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# On-Line Heart Beat Recognition Using Hermite Polynomials And Neuro-Fuzzy Network

Tran Hoai Linh, Stanisław Osowski and Maciej Stodolski

## Abstract

The paper presents the neuro-fuzzy approach to the recognition and classification of heart rhythms on the basis of ECG waveforms. The important part in recognition fulfills the Hermite characterization of the QRS complexes. The Hermite coefficients serve as the features of the process. These features are applied to the fuzzy neural network for the recognition. The results of numerical experiments have confirmed very good performance of such solution.

## Index Terms

Neurofuzzy networks, waveform characterization and measurement, Hermite function expansion, electrocardiography, arrhythmia recognition and classification

## I. INTRODUCTION

The problem of on-line heart beat type recognition on the basis of the registered ECG waveforms belongs to the difficult measurement problems, since the beats differ significantly even for the same type and for the same patient. The ECG waveforms may differ for the same patient to such extent that they are unlike to each other and at the same time alike for different types of beats. This is the main reason that the beat classifier, performing well on the training data behaves badly, when presented with different patients ECG waveforms. Although several algorithms have been already developed, their efficiency is still not satisfactory [2], [3], [4], [5], [6], [7].

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In this paper we will present the new approach to heart beat recognition that is less sensitive to the morphological variation of the ECG. The paper proposes the new solution of the problem by combining two techniques:

- characterization of the QRS complex of ECG by Hermite polynomials and using the coefficients of Hermite kernel expansion as the features of the process
- application of the modified neuro-fuzzy TSK network for ECG pattern recognition and classification.

Instead of the original waveform, we will rely on its description using coefficients of Hermite expansion. These coefficients are used as the input signals to the neuro-fuzzy network, fulfilling the role of recognition and classification system. We have applied the modified structure of the TSK network. Such fuzzy neural network solution is more tolerant to the noise and to the morphological changes of the ECG characteristics. The results of the numerical investigations are presented and discussed.

## II. ECG CHARACTERIZATION USING HERMITE FUNCTION EXPANSION

The ECG is the electrical manifestation of the contractile activity of the heart and can be recorded fairly easily with the surface, noninvasive electrodes placed on the limbs and chest. Fig. 1 shows the typical ECG signal with three indicated waves: the P, QRS and T one. The P wave is the result of slow-moving depolarization (contraction) of the atria. This is the low-amplitude wave of 0.1 - 0.2mV and duration of 60 - 120ms. The wave of stimulus spreads rapidly from the apex of the heart upwards, causing rapid depolarization (contraction) of the ventricles. This results in the QRS complex of the ECG, a sharp biphasic or triphasic wave of about 1mV amplitude and approximately 80 - 100ms duration. Ventricular muscle cells have a relatively long action potential duration of 300 - 350ms. The plateau part of action potential of about 100 - 120ms after the QRS is known as the ST segment. The repolarization (relaxation) of the ventricles causes the slow T

wave with an amplitude of 0.1 - 0.3mV and duration of 100 - 120ms. Between T and P waves there is a relatively long plateau part of small amplitude known as TP segment.

Any disturbance in the regular rhythmic activity of the heart is termed arrhythmia. Fig. 2 shows the real recorded ECG signals corresponding to normal beats (N) and premature ventricular ectopic beat (V). We observe the change of the amplitude and duration as well as the shape of rhythms not only between different beat types but also within the rhythms belonging to the same class.

Different types of abnormal rhythm result from the variations in the site and frequency of the impuls formation, caused by some diseases. The ECG arrhythmia waveforms differ usually with the amplitude and duration of beats. Especially important are QRS complex changes. Hence the ECG, especially its QRS complex, is very important signal, useful in heart-rate monitoring and the diagnosis of cardiovascular diseases.

The proposed system for on-line ECG beat recognition by using proposed approach is shown in Fig. 3. It consists of the following blocks: the ECG registration, QRS detection and Hermite basis functions coefficient extraction, delivering these coefficients as the features to the input of the neural network, performing the role of classifier.

The main idea of expansion of the ECG signal into Hermite basis functions [7] exploits the similarity of the shapes of these polynomials and QRS complexes of the ECG curves. The coefficients of Hermite expansion are used as the features characterizing the shape of ECG beat.

Let us denote by  $x(t)$  the ECG curve. The expansion of it into Hermite series may be presented in the following way

$$\mathbf{x}(t) = \sum_{n=0}^{N-1} a_n \phi_n(t, \sigma) \quad (1)$$

where  $a_n$  ( $n = 0, 1, 2, \dots, N - 1$ ) are the expansion coefficients while  $\phi_n(t, \sigma)$  is the Hermite basis

function defined as

$$\phi_n(t, \sigma) = \frac{1}{\sqrt{\sigma 2^n n! \sqrt{\pi}}} e^{-t^2/2\sigma^2} H_n(t/\sigma) \quad (2)$$

The functions  $H_n(t/\sigma)$  are the Hermite polynomials. With  $H_0(x) = 1$  and  $H_1(x) = 2x$ , the Hermite polynomials are defined recursively by

$$H_n(x) = 2xH_{n-1}(x) - 2(n-1)H_{n-2}(x) \quad (3)$$

For example  $H_2(x) = 4x^2 - 2$ ,  $H_3(x) = 8x^3 - 12x$ , etc. Fig. 4 presents the Hermite basis functions  $\phi_n(t, \sigma)$  as a function of time for different orders:  $n = 0$  (Fig. 4a),  $n = 1$  (Fig. 4b),  $n = 3$  (Fig. 4c) and  $n = 14$  (Fig. 4d).

The higher is the order of the function, the higher its frequency of changes within time domain and the better its capability to reconstruct the quick changes of the ECG paradigms.

To illustrate the way, in which Hermite polynomials approximate the ECG curve, let us present the QRS segment of ECG signal as 91 data points around the R peak (45 points before and 45 ones after). At the data sample rate of 360 Hz, this gives a window of 250 ms, which is long enough to cover most of QRS signals. They have been also expanded by adding 45 zeros signals to each ends of the beats. After that all ECG signals are normalized by linear scaling to the range of  $[-1, 1]$  and subtracting the mean level of the first and the last data points. An example of normalized QRS complex of ECG signal is presented in Fig. 5a.

The modified QRS complex is decomposed onto a linear combination of Hermite basis functions. In the experiments the width  $\sigma$  has been set up to such value, that almost half of the Hermite basis function signal values are close to 0 in the considered range. The expansion coefficients  $a_i$  are obtained by minimizing the sum squared error, defined in the following way

$$E = \left\| \mathbf{x}(t) - \sum_{n=0}^{N-1} a_n \phi_n(t, \sigma) \right\|_2^2 \quad (4)$$

This error function represents the set of linear equations versus  $a_n$  solved in practice by using SVD decomposition and pseudo-inverse technique [12].

