ECG Biometric Analysis Using Walsh–Hadamard Transform

Ranjeet Srivastva and Yogendra Narain Singh

Abstract The electrocardiogram (ECG) signal expresses unique cardiac features among individuals. This paper proposes a novel method to human identification using ECG. The proposed method utilizes a band-pass filter for quality check and autocorrelation (AC) for feature extraction. Furthermore, the Walsh–Hadamard transform (WHT) is used for feature transformation. To get cost- and time-efficient classification performance, the dimensionality of feature vector is reduced using linear discriminant analysis (LDA). Experimental results show the best identification rate of 95 and 97% over MIT-BIH arrhythmia database and QT database, respectively.

Keywords Human identification · Electrocardiogram · Walsh–Hadamard transform · Discriminant analysis

1 Introduction

The identity of a person needs to be determined in many applications of access control. Traditional identity verification methods based on passwords and ID cards are vulnerable to identity theft [1]. In order to offer better security to identity proving systems, many body parts and behaviors are being used from last decade [2, 3]. This class of strategy offers better security to identification system. Among them, some modalities are widely accepted but lack to provide robustness to circumvention or replay attacks and user privacy. In the recent years, researchers have suggested that physiological signals like electrocardiogram (ECG) have potential to be used for identity proofing and provide robustness in identification [4, 5].

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In the literature, it has been shown that the ECG signals of different individuals are heterogeneous [6, 16]. The discriminatory features in ECG are found among individuals due to different levels of ionic potential, plasma level of electrolytes as well as physical structure, position, and size of heart. Different methods are found in the literature to analyze the ECG and its use to biometric application. One of the early studies of use of ECG biometric was presented by Biel et al. [6]. They have used multivariate method on a group of 20 subjects and achieved 100% identification rate. Shen et al. [7] have investigated the feasibility of ECG as a biometric by using time-domain and appearance-based features. They have achieved 95 and 80% classification accuracy by template matching and decision-based neural network approaches, respectively. By combining these two approaches, the reported identification result is 100% for 20 subjects.

Singh et al. [8–10] have analyzed the ECG using signal processing techniques. They have classified the individuals using a variety of features those are extracted from temporal, amplitude, and angle features with an accuracy of over 99%. Plataniotis et al. [11] have introduced a non-fiducial feature extraction method based on autocorrelation (AC) and discrete cosine transform (DCT). They reported the recognition rate of 100% on a data set of 14 healthy subjects. Chan et al. [12] have classified 50 subjects with accuracy of 95%, using three different quantitative measures: residual difference, correlation coefficient, and distance measure using wavelet transform.

A short-time frequency method has been developed by Odinaka et al. [13]. They have performed experiments on a sample of 269 subjects. The equal error rates of verification are found to be 5.58% on multisession data. When training and testing samples are collected from same day, the verification results are improved further. Agrafioti et al. [14] have presented an autocorrelation-based approach in conjunction with DCT and linear discriminant analysis (LDA). Wang et al. [15] have demonstrated the comparison of fiducial-based approach using analytic and appearance attributes and non-fiducial-based approach using AC and DCT. Li et al. [16] have proposed a hybrid approach fusing temporal and cepstral information and achieved identification accuracy of 98.26% on 18 subjects.

The issues related to these studies include individuality of ECG over larger population, sensitivity to exact localization of fiducial points, heart rate variations, different anxiety level. In this paper, a novel method is proposed that addresses the issues like the individuality of ECG and accurate localization of dominant fiducials. The method calculates the AC coefficients from the windows of filtered ECG signal. Further, the AC coefficients are transformed into WHT coefficients and LDA is applied to reduce the dimensionality. Experimental results show that the proposed method outperforms other methods on MIT-BIH arrhythmia database and QT database. The rest of the paper is outlined as follows: Sect. 2 presents the novel method of ECG analysis and its characterization that is used for biometric application. The experimental results are presented in Sect. 3. Finally, the conclusion is noted in Sect. 4.

