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Discrete Wavelet Transform Applied on Personal Identity Verification with ECG Signal

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Abstract

The main purpose of this study is to present a novel personal authentication approach that uses the electrocardiogram (ECG) signal. Because the ECG signal varies from person to person, it can be used as a new biometric for individual verification. The discrete wavelet transform was applied for extracting features. These wavelet coefficients derived from digitized signals were sampled from one-lead ECG signal. Using the proposed approach on 35 normal subjects and 10 arrhythmia patients, 100% verification rate was obtained for normal subjects and 81% verification rate for arrhythmia patients. Furthermore, the performance of the ECG verification system was estimated by calculating the false acceptance rate (FAR) and false rejection rate (FRR). The FAR was 0.83% and FRR was 0.86% for a database containing only 35 normal subjects. When 10 arrhythmia patients were added into the database, the FAR became 12.50% and the FRR 5.11%. The experimental results demonstrate that the proposed approach works well for normal subjects. Therefore, using the ECG as a biometric measure for human identity verification is promising.

***Keywords*:** Electrocardiogram (ECG), Discrete Wavelet Transform, Identity Verification.

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1. Introduction

In many daily life situations our identity must be verified, such as making credit card purchases, accessing restricted areas or Internet resources, traveling abroad, withdrawing money, and many other instances. Identity verification is an important procedure in modern society and has been used extensively in many fields. Traditional user identification systems are based on something that we possess, e.g., a key or a card, or something that we know, e.g., password or a personal identification number (PIN) [1]. However, passwords may be forgotten or guessed by an intruder and cards may be stolen or lost. This means that traditional identification systems are inherently insecure. Especially in the global Internet in which information requires a higher level of security, safer identification systems are a must. All kinds of terroristic attacks involving stolen identity have seriously influenced our social security. Countries around the world are looking forward to an efficient and convenient method for identity verification to preserve our social security. The biometrics market is growing as a result of this need. The International Biometric Group's "Biometrics Market and Industry Report" [2] indicated that global biometric revenue achieved 7.19 billion in 2003 and the trend is predictably increasing.

Biometric recognition, as a mean of personal authentication, is an emerging signal processing area focused on increasing security and convenience in applications where users must be securely identified. Biometrics is the science of identifying people using physiological features [3]. Each individual has unique biometric features. These features could be used to verify one person from another. Unlike traditional identification, biometric identification systems are based on what we are or what we do or produce. These features are inherently associated with a particular individual and are impossible to be forgotten or lost. Several biometrics have been used commercially for human identity verification such as facial geometry, fingerprints and voice analysis. Unfortunately, face recognition can be fooled by a photo, fingerprints can be recreated

in latex and a voice can be imitated. Each biometric system has various benefits and drawbacks.

Electrocardiogram (ECG) analysis is well-known as a very useful diagnostic tool for clinical proposes. The ECG signal varies from person to person due to the differences in position, size, and anatomy of the heart, age, sex, relative body weight, chest configuration and various other factors. These ECG properties can be used as a biometric for human identification. In 2001, Biel et al. [4] first proposed a new approach using ECG signals for identity verification. A standard 12-lead ECG recorded during rest was used as a biometric. Selected features extracted from the ECG were used to identify a person in a predetermined group. Multivariate analysis was used for the identification task. The experimental results showed that it was possible to identify a person using only one-lead ECG signal. In 2002, T. W. Shen et al. [5] used one-lead ECG signal as a biometric for human identification. It is well-known that the shapes of the ECG waveforms from different persons are different but it is unclear whether such differences can be used to identify individuals. Therefore, they tried to demonstrate that it is possible to identify a specific person from a group of candidates using a one-lead ECG. Their research applied two techniques, template matching and a decision-based neural network (DBNN) [6], to implement the identity verification. Using each of the two methods separately on a predetermined group of 20 subjects, the experimental results showed that the rate of correct identity verification was 95% for template matching and 80% for the DBNN. Combining the two methods produced a 100% correct rate. This research showed that ECG analysis is a potentially applicable method for human identity verification.

