ECG-based Human Authentication: A Review

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***Abstract*- The electrocardiogram (ECG) is an emerging novel biometric approach for human identification. This project investigates the possibility of biometric human identification based on the electrocardiogram (ECG). The ECG, being a record of electrical currents generated by the heart, is potentially a distinct human characteristic, since ECG waveforms and other properties of the electrocardiogram depend on the anatomic features of the human heart and body. Many aspects of our everyday lives are becoming dependent on automatic and accurate identity validation. The vast deployment of recognition mechanisms, based on something that people have (entity-based: tokens and ID cards) or something that people know (knowledge-based: PIN numbers and passwords), raises security concerns. The major benefit of security systems based on biometrics is the full dependency on the individual. The main purpose of this study is to present a novel personal authentication approach for human authentication.**

***Keywords*- Human Authentication, Biometrics, Feature Extraction, Security**

I. INTRODUCTION

The potential of ECG as a powerful authentication entity has been lately explored in great depth owing to its characteristics of human anatomy which are almost implausible to replicate and its benefit of persistence and aliveness of the entity. Its prospective use as a biometric, surpassing its sole use of clinical diagnosis can be justified by the aspects like:

- Uniqueness-there are no two individual with identical characteristics,
- Universal-it can be virtually found in every human being,
- Measurability-it can be easily acquired using suitable devices,
- Permanence-does not vanish over time,
- Performance-it has been shown to provide accurate results for the subset population. [23, 30].

The study of ECG and obtaining relevant and consistent data from it and matching it with pre-calculated numerics stored in the database is the key to its success. Extraction of unique features of ECG is a cumbersome task which gives the biometric cutting edge accuracy and uniqueness.

Regarding Template Extraction, existing approaches can be defined as fiducial, partially fiducial and non-fiducial. Fiducial methods use latency, slope, angle and other measurements derived from anchor points within the signal (e.g. P-QRS-T complexes), to create feature vectors that are used as input to the recognizer [19, 26]. Partially-fiducial methods typically only use the R-peak to perform heartbeat waveform segmentation, adopting either the full waveform or a subset of it as input to the recognizer [23]. Non- fiducial methods extract information from the structure of the signals, without the need for any reference points [23,27] these methods are especially advantageous given that the process of identifying fiducial points can be challenging.

1**. Fiducial methods**- It depends on local features of ECG signal for biometric template design, such as temporal or amplitude difference between consecutive fiducial points and used for identification purposes. The drawback of fiducial features is their sensitivity to noise. Furthermore, detection of fiducial features in unusual cases with arrhythmia may include errors in data.[31]

2. **Non-fiducial method**- It was initially proposed by Plataniotis et al. [28,31] in order to remove the necessity of fiducial point localization of the ECG signal. It treats ECG signal or secluded heartbeats holistically and captures features based on the overall morphology of waveform [28,31].

II. ECG BASICS

The human electrocardiogram reflects the specific pattern of electrical activity of the heart throughout the cardiac cycle and can be seen as changes in potential difference. The ECG is affected by a number of physiological factors including age, body weight, and cardiac abnormalities.

Electrocardiogram (ECG) recordings are quantitative measures of the electrical activity of a person's heart over time[18]. It consists of P-wave, QRS-wave, and T-wave. The QRS wave is usually called QRS composite or QRS complex, and it contains the most significant information in that heartbeat. A typical beat in an electrocardiogram comprises of-

1. A low amplitude P-wave, representing atrial depolarization.
2. The QRS complex of much higher amplitude than the P-wave, representing ventricular depolarization.
3. A T-wave of smaller amplitude and larger duration than the QRS complex, representing ventricular repolarization.[25]

