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

Tran Hoai Linh, Stanis¨aw Osowski and Maciej Stodolski

Abstract

The paper presents the neuro-fuzzy approach to the recognition and classi£cation of heart rhythms on the basis of ECG waveforms. The important part in recognition ful£lls the Hermite characterization of the QRS complexes. The Hermite coef£cients 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 con£rmed very good performance of such solution.

Index Terms

Neurofuzzy networks, waveform characterization and measurement, Hermite function expansion, electrocardiography, arrhythmia recognition and classi£cation

I. Introduction

The problem of on-line heart beat type recognition on the basis of the registered ECG waveforms belongs to the dif£cult measurement problems, since the beats differ signi£cantly even for the same type and for the same patient. The ECG waveforms may differ for the same patient to such extend 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 classi£er, performing well on the training data behaves badly, when presented with different patients ECG waveforms. Although several algorithms have been already developed, their ef£ciency is still not satisfactory [2], [3], [4], [5], [6], [7].

T. H. Linh and M. Stodolski are with the Institute of the Theory of Electrical Engineering and Electrical Measurement, Warsaw University of Technology (WUT), Warsaw, pl. Politechniki 1, POLAND (e-mail: linh@iem.pw.edu.pl).

S. Osowski is with the Institute of the Theory of Electrical Engineering and Electrical Measurement, WUT, Warsaw, pl. Politechniki 1, and also with Military University of Technology, Warsaw, POLAND (e-mail: sto@iem.pw.edu.pl).

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 coef£cients of Hermite kernel expansion as the features of the process
- application of the modi£ed neuro-fuzzy TSK network for ECG pattern recognition and classi£cation.

Instead of the original waveform, we will rely on its description using coef£cients of Hermite expansion. These coef£cients are used as the input signals to the neuro-fuzzy network, ful£lling the role of recognition and classi£cation system. We have applied the modi£ed 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 coef£cient extraction, delivering these coef£cients as the features to the input of the neural network, performing the role of classi£er.

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 coef£cients 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

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

where a_n ($n = 0, 1, 2, ..., N-1$) are the expansion coef£cients while $\phi_n(t, \sigma)$ is the Hermite basis function de£ned as

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

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

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

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 substracting the mean level of the £rst and the last data points. An example of normalized QRS complex of ECG signal is presented in Fig. 5a.

The modi£ed QRS complex is decomposed onto a linear combination of Hermite basis functions. In the experiments the width σ 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 coef£cients a_i are obtained by minimizing the sum squared error, de£ned in the following way

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

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) £rst 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 coef£cients for different types of beats. Good features should be stable for the same beat type and differ signi£cantly for different beats. Close analysis of the distribution of the coef£cient 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 coef£cients 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 ¤atter 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 coef£cients 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 coef£cient values of higher variance. At the same time they all occupy similar range of values. The other coef£cients a_n for $n = 0, 1, 2, ..., 14$ 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 ef£ciency.

As a result of such investigation we have decided to represent each QRS complex of ECG waveform by 15 coef£cients a_i ($i = 0, 1, ..., 14$) of Hermite basis function expansion. All these coef£cients form the feature vector **x** put to the input of the neural classi£er.

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 £nal feature vector **x** of each QRS complex contains 17 elements: 15 Hermite coef£cients 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 modi£ed 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 **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]

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

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

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

usually assumed as a crisp linear function of coef£cients p_0, p_1, ..., p_N adjusted at the learning process.

The premise if $\mathbf{x}$ is $\mathbf{A}$ in TSK inference system is implemented as the fuzzi£er, de£ned for each variable x_i as the gaussian or bell function. Both functions are fully de£ned 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 inef£cient 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 ef£cient way of fuzzy clusterization is the application of Gustafson-Kessel (GK) algorithm [10]. It operates with two parameters of the cluster: the center vector $\mathbf{c}_i = [c_{i1}, ..., c_{iN}]^T$ 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 **x** and the center $\mathbf{c}_i$ is described now by using the scaled Euclidean measure

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

On the basis of this distance de£nition the £ring strength of ith rule is determined in the following way [11]

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

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

The TSK approximation function can be now described by []

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

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

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

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

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

The neural network structure, corresponding to this simpli£ed 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 £gure 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 coef£cients, forming the feature vectors. The information contained in the feature vectors of ECG beats has been applied to the input of the modi£ed neuro-fuzzy TSK network, which serves as the recognition and classi£cation 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 £nal classi£cation 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 de£nition 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 classi£cation 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 **x** containing the features representing beats and the destination vector **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 $\mathbf{c}_i$ and to determine the covariance matrices $\mathbf{F}_i$. After this step all centers $\mathbf{c}_i$ and matrices $\mathbf{F}_i$ 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 **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 classi£cation for different beats are presented in table 1 for the learning and the testing data. The ef£ciency of recognition of different beat types is varied from 1% to 11% and re¤ects the diverse complexity of the recognition task. As it is seen the average misclassi£cation rate in both learning and testing set is limited, and the ef£ciency of recognition in the testing mode is above 96%. Observe that the performance of the neural classi£er 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 scienti£c journals. For example the data classi£ed 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 dif£cult since the morphology of heart beats is changing from patient to patient and may present the additional dif£culties in recognition process. This is especially important, since the beats can differ signi£cantly 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 modi£ed TSK neuro-fuzzy network for heart beat recognition and classi£cation. The Hermite coef£cient characterization delivers stable features, relatively insensitive to the morphology variations of the ECG waveforms. Combining these features with good performance of the neuro-fuzzy classi£er have produced the accurate results of beat recognition, competitive to the already known results.

