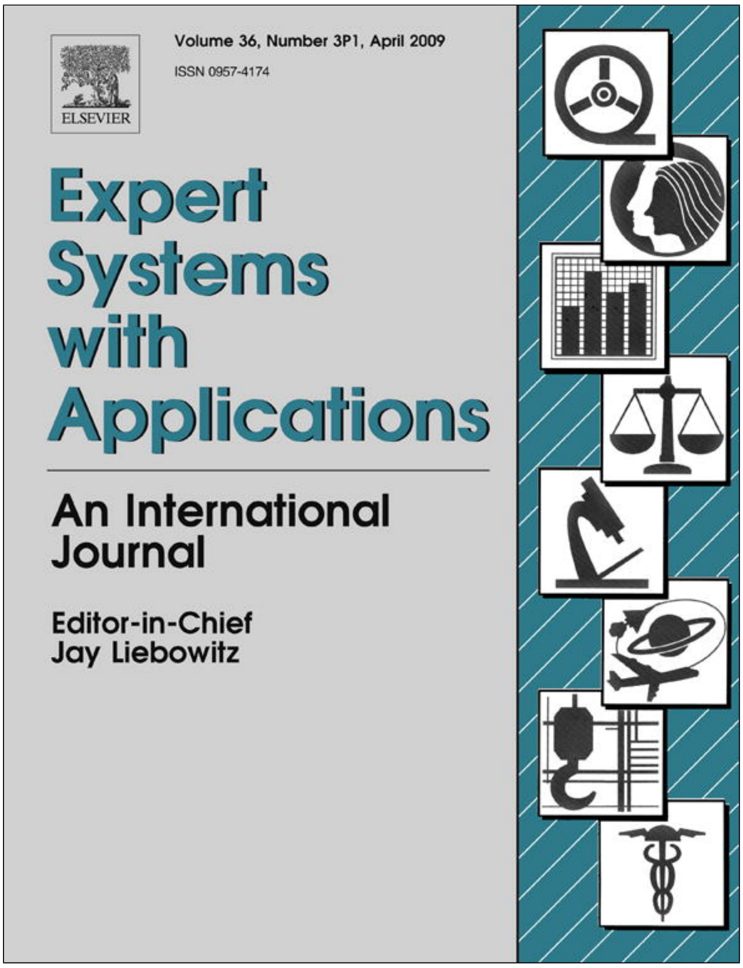
Volume 36, Number 3P1, April 2009
ISSN 0957-4174
ELSEVIER
Expert Systems with Applications
An International Journal
Editor-in-Chief
Jay Liebowitz

Expert Systems with Applications 36 (2009) 4232–4238

Contents lists available at ScienceDirect

Expert Systems with Applications

journal homepage: www.elsevier.com/locate/eswa

An expert system based on least square support vector machines for diagnosis of the valvular heart disease

Davut Hanbay *

Firat University, Technical Education Faculty, Department of Electronics and Computer Science, 23119 Elazig, Turkey

ARTICLE INFO

Keywords:
Valvular heart disease
Wavelet packet decomposition
Entropy
Fast-Fourier transform
Least squares support vector machine

ABSTRACT

There has been a growing research interest in the use of intelligent methods in biomedical studies. This is the result of developments in the area of data analysis and classifying techniques. In this paper, an expert system based on least squares support vector machines (LS-SVM) for diagnosis of valvular heart disease (VHD) is presented. Wavelet packet decomposition (WPD) and fast-Fourier transform (FFT) methods are used for feature extracting from Doppler signals. LS-SVM is used in the classification stage. Threefold cross-validation method is used to evaluate the proposed expert system performance. The performances of the developed systems were evaluated in 105 samples that contain 39 normal and 66 abnormal subjects for mitral valve disease. The results showed that this system is effective to detect Doppler heart sounds. The average correct classification rate was about 96.13% for normal subjects and abnormal subjects.

1. Introduction

In recent years, realized medical studies showed that important causes of human deaths in the world are 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, the early detection of valvular heart diseases is one of the most important medical research areas (Akay, Akay, & Welkowitz, 1992; Turkoglu, Arslan, & Ilkay, 2002). Nowadays, the used methods for diagnosis of the valvular heart diseases 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 echocardiograph) (Nanda, 1993). However, each method is limited in its ability to offer efficient and thorough detection and characterization. All these methods are based on experience and information of physician. Therefore, developing Human–Machine interfaces with the existing methods of studies has become popular in these areas. By using these interfaces, the cardiologist can understand the output of the examination systems more easily and diagnose the problem more accurately (Philpot, Yoganathan, & Nanda, 1993; Turkoglu et al., 2002).