Different numbers of Hermite basis functions have been used to extract the features of QRS complexes. Fig. 5 presents the results of approximation of chosen ECG waveform by applying 6 (Fig. 5b), 9 (Fig. 5c) and 15 (Fig. 5d) first Hermite basis functions.

As it is seen, at 15 functions we got quite good reconstruction of the details of the curve, satisfactory from the point of view of representation of the main features of this curve.

Another problem is the representability of the Hermite coefficients for different types of beats. Good features should be stable for the same beat type and differ significantly for different beats. Close analysis of the distribution of the coefficient values for different rhythm types have revealed, that some of them are better and some less suited for this task. The exemplary distribution of  $a_0$  and  $a_4$  coefficients for different rhythms are presented in Fig. 6a and 6b, respectively. The beat types under investigation included: the premature ventricular ectopic beat (V), the left bundle branch block beat (L), the right bundle branch block beat (R), the atrial premature beat (A), the ventricular flutter wave (I) and the ventricular escape beat (E). It is seen that E and R arrhythmias are very well separated between each other and from the others. The values of coefficients  $a_0$  and  $a_4$  for these rhythm types are stable and of low variance for all investigated samples. However the other arrhythmia types are characterized by their coefficient values of higher variance. At the same time they all occupy similar range of values. The other coefficients  $a_n$  for  $n = 0, 1, 2, \dots, 14$  not shown here, represent different distribution of their values for different rhythm types, generally well separating all of them. Collecting together their separation capabilities we get the set of features capable of separating all rhythm types from each other with good efficiency.

As a result of such investigation we have decided to represent each QRS complex of ECG waveform by 15 coefficients  $a_i$  ( $i = 0, 1, \dots, 14$ ) of Hermite basis function expansion. All these coefficients form the feature vector  $\mathbf{x}$  put to the input of the neural classifier.

Additionally we have also extracted 2 additional parameters representing the duration of the signal (time domain representation), i.e. the RR interval and the average RR interval of 10 last

beats. Both are had been then normalized to  $[0,1]$  range. In this way the final feature vector  $\mathbf{x}$  of each QRS complex contains 17 elements: 15 Hermite coefficients and 2 time domain representation parameters.

### III. FUZZY NEURAL NETWORK CLASSIFIER

As the system recognizing the heart rhythm type and classifying the ECG waveform signals on the basis of the features described in the previous section, we have applied the modified neuro-fuzzy Takagi-Sugeno-Kang (TSK) network of the structure, suited for large scale problem. The fuzzy neural network has been chosen for this task because it is better suited for the representation of the inexact and fuzzy nature of the heart beat variability.

Let us consider the multi-port system of  $N$  inputs characterized by the vector  $\mathbf{x}$  and one output, to be modelled as the fuzzy system of Takagi-Sugeno-Kang type [11]. This system implements in general the inference rules, that can be stated in general vector form as follows [9], [11]

$$\text{if } \mathbf{x} \text{ is } \mathbf{A} \text{ then } y = f(\mathbf{x}) \quad (5)$$

where  $\mathbf{x} = [x_1, x_2, \dots, x_N]^T$  and  $f(\mathbf{x})$  is the TSK function

$$f(\mathbf{x}) = p_0 + \sum_{i=1}^N p_i x_i \quad (6)$$

usually assumed as a crisp linear function of coefficients  $p_0, p_1, \dots, p_N$  adjusted at the learning process.

The premise *if  $\mathbf{x}$  is  $\mathbf{A}$*  in TSK inference system is implemented as the fuzzifier, defined for each variable  $x_i$  as the gaussian or bell function. Both functions are fully defined by their centers and spread values.

It is well known that TSK neuro-fuzzy inference system can serve as the universal approximator of the data with the arbitrary accuracy [11]. The most important point in the designing stage of

the network is creation of the inference rules. The standard TSK system operating on the combination of the membership functions in each variable is inefficient at many inputs, since it results in extremely large number of learning rules, most often empty, i.e., operating in the regions deprived of data. We have solved this problem by applying the fuzzy clusterization of data and associating each cluster with one independent inference rule. The center of the cluster is automatically the center of the premise part of the rule.

The most efficient way of fuzzy clusterization is the application of Gustafson-Kessel (GK) algorithm [10]. It operates with two parameters of the cluster: the center vector  $\mathbf{c}_i = [c_{i1}, \dots, c_{iN}]^T$  and the cluster covariance matrix  $\mathbf{F}_i \in R^{N \times N}$ . Both parameters are adapted in the learning procedure [10]. The center of the cluster denotes the point of the highest membership value of the rule, associated with the cluster. The covariance matrix  $\mathbf{F}_i$  introduces the scaling of the input variables and is responsible for shaping of the cluster. Fig. 7 presents the typical representation of the data obtained by GK approach. The ellipses denote the lines of the same membership function values to the appropriate cluster. The shapes of the obtained clusters are elongated and are perfectly adjusted to the distribution of data (the dots). Observe that all clusters obtained as the result of self-organization, correspond only to the regions, where the data exist.

The distance between the data point  $\mathbf{x}$  and the center  $\mathbf{c}_i$  is described now by using the scaled Euclidean measure

$$d^2(\mathbf{x}, \mathbf{c}_i) = (\mathbf{x} - \mathbf{c}_i)^T \sqrt[{}^N]{\det(\mathbf{F}_i)} \mathbf{F}_i^{-1} (\mathbf{x} - \mathbf{c}_i) \quad (7)$$

On the basis of this distance definition the firing strength of  $i$ th rule is determined in the following way [11]

$$\mu_i(\mathbf{x}) = \frac{1}{\sum_{k=1}^M \left( \frac{d(\mathbf{x}, \mathbf{c}_i)}{d(\mathbf{x}, \mathbf{c}_k)} \right)^{2/(m-1)}} \quad (8)$$

where  $M$  is the number of clusters (rules) and  $m$  is the exponent coefficient (most often  $m = 2$ ).



