A Machine Learning Technique for Person Identification using ECG Signals

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Abstract: - This paper presents a machine learning technique for person identification using electrocardiograms (ECG). The proposed technique consists of four processes; namely, data acquisition, pre-processing, feature extraction, and classification. Data set were collected from the MIT-BIH Arrhythmia database working on 30 subjects using lead II (MLII) obtained by placing the electrodes on the chest. Second process concerns with the noise reduction in ECG by removing baseline drift, power line interference and high frequency noise. Feature extraction process was studied by using a non-fiducial approach based on auto correlation and discrete cosine transform (AC/DCT) .In the last process , artificial neural network (ANN) have been used to classify subjects with a classification accuracy of 97%.

Key-Words: - ECG Signals, Feature Extraction, Classification, Neural Network, Machine Learning

1 Introduction

Biometric recognition provides an important tool for security by identifying an individual based on the physiological or behavioural characteristics [1]. A number of biometrics has been investigated in the past, examples of which include physiological traits such as face, fingerprint, iris, ears, retina, dental, palm print and hand geometry and behavioural characteristics like gait, keystroke, signature, voice, gait, keystrokes. However, these biometrics modalities either cannot provide reliable performance in terms of recognition accuracy and most of them are not robust enough against falsification. For instance, face is sensitive to artificial disguise, fingerprint can be recreated using latex, and iris can be falsified by using contact lenses with copied iris features printed on.

ECG is a tool for clinical diagnosis, which describes the electrical activity of the heart. The electrical activity is related to the impulses that travel through the heart. It provides information about the heart rate, rhythm, and morphology. Normally, ECG is recorded by attaching a set of electrodes on the body surface such as chest, neck, arms, and legs.

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. A crucial issue here is that the reliability of the extracted features is strongly dependent on the accuracy of the detected points, which are prone to error. For instance, physical status of the subject, variability in noise levels, recording conditions, leads attachment, sampling frequency and related practical considerations introduce a potential for considerable variation in fiduciary extraction methods [2-6].

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. However, those approaches usually yield a high

dimension feature space (ex: hundreds of coefficients),which in turn increases the computational overhead, requires more data for training and may contain redundant and irrelevant information that may confuse the classifier [7-12].

This paper is organized as follows. Section2 presents the proposed machine learning methods and the technical aspects of data acquisition, pre-processing, feature extraction and classification processes. In section 3, experimental results are shown. Finally, Section 4 concludes the paper and proposes future research work.

2 Proposed Method

A methodology of a biometric system usually mimics that of a pattern recognition system. Thus, it can be broken down into four main processes, namely; (1) data acquisition, (2) pre-processing; (3) feature extraction and (4) classification (subject identification).

2.1 Data acquisition

Datasets were collected from MIT-BIH Arrhythmia databases. This database contains 47 subjects 25 men aged from 32 to 89 years, and 22 women aged from 23 to 89 years. In most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. In our study we used 30 subjects from the 47 subject as they were recorded using lead II (MLII).Subjects number100,101,103,105,107,109,111,112,113,114,1 15,116,117,118,119,121,122,123,124,215,219,220, 221,222,223,228,230,231,232,234. The ECG beat types in this paper include normal beat (NORMAL) and seven types of ECG arrhythmias including premature ventricular contraction (PVC), paced beat (PACE), right bundle branch block beat (RBBB), left bundle branch block beat (LBBB), atrial premature contraction (APC) as shown in Fig.1.
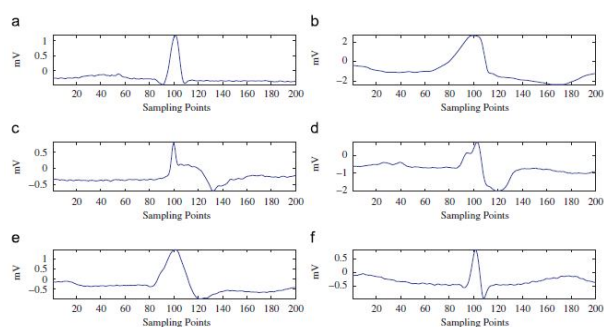

Fig.1 shows six types of ECG heart beats: (a) Normal; (b) PVC; (c) PACE; (d) RBBB; (e) LBBB; (f) APC;

