Identifying Individuals Using Fourier and Discriminant Analysis of Electrocardiogram

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Abstract. From the last one and a half decades, the electrocardiogram (ECG) has emerged as a new modality for human identification. The research shows that the people heartbeats recorded using diagnostic method called ECG exhibit discriminatory features that can distinguish themselves. The ECG as a biometric inherently provides liveness detection and robustness against falsification. This paper presents a novel method of ECG analysis for human identification using Fourier and linear discriminant analysis, which does not require detection of fiducial points of ECG wave. The method utilizes autocorrelation coefficients of filtered ECG signal, to extract significant features of it. The performance of the proposed method is evaluated on MIT-BIH arrhythmia and QT database of physionet. The experimental results show the equal error rate (EER) of 0.17% and 0.03% on MIT-BIH arrhythmia and QT database, respectively that outperform the other methods on these databases.

Keywords: Individual identification · Electrocardiogram Fourier transform · Discriminant analysis

1 Introduction

The emerging technology that recognizes people based on their unique physiological and behavioral characteristics, termed as biometrics. These days, biometric traits are used in a wide variety of applications such as in access control, financial and business transactions, health care and other applications [1]. Automatic and accurate identification of an individual is critical along with reducing the probability of intruders getting access to an authentication system [2]. As the proliferation of computer and internet, identity theft becomes the major concern of the modern society [3]. Traditional personal authentication systems based on passwords, PIN numbers and ID cards are unable to fulfil the requirement of high security applications and they are more susceptible to identity theft [4].

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Biometrics has emerged as a potential tool for accurate and efficient authentication of an individual but there are some challenging issues such as confidentiality and vitalityness making the system more prone to spoofing attacks [5].

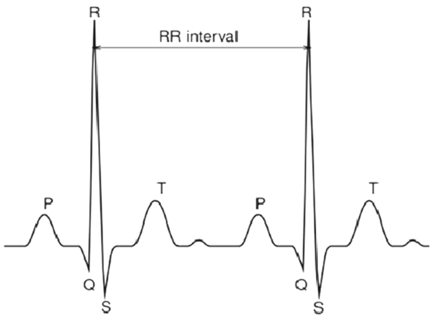


Fig. 1. ECG waveform features.

In order to address these issues one of the state-of-the-art biometrics electrocardiogram (ECG) is a better alternative to the conventional biometrics. ECG is generated from a complex self regulatory system of the heart. It is highly secure, confidential and impossible to mimic. It is universally present in all living individuals thus provides real-time vitality testing [6]. The basic elements of a single heartbeat of ECG consist of P-QRS-T waveforms are shown in Fig. 1.

Beil *et al.* have demonstrated the use of ECG to discriminate 20 subjects using a set of temporal and amplitude features [7]. They have achieved 100% identification rate by multivariate analysis of ECG features. Shen *et al.* have used the appearance and time domain features of the heartbeat and achieved classification accuracy of 95% and 80% for template matching and decision based neural network approaches, respectively [8]. Israel *et al.* have investigated the timing characteristics of ECG signal, from the heartbeat of 29 individuals using linear discriminant analysis (LDA) [9].

Wang *et al.* used analytical feature extraction with discrete cosine transform (DCT) of autocorrelated heartbeat signals [10]. Singh and Gupta have used signal processing methods to delineate ECG wave fiducials from each heartbeat and achieved 98% classification accuracy for 50 subjects [11]. Plataniotis *et al.* have developed an ECG biometric system based on classification of DCT coefficients of the autocorrelated ECG data segment [12]. Agrafioti and Hatzinakos have demonstrated an autocorrelation based feature extraction approach in conjunction with DCT or LDA [13]. In a recent study, Srivastva and Singh have introduced a new method for ECG analysis used in biometric recognition [14,15]. They have reported 97% identification performance using Walsh Hadamard transform and LDA [14]. The authentication performance achieved by DCT and LDA have minimum EER of 0.06% [15].