A. ECG

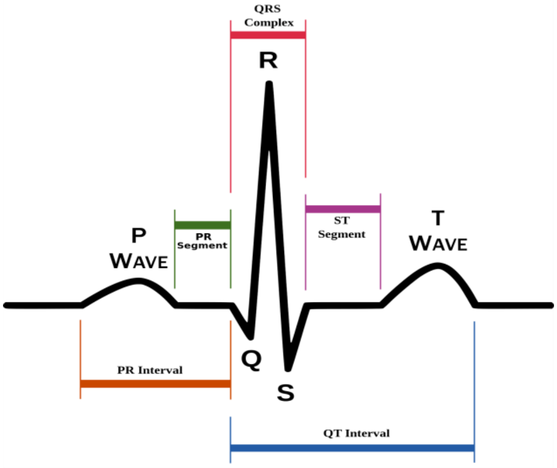

Figure 1: ECG complex[25,29]

ECG is a method to measure and record different electrical potentials of the heart. The ECG may roughly be divided into the phases of depolarization and repolarization of the muscle fibers making up the heart. The depolarization phases correspond to the P-wave (atrial depolarization) and QRS-wave (ventricular depolarization). The repolarization phases correspond to the T-wave and U-wave (ventricular repolarization). The basic elements in the ECG-complex are shown in Fig 1[19, 25].

B. BASIC STEPS INVOLVED IN ECG

The steps involved are as follows:
1. Signal Acquisition
2. Preprocessing
3. Feature extraction
4. Classification [25]

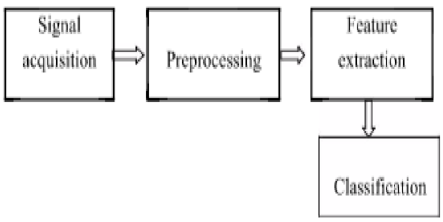

Figure 2: Process Flow for ECG processing [29]

a. Signal Acquisition

The initial step for entire authentication is acquiring the signals using sensors or other hardware devices. The data collected is either processed or raw data is stored in the database which is later used to match the testing dataset for authenticating a valid user.

b. Preprocessing of ECG

The raw ECG is rather noisy and contains distortions which may reduce the effectiveness of feature extraction and classification and thus lead to the decrease in efficiency of the results produced and also the accuracy.

● Digital filtering: It is the primary step of preprocessing. It is used to filter unnecessary noise in ECG signals. Example the digital notch filter is employed to remove the power line interference. A high pass band filter with a cut-off frequency of 0.5 Hz is used to remove the DC offset on the obtained signal.

- Down Sampling: It is a consistent solution for algorithms performance on high sampled signals.
- Peak detection: In peak detection, the unprocessed signal is digitally filtered and the peak index detected is used in the feature selection setup.
- Segmentation: In this step, a particular peak of the signal is identified first then ECG waveform is segmented into an individual heartbeat.[29]

c. Feature Extraction

After pre-processing, the second stage towards classification is to detect certain features of ECG signals mostly QRS complex, P and T waves. Statistical features like Dower matrix, correlation coefficient, covariance matrix etc, wavelet features like ICA, Fourier transform, Discrete Cosine Transform (DCT) etc. techniques are used to extract the features of ECG[25,29]. However, the initial features may include redundant and useless information due to correlation and interdependencies between features. Two methods of feature space reduction are proposed: Principal Component Analysis (PCA) and Wavelet Transform (WT) [30].

d. Classification

The goal of classification is to identify a subject or to verify an identity claim from the sensor observations [29]. Various classification algorithms namely Radial Basis Function (RBF), K Nearest Neighbor (kNN), Bayes Network (BN), Multilayer Perceptron (MLP), soft independent modeling of class analogy (SIMCA), Principle component analysis (PCA), are described in literary works [25, 29].

