New Application of Wavelet Transform in Classification the Arterial Pulse Signals

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Abstract: - The Discrete Wavelet Transform (DWT) is a transformation that can be used to analyze the temporal and spectral properties of non-stationary signals. In this paper we describe some applications of the DWT to the problem of extracting information from normal and abnormal arterial pulses. We shall review a feature extraction algorithm of pulse signals, *wavelet analysis*, with aim of generating the most appropriate input vector for a neural classifier and we will know that the wavelet approach is highly suitable for the analysis of such signals. Some examples of the application of the wavelet transform and artificial network to identify the pulse signals are provided here. Application range from the extraction of normative signals from nonnormative, to extraction of quantitative parameters for clinical purposes.

Keywords: - wavelet analysis, Neural Network, classifier, Arterial Disorders

1 Introduction

Digital clinical data is becoming a major part of the average computer user experience. The increasing amounts of available clinical data require the development of new techniques and algorithms for structuring this information. Although there has been a few research on the problem of information extraction from pulse signals, work on abnormal signals has only appeared recently. The Wavelet Transform (WT) and more particularly the Discrete Wavelet Transform (DWT) is a relatively recent and computationally efficient technique for extracting information about nonstationary signals like pulse. During the last decades time frequency distribution methods are being systematically used for the analysis of biomedical signals and recently methods based on the wavelet transformation have become increasingly popular. In principle they offer much greater flexibility for analyzing and processing data. The main advantage of wavelet lies in the additional "spatial" resolution of the transformed signal. In contrast to the Fourier transformation, the signal is decomposed into waves of finite length, i.e. into waves which are spatially localized – hence the name wavelets. The wavelet transform of a one-dimentional signal has two independent variables – a frequency and a spatial location variable. It leads to a decomposition of, say, a signal into a series of spectra at finer and coarser resolutions. Indeed, there is a close mathematical relationship between the wavelet transformation and the multi-resolution analysis of a signal [9]. Hence the wavelet transform furnishes us with the frequency spectrum of a signal at every spatial location. This feature, besides others, opens new and fruitful ways of processing and analyzing data of various kinds.

One of the most important signals to identify all kinds of heart failures is arterial pulse signal which could be recorded whenever along arterials (has a very little attenuation in amplitude) and has seven kinds: Normal, Hypokinetic, Parvus et tardus, Hyperkinetic, Bisferience, Dicrotic and Alternans. All of these kinds can be used to know more about the heart activity and each kind of them is related to some heart diseases [5]. The waveform of normal arterial pulse is shown in Fig.1 and other kinds of waveforms are shown in Fig.2.

Since a large amounts of data often must be analyzed and stored when examining arterial pulse signals, computers are used to automate signal processing. Artificial neural networks (ANNs) provide one computational tool that is being applied to problems in cardiovascular medicine.

ANNs are modeled after biological neural networks. Implemented as computer programs, ANNs consist of multiple, interconnected neurons arranged in different layers. Although substantially simpler than biological neural networks, the goal in using ANNs is to build computer systems that have learning, generalized processing, and adaptive capabilities resembling those seen in biological neural networks. ANNs can learn to recognize certain inputs and to generate a particular output for a given input. ANNs offer advantages over conventional methods for the analysis of cardiac signals since they are reliable for pattern identification and classification and can detect patterns and make distinctions between different patterns that may not be apparent to human analysis. ANNs perform well for the analysis of signals, such as cardiac arrhythmia signals, that are complex and may contain high levels of noise. With many interconnected neurons, ANNs are massively parallel and thus are suitable for real-time applications. The purpose of the present work is to derive better parameters for reducing the size of the neural network classifier while maintaining good classification accuracy. A prerequisite to this goal is to find parameters that represent each condition with acceptable discrimination capability. The parameters are extracted from wavelet coefficients that would be explained later and are used to provide feature vectors of each ANN classifier.