The major concerns of most of the studies include detection accuracy of fiducial points, selection of features those are insensitive to change in physiology of the heart, variations of heart rate, age and time. The individuality of ECG over a large population is yet to be explored. To address the issues related to ECG biometrics, the paper advocates the use of proposed method. It does not require specific fiducial points of the ECG waveforms and thus not requires pulse synchronization. Therefore, the method is computationally efficient and exhibits better identification performance. The proposed method utilizes the autocorrelation (AC) coefficients, calculated from the filtered ECG signals. The Fourier analysis of autocorrelated ECG segments is performed to form a feature vector. The dimensionality of the feature vector is reduced using LDA before calculating match score for classification. The rest of the paper is outlined as follows: Sect. 2 presents the novel method of ECG waveform analysis and its characterization that is used for the biometric applications. The experimental results are presented in Sect. 3. Finally, the conclusion is noted in Sect. 4.

2 Methodology

Human recognition is essentially a pattern recognition process involves preprocessing, feature extraction, feature normalization, and classification. The proposed biometric system is depicted in Fig. 2. Preprocessing involves noise and artifact removal step. Features are extracted from an ECG data by autocorrelation followed by Fourier transform of ECG window. The LDA is used for

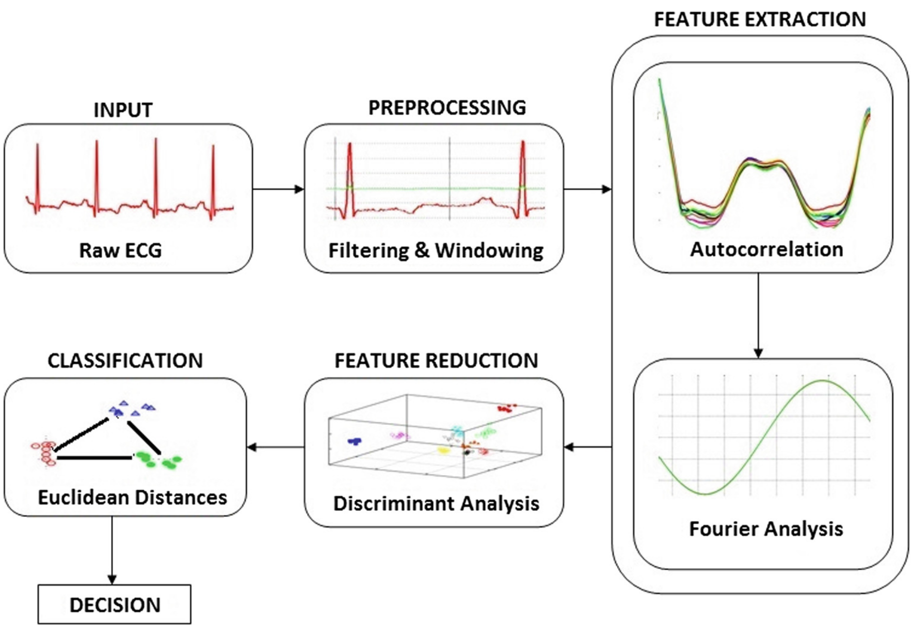


Fig. 2. Proposed ECG biometric system.

dimensionality reduction and the last step of the identification process is classification based on similarity scores of the subjects.

Normally different type of noises contaminate ECG signals. These include low-frequency noise components resulted from baseline oscillations, respiration or body movements and high frequency noise components from power line interferences. The combination of low pass and high pass filters is used to eliminate the effects of noise with the following difference equations, respectively [16].

$$y_n = 2y_{n-1} - y_{n-2} + x_n - 2x_{n-6} + x_{n-12} \tag{1}$$

$$y_n = 32x_{n-16} - (y_{n-1} + x_n - x_{n-32}) \tag{2}$$

The cutoff frequency of low pass filter and high pass filter is about 11 Hz and 5 Hz respectively, which has been chosen considering that the frequency band of normal ECG signal lies within this range.

