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ECG Biometric Identification

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Abstract: The Electrocardiogram (ECG) is the latest modality in field of Biometric identification. The electrocardiogram exhibit some unique cardiac characteristics from individuals, which encourages us for biometric application of ECG signal, robust nature of ECG against falsification makes it more safe for security systems, because it extend ultimate security in every situations. In this study, ECG biometric identification that is Feature extraction of ECG in time domain is used for biometric identification.
***Keywords**: ECG, biometric, DMO, accuracy, specificity*

I. INTRODUCTION

Personal identification play crucial role in modern society and this is widely deployed in many area of identification. Biometric authentication furnish airtight shield by recognizing individuals based on their physiological and behavioral aspects. Each individual possess singular biometric features, which involve physiological features like face, fingerprint, palm, iris, vein and behavioral characteristics such as gait and keystroke. Recently, electrocardiogram (ECG) has been emerged as a field of biometric for human identification. The coherency of ECG biometric identification is braced by the fact that the geometrical parameters of heart change from person to person and exhibit some singularity in their ECG signals. The ECG signal changes from person to person, This is due to the fact that differences in size, geometry, position, physiological feature of the heart, weight structures of thoracic cavity, sex, age, body type and many other factors. A normal ECG wave have mainly three parts i.e. P wave, a QRS complex and a T wave, as shown in Fig. 1. The ECG biometric gives a simple, handful and alternative methodology, which is very useful for certain applications i.e. medical data monitoring for patient, medical records management and physical access control. For example, a family can share remote health monitoring device by which they can check the actual status and there is no need of any user name or password. It can also be used for other biometric measures, or additional feature to improve the efficiency and performance of system.

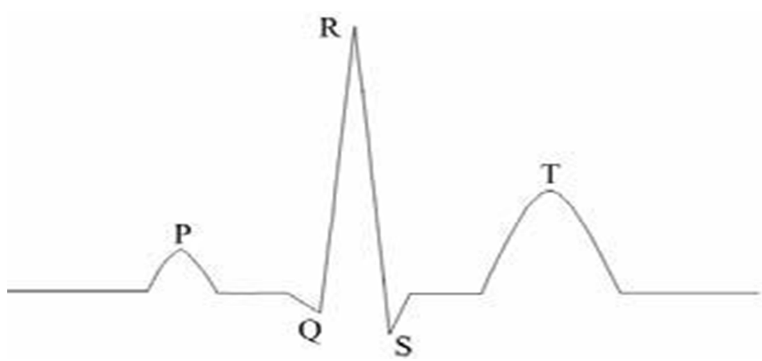

Fig. 1. Basic shape of an ECG signal segment

There are enormous methods to use ECG waveforms as a measure of biometric, however there are problems in performance and accuracy for actual implementation. In this study a new method has been forward put which use Piecewise Linear Representation (PLR) algorithm. It keeps all the necessary information of ECG waveform segments whereas minimize the data dimension. Dynamic Time Warping (DTW) is utilized in similarity between signal segments. Outcomes of the experiment are based upon several ECG databases which shows that the proposed method is able to achieve an improved accuracy and performance compared to existing methods .

II. EXISTING WORK

Shen *et al.* put forward to exact several amplitude and temporal characteristics from the QRST wave of one-lead ECG, combine a template matching method and a decision-based neural network to implement the identity verification system. In this experiment a total of 20 subjects were taken into consideration and accuracy rate was 100%.

Wang suggest the method of integration of appearance and analytic characteristic of heart beats. After processing of ECG signal, amplitude and temporal distance were measured. With these two features for 13 subjects, subject recognition rate was 100% while heart beat recognition rate was 98%.

Dieter Kreiseler, Clemens Elster, suggested vector distance approach for identification using ECG signal. In this experiment a total of 74 subjects were considered for analysis and from these subjects 234 ECG recording were taken. Error was measured based upon vector distance between recordings. Outcomes of this study were categorised on the basis of FNMR(False Non Matching Rate) and FMR(False Matching Rate). A threshold was set, and as distance from threshold level increases error also increases and vice versa. In this method error rate was less than 3%.

D. hatzinakos, K. plataniotis, put forward a method based on temporal distance between fiducial point and amplitude of subjects which are taken up for experiment. Backbone of this method is fiducial detection accuracy. In this method subject identification rate was 98%.

Palaniappan et al. worked on R-R interval and fiducial based characteristics. In this study 10 subjects were taken into consideration having cardiac arrhythmia and accuracy obtained was 97.6%.

Ting and Salleh worked on extended kalman filter for log likelihood ratio and feature extraction for classification. In this experiment identification rate was 87.5% with 13 individuals having cardiac disease.

Agrafioti and Hatzinakos suggested auto correlation based characteristics with minimum distance classifier and accuracy achieved was 96.42%.In this study a set of 56 individuals is used as a database.

III. METHODOLOGY

The overview of proposed methodology is detailed in figure 2. After the acquisition process, data is pre-processed through various steps and after that it is stored in digital form in database. In first step of pre-processing, filtering is done than QRS-complex is detected. Before storing in database outlier removal and pattern extraction are also processed. This complete process is called as enrolment stage. In second stage recognition is done by means of template and raw ECG signal.