The TSK approximation function can be now described by []

$$y(\mathbf{x}) = \frac{\sum_{i=1}^M \mu_i(\mathbf{x}) \left[ p_{i0} + \sum_{j=1}^N p_{ij} x_j \right]}{\sum_{i=1}^M \mu_i(\mathbf{x})} \quad (9)$$

The denominator of this expression fulfills the role of the normalizing term. Observe that this term can be included in the TSK parameters

$$p_{ij} \leftarrow \frac{p_{ij}}{\sum_{r=1}^M \mu_r(\mathbf{x})} \quad (10)$$

Hence the final form of the approximation function of TSK type can be written as follows

$$y(\mathbf{x}) = \sum_{i=1}^M \mu_i(\mathbf{x}) \left[ p_{i0} + \sum_{j=1}^N p_{ij} x_j \right] \quad (11)$$

The neural network structure, corresponding to this simplified equation is shown in Fig. 8.

At proper selection of the centers  $\mathbf{c}_i$  and the covariance matrices  $\mathbf{F}_i$  resulting from the self-organization stage, the equation (11) represents the linear equation of TSK parameters  $p_{ij}$ . At  $p$  learning data points we get in this way the system of  $p$  linear equations of the variables  $p_{ij}$ . The determination of these variables can be done in one step by using the SVD algorithm and the pseudo-inverse technique [12].

Note, that although the considerations given above correspond to one output system, we can easily extend their results to the multi outputs by writing similar set of equations for each output. Only TSK parameters change from output to output. The premise parameters are the same for all channels.

#### IV. THE RESULTS OF NUMERICAL EXPERIMENTS

In the numerical experiments of the recognition of the ECG beat types we have used many different patients taken from MIT/BIH arrhythmia database [1] representing different arrhythmias and the normal (N) sinusoidal rhythm. Fig. 9 presents the set of rhythms typical for N type. Great variability of their morphology can be observed.

Six types of arrhythmia taken from the MIT/BIH arrhythmia database [1] have been considered in the investigations. They include the following types: V, L, R, A, I and E introduced in section II. Fig. 10 presents the exemplary set of original QRS complexes typical for these arrhythmias. As it is seen from the figure there is a great variation of signal morphology among the same type of beats belonging to chosen arrhythmias.

All original waveforms belonging to any type of arrhythmia and normal sinus rhythm have been represented by the appropriately normalized Hermite coefficients, forming the feature vectors. The information contained in the feature vectors of ECG beats has been applied to the input of the modified neuro-fuzzy TSK network, which serves as the recognition and classification system. The applied neuro-fuzzy network contained 17 input nodes (equal to the number of the features of the ECG waveform) and 7 outputs, equal to the number of beat types. Each output represents one type of arrhythmia or normal beat. In the case of presenting the beat type other than the considered, the final classification result is dependent on the level of maximum output signal. If it is below some threshold, all neurons will respond with null. The number of clusters used in the definition of inference rules was found after series of experiments and was equal 21, and this number of inference rules has been applied for each beat type recognition.

The set of the input vectors  $\mathbf{x}_i$  represents the QRS complexes of the individual beats of many patients, representing different types of beats and transformed according to the procedure described in section II.

The ECG beats taking part in classification have been splitted into two groups: one used only in learning and the separate one used only in the testing mode. The learning set contained 3611 pairs (the input vector  $\mathbf{x}$  containing the features representing beats and the destination vector  $\mathbf{d}$  representing the code of the class) distributed among different patients and different types of beats. The testing set was formed of the other 3668 pairs, corresponding to different beat types. Among them was the normal sinusoidal rhythm (N) and 6 types of arrhythmias mentioned above: L, R, A,

V, I and E. Due to varied number of beats available in the MIT database [1] the number of patterns of different beat types taking part in experiments was changing. Especially scarce was the data base of I and E types, so the numbers of these beats were the smallest ones.

The learning process of the neuro-fuzzy network has been performed by applying the GK algorithm for the self-organization to set the positions of the cluster centers  $c_i$  and to determine the covariance matrices  $F_i$ . After this step all centers  $c_i$  and matrices  $F_i$  have been frozen and TSK parameters  $p_{ij}$  adapted using SVD decomposition.

After learning, the network was ready for the retrieval mode of operation, in which only the feature vector  $\mathbf{x}$  is applied to the input of the system. This excitation activates the output neurons of the network.

The activities of output neurons indicate the membership of the individual beats to the appropriate class. The actual output signals of the neurons are rounded to only two levels: one (indicating the membership to the appropriate class) and zero (lack of membership to this class). The obtained results of recognition and classification for different beats are presented in table 1 for the learning and the testing data. The efficiency of recognition of different beat types is varied from 1% to 11% and reflects the diverse complexity of the recognition task. As it is seen the average misclassification rate in both learning and testing set is limited, and the efficiency of recognition in the testing mode is above 96%. Observe that the performance of the neural classifier on the testing data is only slightly worse than on the learning set.

It is interesting to compare our results to the others, presented in scientific journals. For example the data classified by fuzzy hybrid network and HOS used as the feature description [8] have produced the overall error of 4.4%. The application of multilayer perceptron (MLP) and the features based on time domain representation resulted in the error of 10% for 2 heart beat types and 15.5% for 13 beat types [2]. The application of SOM and SVD characterization for 4 beat types resulted in 7.8% error [3], while MLP and Fourier features for 3 beat types have reduced the

recognition error to 2% [5].

However it should be noted that patients and rhythms selected in all compared experiments were different. Hence fair comparison of the methods and their results is very difficult since the morphology of heart beats is changing from patient to patient and may present the additional difficulties in recognition process. This is especially important, since the beats can differ significantly not only among different patients, but also within the same one. Hence the results of such comparison should be treated very carefully.

## V. CONCLUSIONS

The paper has presented the application of Hermite basis function expansion of the QRS complexes of ECG waveforms and modified TSK neuro-fuzzy network for heart beat recognition and classification. The Hermite coefficient characterization delivers stable features, relatively insensitive to the morphology variations of the ECG waveforms. Combining these features with good performance of the neuro-fuzzy classifier have produced the accurate results of beat recognition, competitive to the already known results.

