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An expert system for diagnosis of the heart valve diseases

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Abstract

In this paper, an expert diagnosis system is presented for interpretation of the Doppler signals of the heart valve diseases based on the pattern recognition. This paper especially deals with the feature extraction from measured Doppler signal waveforms at the heart valve using the Doppler Ultrasound. Wavelet transforms and short time Fourier transform methods are used to feature extract from the Doppler signals on the time–frequency domain. Wavelet entropy method is applied to these features. The back-propagation neural network is used to classify the extracted features. The performance of the developed system has been evaluated in 215 samples. The test results showed that this system was effective to detect Doppler heart sounds. The correct classification rate was about 94% for normal subjects and 95.9% for abnormal subjects. © 2002 Elsevier Science Ltd. All rights reserved.

Keywords: Pattern recognition; Doppler heart sounds; Heart valves; Feature extraction; Wavelet decomposition; Spectrograms; Neural networks; Expert systems

1. Introduction

Researches showed that the most of human deaths in the world are due to heart diseases. The heart valve disorders are of importance among the heart diseases. Among them, mitral and aortic valve disorders are the most common ones. For this reason, early detection of heart valve disorders is one of the most important medical research areas (Akay, Akay, & Welkowitz, 1992). Today, the used methods for diagnosis of heart valve disorders are non-invasive techniques (electrocardiograms, chest X-rays, heart sounds and murmur from stethoscope, ultrasound imaging and Doppler techniques) and invasive techniques (angiography, transozefagial echocardiograph (Nanda, 1993). However, each method is limited in its ability to offer efficient and thorough detection and characterization (Plett, 2000). All of these methods are based on experience and information of physician. The researches in this area are focused on improving human–machine interfaces in existing methods. In this way, the cardiologist can understand the output of the examination systems more easily and diagnose the problem more accurately (Philpot, Yoganathan, & Nanda, 1993).

Doppler techniques are the most preferred because of their completely non-invasive and without risk in the serial studies. The technique has improved much since Satomura first demonstrated the application of the Doppler effect to the measurement of blood velocity in 1959 (Keeton & Schlindwein, 1997). In recent years, Doppler technique has found increasing use in the assessment of heart disease (Wright, Gough, Rakebrandt, Wahab, & Woodcock, 1997). 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, Xuemin, Mingshi, & Wie, 1997). However, the factors such as calcified disease or obesity often results in a diagnostically unsatisfactory Doppler techniques assessment and, therefore, it is sometimes necessary to assess the spectrogram of the Doppler shift signals to elucidate the degree of the disease (Wright et al., 1997). A major motivation in our work is to aid the diagnosis in such cases. Among Doppler techniques, the most ubiquitous and straightforward are waveform profile indices such as the pulsatility index (PI), Pourcelot or resistance index (RI) and *A*/*B* Systolic Diastolic ratio, which are highly correlated and led to highly erroneous diagnostic results (Izzetoglu, Erkmen, & Beksac, 1995). These indices rely on the peak systolic and end-diastolic velocities, with only the PI making use of the mean velocity over the cardiac cycle. More sophisticated methods have also been developed such as the Laplace transform and principal components analysis. However, none of the simple or more complex analytical techniques has yielded an acceptable diagnostic accuracy so as to be commonplace in

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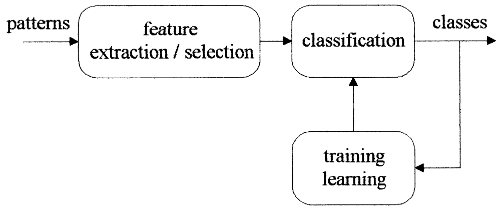

Fig. 1. The pattern recognition approach.

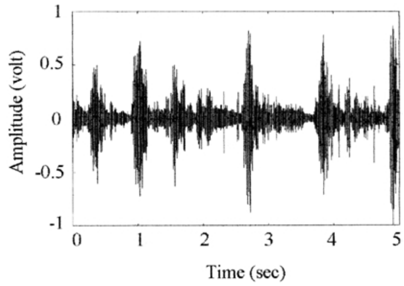

Fig. 2. The waveform pattern of the Doppler heart sound.

the vascular clinic (Wright et al., 1997). In this study, the developed method is an expert diagnosis system and will cause more effective usage of the Doppler technique. Until now, many attempts have been undertaken to automatically classify Doppler signals using pattern recognition (Chan, Chan, Lam, Lui, & Poon, 1997; Guler & Kara, 1995). Nevertheless, the studies on the DHS are fairly limited.

