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A Novel Biometric Authentication Approach Using Electrocardiogram Signals*

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Abstract— **In this work, we present a novel biometric authentication approach based on combination of AC/DCT features, MFCC features, and QRS beat information of the ECG signals. The proposed approach is tested on a subset of 30 subjects selected from the PTB database. This subset consists of 13 healthy and 17 non-healthy subjects who have two ECG records. The proposed biometric authentication approach achieves average frame recognition rate of %97.31 on the selected subset. Our experimental results imply that the frame recognition rate of the proposed authentication approach is better than that of ACDCT and MFCC based biometric authentication systems, individually.**

I. Introduction

Biometric recognition is the automatic authentication of a person based on physiological and/or behavioral features. In the past twenty years, a several biometric modalities such as fingerprint, face, iris, palm print, voice, and gait have been used in the biometric authentication systems [1]. The most important disadvantage of these biometric modalities is that they may not be used as a liveness detector. In other words, even though the biometric authentication systems based on these biometric modalities correctly identify a person, the system cannot guarantee if the person is physically there [2, 3].

The electrocardiogram (ECG) signal, which is a graphical display of the electrical activity of the heart, is one of the essential biological signals for the monitoring and diagnosis of heart diseases [4]. Besides, the ECG signals have distinctive features because of the several personal factors such as position, size, and anatomy of the heart, age, and sex [5, 6]. Therefore, recently, the ECG signals as a biometric modality have been employed in the biometric authentication systems. The most important advantage of the ECG based biometric authentication systems is that they can be utilized as a liveness detector. In other words, the ECG based biometric authentication system guarantees that the person to be identified is physically there [2, 3]. On the other hand, the ECG based biometric authentication systems has an important disadvantage that the data acquisition process of the ECG signal is very cost and impractical for a biometric authentication system.

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Several ECG based biometric authentication systems have been developed and reported during the last ten years [2, 3, 5-17]. In 2001, the first human identification approach by using temporal and amplitude features of the ECG signals was presented [7]. The human identification system used heart rate variability as a biometric modality was proposed in [8]. In 2005, a more extensive set of ECG descriptor that characterized the trace of a heartbeat using 15 temporal and amplitude features was introduced in [9]. Then, a two-step identification scheme based on comparing two QRS complexes by using seven temporal and amplitude features was published in [10]. In 2007, a two-dimensional heart vectors for biometric authentication was described in [11]. In 2008, the ECG based biometric identification system, EigenPulse, based on principle component analysis (PCA) was proposed in [12]. A new biometric authentication approach, AC/DCT method, based on combining the autocorrelation and discrete cosine transform was presented in [2]. A new ECG features set extracted by applying the discrete cosine transform to the autocorrelation sequence of the overlapped ECG segments was introduced in the AC/DCT method. Then, a personal identity verification method that used the discrete wavelet transform based features was presented in [5]. In 2009, a novel unsupervised human identification method based on phase space reconstruction of the ECG signals was introduced in [3]. In 2010, a novel robust ECG biometric algorithm based on both temporal and cepstral information was presented in [13]. The ECG based biometric identification method based on extended Kalman filters was demonstrated in [14]. In 2011, a human identification algorithm tested on Lead-I ECG signals recorded from the palms was presented in [6]. A new ECG feature extraction algorithm known as pulse active ratio for ECG biometric recognition was introduced in [15]. Then, applying Lyapunov exponents and correlation dimension, a novel ECG feature extraction method was presented in [16].

In this paper, we present a new biometric authentication approach based on combining AC/DCT features [2], MFCC features and QRS beat information of the Lead-I ECG signals.

II. Methodology

A. Preprocessing Stage

The preprocessing is one of the most important stages of an biometric authentication system because it plays a crucial role to prepare the signal for feature extraction and classification process. The preprocessing stage is carried out in three steps: filtering, normalization, and segmentation.

