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A computer aided method for diagnose of the heart mitral valve diseases

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SUMMARY

In this paper, a new computer aided diagnosis system is presented for interpretation of the Doppler signals of the heart mitral valve diseases based on the pattern recognition. This paper especially deals with the feature extraction from measured Doppler signal waveforms at the heart mitral valve using the Doppler Ultrasound. Wavelet packet transforms and power spectrum estimate using Yule-Walker AR method 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 105 samples that contain 39 normal and 66 abnormal subjects. The results showed that this system was effective to detect Doppler heart sounds. The correct classification was about 99% for both normal and abnorrnal subjects.

Key words*:* *pattern recognition, Doppler heart sounds, heart valves, feature extraction, wavelet packet, Yule-Walker AR method, neural networks.*

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 [1]. 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 and transozefagial echo-cardiograph) [2]. However, each method is limited in its ability to offer efficient and thorough detection and characterization [3]. 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 [4].

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 [5]. In recent years, Doppler technique has found increasing use in the assessment of heart disease [6]. Doppler heart sounds (DHS) are one of the most important sounds produced by blood flow, valves motion and vibration of the other cardiovascular components [7]. 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 [6]. 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 AB Systolic Diastolic ratio, which are highly correlated and led to highly erroneous diagnostic results [8]. 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 the vascular clinic [6]. In this study, the developed method is an intelligent diagnosis system and will cause more effective usage of the Doppler technique. Up to now, many attempts have been undertaken to automatically classify Doppler signals using pattern recognition [9, 10]. Nevertheless, the studies on the Doppler heart sounds 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 intelligent system for recognition of heart valve disorders. This study uses the powerful mathematics of wavelet packet signal processing and entropy, power spectral density (PSD) to efficiently extract the features from pre-processed Doppler signals for the purpose of recognizing between abnormal and normal of the heart mitral valve. An algorithm called the Intelligent Diagnostic System (IDS) is developed which is advanced pattern recognition approximate.

The Doppler heart sound 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 [10]. 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 on the contrary 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 realistically.

The paper is organized as follows. In Section 2, we review some basic properties of the pattern recognition, the Doppler heart signals, wavelet transform, autoregressive methods for the power spectral density, wavelet entropy and neural networks. A new computer aided 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 diagnosis of heart mitral valve diseases is demonstrated in Section 4. Finally Section 5 presents discussion and conclusion.

2. PRELIMINARIES

In this section, the theoretical foundations for the intelligent 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 demonstrated in Figure l, 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 [11]. The techniques applied to pattern recognition uses artificial intelligence approaches [12].

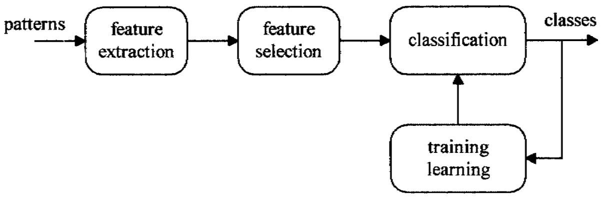

Fig. 1 Block diagram of the pattern recognition approach

2.2 DHS signal

The audio DHS is obtained simply placing the Doppler ultrasonic flow transducer over the chest of the patient [10]. Figure 2 shows a DHS signal. The DHS produced from echoes backscattered by moving blood cells is generally in the range of *0.5* to *10 kHz* [13]. 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 [14].

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 [15]. The following Doppler equation:

$$\Delta f = \frac{2vf \ cos\theta}{c} \qquad (1)$$

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 meter/sec*), 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 [13].