References

[1] R. Mark, G. Moody, MIT-BIH arrhythmia database directory, MIT, 1988

[2] Y. Hen Hu, W. Tompkins, J. L. Urrusti,, V. Alfonso, Application of arti£cial neural networks for ECG signal detection and classi£cation, J. of Electrocardiology, 1994

[3] Y. Hen Hu, S. Palreddy, W. Tompkins, A patient adaptable ECG beat classi£er using a mixture of expert approach, IEEE Tran. Biomedical Eng., 1997, vol. 44, pp. 891-900 arti£cial neural networks for ECG signal detection and classi£cation, J. Electrocardiol., 1994

[4] N. Izeboudjen, A. Farah, A new neural network system for arrhythmia's classi£cation, Neural Network Conference, Vienna 1998, pp. 208 - 216

[5] K. Minami, H. Nakajima, T. Toyoshima, Real-time discrimination of ventricular tachyarrhythmia with Fourier-transform neural network, IEEE Transactions on Biomedical Engineering, vol. 46, No. 2, Feb. 1999, pp. 179 - 185

[6] G. E. Oien, N. A. Bertelsen, T. Eftestol, J. H. Husoy, ECG rhythm classi£cation using arti£cial neural networks, Proc. 1996 IEEE Digital Signal Processing Workshop, 1996, pp. 514 - 517

[7] M. Lagerholm, C. Peterson, G. Braccini, L. Edenbrandt, L. Sornmo, Clustering ECG complexes using Hermite functions and self-organising maps, IEEE Tr. Biomedical Engineering, 2000, pp. 838-847

[8] S. Osowski, L. Tran Hoai, ECG beat recognition using fuzzy hybrid neural network, IEEE Trans. on Biomedical Engineering, 2001, vol. 48, pp. 1265-1272

[9] R. Babuska, H. B. Verbruggen, Constructing fuzzy models by product space clustering, (in ”Fuzzy model identi£cation”, H. Hellendoorn, D. Driankov, Eds., Springer, Berlin, 1998), pp. 53 - 90

[10] D. Gustafson, W. Kessel, Fuzzy clustering with a fuzzy covariance matrix, Proc. IEEE CDC, San Diego, pp. 761-766

[11] J. S. Jang, C. T. Sun, E. Mizutani, *Neuro-fuzzy and soft computing,* Prentice Hall, N. J., 1997

[12] G. Golub, C. Van Loan, Matrix computation, Academic Press, 1991, New York

Tran Hoai Linh was born in Vietnam in 1974. He received the M.Sc., and Ph.D. degrees from Warsaw University of Technology, Warsaw, Poland, in 1997 and 2000, respectively in computer science and electrical engineering. Currently he conducts post-doctoral studies in the Institute of the Theory of Electrical Engineering and Electrical Measurements, Warsaw University of Technology. His research interest in is neural networks and computer aided circuit analysis and design. He is an author or coauthor of 25 scienti£c papers.

Stanislaw Osowski was born in Poland in 1948. He received the M.Sc., Ph.D., and Dr.Sc. degrees from the Warsaw University of Technology, Warsaw, Poland, in 1972, 1975, and 1981, respectively, all in electrical engineering. Currently he is a professor of electrical engineering at the Institute of the Theory of Electrical Engineering and Electrical Measurements, Warsaw University of Technology. His research and teaching interest are in the areas of neural networks, optimization techniques, and computer-aided circuit analysis and design. He is an author or coauthor of more than 200 scienti£c papers and ten books.

Maciej Stodolski was born in 1965 in Warsaw. He graduated from Warsaw University of Technology, Faculty of Electrical Engineering in 1989. In 1998 he got the Ph.D. degree from the same University. Currently he is an Assistant Professor at the Institute of the Theory of Electrical Engineering and Electrical Measurements, Warsaw University of Technology. His main scienti£c interest is in optimization methods, learning algorithms of neural networks, object programming and data bases.