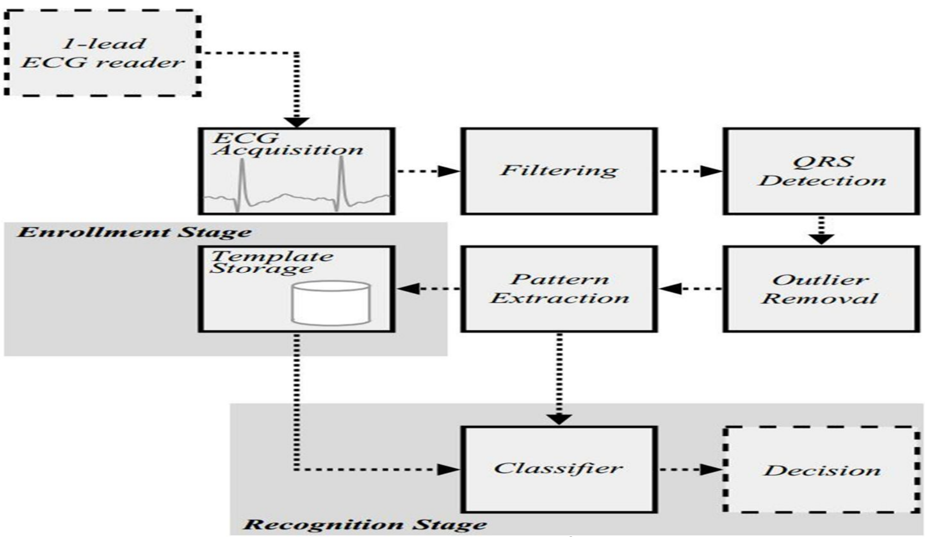

Fig. 2. Flow diagram of proposed approach

A. Data Acquisition And Pre-Processing

ECG signal have so many types of noise by which signal get distorted. These noise are due to motion artifacts, muscle contraction, base line wandering etc. So to remove these noises an IIR notch filter is designed having cut off frequency of 60 Hz.

By doing so ECG signal will get filtered and features of ECG signal can be extracted easily.

B. R-peak and QRS-complex detection

R-peak is the most important parameter of ECG signal, it is the highest peak in the signal. To detect this peak high value threshold is set so that all other peaks get suppressed. To detect QRS-complex DOM (difference operation method) is used.

Slope(Q,R)= (Q-R)/D1

Slope(R,S) = (S-R)/D2

QR and RS are segment of ECG signal, D1 and D2 are distances between QR and RS. DOM basically contain two part, one is thresholding and other is subtraction. In this, algorithm proceed in such a way that each sampled value is subtracted from its predecessor value, and at some point slope becomes zero, zero slope is indication of peak thereafter sign of slope will decide the peak.

$$y[n] = x[n] - x[n-1]$$

C. Feature Extraction

Initially interferences are to be removed to get filtered signal because all the features are to be correctly extracted to get better outcomes. After this ECG signal is analysed for detection of QRS-complex, R-peak, S-peak because these are handful for calculation of sharpness, slope, duration, amplitude of peak.

1) *Sharpness*: It is used for classification of normal and abnormal signal. Sharpness is a measure of peak,
   Sharpness= (slope of QR)-(slope of RS)
2) *Duration:* Duration is one of the important parameter in the process of feature extraction. Lesser the duration, higher will be the slope. Higher the slope means sharpness will be high and vice versa.

D. Classification and Detection

All extracted features are applied to linear classifier and it gives result in the form of accuracy and specificity A linear classifier makes classification based on the combination of linear characteristics.

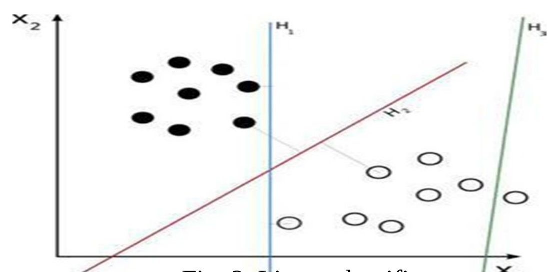

Fig. 3 Linear classifier

In this case, any classifier can classify empty and solid dots correctly. Blue are classified by H1, while Red are by H2. H2 could be considered "better" in the sense that it is also furthest from both groups. H3 (green) is not able to classify dots correctly.

e[n]=error, x[n]=actual value, x*[n]=predicted value

$$\mathbf{e[n] = x[n] - x^{*}[n]}$$

Accuracy = {Correct detection ÷ Total detection}×100 %

IV. RESULT

In this section, analysis of data is carried out. Data is taken from MIT-BIH arrhythmic record at physionet.org. In this section, out of database 7 subjects are taken randomly. These subjects into segments and hence data has been processed segment wise. Final result is based upon the average of all the subject.

Table I Subject Wise Accuracy Of Data

S.No.	Subject	Accuracy in %
1	Subject 1	100
2	Subject 2	87.3
3	Subject 3	97.5
4	Subject 4	95.83
5	Subject 5	94.83
6	Subject 6	95.83
7	Subject 7	99
	Average	95.76

In this study, first system is trained with 7 subjects after that some 20 more subjects were also given to system for training. With 7 subjects accuracy of system was 95.76%, while increasing the no. of subject ,performance of system is decreased by around 1%, this is due to increase in data base. Even after this, it is possible to identify abnormal and normal signal.

V. CONCLUSION

ECG signal is a very handy tool for indication of heart diseases. In our study we have extracted characteristics of ECG waveform for biometric purpose. In the process of feature extraction R-peak, QRS-complex, duration, sharpness are extracted and all these are given to linear classifier as input.

The overall accuracy obtained by this method is approximately 96%.

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