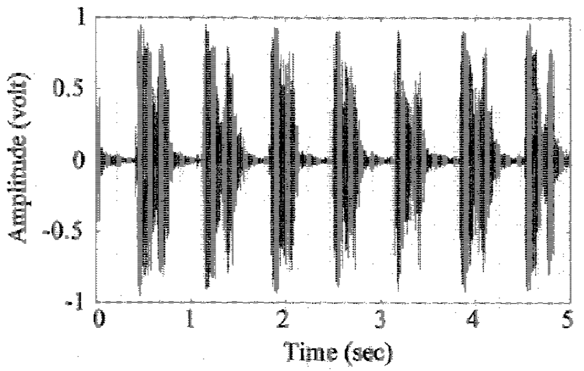

Fig. 2 The waveform pattern of the Doppler heart sound from heart mitral valve

2.3 Wavelet packet decomposition

Wavelet transforms are rapidly surfacing in fields as diverse as telecommunications and biology. Due to their suitability for analysing non-stationary signals, they have become a powerful alternative to Fourier methods in many medical applications, where such signals abound [5, 16, 17].

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 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 [18].

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:

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

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:

$$\begin{aligned} d[n] &= x[n] * h[n] \\ c[n] &= x[n] * g[n] \end{aligned} \qquad (3)$$

where $h[n]$ is the impulse response of the high pass filter and $g[n]$ is the impulse response of the low pass filter [19].

Wavelet packet analysis is an extension of the discrete wavelet transform (DWT) [20] 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 as can be seen from Figure 3. 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 [5].

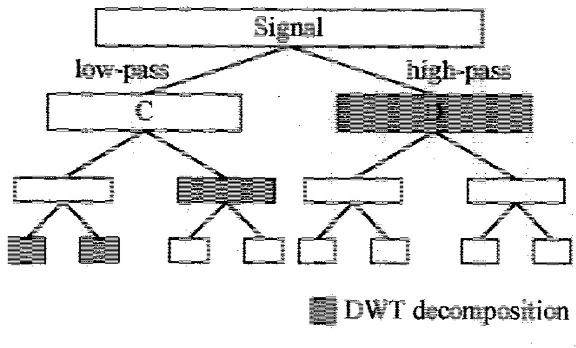

Fig. 3 Total decomposition tree of a time varying signal using wavelet packet analysis

2.4 Autoregressive methods (AR)

The most common parametric method employs autoregressive models (AR) in which it is assumed that a data value at a given time can be predicted from the preceding p data values and a noise term. An advantage of this method is that any power spectrum can be modelled by an AR process of some order p: however, the value of p may exceed the length of the time series.

The AR model is written as:

$$x_t = \sum_{k=1}^{p} a_k \cdot x_{t-1} + n_t \quad ; \quad t \geq 1 \tag{4}$$

where x_t represents time samples, a_k are the coefficients of the AR process, p is the model order, and n_t are samples of a stationary white noise process. AR systems can also be described by the power spectrum:

$$\frac{\sigma_p^2 \Delta t}{\left| 1 - \sum_{k=1}^{p} a_k \cdot e^{-j2\pi 2\pi fk} \right|^2} \tag{5}$$

where σ_p^2 is the variance of the noise term, n; f is frequency; Δt is the time between samples [3, 19].

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 [21]. 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 [22]. The types of entropy computing are shannon, threshold, norm, log energy and sure [21].

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 [23]. The Doppler heart sounds, 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 [24]. Applications of ANNs in the medical field include EMG pattern identification [25], images of human breast disease [26], medical data mining [27], Brachytherapy cancer treatment optimisation [28], interpretation of heart sounds [29], and EEG pattern identification [30]; however, to date neural network analysis of Doppler heart sounds is a relatively new approach.

3. METHODOLOGY

Figure 4 shows the computer aided diagnostic system we developed. It consists of three parts: a) Data acquisition and pre-processing; b) Feature extraction; and c) Classification using neural network.