III. COMPARISON

The given table performs a comparison between different approaches used in the referred research papers.
It compares the following factors:
1. Features
2. Feature Extraction Methods
3. No. of subjects
4. Accuracy

Paper Studied	Features	Feature Selection Methods	No. of subjects used	Accuracy
Sebastian et al. [14]	Fiducial	Template Matching	73 records (Physionet database)	81.82%
Choudhary et al. [15]	Amplitude of QRS complex R-peak alignment	Discrete Cosine Transform (DCT) and Template Matching	3969 imposters and 19404 test segments	FRR-11.6% FAR-5.8% Detection Accuracy-100%
Safie et al. [16]	The peak of P to the peak of T (P2T)	Multiple Pulse k-Nearest Neighbor (MPkNN)	20	Classification-100%
Kumar et al. [18]	ICA components and wavelet coefficients	Wavelet Transform (WT) and Independent Component Analysis (ICA)	The proposed method was tested on three public ECG databases.[1]	Recognition 99.6%
Biel et al. [19]	Temporal, amplitude and slope	Correlation matrix	20	100%
Belgacem et al. [21]	Amplitude and normalized time distances between successive fiducial points.	Discrete Wavelet Transform & Random Forest Algorithm-Authentication	20	100%
Singh et al. [22]	Fiducial points P-QRS-T Complexes	Template Matching	50	98%
Fred et al. [23]	Partial Fiducial Approach(Use of R wave to perform segmentation)	Template Matching & SVM	64	EER- 9.1%
Shen [13]	Fiducial	Template Matching + DBNN	20	100%
Israel [11]	Fiducial	LDA	29	98%
Chiu[12]	Non Fiducial	Wavelet Distance+LDA	35	100%
Janani, David[9]	Both	KNN + Bayesian	17	88%

Table 1. *Comparison of methodology* [25]

IV. EXISTING LITERATURE

The features, in most biometric methods, were extracted in the direct time-domain, frequency-domain and time-frequency-domain representation of the ECG signal. The spectral features are extracted from the Fourier transform (FT) of time-domain ECG signal or decomposed ECG signals. The performance of different methods depends on classifiers such as K-nearest neighbor (KNN), back-propagation neural network (BPNN), hidden Markov model (HMM), Bayes Network (BN), Naive Bayes (NB), and support vector machine (SVM). Certain methods are based on feature analysis, using one or more techniques such as LDA, principal component analysis (PCA), independent component analysis (ICA), random projection (RP) in conjunction with K- SVD based dictionary learning, and within-class covariance normalization (WCCN) for dimensionality reduction. The test was conducted using the ECG signals taken from the well-known ECG databases: MIT-BIH arrhythmia (MITADB), MIT-BIH supra-ventricular arrhythmia database (MITSADB), MIT-BIH Normal sinus rhythm (NSRDB), Physikalisch-Technische Bundesanstalt (PTB) and European ST-T (ESTTDB) [1].

In this section, we provide a review of the related literary works on ECG-based human authentication. Biel et al. [3] are among the earliest initiatives that demonstrate the plausibility of utilizing ECG for human identification purposes. A set of temporal and amplitude features are extracted from a SIEMENS ECG equipment directly. A feature selection algorithm based on simple analysis of correlation matrix is used to reduce the dimensionality of features. A multivariate analysis based method is employed for classification. The system was tested on a database of 20 individuals, and 100% identification rate was achieved, based on empirically selected features. A major limitation of Biel et al.'s method is the lack of automatic recognition due to the usage of specific equipment for feature extraction. This declines the scope of applications. Irvine et al. [26] proposed a system to use heart rate variability (HRV) as a biometric for human identification. Israel et al. [11] proposed a more extensive set of descriptors to characterize ECG signal. An input ECG signal is first preprocessed by a bandpass filter. The peaks are established by finding the local maximum in a region surrounding each of the P, R, T complexes, and minimum radius curvature is used to find the onset and end of P and T waves. A total number of 15 features, which are time duration between detected fiducial points, are extracted from each heartbeat. This system was tested on a database of 29 subjects with 100% human identification rate and around 81% heartbeat recognition rate can be achieved. Shen et al. [13] introduced a two-step scheme for identification from one-lead ECG. A template matching method is first employed to compute the correlation coefficient for comparison of two QRS complexes. A decision-based neural network (DBNN) approach is then applied to complete the verification from the plausible candidates selected with template matching. The inputs to the DBNN are seven temporal and amplitude features extracted from QRS-T wave. The experimental results from 20 subjects showed that the correct verification rate was 95% for template matching, 80% for the DBNN, and 100% for combining the two methods[25]. Shen [13] extended the proposed methods in a larger database that contained 168 healthy subjects. Template matching and mean square error (MSE) methods were compared for prescreening, and distance classification and DBNN compared for second-level classification. The features used for the second-level classification are seventeen temporal and amplitude features. The best identification rate for 168 subjects is 95.3% using template matching and distance classification.[25]