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## LIST OF FIGURES

1	<i>The typical ECG waveform . . . . .</i>	15
2	<i>The examples of real ECG recording of 2 different rhythm types . . . . .</i>	16
3	<i>The proposed system of ECG recognition . . . . .</i>	17
4	<i>The chosen Hermite functions for <math>\sigma = 1</math> plotted as a function of time: a) <math>n=0</math>, b) <math>b=1</math>, c) <math>n=3</math>, d) <math>n=14</math> . . . . .</i>	18
5	<i>The expanded QRS complex of ECG waveform (left,up) and its estimation using 6 (right, up), 9 (left, down), 15(right, down) Hermite basis functions . . . . .</i>	19
6	<i>The distribution of the <math>a_0</math> (a) and <math>a_4</math> (b) Hermite coefficients for different heart beats of the same patient . . . . .</i>	20
7	<i>The representation of the data points by the clusters. The lines indicate equal membership values of the data to the appropriate center . . . . .</i>	21
8	<i>The fuzzy neural network structure corresponding to the modified TSK system described by equation (11) . . . . .</i>	22
9	<i>The original ECG data corresponding to the normal sinus rhythm of the heart beat . .</i>	23
10	<i>The original data ECG corresponding to six types of arrhythmia beats: L, R, A, V, I, E</i>	24

