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A New Approach to ECG Biometric Systems: A Comparitive Study between LPC and WPD Systems

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Abstract—In this paper, a novel method for a biometric system based on the ECG signal is proposed, using spectral coefficients computed through linear predictive coding (LPC). ECG biometric systems have traditionally incorporated characteristics of fiducial points of the ECG signal as the feature set. These systems have been shown to contain loopholes and thus a non-fiducial system allows for tighter security. In the proposed system, incorporating non-fiducial features from the LPC spectrum produced a segment and subject recognition rate of 99.52% and 100% respectively. The recognition rates outperformed the biometric system that is based on the wavelet packet decomposition (WPD) algorithm in terms of recognition rates and computation time. This allows for LPC to be used in a practical ECG biometric system that requires fast, stringent and accurate recognition.

Keywords—biometric, ecg, linear predictive coding, wavelet packet decomposition

I. Introduction

A BIOMETRIC system is a system that is able to identify and distinguish between individuals based on a certain physiological trait. In the past, these systems employed fingerprints, iris, voice and facial recognition to accomplish this task. Although these traits are unique to individuals, there are nonetheless loopholes within each of the systems which can compromise security.

Thus a lot of research was conducted in search of a biometric that is hard to forge and duplicate. Within the past decade, studies have looked into the viability of using electrocardiograph (ECG) as a biometric. Biel et al. (1999) first provided experimental evidence that ECG carried information specific to individuals [2], [3].

Figure 1 shows an example of an ECG signal. The ECG signal is divided into three main portions: the P wave, the QRS complex wave and the T wave. The P wave occurs during a normal atrial depolarization, followed by the rapid depolarization of the right and left ventricles producing the QRS complex wave and lastly the repolarization of the ventricles which creates the T wave.

The different stucture of the heart between individuals affect the shape of the ECG signal [6], [8], [18]. This allows for a biometric system to use this physiological trait for human identification purposes. Many systems rely on time-domain features such as the interval of the QRS complex and the amplitude of the P wave. The inherent drawbacks of such systems are that they have a higher chance of being fooled by a fake ECG signal if the locations and amplitudes of the PQRST points have been guessed [21]. There is also no universally accepted boundaries of the waves and thus the values obtained varies depending on the equipment that was used to acquire them and the location of the electrode [15].

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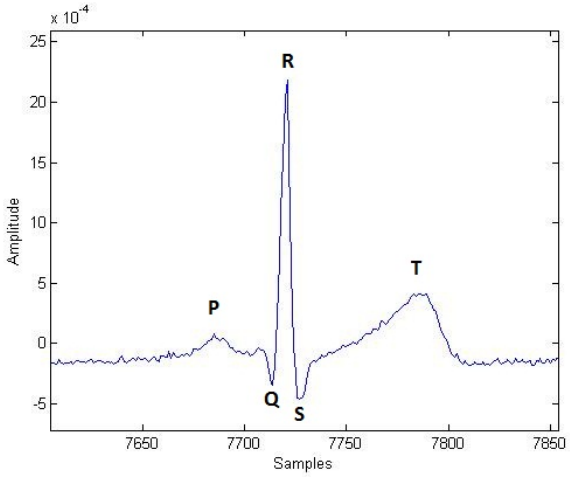

Fig. 1. Example of an ECG signal with the P, Q, R, S and T regions labelled.

Thus a new method for ECG identification is proposed, using an approach that operates in the frequency domain, specifically linear predictive coding (LPC). LPC has been used extensively in the analysis of vowel recognition in speech recognition systems because of its ability to detect poles. Even though the ECG signal is not a speech signal, it shows similar quasi-periodic properties to a phonetic segment of speech. In terms of the use of LPC for ECG recognition, the authors are aware of only one research paper whose objectives were for the purposes of differential diagnosis [7]. In this project, LPC was used to compute the spectral envelope of the ECG signal. Subsequently, the first fourty spectral coefficients were extracted as features of the classification algorithm.