List of Figures

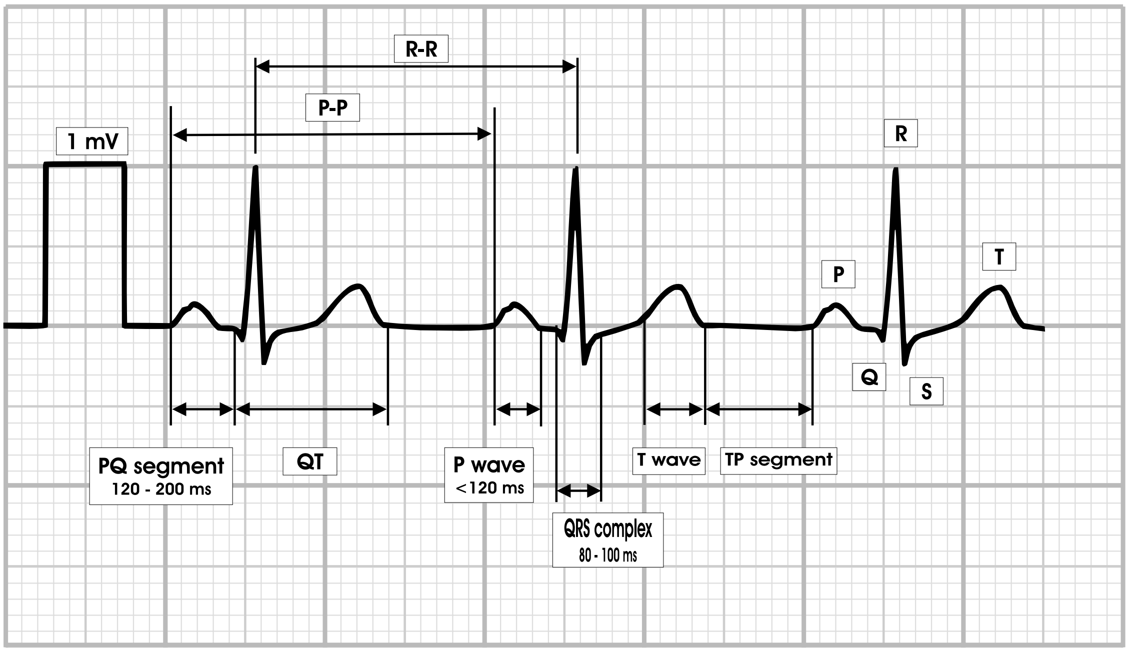


Fig. 1. *The typical ECG waveform*

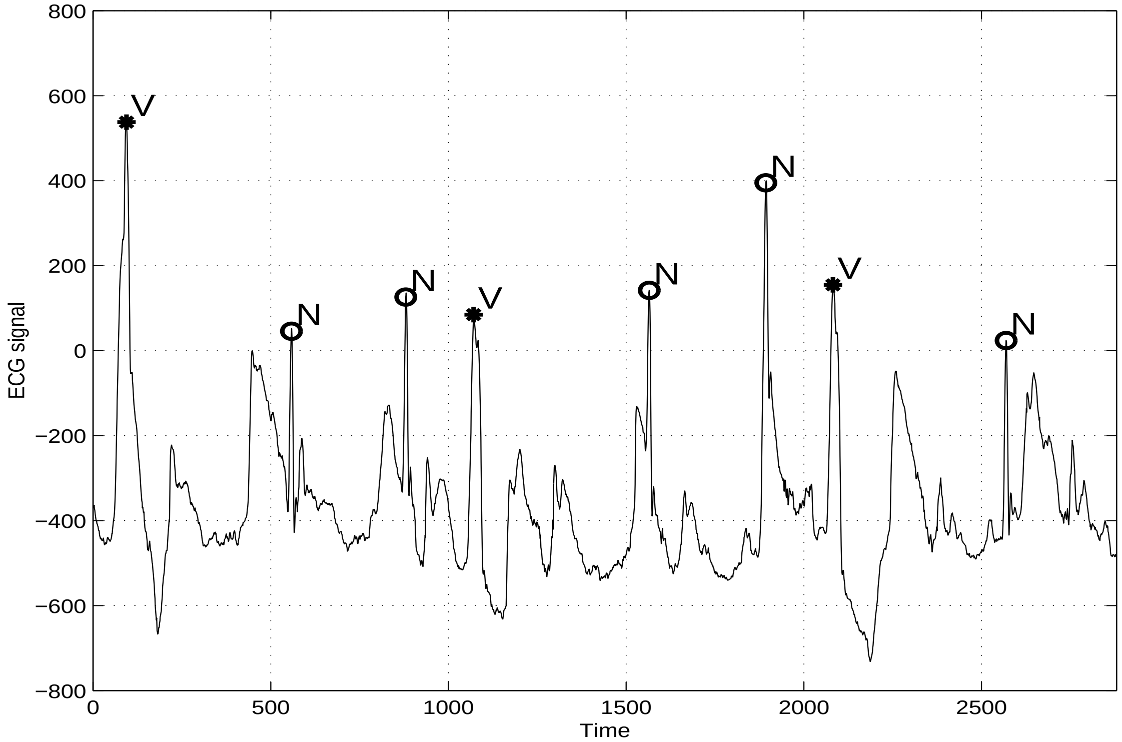


Fig. 2. *The examples of real ECG recording of 2 different rhythm types*