Doppler techniques are the most preferred methods because they are completely non-invasive and without a risk in the serial studies (Keeton & Schlindwein, 1997; Turkoglu et al., 2002). In the recent years, Doppler technique has found increasing use in the medical area (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 result in a diagnostically unsatisfactory Doppler techniques assessment, 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). The main aim of our work is to aid the diagnosis in such cases. Among Doppler techniques, the most ubiquitous and straightforward are the 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; Turkoglu et al., 2002). 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 (Wright et al., 1997). In this study, the developed method is a decision support system and will cause more effective usage of the Doppler technique. Until now, many studies have been realized to automatically classify Doppler signals using pattern recognition techniques (Chan, Chan, Lam, Lui, & Poon, 1997; Guler & Kara, 1995; Turkoglu et al., 2002). Nevertheless, the effective studies on the Doppler heart sounds are also limited (Turkoglu, Arslan, & Ilkay, 2002a).

The Doppler heart sounds can be obtained simply by placing the Doppler ultrasonic flow transducer over the chest of the patient.

* Tel.: +90 424 2370000 4257; fax: +90 424 2367064.
E-mail address: dhanbay@firat.edu.tr

0957-4174/$ - see front matter © 2008 Elsevier Ltd. All rights reserved.
doi:10.1016/j.eswa.2008.04.010

But the 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 the physician's attention by perceiving them, even if the physician does not pay a continuous attention (Turkoglu, Arslan, & Ilkay, 2002b).

Up to now, several papers have been proposed for classifying Doppler signals by using pattern recognition techniques (Chan et al., 1997; Çomak, Arslan, & Türkoğlu, 2007; Turkoglu et al., 2002b; Uguz, Arslan, & Türkoğlu, 2007; Wright et al., 1997). The data set which was obtained by Turkoglu et al. (2002b) was used by Çomak et al. (2007) and Uguz et al. (2007) too. Çomak et al. proposed to develop a decision support system based on wavelet decomposition and short-time Fourier transform to develop the performance of Turkoglu et al. (2002b). Uguz et al. proposed a biomedical system based on continuous hidden Markov model classifier for the diagnosis of valvular heart diseases. The proposed methodology was composed of two stages. At the first stage, the initial values of average and standard deviation were calculated by separating observation symbols into equal segments according to the state number and using observation symbols appropriate to each segment. At the second stage, the initial values of average and standard deviation were calculated by separating observation symbols into the clusters (FCM or K-means algorithms) that have equal number of states and using observation symbols appropriate to the separated clusters.

Least square SVM uses equality constraints and solves a set of linear equations in the dual space instead of solving a quadratic programming problem as for the standard SVM. This simplifies the computations and enhances the speed considerably. There exists a link between the LS-SVM classifier formulations with the well-known Fisher discriminant analysis, namely by extending it to a high-dimensional feature space. Some parameters have to be tuned to achieve a high level performance of the LS-SVM, including the regularization parameter and the kernel parameter corresponding to the kernel type (Lukas, Devos, Suykens, et al., 2004; Suykens & Vandewalle, 1999).

This study will introduce the technique that will aid clinical diagnosis, enable the further research of VHD, and provide a decision support system for recognition of VHD. This study uses the powerful mathematics of wavelet signal processing and entropy, FFT to efficiently extract the features from pre-processed Doppler signals for the purpose of recognizing between abnormal and normal subjects of the VHD. Thus, the doctor can make a comparison between the diagnoses by the developed method and the diagnoses by the 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.

This paper is organized as follows. In Section 2, we review some basic properties of the pattern recognition, the Doppler heart signals, WPD, FFT, wavelet entropy and LS-SVM. In Section 3, the implementation stage is described and the effectiveness of the proposed method for the classification of Doppler signals in the diagnosis of VHD is demonstrated. Finally, conclusion is presented in Section 4.

2. Preliminaries

In this section, the theoretical foundations of the presented study are given in the following subsections.

2.1. Pattern recognition

Pattern recognition consists of some sequential stages, the first stage is feature extraction from the patterns, which is the conversion of patterns to features that are regarded as a condensed representation, ideally containing all-important information. The second stage is feature selection. At which a smaller number of meaningful features that best represents the given pattern without redundancy is identified. The next stage is classification. At which a specific pattern is assigned to a specific class according to the characteristic features selected for it. This general abstract model 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 as a set of images of a patient. The classes obtained represent the variety of different possible diagnoses or diagnostic statements (Dickhous & Heinrich, 1996; Turkoglu et al., 2002). The techniques applied to pattern recognition use artificial intelligence approaches (Bishop, 1996; Turkoglu et al., 2002).

2.2. DHS signals

The audio DHS can be obtained by simply placing the Doppler ultrasonic flow transducer over the chest of the patient (Chan et al., 1997; Turkoglu et al., 2002). (Fig. 2) shows a DHS signal. 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 employs Fourier-based methods to obtain the blood flow spectra and blood flow measurements (Madeira, Tokhi, & Ruano, 2000; Turkoglu et al., 2002).