In the preprocessing stage, first of all, the several noise components on the ECG signals such as power-line interference, baseline wander, and high frequency noise are

TABLE I. CONTINGENCY MATRIX FOR THE PROPOSED APPROACH

Known inputs \ Detected inputs	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30
1	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
2	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
5	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	0	43	0	0	0	0	0	0	0	0	0	0	0	0	2	0	0	0	0	0	0	0	0	0	0	0
7	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
9	0	0	0	0	0	0	10	0	35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0	0	0	0	0	0	0	0	0	29	0	0	15	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0
11	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
12	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0	0	0	0	0	0	0	0	0	0	0	0	0	29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
15	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	14	0	0	0	0	0	0	0	0	0	0	0	0	0
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0	0	0
20	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	46	0	0	0	0	0	0	0	0	0	0
21	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	45	0	0	0	0	0	0	0	0	0
22	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0	0	0
23	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	1	0	33	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0	0
25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0	0
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0	0	0
27	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	4	0	0	0	0	0	0	0	1	42	0	0	0
28	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47	0
30	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	47

filtered by utilizing the Butterworth band-pass filter with a passband from 1Hz to 40 Hz. Then, the filtered ECG signals are normalized using the following formula

$$X_{norm} = \frac{X - \mu_X}{\sigma_X} \quad (1)$$

where X_{norm}, X, μ_X, and σ_X represents the normalized ECG signals with zero mean and unit variance, the filtered ECG signal, the mean, and standard deviation of the filtered ECG signals, respectively. Finally, the normalized ECG signals are divided into 5s frames with 50% overlapped.

B. Feature Extraction and Classification

Three different methods were employed to extract the features from the ECG signals in the training dataset in the proposed approach. The first feature set was extracted by applying the AC/DCT method given in [2]. At the same time, Mel-Frequency Cepstrum Coefficients (MFCC) computed from the spectrum of the ECG signals were used as the second feature set, which is commonly used as a features set in the speech recognition systems. In the proposed approach, we employed the first 20 AC/DCT features and 13 MFCC features. In addition to these feature sets, R points for each ECG signal were determined by applying the Pan-Tompkins QRS detection algorithm [17]. Then, the R points were aligned by taking the 60 sample before and after from the R points. Thus, the QRS beats which consist of 120 samples were obtained to be used as the third feature set.

In the proposed approach, both AC/DCT and MFCC features extracted from all ECG frames in the training dataset were classified by using the LDA (Linear Discriminant Analysis) classifiers. On the other hand, the 3-Nearest-Neighbor (3-NN) classifier was utilized to classify the QRS beats extracted from all ECG frames in training dataset. For 3-NN classifier, the Euclidean distance was selected as the similarity measure metric.

$$\varepsilon = \sqrt{(f_T - f_{IN})(f_T - f_{IN})^T} \quad (2)$$

where f_T and f_{IN} represent the template feature vector stored in the authentication system and the feature vector of the unknown ECG frame.

In this research work, we present a novel ECG based biometric authentication approach which combines the AC/DCT features with MFCC features and QRS beat information extracted from the ECG frames with 50% overlapped. As it can be seen from Figure 1, for an unknown ECG frame, the AC/DCT features are extracted and the candidate-A is determined by the corresponding LDA classifier. Simultaneously, the MFCC features are computed for the same unknown ECG frame. The LDA classifier corresponding to the MFCC features provides the other candidate, candidate-B, for the same unknown ECG frame. If the two distinct LDA classifiers agree with the decision, the candidate-A or candidate-B is fixed as the ID number for the unknown ECG frame. Otherwise, the 3-NN classifier is retrained according to the QRS beats stored in training database for the candidate-A and candidate-B. Then, the QRS beats are extracted from the unknown ECG frame.

