A study on the Intelligent Techniques of the ECG-based Biometric Systems

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Abstract— Electrocardiogram (ECG) signal reflects the recorded cardiac electrical activity of an individual over time; it has been emerged as an important biometric trait. It has the advantages of being a unique aliveness indicator as it is difficult to spoofed and falsified. In this paper, we will present a comprehensive survey on the employment of ECG in biometric systems. An overview of ECG, its techniques and methods followed by a series of studies are presented. We will demonstrate the most datasets used in ECG and also the devices needed to capture them. ECG based biometric systems can be fiducial or non-fiducial according to the utilized features. In particular, we categorize the methodologies based on features extraction, reduction and classification schemes. Finally, we present a comparative analysis of the authentication performance of ECG biometric systems.

Keywords— Biometric, Electrocardiogram, Machine Learning, Preprocessing, Feature Extraction, Feature Reduction, Classification.

I. Introduction

With the rapid development of transportation, communication, and network technology in modern society, the scope of human activities is broadening, while the importance of identification becomes increasingly prominent. Traditional identification methods are generally divided into two kinds: items that people remember, such as user names, passwords, etc. and items that people own, such as keys, identification cards, etc. The two types both have limitations in that they may be easily forgotten and lost. These traditional identification techniques cannot meet the higher security demands of a highly modernized society. Biological recognition technology refers to individual identification based on unique physiological or behavioral characteristics of the human body [1].

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The main objective of this study is to identify the most commonly used methods and techniques used for ECG as a biometric identification system determining the datasets used in biometric identification, the features extraction and classification methods used. We will determine the most efficient techniques that lead to a high identification rate and accuracy and number of subjects used for identification. To achieve this objective the rest of the paper is organized as follows. Section II gives a general methodology of using ECG as a biometric. Section III presents some of the recent works in ECG. Section IV presents the discussion; Section V presents the conclusion and future work and Section VI presents the references

II. General Methodology of ECG Biometric

The ECG signal measures the change in electrical potential over time. The trace of each heartbeat consists of three complexes: P, R, S, T, and U. these complexes are defined by the fiducial that is the peak of each complex. Fig. 1 documents the commonly used medical science ECG fiducials.

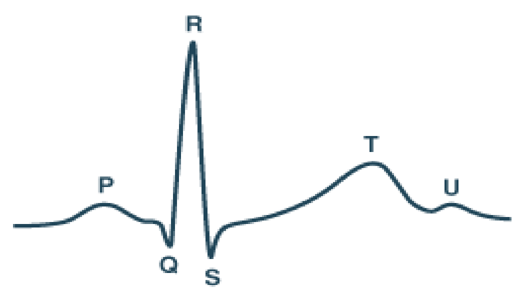

Fig. 1 Ideal ECG signal containing P, Q, R, S, T, U peaks

ECG biometric recognition system consists of a set of stages starting from data acquisition, preprocessing, using fiducial or non fiducial approach, feature extraction, feature reduction and classification as shown in Fig. 2.