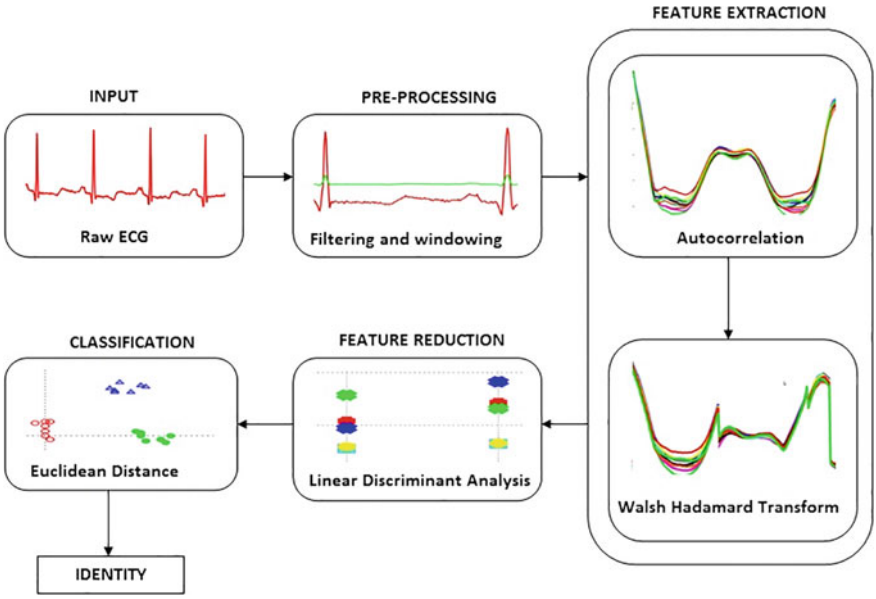

Fig. 1 A schematic of proposed ECG biometric system

2 Proposed Methodology

A schematic diagram of proposed biometric system is depicted in Fig. 1. It involves mainly: preprocessing, feature extraction, feature reduction, and classification. Different types of noise and artifacts are removed in preprocessing step. Features are extracted from an ECG trace of 50 seconds, by autocorrelation followed by Walsh–Hadamard transform (WHT). The LDA is used for feature reduction, and the last step of the identification process is classification based on match scores of the subjects.

ECG signals may have different type of noises such as low-frequency noise components including baseline oscillations, respiration or body movements and high-frequency noise components due to power line interferences. A band-pass filter is used to eliminate the effects of noise by combining a low-pass (Eq. 1) and a high-pass (Eq. 2) filter [17]. The cutoff frequency of low-pass filter and high-pass filter is about 11 and 5 Hz, respectively. The reason behind selecting this combination of filter is that most of the energy of ECG signal lies within the above frequency range.

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

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

The filtered ECG signal is divided into non-overlapping segments. The windowing criteria are followed with the motivation that the maximum correlation among data

samples can be found, if the window size is at least two heartbeats. The length of window can be chosen heuristically according to the sampling rate of signals. For this experiment, all the data is sampled at 200 Hz, and the data window of size 50 seconds is chosen.

The fiducial-based feature extraction techniques may not achieve better classification performance, since it is highly dependent on the accurate localization of dominant fiducials of ECG wave. Several factors may affect the exact delineation of fiducial points such as noise present in the ECG signal. This motivates us to adopt a method which is independent of fiducial points of ECG signal. To extract features from ECG signal without localization of fiducial points, autocorrelation (AC) is applied on windowed ECG. The AC shows similarity of samples as a function of time lag between them. The AC provides an automatic, shift-invariant representation of similarity features over multiple cardiac cycles. The normalized AC ($\widehat{AC}_{yy}[t]$) for ECG signal, $y[i]$ of length n can be computed as follows,

$$\widehat{AC}_{yy}[t] = \sum_{i=0}^{n-|t|-1} \frac{y[i]y[i+t]}{\widehat{AC}_{yy}[0]} \tag{3}$$

where $y[i+t]$ is determined by shifting windowed ECG with a time lag of $t = 0, 1, \ldots (m-1)$; $m << n$.