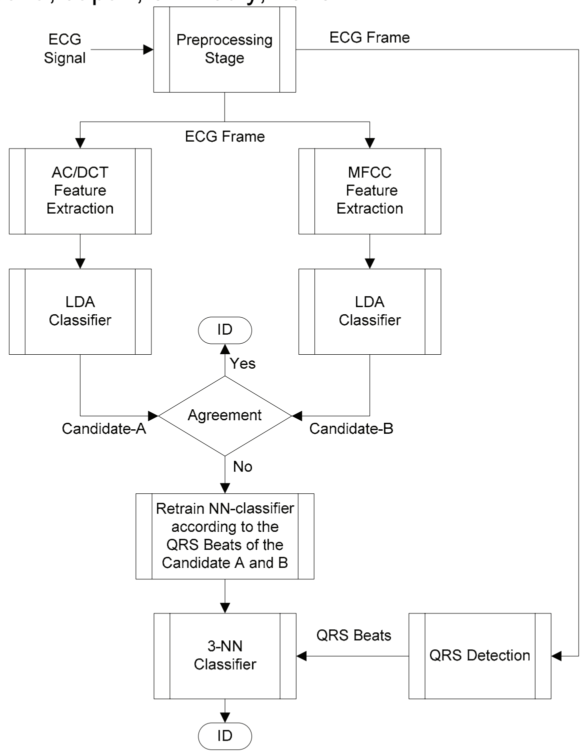

Figure 1. Block diagram of the proposed approach.

Finally, the 3-NN classifier provides a decision between the candidate-A and candidate-B by using the majority voting strategy and Euclidean distance similarity.

In the following section, the data sets and simulation results for the proposed approach are presented.

III. Experimental Results

A. Data Sets

In this experimental research work, we used the PTB diagnostic ECG database [18, 19] to evaluate the performance of the proposed approach. The PTB diagnostic ECG database consists of 549 ECG records from 290 healthy and non-healthy subjects. Each subject has one to five ECG records. For same subject in the database, the average interval time between any two ECG records is about 500 days [2, 11]. Each record in the database was sampled at 1 kHz and quantized at 16-bit resolution [18, 19]. The PTB diagnostic ECG database contains the conventional 12-leads and 3-Frank leads [2]. In our experiment, we use only the Lead-I configuration which is recorded between left and right wrist since the Lead-I configuration is more convenient for biometric authentication systems [15].

The performance of proposed approach was evaluated on a subset of 30 subjects selected from the PTB database. The subset consists of 13 healthy and 17 non-healthy subjects which have two different ECG records. For each subject in the subset, one of the ECG records was used as a training ECG data while the other record was used as test ECG data.

B. Evaluation Metrics

The classification performance of the proposed approach is evaluated by using four statistical measures which are the sensitivity, specificity, F_{SCORE}, and frame recognition rate.

The sensitivity is defined as the proportion of positive samples which are correctly identified. On the contrary, the specificity measures the proportion of the negative samples which are correctly identified. The sensitivity and specificity are given by

$$Sensitivity\ (Recall) = \frac{TP}{TP + FN} \tag{3}$$

$$Specificity = \frac{TN}{TN + FP} \tag{4}$$

where TP, TN, FP, and FN are defined as true positive, true negative, false positive, and false negative, respectively.

The F_{SCORE} shows the accuracy of the experiment and is defined as the harmonic mean of the precision and recall.

$$F_{SCORE} = 2 \times \frac{Precision \times Recall}{Precision + Recall} \tag{5}$$

where

$$Recall = Sensitivity \qquad Precision = \frac{TP}{TP + FP} \tag{6}$$

The Frame Recognition Rate is defined as the ratio between the number of frame correctly identified and the total number of frame for each subject. The ratio is given by

$$Frame\ Recognition\ Rate = \frac{N_{TP}}{N_F} \tag{7}$$

where N_{TP} and N_F represent the number of frame correctly identified and the total number of frame for each subject.

