ECG SIGNAL RECOGNITION BASED ON WAVELET TRANSFORM USING NEURAL NETWORKS AND FUZZY SYSTEMS

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ABSTRACT

This work presents aneural and fuzzy based ECG signal recognition system based on wavelet transform. The suitable coefficients that can be used as a feature for each fuzzy network or neural network is found using a proposed best basis technique. Using the proposed best bases reduces the dimension of the input vector and hence reduces the complexity of the classifier. The fuzzy network and the neural network parameters are learned using back propagation algorithm.

Keywords: Pattern recognition, ECG recognition, Wavelet transform, Fuzzy system, Neural networks.

تمييز الإشارات ألقلبيه باستخدام الشبكات ألعصبيه والانظمه المضببه وتحليل المويجه

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الخلاصة

يتناول هذا البحث تميز الإشارات القلبيه باستخدام كل من الشبكات العصبية والمنطق المضبب وباستخدام تحليل المويجه. يتم الحصول على الخصائص المناسبة لأغراض التمييز باستخدام نظام مقترح وهو نظام استخلاص أفضل الخصائص. أن استخدام هذه التقنية يؤدي إلى تقليل أبعاد متجه الإدخال مما يؤدي إلى تقليل تعقيدات منظومة التصنيف. تمت عملية تعليم ألشبكه العصبية والشبكة المضببه باستعمال الانسياب العكسي.

1. INTRODUCTION

The electrocardiogram is produced by the fluctuation in potentials that represent the algebraic sum of the action potentials of myocardial fibers, which can be recorded from the surface of the body [1]. The standard shape of the normal ECG signals facilitates the process of finding the malfunctions of heart, which is called heart diseases. The abnormalities of ECG signal refer to certain disease.

By comparing the tested signal with healthy control one, it could be possible to diagnose the disorder. In order to use the Neural or Fuzzy network in the classification of ECG signals, it is recommended to reduce the dimension of input vector down to the appropriate features [2-6]. The reduction of input vector will decrease the complexity of the network. In this paper, wavelet transform is used as feature extraction methods to analyze the ECG signal. In order to extract the best features, an algorithm is invested to select convenient features for each class of ECG signal. Each class represents a certain heart disease. The reduced vector is then used as a train input to a fuzzy network

II. THE RECOGNITION SYSTEM

After recoding the ECG signal, the R-Peak measurement is found by looking for the zero crossing points, as well as the local maximum.

Feature extraction is affected by the peak-to-peak magnitudes, the offset of the signal, and R-peak position in the windowed ECG. These effects are due to the physiology, sex and age of the patient, and the parameters of the measurement system. The dependence of the feature extraction method to the offset and the peak-to-peak magnitude of the signal are decreased by the normalization. The signal is then processed using wavelet transform

III. SELECTION OF BEST FEATURES

When using the DWT in order to obtain a compact representation of the signal data we need to choose how many the best wavelet coefficients to retain that will still adequately describe the signal. The statistical parameters may be a good tool for describing the signal. As a starting point, all the training data needs to be represented by matrices. If we have two classes, could be then generalized for more than two classes, which can be referred to as C1 and C2 (class 1 and class 2). The next step is to calculate the mean of each data set and the mean of the entire data set. The overall mean can be calculated by merging the means of the individual data sets as shown in equation (1)

$$\mu_{all} = (p_1 \times \mu_1) \div (p_2 \times \mu_2) \quad \text{.................(1)}$$

Where

$$\mu_j = \frac{1}{N}\sum_{i=1}^{N} x_i \quad \text{.................(2)}$$

In which μall is the overall mean and p refers to the apriori probability of that class and μj is the mean of class j . In a problem with two classes of equal representation the probability factor can be assumed to be 0.5, and N is the number of data points.

The within-class and between-class scatter are used to formulate the criteria for class separability, where the within-class scatter is basically the expected variance of a class (the variance of each vector point). The variance matrix for data set j (class j) can be calculated as,

$$Var_j = \frac{1}{N}\sum_{i=1}^{n} (x_i - \mu_j)^2 \quad \text{.................(3)}$$

where xj is a matrix representing the data of that class.

Now it is possible to calculate the within-class scatter (Sw) to be,

$$S_w = \sum_j (p_j \times Var_j) \quad \text{.................(4)}$$

where the variance of each class is adjusted to its apriori probability before being summed together and Sw is the resulting within-class scatter.