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

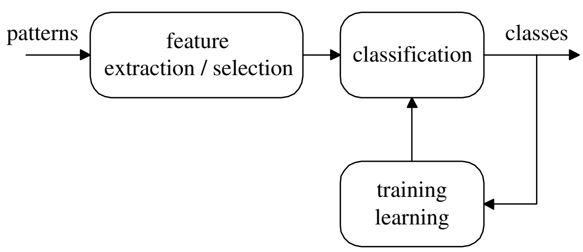

Fig. 1. The general abstract model of pattern recognition approach.

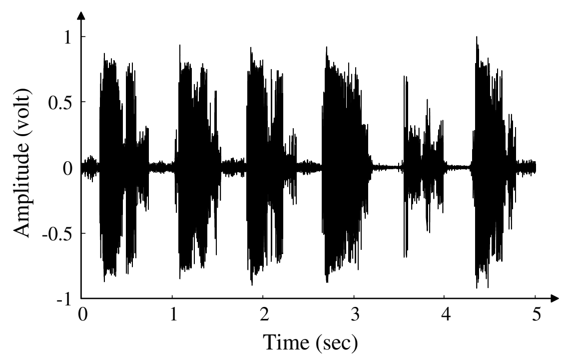

Fig. 2. The waveform pattern of the Doppler heart sound.

and spatially varying velocity also affect the signal (Turkoglu et al., 2002). The following is the 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; Turkoglu et al., 2002).

2.3. Wavelet packet decomposition

Wavelet transforms are finding inversed use 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 applications, where such signals abound (Akay, 1997; Burrus, Gopinath, & Guo, 1998; Coifman & Wickerhauser, 1992; Devasahayam, 2000; Karabetsos, Papaodysseus, & Koutsouris, 1998; Liang & Nartimo, 1998; Quiroga, 1998; Quiroga, Roso, & Basar, 1999).

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 the requirement for stationary (Quiroga, 1998). Wavelet decomposition uses the fact that it is possible to resolve high-frequency components within a small time window, while only low-frequency 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 scale. The wavelet decomposition functions at level m and time location t_m can be expressed as the following equation:

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

where Ψ_m is the decomposition filter at the 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 scales. Wavelet packet analysis is an extension of the discrete wavelet transform (DWT) (Burrus et al., 1998) and it turns out that the DWT is only one of the much possible decomposition that could be performed on the signal. Instead of just decomposing the low-frequency component, it is therefore possible to subdivide the whole time-frequency plane into different time-frequency pieces as can be seen from Fig. 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 (Keeton & Schlindwein, 1997).

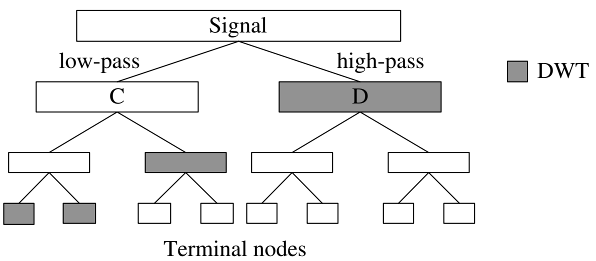

Fig. 3. Wavelet packet decomposition.

2.4. Fast-Fourier transform

The discrete Fourier transform (DFT) of a sequence can be evaluated directly by the following equation, which involves the order of N^2 complex multiplications and additions, so these processes need more computation time. Because of this problem, a quicker method must be used to evaluate this equation. The fast-Fourier transform (FFT) provides such methods

$$F(k\Omega) = \sum_{n=0}^{N-1} f(nT)e^{-j\Omega Tnk} \quad 0 \leqslant k \leqslant N-1 \tag{3}$$

where f is the impulse response of a finite impulse response filter, N is finite number, the Eq. (3) can be written in the form of

$$F(k\Omega) = \sum_{n=0}^{N-1} f(nT)W_N^{nk} \tag{4}$$

where $W_N = e^{-j(2\pi/N)}$. If N is even, then we can split the sequence f into even and odd terms. If $N = 1024$, then the FFT requires 1% of the time required for the discrete calculation of DFT (Banks, 1991).

2.5. Least square SVM

LS-SVM was proposed by Suykens and Vandewalle (1999). It is the reformulation of the standard SVM, which was intended by Vapnik in 1995 (Lukas et al., 2004). LS-SVMs generalization performance was compared with the standard SVM by Van Gestel et al. We review the LS-SVM formulation as follows: we are given a training data set of n data points $\{x_i, y_i\}_{i=1}^n$, where $x_i \in R^d$ is the ith input vector and $y_i \in R$ is the label of ith class. For binary classification, y_i takes only two values {-1,+1}, in regression stage it can take any real value. In kernel designs, the idea was to transform the input patterns into Reproducing Kernel Hilbert Space (RKHS) by a set of mapping functions $\phi(x)$ If reproducing kernel denoted in RKHS as $K = (x, x')$, which is defined as (Lukas et al., 2004; Suykens & Vandewalle, 1999)