Because ECG signals vary from person to person, and the results from previous researches, one-lead ECG signal was used as a new biometric for individual verification in our study. The impetus of this research is to develop an accurate and efficient system for individual verification. Research presented in this paper is extended from our previous work [7] with more detail

description of the ECG identification system consisted of signal acquirement, signal pre-processing, feature extraction, database and identity verification. Some samples of our ECG signals obtained from a QT database [8] and others were acquired by using a commercial ECG recorder. The characteristic waveform in the time domain was detected using the "So and Chen" algorithm [9]. The discrete wavelet transform [10-11] was applied for extracting frequency-domain features. The wavelet coefficients were derived from digitalized signals sampled from a one-lead ECG signal. These features were used to represent each individual for the purpose of identity verification. Flow chart of ECG identification process proposed in this study as shown in Fig. (1). Discrete Wavelet Transform (DWT) will be briefly reviewed in the next section for soundness of paper.

2. Methodology

Wavelets [10-11] are mathematical functions that satisfy certain criteria, like a zero mean, and are used for analyzing and representing signals or other functions. A set of dilations and translations, $\psi_{j,k}(t)$ of a chosen mother wavelet $\psi(t)$ is used for signal analysis. In Discrete Wavelet Transform, dilation factors are chosen at a power of 2 and the set of dilation and translation of the mother wavelet is defined as $\psi_{j,k}(t) = 2^{-j/2}\psi(2^j t - k)$. Where *j* is the scaling factor and *k* is the translation factor. It is obvious that the dilation factor is a power of 2. A scaling function $\phi(t)$ is defined as

$$\phi(t) = \begin{cases} 1 & if\ t \in [0,1) \\ 0 & otherwise \end{cases} \tag{1}$$

and the set of dilation and translation of the scaling function is $\phi_{j,k}(t) = \sqrt{2^j}\phi(2^j t - k)$.To span our data domain at different resolutions, the wavelet is reprsented in a scaling equation $\psi_{j,k}(t) = \sum_k C_k \phi(2^j\ t - k)$.Where C_k are the wavelet coefficients and they must satisfy linear

and quadratic constraints With scaling basis $\phi_{j,k}(t)$ and wavelet basis $\psi_{j,k}(t)$, we can decompose any function *f(t)* as $f(t) = C_{00}\phi(t) + \sum_{j=0}^{n-1} C_{j,k}\psi_{j,k}(t)$. The coefficients C_{00} and $C_{j,k}$ are selected as features for personal identity verification approach.

3. Materials and Methods

3.1 ECG Data Sources

The ECG data were obtained from two different sources: (1) QT database [8] - the ECG database on the internet. Ten normal beats and 10 arrhythmia beats from ECG data were obtained from this database. We took a 2-minute data length from the total 15-minute data length for each sample. (2) Signals were measured using a commercial ECG recorder-FUKUDA DENSHI AUTO CARDINER FCP-145U. We acquired ECG data from 25 normal people with an age range between 20 and 30 years old. The measurement duration was also two minutes. Forty-five sampled ECG signals from 45 different people were taken as our samples. All of these signals were sampled at a 250Hz sampling rate. The data length was set at two minutes. The first minute was taken as our training data to build the ECG verification system database. The second minute was used as the test data for our system. The lead II ECG signals were acquired in this research.

The QT Database includes many ECGs being chosen to represent a wide variety of QRS and ST-T morphologies. The records were chosen primarily from existing ECG databases, including the MIT-BIH arrhythmia database [12-13], the European Society of Cardiology ST-T database [14], and several other ECG databases collected at Boston's Beth Israel Deaconess Medical Center. The existing databases are an excellent source of varied and well characterized data, to which have been added reference annotations marking the waveform boundary locations. The QT database contains a total of 105 fifteen-minute excerpts of two channel ECGs. As shown in Fig(2), the first channel is a modified limb lead II (ML II), the second channel is usually chest lead V1

(sometimes V2, V3, V4 or V5, depending on the subject). All these ECGs were selected to avoid significant baseline wander or other artifacts.