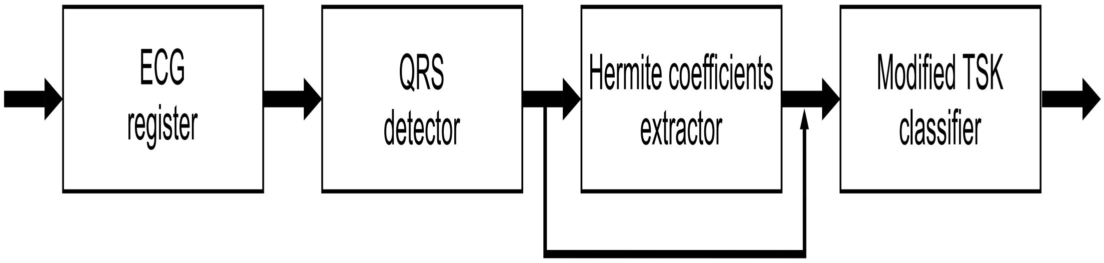


Fig. 3. *The proposed system of ECG recognition*

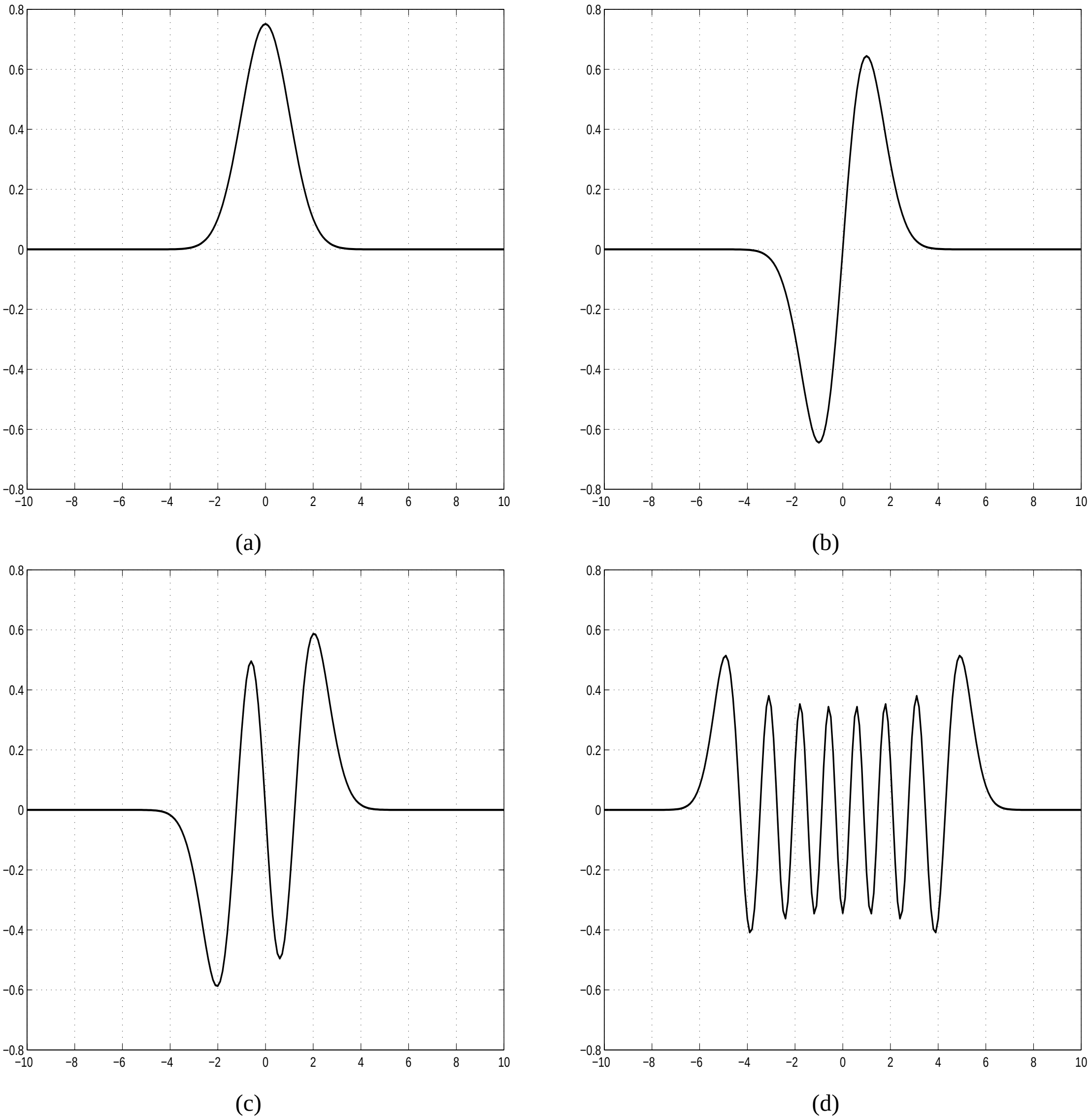


Fig. 4. *The chosen Hermite functions for $\sigma = 1$ plotted as a function of time: a) n=0, b) b=1, c) n=3, d) n=14*

