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ECG Biometric Identification - A Review

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ABSTRACT

The electrocardiogram (ECG) is one of the latest biometric modality. This paper takes into account most of the technique which are applied to use the electrocardiogram as a biometric identification. Here we differentiate the approach based on features and classification scheme finally a comparative study of authentication performance of few ECG biometric is presented by using available database. The comparative analysis includes the cases where training and testing data is received from different sessions of same day or from different days. In this authentication process it is observed that most of the algorithm perform as per requirement when training data is received from the same session but a degradation occur when data is received from the different session. Due to degradation in performance, multiple training sessions are used.

Keyword: Identification, Recognition, Verification, Classification, Biometrics, ECG.

I. INTRODUCTION

Biometric technologies are among fast-developing methodologies in the fields of information security and these are entering in all aspect of human activity .This development aims to an identification system based on ECG electric current. Electric currents which are generated by heart as its beats spread in heart as well as I other parts of body. Hence shapes of ECG waveforms depend not only on heart but also anatomic feature of body. Thus ECG can be considered as human biometric characteristic.

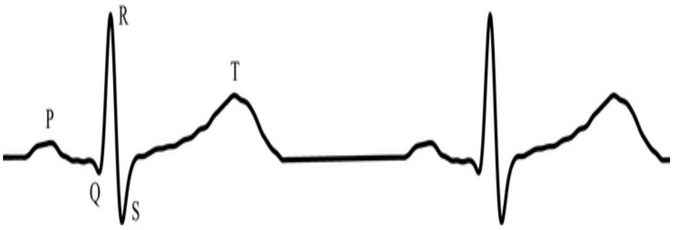

Figure 1. Standard ECG signal

ECG signal contain three main components:

A. P-wave:

It occurs due to atrial depolarization (contraction) with a duration of less than 80msec.Its frequency components are in range of 10Hz-15Hz.

B. QRS-complex:

It occurs due to ventricular de-polarization with frequency component 10Hz-40Hz.Due to large muscle mass in ventricle as compare to atria, QRS complex has much higher amplitude than P-wave and its duration ranges from 80-100 msec.

C. T-wave:

It occur due to ventricular re-polarization with average duration of 160 msec. Position of T-wave corresponding to QRS-complex is highly dependent on heart rate of subject, lesser the distance between these two results in higher heart rate and vice-versa.

Table 1. SPECIFICATION OF ECG SIGNAL

S.no.	Characteristics	voltage level(mV)	Time duration (msec)
1	P – wave	0.1 – 0.2	60 - 80
2	PR –interval	-	50 – 200
3	QRS - complex	1	80 – 120
4	ST – segment	-	100 – 130
5	T – wave	0.1 – 0.3	120 - 160
6	ST – interval	-	320 - 360
7	RR – interval	-	400 - 1200

II. FACTOR AFFECTING ECG SIGNAL

ECG offers idiomatic amalgamation of feature that differentiates it from other biometric modalities. ECG biometric system should consider the peculiarity of this approach and assess its performance under different factors which affect it, such as:

A. Exercise

Exercise plays vital role in the heart beat rate and changes the frequency component of ECG signal. Due to variation in frequency content, the accuracy of ECG biometric is affected highly. Variations in beat rate are highly prone to relative position of T-wave as compared to P- wave or QRS-complex. Stability of P-wave and QRS-complex is high as compared to T-wave. By comparing active and resting state of body, it is concluded that T-wave moves nearer to QRS-complex in active state. Prior work outcomes are such that heart beat rate effect can be nullified by time domain normalization of ECG feature.

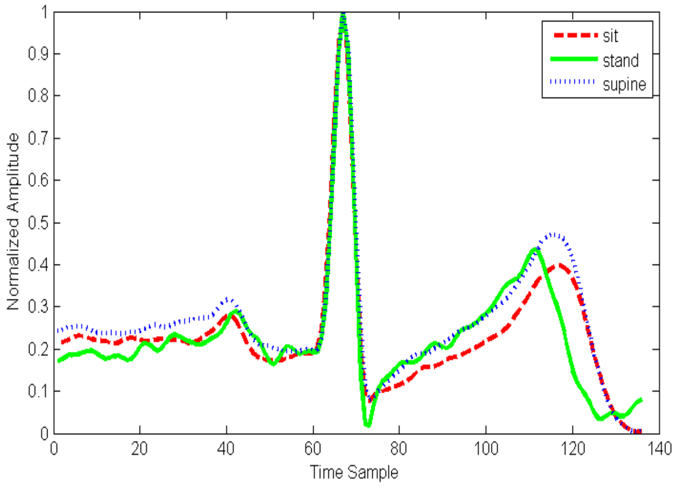

Figure 2. ECG signals in different body position.