The between class scatter (Sb) is determined from

$$S_b = \sum_j (\mu_j - \mu_{all})^2 \quad \text{.................(5)}$$

The resulting criterion, which maximizes the ratio of between class scatter to within-class scatter (crit) is the ratio of between class scatter and within class scatter, or,

$$crit = \frac{S_b}{S_w} \quad \text{.................(6)}$$

The wavelet coefficients that can be used for the recognition is the coefficients with high criterion. Therefore on can detect the parameters that is containing the information required for the recognition process. Fig.1 shows the statistics of the normal ECG signal as an example of how the data dimensions are reduced. As can be seen, only components of high criterion is used in the recognition process because these points are characterizing that class from other classes.

IV. THE NURAL AND FUZZY NETWORKS

In order to classify different classes using neural network or fuzzy network, each class should have its own features to distinguish it form other classes. For the problem of N-class classification there are two types of features: common features between two or more classes and independent features, which are, belong to one class. In order to generalize the network and make it adaptive for new classes, a network is proposed for each class. Both neural networks and fuzzy networks are used for the recognition process. Each of these networks is trained using back propagation algorithm.

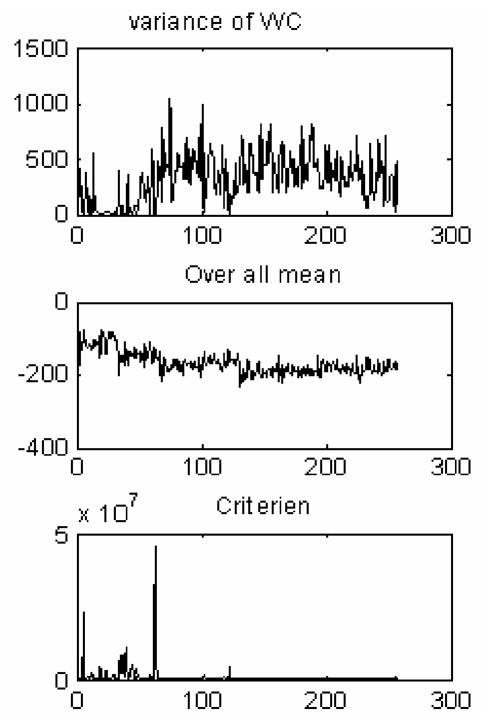

Fig.1 Statistics of the Normal ECG wavelet parameters.

V. RESULTS:

The introduced recognition system is evaluated with eight classes of ECG signals, taken from two ECG data bases: MIT-BIH data base and ST-T data. These classes are: normal beat (N), left bundle branch block (LBB), right bundle branch block (RBB), paced beat (P), premature ventricular contraction (V), atrial premature beat (A), ischemic heart beat (I), and myocardial infarction (MI). Fig.1 shows the statistical analysis for wavelet coefficients for one case (Normal). As can be seen from the results, three coefficients form the wavelet coefficients distinguishes the normal class from other classes.

The performances of the recognition process are determined by the following parameters: Sensitivity (SE), positive productivity (PP), and Total Classification Accuracy (TCA). These definitions are as follows:

$$Sensitivity(Se) = \frac{TP_i}{TP_i + FN_i} \quad ....(7)$$

$$Positive \ \Pr edictivity(PP) = \frac{TP_i}{TP_i + FP_i} \quad ....(8)$$

$$TCA = \sum_{j=1}^{8} \frac{TP_i}{Tr} \quad ....(9)$$

where (TPi) is the number of correctly classified episodes of the ith class; (FPi) is the number of correctly classified as another class episodes; (FNi) is the number of miss classified episodes; and (Tr) is the number of all beats in the training set. The obtained results are shown in tables 1-6 for different wavelet filter orders.

VI. CONCLUSIONS:

In this study, neural network and fuzzy network with wavelet based feature extraction method are used to classify eight classes of normal and abnormal ECG beats.

The ECG beats are taken from MIT-BIH Arrhythmia database and European ST-T database. Decision-making is obtained by three stages: normalization process, feature extraction, and neural or fuzzy network.

In order to generalize the classification process, two different sets of ECG beats are taken from two different patients, used for the training and testing processes of the ECG classifier.

The interpretation of decision-making is an advantage of fuzzy network over the neural network.

