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Diagnosis System Based on Wavelet Transform, Fractal Dimension and Neural Network

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Abstract: In this study we introduce a diagnosis system based on wavelet and fractal dimension for diagnose the Heart Mitral Valve Diseases. This study deals with the feature extraction from the Doppler signal waveform at heart mitral valve using ultrasound. Wavelet packet transforms, Fourier transform and Fractal Dimension methods are used for feature extraction from the DHS signals. The back-propagation neural network is used to classify the extracted features. The system has been evaluated in 162 samples that contain 89 normal and 73 abnormal. The results showed that the classification was about 91% for normal and abnormal cases.

Key words: Fractal dimension, wavelet packet, neural network, Doppler heart sound

INTRODUCTION

Doppler techniques are the most preferred technique for diagnose mitral valve diseases because of their completely non-invasive and without risk in the serial studies. Doppler Heart Sounds (DHS) are one of the most important sounds produced by blood flow, valves motion and vibration of the other cardiovascular components (Jing *et al*., 1997). This study will introduce the technique that will aid clinical diagnosis, enable further research of heart valve disorders and provide a system for recognition of heart valve disorders. This study uses the powerful mathematics of wavelet packet signal processing and the fractal dimension to efficiently extract the features from pre-processed Doppler signals for the purpose of recognizing between abnormal and normal.

PRELIMINARIES

Here, the theoretical foundations for the diagnosis system used in the presented study are given in the following subsections.

Pattern recognition: Pattern recognition can be divided into a sequence of stages, starting with feature extraction from the occurring patterns, which is the conversion of patterns to features that are regarded as a condensed representation, ideally containing all-important information. In the next stage, the feature selection step, a smaller number of meaningful features that best represents the given pattern without redundancy are identified. Finally, the classification is carried out, i.e., a specific pattern is assigned to a specific class according to the characteristic features selected for it. This general abstract model, which is shown in Fig. 1, allows a broad variety of different realizations and implementations. Applying this terminology to the medical diagnostic process, the patterns can be identified, for example, as particular, formalized symptoms, recorded signals, or a set of images of a patient. The classes obtained represent the variety of different possible diagnoses or diagnostic statements (Dickhous and Heinrich, 1996). The techniques applied to pattern recognition use artificial intelligence approaches (Bishop, 1996).

Wavelet packet: Wavelet transforms are rapidly surfacing in fields as diverse as telecommunications and biology (Keeton and Schlindwein, 1997). A reason for the popularity of wavelet is its effectiveness in representation of nonstationary signals. Since most of natural and human made signals are transient in nature, different wavelets have been used to represent this much large based analyses that use global sine and cosine functions as bases, wavelet analysis use bases that are localized in time and frequency to represent nonstationary signals more effectively (Goswami, 1999). They have become a powerful alternative to Fourier methods in many medical applications.

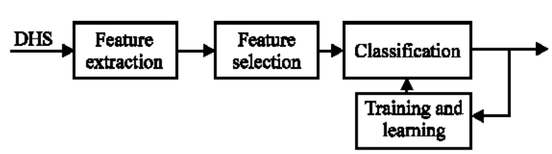

Fig. 1: Block diagram of a pattern recognition approach

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The main advantage of wavelets is that they have a varying window size, being wide for slow frequencies and narrow for the fast ones, thus leading to an optimal time-frequency resolution in all the frequency ranges. Furthermore, owing to the fact that windows are adapted to the transients of each scale, wavelets lack of the requirement of stationarity (Quiroga, 1998).

The property of time and frequency localization is known as compact support and is one of the most attractive features of the WT. The main advantage of the WT is that it has a varying window size, being broad at low frequencies and narrow at high frequencies, thus leading to an optimal time-frequency resolution in all frequency ranges (Devasahayam, 2000; Rovithakis *et al*., 2001).

Wavelet packet analysis is an extension of the Discrete Wavelet Transform (DWT) and it turns out that the DWT is only one of the many possible decompositions that could be performed on the signal. It is therefore possible to subdivide the whole time-frequency plane into different time-frequency pieces. The advantage of wavelet packet analysis is that it is possible to combine the different levels of decomposition in order to achieve the optimum time-frequency representation of the original signal (Gnitecki and Moussavi, 2004). All wavelet transforms can be specified in terms of a low-pass filter. The normalized wavelet and scale basis functions $\varphi_{i,l}(k)$, $\psi_{i,l}(k)$ can be defined as:

$$\begin{aligned}\varphi_{i,l}(k) &= 2^{i/2} h_i(k - 2^i l)\\ \psi_{i,l}(k) &= 2^{i/2} g_i(k - 2^i l)\end{aligned} \qquad (1)$$

Where, the factor $2^{i/2}$ is inner product normalization, i and l are the scale parameter and the translation parameter, respectively. The discrete wavelet transform decomposition can be described as:

$$\begin{aligned}s_{(i)}(l) &= x(k) * \varphi_{i,l}(k)\\ d_{(i)}(l) &= x(k) * \psi_{i,l}(k)\end{aligned} \qquad (2)$$

Where, $s_{(i)}$ (l) and $d_{(i)}$ (l) are the approximation coefficients and the detail coefficients at resolution i, respectively (Devasahayam, 2000; Rovithakis *et al*., 2001).