TABLE II. Frame Recognition Rates

ID	Number of Frames	Frame Recognition Rate (%)		
		AC/DCT	MFCC	Proposed Approach
1	45	100,00	100,00	100,00
2	45	100,00	100,00	100,00
3	45	100,00	100,00	100,00
4	45	100,00	100,00	100,00
5	45	100,00	100,00	100,00
6	45	0,00	95,56	95,56
7	45	100,00	66,67	100,00
8	45	100,00	95,56	100,00
9	45	77,78	0,00	77,78
10	45	2,22	64,44	64,44
11	45	100,00	95,56	100,00
12	45	100,00	86,67	100,00
13	45	100,00	95,56	100,00
14	29	100,00	72,41	100,00
15	45	100,00	95,56	100,00
16	45	100,00	86,67	100,00
17	14	100,00	100,00	100,00
18	45	100,00	100,00	100,00
19	45	100,00	100,00	100,00
20	47	97,87	68,09	97,87
21	45	95,56	100,00	100,00
22	47	21,28	100,00	100,00
23	35	0,00	97,14	94,29
24	47	100,00	100,00	100,00
25	47	100,00	97,87	100,00
26	47	100,00	95,74	100,00
27	47	51,06	87,23	89,36
28	47	100,00	100,00	100,00
29	47	100,00	100,00	100,00
30	47	100,00	100,00	100,00

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C. Results and Discussion

In this experimental research work, the proposed approach was compared to the AC/DCT [2] and MFCC. In order to carry out a precise comparison among the proposed approach and the other methods, all these methods were evaluated on the same test dataset which contains 1311 ECG frames obtained from 30 ECG signals.

The contingency matrix for the proposed approach is presented in Table 1. As it can be seen from Table 1, most of the ECG frames in the test dataset can be correctly identified. In the Table 2, the frame recognition rates of the proposed approach and the other methods are presented for each ECG signal in the test dataset. We observed that the AC/DCT method provides very low frame recognition rate especially for some ECG signals recorded from non-healthy subjects. Therefore in the proposed approach, the frame recognition rates for each ECG signal in the test database are significantly increased by combining the AC/DCT features with MFCC features and utilizing the QRS beat information in the decision process as shown in Table 2.

In Table 3, the values of sensitivity, specificity, F_{SCORE}, and average frame recognition rate are given for both the proposed approach and the other methods, respectively. As it can be seen from Table 3, the proposed approach achieves the average frame recognition rate of 97.31% while the AC/DCT and MFCC methods provide the frame recognition rate of 84.97% and 90.01%, individually. In other words, the proposed approach achieves almost 10% higher the average frame recognition rate in comparison with the others for the same test dataset. The performance evaluation in terms of the parameters given in Table 3 between the proposed approach and the other methods is illustrated in Figure 2.

TABLE III. COMPARISON OF THE CLASSIFICATION PERFORMANCE OF THE PROPOSED APPROACH TO THE OTHER METHODS

Methods	Sensitivity	Specificity	F_{SCORE}	Average Recognition Rate
ACDCT [2]	%84.97	%99.48	%84.97	%84.86
MFCC	%90.01	%99.65	%90.01	%90.02
Proposed Approach	%97.25	%99.91	%97.25	%97.31

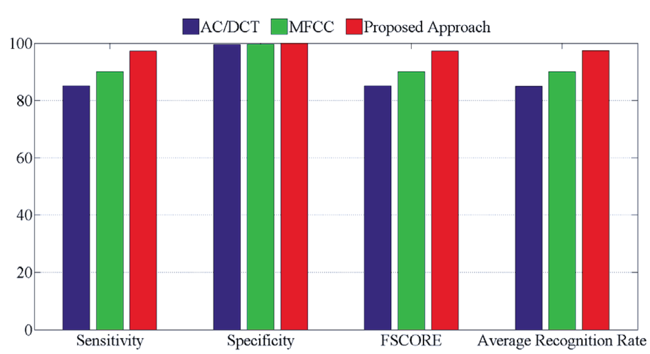

Figure 2. Comparison of the classification performance of the proposed approach to the other methods.

IV. CONCLUSION

We have introduced a novel ECG based biometric authentication approach. The proposed approach is based on combining AC/DCT features, MFCC features, and QRS beat information of the ECG signals. In this experimental research work, we demonstrated that the proposed approach achieves the average frame recognition rate of 97.31% on the ECG test database which consists of healthy and non-healthy subjects.

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