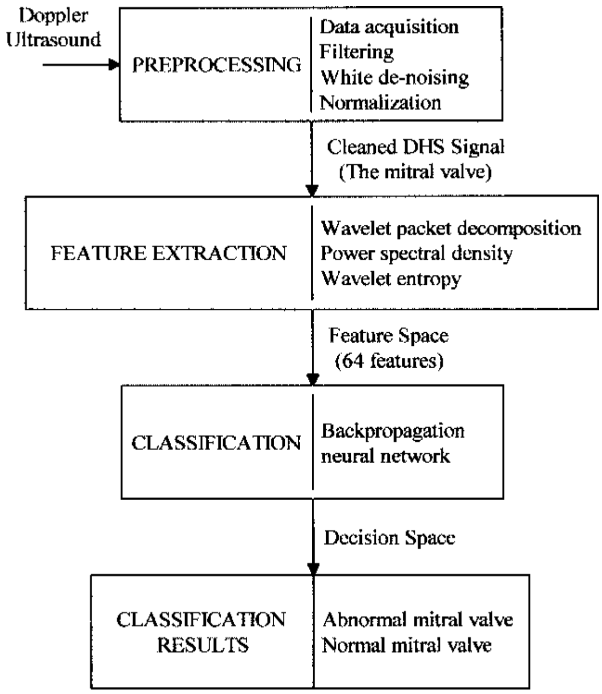

Fig. 4 The algorithm of the DHS computer aided diagnostic system

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* seconds 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 an operating mode of *2 MHz* continuous wave. The Doppler signals of the heart mitral valve were obtained by placing the transducer over the chest of the patient with the aid of ultrasonic image. The digitised data, which has 39 normal and 66 abnormal subjects, were stored on hard disk of the PC. The subject group consisted of 58 males and 47 females with the ages ranging from 19 to 78 years. The average age of the subjects was 47.5 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 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.

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 [19]. The DHS signals were filtered from removing the white noise by using wavelet packet. The white de-noising procedure contains three steps [31]:

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.

iii) ***Normalization***: The DHS signals in this study were normalized using Eq. (6) so that the expected amplitude of the signal is not affected from the rib cage structure of the patient:

$$DHS_{signal} = \frac{DHS_{signal}}{\left|\left(DHS_{signal}\right)_{max}\right|} \qquad (6)$$

3.2 Feature extraction

Feature extraction is the key to pattern recognition so that it is arguably the most important component of designing the intelligent 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 mitral valve 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 realised, 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 packet decomposition***: For wavelet packet decomposition, the tree structure used a binary tree at depth 6 as illustrated in Figure 5. Wavelet packet decomposition was applied to the DHS signal with the Daubechies-10 wavelet packets using the norm entropy defined as:

$$E(s) = \sum_i |s_i| \qquad (7)$$

where s is the DHS signal and (s_i) are the coefficients of wavelet packet decomposition of s. A representative example of the wavelet packet decomposition of the Doppler sound signal of the heart mitral valve is shown in Figure 6.

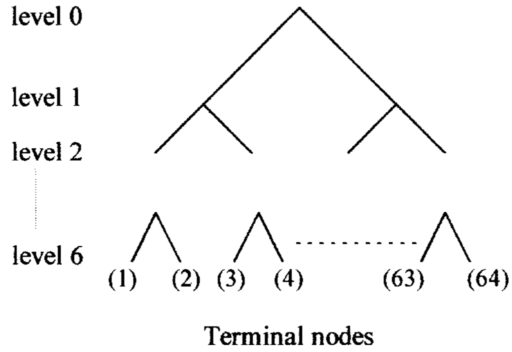

Fig. 5 The structure of decomposition tree

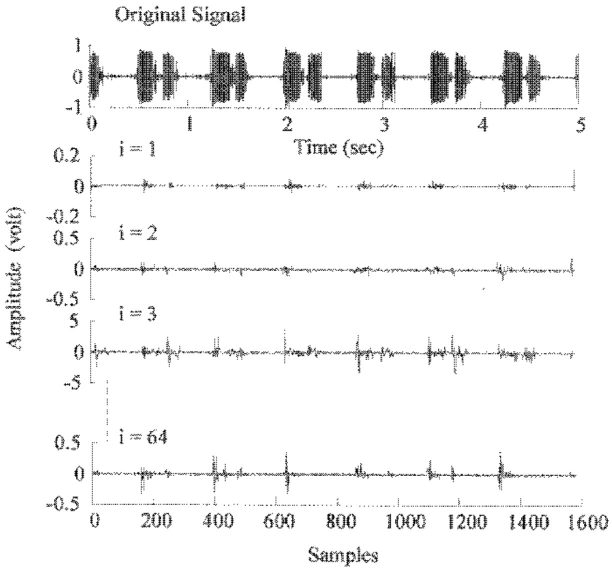

Fig. 6 The waveforms of terminal nodes (i=1 to 64) of wavelet packet decomposition at six-level of the DHS signal