$$K(x, x') = \phi(x) \cdot \phi(x)' \tag{5}$$

In the RKHS, a linear classification is performed. The discriminant function takes the form

$$y(x) = \sum_{i=1}^{n} w \cdot \phi(x) + b \tag{6}$$

where w is the weight vector in the RKHS, and $b \in R$ is bias term. The discriminant function of LS-SVM classifiers is constructed by minimizing the following primal problem:

$$\min_{w,b,\xi} P(w, b, \xi) = \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{n} \xi_i^2 \tag{7}$$

subject to the equality constraints $y_i - (w \cdot \phi(x_i) + b) = \xi_i \forall_i$, where the regularization parameter, $C > 0$. Note that the formulation for classifier design is same as that for regression. Traditionally, an inequality constraint is exploited on the slack variables ξ_i to punish the misclassified patterns only. Nevertheless, the formulation of LS-SVM produces penalty to all the patterns if their discriminant function is not equal to the corresponding target value, as the traditional regression formulation does. Standard Lagrangian techniques are used to derive the dual problem (Lukas et al., 2004; Suykens & Vandewalle, 1999). The Lagrangian for the primal problem is

$$L(w, b, \xi; \alpha) = \frac{1}{2}\|w\|^2 + \frac{C}{2}\sum_{i=1}^{n} \xi_i^2 + \sum_{i=1}^{n} \alpha_i\{yi - (w.\phi(x) + b) - \xi_i\} \tag{8}$$

where α_i are Lagrangian multipliers. The Karush–Kuhn–Tucker (KKT) conditions for the primal problem are

$$\frac{\partial L}{\partial w} = 0 \Rightarrow w = \sum_{i=1}^{n} \alpha_i \phi(x_i) \tag{9}$$

$$\frac{\partial L}{\partial b} = 0 \Rightarrow \sum_{i=1}^{n} \alpha_i = 0 \tag{10}$$

$$\frac{\partial L}{\partial \xi_i} = 0 \Rightarrow \alpha_i = C\xi_i \quad \forall_i \tag{11}$$

Together with the KKT conditions for Lagrangian multipliers α_i, Suykens and Vandewalle (1999) write them as a linear system, and suggest to solve two linear systems and then combine the results to get the final solution to the KKT linear system.

3. Methodology

Fig. 4 shows the used decision support system block diagram. It consists of three parts: (a) data acquisition and pre-processing, (b) feature extraction, and (c) classification by LS-SVM.

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 a 16-bit A/D conversion resolution and a 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 at 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 an ultrasonic image. The digitised data, which have 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.

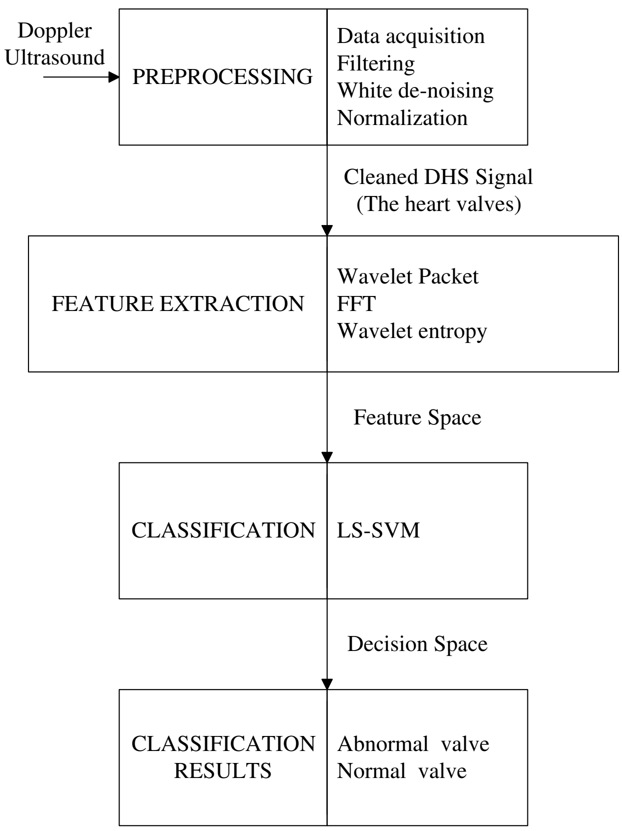

Fig. 4. The algorithm of the expert system.

3.1.1. 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 0.5–10 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.

3.1.2. 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 a 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.

3.1.3. Normalization

The DHS signals in this study were normalized using the following equation so that the expected amplitude of the signal is not affected by the rib cage structure of the patient,

$$\mathrm{DHS}_{\mathrm{signal}} = \frac{\mathrm{DHS}_{\mathrm{signal}}}{|(\mathrm{DHS}_{\mathrm{signal}})_{\max}|} \tag{12}$$

3.2. Feature extraction

Feature extraction is one of the important steps of pattern recognition so that it is the most important step of designing the decision support system based on pattern recognition because the best classifier performance will decrease if the features are not chosen well. The feature extraction stage must 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. In this study, the goal of the feature extraction is to extract features from these patterns for 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.