This study will introduce the technique that will aid clinical diagnosis, enable further research of heart valve disorders, and provide a novel expert system for recognition of heart valve disorders. This study uses the powerful mathematics of wavelet signal processing and entropy, short-time Fourier transform (STFT) to efficiently extract the features from pre-processed Doppler signals for the purpose of recognizing between abnormal and normal of the heart valve. An algorithm called the expert diagnostic system is developed which is approximately the advanced pattern recognition.

The DHS can be obtained simply by placing the Doppler ultrasonic flow transducer over the chest of the patient. A disadvantage of the Doppler method is that it requires the constant attention of the doctor to detect subtle changes in the DHS (Chan et al., 1997). The presented method prevents subtle changes in the DHS from escaping physician's eye by perceiving them, even if the physician does not pay a continuous attention.

The realized study has the stages of decision and evaluation contrary to the existing diagnosis methods. Thus, the doctor can make a comparison between the diagnoses of developed method and the diagnoses of existing methods. If the results are different, the examinations can be repeated or performed more carefully. In this way, the physician can decide more realistic.

The paper is organized as follows. In Section 2, we review some basic properties of the pattern recognition, the Doppler heart signals, wavelet decomposition, STFT, wavelet entropy and neural networks. A new expert diagnostic system is described in Section 3. This new method enables a large reduction of the Doppler signal data while retaining problem specific information which facilitates an efficient pattern recognition process. The effectiveness of the proposed method for classification of Doppler signals in the diagnosis of heart valve diseases is demonstrated in Section 4. Finally Section 5 presents discussion and conclusion.

2. Preliminaries

In this section, the theoretical foundations for the expert diagnosis system used in the presented study are given in the following subsections.

2.1. 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 is 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 & Heinrich, 1996). The techniques applied to pattern recognition uses artificial intelligence approaches (Bishop, 1996).

2.2. DHS signals

The audio DHS is obtained by simply placing the Doppler ultrasonic flow transducer over the chest of the patient (Chan et al.,, 1997). Fig. 2 shows a DHS signal from heart aortic valve. The DHS produced from echoes backscattered by moving blood cells is generally in the range of 0.5–10 kHz (Saini, Nanda, & Maulik, 1993). DHS signal spectral estimation is now commonly used to evaluate blood flow parameters in order to diagnose cardiovascular diseases. Spectral estimation methods are particularly used in Doppler ultrasound cardiovascular disease detection. Clinical diagnosis procedures generally include analysis of a graphical display and parameter measurements, produced by blood flow spectral evaluation.

Ultrasonic instrumentation typically employ Fourier based methods to obtain the blood flow spectra, and blood flow measurements (Madeira, Tokhi, & Ruano, 2000).

A Doppler signal is not a simple signal. It includes random characteristics due to the random phases of scattering particles present in the sample volume. Other effects such as geometric broadening and spatially varying velocity also affect the signal (Karabetsos, Papaodysseus, & Kountsouris, 1998).

The following Doppler equation:

$$\Delta f = \frac{2vf\cos\theta}{c} \tag{1}$$

where v equals the velocity of the blood flow, f equals the frequency of the emitted ultrasonic signal, c equals the velocity of sound in tissue (approximately 1540 m/s), Δf equals the measured Doppler frequency shift, and θ equals the angle of incidence between the direction of blood flow and the direction of the emitted ultrasonic beam (Saini et al., 1993).

2.3. Wavelet decomposition

Wavelet transforms are rapidly surfacing in fields as diverse as telecommunications and biology. Because of their suitability for analyzing non-stationary signals, they have become a powerful alternative to Fourier methods in many medical applications, where such signals abound (Akay, 1997; Keeton & Schlindwein, 1997; Liang & Nartimo, 1998).

The main advantages 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 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).

