, the raw ECG signal should be processed. ECG signal processing can be roughly divided into two stages by functionality: Preprocessing and Feature Extraction. The Preprocessing stage removes or suppresses noise from the raw ECG signal. Feature Extraction is performed to form distinctive personalized signatures for every subject. The purpose of the Feature Extraction process is to select and retain relevant information from original signal

Wavelet Selection

A number of techniques have been devised by the researchers to detect the characteristics in ECG [11-14]. Recently wavelet transform has been proven to be useful tool for non-stationary signal analysis [15]. The use of the Wavelet Transform has gained popularity in time-frequency analysis because of the flexibility it offers in analyzing basis functions. The choice of wavelet depends upon the type of signal to be analyzed. The wavelet similar to the signal is usually selected. Among the existing wavelet approaches, (continuous, dyadic, orthogonal, biorthogonal), we use real dyadic Wavelet Transform because of its good temporal localization properties and its fast calculations. Daubechies (Db4) Wavelet has been found to give details more accurately than others. Moreover, this Wavelet shows similarity with QRS complexes and energy spectrum is concentrated around low frequencies. Therefore, we have chosen Daubechies (Db4) Wavelet for extracting ECG features in our application [16-17]. The Daubechies Wavelet is shown in Figure - 5

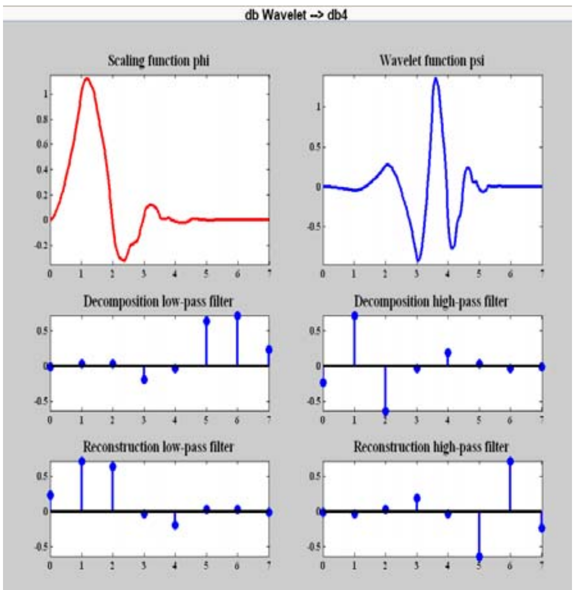

Figure - 5 Daubechies4 Wavelet

Pre-processing

Generally, the presence of noise will corrupt the signal, and make the feature extraction and classification less accurate. The collected ECG data in raw format usually contains lot of noise, which include low-frequency components that cause baseline wander, and high-frequency components such as power-line interferences.

Baseline Drift Removal

Baseline wandering is one of the noise artifacts that affect ECG signals. We use median filters (200-ms and 600-ms) to eliminate baseline drift of ECG signal [18]. The process is as follows

- The original ECG signal is processed with a median filter of 200-ms width to remove QRS complexes and P waves.
- The resulting signal is then processed with a median filter of 600-ms width to remove T waves. The signal resulting from the second filter operation contains the baseline of the ECG signal.
- By subtracting the filtered signal from the original signal, a signal with baseline drift elimination can be obtained.

Noise Removal

After removing baseline wandering, the resulting ECG signal is more stationary and explicit than the original signal. However, some other types of noise might still affect Feature Extraction of the ECG signal. To remove the noise, we use Discrete Wavelet Transform. This first decomposes the ECG signal into several subbands and then modifies each wavelet coefficient by applying a threshold function, and finally reconstructs the denoised signal. The high frequency components of the ECG signal decreases as lower details are removed from the original signal. As the lower details are removed, the signal becomes smoother and the noises disappears since noises are marked by high frequency components picked up along the ways of transmission.

Feature Extraction

QRS-Detection

The QRS complex is considered as the most striking waveform of the electrocardiogram and hence used as a starting point for further analysis or compression schemes. The detection of the QRS complex is based on modulus maxima of the Discrete Wavelet Transform (Daubechies (Db4)). The QRS complex produces two modulus maxima with opposite signs, with a zero crossing between them. Therefore, detection rules (thresholds) are applied to the Wavelet Transform of the ECG signal [19].