B. Cardiac disorder

Cardiac abnormalities (arrhythmias) also affect ECG signals. Premature heartbeats and atrial or ventricle arrhythmias are common examples which affect ECG waveform.

C. Time evolution

ECG signals highly depend on time and action. Change in the ECG signal over time includes drug use, diet, daily activities and other. Based upon the findings, it is concluded that high accuracy is achieved when testing and enrolment are processed in the same session.

D. Psychology

Emotions of a person change continuously, these changes have direct effect on ECG signal variation.

E. Data base size

Typical data base are limited to nearly 100 individual. Evaluation over large data base can provide better outcomes in uniqueness of this biometric. It is observed that efficiency of biometrics system decrease with increase in testing data base.

III. RELATED WORK

Although Philipson L. Bie.L.,Pettersson O., Wide P were among the first to demonstrate the feasibility of ECG biometrics. In the demonstration, their approach was to retrieve a set of amplitude and temporal feature from ECG which are used in clinical diagnosis. In this experimental setup 20 subjects were involved of varying age. Features of ECG signals are directly obtained from SIEMENS ECG equipment and dimensions of these samples are reduced by with the help of correlation matrix. In this setup identification rate was 100% but major drawback was dearth of automatic identification as specific apparatus were used in this study for feature extraction.

Shen gave different method based on one lead ECG identity verification. In this method, an integral approach was used. In this integral approach first template matching was used for correlation coefficient computing among QRS-complexes for verification of possible candidate after that DBNN (decision based neural network) was used for proper validation of identity of first step. In this experimental setup when 20 subjects were tested, recognition rate was 95% for template matching, for DBNN it was 80%. For combination of these two results, it was 100%. Later shen extended this methodology for larger data base which contain 168 subjects and in this highest achieved recognition rate was 95.3%.

Wang suggestion was integration of appearance and analytic feature of heart beats. ECG signal was preprocessed and temporal and amplitude distances were measured. When these two features were combined with 13 subjects, heart beat recognition rate was 98% while subject recognition rate was 100%.

D. hatzinakos, K.plataniotis, presents a method which is based on the amplitude and temporal distance between fiducial point which are under consideration. Fiducial detection accuracy is the backbone of this method. Subject identification rate was 98%.

Dieter Kreiseler ,Clemens Elster, reported a method of identification using ECG signals based on vector distance. In this study 74 subjects were taken in analysis and from these subjects 234 ECG recordings were taken. Based on the vector distance between recordings, error was measured. Results of this study were based on FMR (false matching rate) and FNMR (false non matching rate).Errors were calculated based on threshold i.e. more the distance of original level from threshold level indicates more error. By this method achieved equal error rate was less than 3%.

Table 2. Comparison of characteristics and key feature of different studies

Study	Biel et al.	Yi et al.	Shen et al.
Number and age of individual	20 (20-55 years)	9 (22-28 years)	20 (20-35 years)
ECG Acquisition method	12 Lead	Wireless and 30 minutes long	Lead 1
No. of ECG record	135	50	20
Record from each individual	4-10	2	1
Training set	85 records	9 records and 30 fragments of each record	20
Test set	50 record	9 record	1 record for every beat
Reduction method	-	Principle component analysis	-

IV.CONCLUSION

ECG biometric system is new in the field of biometric identification. The main objective of biometric system is to identify and recognize living being. It improves security system as well as provides a new way of research in the field of biometrics. After collection of ECG signals from various subjects and time instants, correlation was made among these by using different-different modalities. Main aim of each study is to minimize error rate and maximize recognition rate. It is observed that success rate decrease with increase in database i.e. no. of samples or no. of subjects.

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