3.2 Pre-processing

ECG is the recording of the heart's electrical potential versus time. This signal is normally corrupted with noises such as muscle contractions or Electromyographic (EMG) interference, baseline drift, ECG amplitude modulation due to respiration, power line interference, electrode contact noise, instrumentation noise, radiofrequency, etc. To eliminate these noises, the signals were processed with a filter. The filter is a combination high-pass filter and low- pass filter. A high-pass filter with a cutoff frequency of 0.5Hz was used to eliminate the baseline drift. A low-pass filter with a cutoff frequency of 45Hz was used to eliminate high frequency noise such as power line interference.

3.3 Feature Extraction

The original ECG signals were a one dimensional array and were large and redundant. The detailed steps of feature extraction are described as follows and the flow chart of feature extraction is shown in Fig(3). We described how to extract the features from the original ECG signals.

3.3.1 The Detection of QRS-Complex

From an electrocardiogram (ECG) much useful information on the condition of heart can be read. Most ECG diagnosis techniques require an accurate detection of the ECG characteristics. The ECG signal is formed mainly of a P wave, QRS-complex and T wave. In consideration of speed and accuracy, the “So and Chan” method proposed by H.H. So et al. [9] was adopted to detect the QRS-complexes. The ”So and Chan” method evaluated the slope in the time domain for advanced comparison. The QRS-complexes have the maximum variation in the slopes. Based on this property and an adaptive threshold was applied to detect the positions of the

QRS-complexes. The ECG characteristic waves could be detected accurately without distortion when no filter was added.

The "So and Chan" QRS detection method was implemented onto an ambulatory ECG monitor. The computational requirement was kept at a reasonable level without compromising its accuracy. Therefore, the first derivative approach was selected and made substantial improvement to that technique. First, let $x(n)$ represent the amplitude of the ECG data at a discrete time n. The slope of the ECG wave is obtained using equation (2).

$$slope = -2x(n-2) - x(n-1) + x(n+1) + 2x(n+2) \tag{2}$$

The slope threshold is computed using equation (3).

$$Slope\_thresh = \frac{thresh\_param}{16} * \max i \tag{3}$$

When two consecutive ECG data satisfy the condition that $slope(n) > slope\_thresh$, the onset of the QRS-complex is detected. According to the suggestion given in [16], the parameter $thresh\_param$ can be set as 2, 4, 8 or 16. After detection of the onset of the QRS-complex, we shifted forward from the onset point to find the maximum point ($\max i$) and take the R point. $\max i$ is then updated using equation (4).

$$\max i = \frac{first\_\max - \max i}{filter\_param} + \max i \tag{4}$$

The $first\_\max$ is defined by equation (5).

$$first\_\max = height\ \ of\ \ R\ \ point - height\ of\ QRS\ \ onset \tag{5}$$

This is a one-pole filter that smoothes out the effect of any abrupt change. According to the suggestion given in [16], the parameter *filter_param* can be set to 2,4,6,8 or 16. The initial

$\max i$ is the maximum slope within the first 250 data points in the ECG file. Based on the best result in [9], we choose the *slope_thresh* as 8 and the *filter_param* as 16. An example for applying the "So and Chan" method is detecting the positions of the R wave as shown in Fig(4).

3.3.2 Synthesis Signals

Let the original ECG signals *S* obtained in this research be sampled at 250 Hz.

$$S\ (n), \qquad n = 1,2,3...N \tag{6}$$

Using the "So and Chan" method [9] to detect the QRS-complex of the ECG signals, the positions of the R waves in each signal could found, and denoted as:

$$R(n_k), \quad k = 1,2,3..., M \tag{7}$$

Where n_k is the location of *R* point. Since the positions of *R* wave $R(n_k)$ are determined, a 128-point signal segment SS_k can be obtained by taking data points form the backward 43rd point to the forward 84th point as shown in Fig(5), which is denoted as:

$$SS_k = [S(n_k - 43) : S(n_k + 84)] \tag{8}$$

Four such signal segments form a 512-points synthesis signal F that is denoted as $F = [SS_1\ \ SS_2\ \ SS_3\ SS_4]$.

