IMPROVING AN AUTOMATIC ARRHYTHMIAS RECOGNISER BASED IN ECG SIGNALS

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Abstract: In the present work, we have developed and improved a tool for the automatic arrhythmias detection, based on neural network with the "more-voted" algorithm. Arrhythmia Database MIT has been used in the work in order to detect eight different states, seven are pathologies and one is normal. The unions of different blocks and its optimization have found an improvement of success rates. In particular, we have used wavelet transform in order to characterize the patron wave of electrocardiogram (ECG), and principal components analysis in order to improve the discrimination of the coefficients. Finally, a neural network with more-voted method has been applied.

1 INTRODUCTION

In Europe, cardiovascular diseases are one of most important causes of death, with a great repercussion in health assistance budget. For instance, to obtain an early exact cardiovascular diagnosis is one of the most important missions for the physicians. The electrocardiogram is the graphic description of the heart electric activity registered from the body surface and is a basic element in the diagnosis of different heart diseases.

The objective of this study is to make deeper in the extraction of characteristics and the later automatic classification of heart pathologies, analyzing every aspect that takes parting.

To carry on with this objective, we have developed Matlab software (Matlab, 2006), clear and easy, where users have three options to practise with all tools at their hands: making a pre-processing with wavelet transform and in order to play with the developed filing.

Wavelet transform (Romero-Legarreta, 2005) is a mathematics technique that has gained importance in the last years in all kind of applications related with non-stationary signal process.

Although the decomposition in well defined blocks in time and frequency, wavelet transform can characterise the local sign regularities. This skill allows distinguishing electrocardiogram waves (ECG) from noise and other artefacts.

In this paper, we establish the use of approximated wavelet coefficients taken out from the ECG signal in order to classify eight types of beat: normal pulse (N), extra-systole (L), premature ventricular contraction (R), premature auricular contraction (/), blockade left branch (A), blockade right branch paced beat (V), fusion of normal and paced beat (f) and fusion of normal and premature ventricular contraction (F).

The use of principal component analysis (PCA) (Bianchi, 2006) on the wavelet coefficients has improved their discrimination. Finally, we have used an automatic classification based on artificial neural networks (NN) (Bishop, 1995), (Juang, 1992). An improvement have been applied to NN, we have implemented the "more voted" method, obtaining better success rates.

2 WAVELET TRANSFORM: FEATURE EXTRACTION

The ECG features are extracted through a pre-processing stage in which the Wavelet transform is applied to original ECG signal.

The Discrete Wavelet Transform (DWT) is defined as follows:

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$$C[j,k] = \sum_{n \in \mathbf{Z}} f[n]\psi_{j,k}[n] \quad (1)$$

where $\psi_{j,k}$ is the transform function:

$$\psi_{j,k}[n] = 2^{\frac{-j}{2}} \cdot \psi\left[2^{-j}n - k\right] \quad (2)$$

The application of different mother families on pre-processing (artefacts elimination) and on the feature extraction has got a set of good and discriminate parameters.

3 PRINCIPAL COMPONENT ANALYSIS

Principal components analysis (PCA) is a technique used to reduce multidimensional data sets to lower dimensions for analysis. The applications include exploratory data analysis data and for generating predictive models. PCA involves the computation of the eigenvalue decomposition or Singular value decomposition of a data set, usually after mean centering the data for each attribute. The results of a PCA are usually discussed in terms of scores and loadings. This process applied to ECG arrhythmias is named blind source separation, where there are fewer sources than input channels.

The blind source separation consists in several sources that are mixed in a system, these mixtures are recorded and then they have to be separated to obtain the estimations of the original sources. The following figure shows the mixing system:

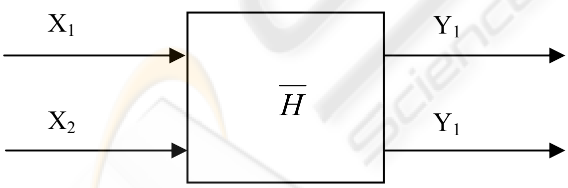

Figure 1: 2 Sources – 2 Mixtures system.

