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ECG beat classification using neuro-fuzzy network

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Abstract

In this paper we have studied the application on the fuzzy-hybrid neural network for electrocardiogram (ECG) beat classification. Instead of original ECG beat, we have used; autoregressive model coefficients, higher-order cumulant and wavelet transform variances as features. Tested with MIT/BIH arrhythmia database, we observe significant performance enhancement using proposed method.

Keywords: ECG beat classification; MIT/BIH database; Neuro-fuzzy networks; Higher-order statistics; Wavelet transform; AR modelling; Pattern recognition

1. Introduction

The recognition of the ECG beats is a very important task in the coronary intensive unit, where the classification of the ECG beats is essential tool for the diagnosis. Up to now, many algorithms have been developed for the recognition and classification of ECG signal. Some of them use either time or frequency domain representation, on the basis of which many specific attributes are defined, allowing the recognition between the beats belonging to different pathological classes. The ECG waveforms may differ for the same patient to such extent that they are unlike each other and at the same time alike for different types of beats (Osowski and Linh, 2001). Artificial neural network and fuzzy-based techniques were also employed to exploit their natural ability in pattern recognition task for successful classification of ECG beats (Hu et al., 1997).

Analysis of the ECG signals is of the great importance in the detection of cardiac anomalies. One of the most important ECG components is the QRS complex, which is associated with electrical ventricular activation (Barro et al., 1998). ECG pattern recognition can be divided into a sequence of stages; starting with feature extraction from the

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occurring patterns, which is the conversion of the patterns to features that are regarded as a condensed representation. In the next step, the feature selection, smaller number of meaningful features, that the best represents the given pattern without redundancy, is defined. Finally, the classification is carried out, i.e., specific pattern is assigned to a specific class according to the characteristic features selected for it (Dickhaus and Heinrich, 1996).

In this paper, we present the approach to ECG beat classification that is based on using three different types of feature sets. Auto-regressive (AR) model coefficients, third-order cumulant and the variance of the Discrete Wavelet Transform (DWT) of the related ECG beat, are used to construct features vector. Wavelet transform have a lot of potential for the representation of non-stationary signals. Thus, the ECG signal, being highly non-stationary within each beat, lends itself quite well to wavelet transform based features using. On the other hand, it will be shown that the higher-order statistics are less sensitive to the variation of the morphology of the ECG (Osowski and Linh, 2001). Non-Gaussian processes are not completely characterized by their second-order statistics; by using higher-order statistics, we are exploiting more of the information contained in the data. Specific features of the signal spectra were used to differentiate between normal and diseased patients. The application of parametric methods to signal recognition problems, particularly in the presence of high background noise is important. AR model has been applied to many fields including speech processing and biomedical signal processing.

In the classification stage, we have used the so-called fuzzy-hybrid neural network which is composed of two sub-networks connected in cascade: the fuzzy self-organizing layer performing the pre-classification task and the following multilayer perceptron working as the final classifier.

The numerical experiments including networks training and testing concentrated on the recognition between fourth different types of signal class. The results of experiments will be given and compared with different networks, presented in the literature.

2. Pre-processing of ECG signals

Arrhytmia detection algorithm consist of following parts: (a) R wave detection; (b) Features extraction; (c) Classification.

Fig. 1 shows block diagram of the whole algorithm.

After receiving signals from MIT/BIH arrhytmia database (Physiobank, 2003), the ECG signals

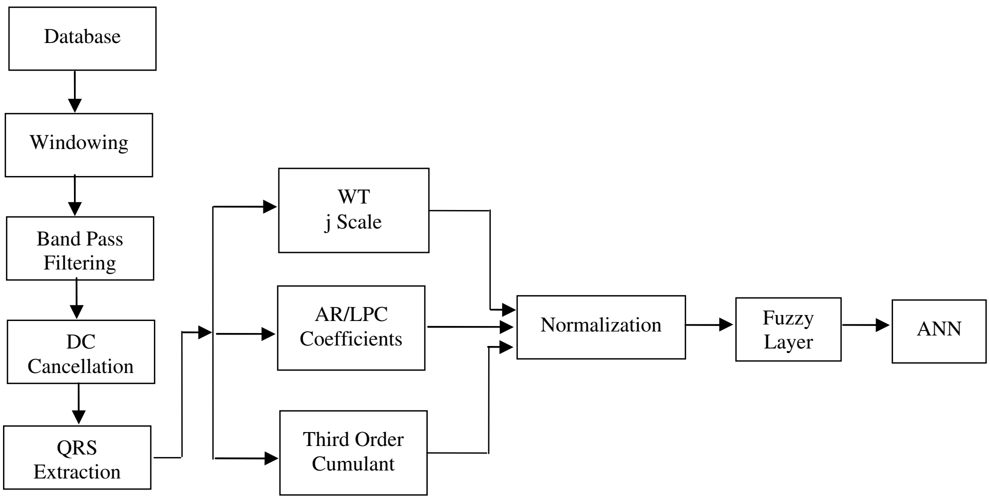

Fig. 1. Block diagram of classification process.