This paper explores the use of the DWT in two parts. The first part is the automatic classification of normal pulse signal from abnormal kinds using feature vectors derived from the wavelet analysis. The second part is the classification of normal and abnormal pulse signals using neural network.

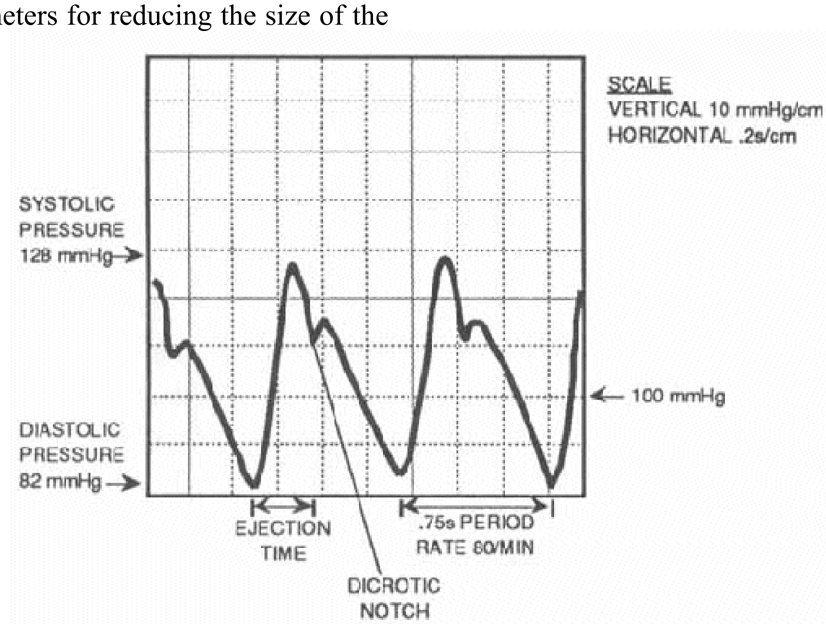


Fig.1. normal arterial pulse waveform

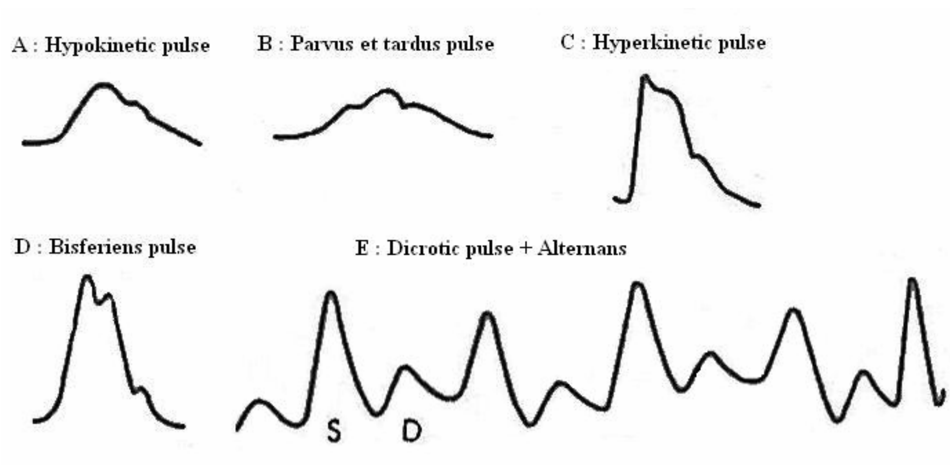


Fig.2. Other kinds of arterial pulse waveform

1.1 The Discrete Wavelet Transform

The wavelet transform is a linear distribution and continues wavelet transform (CWT) is defined as the sum over all time of the signal multiplied by scaled, shifted versions of the wavelet function Ψ:

C(scale,position) = ∫ f(t) Ψ(scale,position,t) dt (1)

The results of the CWT are wavelet coefficients C, which are a function of scale and position. Multiplying each coefficient by the appropriately scaled and shifted wavelet yields the constituent wavelets of the original signal f(t).