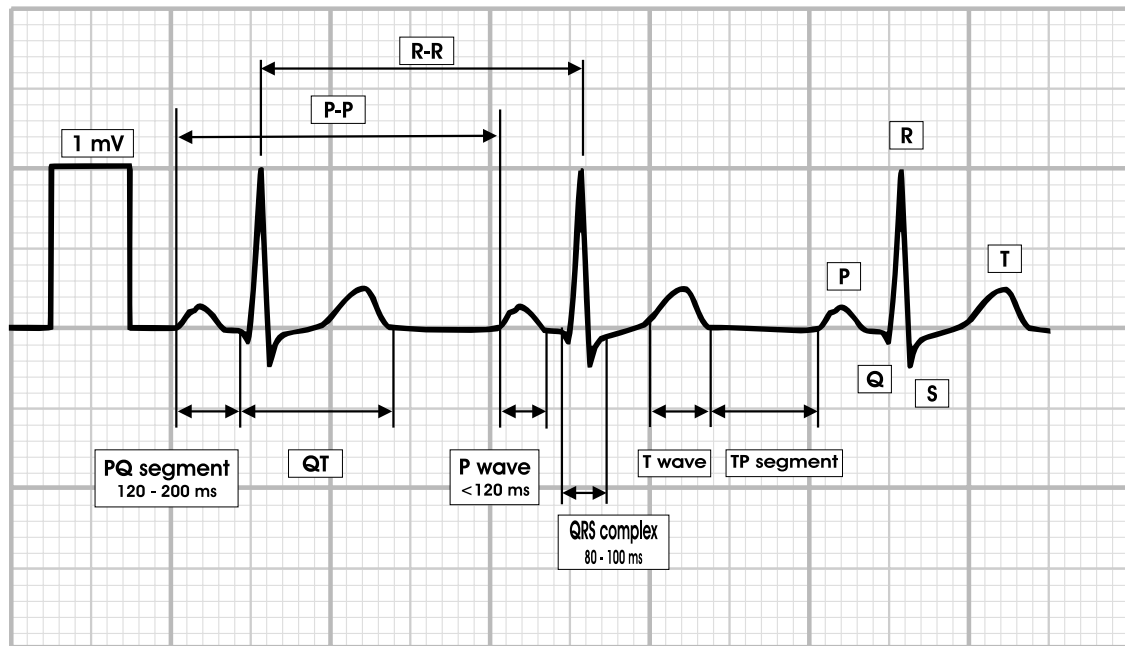


Fig. 1. The typical ECG waveform



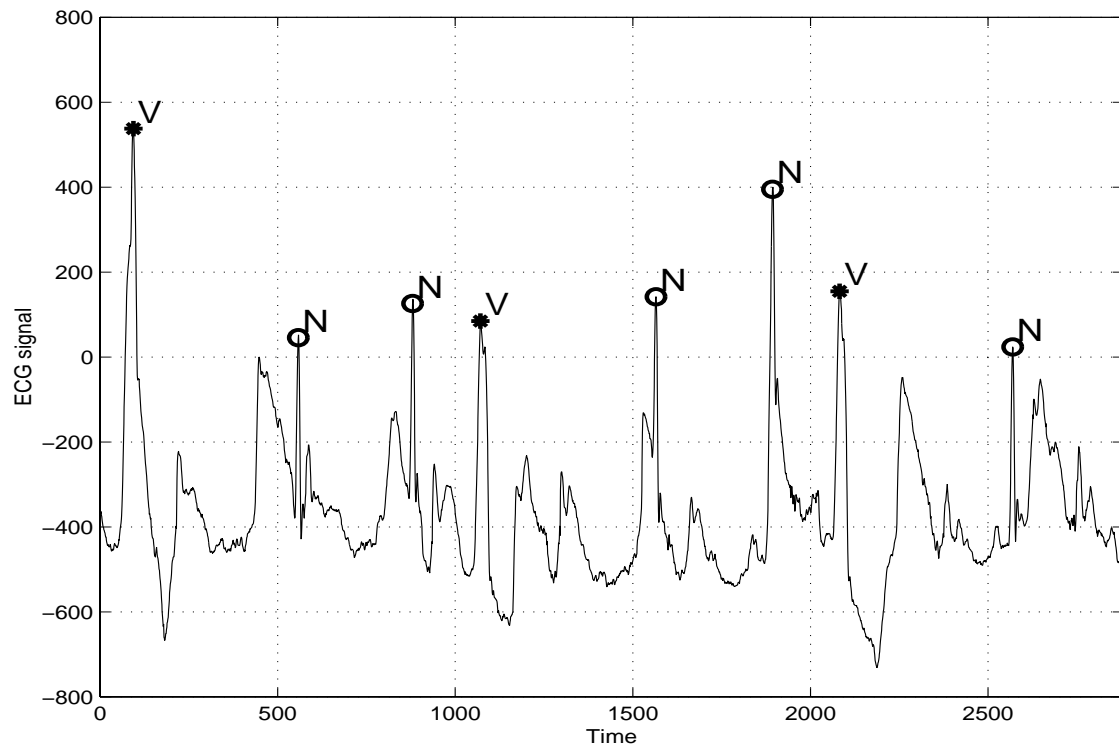


Fig. 2. The examples of real ECG recording of 2 different rhythm types

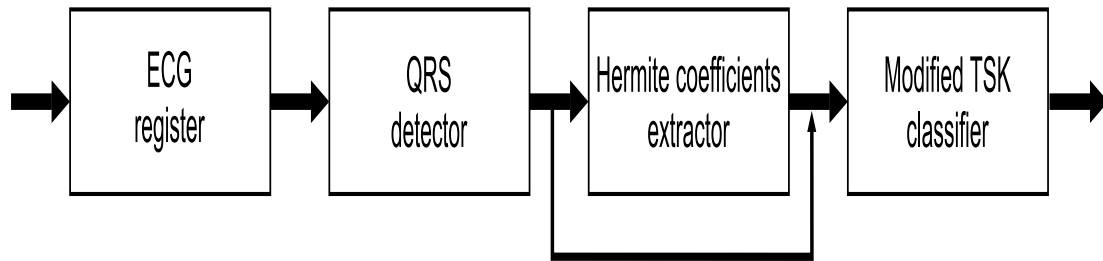


Fig. 3. *The proposed system of ECG recognition*

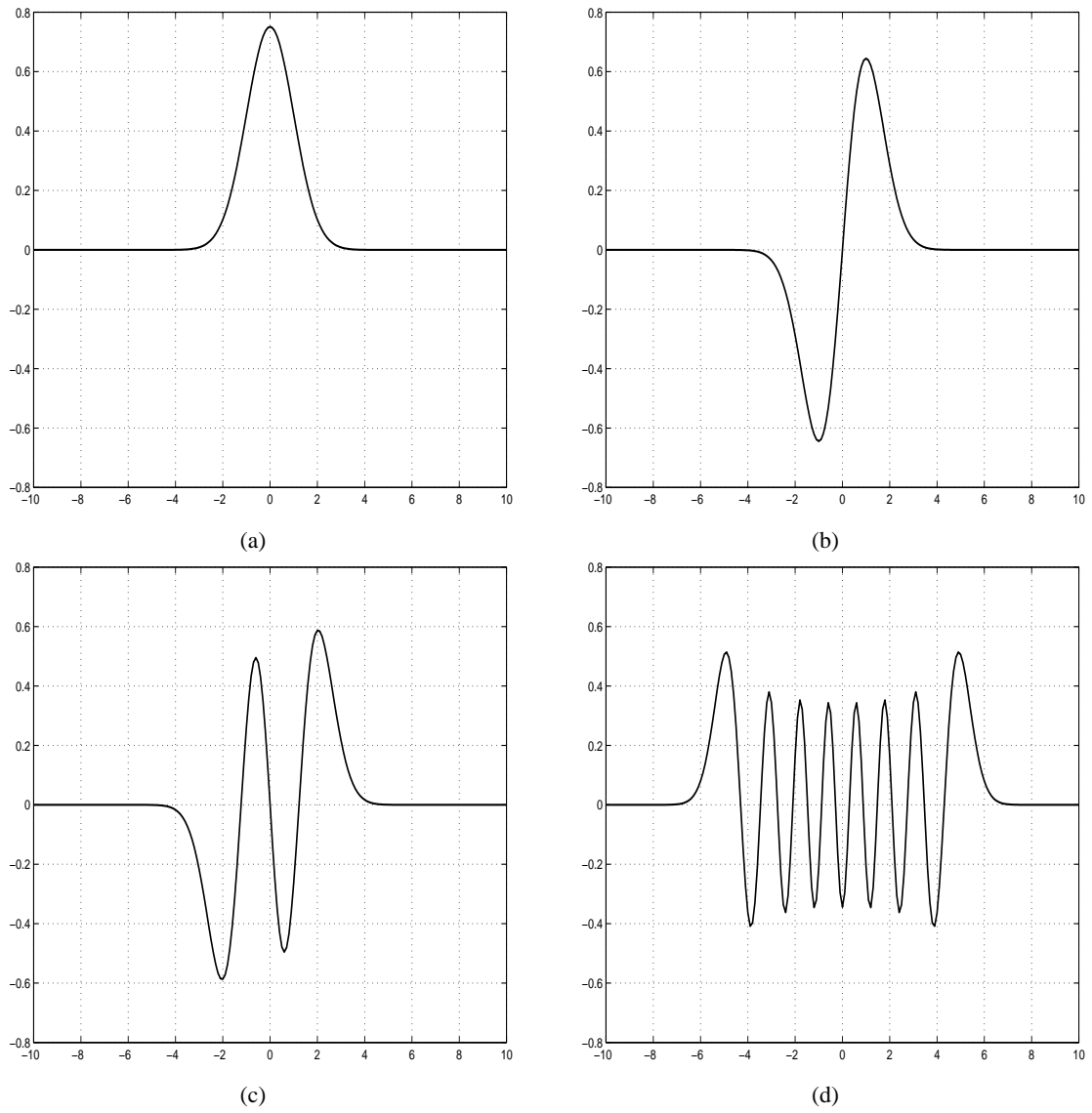


Fig. 4. The chosen Hermite functions for  $\sigma = 1$  plotted as a function of time: a)  $n=0$ , b)  $b=1$ , c)  $n=3$ , d)  $n=14$