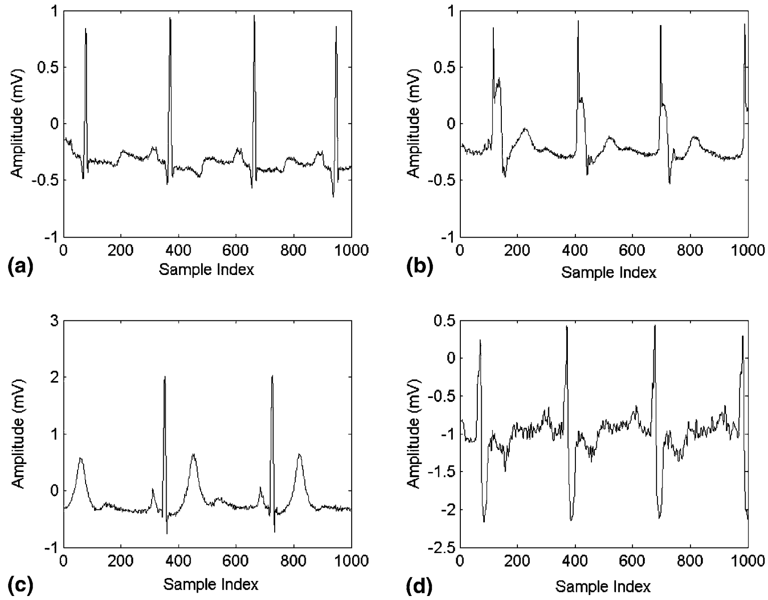

Fig. 2. ECG signals belong to four classes: (a) Normal Sinus rhythm beats; (b) Non-Conducted P-Wave; (c) Premature Ventricular contraction beats; (d) Right bundle branch block beats.

were filtered with bandpass of 1–100 Hz by Butterworth filter. The ECG waveform contains, in addition to the QRS complex P and T waves, 60 Hz noise from power line interferences, EMG from muscles, motion artefacts from the electrode and skin interface. Many clinical instruments such as a cardiotachometer and an arrhytmia monitor require accurate real-time QRS detection. We can summarize the relative power spectra of ECG, QRS complexes, P and T waves, motion artefact, and muscle noise based on previous research (Thakor et al., 1993). As shown in this mentioned study, the power spectrum of ECG extends to 40 Hz, effectively. But, we consider the limits of the bandpass filtering as the range of 1–100 Hz. Also, ECG signals were filtered with pass band of 1–100 Hz as given in the other study (Minami et al., 1999). In order to detect R wave, peak detection process is employed on ECG data. The Remez algorithm (Lang, 1998) based differentiative filter, squaring process and the thresholding process are implemented, respectively. Centered on the detected R-wave peak, the ECG beats are extracted by applying a Hamming window with 160 samples of length. After removing of mean value of ECG segments, the obtained ECG set which consist of 15 ECG beats, applied to classification block. In Fig. 2, ECG signals belong to four classes are shown.

3. Feature extraction

Usually, automatic ECG beat recognition and classification has been performed in the part either by the neural network or by the other recognition systems relying in various features, time domain representation, extracted from the ECG beat (Hu et al., 1997), or the measure of energy in a band of frequencies in the spectrum (frequency domain representation) (Minami et al., 1999). Since these features are very susceptible to variations of ECG morphology and the temporal characteristics of ECG, it is difficult to distinguish one from the other on the basis of the time waveform or frequency representation. In our work, we have used three different classes of feature set belonging to the isolated ECG beats including; third-order cumulant, auto-regressive model parameters and the variance of discrete wavelet transform detail coefficients for the different scales (1–6 scales).