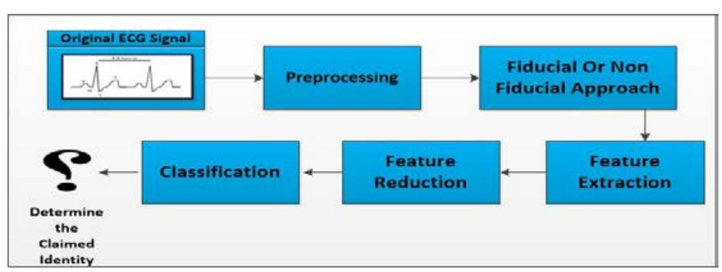

Fig.2 ECG Biometric Recognition System stages

A. Data Acquisition

There are two methods to obtain ECG signals:
First method is using a device to capture ECG. There are different devices to capture ECG, like heal force color portable ECG monitor with ECG leads cables it is a compact, potable handy device for patients to record 30 seconds of ECG data anytime or anywhere, comfortably, with or without electrodes and the measure ECG data can be transferred to PC, laptop. Another device is mini portable heart health care device micro ECG recorder it have different recording mode, quick mode, event mode, holter mode and monitor mode, lead connection limb lead (I, II, III), chest lead (V1, V3, V5) and sampling rate 100/200/400sps, and can be user adjustable, input band width 0.05Hz – 150 Hz and can be user adjustable and the heart rate range from 30bpm~250bpm and the threshold of the heart rate alarm is adjustable
Second is collecting database for an ECG signal from the internet and using them for performing the biometric system stages. There are some data sets available for identification of ECG, and the most commonly used First a database called MIT-BIH Arrhythmia Database it contains 48 half-hour excerpts of two-channel ambulatory ECG recordings, obtained from 47 subjects studied by the BIH Arrhythmia Laboratory between 1975 and 1979. Twenty-three recordings were chosen at random from a set of 4000 24-hour ambulatory ECG recordings collected from a mixed population of inpatients (about 60%) and outpatients (about 40%) at Boston's Beth Israel Hospital; the remaining 25 recordings were selected from the same set to include less common but clinically significant arrhythmias that would not be well-represented in a small random sample.

Second a database called PTB this database contains 549 records from 290 subjects (aged 17 to 87, mean 57.2; 209 men, mean age 55.5, and 81 women, mean age 61.6; ages were not recorded for 1 female and 14 male subjects). Each subject is represented by one to five records. There are no subjects numbered 124, 132, 134, or 161. Each record includes 15 simultaneously measured signals: the conventional 12 leads (i, ii, iii, avr, avl, avf, v1, v2, v3, v4, v5, v6) together with the 3 Frank lead ECGs (vx, vy, vz). Each signal is digitized at 1000 samples per second, with 16 bit resolution over a range of ± 16.384 mV.

Third a database called Fantasia it contains twenty young (21 - 34 years old) and twenty elderly (68 - 85 years old) rigorously-screened healthy subjects underwent 120 minutes of continuous supine resting while continuous electrocardiographic (ECG), and respiration signals were collected; in half of each group, the recordings also include an uncalibrated continuous non-invasive blood pressure signal. Each subgroup of subjects includes equal numbers of men and women. The continuous ECG, respiration, and (where available) blood pressure signals were digitized at 250 Hz. Each heartbeat was annotated using an automated arrhythmia detection algorithm, and each beat annotation was verified by visual inspection.

Last database is called ECG-ID it contains 310 ECG recordings, obtained from 90 persons. Each recording contains: ECG lead I, recorded for 20 seconds, digitized at 500 Hz with 12-bit resolution over a nominal ±10 mV range; the records were obtained from volunteers (44 men and 46 women aged from 13 to 75 years who were students, colleagues, and friends of the author). The number of records for each person varies from 2 (collected during one day) to 20 (collected periodically over 6 months).

B. Preprocessing

Preprocessing is called de-nosing of signal in which the noise is removed from the original signal. (ECG) signals they will be preprocessed in order to remove baseline wander , dc shift , power-line noise , high frequency interference and also if the signal is not captured well due to human error or movement of the stethoscope during taking the signal. Most of these noises are removed using low pass filter, band stop and pass filters, high pass filters; also wavelets play an important role in removing these noises to produce filtered signals.

C. Fiducial or Not Fiducial approach

The existing ECG-based biometric system can be categorized into fiducial or non-fiducial systems according to the utilized approach to feature extraction. The fiducial approach requires the detection of fiducial points from heartbeat in an ECG trace. These fiducial points allow us to produce fiducial features represent the temporal and amplitude distances between fiducial points along with angle features. On the other hand, non-fiducial approaches usually operate in the frequency domain (ex: wavelet, discrete cosine transform (DCT) …), and they have the advantage of relaxing the detection process to include only the R peak, which is considered the easiest point to detect due to its strong sharpness, and for some approaches, no detection is needed at all.

D. Feature Extraction and Reduction

The most important process after collecting the database and preforming pre-processing is the feature extraction and feature reduction process. We select the most discriminant values in the features. If these features were large enough so it is reduced to small amount of data. Most of the techniques used in feature extraction and reduction for ECG are based on non fiducial approaches such as, Wavelet Transform Techniques, Rough sets, Cross-correlation, Auto correlation and fiducial approaches that is based on selecting 11 or 15 or 19 or 36 features from the ECG signal representing distance, amplitudes and angles features, including also RR interval, also QRS and P and T delineation methods and also some morphology and segmentation techniques to select the ECG features as shown in the survey in Table.1.