The filtered ECG signals are segmented into non-overlapping segments. The only restriction regarding the division of ECG data is that the segments have to be longer than the normal cardiac cycle to include at least two or more heartbeats. The length of the window can be chosen heuristically and varies with the sampling frequency of data. For this experiment, all the records are re-sampled at the sampling rate of 200 Hz, and the data window of 50 s and 10 s are selected for MIT-BIH arrhythmia database and QT database, respectively.

ECG is highly repetitive signal that exhibits distinctive characteristics in a population. ECG analysis based on its dominant fiducials require pulse synchronization, and exact localization of wave boundaries. To extract features from ECG data without fiducial detectors, autocorrelation is applied on windowed ECG, that blend samples into a sequence of sums of products. The AC provides an automatic, shift invariant representation of similarity features over multiple cardiac cycles. The normalized AC ($\widehat{R}_{xx}[m]$) of filtered ECG signal, $x[i]$ of length N is computed using the following formula,

$$\widehat{R}_{xx}[m] = \sum_{i=0}^{N-|m|-1} \frac{x[i] * x[i+m]}{\widehat{R}_{xx}[0]} \tag{3}$$

where $x[i+m]$ is the time shifted version of the windowed ECG with a time lag of $m = 0, 1, \ldots.(M-1); M << N$.

The discrete Fourier transform (DFT) coefficients are calculated from autocorrelated ECG signals. It maximizes the inter-class variability and intra-class similarity. The DFT is frequency domain representation of the original input sequence in the time domain. Let $x_0, x_1 \ldots\ldots\ldots x_{N-1}$ be the sequence of N complex numbers. It can be transformed into an N-periodic sequence of complex numbers by the following formula,

$$X_k = \sum_{n=0}^{N-1} x_n e^{\frac{-2\pi ikn}{N}}, \quad k = 0, 1 \ldots N-1 \tag{4}$$

Here each X_k is a complex number, that encodes both amplitude and phase of a complex sinusoidal component ($e^{2\pi ikn/N}$) of function x_n. The sinusoid's frequency is k cycles per N samples.

The LDA is a known method of dimensionality reduction and feature extraction. It preserves the class specific discriminability by linearly transforming the feature characteristics into a low dimension space. More formally, for a given training set $Z = \{Z_i\}_{i=1}^{C}$ containing the patterns of C classes. Each class $Z_i = \{Z_{ij}\}_{j=1}^{C_i}$ has a number of windows Z_{ij} and a set of K feature basis vectors $\{\psi_m\}_{m=1}^{K}$ is estimated by maximizing Fisher's ratio. This ratio is defined as the between-class to within class scatter matrix. The maximization is equivalent to the solution of the following eigenvalue problem:

$$\psi = arg\max\left(\frac{|\psi^T S_b \psi|}{|\psi^T S_w \psi|}\right) \tag{5}$$

where $\psi = [\psi_1, \ldots, \psi_K]$, and S_b and S_w are the between and within class scatter matrices, respectively defined as,

$$S_b = \frac{1}{N}\sum_{i=1}^{C} C_i(Z_i - \overline{Z})(Z_i - \overline{Z})^T \tag{6}$$

$$S_w = \frac{1}{N}\sum_{i=1}^{C}\sum_{j=1}^{C_i}(Z_{ij} - \overline{Z_i})(Z_{ij} - \overline{Z_i})^T \tag{7}$$

where $\overline{Z_i} = \frac{1}{C_i}\sum_{j=1}^{C_i} Z_{ij}$ is the mean of class Z_i and N is the total number of training windows and $N = \sum_{i=1}^{C} C_i$. The LDA finds ψ as the K most significant eigenvectors of $(S_w)^{-1}S_b$ that correspond to the first K largest eigenvalues. Using these basis vectors, a test input window Z is subjected to the linear projection $y = \psi^T Z$.