3.1. Wavelet transformation

Physiological used for diagnostic purposes are frequently characterized by a non-stationary time behaviour. For such patterns, time frequency representations are desirable. The frequency characteristics as well as the temporal behaviour can be described with respect to uncertainty principle. The wavelet transform is capable of representing signals in different resolutions by dilating and compressing its basis functions. While the dilated functions adapt to slow wave activity, the compressed functions captures fast activity and sharp spikes. The optimum choice of types of wavelet functions for pre-processing is problem dependent. In our study, we used Daubechies wavelet function (db5) which is called compactly supported orthonormal wavelets (Daubechies, 1998). The DWT is obtained by making discretization the scaling factor and position factor. For orthonormal wavelet transform, a discrete signal $x(n)$ can be expanded in to the scaling function at j level, as follows:

$$x(n) = D_{j,k}[x(n)] + A_{j,k}[x(n)], \quad n \in Z \tag{1}$$

where $D_{j,k}$ represents the detailed signal at j level. Note that j controls the dilation or contraction of the scale function $\Phi(t)$ and k denotes the position of the wavelet function $\Psi(t)$, and n represents the sample number of the $x(n)$. Here $n \in Z$ represents the set of integers. In the wavelet decomposition, the frequency spectrum of the signal is divided into high frequency and low frequency as the band increases ($j = 1, \ldots, 6$).

Wavelet transform is a two-dimensional time-scale processing method for non-stationary signals with adequate scale values and shifting in time (Thakor, 1993; Clarek, 1995).

Multiresolution decomposition can effectively provide simultaneous characteristics, in term of the representation of the signal at multiple resolutions corresponding to different time scales. The normalized variances of detail coefficients of the DWT belonging to related scales are used to construct features vector.

3.2. Higher-order statistics and AR modelling

In automatic ECG beat recognition and classification, the main problem is that related features are very susceptible to variations of ECG morphology and temporal characteristics of ECG. In the study (Osowski and Linh, 2001), the set of original QRS complexes typical for six types of arrhytmia taken from the MIT/BIH arrhytmia database, there is a great variations of signal among the same type of beats belonging to the same type of arrhytmia. Therefore, in order to solve such problem, we will rely on the statistical features of the ECG beats. In our work for this aim, third-order cumulant has been taken into account, which can be determined (for zero mean signals) as follows (Osowski and Linh, 2001):

$$C_{2x}(k) = E\{x(n)x(n+k)\} \tag{2}$$

$$C_{3x}(k,l) = E\{x(n)x(n+k)x(n+l)\} \tag{3}$$

$$\begin{aligned} C_{4x}(k,l,m) = {} & E\{x(n)x(n+k)x(n+l)x(n+m)\} \\ & - C_{2x}(k)C_{2x}(m-l) - C_{2x}(l)C_{2x}(m-k) \\ & - C_{2x}(m)C_{2x}(l-k) \end{aligned} \tag{4}$$

where E is the expectation operator, and k, l, and m are the time lags. In our work, we have used third-order cumulant of selected ECG beats. Normalized ten points representing cumulant evenly distributed with in the range of 25 lags.

Linear prediction models each successive samples of a signal as a linear combination of previous samples, that is, as the output of an all-pole IIR filter. This process finds the coefficients of an nth-order auto-regressive linear process that models the time series x as

$$\begin{aligned} x(k) = {} & -a(2)x(k-l) - a(3)x(k-2) \\ & - \cdots - a(n+1)x(k-n-1) \end{aligned} \tag{5}$$

where x is the real input time series (a vector), and n is the order of the denominator polynomial $a(z)$. In the block processing, one of the modelling methods is autocorrelation method of all-pole modelling to find the linear prediction coefficients. This method is also called the maximum entropy method (MEM) of spectral analysis. In this study, we have selected model order as 2, which is able to represent many types of ECG classes.

4. Classification

The pattern recognition of the type of ECG waveform, different solutions presented in the literature, such MLP approach (Hu and Tompkins, 1985), the self-organizing map (Hu et al., 1997) are given. We will present the combination of the fuzzy self-organizing layer and the MLP connected in cascade, named the fuzzy-hybrid neural network. Structure of such a network is shown in Fig. 3.

Self-organizing layer is responsible for the clusterization of the input data (i.e., feature vector). Outputs of this block (membership values) form the input vector to the second sub-network (MLP). This block has an input layer (18 input neurons), one hidden layer (14 neurons) and output layer (2 terminals).