3.3.3 Wavelet Coefficients of Discrete Wavelet Transform

One synthetic signal extracted from original ECG signal with 512- points data length is shown in Fig(6). With Haar wavelet, the 512-points wavelet coefficients decomposed from the signal were used as the biometric "identity card" of the subject. We decompose the signal with level-9 decomposition. Wavelet coefficients decomposed from 512-points synthetic signal is shown in Fig(7).

3.4 Enrollment and Verification

In the ECG verification system, there are two separate stages: enrollment phase and verification phase. During enrollment, features were extracted from the ECG signal with one minute data length to train a model of each user. The resultant model was taken as a representation of the enrolled user. In the verification phase, extracted features were verified against the enrolled models.

3.4.1 Enrollment

In this phase, 35 normal subjects and 10 arrhythmia patients were enrolled to set our database. Features were extracted from the first minute of the obtained 45 ECG signals from these 45 individuals.

In one minute, finite numbers of 512-points synthesis signal could be extracted. A mean 512-point synthesis signal was derived by averaging all of the extracted 512-points synthesis signals. Using the discrete wavelet transform to decompose the mean 512-points synthesis signal into 512-points wavelet coefficients, the obtained 512-points wavelet coefficients were used as a model to represent the user. Forty-five models were saved in our database.

3.4.2 Euclidean Distance Measure for Identity Verification

In verification phase, Euclidean distance measure was adopted for verification. The Euclidean distance between two feature vectors $\vec{X}$ and $\vec{Y}$ was denoted as $\left\|\vec{X}-\vec{Y}\right\|$. When an unknown subject $\vec{X}$ is entered into our ECG verification system, an Euclidean distance measure is applied to calculate the difference in the 512-point wavelet coefficient feature set between the unknown subject $\vec{X}$ and all enrolled 45 subjects $\vec{Y}_i$ ($i = 1,2,3,..,45$) in our database. The unknown subject could be determined by finding the argument of the minimum values in the distance between $\vec{X}$ and $\vec{Y}$ as shown below.

$$\arg\min_i \left\|\vec{X}-\vec{Y}_i\right\| \qquad i = 1,2,3,..,45 \tag{9}$$

4. Results and Discussion

The experimental results are illustrated to show the validity of our method. The sensitivity of QRS-complex detection would affect the verification rate of the ECG verification system. After checking the results from applying the "So and Chan" method, the verification results will be presented.

4.1 Evaluation of QRS-Complex Detection

The QRS-complex detection results obtained by applying the "So and Chan" algorithm are presented as follows. (a) Normal heart beat results are shown in Table(1). ECG data (sel16265~sel17453) are normal samples obtained from QT database and ECG data (S_11~S_35) are normal samples by commercial ECG recorder. (b) The arrhythmia heart beat results are shown in Table(2). ECG data (sel110~ sel233) arrhythmia samples obtained from QT database. In accuracy assessment, defined in equation (10), in the QRS-complex detection method two types of false readings were defined as below:

False Positive (FP): total number of wrong positions detected in the QRS-complex
False Negative (FN): total number of correct positions missed in the QRS-complex

$$Accuracy\ \ (\%) = (1 - (FP + FN) / Total\ \ Beats) \times 100\% \tag{10}$$

The average detection accuracy was 99.92% in the normal beats category. The average detection accuracy in the arrhythmia samples was only 89.60%. As shown in Table(2), the accuracy of some arrhythmia samples was not good enough, such as "sel114", "sel116" and "sel233".