In the present study, the wavelet coefficients were computed using the Daubechies wavelet of orders one.

Neural networks: An Artificial Neural Network (ANN) is a mathematical model consisting of a number of highly interconnected processing elements organized into layers,

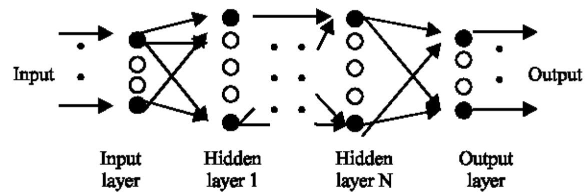

Fig. 2: Neural network architecture

the geometry and functionality of which have been likened to that of the human brain (Fig. 2). The ANN may be regarded as the process of learning capabilities in as much as it has a natural propensity to store experimental knowledge and to make it available for later use. By virtue of its parallel distribution, an ANN is generally robust, tolerant of faults and noise, able to generalize well and capable of solving non-linear problems (Haykin, 1994). The Doppler heart sounds, diseased or healthy, may be regarded as an inherently non-linear system due to the absence of the property of frequency preservation as required by the definition of a linear system (Nichols and O'Rourke, 1990). Applications of ANNs in the medical field include EEG pattern identification (Saraoglu *et al*., 1999), interpretation of heart sounds (Turkoglu and Arslan, 2001), discriminating pathologic from normal peripheral vascular tissue (Rovithakis *et al*., 2001); however, to date neural network analysis of Doppler heart sounds is a relatively new approach.

Fractal dimension: Before attempting to calculate the fractal dimension for the DHS, it is important to establish the evidence that the waveforms may be characterized as fractals. Fractal dimension values indicate the complexity of a pattern, or the quantity of information embodied in a pattern in terms of morphological, entropy, spectral and variance (Gnitecki and Moussavi, 2004).

EXPERIMENTAL SECTION

The intelligent pattern recognition system consists of three parts: (a) Data Acquisition and Pre-processing, (b) Feature Extraction and (c) Classification Using Neural Network.

Data recording and pre-processing: DHS signals were recorded from the Doppler Ultrasound system and the data were stored in digital form using software stored in a digital computer.

Then the following operation was made to the digitized signal in the following order:

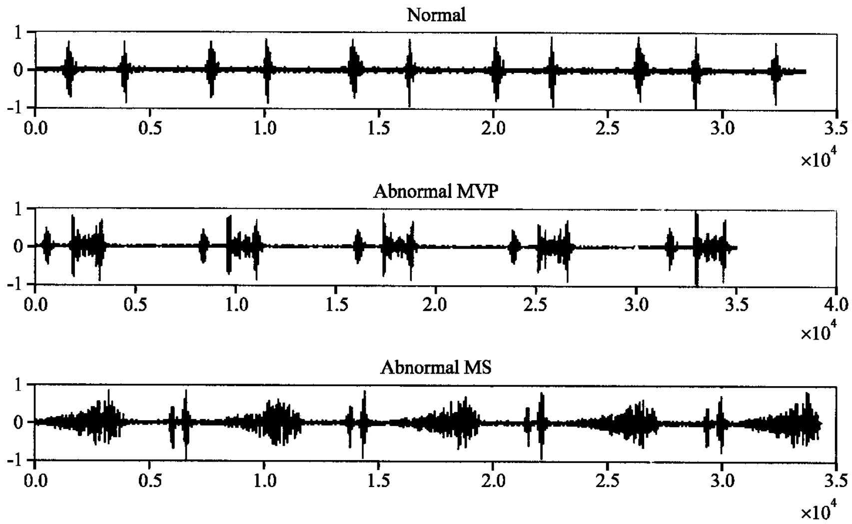

Fig. 3: The waveform of normal and abnormal cases

- **Filtering:** The reserved DHS signals were high-pass filtered to remove unwanted low frequency components, because the DHS signals are generally in the range of 0.5 to 10 kHz. The filter is a digital FIR, which is a fiftieth-order filter with a cut-off frequency equal to 500 Hz and window type is the 51-point symmetric Hamming window.
- **White de-noising:** White noise is a random signal that contains equal amounts of every possible frequency, i.e., its FFT has a flat spectrum (Devasahayam, 2000). The DHS signals were filtered from removing the white noise by using wavelet packet. The signal is decomposed by using the Daubechies wavelet packet and applying a threshold to the details coefficients then reconstructs the signal.
- **Normalization:** The DHS signals in this study were normalized using Eq. 1 so that the expected amplitude of the signal is no affected from the rib cage structure of the patient.