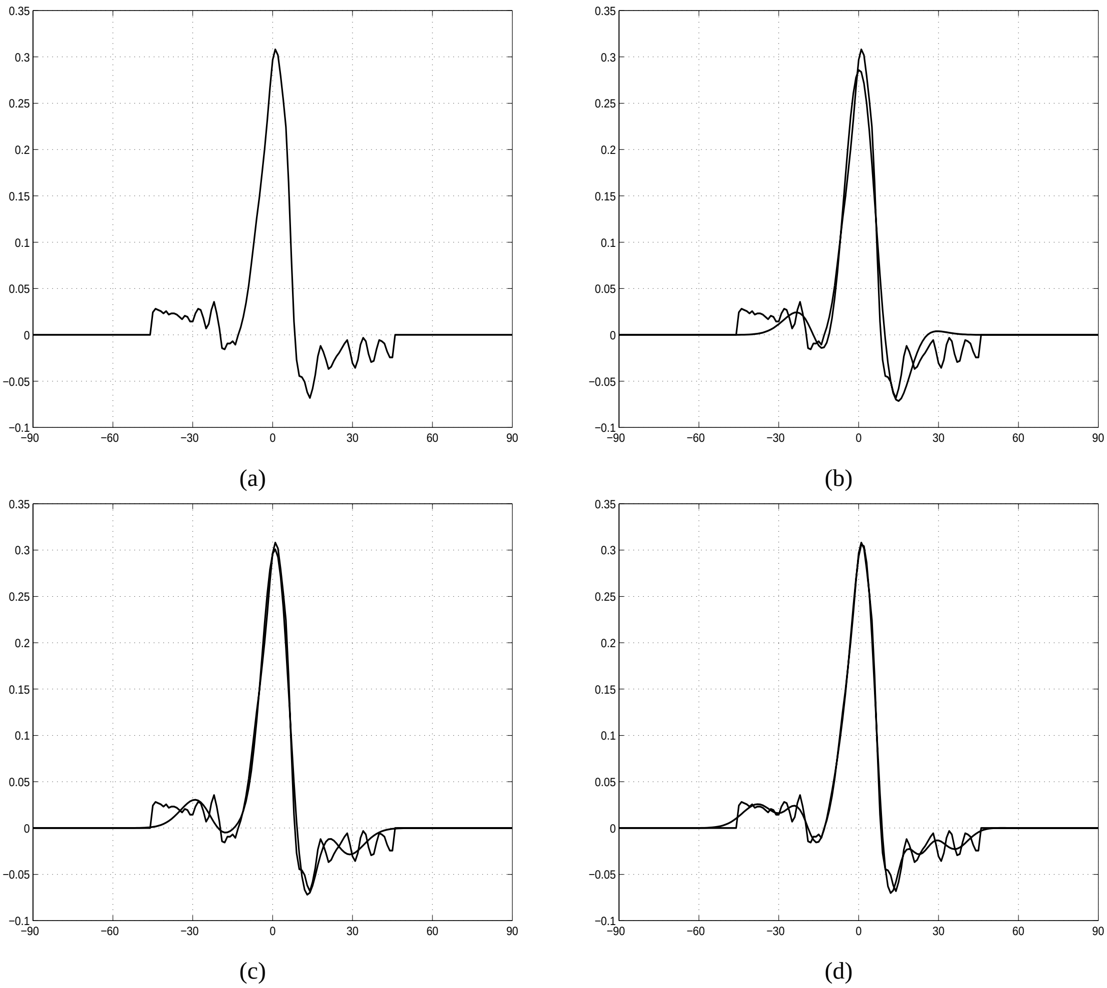
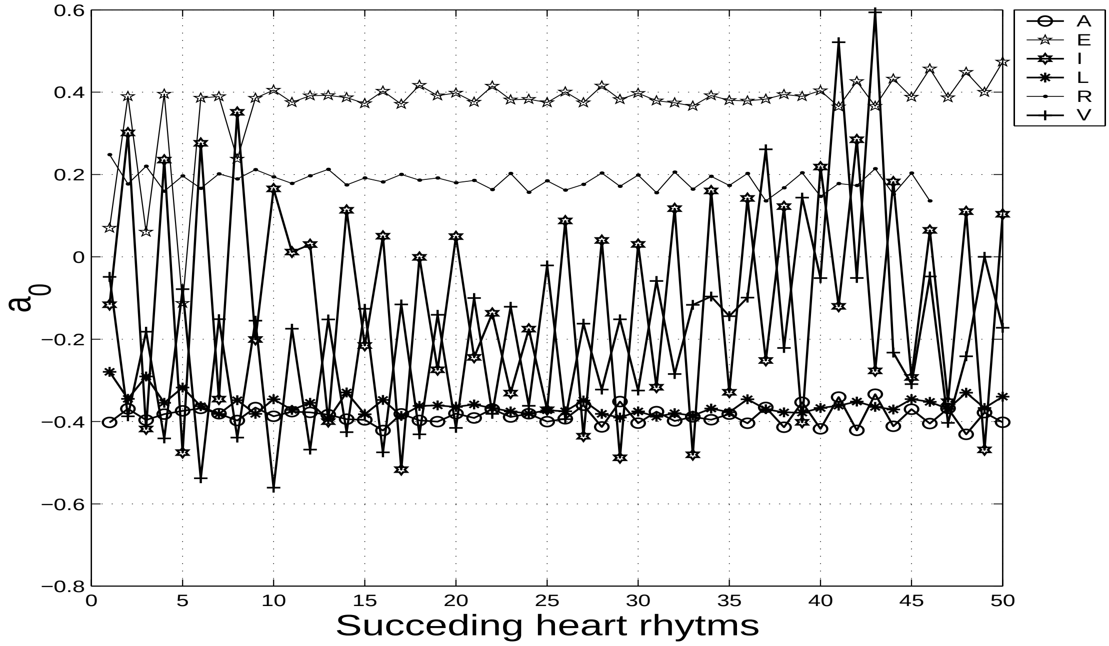