Generally, there are n source signals statistically independent $s(t) = [s_1(t),...,s_n(t)]$, and m observed mixtures that are linear and instantaneous combinations of the previous signals $x(t) = [x_1(t),...,x_n(t)]$. Beginning with the linear case, the simplest case, we have that the mixtures are:

$$x_i(t) = \sum_{j=1}^{n} h_{ij} \cdot s_j(t) \quad (3)$$

Now, we need to recover s(t) from x(t). It is necessary to estimate the inverse matrix of H, where h_{ij} are contained. Once we have this matrix:

$$y(t) = \overline{W} \cdot x(t) \quad (4)$$

Where y(t) contains the estimations of the original source signals, and is the inverse mixing matrix. Now we have defined the simplest case, it is time to explain the general case that involves convolutive mixtures. The process is defined as follows:

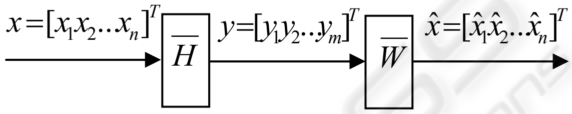

Figure 2: BSS General problem.

Where $\overline{H}$ is the mixing system:

$$\overline{H} = \begin{bmatrix} h_{11} & \dots & h_{1n} \\ \dots & \dots & \dots \\ h_{n1} & \dots & h_{nn} \end{bmatrix} \quad (5)$$

The h_{ij} are FIR filters, each one represents an acoustic transference multipath function from source, *i*, to sensor, *j*. *i* and *j* represent the number of sources and sensors.

4 NEURAL NETWORK

For this present work, we have implemented a supervised classification system for the discrete wavelet coefficients. Firstly, a neural network classification system using time intervals obtained from the previous extraction process is implemented.

This classifier has used a Feed-Forward Neural Network (NN) with a Back-propagation algorithm for training (Bishop, 1995), (Juang, 1992), where the number of input units is given by the dimension of the vector of features. And the number of output units is given by the number of pathologies to identify. Too, we have researched with different number of neurons in the hidden layer, in order to get the optimum recogniser.

Besides, the found success has been improved using the method of the ‘more voted’, where we have built a schedule with different neural networks (see figure 1).

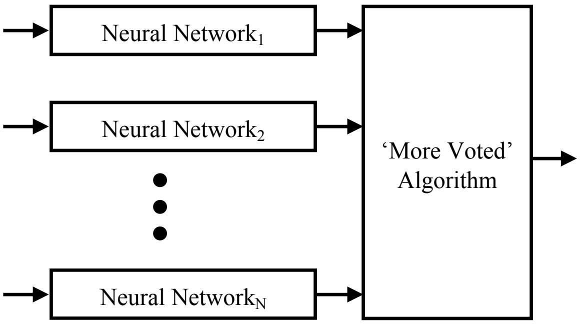

Figure 3: Classification System with 'more voted' algorithm, based on NN.

5 EXPERIMENTS

We have taken 24 signals from the MIT-BIH ARRHYTHMIA database (MITDB)(MIT-BIH, 2007), choosing 750 samples from each class, 6000 beats to classify; some of them are recognized by the MIT as difficult classifying signals. To remove noise from signals, the net interferences and the base line variations, we have use techniques proposed in (1). It consists in obtaining detail coefficients for different wavelet levels, to apply them a non-lineal form threshold, using a soft-thresholding calculated by the inverse transform to obtain the result signal. The threshold follows this expression: $\partial = \sqrt{2\log(N)}\hat{\sigma}$; where N is the number of decomposition levels and coefficients represent the details coefficients for the level to filter. In function of the wavelet family and the decomposition level, the result will change. In this work, we take Daubechies 3 of level 3 following our studies. Also we take different types of parameters as temporal as Fourier and Wavelet coefficients.

With temporal parameters took out from our previous works and algorithms (the time of Pwave, PR segment, QRS complex, QT segment and T wave, and the area of P wave, QRS complex and the T wave) we did not get to characterize any kind of beats, the same result were taken with Cosen Fourier Transform (DCT).