3 Experimental Results

The performance of the identification system is analyzed through equal error rate (EER) [17]. The EER is an error rate where the frequency of false acceptance (FAR) and the frequency of false rejection (FRR) assume the same value. In order to confirm the benefit of the combined system the receiver operating characteristics (ROC) curve of the authentication process has also been considered. The ROC curve is a two-dimensional measure of classification performance that plots the likelihood of false acceptance (FAR) against the likelihood of genuine acceptance (GAR) [5]. The accuracy of the identification system can be defined as,

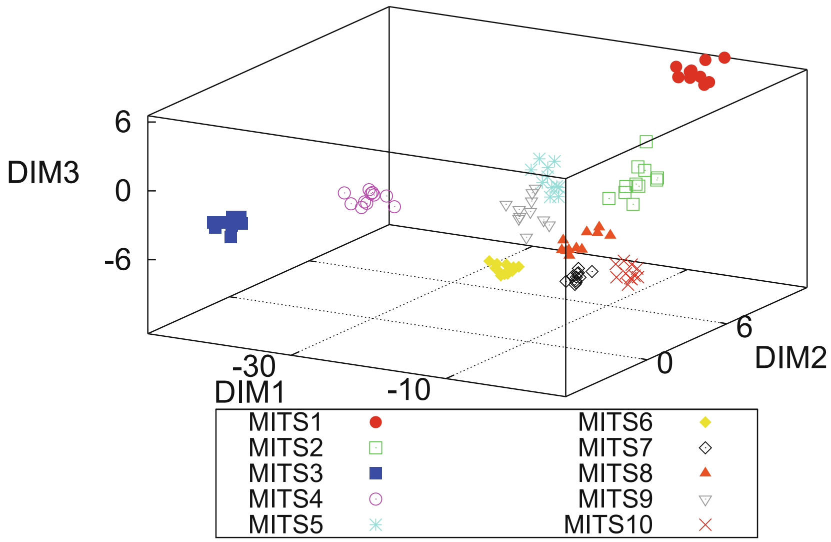
$$Accuracy(\%) = 100 - EER(\%) \tag{8}$$

The performance of the proposed method is tested on MIT-BIH arrhythmia database and QT database of physionet [22]. Both databases include ECG recordings of normal subjects and arrhythmia patients (men and women) of age between 20 and 84 years. Forty-eight ECG recordings of MIT-BIH arrhythmia database and thirty-nine records of QT database are used in this study. The original sampling rate is 360 Hz and 250 Hz for MIT-BIH arrhythmia and QT database, respectively. All these records are re-sampled at 200 Hz for this experiment. After preprocessing, eleven windows of 50 s (10000 samples) and 10 s (2000 samples) in length are chosen from preprocessed ECG signal of MIT-BIH arrhythmia database and QT database, respectively. The windows exclude the 10 s samples from start and end of the recording to avoid sensor and body stabilization effects. To extract features a data set of $528(48 \times 11) \times 10000$ for MIT-BIH arrhythmia database and of $429(39 \times 11) \times 2000$ for QT database are formed.

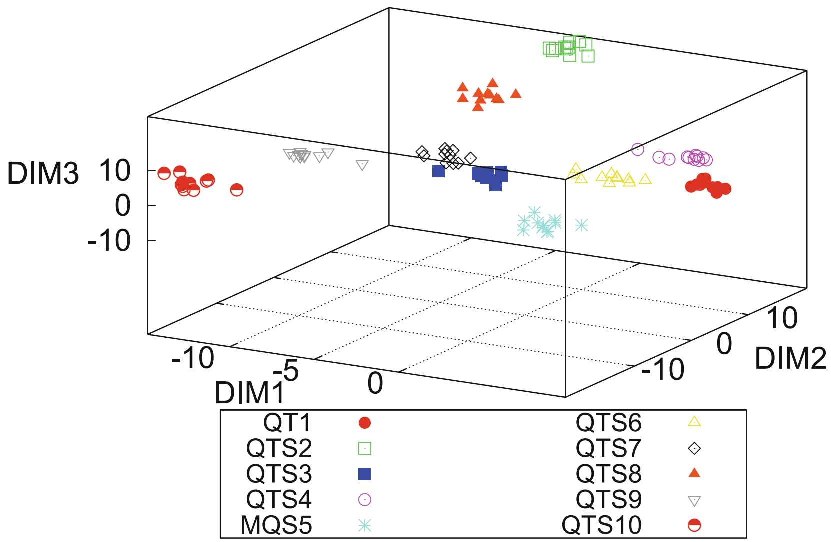
Autocorrelation is applied to these data set which forms a feature vector of 528×180 and 429×180 for MIT-BIH arrhythmia database and QT database, respectively. The autocorrelation time lag can be set to different settings for maximum correlation between samples. For this experiment, it is set to 180 samples due to the fact that a normal heart rate for adults ranges from 60 to 100 beats a minute. The Fourier analysis of these feature vectors is performed in order to minimize the intrasubject variations and to maximize the intersubject variations. The LDA is used for dimensionality reduction of feature vectors to different dimensions. The intrasubject variability and intersubject similarity on first three dimensions as achieved by LDA for ten subjects from each database is shown in Fig. 3.