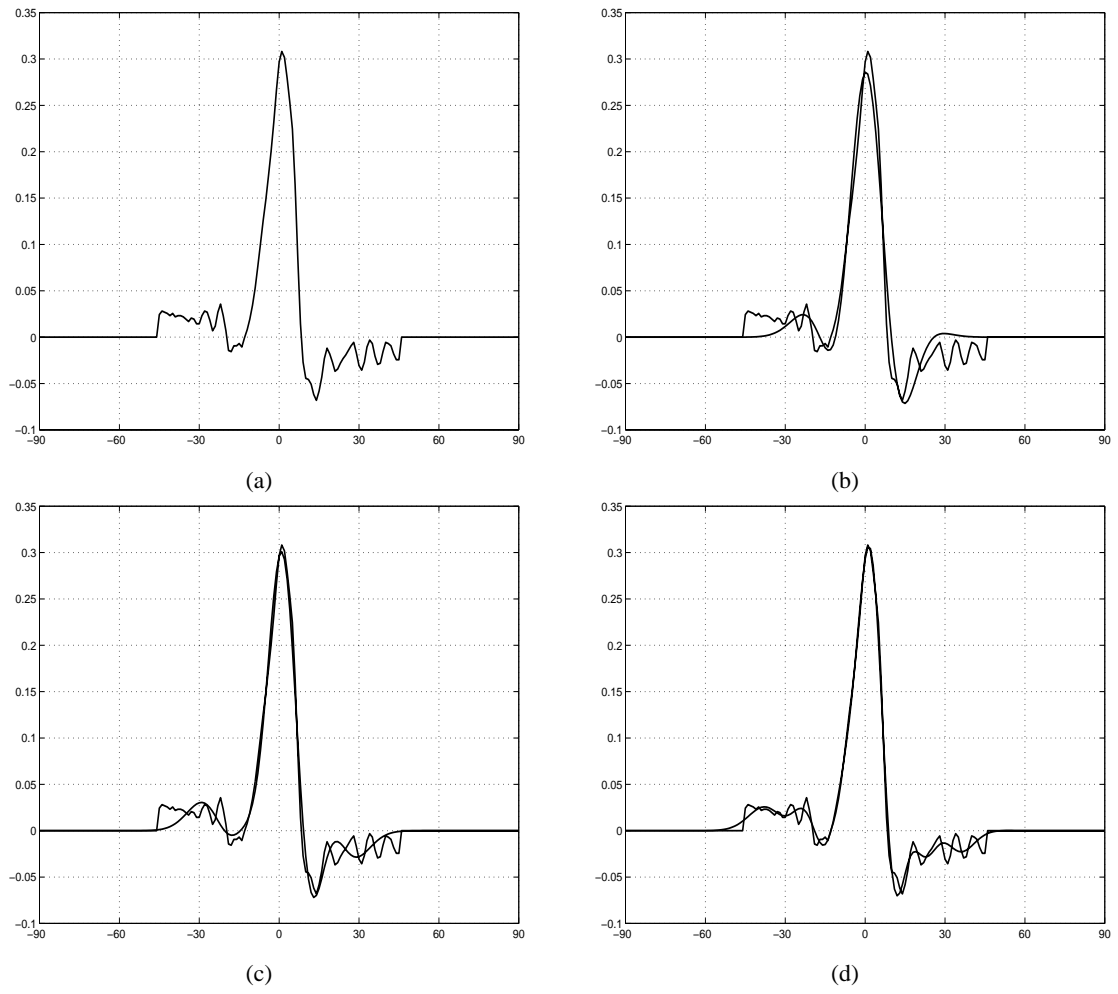
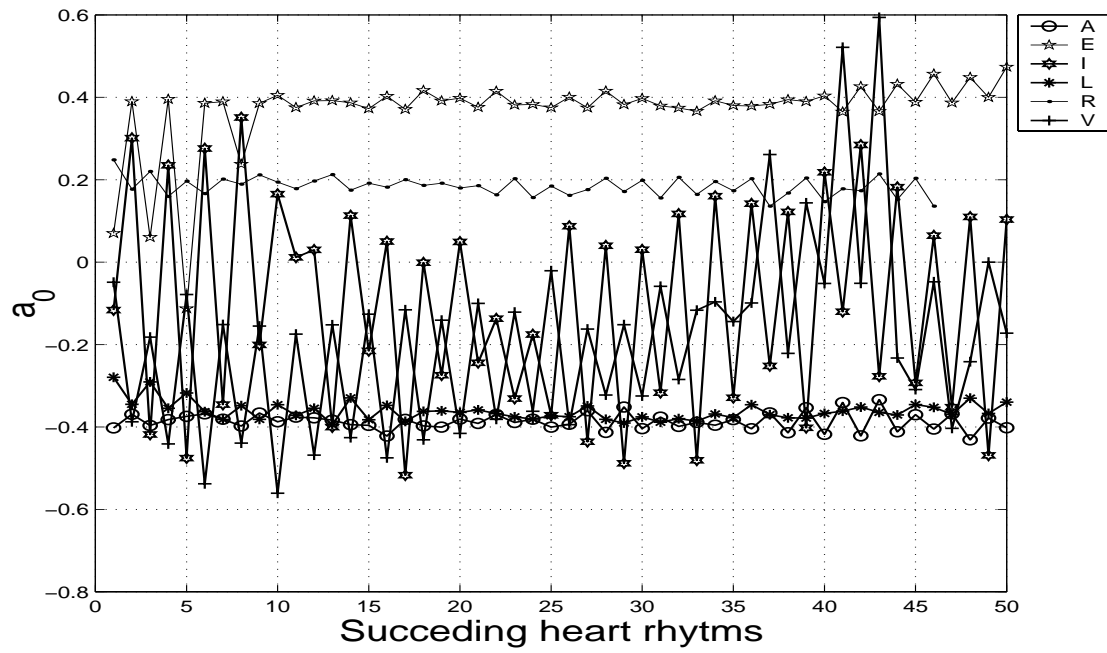
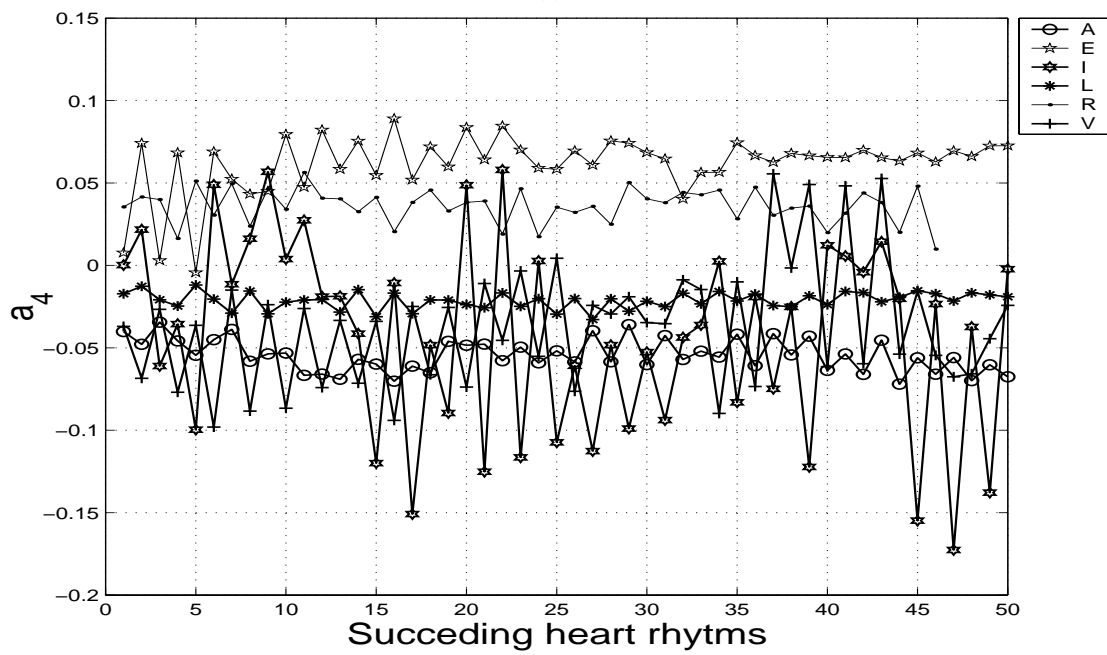


Fig. 5. The expanded QRS complex of ECG waveform (left, up) and its estimation using 6 (right, up), 9 (left, down), 15 (right, down) Hermite basis functions



(a)



(b)

Fig. 6. The distribution of the  $a_0$  (a) and  $a_4$  (b) Hermite coefficients for different heart beats of the same patient