Wavelet packet decomposition (WPD) has been used in the classification of electroencephalogram (EEG) signals [20]. WPD is able to provide information in the time and frequency domain and it is also a nonfiducial-point based feature extraction method. The results of WPD feature extraction method will be compared to the LPC approach for comparison.

II. Biometric Systems using ECG

Research on ECG as biometrics in the past can largely be categorised into fiducial-point based systems and nonfiducial-

point based systems. Kyoso M. et al. (2001) used as little as 2 time-domain features for classification with an accuracy exceeding 90% [13]. In another system, Shen et al. (2002) used 7 features from the fiducial points [17].

Zhaomin Z. and Daming W. (2006) combined 14 time-domain features with Bayes' theorem for a recognition rate of 97.4% [24]. Kyoso M. (2003) used a total of 34 time-domain features in order to avoid false acceptance in ECG identification [12]. Several other studies have pre-determined the top features from the fiducial points and only incorporated those for their systems [8], [9]. Palaniappan et al. (2004), Adrian et al. (2006) and Singh et al. (2008) have also used features from the time-domain and garnered an accuracy of 97.6%, 90.8% and 99% respectively [5], [14], [18].

Yongjin et al. (2006) integrated fiducial features as well as linear discriminant analysis (LDA) and principal component analysis (PCA) in a hierarchical scheme and achieved 98.90% heartbeat recognition rate and 100% recognition rate for 13 subjects [22]. Several approaches to non-fiducial point based systems have been tried, such as the Fourier transform [11], [16], dicrete wavelet transform [6], [23], autocorrelation [15], [19], Legendre polynomials [10] and PCA/LDA [4] with a recognition rate ranging from 77% to 100% for as many as 35 subjects.

Agrafioti F. and Hatzinakos D. (2008) showed that while many systems used 1 lead for ECG identification tasks, it is possible to achieve 100% window recognition rate and 100% subject recognition rate with a database of 249 subjects in a 12 lead ECG system with a decision level fusion [1]. Nonetheless while the results are impressive, it is very impractical to use 12 leads in a realistic biometric system.

III. Methodology

A biometric system is essentially a pattern recognition problem and thus the methodology for this experiment can be broken down into 4 parts: (i) experimental setup, (ii) pre-processing, (iii) feature extraction and (iv) classification. Each part will be explained in detail in the following subsections.

A. Experimental Setup

ECG signals were recorded using a gMobilab+ console by Guger Technologies that was connected to a computer and captured using the Matlab Data Acquisition Toolbox with a sampling frequency of 256 Hz. A single lead ECG recording was done by following the connections in Figure 2. Participants were required to remain calm and relaxed throughout the recording session.

A total of 15 healthy subjects participated in this study. All were male students at Multimedia University between the ages of 18 to 22. Two ECG recordings were obtained from each participant with a duration of 65 seconds for each recording. The recordings are made on the same day for every participant, though not in the same session. The first 2.5 s and the last 2.5 s of the signal were removed and the remaining 60 s of the signal was used for training and testing.

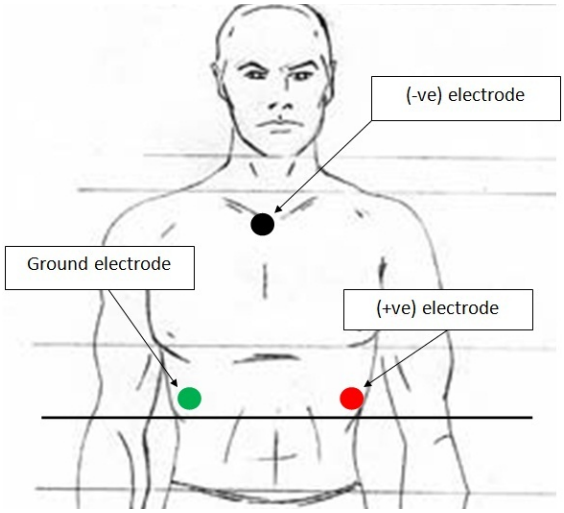

Fig. 2. Placement of the ECG electrodes for 1 lead recording.