Wavelet decomposition uses the fact that it is possible to resolve high frequency components within a small time window, and only low frequencies components need large time windows. This is because a low frequency component completes a cycle in a large time interval whereas a high frequency component completes a cycle in a much shorter interval. Therefore, slow varying components can only be identified over long time intervals but fast varying components can be identified over short time intervals. Wavelet decomposition can be regarded as a continuous time wavelet decomposition sampled at different frequencies at every level or stage. The wavelet decomposition function at level m and time location t_m can be expressed as Eq. (2):

$$d_m(t_m) = x(t)\Psi_m\left(\frac{t - t_m}{2^m}\right) \tag{2}$$

where Ψ_m is the decomposition filter at frequency level m. The effect of the decomposition filter is scaled by the factor 2^m at stage m, but otherwise the shape is the same at all stages. The synthesis of the signal from its time–frequency coefficients given in Eq. (3) can be rewritten to express the composition of the signal $x[n]$ from its wavelet coefficients.

$$d[n] = x[n]h[n], \qquad c[n] = x[n]g[n] \tag{3}$$

where $h[n]$ is the impulse response of the high pass filter and $g[n]$ is the impulse response of the low pass filter (Devasahayam, 2000).

Wavelet packet analysis is an extension of the discrete wavelet transform (DWT) (Burrus, Gopinath, & Guo, 1998) and it turns out that the DWT is only one of the many possible decompositions that could be performed on the signal, instead of just decomposing the low frequency component as well. 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 (Keeton & Schlindwein, 1997).

2.4. Short-time Fourier transform

STFT, also known as the time-dependent or the windowed Fourier transform, attempts to analyze non-stationary signals by dividing the whole signal into shorter data frames. In short, the STFT can be compactly represented by Eq. (4):

$$X(k) = \sum_{n=0}^{N-1} x(n)\omega(n - n_0)\exp\left(-\frac{\mathrm{j}2\pi nk}{N}\right) \tag{4}$$

where $\omega(n - n_0)$ is a window function to suppress side lobes while minimizing the main lobe leakage. The output of successive STFTs can provide a time–frequency representation of the signal. To accomplish this the signal is truncated into short data frames by multiplying it by a window so that the modified signal is zero outside the data frame. The frequency spectrums for the data frame is calculated using the fast Fourier transform. One of the limitations of STFT is that the time frame for analysis of the signal is fixed (Keeton & Schlindwein, 1997).

2.5. Wavelet entropy

Entropy-based criteria describe information-related properties for an accurate representation of a given signal. Entropy is a common concept in many fields, mainly in signal processing (Coifman & Wickerhauser, 1992). A method for measuring the entropy appears as an ideal tool for quantifying the ordering of non-stationary signals. An ordered activity (i.e. a sinusoidal signal) is manifested as a narrow peak in the frequency domain, thus having low entropy. On the other hand, random activity has a wide band response in the frequency domain, reflected in a high entropy value (Quiroga, Roso, & Basar, 1999). The types of

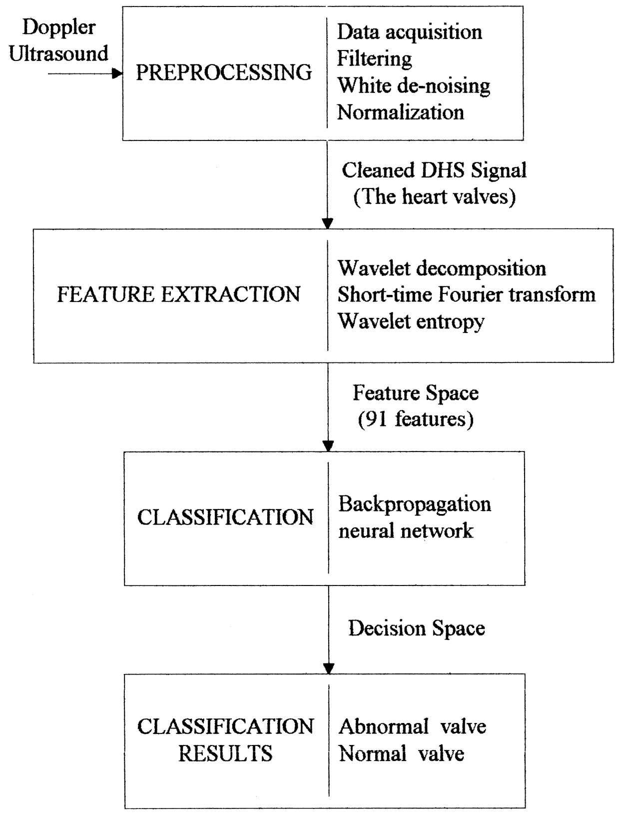

Fig. 3. The algorithm of the expert diagnostic system.

entropy computing are shannon, threshold, norm, log energy, and sure (Coifman & Wickerhauser, 1992).

