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Pattern Recognition Letters 24 (2003) 617–629

Pattern Recognition Letters

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Classification of heart sounds using an artificial neural network

Tamer Ölmez, Zümray Dokur *

Department of Electronics and Communication Engineering, Istanbul Technical University, 80626 Maslak, Istanbul, Turkey

Received 25 September 2001; received in revised form 20 August 2002

Abstract

A novel method is presented for the classification of heart sounds (HSs). Wavelet transform is applied to a window of two periods of HSs. Two analyses are realized for the signals in the window: segmentation of the first and second HSs, and extraction of the features.

After the segmentation, feature vectors are formed by using the wavelet detail coefficients at the sixth decomposition level. The best feature elements are analyzed by using dynamic programming. Grow and learn (GAL) network and linear vector quantization (LVQ) network are used for the classification of seven different HSs.

It is observed that HSs of patients are successfully classified by the GAL network compared to the LVQ network.

Keywords: Heart sounds; Classification of murmurs; Artificial neural network; Segmentation of heart sounds; Wavelet transform

1. Introduction

Auscultation is a technique in which a stethoscope is used to listen to the sounds of a body. The structural defects of the heart are often reflected in the sounds the heart produces. Physicians use the stethoscope as a device to listen to a patient's heart and make a diagnosis accordingly. They are particularly interested in abnormal sounds, which may suggest the presence of a cardiac pathology and also provide diagnostic information. For instance, a very important type of abnormal sound is the "murmur", which is a sound caused by the turbulent flow of blood in the cardiovascular system. The timing and pitch of a murmur are of significant importance in the diagnosis of a heart condition, for example, murmurs during diastole are signs of malfunctioning of heart valves but murmurs during systole may correspond to either a pathological or healthy heart, depending on the acoustic characteristics of the murmurs.

Time–frequency/scale methods have been applied to characterize heart sounds (Debjais et al., 1997; Bently, 1996). In previous publications, the authors have discussed the characterization of heart murmurs using time–frequency methods over a number of cardiac cycles (Leung et al., 1998; Yoshida et al., 1997) and showed that features hence obtained were suitable for classification (Leung et al., 1999).

* Corresponding author. Fax: +90-212-2853565.
E-mail address: zumray@ehb.itu.edu.tr (Z. Dokur).

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PII: S0167-8655(02)00281-7

In this study, wavelet transform is proposed to analyze heart sounds (HSs) in time and frequency domains simultaneously. Each class of HSs contains characteristic and distinctive information that exists in time and frequency domains. Feature vectors are formed by using wavelet transform. Classification performance highly decreases if the right feature space is not constituted. Artificial neural networks (ANNs) are used as classifiers to increase the classification performance. The most prominent advantages of using an ANN as a classifier are: (i) Weights representing the solution are found by iteratively training, (ii) ANN has a simple structure for physical implementation, (iii) ANN can easily map complex class distributions, and (iv) generalization property of the ANN produces appropriate results for the input vectors that are not present in the training set.

In the literature, it is observed that multi-layer perceptron (MLP) (Lippmann, 1987) is widely used in the recognition of patterns with neural networks (Miller et al., 1992) and is also used to classify heart sounds (Barschdorff et al., 1995; Liang and Hartimo, 1998). One major problem encountered in MLP is its back-propagation algorithm (an iterative scheme) which takes too long time during learning. The second problem is the structure of the network, i.e., the number of hidden units and their interconnections, is defined by the programmer and the learning rule can modify only the connection weights. There is no rule which allows one to determine the necessary structure from a given application or training set. Lastly, the MLP may be caught by local minima, which decreases network performance.

In this study, an incremental and competitive learning network is proposed to handle the problems mentioned above and to increase the classification performance of HSs. In the literature, linear vector quantization (LVQ) and adaptive rezonance theory (ART) can be seen as the most basic schemes of the competitive learning network. A major advantage of the LVQ network is its fast learning speed. The major disadvantages are; it is not an incremental network, and the network generates feature vectors throughout the inside of a class homogeneously rather than concentrating them on the boundaries between classes. This causes the generation of an excessive number of feature vectors. ART2 (Carpenter and Grossberg, 1987) is a neural network that self-organizes stable recognition code patterns in real-time in response to arbitrary sequences of input patterns. The classification performance of the ART2 may decrease when the vigilance value is not carefully chosen. There is no direct way for choosing appropriate vigilance value, and a trial-and error process is usually time-consuming. The problem may be solved by using 'slow learning mode', but the learning speed of the ATR2 network slows down considerably. With 'fast learning' mode, the learning and clustering speed of ART2 models may improve; however, the non-centroid computation sometimes causes problems on the clustering results. The learning of a new pattern in ART2 tends to overwrite the previously stored information (Chin-Der and Stelios, 1997).