ii) ***Power spectral density***: The PSD of waveforms of terminal nodes was computed using the Yule- Walker AR method. In the AR model, the model order was chosen as *p=5* for the all-pole filter and the FFT length was selected as double the amount of length of the terminal node signals. A representative example of the PSD spectrums of waveform of a terminal node is indicated in Figure 7.

iii) ***Wavelet entropy***: We next calculate the norm entropy of waveforms of the PSD spectrums, defined as:

$$E(s) = \sum_i |s_i|^{3/2} \qquad (8)$$

where s is the PSD spectrum and (s_i) are the coefficients of s. The resultant entropy data, which were normalized with *1/50*, were plotted in Figure 8. The plot of the entropy data includes 64 features obtained from 64 terminal nodes which each one contains waveform of one frequency spectrum per DHS signal. Thus, the feature vector was obtained by computing the wavelet packet entropy values for each DHS signal.

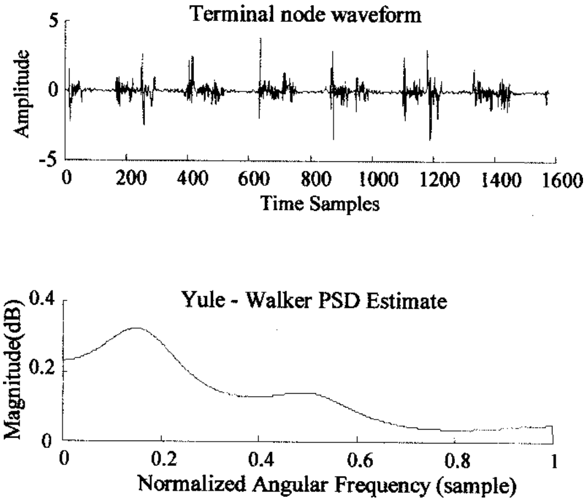

Fig. 7 The PSD spectrum of a terminal node waveform

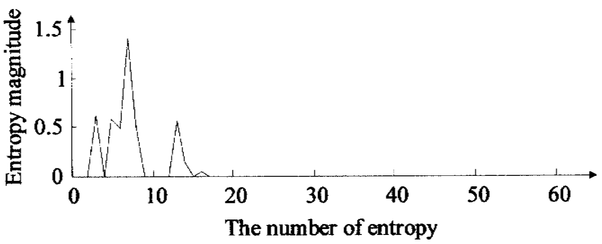

Fig. 8 The walvelet packet entropy of a DHS signal

3.3 Classification using neural network

The objective of classification demonstrates 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 shown 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. Figure 9 shows the ANN training performance.

4. EXPERIMENTAL CLASSIFICATION RESULTS

We performed experiments using 105 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 53

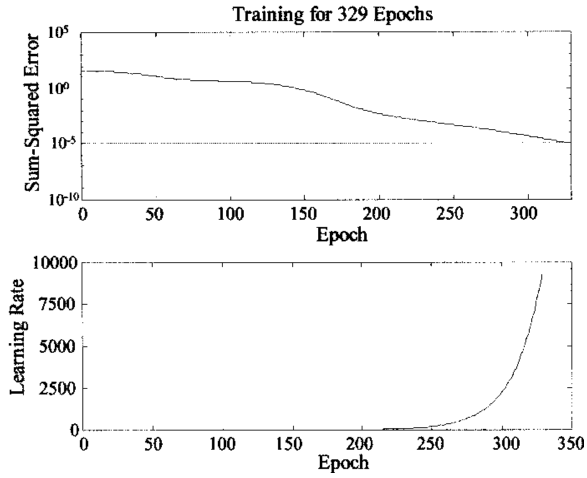

Fig. 9 The ANN training performance

feature vectors from 33 abnormal and 20 normal individuals. The testing sets comprised 52 input feature vectors from 33 abnormal and 19 normal individuals. In this experiments, 100 percent 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 tabulated in Table 2.