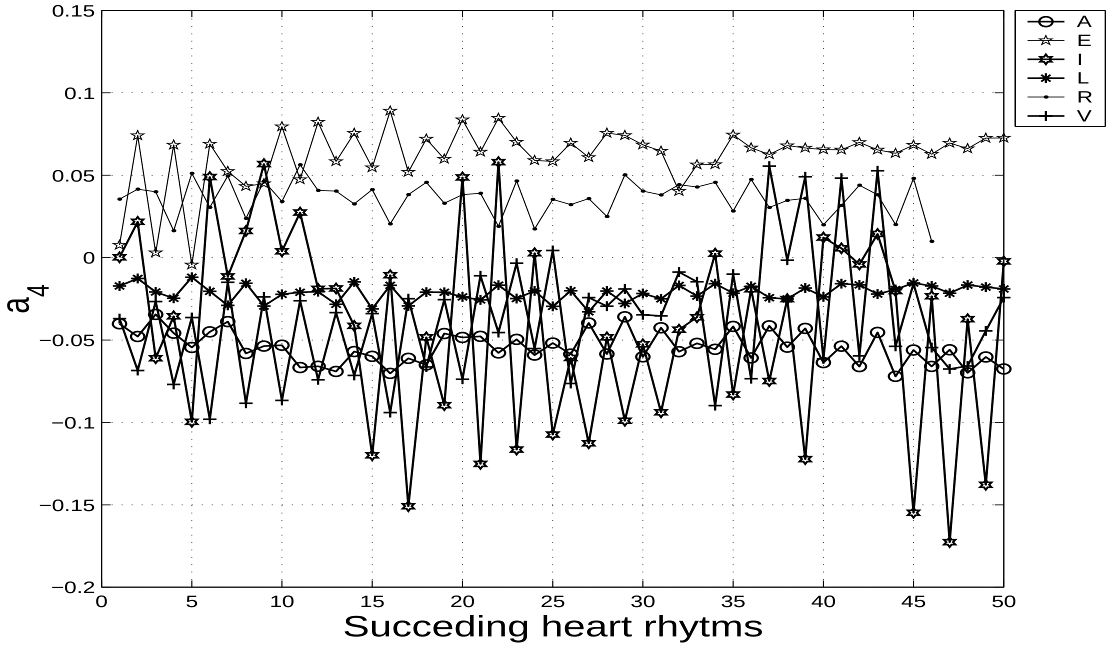