The *Wavelet Transform* is a technique for analyzing signals. It was developed as an alternative to the short time Fourier Transform (STFT) to overcome problems related to its frequency and time resolution properties. More specifically, unlike the STFT that provides uniform time resolution for all frequencies the DWT provides high time resolution and low frequency resolution for high frequencies and high frequency resolution and low time

resolution for low frequencies. In that respect it is similar to the human ear which exhibits similar time-frequency resolution characteristics. The Discrete Wavelet Transform (DWT) is a special case of the WT that provides a compact representation of a signal in time and frequency that can be computed efficiently.

The DWT is defined by the following equation:

$$W(j,k) = \sum_j \sum_k x(k) 2^{-j/2} \psi(2^{-j} n - k)$$

Where $\psi(t)$ is a time function with finite energy and fast decay called the mother wavelet.

1.2 Neural network classifier architecture

Our experiments were performed using the neural network tool box in Matlab 6.5. During our experiment the limitations encountered with the use of the back-propagation algorithm are related to the lack of criteria for determining the optimum network structure, learning coefficient and momentum. These parameters depend on the nature, distribution and complexity of the input data. In the present study, they were determined by a trial-and-error approach. The number of neurons in the input layer was fixed by the number of elements in the input feature vector. Therefore the input layer had 8 neurons for the first ANN classifier, because of considering eigth of the best extracted features, 24 neurons for the second, and 7 neurons for the third one using *wavelet transform*. The output layers was determined by the number of classes desired. In our study, the 7 neurons of the output layer corresponds to the normal and other nonnormal pulses. In practice, the number of neurons in the hidden layer varies according to the specific recognition task and is determined by the complexity and amount of training data available. If too many neurons are used in the hidden layer, the network will tend to memorize the data instead of discovering the features. This will result in failing to classify new input data. Using a trial-and-error method, we tested hidden layers varying between two and 50 neurons. The optimum number of neurons in the hidden layer was found to be twenty four for the first ANN classifier, three for the second and four for the last one. Consequently, we used one network structure of 8-24-7 (i.e. eigth neurons at the input layer, twenty four at the hidden layer and seven at the output layers), and the two other structures respectively of eigth-three-seven and eigth-four-seven. With large values of the learning coefficient and momentum, a network may go through large oscillations during training and may never converge. Smaller learning coefficient and momentum tend to create a more stable network but require a long training time. For a good compromise between training speed and network stability, the learning coefficient and momentum were selected in such a way that their values decreased with the increase of the training epoch. To generate an efficient network, different learning coefficients and momenta were selected for different layers. In the present work, the normalized root-mean-square (RMS) error of the output layer was used as a criterion to select these parameters.

The selected learning coefficients and momenta correspond to the deepest slope of the normalized RMS error. Fig.3 shows the change in the RMS error during a training process.

Using the hyperbolic tangent sigmoid as the neural transfer function, the input feature vectors were scaled to the range from -1 to +1 to fit into the dynamic range of this function. Before the training process was started, all the weights were initialized to small random numbers. This ensured that the classifier network was not saturated by large values of the weights. The threshold of convergence was set at 10^-5 of the normalized RMS error. Training was stopped when the convergence threshold was reached or when the 500th epoch was encountered. In this experiment, training set was formed by choosing 10 normal pulses and 6*10 non-normal pulses obtained from the following records signals for a second. In order to enhance the generalization capability of the neural network, the training and the test sets are formed by data obtained from different patients. It is observed that for some pulse types, there are waveform variations among the vectors belonging to the same class.