E. Classification

The extracted features are compared against the stored templates to generate match scores. In a heart-based biometric system, the number of matching data between the input and the template feature sets is determined and a match score

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reported. The match score may be moderated by the quality of the presented biometric data. Most of the techniques used in classification for ECG are Vector Quantization, Gaussian Mixture Mode (GMM) , Support Vector Machine (SVM), Artificial Neural Network (ANN), Radial Bias Function Neural Network (RBFNN), Euclidean Distance (ED) , and K-nearest neighbor (KNN), template matching ,Similarity Distance and Hidden Marchov Models.

III. Analysis of Techniques USED IN ECG Recognition

Table. 1 Machine learning techniques used in the ECG identification

Author	Database Size	Feature Set	Classification	Accuracy
Tatiana, et. Al, 2005 [2]	Data set of 90 persons ECG-ID Database Age from (13 – 75) 195 Train 115 Test	Wavelet + (PCA) Principle Component Analysis)	Linear Discriminant analysis (LDA) and Majority Vote Classifier	96%
Steven, et. al, 2005 [3]	29 Individual Male and Female Age from (22 – 48)	In total 15 features were extracted from each heartbeat	Standard linear discriminant analysis.	According to the sensor location 100% (neck and chest) Within Anxiety state 97% (low, high stress) Between Anxiety state 98% (low, high stress)
Saechia, et.al, 2005 [4]	MIT-BIH Database Sample size = 35	Fourier Transform (FT)	Multilayer Perceptron (MLP) Back Propagation (BP)	97.15%
Plataniotis, et.al, 2006 [5]	PTB Database No of subjects = 14	Auto Correlation and Discrete cosine transform (AC/DCT)	Normalized Euclidean distance Normalized Gaussian log likelihood	100% for both Normalized ED Normalized Gaussian log likelihood
Molina, et.al, 2007 [6]	Sample size = 10	Depends on the R-R interval segmentation using Morphology Getting Amplitude and length normalization	Similarity score compared with a threshold θ	98%
Yongjin, et.al, 2007 [7]	PTB Database No of subjects = 294 MIT-BIH Database No of subjects = 13	Two Approaches 1st is 15 Temporal features 6 Amplitude features PCA , LDA 2nd (AC / DCT)	ED Nearest Neighbor (NN)	Accuracy of (95.5%) with (PTB + PCA), (93%) with (PTB + LDA) and (98%) with (MIT+PCA), (98%) with (MIT+LDA) and (94%) with AC (DCT).
Adrian, et.al, 2008 [8]	No of subjects = 50 45 male , 5 female Ages from (18 – 40)	PQRST complexes were automatically detected using the multiplication of backward differences algorithm. Correlation coefficients were computed between PQRST complexes	Three different quantitative measures: percent residual difference (PRD) Correlation Coefficient (CC) Wavelet distance measure(WDIST)	PRD = 70% CCORR = 80% WDIST = 89%
Yogendra, et.al, 2008 [9]	A test set of 250 ECG recordings prepared from 50 subjects ECG from Physionet	19 features based on time intervals, amplitudes and angles.	Template Matching	99%