4.2 Verification Results

In this section, the proposed system verification rate is presented. The verification results tested using training and test data are shown separately in Tables(3)-(4). The verification rates for normal and arrhythmia people are calculated. The verification rate is defined below:

$$Verification\ rate\ (\%) = \frac{total\ number\ of\ correctly\ verified\ \ samples\ \ N_C}{total\ number\ of\ testing\ \ samples\ \ N_T} \times 100\% \qquad (11)$$

In the 45 one-minute training data or 45 one-minute test data, we could extract finite numbers from a 512-point feature set as our test samples. The total number of extracted numbers (N_T) from the 512-point feature set extracted from the training data was 826, and 791 from the test data. As we can see in Tables(3)-(4), the verification rate for the training data was 97.31% and 95.71% for the test data. The average training and test data verification rate was 100% for normal samples and 81% for arrhythmia samples. Furthermore, the false acceptance (FAR) and false rejection rates (FRR) were calculated to estimate the performance of the proposed ECG verification system. Twelve samples not belonging to the 45 samples in our database were obtained. Ten test samples were extracted from each of these samples to test the FAR. To test the FRR, 10 test samples were extracted from each of the 45 samples in our database. The FRRs and FARs tested with Database_1 (only containing 35 normal-beat samples) and Database_2 (containing all 45 samples: 35 normal-beat samples and 10 arrhythmia patients) are shown in Table(5).

The false acceptance (FAR) and false rejection rates (FRR) for Database_1 were 0.83% and 0.86%. The false acceptance (FAR) and false rejection rates (FRR) from Database_2 were 12.50% and 5.11%.

4.3 Discussion

One-lead ECG signals were obtained from normal subjects and patients with arrhythmia and adopted to test our verification system. The results revealed that the proposed method for verifying normal subjects was very effective with 100% verification rate. On the other hand, 81% was achieved with arrhythmia subjects. The possible reasons resulting in a lower verification rate

for arrhythmia subjects that for normal subjects could be: (1) missing or incorrect detection during the QRS-complex detection procedure. As we can see in Table(2), the detection accuracy for arrhythmia samples was not good enough; (2) unstable QRS-complex waveforms were obtained from the electrocardiogram. These abnormal waveforms appeared aperiodically and caused the extracted features to change.

According to the results in Table(4), the FARs and FRRs from Database_1 and Database_2 were different. The verification performance of Database_2 was worse than that for Database_1. The difference between Database_1 and Database_2 was that Database_2 contained arrhythmia patients. For these arrhythmia patients, the lower verification rates as shown in Tables(2)-(3) caused the higher FRR and FAR for Database_2.

5. Conclusion

We presented a novel personal identity verification approach that used one-lead ECG signal. The features were extracted by applying the discrete wavelet transform. The Euclidean distance was used as a measure for the verification mechanism. Using this approach, 100% verification rate was achieved for normal subjects and 81% verification rate for arrhythmia patients. The results demonstrated the validity of our proposed method and the feasibility of using the ECG as a biometric measure for human identity verification. The advantages of our ECG verification system are as follows. (1) Only living persons have this biometric. The heart beats exist only in living individuals and stop working when then die. The system cannot be cheated using an artifact. (2) The ECG signal is difficult to imitate. The ECG varies from person to person due to many factors and is not an exterior feature. Therefore, this biometric is difficult to learn or imitate by others. (3) It is suitable in combination with other biometrics. Multimodal biometrics are a trend for future biometric identification systems. The ECG is an interior feature and easy to

combine with other exterior biometric features. (4) It has a reasonable training time. (5) Good verification rate for verifying normal people is obtained. The verification results in this investigation were achieved using an off-line test. There are many other changing factors in the on-line test. Future work will be to investigate the on-line test to demonstrate the practicability of our verification system. An investigation of how the ECG will vary over a long time period which may affect the verification rate should also be studied. Moreover, the ECG hardware recorder should be designed to be convenient for low cost, easy application ambulatory measurement as security tool in daily life.

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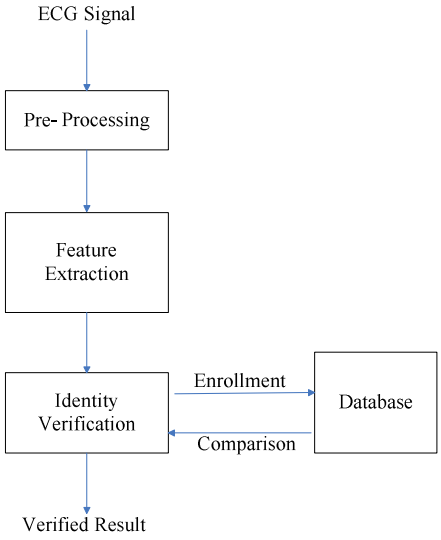

Fig. 1 Flow chart of ECG identification process proposed in this study.