3.2.1. Wavelet packet decomposition: to decomposition

To evaluate the wavelet packet decomposition, the tree structure was used. Wavelet packet decomposition was applied to the DHS signal with the Daubechies-1 wavelet packets using the Shannon entropy as defined in the following equation. In this equation, s is the DHS signal and s_i is ith 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 Fig. 5,

$$E(s) = -\sum_i s_i^2 \cdot \log(s_i^2) \tag{13}$$

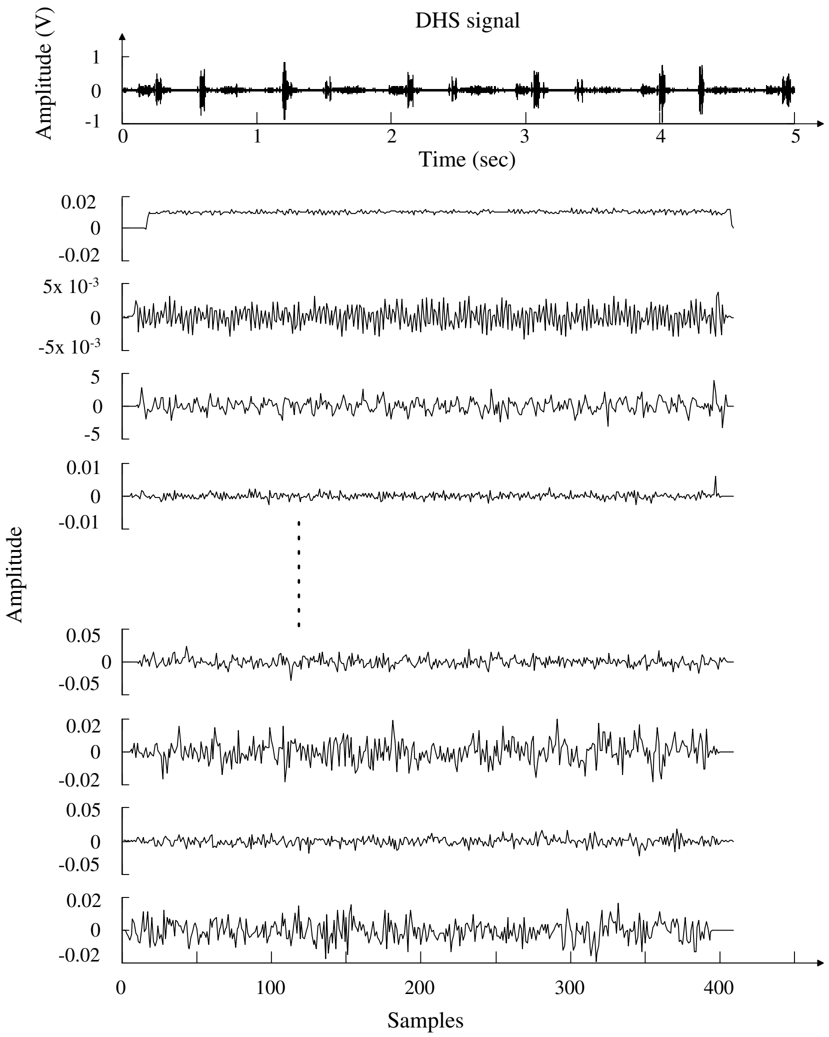

Fig. 5. The waveforms of terminal nodes (i = 1–256) of wavelet packet decomposition at eight-level of the DHS signal.

3.2.2. Fast-Fourier transform

The FFT is the most robust and understood one of the various time-frequency representations (Keeton & Schlindwein, 1997; Turkoglu et al., 2002). Convert to frequency domain of waveforms of terminal nodes was computed using a 512-point FFT. Because the length of the terminal node signal was less than 512, FFT pad of the terminal node signal was constituted with trailing zeros to length 512. A representative example of the FFT spectrum of waveform of a terminal node is indicated in Fig. 6.

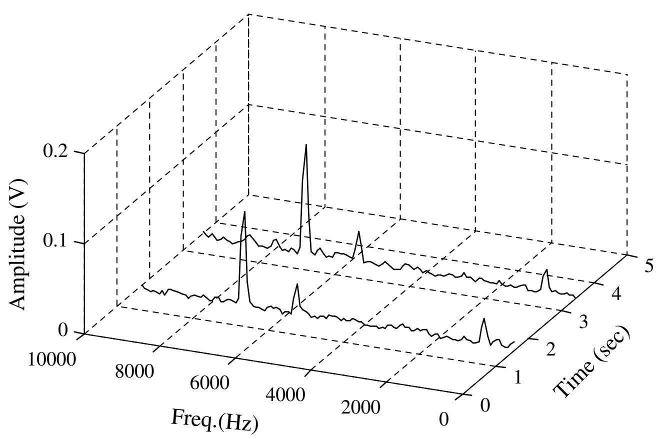

Fig. 6. The WPD-FFT based time-frequency representation.