The AC coefficients are transformed using WHT to maximize the inter-class dissimilarity and intra-class similarity. Walsh function offers a fast method of solving nonlinear differential and integral equations with the reduction in calculation speed and storage space [18]. The Walsh function has only three possible values:$+1$ or -1 in the interval $0 \leqslant x \leqslant 1$ and a value zero outside this interval. The Walsh transform of a given series of numbers $x_0, x_1, x_2 \ldots x_{N-1}$ can be calculated as follows,

$$a_j = \frac{1}{N} \sum_{t=0}^{N-1} x_t * w_j(x_t), \quad j=0,1,\ldots N\text{-}1 \tag{4}$$

where N is the number of samples in the series, and w_j is the Walsh function calculated as:

$$w_j(x) = 0, \quad for \quad x < 0 \; or \; x > 1 \tag{5}$$

$$w_0(x) = 1, \quad for \quad 0 <= x <= 1 \tag{6}$$

$$w_{2j}(x) = w_j(2x) + (-1)^j w_j[2(x-1/2)] \tag{7}$$

$$w_{2j+1}(x) = w_j(2x) - (-1)^j w_j[2(x-1/2)], \quad for \quad j=0,1,\ldots N\text{-}1 \tag{8}$$

The feature vectors formed with Walsh coefficients have higher dimension. To retain the discriminatory information even with lower dimension, LDA is applied to the feature vector. The LDA seeks to reduce dimensionality while preserving as much

the class discriminability as possible. It linearly transforms the feature characteristics in a lower dimension space. More formally, let us assume that training set $\chi = \{\chi_i\}_{i=1}^{N}$ contains the patterns of N classes. Each class $\chi_i = \{\chi_{ij}\}_{j=1}^{N_i}$ with χ_{ij} windows and a set of M feature basis vectors $\{\mho_t\}_{t=1}^{M}$ are estimated by maximizing Fisher's ratio. Fisher's ratio is defined as the ratio of between-class scatter to within-class scatter. The maximization can be formulated as follows,

$$\mho = arg\max\left(\frac{|\mho^T S_b \mho|}{|\mho^T S_w \mho|}\right) \tag{9}$$

where $\mho = [\mho_1, \ldots, \mho_K]$, and S_b and S_w are the between- and within-class scatter matrices, respectively, defined as:

$$S_b = \frac{1}{n}\sum_{i=1}^{N} N_i(\chi_i - \overline{\chi})(\chi_i - \overline{\chi})^T \tag{10}$$

$$S_w = \frac{1}{n}\sum_{i=1}^{N}\sum_{j=1}^{N_i}(\chi_{ij} - \overline{\chi_i})(\chi_{ij} - \overline{\chi_i})^T \tag{11}$$

where $n = \sum_{i=1}^{N} N_i$, is the total number of training windows. The mean of class χ_i is $\overline{\chi_i} = \frac{1}{N_i}\sum_{j=1}^{N_i}\chi_{ij}$. The discriminatory feature vectors can be found corresponding to the vectors of largest eigenvalues. In this experiment, set $\mho$ contains eigenvectors corresponding to k eigenvalues computed from $(S_w)^{-1}S_b$.

3 Experimental Results

The proposed ECG biometric method is tested on MIT-BIH arrhythmia database and QT database of physionet [19]. Both databases include ECG recordings of men and women with the age between 20 and 84 years. The databases have ECG recording of normal and arrhythmia patients. For this experiment, ECG recordings of 48 subjects from MIT-BIH arrhythmia database and 39 subjects of QT database are used. The original sampling rate for MIT-BIH arrhythmia database and QT database is 360 and 250 Hz, respectively. All these records are re-sampled at 200 Hz for this experiment. Each signal is processed with a band-pass filter. Eleven windows of 50 seconds (10,000 samples) and 10 seconds (2000 samples) in length are chosen from processed ECG signal of MIT-BIH arrhythmia database and QT database, respectively. To avoid the sensor and body stabilization effects, the windows are chosen from the middle of each recording. A data set of $528(48 \times 11) \times$ 10,000 for MIT-BIH arrhythmia database and of $429(39 \times 11) \times 2000$ for QT database is formed for feature extraction.