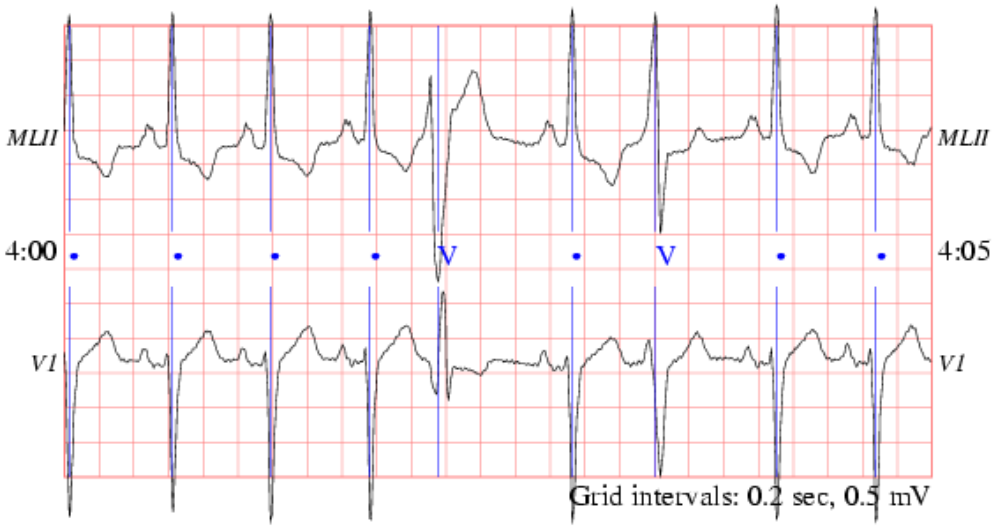

Fig. 2 An arrhythmia ECG signal [15].

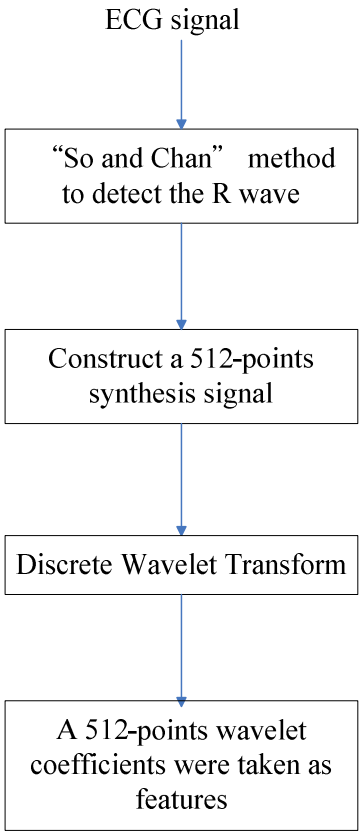

Fig. 3 Flow chart of feature extraction.