Fatemian, et.al, 2009 [10]	PTB Database No of subjects = 294 MIT-BIH Database No of subjects = 13	QRS detection and delineation of T and P wave then PCA LDA	Template Correlation	99.61%
Boumbarov, et.al, 2009 [11]	No of subject = 9 20 complete cardiac cycles for each.	linear subspace projection using PCA and improving the separability by LDA	RBFNN	86.1%
Can Ye, et.al, 2010 [12]	MITBIH Arrhythmias Database, MIT-BIH Normal Sinus Rhythm Database and Long-Term ST Database	Wavelet Transform (WT) and Independent Component Analysis (ICA) methods are applied to extract morphological features.	SVM RBFNN	99.6%
Jun Shen, et.al, 2011 [13]	PTB Database No of subjects = 13 MIT-BIH Database No of subjects = 14 Self-collected = 15	Piecewise Linear Representation (PLR) is used to keep important information of an ECG signal segment	(DTW) Dynamic Time Warping	100%
Khairul, et.al, 2012 [14]	No of subjects = 30 obtained from a non-invasive measurement called the Revitus ECG module	With Normalized QRS complex Without Normalized QRS Complex	MLP	With Normalized QRS complex it has an accuracy of 96.1% Without Normalized QRS complex it has an accuracy of 93.4%
Manal, et.al, 2013 [15]	PTB Database Starting from 13,25,50, 75 and to 90 subjects	1st approach Wavelet and reduced coefficients to examine the utilization of QT and QRS intervals and RR interval 2nd approach (AC / DCT)	RBFNN	1st approach 100% for RR from (13 to 90) 100% for QT For 13 and 83.3% for 25,50,70,90, 100% for QT For 13 and 83.3% for 25,50,70 for 90 66.67% 2nd approach 100%
Vuksanovic, et.al, 2014 [16]	Training set = 13 subjects Test set includes another same 13 subjects.	QRS detection, various temporal, amplitude and AR coefficients are extracted	ANN	Accuracy using width is 55.56% , Amplitude 98.89% With Amplitude and Ar coefficients is 95% Amplitude, Ar, Time, Width is 100%
X. Tang1, et.al, 2014 [17]	MIT–BIH arrhythmia	Rough set	Quantum Neural Network	91.7%
Tiago, et.al, 2015 [18]	ECG data were collected from 63 subjects during two data-recording sessions separated by six months (Time Instance 1, T1, and Time Instance 2, T2).	Morphology and Segmentation of RR heartbeats	KNN classifier, using the mean wave's Euclidean distances	95.2% for the First Test 90.2% for the Second Test
Sandeep, et.al, 2015 [19]	MIT-BIH	A Multitask learning approach i in which feature extraction and classifier design are carried out simultaneously	KNN	94.5%

IV. Discussion

According to the survey, we have presented novel biometric identification techniques that are based on heart sounds. The most techniques used were based fiducial and non fiducial approach fiducial features represent the temporal and amplitude distances between fiducial points along with angle features. Hence, they require the detection of 11 fiducial points from each heartbeat: three peak points (P, R and T), two valleys (Q and S) and the six onsets and offsets for the three heartbeat waves.

Thus, the efficiency of the fiducial approach significantly relies on the accuracy of the fiducial detection process, which is a big challenge by itself especially for the onsets and the offsets points, since they are susceptible to error and there is no universally acknowledged rule for defining exactly where the wave boundaries lie.

On the other hand, non-fiducial based approaches usually investigate the ECG spectra. Only the R peak is needed for such approaches and for some of them; no detection is needed at all. However, non-fiducial approaches usually result in a high dimension feature space (hundreds of coefficients), which in turn has its limitation.

Some of these techniques achieved a high accuracy even reached to 100% accuracy using QRS detection and delineation, P and T wave detection and delineation followed by LDA and PCA and Piecewise linear representation.
But most of them share the problem that the evaluation is carried over small databases, making the results obtained difficult to generalize. In fiducial approaches entropy and energy of the ECG signal can be introduced to improve the features obtained, also a combined approach using fiducial and non fiducial approach must be introduced deeply as it can have a lot of computational overload but it will improve the accuracy. Most of the previously mentioned studies evaluated the biometric system performance regardless of many combined effectual factors, such as age, database scale, race, and gender and disease status. It is showed from the studies that there are two different classification approaches. The first approach is based on the concept of similarity; such as template matching and KNN are used in my studies. Second one is to construct decision boundaries by optimizing certain error criterion. Examples are ANN, RDF and SVM. Also the recognition performance could be more efficient if fusion between different classifiers is introduced.

V. Conclusion

This review discussed on one of the most extensively studied medical biometric systems, the ECG. The ECG signal measures the change in electrical potential over time. We presented in this paper several intelligent techniques that were used in user identification systems based on ECG. Each technique is explained with its data set used. The best accuracy was achieved by Jun Shen, et.al, using dynamic time wrapping , Can Ye using support vector machine and radial bias function and S.Zahra Fatemian, et.al, using template correction . In the future, we plan to work on a new ECG system that will use a large dataset. The system will use existing dataset for user identification.