2.2 Preprocessing

ECG records usually contain noise Fig.2. This noise can be contributed, but not limited to recording conditions, body movement, electrodes attachment and physical conditions of the subject. There exist three types of noises in the ECG signal, power line noise, high-frequency noise and baseline drift. Visual analysis of noisy ECG shows that the pre-processing stage should perform three major tasks: baseline drift correction, frequency-selective filtering and signal enhancement. As a result of a series of experiments, the following combination of methods was selected for the pre-processing stage. Baseline drift correction was done using wavelet decomposition with wavelet name db8 with N = 9 using a soft threshold = 4.29, Adaptive band stop filter fairly well suppresses power-line noise with Ws = 50 Hz and dA = 1.5, low pass Butterworth filter with Wp = 40 Hz, Ws = 60 Hz, Rp = 0.1 dB and Rs = 30 dB is used to remove the remaining noise components, caused by possible high-frequency distortions, last step smoothing the signal with N = 5 to produce the pre-processed signal Fig.3.
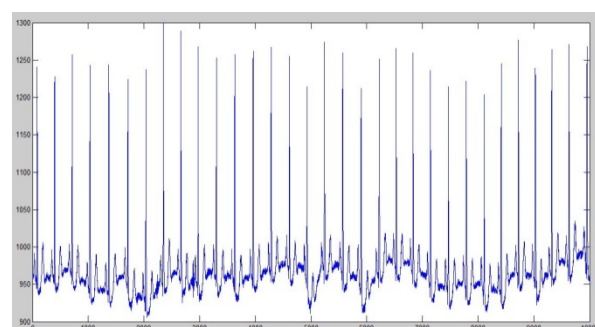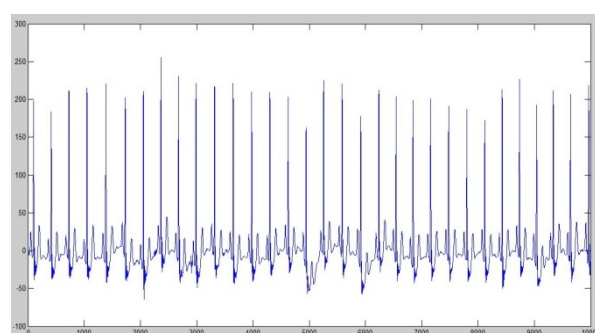

Fig.2 MIT-BIH Subject 101 Original Signal

Fig.3 MIT-BIH Subject 101 Filtered Signal

2.3 Feature Extraction

The AC/DCT method considers a window of the ECG pulses; the AC/DCT method considers a window of the ECG trace data of arbitrary length and origin. The only requirement imposed is that the data window of length N is longer than the underlying average heart beat rate so in the normal situations it can contain all complete heartbeat periods. Thus, contrary to most exiting heart beat biometric identification methods; this method introduces two main advantages a) extract heart rate detection which may vary between different records or even within the same record of data, is not required; b) no synchronization of heartbeat pulses is necessary. These contribute to the appealing computational simplicity and robustness of the proposed approach.

Depending on the sampling rate, the length of the data window may vary. This offers a compromise between representing a multiple of unique and varying subject characteristics and computational complexity. Based on experimentation, a data window of 10 seconds has been found to be a good choice for AC/DCT method.

The autocorrelation (AC) is applied to accomplish the following objective: to blend in all samples in the ECG window to a sequence of sums of products so that the actual locations of the fiducials will not be required to be explicitly found, The estimated and normalized AC formula used for this approach is shown here:

$$R_{xx}^{\wedge}[m] = \frac{\sum_{i=0}^{N-|m|-1} x[i]x[i+m]}{R_{xx}^{\wedge}[0]} \qquad (1)$$

Where x[i] is the windowed ECG and x [i + m] is the time-shifted version of the windowed ECG with the time lag of m = 0, 1… (M-1); M << N. M is a parameter that is to be chosen and this will be discussed later. The reader should note that it does not matter if the estimation is biased or unbiased because the division with the maximum value $R_{xx}^{\wedge}[0]$, cancels out the biasing factor.