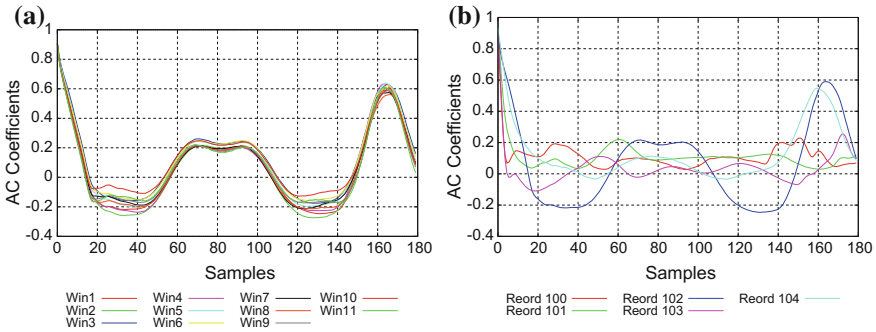

Fig. 2 AC representation of filtered ECG signals: **a** single subject for different windows (eleven) and **b** single window for different subjects (five)

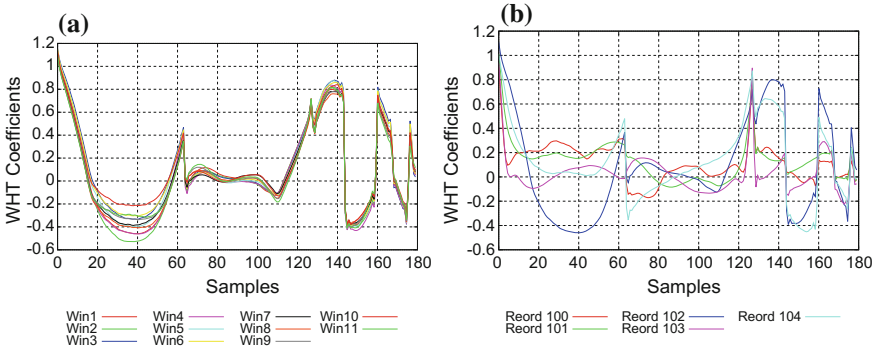

Fig. 3 Plots for Walsh transform of autocorrelated ECG signals: **a** single subject for different windows (eleven) and **b** single window for different subjects (five)

On applying AC to these data sets, the feature vectors of 528 × 180 and 429 × 180 are formed for MIT-BIH arrhythmia database and QT database, respectively. The AC time lag of 180 samples is set for this experiment by considering the fact that a normal heart beats 60 to 100 times a minute. The plots of normalized AC for eleven windows of a subject and for five different subjects are shown in Fig. 2a and in Fig. 2b, respectively. These feature vectors are transformed by WHT, in order to minimize the intrasubject variations and to maximize the intersubject variations. The results of WHT for eleven windows of single subject and single window of five different subjects are shown in Fig. 3a and in Fig. 3b, respectively. The LDA is applied for dimensionality reduction of feature vectors to different dimensions such as 2, 5, 7, 10, 13, 15, 20, 22, 25, and 30. The intrasubject variability and intersubject similarity on first three dimensions as achieved by LDA for ten subjects for each database are shown in Fig. 4.