Hence we only select the approximation wavelet parameters like "in-parameters". The classification is realised with a neural networks using back-propagation. Once took out the wavelet coefficients with sym4 family and the third decomposition level, the neural networks has three layers. To obtain the number of neurons of the hidden layer, we tried with different numbers and with 45 we got the best result with an error of 26%. How the error is too much, we make principal components analysis, since with it, the network size and the computational cost are reduced. With this study the characteristic vector is ortogonalised to avoid the correlations of his components, is arranged and the components with less information are deleted. The algorithm is applied to the characteristic vector, the mean is established in cero and the standard deviation in one, after, the PCA is applied, in this case with 0,02%. The variations are showed in the next figures:

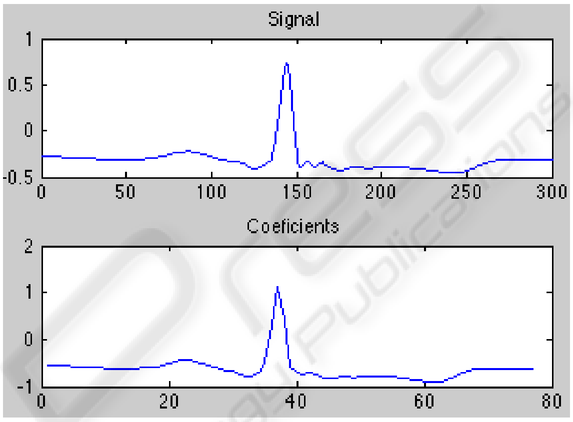

Figure 4: Signal and its coefficients.

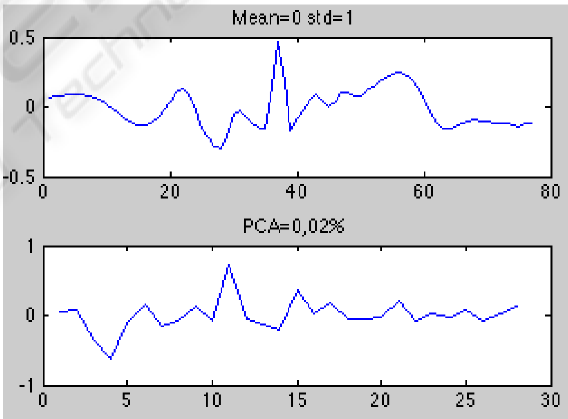

Figure 5: Modification of the coefficients.

With this technique, the network in trained again with the same conditions and the result with 55 neurons in the least error: 2,27%. This shows us a satisfactory study. Many trainings are realises where characteristics are: 3.000 beats (375 per class) for the training stage and the same quantity for the test stage, different PCA values (0,02%, 0,2 % and 2 %) the second, the third and the fourth decomposition level and ten wavelet families (Bior2.4, Bior5.5, Bior 6.8, Harr, Sym2, Sym4, Sym5, Sym8, rBio3.1, rBio5.5). With the result obtained we noticed is better have a lot of approximation coefficients and alter make a PCA, instead of hace less quantity of approximation coefficients, then in better a low level and apply PCA. The best result were obtained with the wavelet rBio 3.1 at level 2 and PCA= 0,02% with 1,97% of error. "The most voted" technique is applied to boot the result. This model consist of select some networks an apply to all the same test in parallel. Finally, the results are compared and the result most voted is selected. In the figure 4 a double network is represented with only two parallel networks.

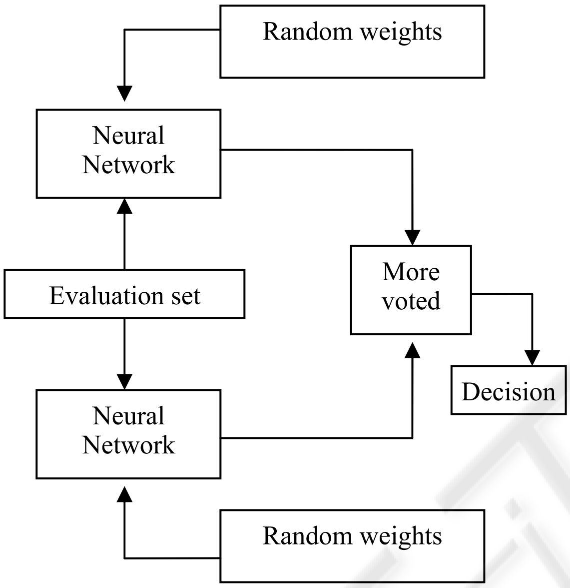

Figure 6: Parallel neural network.