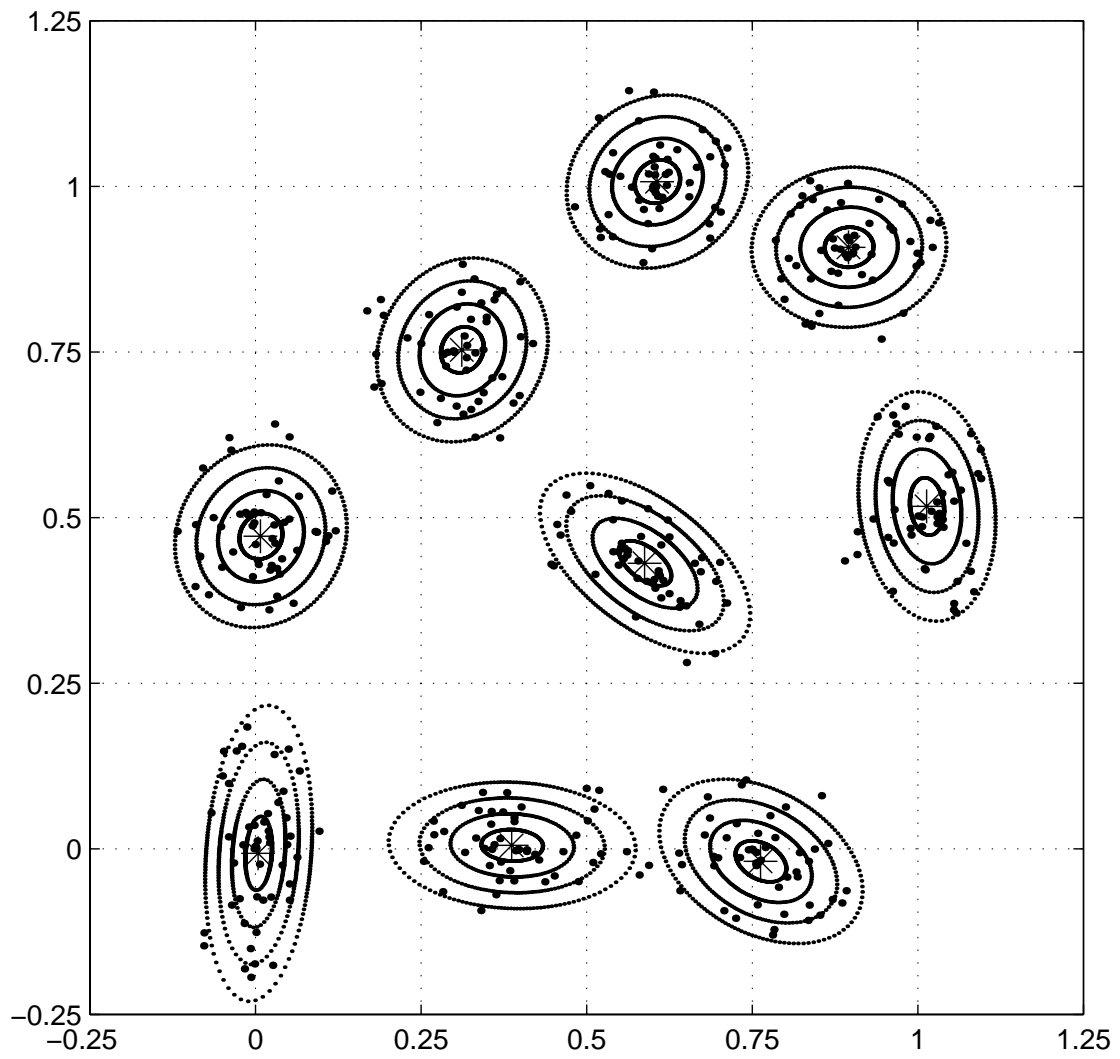


Fig. 7. The representation of the data points by the clusters. The lines indicate equal membership values of the data to the appropriate center

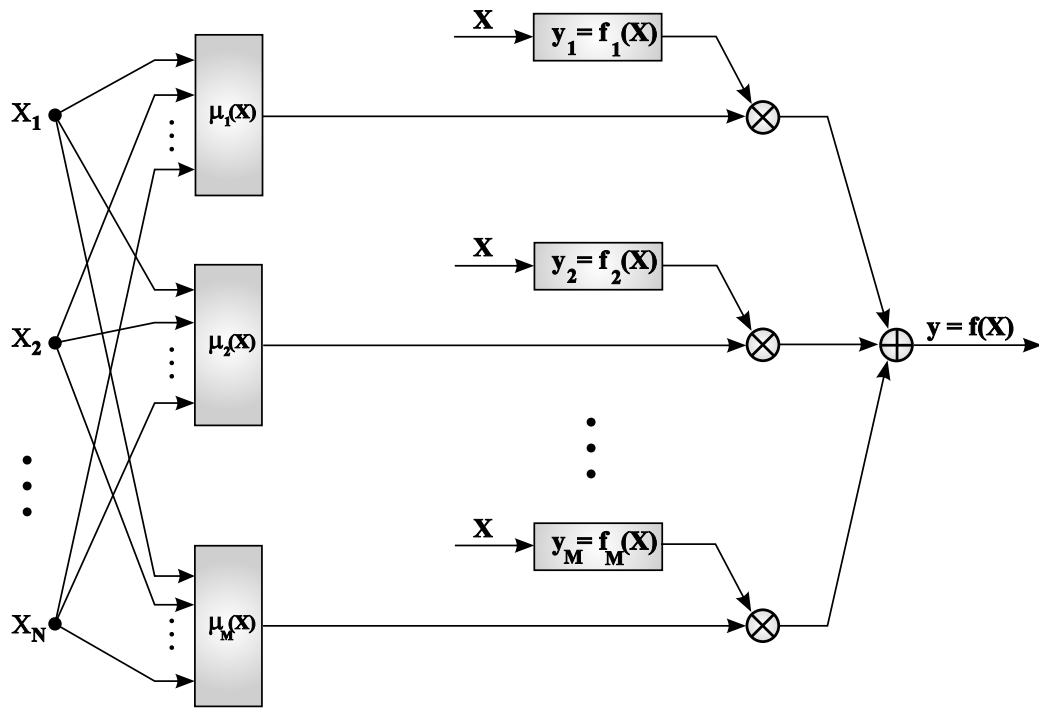


Fig. 8. The fuzzy neural network structure corresponding to the modified TSK system described by equation (11)