Fig. 5. *The expanded QRS complex of ECG waveform (left,up) and its estimation using 6 (right, up), 9 (left, down), 15(right, down) Hermite basis functions*



(a)



(b)

Fig. 6. *The distribution of the* a_0 *(a) and* a_4 *(b) Hermite coef£cients for different heart beats of the same patient*

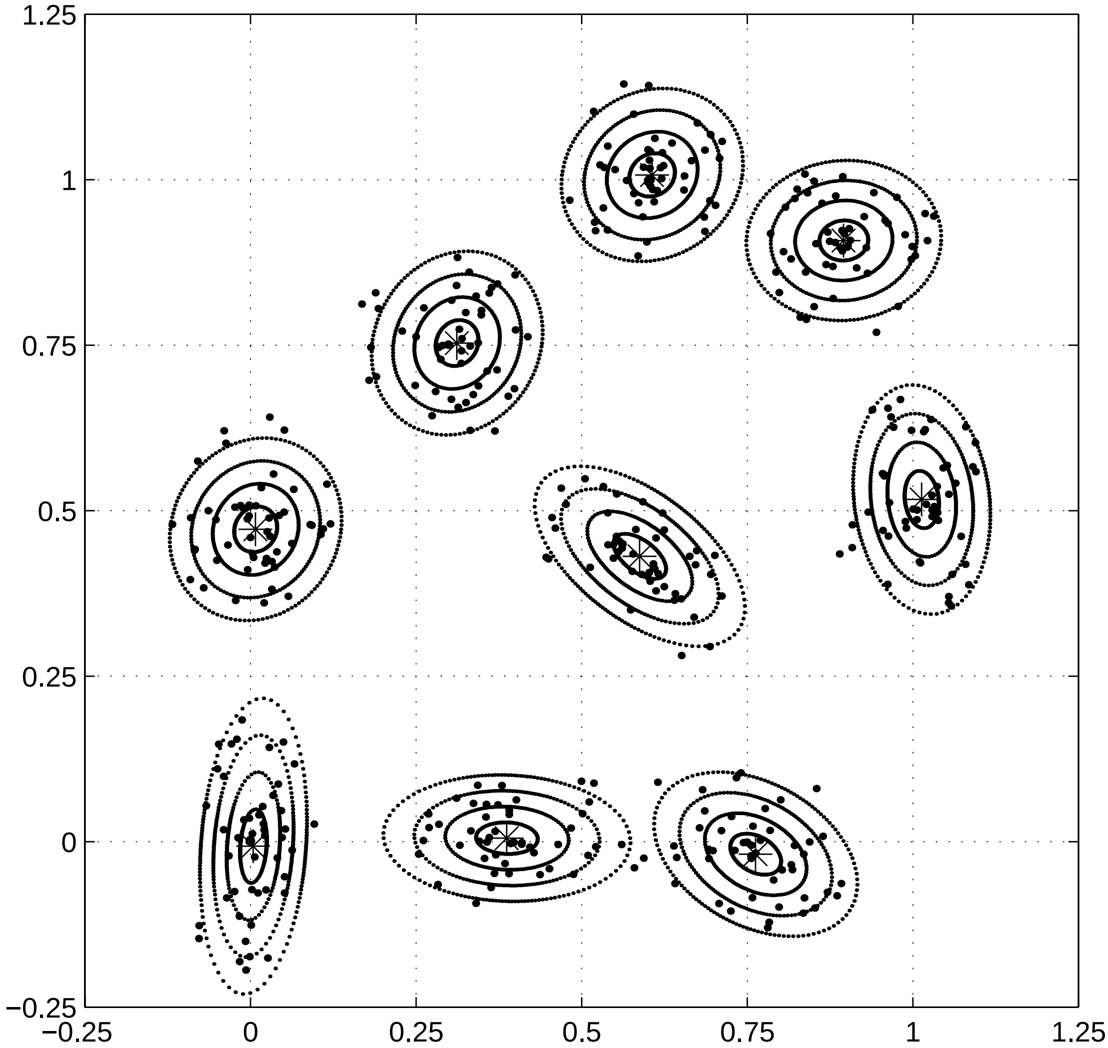


Fig. 7. *The representation of the data points by the clusters. The lines indicate equal membership values of the data to the appropriate center*

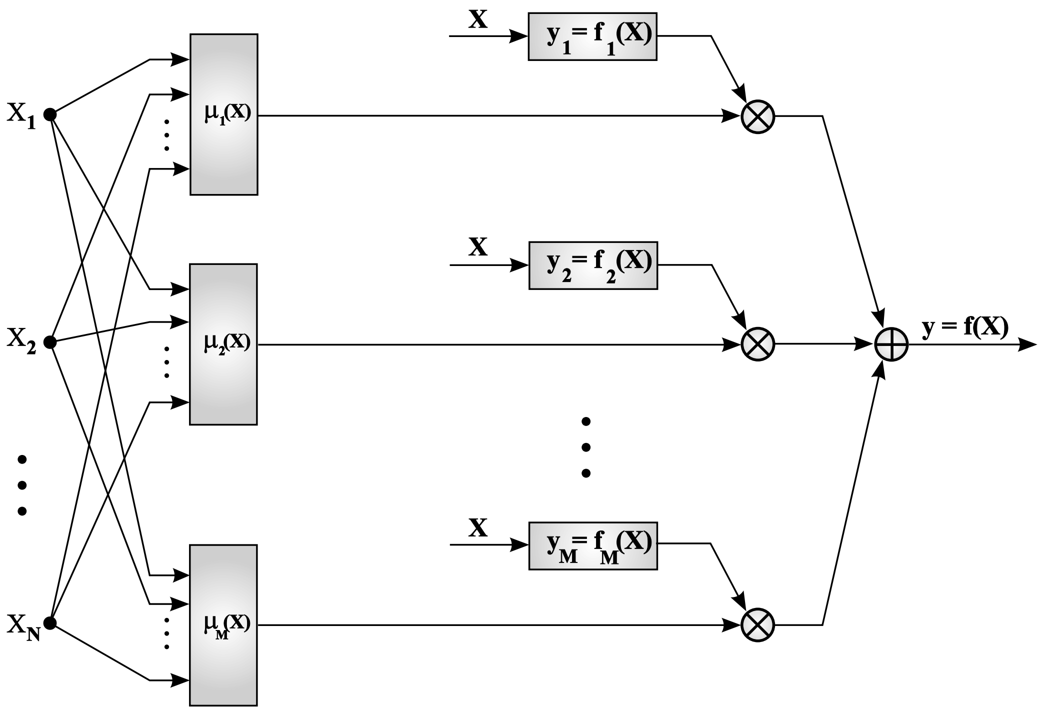


Fig. 8. *The fuzzy neural network structure corresponding to the modi£ed TSK system described by equation (11)*