B. Preprocessing

Preliminary processing prepares the signal for the feature extraction stage. This stage consists of two parts:

1) Pre-emphasis Filter: The ECG signal is put through a pre-emphasis filter with the following equation:

$$y[n] = x[n] - 0.95.x[n-1] \tag{1}$$

where $x[n]$ is the input signal and $y[n]$ is the output signal after pre-emphasis. The pre-emphasis filter is used to boost the higher frequency region of the signal in order to flatten the spectrum. This in turn allows for better calculation of the coefficients using LPC.

2) Segmenting: The signal is subsequently divided into 5 s segments with 50% overlap. In calculating the spectral envelope of the ECG signal, a longer signal will actually provide better estimation. Nonetheless the signal was segmented in order to increase the amount of training samples used for training the neural network. Preliminary testing shows that 5 s of signal was appropriate because reducing the duration of the segment will reduce the accuracy of the spectral envelope estimation and increasing the durations will result in fewer training samples.

C. Feature Extraction

Two methods were used for feature extraction. In general, for LPC, the first fourty coefficients of the ECG LPC spectrum is extracted and is used as features for the classification algorithm. For the WPD method, the features were extracted using the 'db2' wavelet in a 5-level wavelet packet decomposition.

1) Linear Predictive Coding: LPC is a technique of time series analysis that is used to predict future values of a signal as a linear function of previous samples. The predicted value can be calculated from the following equation:

$$\hat{x}[n] = -\sum_{i=1}^{p} a_i x[n-i] \tag{2}$$

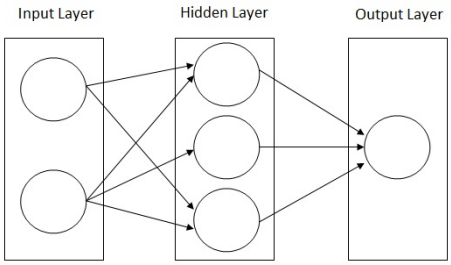

Fig. 3. A neural network consists of three layers: input, hidden and output layer.

where $x[n-i]$ are the previous values, a_i are the LPC coefficients and p is the order of the LPC. The error produced from this estimate is then the difference of the predicted value and the actual value:

$$e[n] = x[n] - \hat{x}[n] \tag{3}$$

where $x[n]$ is the actual value. The error is minimized and the LPC coefficients are found using the Levinson-Durbin recursion. The first 40 points of the LPC spectrum are taken as the feature set of the ECG signal.

2) Wavelet Packet Decomposition: In the WPD method, the signal is applied a 5-level wavelet packet decomposition using the 'db2' wavelet. Unlike the discrete wavelet transform which only decomposes the lower frequency region of the signal, WPD decomposes both the approximation and the detail coefficients to give a better representation of the signal throughout the frequency range.

The coefficients from each node were extracted and five statistical parameters were calculated from them, i.e., maximum, minimum, mean, standard deviation and entropy. These nodes represent the frequency range of 0 to 40 Hz with a resolution of 4 Hz per node. In total, there are are total of 50 parameters that are used as the feature set for WPD.

D. Classification

A neural network system consists of three layers: input, hidden and output layer as shown in Figure 3. The input layer is the feature set to be trained or classified. The hidden layer consists of many interconnected artificial neurons working in parallel to model the relationship between the input layer and the output layer. The output layer is the result obtained after running the input layer through the hidden layer.

Each neuron in the hidden layer performs a simple task which is described by this equation:

$$a = f(wp + b) \tag{4}$$

where p is the input, f is the transfer function, w is the weight to be multiplied to the input, b is the bias to be added to the input and a is the output of the neuron. The bias can be thought of as a weight, except that its value is always 1. The bias is added to the weighted input and run through the selected transfer function. If the output exceeds a certain threshold, the neuron fires. Otherwise it does nothing. A back-propagation neural network is adopted whereby the signals travel from both the input to the output and vice versa and the weights of the neurons are contiously changed until the performance goal of the system is met or the system reaches equilibrium.