The last window from each record is used as template to form gallery data set. A probe data set is prepared from rest of the windows from each record. The matching

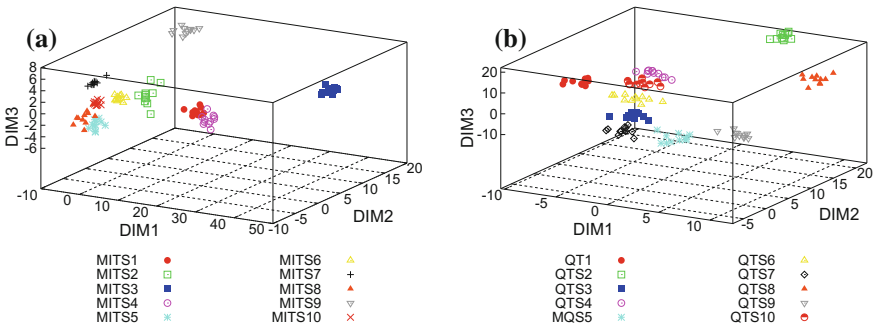

Fig. 4 Intrasubject similarity and intersubject variability represented by first three dimensions as shown by DIM 1, DIM 2, and DIM 3 for ten different subjects of **a** MIT-BIH arrhythmia database and **b** QT database

scores (genuine and imposter) are generated by comparing each projected feature vector from gallery data set to all projected feature vectors in the probe data set. Euclidean distance is used as similarity measure between gallery and probe data sets. The match scores are genuine scores, if they are generated by comparing the attribute sets of probe and gallery data of the same subject; otherwise, the scores are impostor scores. Thus, 48 genuine scores and 2256(48×47) impostor scores are generated, for the population of MIT-BIH arrhythmia database. For the population of QT database, the system generates 39 genuine scores and 1482(39×38) impostor scores. The performance of the proposed identification system is evaluated using classification accuracy by rank-k. The percentage of probe signals that have the correct class as one of the top k scores is known as the rank-k classification accuracy of the system. Further, the cumulative match characteristic (CMC) curve has been drawn after computing the average rank classification accuracies.

The CMC results at different dimensions for MIT-BIH arrhythmia database are shown in Fig. 5a. The rank-1 classification accuracies of the system at dimensions 10, 13, 15, 20, 27, and 30 are found to be 66, 72, 81, 85, 62, and 60%, respectively. It shows that the rank-1 classification accuracies increase with the increase in dimensions up to twenty (DIM 20) and decreases above DIM 20. The system achieves the better rank-1 classification accuracy of 85% at DIM 20. The CMC curve for DIM 10 shows poor classification performance and reported accuracies of 68% at rank-2, 80% at rank-3, 84% at rank-8, 86% at rank-10, 90% at rank-12, and 100% at rank-36. The classification accuracies at DIM 13 are found to be 80% at rank-3. It increases with the increase in rank and reported as 86% at rank-10, 90% at rank-18, 96% at rank-25, and 100% at rank-29. The classification accuracies are improved at DIM 15 and achieve 100% accuracy at rank-28. The accuracies at other ranks are reported as 85% at rank-2, 91% at rank-9, 97% at rank-25. At DIM 20, the classification accuracies are 91% at rank-2, 95% at rank-10, 97% at rank-19, and 100% at rank-37. The classification accuracies show degradation of performance above DIM 20. At DIM 27, it reports accuracies of 89% at rank-2, 95% at rank-16, 97% at rank-23,

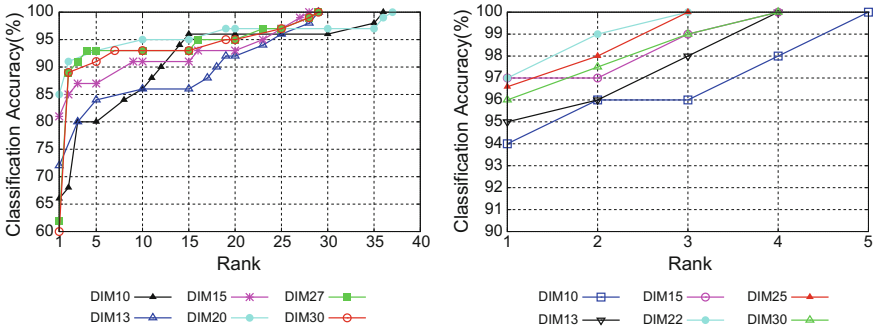

Fig. 5 Cumulative match characteristic curves for rank-based classification accuracies: **a** MIT-BIH arrhythmia database and **b** QT database

and 100% at rank-29. The classification accuracies at DIM 30 are found to be 89% at rank-2, 95% at rank-19, 97% at rank-25, and 100% at rank-29.