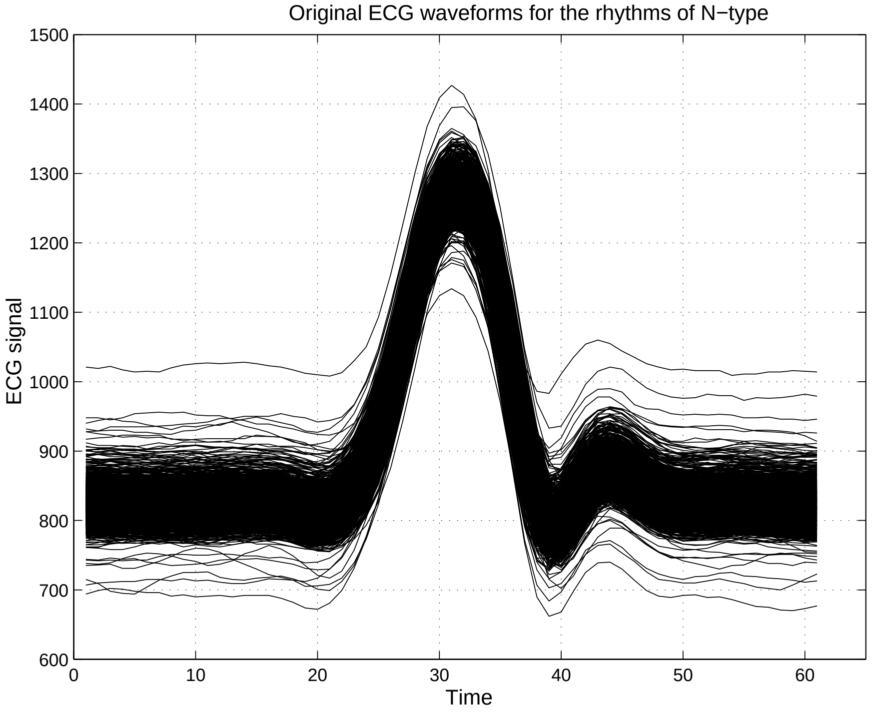


Fig. 9. *The original ECG data corresponding to the normal sinus rhythm of the heart beat*

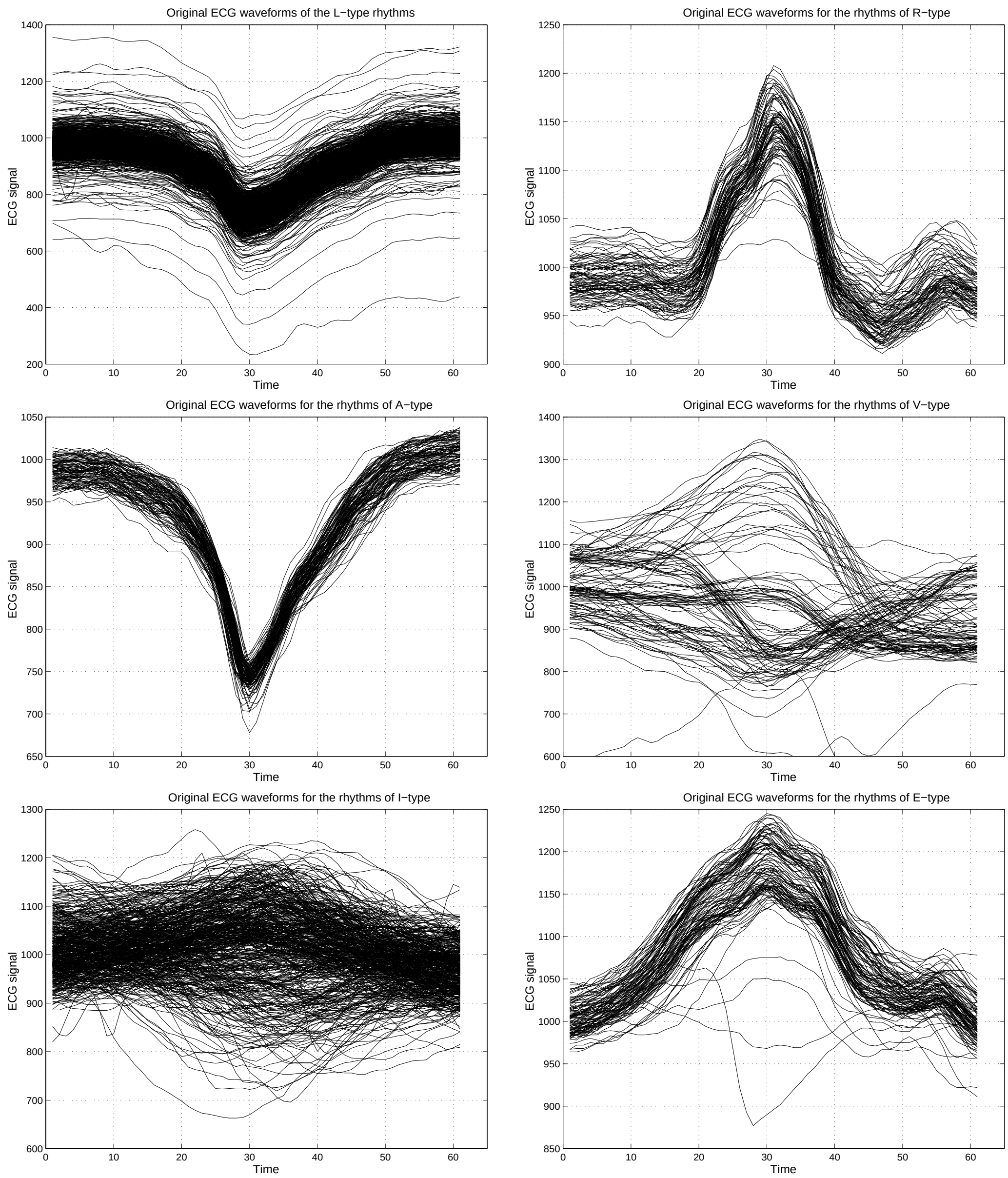


Fig. 10. *The original data ECG corresponding to six types of arrhythmia beats: L, R, A, V, I, E*

List of Tables

TABLE I

RESULTS OF MISCLASSIFICATIONS OF DIFFERENT RHYTHMS ON THE LEARNING AND TESTING DATA

Type	Number of rhythms		Misclassi£cation number		Rate of misclassi£cation [%]	
	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%