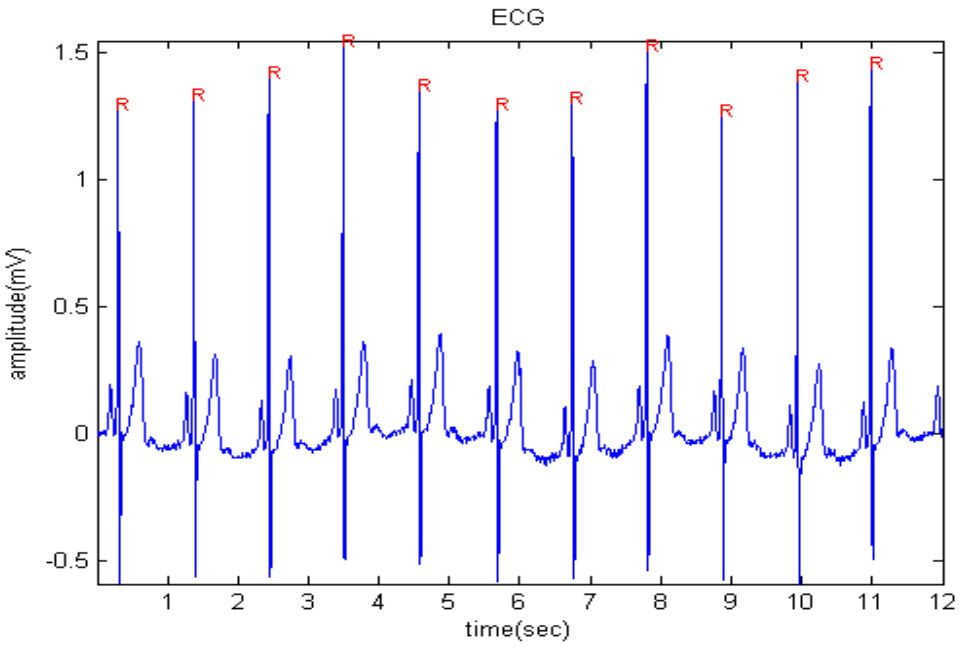

Fig. 4 The detection of R waves.

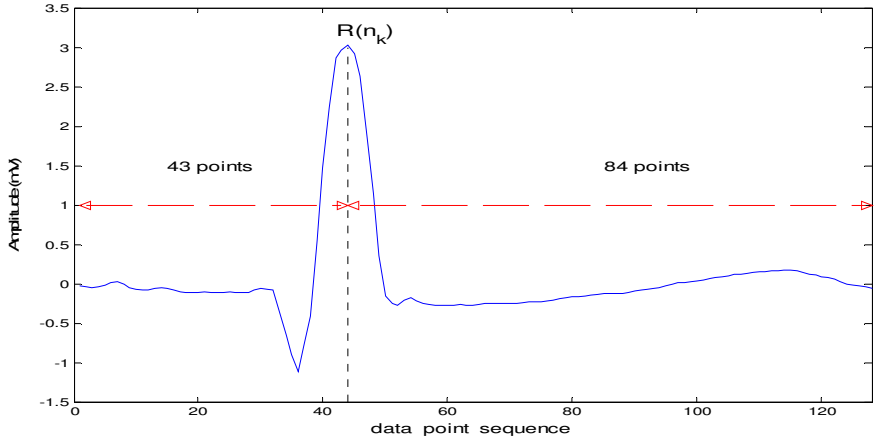

Fig. 5 A 128-points signal segment.

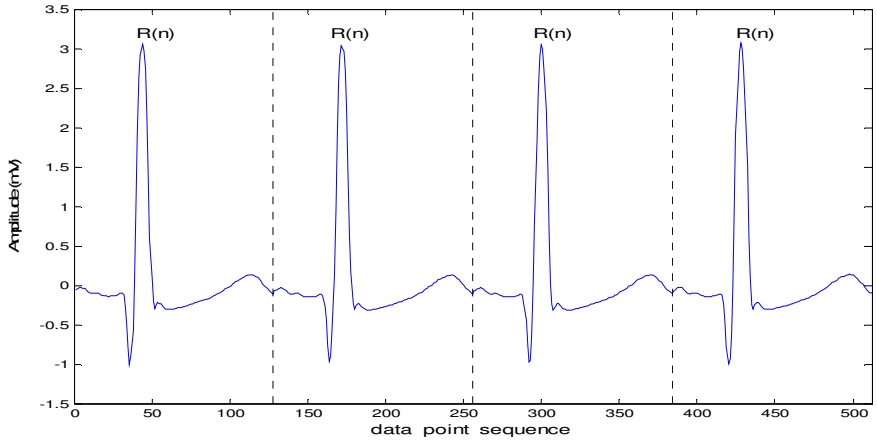

Fig. 6 One synthetic signal extracted from original ECG signal with 512- points data.