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TABLE 1. CLASSIFICATION RESULTS BY USING WT (DB1)

	Neural Network					Fuzzy Network				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
N	75	10	15	0.882353	0.833333	80	10	10	0.888889	0.888889
LBB	72	18	10	0.8	0.878049	82	8	12	0.911111	0.87234
RBB	71	10	19	0.876543	0.788889	79	12	9	0.868132	0.897727
P	70	15	15	0.823529	0.823529	81	15	4	0.84375	0.952941
A	75	10	15	0.882353	0.833333	85	5	10	0.944444	0.894737
V	70	5	25	0.933333	0.736842	82	10	8	0.891304	0.911111
I	69	20	11	0.775281	0.8625	80	10	10	0.888889	0.888889
MI	73	13	14	0.848837	0.83908	78	12	10	0.866667	0.886364
TCA	71,8 %					80,8 %				

TABLE 2. CLASSIFICATION RESULTS BY USING WT (DB2)

	Neural Network					Fuzzy Network				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
N	80	10	10	0.888889	0.888889	85	5	10	0.944444	0.894737
LBB	81	15	4	0.84375	0.952941	88	2	10	0.977778	0.897959
RBB	81	4	15	0.952941	0.84375	87	3	10	0.966667	0.896907
P	82	8	12	0.911111	0.87234	90	4	6	0.957447	0.9375
A	80	7	13	0.91954	0.860215	91	3	6	0.968085	0.938144
V	83	7	10	0.922222	0.892473	88	6	6	0.93617	0.93617
I	84	2	14	0.976744	0.857143	87	6	7	0.935484	0.925532
MI	80	2	18	0.97561	0.816327	91	4	5	0.957895	0.947917
TCA	**81,4 %**					**88,4 %**				

TABLE 3. CLASSIFICATION RESULTS BY USING WT (DB3)

	Neural Network					Fuzzy Network				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
N	89	5	6	0.946809	0.936842	100	0	0	1	1
LBB	87	3	10	0.966667	0.896907	96	2	2	0.979592	0.979592
RBB	86	6	8	0.934783	0.914894	94	2	4	0.979167	0.959184
P	89	3	8	0.967391	0.917526	98	1	1	0.989899	0.989899
A	82	8	10	0.911111	0.891304	97	2	1	0.979798	0.989796
V	80	12	8	0.869565	0.909091	99	1	0	0.99	1
I	85	5	10	0.944444	0.894737	96	1	3	0.989691	0.969697
MI	80	10	10	0.888889	0.888889	97	0	3	1	0.97
TCA	**84.8 %**					**97.1 %**				

TABLE 4. CLASSIFICATION RESULTS BY USING WT (DB4)

	Neural Network					Fuzzy Network				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
N	85	5	10	0.944444	0.894737	98	2	0	0.98	1
LBB	83	5	12	0.943182	0.873684	97	1	2	0.989796	0.979798
RBB	84	6	10	0.933333	0.893617	98	2	0	0.98	1
P	83	5	12	0.943182	0.873684	99	1	0	0.99	1
A	82	4	14	0.953488	0.854167	99	1	0	0.99	1
V	85	8	7	0.913978	0.923913	98	1	1	0.989899	0.989899
I	82	9	9	0.901099	0.901099	97	1	2	0.989796	0.979798
MI	84	10	6	0.893617	0.933333	98	1	1	0.989899	0.989899
TCA	**83,5 %**					**98 %**				

TABLE 5. CLASSIFICATION RESULTS BY USING WT (DB5)

	Neural Network					Fuzzy Network				
	TP	FN	FP	Se	PP	TP	FN	FP	Se	PP
N	86	6	8	0.934783	0.914894	99	1	0	0.99	1
LBB	85	8	7	0.913978	0.923913	97	1	2	0.989796	0.979798
RBB	85	5	10	0.944444	0.894737	96	2	2	0.979592	0.979592
P	85	7	8	0.923913	0.913978	97	2	1	0.979798	0.989796
A	84	9	7	0.903226	0.923077	96	1	3	0.989691	0.969697
V	86	4	10	0.955556	0.895833	96	2	2	0.979592	0.979592
I	85	6	9	0.934066	0.904255	97	2	1	0.979798	0.989796
MI	84	3	13	0.965517	0.865979	98	1	1	0.989899	0.989899
TCA	**85 %**					**97 %**				

TABLE 6. CLASSIFICATION RESULTS BY USING WT (DB6)

	Neural Network					Fuzzy Network				
	TP	**FN**	**FP**	**Se**	**PP**	**TP**	**FN**	**FP**	**Se**	**PP**
N	80	8	12	0.909091	0.869565	90	3	7	0.967742	0.927835
LBB	79	10	11	0.88764	0.877778	89	4	7	0.956989	0.927083
RBB	79	6	15	0.929412	0.840426	88	4	8	0.956522	0.916667
P	78	12	10	0.866667	0.886364	87	5	8	0.945652	0.915789
A	78	9	13	0.896552	0.857143	88	6	6	0.93617	0.93617
V	77	13	10	0.855556	0.885057	87	6	7	0.935484	0.925532
I	76	14	10	0.844444	0.883721	86	6	8	0.934783	0.914894
MI	75	12	13	0.862069	0.852273	88	5	7	0.946237	0.926316
TCA	**77,75 %**					**87,78 %**				