3.2.3. Wavelet entropy

We next calculated the norm entropy as defined in the following equation of waveforms of the FFT spectrum:

$$E(s) = \sum_i |s_i|^{3/2} \tag{14}$$

where s is the FFT spectrum and s_i is ith coefficients of s Quiroga et al. (1999). The resultant entropy data, which were normalized with 1/1000, are plotted in Fig. 7. The plot of the entropy data includes 256 features obtained from 256 terminal nodes, where 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.

3.3. Classification using LS-SVM

The objective of the 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 LS-SVM classifier. The KULeuven's LS-SVMlab MATLAB/C Toolbox was used for the purpose of training and testing. RBF

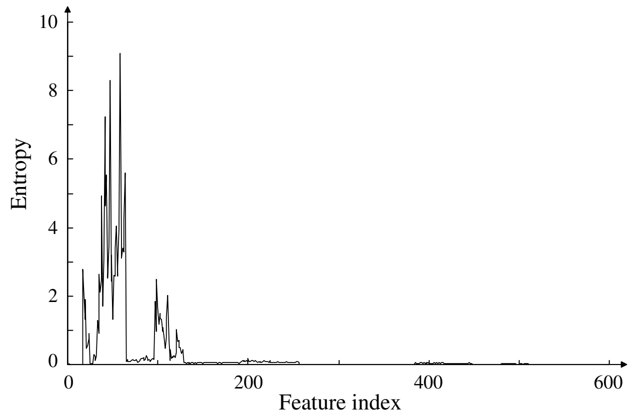

Fig. 7. The WP entropy of DHS signal.

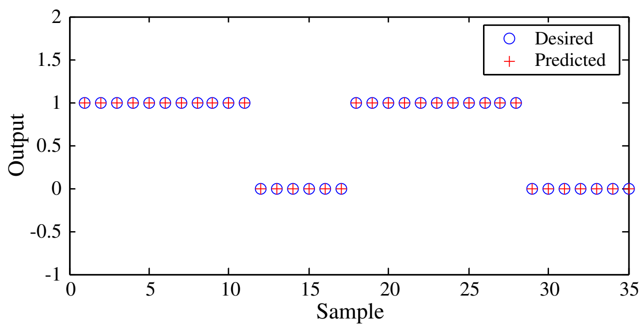

Fig. 8. The best test performance of LS-SVM model for mitral valve diseases.

Table 1
Threefold test performance of LS-SVM model

Data set (105)		Correct classified	Wrong classified	Performance (%)
Training sets	Test sets			
Set-1, set-2 (70)	Set-3 (35)	35	0	100
Set-1, set-3 (70)	Set-2 (35)	33	2	94.2
Set-2, set-3 (70)	Set-1 (35)	33	2	94.2
Average performance				96.13

kernel is used. Grid search algorithm is used to tune the γ regularization constant and σ width of RBF kernel parameters. The determined optimal γ value is 2.8439 and optimal σ value is 29.316 for predicting mitral valve diseases. Threefold cross-validation method was applied to the 105 experimental data sets for computing the validation of LS-SVM model. In k-fold cross-validation method, the data set is divided into k subsets, and the holdout method is repeated k times. At each time, $k-1$ subsets are used for training and kth subset is used for testing. Then the average error across all k trials is computed. Therefore, every data point gets to be in a test set exactly once, and gets to be in a training set k-1 times. Different evaluation methods were used for calculating the performance of the proposed expert system. The best test performance of LS-SVM model is graphically presented in Fig. 8. As seen in Fig. 8, LS-SVM model predicts the measured values at a high accuracy rate. Threefold test performance of LS-SVM model is shown in Table 1. The average correct classification rate is 96.13%.

4. Conclusions

In this study, a decision support system was developed for the interpretation of the DHS signals using pattern recognition, and demonstrated the diagnosis performance of this method on the heart mitral valves. The task of feature extraction was performed using the wavelet packet decomposition for multi-scale analysis, FFT for time-frequency representations, and the wavelet entropy, while classification was carried out by LS-SVM. The stated results show that the proposed method can make an efficient interpretation.

The feature choice was motivated by a realization that wavelet decomposition essentially is a representation of a signal at a variety of resolutions. In brief, the wavelet packet decomposition has been demonstrated to be an effective tool for extracting information from the DHS signals. Moreover, the proposed feature extraction method is robust against the 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 proved not to be trivially related with the energy and consequently with the amplitude of the 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.