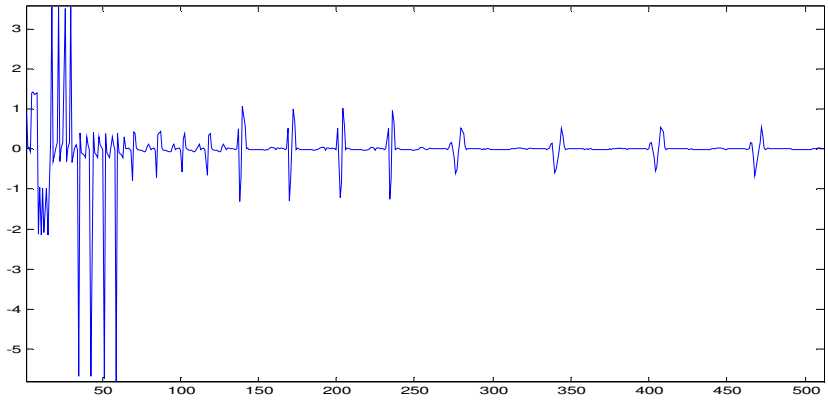

Fig. 7 Wavelet coefficients decomposed from 512-points synthetic signal.

Table 1 QRS detection results of normal samples.

File	Total Beats	False Positive	False Negative	Accuracy (%)
sel16265	67	0	0	100.00
sel16272	56	0	0	100.00
sel17273	79	0	0	100.00
sel16420	71	0	0	100.00
sel16483	71	0	0	100.00
sel16539	60	0	0	100.00
sel16773	65	0	0	100.00
sel16786	59	0	0	100.00
sel16795	51	0	0	100.00
sel17453	70	0	0	100.00
S_11	65	0	1	98.46
S_12	74	0	0	100.00
S_13	71	0	0	100.00
S_14	64	0	0	100.00
S_15	68	0	0	100.00
S_16	70	0	0	100.00
S_17	96	0	0	100.00
S_18	85	0	0	100.00
S_19	71	0	0	100.00
S_20	66	0	0	100.00
S_21	77	0	0	100.00
S_22	79	0	1	98.73
S_23	91	0	0	100.00
S_24	78	0	0	100.00
S_25	60	0	0	100.00
S_26	71	0	0	100.00
S_27	69	0	0	100.00
S_28	87	0	0	100.00
S_29	70	0	0	100.00
S_30	67	0	0	100.00
S_31	91	0	0	100.00
S_32	76	0	0	100.00
S_33	94	0	0	100.00
S_34	64	0	0	100.00
S_35	69	0	0	100.00
Total	**2522**	**0**	**2**	**99.92**

Table 2 QRS detection results of arrhythmia samples.

File	Total Beats	False Positive	False Negative	Accuracy (%)
sel100	69	0	0	100.00
sel114	45	6	2	82.22
sel116	76	22	0	71.05
sel223	101	1	3	96.04
sel221	74	6	0	91.89
sel223	81	0	3	96.30
sel230	64	0	0	100.00
sel231	47	0	0	100.00
sel232	54	0	0	100.00
sel233	94	28	11	58.51
Total	705	63	19	89.60

Table 3 Verification rate of test by training data.

	N_T	N_c	N_f	Verification rate
normal	628	628	0	100.00%
arrhythmia	198	164	34	81.92%
Total	**826**	**792**	**34**	**97.31%**

N_T : Total numbers the samples. N_c : Numbers of correctly verified samples.

N_f : Numbers of wrong verified samples.

Table 4 Verification rate of test by testing data.

	N_T	N_c	N_f	Verification rate
normal	604	604	0	100.00%
arrhythmia	187	152	36	81.63%
Total	**791**	**753**	**38**	**95.92%**

N_T : Total numbers the samples. N_c : Numbers of correctly verified samples.

N_f : Numbers of wrong verified samples.

Table 5 FRR and FAR results.

	Database _1	Database _2
FAR	0.83%	12.50%
FRR	0.86%	5.11%

"Database_1": contains 35 normal beat users; "Database_2": contains 35 normal beat users and 10 arrhythmia patients.