5. DISCUSSION AND CONCLUSION

In this study, we developed an intelligent pattern recognition 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, PSD for time-frequency representations, and the wavelet packet 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. The correct classification rate was about *99%* for normal subjects and abnormal subjects.

The feature choice was motivated by a realization that a 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.

In this paper, the application of the wavelet packet entropy (WPE) to the feature extraction from DHS signals was shown. WPE proved to be a very useful

Table 1 ANN arhitecture and training parameters

ANN architecture			Training parameters		
The number of layers	:	*3*	*Learning rule*	:	*Back-propagation*
The number of neuron on the layers	:	*Input : 64*	*Adaptive learning rate*	:	*Initial : 0.001*
		Hidden : 4			*Increase : 1.05*
		Output : 2			*Decrease : 0.7*
The initial weights and biases	:	*The Nguyen-Windrow method*	*Momentum constant*	:	
Activation Functions	:	*Log-sigmoid*	*Sum-squared error*	:	

Table 2 Performance of the computer aided diagnostic system

	The heart mitral valve	
	Normal	*Abnormal*
Total number of samples	*19*	*33*
Number of correct classification	*19*	*31*
Number of incorrect classification	*-*	*2*
Tve average recognition (%)	*99.8*	*99.78*
The highest recognition (%)	*99.99*	*99.99*
The lowest recognition (%)	*97.74*	*94.91*

tool for characterizing the DHS signal, furthermore the information obtained with the WPE probed not to be trivially related with the energy and consequently with the amplitude of signal. This means that with this method, a new information can be accessed with an approach different from the traditional analysis of amplitude of DHS signal.

The most important aspect of the intelligent pattern recognition 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 intelligent pattern recognition 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.

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

Although our computer aided diagnosis system was carried out on the heart mitral valve, similar results for the other valves (aortic, tricuspid, pulmonary) and the other Doppler studies can be expected. Besides the feasibility of a real-time implementation of the computer aided 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.

6. ACKNOWLEDGMENTS

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KOMPJUTORSKA METODA ZA DIJAGNOZU BOLESTI POLUMJESEČASTOG SRČANOG ZALISKA

SAŽETAK

Ovaj rad iznosi novu kompjutorsku dijagnozu za tumačenje Doppler-ovog signala bolesti srčanog polumjesečastog zaliska koja se bazira na prepoznavanju obrasca. Ovaj se rad ponajviše bavi ekstrakcijom obilježja iz izmjerenih valnih oblika Doppler-ovog signala srčanog polumjesečastog zaliska koristeći se Doppler-ovim ultrazvukom. Koristi se metoda transformacije paketa valova i procjena spektra snage pomoću Yule-Walker AR metode radi obilježavanja ekstrakta iz Doppler-ovog signala u području vremenske frekvencije. Na ovim obilježjima primijenjena je metoda entropije valova. Koristi se propagacija neuralne mreže da bi se klasificirala prepoznata obilježja. Djelotvornost razvijenog sustava procijenjena je na temelju 105 uzoraka koji sadrže 39 normalnih i 66 abnormalnih slučajeva. Rezultati su pokazali da je ovaj sustav djelotvoran za detekciju Doppler-ovih zvukova srca. Ispravna klasifikacija bila je oko 99% za normalne i abnormalne slučajeve.

Ključne riječi: *prepoznavanje obrasca, Doppler-ovi srčani zvukovi, srčani zalisak, ekstrakcija obilježja, paket valova, Yule-Walker-ova AR metoda, neuralna mreža.*