P wave detection

The P wave generally consists of modulus maxima pair with opposite signs, and its onset and offset correspond to the onset and offset of this pair. This pair of modulus maxima is searched for within a window prior to the onset of the QRS complex. The search window starts at 200 ms before the onset of the QRS complex and ends with the onset of the QRS complex. The zero crossing between the modulus maxima pair corresponds to the peak of the P wave.

T wave detection

A normal T wave also consists a modulus maxima pair with opposite signs [20]. The T wave is found at the zero-crossing between the two modulus maxima. The T wave's energy is mainly preserved between the scales 2^3 and 2^4. Therefore it was more appropriate to turn away from the dyadic scales and to choose the scale 10 for the WT. At scale 10 we analyze the signal and search for modulus maxima larger than a threshold ε . This threshold is determined by using the Root Mean Square (RMS) of the signal between two R-peaks. The zero crossing between the modulus maxima pair corresponds to the peak of the T wave. The Features Extracted are shown in Figure -6

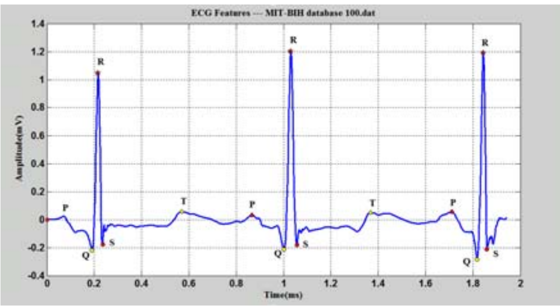

Figure - 6 Features Extracted from ECG Signal

Selected Features

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. It is observed that amplitude of P wave in ECG does not change with time. Similarly other amplitude features are changes on small scale.

Since the amplitude features have minimum change with age (amplitude of P wave remain constant throughout life), maximum amplitude features are selected for individual Identification. Some features selected for our work are PR, RQ, RS, RT, PS, TS, PQ, TQ amplitude shown in Figure - 7.

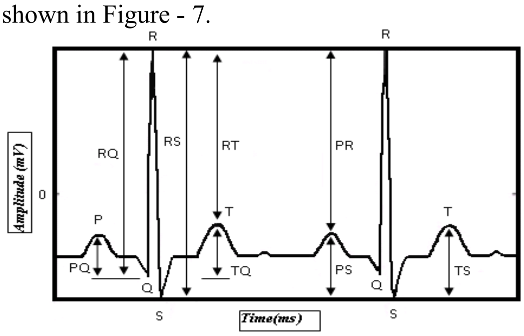

Figure - 7 Amplitude features

Identification Process

The biometric Identification is a “one-to-many” problem, where an unknown signal is compared to the entries stored in the database. There are two Processes

- Enrolment Process
- Identification Process.

In enrolment process, the features are extracted from the subject (individual) and stored in the database. In Identification process, the features are extracted from the template and compared against the stored features. The comparison is performed using Template Matching with the Correlation Coefficient (CC) [21] and Mean distance measure.

The Correlation Coefficient is a statistical criterion, showing the degree of similarity of any two signals. It takes values in [−1, 1] with 1 demonstrating a perfect match between signal and template, 0 non related signals and -1 an inverse relationship. When the average correlation coefficient is less than 85% then there is no match between the template and the subject. If the average correlation coefficient is greater than 85% then there is match between the template and the subject. For the CC measure, the person associated with the enrolled data with the highest CC is selected as a match. The correlation coefficient is

$$r_{xy} = \frac{\sum_{n=1}^{N}\left(x_n - \bar{x}\right)\left(y_n - \bar{y}\right)}{\sqrt{\sum_{n=1}^{N}\left(x_n - \bar{x}\right)^2 \sum_{n=1}^{N}\left(y_n - \bar{y}\right)^2}} \tag{1}$$