The results of EER at different dimensions on different databases are presented in Table 1. On MIT-BIH arrhythmia database the EER value is found to be 10% at dimension 1, and it decreases to 0.17% at dimension 10. The EER is linearly increasing above the dimension 10. On QT database the EER values are found to be 12%, 1.9%, 0.35%, 0.2%, 0.35%, 0.04% 0.04% and 0.03% at dimensions 1, 2, 4, 5, 7, 10, 13 and 15, respectively. The EER value increases above dimension 15. The lowest values of EER are reported to 0.17% and 0.03%, respectively on MIT-BIH arrhythmia database and QT database at dimension 10 and 15, respectively. The ROC curves represent the ratio of GAR and FAR at different dimensions are shown in Fig. 4. The identification results on MIT-BIH arrhythmia database achieve 100% GAR on FAR of 0.75%, 0.22%, 0.71%, 0.35% and 0.35% at the dimensions 5, 10, 15, 20 and 25, respectively that are shown in Fig. 4(a). Similarly, the performance on QT database achieves 100% GAR on FAR of 0.2%, 0.13%, 0.07%, 0.07% and 0.2% at the dimensions 5, 10, 15, 20 and 25, respectively that are shown in Fig. 4(b).

The highest identification accuracy on both databases is found to be about 100% which is better than all known approaches tested on these databases. For example, when we compare the proposed method with fiducial based identification methods, it's performance is better than [18]. Although [7,8] achieve 100% identification accuracy, these methods were tested on only a group of 20 subjects. The result of proposed method can also be compared with non-fiducial based ECG identification methods [10,12,19–21]. Among these, the methods

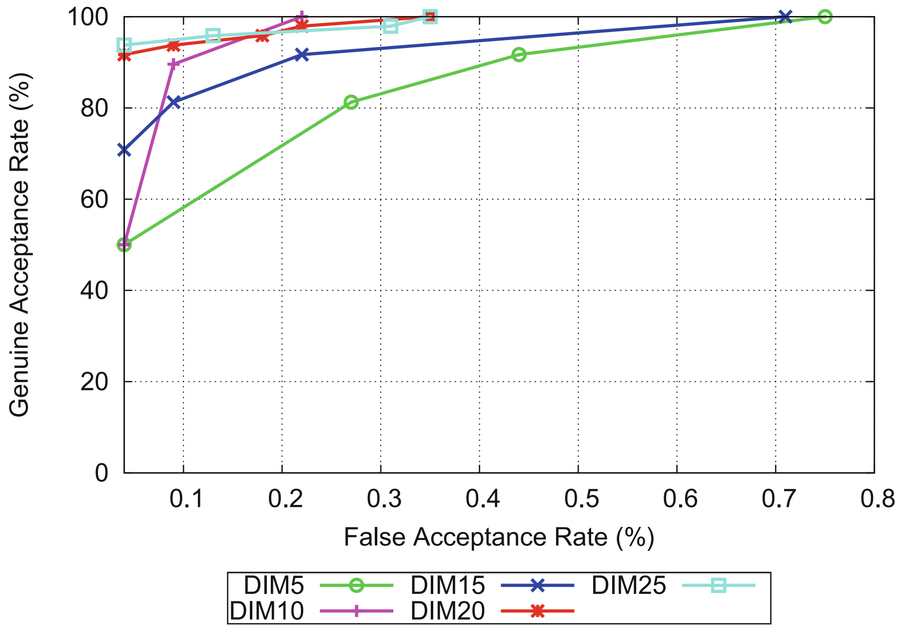


(a)