VI. References

1. A. ROSS, A.K. JAIN, “Human Recognition using biometrics: an Overview,” Annals of Telecommunications, vol. 62, Jan/Feb 2007, pp. 11-35.
2. A.P. Nemirko, T.S. Lugovaya, “Biometric human identification based on electrocardiogram,” Proc. XII-th Russian Conference on Mathematical Methods of Pattern Recognition, Moscow, MAKS Press, 2005, pp. 387-390.
3. A. Israel, M. Irvine, A. Cheng, D. Wiederhold, K.Wiederhold, “ECG to identify individuals,” Pattern Recognition 38, (2005), pp. 133 – 142.
4. S. Saechia, J. Koseeyaporn, P. Wardkein, “Human Identification System Based ECG Signal,” TENCON IEEE Region 10 Melbourne, Qld, 2005, pp. 1 - 4.
5. N. Plataniotis, D. Hatzinakos, K.M. Lee, “ECG biometric recognition without fiducial detection,” *Proc. of Biometrics Symposiums (BSYM)*, Baltimore, Maryland, USA, 2006.
6. G.G. Molina, F. Bruekers, C. Presura, “Morphological synthesis of ECG signals for person authentication,” *15th European Signal Proc. Conf .Poznan*, Poland , September 3-7, 2007.
7. Y. Wang, F. Agrafioti, D. Hatzinakos, N. Plataniotis. “Analysis of Human Electrocardiogram for Biometric Recognition” Hindawi Publishing Corporation EURASIP Journal on Advances in Signal Processing Volume 2008,
8. D.C. Chan, M. Hamdy, A. Badre, V. Badee,”Wavelet distance measure for person identification using electrocardiograms,” *Instrumentation and Measurement, IEEE Transactions on* 57(2), pp.248 –253.
9. Y. Singh, P. Gupta, “ECG to individual identification, “2*nd IEEE Int. Conf. on Biometrics: Theory, Applications and Systems* 2008.
10. S. Fatemian, D. Hatzinakos, “A new ECG feature extractor for biometric recognition,” *16th International Conference on Digital Signal Processing*, 2009, pp. 1 –6.
11. O.Boumbarov, Y.Velchev, S.Sokolov,”ECG personal identification in subspaces using radial basis neural networks,” *IEEE Int. Workshop on Intelligent Data Acquisition and Advanced Computing Systems*, 2009, pp. 446 –451.
12. *C. Ye, M.T. Coimbra, B. Vijaya*, “Arrhythmia Detection and Classification using Morphological and Dynamic Features of ECG Signals,” 32nd Annual International Conference of the IEEE EMBS Buenos Aires, Argentina, August 31 - September 4, 2010.
13. J. Shen, S. Bao, “The PLR-DTW Method for ECG Based Biometric Identification,” 33rd Annual International Conference of the IEEE EMBS Boston, Massachusetts USA, August 30 - September 3, 2011.
14. K. Azami, I. Khalil, M. Smole, “ECG Biometric Recognition in Different Physiological Conditions using

ISBN: 978-1-61804-351-1

Robust Normalized QRS". Complexes.cinc.org Computing in Cardiology 2012; vol.39, pp.97-100.

15. M. Tantawi, K. Revett, A.M. Salem, M.F. Tolba." A wavelet feature extraction method for electrocardiogram (ECG)-based biometric recognition". © Springer-Verlag London 2013.
16. B. Vuksanovic , M. Alhamdi. "Analysis of Human Electrocardiogram for Biometric Recognition Using Analytic and AR Modeling Extracted Parameters". *International Journal of Information and Electronics Engineering, Vol. 4, No. 6, November 2014.*
17. X. Tan , LShu. "Classification of Electrocardiogram signal with RS and Quantum neural networks". International Journal of Multimedia and Ubiquitous Engineering Vol.9, No.2 (2014), pp.363-372.
18. T. Araújo, N. Nunes, H. Gamboa, A. Fred. "Generic Biometry Algorithm Based on Signal Morphology Information," © Springer International Publishing Switzerland 2015
19. S. Gutta, Qi. Cheng, "Joint Feature Extraction and Classifier Design for ECG Based Biometric Recognition," IEEE Journal of Biomedical and Health Informatics, 2015.

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