A typical ECG pulse consists of mainly three high amplitude waveforms: the P complex, the QRS complex, and the T complex. These complexes are the main contributors to this sum when the autocorrelation coefficients are calculated on the section of the ECG signal.

Discrete cosines transform (DCT) The DCT is applied to the AC coefficients for dimensionality reduction. After DCT is performed, the number of important coefficients is reduced even more because a lot of the DCT coefficients will become near-zero values. This is a result of the energy compaction property of the DCT transform. Therefore, assuming we take an M – point DCT, only C << M DCT coefficients will be much significant. The C first coefficients of the DCT form the feature vector of the proposed AC/DCT biometric identification method as shown in Fig.4.
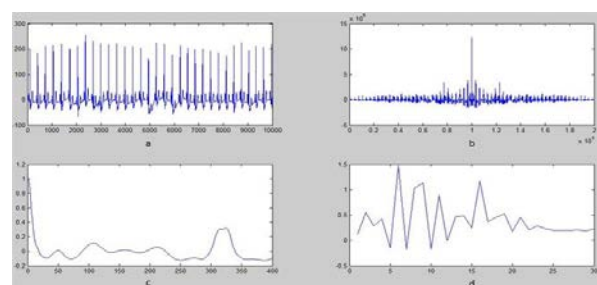

Fig.4 (a) shows MIT-BIH Subject 101 the preprocessed signal (b) show the normalized autocorrelation sequence (c) Zoomed in to 400 AC coefficients from the maximum (d) DCT of the 400 AC coefficient from 10 ECG windows including the one on top

2.4 Classification

The classification operation of the neural network begins with sum of multiplication of weights and inputs plus bias at the neuron, if the sum is positive then only output elements fires. Otherwise it doesn't fire. The artificial neural network is an adaptive system, in other words, the system adopting itself and changes the system weights during the operation [13].

Our neural network consists of three layers input, hidden and output layers. The input layers size depends on the attributes or the feature values while the output layer size depends on the number of classes and the hidden layers are calculated based on the summation of number of attributes and the number of classes divided by 2.

This neural network is trained using momentum back propagation learning method with gradient descent, in the gradient descent the weights are moved along the negative gradient of performance function with a momentum constant equal to 0.3 , learning rate equals to 0.2 and number of epochs about 1000 iterations.

3   Experiments and Results

Data Set	Type	File Number	Accuracy
Training Subset 40000 samples from each individual	Normal PVC PACE RBBB LBBB APC	100,101,103,105,112,113,114,115,117 121,122,123,219,230,234 116,119,215,221,228 107 118,124,231 109,111 222,232,220,223	Number of training samples = 120000 Number of testing samples = 60000
Testing Subset 20000 samples from each individual	Normal PVC PACE RBBB LBBB APC	100,101,103,105,112,113,114,115,117 121,122,123,219,230,234 116,119,215,221,228 107 118,124,231 109,111 222,232,220,223	Classification accuracy using ANN 97 %

Table 1 Classification performance of the proposed scheme

The experiments were carried out on the platform of core i7 with 3 GHz main frequency and 6 G memory, running under window8 64 bit operating system. The algorithms were developed via the discrete wavelet transform toolbox Matlab 2014b (The Math works). Our Classification algorithms were used from the weka software. We have an ECG identification system that was based MIT-BIH Arrhythmia database.

Our feature extraction was done using AC / DCT approach. Our classification was done using ANN. As shown in Table 1 the number of subjects used in training and testing are 30 subjects and their different types of ECG beats.

 For each individual 40000 samples are used for training and 20000 samples are used for test leading to 4 records were used for training and 2 records were used for test for each individual. So the number of classified records was 58 records from 60 achieving an accuracy of 97 % using ANN classifier.

4   Conclusions and Future Work

This paper proposes an intelligent ECG recognation method. The proposed method contains pre-processing, feature extraction, and classification stages. ECG Signals obtained from the MIT-BIH Arrhythmia and it was used for the training and testing processes. We have applied a method for feature extraction based on non-fiducial, approach and artificial neural network classifier was used for classification of ECG signals in both databases.

A feature vector is formed by non-fiducial approach this feature vector consists of 30 samples that are used as an input to the classifiers. ANN is trained using the obtained features. The results showed accuracy of 97%   for MIT-BIH Arrhythmia database.

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