2 Method

Whenever, using computers in therapeutic and diagnostic systems have been greatly increased, One of most important application is the classification of medical data and arrhythmia recognition in consequence. On the other hand, analysis and recognition of diseases, particulary the heart failures, is possible by classified pulse signals. Furthermore, these signals can be recorded easily and contain a lot of information. Besides, we have so many ways to record this signal, devices such as pulseoximeter and etc. One of these ways which is useful for data recognition, is artificial neural network that uses classified information for an intelligence network training. One of these programs that used for classification and clustering, is wavelet transform. We can cluster and classify signals by wavelet. Thus, try to obtain necessary coefficients for clustering all kinds of pulses using wavelet transform and finally diagnose some kinds of heart diseases.

2.1 Features

The extracted wavelet coefficients provide a compact representation that shows the energy distribution of the signal in time and frequency. In order to further reduce the dimensionality of the extracted feature vectors, statistics over the set of the wavelet coefficients are used.

In this project, we have extracted 12 features extracted from coefficients of three level wavelet decomposition of pulse signals: the energy, std, norm and mean of some detail and approximation coefficients of the second or third level. The 8 of best selected features were more distinguished from the others.

3 Validation and Performance

The performance of the neural classifiers was evaluated by computing the percentages of correct classification, which is achieved by comparing the known type signals and the neural network outputs. Table 1 is a summary of the average (Avr) of feature extracted from wavelet coefficients of all kinds of pulse signals. The results of the evaluation of the neural classifier in terms of correct classification of ten to twenty four hypokinetic signals, is summarized in table 2 (percentage) or chart 1. The results of performance of all neural classes could be given(charted) in other tables that are not shown.

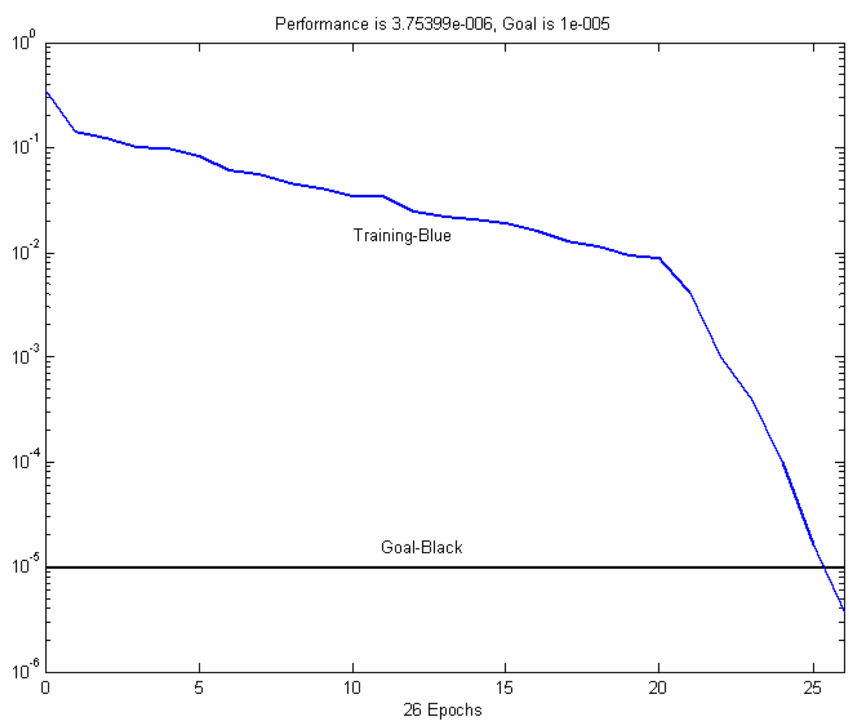


Fig.3. RMS error of the first classifier during the training process

Table1. Avr of 8 features, extracted from wavelet coefficients of all kinds of 24 pulse signals