Wang et al. [8] made the initial efforts that did not depend on fiducial based features and relied on the combination of a set of analytic features derived from Fiducial points with appearance features obtained using PCA and LDA(principal component analysis and linear discriminate analysis) for feature extraction and data reduction. The accuracy for 13 subjects was 84% using analytic features alone and 96% using LDA with K-NN(K-nearest neighbor). The combination of the types of features was used to achieve 100% accuracy. Janani, et al [9] handled activity induced ECG variation by extracting a set of accelerometer features that characterize different physical activities along with fiducial and non fiducial ECG features. Chan et al. [10] proposed another non-Fiducial feature extraction framework using a set of distance measures including a novel wavelet transform distance. Data was collected from 50 subjects using button electrodes held between the thumb and finger. The wavelet transform distance outperforms other measures with an accuracy of 89%.[25]

Sebastian et al. [14] proposed biometric authentication algorithm for mobile devices. In this approach, the user touches two ECG electrodes (lead I) of the mobile device to gain access. The algorithm was tested with a cell phone case heart monitor in a controlled laboratory experiment at different times and conditions with ten subjects and also with 73 records obtained from the Physionet database. The obtained results reveal that our algorithm has 1.41% false acceptance rate and 81.82% actual acceptance rate.

Choudhary et al. [15] presented a simple unified accumulation of averaged heartbeat extraction framework for noise-robust ECG-based biometric authentication using pulse morphology. There are three major steps involved in the proposed method: preprocessing, combined averaged beat construction, and similarity matching. The signal blocking and mean removal operations are performed at the preprocessing stage. The ensemble averaging step includes discrete cosine transform (DCT) based filter for simultaneous removal of BW and PLI noises, straightforward Gaussian derivative filter (GDF)-based R-peak detector, peak-centering and period normalization, and ensemble averaging computation.A modified version of the k-Nearest Neighbor (kNN) classifier named Multiple Pulse k-Nearest Neighbor (MPkNN) was introduced by Safie et al. [16].Combining the distinctive characteristic of the Pulse Active Width (PAW) technique with kNN led to the development of MPkNN. This approach was implemented for class attendance system. Kumar et al. [18] used Wavelet Transform (WT) and Independent Component Analysis (ICA) methods to extract morphological features that appear to offer sharp distinction among subjects. The proposed method is aimed at the two-lead ECG configuration that is routinely used for long-term continuous monitoring of heart activity. To achieve improved subject identification, the information from the two ECG leads is fused.