The aforementioned system performs better on QT database. The CMC curve is shown in Fig. 5b. The classification accuracies reported at dimension 22 (DIM 22) are found to be 97% at rank-1, 99% at rank-2, and 100% at rank-3. The CMC curve for DIM 10 shows poor performance, and reported accuracies are 94% at rank-1, 96% at rank-2, 98% at rank-4, and 100% at rank-5. At DIM 15, it reports classification accuracies of 97% at rank-1, 99% at rank-3, and 100% at rank-4. The classification accuracies at DIM 30 are found to be 96% at rank-1, 99% at rank-3, and 100% at rank-4.

The average rank classification accuracies on different databases at different dimensions are presented in Table 1. On MIT-BIH arrhythmia database, the average rank classification accuracies are found to be 80, 86, 91, 95, 94, 94, and 91% at dimensions 10, 13, 15, 20, 22, 25, and 30, respectively. The average rank classification accuracies on QT database at dimensions 10, 13, 15, 20, 22, 25, and 30 are reported as 96, 97, 97, 97, 97, 96.6, and 96% respectively. These results reported the highest average rank classification accuracies as 95% at DIM 20 on MIT-BIH arrhythmia database and 97% at DIM 22 on QT database. For both databases, the performance of the system degrades at higher dimensions. For example, above DIM

Table 1 Results of average rank classification accuracies at different dimensions for MIT-BIH arrhythmia database and QT database.

Dimensions	*Average rank classification accuracy(%)*						
	10	13	15	20	22	25	30
Database							
MIT-BIH arrhythmia database	80	86	91	**95**	94	94	91
QT database	96	97	97	97	**97**	96.6	96

20 on MIT-BIH arrhythmia database and above DIM 22 on QT database, the average rank classification accuracies are linearly decreasing.

These results show that the proposed method reports better identification performance in comparison to the other methods of ECG biometric. For example, the proposed method reports better result than fiducial-based identification method [2]. Although the identification accuracy of 100% was achieved by fiducial point-based methods [6, 7], these methods were tested on only group of 20 subjects. The result of proposed method can also be compared with non-fiducial-based ECG identification methods [4, 11, 12, 15, 16]. Among these, the methods [4, 11, 15, 16] report better performance but they are tested only at 74 healthy subjects, 14 healthy subjects, two sets of 13 subjects each, and 18 subjects only. The proposed method proved to be better in handling the issues like sensitivity to accurate localization of fiducial points of ECG wave and individuality of ECG over larger population.

4 Conclusion

The ECG has emerged as a potential tool for biometric recognition due to its unsusceptibility against spoofing and vitality detection features. The ECG analysis methods based on fiducial points take advantage of different morphological features. Temporal, amplitude, and angle features are significantly different among individuals. These methods rely on accurate localization of fiducial points and their onset and offset. There is no universally acknowledged algorithm to find accurate wave boundaries. This study has analyzed the ECG signal to use as a biometric without detection of its dominant fiducials. The autocorrelation is used to compute the discriminative information available to the ECG signals among population. The autocorrelated signals are transformed into their Walsh coefficients to distinguish the features among them. Further, linear discriminant analysis is used to reduce the dimension of feature vectors to result time- and cost-efficient classification performance. The experimental result has demonstrated that the proposed method of ECG analysis proved to be benchmark for biometric research community as it achieves high identification rate for healthy subjects as well as the subjects having arrhythmia.

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