normal	alternans	bisferiens	dicrotic	hyperkinetic	hypokinetic	parvus
-0.2742	-0.2682	-0.3332	-0.2769	-0.3027	-0.3248	-0.2587
0.2644	0.2625	0.3347	0.2931	0.3044	0.3598	0.3168
-0.1766	-0.1657	-0.1707	-0.1806	-0.1902	-0.2483	-0.2497
-0.0504	-0.0882	-0.0474	-0.0762	-0.0242	0.0321	-0.1271
0.2249	0.216	0.2921	0.2057	0.2311	0.0341	-0.1082
0.063	0.0777	0.1581	0.1148	0.1405	0.3799	0.4114
0.0204	0.0015	0.0467	-0.021	0.1227	0.1604	-0.0129
0.2728	0.4268	0.3687	0.446	0.4221	0.8042	1

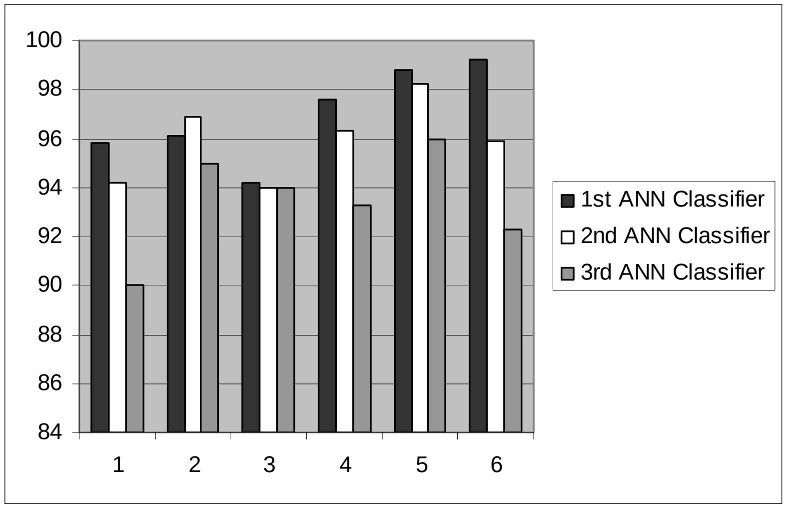
Table2. performance of 1^{st}, 2^{nd}, 3^{rd} of the hypokinetic class of neural classifier

the number of signals	1^{st} neural classifier Avr.	2^{nd} neural classifier Avr.	3^{rd} neural classifier Avr.
10	98.8	98.2	96
12	98.1	97.9	92
14	95.5	64	89.3
16	95.6	93.9	87.1
18	95.5	96.5	73.4
20	95.5	95.1	72
22	96	95	72.1
24	92.5	92	70.1

Table3. Performance of 1^{st}, 2^{nd}, 3^{rd} of all kinds of 10 pulse signals of neural classifier

signal	1^{st} neural classifier Avr (10 signals)	2^{nd} neural classifier Avr (10 signals)	3^{rd} neural classifier Avr (10 signals)
1.alternans	95.8	94.2	90
2.bisferiens	96.1	96.9	95
3.dicrotic	94.2	94.0	94.0
4.hyperkinetic	97.6	96.3	93.3
5.hypokinetic	98.8	98.2	96
6.parvus	99.2	95.9	92.3

Chart1. Performance of 1st , 2nd , 3rd of all kinds of 10 pulse signals of neural classifier



4 Conclusion

Table 1 show the classification results for classified pulse signals. We noticed that the 20 to 24 signals presents the worst results due to the noise altered the signal during the acquisition data so in this study we decided to investigate the effect of reducing the number of features on the accuracy of the classifiers. This work comparatively evaluates the performances of three neural classifiers. The best performance was achieved by the first ANN classifier using Wavelet transform method. This performance was achieved because we did not need to filter the pulse signals which may have altered them. These results demonstrate that nonlinear classification models, such as neural networks, offer significant advantages overclassical approaches in pulses signals classification. With a good feature selection, it is possible to get robust neural classifier for a larger class of cardiac arrhythmias. Such neural network classifier can be hardware implemented and used in intensive care units.

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