TABLE I
CRR OF THE SYSTEM VARYING THE ORDER OF THE LPC AND USING 120 POINTS OF THE LPC SPECTRUM.

Order of LPC	CRR (%)
4	97.81
6	99.24
8	99.10
10	99.33
12	99.62
14	99.14
16	99.05

The extracted features from each segment are randomly divided into training and testing sets each time the system is executed with a ratio of 70% of the features used for training and the remaining 30% for testing. The training set is normalised to a mean of 0 and a standard deviation of 1 before training:

$$\hat{v} = \frac{v - \mu_v}{\sigma_v} \tag{5}$$

where $\hat{v}$ is the normalised feature vector, μ_v is the mean and σ_v is the standard deviation of features of the training set. The same process used to normalise the training set will be used to normalise the testing set during the testing of the system. Two hidden layers with 100 nodes in each layer are employed and the training function used was the scaled conjugate gradient. The training is deemed succesful only when the performance of the system calculated using mean square error reaches or falls below 10^{-3}. Otherwise the system is retrained to achieve optimal performance.

IV. Results and Discussion

The results of this experiment will be based on the average correct recognition rate:

$$\text{CRR}_{ave} = \frac{1}{R}\sum_{i=1}^{R}\frac{C_i}{T_i} \times 100 \tag{6}$$

where C_i is the number of correct classifications, R is the number of runs and T_i is the total number of testing samples. The number of runs is defined as the number of times the classification task was executed in order to obtain an average CRR. In this paper, each task was executed 5 times, since the training and testing samples for every run are randomised.

Figure 4 shows the ECG LPC spectrum of all the segments of the ECG for 5 different subjects. Visual analysis shows us that the LPC spectrum of the ECG is unique between individuals and this provides the mean to classify these individuals.

Table I shows the CRR_{ave} of the system when the order of the LPC was varied and 120 points of the LPC spectrum was used as the feature set. It can be seen that setting the order of the LPC to 4 causes the CRR_{ave} to drop. LPC of orders 6 onwards produced constant CRR_{ave} of above 99%. This is

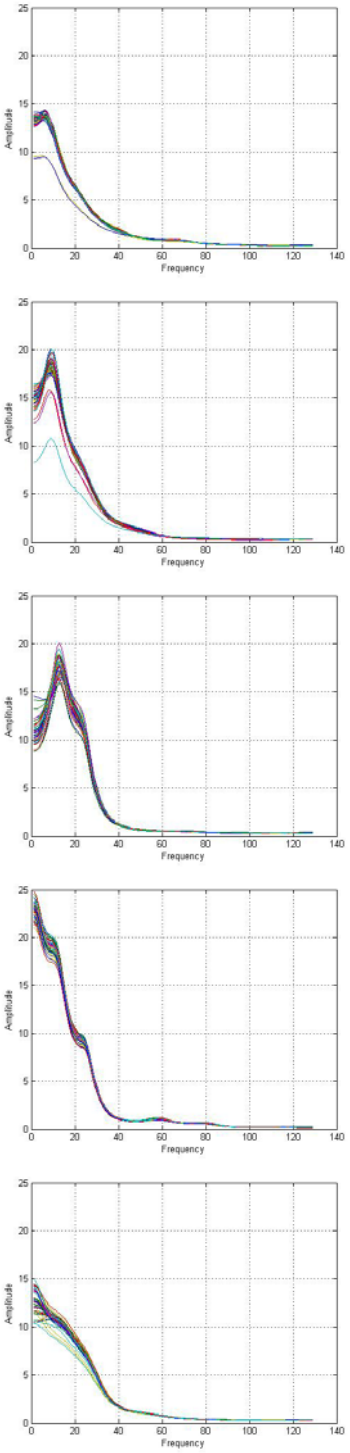

Fig. 4. The ECG LPC spectrum of 5 different subjects. It can be seen that the ECG LPC spectrum differs substantially between individuals.