2.6. Neural networks

An artificial neural network (ANN) is a mathematical model consisting of a number of highly interconnected processing elements organized into layers, the geometry and functionality of which have been likened to that of the human brain. The ANN may be regarded as processing learning capabilities inasmuch as it has a natural propensity for storing experimental knowledge and making 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 DHS, be it 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 & O'Rourke, 1990). Applications of ANNs in the medical field include EMG pattern identification (Asres, Dou, Zhou, Zhang, & Zhu, 1997), images of human breast disease (Allan & Kinsner, 2001) medical data mining (Brameier & Banzhaf, 2001), Brachytherapy cancer treatment optimization (Miller, Bews, & Kinsner, 2001), interpretation of heart sounds (Turkoglu & Arslan, 2001), EEG pattern identification (Saraoglu, Yumusak & Ferikoglu, 1999); however, to date neural network analysis of DHS is a relatively new approach.

3. Methodology

Fig. 3 shows the expert diagnostic system we developed. It consists of three parts: (a) data acquisition and pre-processing, (b) feature extraction, (c) classification using neural network.

3.1. Data acquisition and pre-processing

All the original audio DHS signals were acquired from the Acuson Sequoia 512 Model Doppler Ultrasound system in the Cardiology Department of the Firat Medical Center. DHS signals were sampled at 20 kHz for 5 s and signal to noise ratio of 0 dB by using a sound card which has 16-bit A/D conversion resolution and computer software prepared by us in the MATLAB (version 5.3) (The MathWorks Inc. Natick, MA, USA). The Doppler ultrasonic flow transducer used (Model 3V2c) was run on an operating mode of 2 MHz continuous wave. The Doppler signals of the heart valves were obtained by placing the transducer over the chest of the patient with the aid of ultrasonic image. The digitized data, which has 95 normal and 120 abnormal subjects, were stored on hard disk of the PC. The subject group consisted of 132 males and 83 females with the ages ranging from 15 to 80 years. The average age of the subjects was 48.77 years. Pre-processing to obtain the feature vector was performed on the digitized signal in the following order:

i. Filtering: The reserved DHS signals were high-pass filtered to remove unwanted low-frequency components, because the DHS signals is generally in the range of 0.5–10 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.
ii. 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 by removing the white noise by using wavelet packet. The white de-noising procedure contains three steps (Bakhtazad, Palazoglu, & Romagnoli, 1999):
    1. Decomposition: Computing the wavelet packet decomposition of the DHS signal at level 4 and using the Daubechies wavelet of order 4.
    2. Detail coefficient thresholding: For each level from 1 to 4, soft thresholding is applied to the detail coefficients.
    3. Reconstruction: Computing wavelet packet reconstruction based on the original approximation coefficients of level 4 and the modified detail coefficients of levels from 1 to 4.

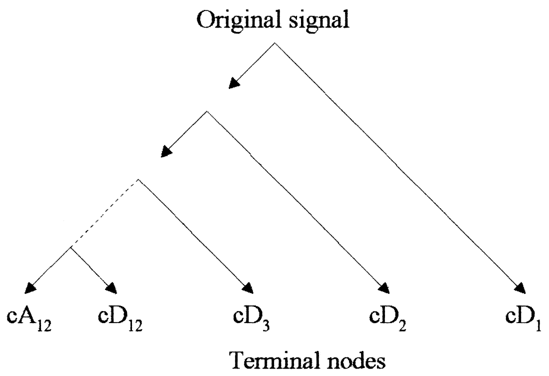

Fig. 4. The decomposition structure in level-12.

iii. Normalization: The DHS signals in this study were normalized using Eq. (5) so that the expected amplitude of the signal is not affected from the rib cage structure of the patient.

$$\mathrm{DHS}_{\mathrm{signal}} = \frac{\mathrm{DHS}_{\mathrm{signal}}}{|(\mathrm{DHS}_{\mathrm{signal}})_{\max}|} \tag{5}$$

3.2. Feature extraction

Feature extraction is the key to pattern recognition so that it is arguably the most important component of designing the expert diagnosis system based on pattern recognition since even the best classifier will perform poorly if the features are not chosen well. 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 valves are rich in detail and highly non-stationary. 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 using MATLAB with the Wavelet Toolbox and the Signal Processing Toolbox:

i. Wavelet decomposition: For wavelet decomposition of the DHS waveforms, the decomposition structure, reconstruction tree at level 12 as shown in Fig. 4 was used. Wavelet decomposition was applied to the DHS signal using the Daubechies-10 wavelet decomposition filters. Thus, obtaining two types of coefficients: one-approximation coefficients cA and twelve-detail coefficients cD. A representative example of the wavelet decomposition of the Doppler sound signal of the heart aortic valve was shown in Fig. 5.