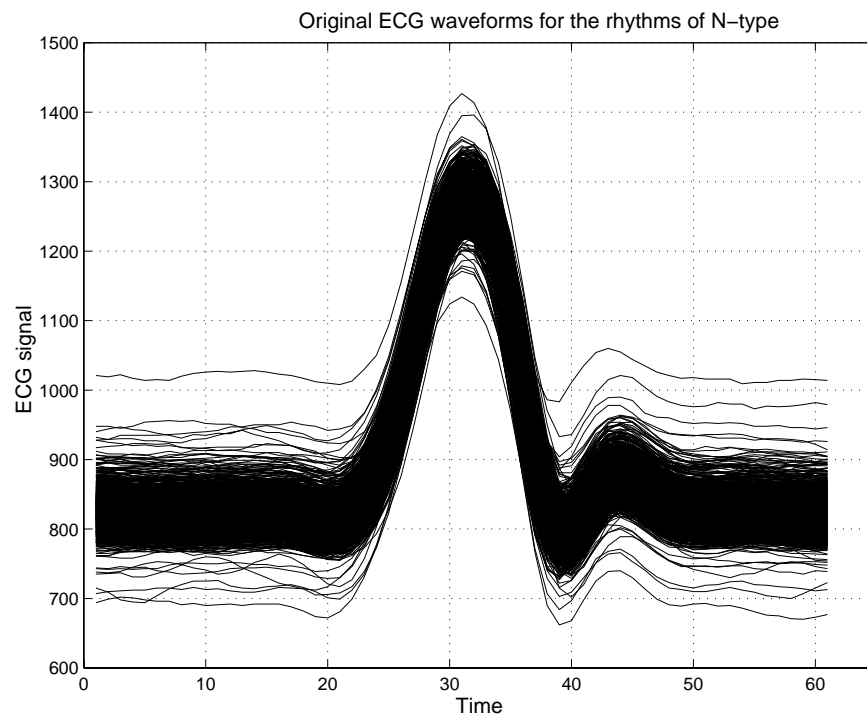


Fig. 9. *The original ECG data corresponding to the normal sinus rhythm of the heart beat*



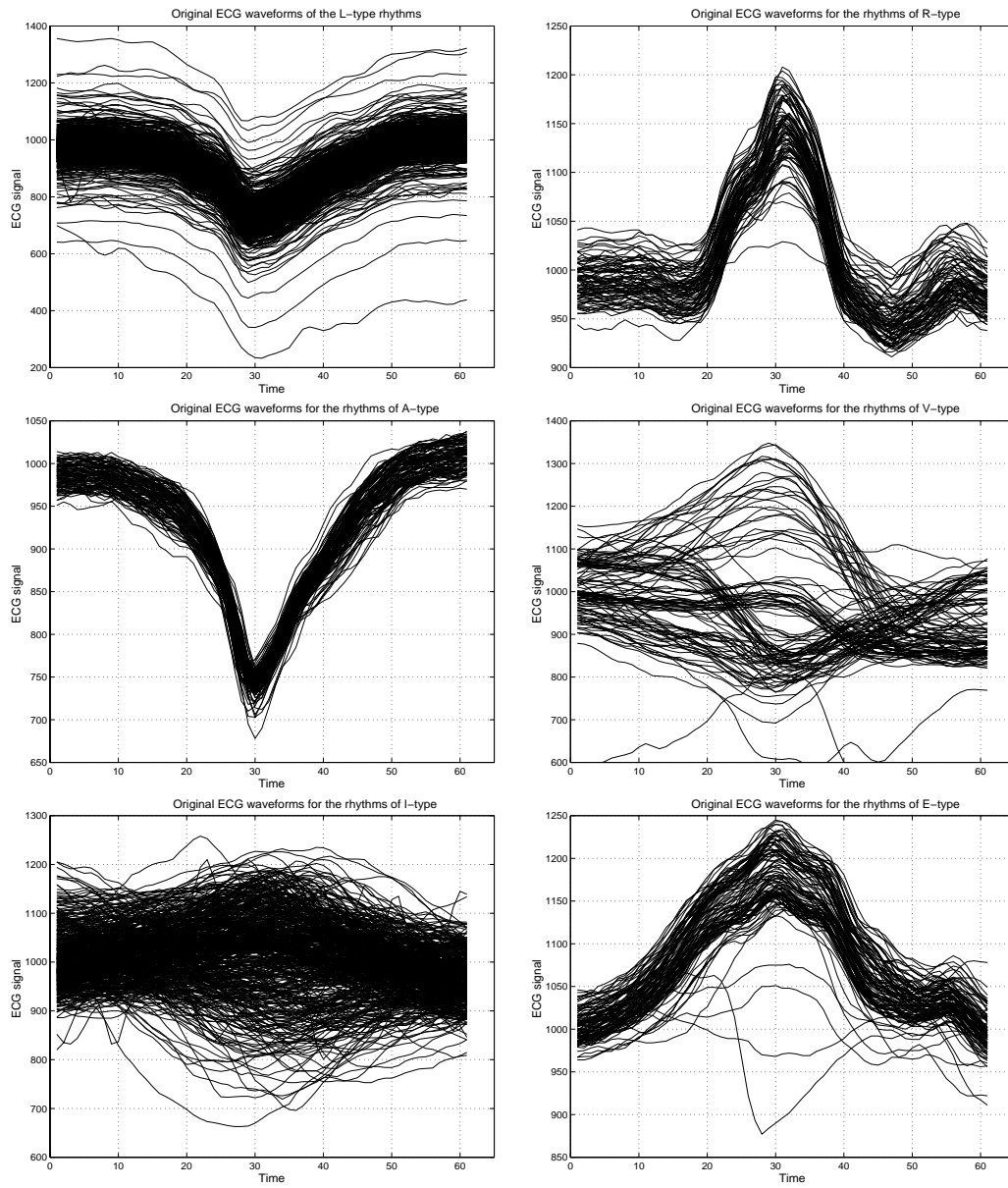


Fig. 10. The original data ECG corresponding to six types of arrhythmia beats: L, R, A, V, I, E

## LIST OF TABLES

I	Results of misclassifications of different rhythms on the learning and testing data . . .	26
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TABLE I  
RESULTS OF MISCLASSIFICATIONS OF DIFFERENT RHYTHMS ON THE LEARNING AND TESTING DATA

Type	Number of rhythms		Misclassification number		Rate of misclassification [%]	
	Learning	Testing	Learning	Testing	Learning	Testing
N	1000	1500	13	24	1.3%	1.6%
L	700	500	25	55	3.57%	11%
R	600	500	2	5	0.33%	1%
A	484	418	28	38	5.79%	9.09%
V	500	500	12	18	2.4%	3.6%
I	272	200	3	3	1.1%	1.5%
E	55	50	3	2	5.45%	4.0%
Total	3611	3668	86	145	2.38%	3.95%