This system is of better clinical application over others, especially for earlier survey of a population. However, the position of the ultrasound probe, which is used for data acquisition from the heart valves, must be taken into consideration by a physician. Although this decision support system was carried out on the heart mitral valves, similar results for the other valves (tricuspid and pulmonary) and other Doppler studies can be expected. Besides the feasibility of a real-time implementation of the decision support 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.

Acknowledgments

The author thanks Dr. Ibrahim Turkoglu for his valuable support and suggestion in improving the technical presentation of this paper. The author thanks Dr. Erdogan ILKAY and the Cardiology Department of the Firat Medicine Center, Elazig/Turkey for providing the DHS signals too.

References

Akay, M. (1997). Wavelet applications in medicine. *IEEE Spectrum, 34*(May), 50–56.
Akay, M., Akay, Y. M., & Welkowitz, W. (1992). Neural networks for the diagnosis of coronary artery disease. *International Joint Conference on Neural Networks, IJCNN, 2*, 419–424.
Bakhtazad, A., Palazoglu, A., & Romagnoli, J. A. (1999). Process data de-noising using wavelet transform. *Intelligent Data Analysis, 3*.
Banks, S. P. (1991). *Signal processing, image processing and pattern recognition*. NJ, USA: Prentice Hall.
Bishop, C. M. (1996). *Neural networks for pattern recognition*. Oxford: Clarendon Press.
Burrus, C. S., Gopinath, R. A., & Guo, H. (1998). *Introduction to wavelet and wavelet transforms*. NJ, USA: Prentice Hall.
Chan, B. C. B., Chan, F. H. Y., Lam, F. K., Lui, P. W., & Poon, P. W. F. (1997). Fast detection of venous air embolism is Doppler heart sound using the wavelet transform. *IEEE Transactions on Biomedical Engineering, 44*(4), 237–245.
Coifman, R. R., & Wickerhauser, M. V. (1992). Entropy-based Algorithms for best basis selection. *IEEE Transactions on Information Theory, 38*(2), 713–718.
Çomak, E., Arslan, A., & Türkoğlu, I. (2007). A decision support system based on support vector machines for diagnosis of the heart valve diseases. *Computers in Biology and Medicine, 37*(1), 21–27.
Devasahayam, S. R. (2000). *Signals and systems in biomedical engineering*. Kluwer Academic Publishers.
Dickhous, H., & Heinrich, H. (1996). Classifying biosignals with wavelet networks. *IEEE Engineering in Medicine and Biology*, 103–111.
Guler, I., & Kara, S. (1995). Detection of mitral stenosis by a pulsed Doppler flow meter and autoregressive spectral analysis method. *14th Conference of the biomedical engineering society of India. An international meeting, proceedings of the first regional conference, IEEE (pp. 2/91–2/92)*.
Izzetoglu, K., Erkmen, A. M., & Beksac, S. (1995). Intelligent classification of fetal Doppler blood velocity waveform abnormalities using wavelet transform and

vector quantization algorithm. *IEEE International Conference on Systems, Man and Cybernetics, Intelligent Systems for the 21st Century, 1*, 724–729.
Jing, F., Xuemin, W., Mingshi, W., & Wie, L. (1997). Noninvasive acoustical analysis system of coronary heart disease. In Biomedical engineering conference, proceedings of the 1997 sixteenth southern (pp. 239–241).
Karabetsos, E., Papaodysseus, C., & Koutsouris, D. (1998). Design and development of a new ultrasonic doppler technique for estimation of the aggregation of red blood cells. *Measurement, 24*, 207–215.
Madeira, M. M., Tokhi, M. O., & Ruano, M. G. (2000). Real-time implementation of a Doppler signal spectral estimator using sequential and parallel processing techniques. *Microprocessors and Microsystems, 24*, 153–167.
Nanda, N. C. (1993). *Doppler echocardiography* (2nd ed.). London: Lea & Febiger.
Philpot, E. F., Yoganathan, A. P., & Nanda, N. C. (1993). *Future directions in Doppler echocardiography*. *Doppler echocardiography*. London: Lea & Febiger Philadelphia.
Quiroga, R. Q. (1998). *Quantitative analysis of EEG signals: Time–frequency methods and Chaos theory*. Intitute of Physiology – Medical University Lübeck.
Quiroga, R. Q., Roso, O. A., & Basar, E. (1999). *Wavelet entropy: A measure of order in evoked potentials*. *Evoked potentials and magnetic fields* (Vol. 49). (pp. 298–302).
Saini, V. D., Nanda, N. C., & Maulik, D. (1993). *Basic principles of ultrasound and Doppler effect*. *Doppler echocardiography*. London: Lea & Febiger Philadelphia.
Suykens, J. A. K., & Vandewalle, J. (1999). Least squares support vector machine classifiers. *Neural Processing Letters, 9*(3), 293–300.
Turkoglu, I., Arslan, A., & Ilkay, E. (2002). A pattern recognition system for diagnose of the heart mitral valve diseases based on wavelet packet and neural network. *Fırat University, Journal of Science and Technology, 14*(1), 1–10.
Turkoglu, I., Arslan, A., & Ilkay, E. (2002a). A decision support system for diagnose of the heart valve diseases. *Journal of the Institute of Science and Technology of Sakarya University, 6*(2), 57–64.
Turkoglu, I., Arslan, A., & Ilkay, E. (2002b). An expert system for diagnosis of the heart valve diseases. *Expert Systems with Applications, 23*(3), 229–236.
Uguz, H., Arslan, A., & Türkoğlu, I. (2007). A biomedical system based on hidden Markov model for diagnosis of the heart valve diseases. *Pattern Recognition Letters*.
Wright, I. A., Gough, N. A. J., Rakebrandt, F., Wahab, M., & Woodcock, J. P. (1997). Neural network analysis of Doppler ultrasound blood flow signals: A pilot study. *Ultrasound in Medicine and Biology, 23*(5), 683–690.