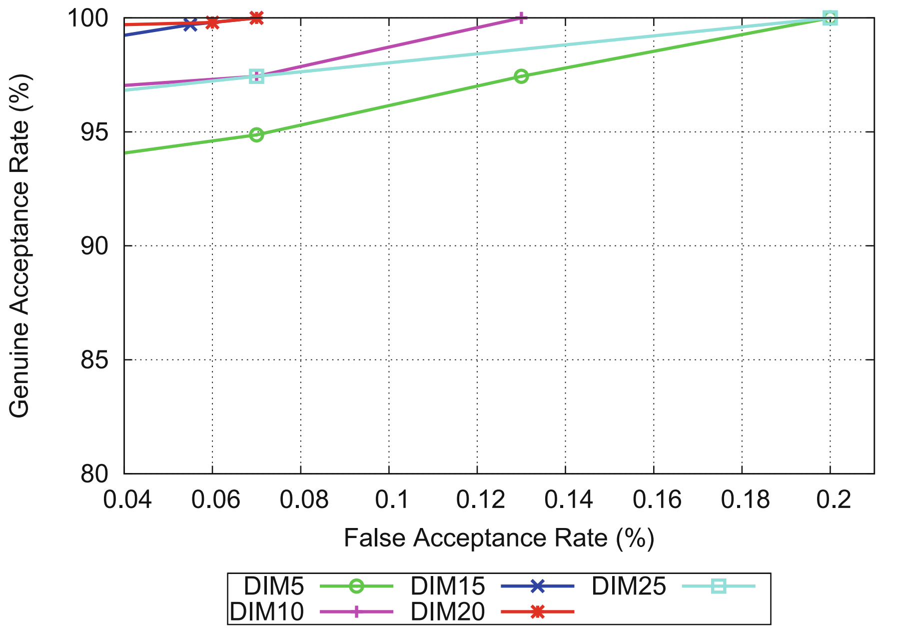


(b)

Fig. 3. Intrasubject similarity and intersubject variability represented by first three dimensions as shown by DIM1, DIM2 and DIM3 for ten different subjects of (a) MIT-BIH Arrhythmia database and (b) QT database.



(a)



(b)

Fig. 4. ROC curve for (a) MIT-BIH Arrhythmia database, and (b) QT database.

[10,12,19,21] reports better performance but these methods were tested only on small set of subjects. The issues like sensitivity to the accurate localization of fiducial points of ECG wave and individuality of ECG over larger population are resolved by applying the proposed method.

Table 1. Equal error rates for different databases at different dimensions

Number of dimensions	Equal error rate (%)											
	1	2	4	5	7	10	13	15	18	20	22	25
MIT-BIH Arrhythmia database	10	5	0.84	0.79	0.37	**0.17**	0.21	0.37	0.52	0.59	0.69	0.73
QT database	12	1.9	0.35	0.2	0.35	0.04	0.04	**0.03**	0.035	0.035	0.04	0.2

4 Conclusion

The conventional biometrics are susceptible to the falsification and spoofing attacks. The ECG has the strong potential to overcome these issues of conventional biometrics. It is proven to be a liveliness indicator. The paper has proposed a novel method of human identification using Fourier and discriminant analysis of the ECG. The method need not to require any fiducial point detection of ECG waveforms rather it has inherently explored the significant points of the ECG signals. Fourier analysis is used to represent the discriminatory features of the ECG while LDA is used to preserve them. The proposed method is proved to be robust as it has reported higher accuracy to normal subjects as well as subjects suffering from severe arrhythmia.

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