With this new structure, the filing reduces error to 1.8% in the simulation and 1.4 in the train process. For the entire database, it has an error of 1.6%.

Table 1: Matrix confusion.

		OUTPUT CLASSES							
		N	L	R	/	A	V	f	F
INPUT CLASSES	N	375	0	0	0	0	0	0	0
	L	0	372	0	0	0	0	3	0
	R	1	0	372	0	2	0	0	0
	/	0	0	0	375	0	0	0	0
	A	16	0	3	2	351	1	1	1
	V	0	0	0	0	2	369	3	1
	f	0	0	0	4	0	0	371	0
	F	0	1	0	2	4	0	7	361

In the confusion matrix we can see, that the class that has more errors is the premature ventricular contraction, classifying this as normal beat, this is because the morphology of the auricular premature contraction is similar to the normal. Respect to the classification between normal and pathologic signals the filing detect the healthy signals whit a 100% and the pathologic signal with a 99,35 % being the total classification between this two classes a 99.7%. Respect to the computational time, we remember that the filing has three parts: the extractions of wavelet characteristics, the principal components analysis and the test process. This time are detailed in the table 2:

Table 2: Load times in seconds.

Process	Computational Time
Wavelet	0,010623 s
PCA	0,002571 s
Test	0. 111877 s
TOTAL	**0,1251 s**

Having in mind that a full beat has an approximated duration of 800 ms, the filing will classify the beat only 125 ms later, without the time of pre-processing and segmentation. These times are Matlab time. The part of classification depends on a well segmentation process, this is we propose to make a robust segmentation for noise and cardiac pathologies.

Finally, we have compared our results with other authors (Song, 2005), (Zimmerman, 2004), (Jankowski, 2003). The new blocks used for this application and with the optimization of the remainder of the blocks, we can observe as our results are better than the previous references.

6 CONCLUSIONS

It has been implemented and improved an automatic arrhythmias recogniser using a neural network with more voted algorithm. We have found error rate of 1.8% with independent samples, only using for the test (8 different classes); and an error rate of 0.3% for pathology or normal class.

The ECG signal used is from MIT arrhythmias database, and it has been parameterized with DWT coefficients and selected with PCA.

REFERENCES

Matlab 2006, http://www.mathworks.com. The Mathworks. Last Visit: 07-16-2006

Romero-Legarreta, I.,. Addison, P.S, Reed, M.J., Grubb, N.R., Clegg, G.R., Robertson, C.E., Watson, J.N., 2005. Continuous wavelet transform modulus maxima analysis of the electrocardiogram: Beat-to-beat characterization and beat-to-beat measurement, *Int. J. Wavelets, Multiresolution and Information Processing*, Vol.3, pp. 19-42.

Bianchi, M.F.de, Guido, R.C., Nogueira, A.L., Padovan, P., 2006. "A wavelet-PCA approach for content-based image retrieval" *Proceeding of the Thrity-Eighth Southeastern Symposium on System Theory*, pp. 439 – 442.

Bishop, C.M., 1995. *Neural Networks for Pattern Recognition*, Oxford University Press.

Juang, B.H., Rabiner, L.R., 1992. Spectral representations for speech recognition by neural networks-a tutorial" Proceedings of the *Proceedings of the Workshop Neural Networks for Signal Processing*, 1992, pp. 214 – 222.

MIT-BIH, 2007, http://www.physionet.org/physiobank/mitdb. MIT-BIH Arrhythmia Database. Last Visit: 07-16-2007.

Song, M.H., Lee, J., Cho, S.P., Lee, K.J., Yoo S.K, 2005. Support Vector Machine Based Arrhythmia Classification Using Reduced Features. *International Journal of Control, Automation, and Systems*. Vol. 3. nº. 4. 571-579.

Zimmerman, M.W., Povinelli, R.J., 2004. On Improving the Classification of Myocardial Ischemia Using Holter ECG Data. *Computers in Cardiology. Chicago. Illinois*, 377-380.

Jankowski, S., Oreziak, A., 2003. Learning System for Computer-Aided ECG Analysis Based on Support Vector Machines. *International Journal of Bioelectromagnetism*. Vol. 5. nº 1. 175–176.