4.1. Fuzzy *c*-means algorithm

The fuzzy *c*-means algorithm searches for the partition matrix and cluster centers such that the following objective functions are minimized (Wang, 1997):

$$J(U,V) = \sum_{k=1}^{n} \sum_{i=1}^{c} (u_{jk})^m \|x_k - v_i\|^2 \tag{6}$$

Here, $U = [u_{jk}]$ and $V = (v_1 \cdots v_c)$ represent the partition matrix and the cluster center matrix, respectively. The input vector x_i will be partitioned c clusters. The entries of the U is representing the membership degrees of the data vector x_k

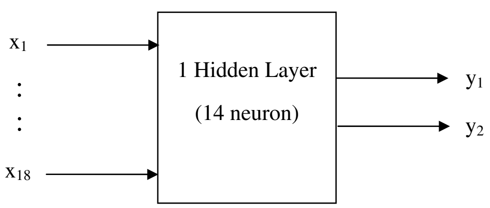

Fig. 3. The structural diagram of the fuzzy-hybrid neural network.

($k = 1, 2, \ldots, n$). The parameter m control the fuzziness of the clusters (typically $m = 2$). The distance between the data vector x_k and the center c_i is defined as Euclidean distance.

4.2. MLP sub-network

The number of input nodes of MLP is equal to the number of self-organizing neurons. On the other hand, at the output of MLP, there are two neurons so that four different pattern classes can be coded. Learning of the MLP belongs to the standards in neural network (Haykin, 1994). Weights are adapted in the learning phase of the network using the Gradient descent and Back-propagation algorithm. In the gradient method of learning, we adopt the weights from cycle to cycle to minimize error function:

$$J = (1/2) \cdot \sum (T_i - D_i)^2 \tag{7}$$

where T_i is target values and D_i is actual result for ith decision. In the experimental process, we have implemented 20,000 iterations for fuzzy *c*-means algorithm at the learning and the testing modes.

After completing the learning procedure of the whole network, the clusters and weights of MLP are frozen and ready for use in the testing mode.

5. The results of experimental studies

The input to the classifier is the set of vectors x_i, representing the ECG beats of different patients, representing different types of arrhytmia. Four different types of ECG classes (Normal, Non-conducted P wave, Premature ventricular contraction beats, and Right bundle branch block beats) taken from Physiobank, MIT/BIH arrhytmia database (Physiobank, 2003) have been considered in the numerical experiments (patient numbered 100, 102, 106, and 118). Each beat of the normal human heart originates in the SA node. Because many parts of the heart possess an inherent rhythmicity (normal tissue, Purkinje fibers of the specialized conduction system, and atrial tissue, for example), any part under abnormal conditions can become the dominant cardiac pacemaker. This can happen become when the activity of the SA node is depressed, or when the bundle of His is interrupted or damaged, or in specialized conduction system tissue in the ventricles discharges at a rate faster than the SA node. As shown in the study of Hu et al. (1997), right bundle branch block beats were used as a different pathological type. The American Association of Medical Instrumentation (AAMI) recommended practice has provided a protocol which allows using this type of beats (Hu et al., 1997).

I have limited the number of patients to provide approximate proportions of different arrhytmia cases taking part in experiments. Most beats belong to the normal sinus rhythm. The learning set contained 800 beats. The testing set was formed 400 beats, corresponding to four classes. The number of different beat types used in the numerical experiments, are given in Table 1.

In these experiments, Input vector containing the features representing beats and destination vector representing the code of class.

The parts of data vectors, not taking part in learning process, have been used to test of the given network. As shown in Table 2 the average misclassification rate in learning and testing step is limited. The efficiency for all testing data is 98% and is defined only based on testing mode:

$$\%\eta = \frac{TotalRecogniziedBeats - TotalMisclassifiedBeats}{TotalRecognizedBeats} \quad (8)$$

Observe that the performance of the proposed classifier on the testing data is only slightly worse than on the learning set. In all experiments, fuzzy cluster number c is set to 18 by experimentally. In the case of smaller of these parameter values, the classification performance is being worse for learning and testing mode. In Fig. 4, we have produced error curve for proposed classifier.