EXPERT SYSTEMS WITH APPLICATIONS

An International Journal

Editorial Office: Jay Liebowitz, 966 Farm Haven Drive, Rockville, Maryland 20852, USA. Tel./Fax: (+1) 301-770-2978; e-mail: jliebow1@jhu.edu

Author enquiries: For enquiries relating to the submission of articles (including electronic submission where available) please visit this journal's homepage at http://www.elsevier.com/locate/eswa. You can track accepted articles at http://www.elsevier.com/trackarticle and set up e-mail alerts to inform you of when an article's status has changed. Also accessible from here is information on copyright, frequently asked questions and more.

Contact details for questions arising after acceptance of an article, especially those relating to proofs, are provided after registration of an article for publication.

Publication information: *Expert Systems with Applications* (ISSN 0957-4174). For 2009, volumes 36, 37 are scheduled for publication. Subscription prices are available upon request from the Publisher or from the Regional Sales Office nearest you or from this journal's website (http://www.elsevier.com/locate/eswa). Further information is available on this journal and other Elsevier products through Elsevier's website: (http://www.elsevier.com). Subscriptions are accepted on a prepaid basis only and are entered on a calendar year basis. Issues are sent by standard mail (surface within Europe, air delivery outside Europe). Priority rates are available upon request. Claims for missing issues should be made within six months of the date of dispatch.

Advertising information: Advertising orders and enquiries can be sent to: James Kenney, Elsevier Ltd., 32 Jamestown Road, London NW1 7BY, UK; phone: (+44) 207 424 4216; fax: (+44) 1865 853 136; e-mail: j.kenney@elsevier.com. Customers in the US and Canada can also contact: Mr Tino DeCarlo, Advertising Department, Elsevier Inc., 360 Park Avenue South, New York, NY 10010-1710, USA; phone: (+1) (212) 633 3815; fax: (+1) (212) 633 3820; e-mail: t.decarlo@elsevier.com.

Orders, claims, and journal enquiries: please contact the Regional Sales Office nearest you:

St. Louis: Elsevier, Customer Service Department, 11830 Westline Industrial Drive, St. Louis, MO 63146, USA; phone: (877) 8397126 [toll free within the USA]; (+1) (314) 4537076 [outside the USA]; fax: (+1) (314) 5235153; e-mail: JournalCustomerService-usa@elsevier.com

Amsterdam: Elsevier, Customer Service Department, PO Box 211, 1000 AE Amsterdam, The Netherlands; phone: (+31) (20) 4853757; fax: (+31) (20) 4853432; e-mail: JournalsCustomerServiceEMEA@elsevier.com

Tokyo: Elsevier, Customer Service Department, 4F Higashi-Azabu, 1-Chome Bldg, 1-9-15 Higashi-Azabu, Minato-ku, Tokyo 106-0044, Japan; phone: (+81) (3) 5561 5037; fax: (+81) (3) 5561 5047; e-mail: JournalsCustomerServiceJapan@elsevier.com

Singapore: Elsevier, Customer Service Department, 3 Killiney Road, #08-01 Winsland House I, Singapore 239519; phone: (+65) 63490222; fax: (+65) 67331510; e-mail: JournalsCustomerServiceAPAC@elsevier.com

USA mailing notice: *Expert Systems with Applications* (ISSN 0957-4174) is published 10 issues per annum in January, March, April, May, July, August, September, October, November, December by Elsevier Ltd. (The Boulevard, Langford Lane, Kidlington, Oxford OX5 1GB, UK). Periodical postage paid at Rahway NJ and additional mailing offices.

USA POSTMASTER: Send change of address: *Expert Systems with Applications*, Elsevier, Customer Service Department, 11830 Westline Industrial Drive, St. Louis, MO 63146, USA. Periodical postage paid at Rahway NJ and additional mailing offices.

AIRFREIGHT AND MAILING in USA by Mercury International Limited, 365, Blair Road, Avenel, NJ 07001.