In [21], the cardiac signals were used to identify a total of 80 individuals obtained from four ECG databases from the Physionet database (MIT-BIH, ST-T, NSR, PTB) and an ECG database collected from 20 student volunteers from Paris Est. University. Discrete Wavelet Transform (DWT) was used to perform Feature extraction. Wavelets have turned out to be particularly effective for extracting distinct features in ECG signal classification. The Random Forest was then suggested for the ECG signals authentication. Preliminary experimental results indicate that the system is accurate and can achieve a low false negative rate, low false positive rate and a 100% subject recognition rate for healthy subjects with the reduced set of features. In [22], a new authentication strategy is suggested, which uses the outlined features and taking identification decisions with respect to the template database on the basis of match scores. The performance of the system is measured in both a unimodal framework and also in the multimodal framework where ECG is combined with the face biometric and with the fingerprint biometric. The equal error rate (EER) result of the unimodal system is 10.8%, while the EER results of the multimodal systems are reported to 3.02% and 1.52%, respectively for the systems when ECG is combined with the face biometric and ECG integrated with the fingerprint biometric. Fred et al. [23] employed the use of SVM and template matching for feature selection. The approach is partially fiducial as it focuses on R-wave segmentation.

V. CONCLUSION

An exhaustive search of the literature on ECG as a biometric for authentication has led to strong proposal of its use because its non-mimicable characteristic can provide a more robust and efficient human identification system. To increase the intricacies of the system, the unimodal ECG can be combined with other previously explored biometric like finger and retina scan to develop a multimodal system that is impossible to spoof by a spurious user. The integrity and accuracy of the system depend on the feature extraction algorithms. The future work essentially focuses on fast and correct feature extraction by utilizing more statistical data.

REFERENCES

[1] L. Goldberger et al., “PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals,” Circulation, vol. 101, no. 23, pp. 215-220, 2000.

[2] Dr. Boo-Ho yang, Prof Haruhiko H. Asada ,Yi Zhang “Cuff-less continuous monitoring of beat-to-beat Blood pressure using a kalman filter and sensor” ,Fusion-first joint IEEE conference of bmes/embs,1999.

[3] L. Biel, O. Pettersson, L. Philipson, and P. Wide. " ECG analysis: a new approach in human identification". Proceedings of the 16th Instrumentation and Measurement Technology Conference, IEEE, volume 1,1999.

[4] Julio C.D Conway,Claudionor J.N Coelho ,Luis C.G Andrade, “Wearable computer as a multi-parametric monitor for physiological signals” IEEE international conference on bioinformatics and biomedical engineering, pp-236-242,2000.

[5] M. Sanjeev Dasrao,Yeo Joon Hock,Eugene KW sim, “Diagnostic blood pressure wave analysis and ambulatory monitoring using a novel”, non-invasive portable device-proceeding of international conference on biomedical engineering, pp 267-272, 2001.

[6] Peter Varady Benyo ,Balazs, “An open architecture patient monitoring system using Standard technologies”, IEEE transactions on information technology in biomedicine, vol. 6, 2002.

[7] Paul Lucowicz, Urs Anliker, Jamie Ward, Gerhard Troster, “Amon: a wearable medical computer for high risk patients”, IEEE computer society, 6th international symposium on wearable computers (iswc.02), 2002.

[8] Y. Wang, F. Agrafioti, D. Hatzinakos, and K. N. Plataniotis, "Analysis of human electrocardiogram for biometric recognition", EURASIP Journal on Advances in Signal Processing, 2008.

[9] Janani S., Minho S., Tanzeem C., David K., ”Activity-aware ECG-based patient authentication for remote health monitoring”; , International Conference on Mobile Systems,ACM,Nov,2009.

[10] D. C. Chan, M. M. Hamdy, A. Badre, and V. Badee. ”Wavelet distance measure for person identification using electrocardiograms”, Transactions on Instrumentation and Measurement, IEEE, Volume 57, issue 2, 2008.

[11] Steven A. Israel, Jhon M.I,Andrew C.,Mark D.W,”ECG to identify individuals”, Virtual reality medical center, USA, Pattern Recognization, Volume 38,issue1,2005.

[12] C. Chiu, C. Chuang, and C. Hsu. “A novel personal identity verification approach using a discrete wavelet transform of the ECG signal”, Proceedings of the International Conference on Multimedia and Ubiquitous Engineering, Volume 6, issue 4,2008.