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 m full heart beats, where each beat contains a QRS complex, a T wave and a P wave.
The complete Extracted ECG feature set contains of all P waves, QRS complexes, T waves and Amplitudes of enrolment data x_n. During the Identification process, the template data y_n is compared against the enrolment data bounded by a threshold τ . The threshold is introduced because of the reality that the recognition data can never be exactly identical as the enrolment data in ECG.
During the Identification stage (when matching is performed on a one-to-one basis), a person claims that he or she is the person with identity. The decision logic (DL) is used as verification function to provide its decision $\{H_0, H_1\}$. H_0 - indicates the claim is true and H_1 - the claim is false.
In Mean distance measure, the amplitude feature from each beat is obtained and the mean value is calculated for all feature of a particular subject and stored in the memory. Testing is done by comparing the stored features with the features extracted from the Template. If the Template feature is laying in between ±10% of the stored reference mean of the subject, then it is assumed true

5. RESULT AND CONCLUSION

The proposed method was tested on ECG data from MIT/BIH Arrhythmia Database [22], which was sampled at 360 Hz with 11 bit resolution. The methods were developed under Matlab software.
In enrolment process we select $m=8$ full heart beats from a particular subject, extract the amplitude feature from each beat and calculate the mean and save this data in memory as Average amplitude features. The stored amplitude features of 10 Subject are shown in Table – 1.
The result of Identification process on the sample data taken from MIT/BIH database has been shown in Table – 2. Here the result of each individual is verified with different cases. The table presents the matching of the data
The information about the Features obtained is very useful for ECG Classification, Authentication, and Identification performance. The overall sensitivity of the detector improves. A more robust level of security and protection can be achieved in the Identification process. The result shows that ECG data is unique to an individual and that the features extracted are feasible biometric. By using Template Matching, data acquisition time is minimized and yields the correct decision. 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 in the database. Also the normalization of the Extracted features serves as an input to a system that allows automatic cardiac diagnosis. Further verification of individuals can be done used statistical theory of sequential probability procedures.

Table – 1 Average amplitude features

	PQ	PS	TS	TQ	RP	RQ	RS	RT
Subject 1	0.2753	0.2165	0.2278	0.2866	1.1000	1.3752	1.3164	1.0886
Subject 2	0.1905	0.1449	0.2475	0.2930	1.2828	1.4733	1.4277	1.1802
Subject 3	0.0580	0.3233	0.4460	0.1807	1.0069	1.0835	1.3489	0.9029
Subject 4	0.2822	0.4924	0.4711	0.2608	0.9921	1.2742	1.4845	1.0134
Subject 5	0.1907	0.3089	0.4383	0.3201	1.3211	1.5118	1.6299	1.1917
Subject 6	0.4331	0.7290	1.2029	0.9070	1.9597	2.3927	2.6887	1.4857
Subject 7	0.0453	0.0468	0.1523	0.1508	0.2421	0.2874	0.2889	0.1366
Subject 8	0.1111	0.5856	0.7534	0.2789	0.9148	1.0259	1.5004	0.7470
Subject 9	0.0853	0.2269	0.5759	0.4343	1.3509	1.4551	1.5966	1.0208
Subject 10	0.3055	0.3509	0.1976	0.1522	0.6086	0.9142	0.9596	0.7620

Table - 2 The result of Identification process

	Subject 1	Subject 2	Subject 3	Subject 4	Subject 5	Subject 6	Subject 7	Subject 8	Subject 9	Subject 10
Subject 1	8	5	2	5	2	0	0	1	3	0
Subject 2	5	8	1	1	5	0	0	2	2	0
Subject 3	2	1	8	2	2	0	0	2	0	1
Subject 4	5	1	2	8	2	0	0	3	2	1
Subject 5	2	5	2	2	8	0	0	0	3	0
Subject 6	0	0	0	0	0	7	2	0	0	0
Subject 7	0	0	0	0	0	0	8	0	0	0
Subject 8	1	2	2	3	0	0	0	8	0	0
Subject 9	3	2	0	2	0	0	0	0	8	0
Subject 10	0	0	1	1	0	0	1	0	0	8

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