ii. Short-time Fourier transform: The STFT is the understood and the most robust of the various time–frequency representations. The STFT of waveforms of terminal nodes was computed using a Hanning window function of 25 000-points, the sections overlap of 12 500 points between scans and zero padding the sections if the length of the window exceeds 25 000-points. A representative example of the STFT spectrums of a terminal node waveform is shown in Fig. 6.

iii. Wavelet entropy: We next calculated the norm entropy

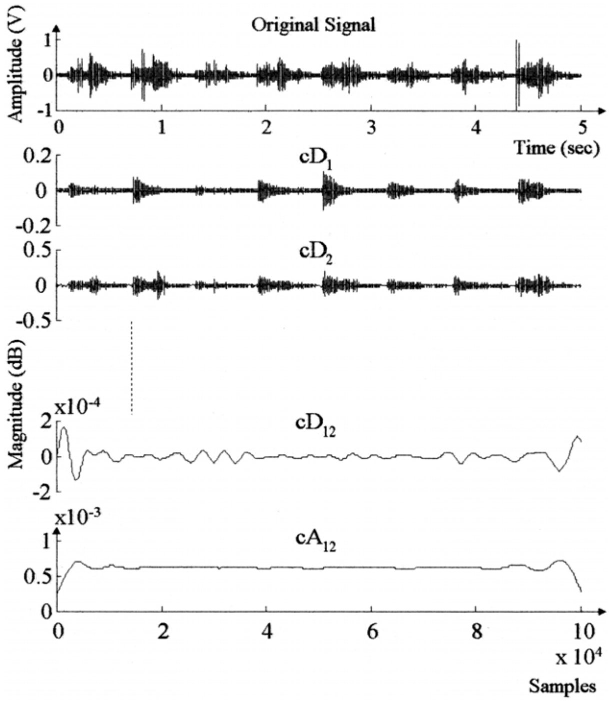

Fig. 5. The terminal node waveforms of wavelet decomposition at 12 levels of the DHS signal.

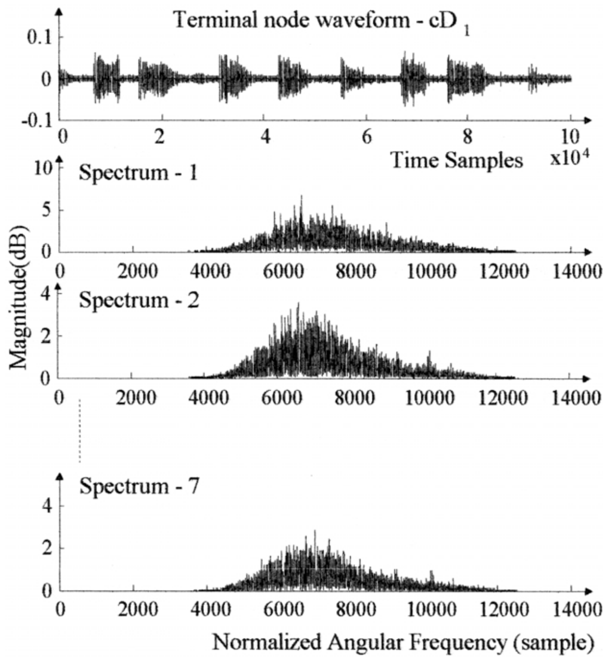

Fig. 6. The STFT spectrums of a terminal node waveform.

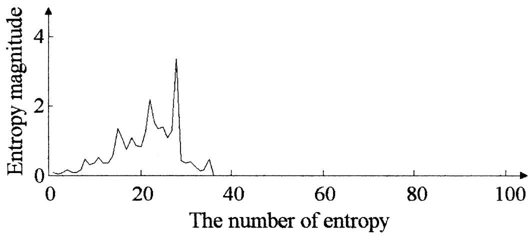

Fig. 7. The wavelet entropy of the DHS signal.

as defined in Eq. (6) of waveforms of the STFT spectrums.

$$E(s) = \sum_i |s_i|^{3/2} \tag{6}$$

where s is the STFT spectrum and (s_i) represents the i coefficients of s. The resultant entropy data, which were normalized with 1/50 000, were plotted in Fig. 7. The plot of the entropy data includes 91 features obtained from 13 terminal nodes where each one contains waveform of seven frequency spectrums per DHS signal. Thus, the feature vector was extracted by computing the wavelet entropy values for each DHS signal.