TABLE II
CRR$_{ave}$ OF THE SYSTEM VARYING THE NUMBER OF POINTS OF THE LPC SPECTRUM AND USING AN LPC OF ORDER 12.

Number of points of the LPC spectrum	CRR$_{ave}$ (%)
80	99.71
70	99.90
60	99.52
50	99.67
40	99.52
30	98.88
20	97.43

TABLE III
COMPARISON BETWEEN LPC AND WPD AS THE FEATURE EXTRACTION METHOD FOR THE SYSTEM.

	WPD	LPC
Segment CRR$_{ave}$ (%)	91.52	99.52
Subject CRR$_{ave}$ (%)	92.00	100.00
Feature Extraction Time (s)	16.226	0.567

because a low order of LPC is unable to accurately model the envolope of the spectrum for each person thus decreasing the separability between the subjects. From the results, the optimal order of the LPC for the system is 12.

Table II shows the CRR$_{ave}$ of the system with the order of the LPC fixed at 12 with varying number of points of the LPC spectrum. It can be observed from the table that the system averages out at over 99% when points of 40 and above are used. The CRR$_{ave}$ starts to fall when the number of points are set to 30 and below. Looking at Figure 4, most of the energy and thus information of an individual's ECG signal are below 40 Hz. Henceforth setting the number of points to be below 40 essentially removes the important information regarding a person's ECG and consequently reduces separability.

Table III shows a comparison between the LPC spectrum and the WPD coefficients when used as the feature extraction method for the biometric system. The LPC system has the order set to 12 and the number of points set to 40 and the total number of WPD coefficients are 50. Here, two different approaches were taken to calculate the CRR$_{ave}$.

For the *segment* CRR$_{ave}$ listed in the second row in Table III, the classification algorithm was executed in the manner described in the earlier part of this discussion. However, for computation of the *subject* CRR$_{ave}$, a subject is considered to be correctly identified if the number of correctly identified segments of the signal exceeds a certain threshold. For this case, the threshold is set to 50% (i.e., more than half of the total number of segments are correctly identified).

It was observed from Table III that the WPD system managed to obtain 91.52% segment CRR$_{ave}$ and 92.00% subject CRR$_{ave}$. On the other hand, the LPC system resulted in a segment CRR$_{ave}$ of 99.52% and a 100% subject CRR$_{ave}$. Out of the 23 segments from 60 seconds of the signal, the LPC system incorrectly classified a maximum number of 4 segments only. This means that the threshold can be set as high as 82% and the LPC system will still be able to deliver 100% classification rate, allowing the LPC system to be used

in situations where high levels of security are necessary.

A further analysis into the feature extraction time reveals the fast computation time for LPC systems, taking an average of 0.567 s for 5 runs for all 15 subjects' signals. WPD proved to be more costly in terms of computation time as it takes 16.225 s to execute on average. In short, the LPC system is 28 times faster and therefore more practical for a realtime biometric system.

V. Conclusion

To conclude, a new method for ECG biometric systems was successfully implemented by using the coefficients of the LPC spectral envelope as features with classification rates of 99.52% and 100% for segment CRR_{ave} and subject CRR_{ave} respectively. In comparison, a system using WPD only managed 91.52% segment CRR_{ave} and 92.00% subject CRR_{ave}. If the segmenting approach was used, the threshold for subject identification can be set as high as 82% for LPC systems while still maintaining 100% subject identification. The LPC system is also 28 times faster in computation time compared to WPD. This makes LPC a very viable feature extraction method for situations requiring a fast, stringent and accurate security system. These results along with the 1 lead ECG signal acquisition setup of this experiment make LPC a suitable feature extractor for a practical ECG biometric system.

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