I have not numerical results belong to other classifiers for same data classes. But we can provide some statistical parameters such as the sensitivity, specificity, and accuracy rates for their data classes of given classifiers (Hu et al., 1997) to compare with results of proposed method. For this aim, we have provided Table 3. Comparations

Table 1
MIT/BIH Arrhytmia data base selected beats

Number of class	Record number	Description
0	100	Normal Sinus rhythm beats
1	102	Non-Conducted P-Wave
2	106	Premature Ventricular contraction beats
3	118	Right bundle branch block beats

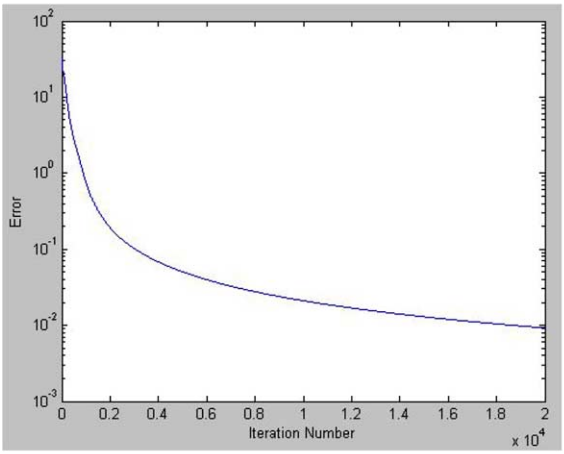

Fig. 4. The error curve of the proposed classifier.

Table 2
Data distributions of the experiment

Number of class	Number of rhythms		Misclassification number		Rate of misclassification (%)		Code of classes
	Learning	Testing	Learning	Testing	Learning	Testing	
0	200	100	3	7	1.5	7	00
1	200	100	1	0	0.5	0	01
2	200	100	3	0	1.5	0	10
3	200	100	2	1	1	1	11
Total	800	400	9	8	1.12	2	–

Table 3
Comparation of performance for all classifiers

Records	Sensitivity (%)				Specificity (%)				Accuracy (%)			
	GE	LE	ME	NF	GE	LE	ME	NF	GE	LE	ME	NF
200	53.6	93.0	66.9	–	97.4	98.7	93.3	–	62.3	97	81	–
205	59.2	0	33.8	–	100	100	100	–	81.2	97.1	97.1	–
213	58.3	0	14.2	–	78.6	100	99.8	–	74.4	92.8	91.9	–
230	100	0	0	–	75.3	100	99.5	–	72.4	100	99.1	–
102	–	–	–	100	–	–	–	93	–	–	–	93.5
106	–	–	–	100	–	–	–	93	–	–	–	93.5
118	–	–	–	99	–	–	–	100	–	–	–	93.4
Avg.	67.8	23.3	28.7	99.6	87.8	99.7	98.2	95.3	75.6	96.7	92.3	93.5

NF: Proposed classifier.

Table 4
Comparative results of the ECG beat classifiers

	Number of beat types	Efficiency (%)
Proposed classifier	4	98
FHyb-HOSA	7	96.06
MLP1	13	84.5
SOM-LVD	4	92.2
MLP-LVQ	2	96.8
MLP2	12	92
MLP-Fourier	3	98

were done for following classifiers: GE (Global Expert), LE (Local Expert), ME (Mixture of Experts) and NF (Proposed classifier). In the first three classifiers, 20 records coming from MIT–BIH data base (numbered from 200–234) are used. Records in this group include complex ventricular, junctional, and supraventricular arrhytmias and conduction abnormalities. As shown in Table 3, the averaged sensitivity of NF is superior to that of other classifiers. Specificity and accuracy values are located in moderate ranges.

To compare obtained figures with the results presented in the literature by using different techniques of beat recognition; we have investigate results of following beat recognition systems (Osowski and Linh, 2001): multistage systems using MLP (MLP1), multistage systems using MLP (MLP2), expert systems using Kohonen and SVD (SOM-SVD), LVQ and autoregression AR MLP (MLP-LVQ), Fourier and MLP (MLP-Fourier) and FHyb-HOSA.

Table 4 represents the comparative figures of the efficiency of beat recognition algorithms using the other systems mentioned above.

As shown in Table 4, the comparison denotes high recognition rate of the proposed method. But, it is really difficult to compare the results respect to same beat type and same beat numbers.

6. Conclusions

In this paper, a novel ECG beat classification system proposed and applied to MIT/BIH, arrhytmia data base. The algorithm consists of fuzzy *c*-means classifier and MLP neural network.

The wavelet transforms variance, third-order cumulant and AR model parameters have been used for the features selection. The recognition results of class 2 and class 3 are better than others. But, all recognition of normal and pathological beats representing the different arrhytmias have been done with a moderate accuracy. We hope that the performance of the method will be better if the number of the beats for the learning is increased.

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