[13] T. W. Shen, W. J. Tompkins, and Y. H. Hu "One-lead ECG for identity verification",Proceedings of the 24th Annual Conference on Engineering in Medicine and

Biology and the Annual Fall Meeting of the Biomedical Engineering Society, Volume 57, issue 2, 2002.

[14] Arteaga-Falconi, Juan Sebastian, Hussein Al Osman, and Abdulmotaleb El Saddik. "ECG Authentication for Mobile Devices." IEEE Transactions on Instrumentation and Measurement 65.3 (2016): 591-600.

[15] Choudhary, Tilendra, and M. Sabarimalai Manikandan. "A novel unified framework for noise-robust ECG-based biometric authentication." Signal Processing and Integrated Networks (SPIN), 2015 2nd International Conference on. IEEE, 2015.

[16] Safie, Sairul, et al. "Multiple pulse K-Nearest Neighbors authentication for Malay ECG based class attendance system." Engineering Technology and Technopreneuship (ICE2T), 2014 4th International Conference on. IEEE, 2014.

[17] Kaul, Amit, A. S. Arora, and Sushil Chauhan. "ECG based human authentication using synthetic ECG template." Signal Processing, Computing and Control (ISPCC), 2012 IEEE International Conference on. IEEE, 2012.

[18] Ye, Can, Miguel Tavares Coimbra, and BVK Vijaya Kumar. "Investigation of human identification using two-lead electrocardiogram (ECG) signals."Biometrics: Theory Applications and Systems (BTAS), 2010 Fourth IEEE International Conference on. IEEE, 2010.

[19] Biel, Lena, et al. "ECG analysis: a new approach in human identification."IEEE Transactions on Instrumentation and Measurement 50.3 (2001): 808-812.

[20] Matos, André Cigarro, André Lourenço, and José Nascimento."Embedded system for individual recognition based on ECG Biometrics." Procedia Technology 17 (2014): 265-272.

[21] Belgacem, Noureddine, et al. "ECG based human authentication using wavelets and random forests." Int J Cryptography Inf Secur 2 (2012): 1-11.

[22] Singh, Yogendra Narain, and Sanjay Kumar Singh. "Evaluation of electrocardiogram for biometric authentication." (2011).

[23] Da Silva, Hugo Plácido, et al. "Finger ECG signal for user authentication: Usability and performance." Biometrics: Theory, Applications and Systems (BTAS), 2013 IEEE Sixth International Conference on. IEEE, 2013.

[24] Lourenço, André, Hugo Silva, and Ana Fred. "Unveiling the biometric potential of finger-based ECG signals." Computational intelligence and neuroscience 2011 (2011): 5.

[25] Nawal, Meenakshi, and G. N. Purohit. "Ecg based human authentication: A review." Int. J. Emerg. Eng. Res. Technol 2.3 (2014): 178-185.

[26] Israel, J. Irvine, A. Cheng, M. Wiederhold, and B. Wieder- hold. ECG to identify individuals. Pattern Recognition, 38(1):133–142, 2005.

[27] Coutinho, David Pereira, Ana LN Fred, and Mario AT Figueiredo."One-lead ECG-based personal identification using Ziv-Merhav cross parsing. "Pattern Recognition (ICPR), 2010 20th International Conference on. IEEE, 2010.

[28] Plataniotis, Konstantinos N., Dimitrios Hatzinakos, and Jimmy KM Lee. "ECG biometric recognition without fiducial detection." 2006 Biometrics Symposium: Special Session on Research at the Biometric Consortium Conference. IEEE, 2006.

[29] Ahuja, Pooja, and Abhishek Shrivastava. "A Review on ECG based Human Authentication." (2016)

[30] Lugovaya, Tatiana S. "Biometric Human Identification Based On ECG." (2005).

[31] Kaur, Gaganpreet, Dheerendra Singh, and Simranjeet Kaur."Electrocardiogram (ECG) as a Biometric Characteristic: A Review." (2015).