$$DHS_{signal} = \frac{DHS_{signal}}{|(DHS_{signal})_{max}|} \tag{3}$$

Feature extraction: Feature construction is one of the key steps in the data analysis process, largely conditioning the success of any subsequent statistics or machine learning endeavor (Guyon *et al*., 2001). A feature extractor should reduce the pattern vector (i.e., the original waveform) to a lower dimension, which contains most of the useful information from the original vector. The DHS waveform patterns from heart mitral valve are rich in detail and highly non-stationary. The waveforms for normal and abnormal cases are shown in Fig. 3.

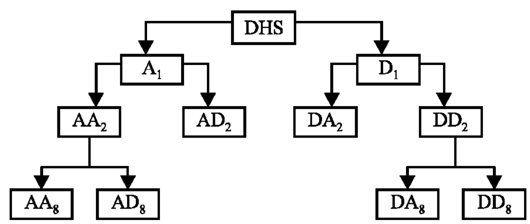

Fig. 4: The structure of decomposition tree

The goal of the feature extraction is to extract features from these patterns for reliable intelligent classification. After the data pre-processing has been realized, three steps are proposed in this paper to extract the characteristics of these waveforms.

- **Wavelet packet decomposition:** For wavelet packet decomposition, the tree structure was used a binary tree at depth 6 as shown in Fig. 4. Wavelet packet decomposition was applied to the DHS signal with the Daubechies-1 wavelet packets A representative example of the wavelet packet decomposition of the Doppler sound signal of the heart mitral valve is shown in Fig. 5.
- **Fast fourier transform:** The FFT is the most robust and understood one of the various time-frequency representations (Keeton and Schlindwein, 1997). We compute the FFT for the waveforms of terminal nodes using a 512-point FFT.
- **Fractal dimension:** We next calculated the fractal dimension of waveforms of the FFT spectrum using Higuchi's Algorithm. Consider x(1), x(2), ..., x(N) the signal point to be analyzed. Construct k new signals x_m^k as:

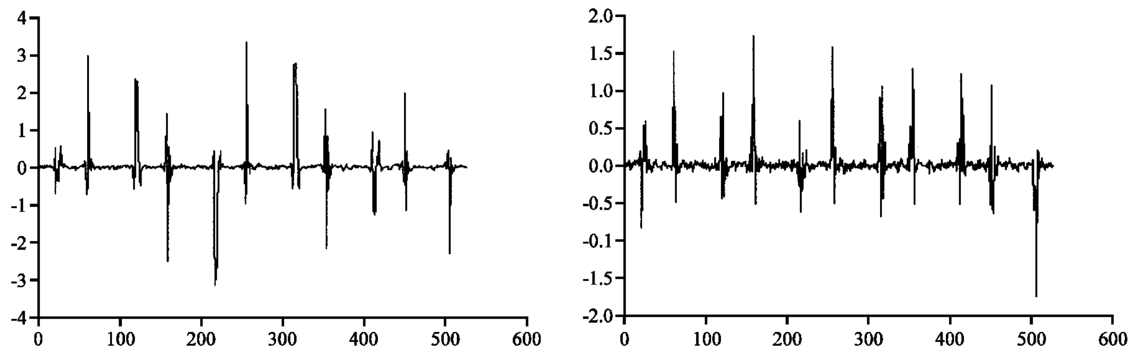

Fig. 5: The waveforms of some terminal nodes of wavelet packet decomposition at six-level of the DHS signal