3.3. 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 training parameters and the structure of the neural network used in this study are as listed in Table 1. These were selected for the best performance, after several different experiments, such as the number of hidden layers, the size of the hidden layers, value of the moment constant and learning rate, and type of the activation functions. Fig. 8 shows the ANN training performance.

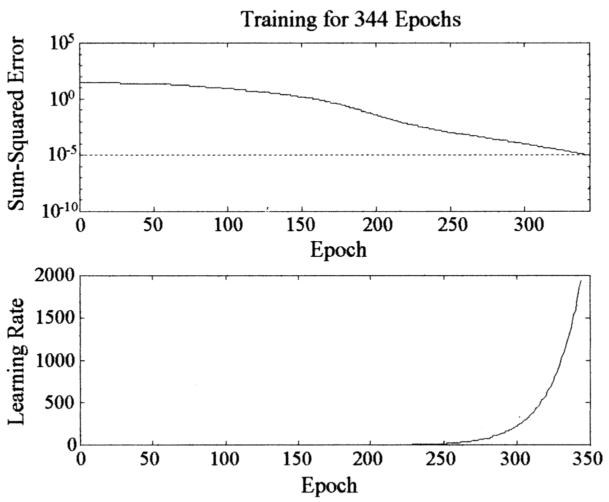

Fig. 8. The ANN training performance.

Table 1
ANN architecture and training parameters

ANN architecture	
The number of layers	3
The number of neuron on the layers	Input: 100 Hidden: 50 Output: 2
The initial weights and biases	The Nguyen-Widow method
Activation functions	Log-sigmoid
ANN training parameters	
Learning rule	Back-propagation
Adaptive learning rate	Initial: 0.0001 Increase: 1.05 Decrease: 0.7
Momentum constant	0.95
Sum-squared error	0.00001

4. Experimental classification results

We performed experiments using 215 heart aortic and 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. In these experiments, 100% correct classification was obtained at the ANN training among the two signal classes. It clearly indicates the effectiveness and the reliability of the proposed approach for extracting features from DHS signals for the purpose of pattern recognition. The ANN testing results are given in Table 2.

5. Discussion and conclusion

In this study, we developed an expert diagnostic system for the interpretation of the DHS signals using pattern recognition, and the diagnosis performance of this method was demonstrated on the heart aortic and mitral valves. The task of feature extraction was performed using the wavelet

Table 2
Performance of the expert diagnostic system

	The heart aortic valve		The heart mitral valve	
	N	AN	N	AN
Total number of samples	31	40	19	33
Correct classification #	28	38	19	32
Incorrect classification #	3	2	–	1
The average recognition %	98.7	99.8	98.5	99.4
The highest recognition %	100	100	100	100
The lowest recognition %	52.1	84.2	72.3	94.2

N: normal, AN: abnormal.

decomposition for multi-scale analysis, STFT for time–frequency representations, and the wavelet entropy, 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 95.9% correct classification, the normal subjects were provided 94% correct classification.

The feature choice was motivated by a realization that wavelet decomposition is essentially a representation of a signal at a variety of resolutions. In brief, the wavelet 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 noise in the DHS signals.

In this paper, the application of the wavelet entropy to the feature extraction from DHS signals was shown. Wavelet entropy proved to be a very useful tool for characterizing the DHS signal, furthermore the information obtained with the wavelet entropy probed not to be trivially related to the energy and consequently with the amplitude of signal. This means that with this method, new information can be accessed with an approach different from the traditional analysis of amplitude of DHS signal.

The most important aspect of the expert diagnostic 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 expert diagnostic system suitable for automatic classification in interpretation of the DHS signals. These results point out the ability of design of a new intelligent assistance diagnosis system.

The diagnosis performances of this study shows the advantages of this system: it is rapid, easy to operate, non-invasive, and not expensive. This system is of the better clinical application over others, especially for earlier survey of population. However, the position of the ultrasound probe, which is used for data acquisition from the heart valves, must be taken into consideration by physician.

Although our expert diagnosis system was carried out on the heart aortic and mitral valves, similar results for the other valves (tricuspid and pulmonary) and the other Doppler studies can be expected. Besides the feasibility of a real-time implementation of the expert diagnosis system, by increasing the variety and number of DHS signals additional information (i.e. quantification of the heart valve regurgitation and stenosis) can be provided for diagnosis.

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