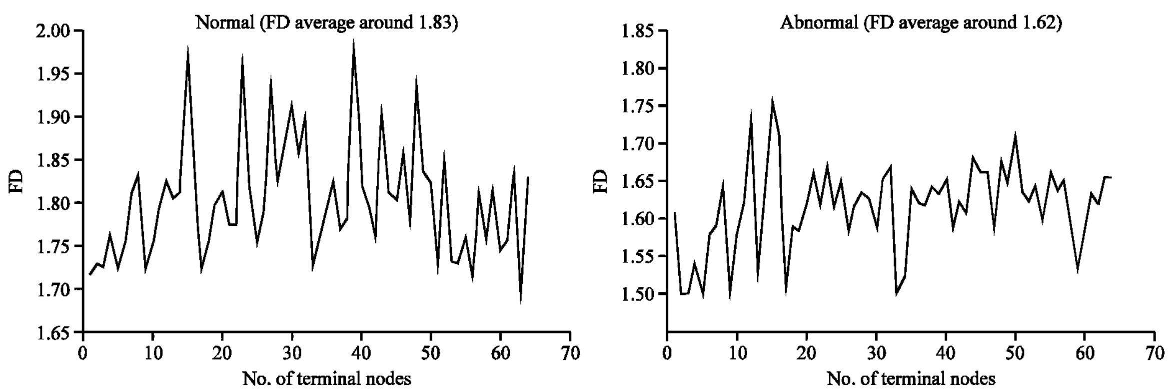

Fig. 6: The fractal dimension for normal and abnormal cases

$$x_m^k = \{x(m),\ x(m+k),\ x(m+2k),....,\ x(m+\mathrm{int}\left[\frac{N-m}{k}\right]k)\} \tag{4}$$

for m = 1, 2, ..., k

Where:

m = The initial time value,
k = The discrete time interval between points (delay),
int = The integer part (Fig. 6).

For each of the curves or signals x_m^k constructed, the average length L_m (k) is computed as:

$$L_m(k) = \frac{(N-1)\sum_{i=1}^{\mathrm{int}((N-m)/k)} \left|x(m+ik) - x(m+(i-1)k)\right|}{k * \mathrm{int}((N-1)/k)} \tag{5}$$

Where:

N = The total length of the data sequence x ,
(N – 1)/(k * int((N – 1)/k)) = A normalization factor.

An average length is computed for all signals having the same delay k, as the mean of the k lengths L_m (k) for m = 1, …, k.

This procedure is repeated for each k ranging from 1 to k_{max}, yielding a sum of average lengths L(k) for each k as follows:

$$L(k) = \sum_{m=1}^{k} L_m(k) \tag{6}$$

L(k) is proportional to k^{-D} where D is the fractal dimension. In the curve of ln(L(k)) versus ln(1/k), the slope of the least squares linear best fit is the estimate of the fractal dimension (Esteller and Vachtsevanos, 2003).

Classification using neural network: The objective of classification is to demonstrate the effectiveness of the proposed feature extraction method from the DHS signals. For this purpose, the feature vectors were applied as the input to an ANN classifier. The classification by neural network was performed using MATLAB with the Neural Network Toolbox, the architecture of the neural network shown in Table 1.

Table 1: ANN architecture and training parameters

Architecture		Training parameters	
The No. of layers	3	Learning rule	Back-propagation
The No. of neuron on the layers	Input:64	Adaptive learning rule	Initial:0.001
	Hidden:4		Increase:1.05
	Output:2		Decrease:0.7
The initial weights and biases	The Nguyen-Window method	Momentum constant	0.95
Activation function	Log-sigmoid	Sum-square error	0.0001

Table 2: Performance of the intelligent pattern recognition system

Parameters	Normal	Abnormal
Total No. of samples	54.0	48.0
No. of correct classification	50.0	43.0
No. of incorrect classification	4.0	5.0
The average recognition (%)	92.6	89.6

EXPERIMENTAL CLASSIFICATION RESULTS

We performed experiments using 162 the heart mitral valve Doppler studies taken from different individuals. The data from a part of the DHS signal samples were used for training and another part in testing the ANN. The training data comprised a random selection of 60 feature vectors from 25 abnormal and 35 normal individuals. The testing sets comprised 102 input feature vectors from 48 abnormal and 54 normal individuals Table 2.

DISCUSSION

In this study, we developed a diagnosis system for the interpretation of the DHS signals using pattern recognition and the diagnosis performance of this method demonstrated on the heart mitral valve. The task of feature extraction was performed using the wavelet packet decomposition for multi-scale analysis, FFT for time frequency representations and the fractal dimension, while classification was carried out by the back-propagation neural network. The stated results show that the proposed method can make an efficient interpretation. Although the abnormal subjects were attained 89.6% correct classification, the normal subjects were provided 92.6% correct classification. The feature choice was motivated by a realization that wavelet packet decomposition essentially is a representation of a signal at a variety of resolutions and that fractal dimension is an attribute of the signal that determines the variation in its curve length at varying resolutions. In brief, the wavelet packet decomposition has been demonstrated to be an effective tool for extracting information from the DHS signals. However, the proposed feature extraction method is robust against to noise in the DHS signals.

The most important aspect of the diagnosis system is the ability of self-organization of the neural network without requirements of programming and the immediate response of a trained net during real-time applications. These features make the diagnosis system suitable for automatic classification in interpretation of the DHS signals. These results point out the ability of design of a new intelligence diagnosis assistance system.

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