It is observed that incremental networks are widely used in the literature (Berlich et al., 1996; Burzevski and Mohan, 1996; Bruske and Sommer, 1995; Martinetz et al., 1993; Martinetz and Schulten, 1994; Fritzke, 1994, 1995). A number of approaches, advanced from SOM, have been proposed to achieve the objectives of retaining both the topology preserving and clustering properties. Fritzke (Fritzke, 1995) proposed a growing cell structure (GCS) for self-organizing clustering and topology preserving. The GCS approach starts the self-organizing with a k-dimensional simplex that is distributed over the input manifold. The GCS conditionally adds new nodes and removes old nodes based on a heuristic criterion that takes the relative winning frequency of a node or accumulated error into account, which is called a 'resource' of the output nodes. The resources of the winner and its neighbors determine the location of the added nodes. By computer simulation, Fritzke showed that output maps could be formed that resemble the topological structure of the input data in many different cases. To its simplicity, the competitive Hebbian rule has been used for topology learning in the growing neural gas (GCS) (Fritzke, 1994) and dynamic cell structure (Bruske and Sommer, 1995). However, these algorithms add and delete nodes based on the 'resource' used in GCS. This has created some complexity in its implementation.

In this study, grow and learn (GAL) is proposed as an incremental and competitive learning network to increase the classification performances of heart sounds. In a previous study (Ölmez et al., 1998) it is observed that GAL has fast training and classification, implementation simplicity, and satisfactory performance. Hence in order to carry out HS classification in real-time, we preferred to use GAL as an incremental neural network.

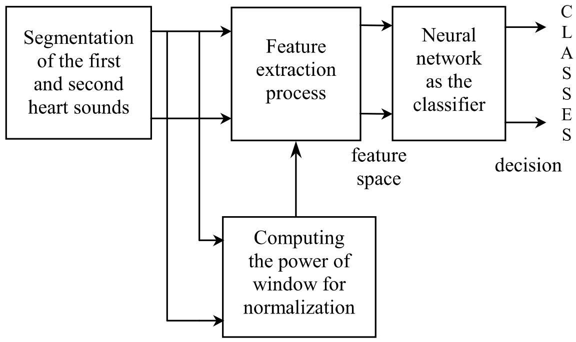

Fig. 1. Decision making blocks for the classification of HSs.

2. Methods

Decision making is performed in four stages: Segmentation of the first and second HSs, normalization process, feature extraction, and classification by the artificial neural network.

Firstly, a window is formed by the discrete data that contains two periods of HSs. Then, positions of the first (S1) and the second (S2) HSs within the window are determined (Huiying et al., 1997) by using wavelet detail coefficients at the sixth decomposition level.

By selecting S1 as the starting point, a new window which contains a single period of the HS is formed. Wavelet detail coefficients at the second decomposition level are used to determine the elements of the feature vectors.

After the feature vectors are formed, they are normalized, and then applied to the input of the neural networks for training or classification purposes. The overall block diagram of the decision making system is shown in Fig. 1.

2.1. Segmentation of the first and the second heart sounds

By decomposing signals into elementary building blocks that are well localized both in time and frequency, the wavelet transform can characterize the local regularity of signals. In this study, wavelet detail coefficients at the sixth decomposition level are used to determine S1 and S2. We observed that these coefficients give more significant information about the positions of them.

The actual HS recordings are very complicated and patterns of HSs vary significantly from recording to recording. There are some problems preventing us from using a simple threshold to pick up all the S1s and S2s. There might be extra 'peaks' due to the second part of the splitted S2 or other events, like systolic or diastolic clicks caused by dysfunction of the heart. In addition, some peaks, usually the first HSs, can be too weak compared with other peaks to be marked. Moreover, artefacts resembling the real peaks both in duration and amplitude might be recorded and will be selected as S1s or S2s. In order to solve these problems, modifications in the threshold setting and detection rules of picking S1s and S2s has been made. Firstly, simple threshold was used to mark all the peak locations of continuous segments exceeding the threshold limit. Then time intervals between two adjacent marks were calculated. According to the mean value and standard variation of the intervals, both lower and higher time interval limits were calculated. These limits were used to remove extra peaks and find lost weaker peaks.

After the suspected S1s and S2s have been marked, it is needed to identify which one is S1 and S2. Here, the identification is based on the following two facts: (i) the longest time interval between two adjacent peaks in the recording (within 20 s) is the diastolic period (from the end of S2 to the beginning of S1); (ii) the duration of the systolic period (from the end of S1 to the beginning of S2) is relatively constant compared to the diastolic one. After the longest time interval was found, the start and the end marks of that interval were set as S2 and S1 respectively. Then the intervals forward and backward from the longest interval on were checked. Those marks which destroyed constancy limitations of systolic and diastolic period were discarded and the rest S1s and S2s were identified. The artefacts were discarded in this identifying procedure.

2.2. Normalization process

Feature extraction processes are affected by the peak-to-peak magnitudes and the offset of the signal in the windowed HS signal. These effects are due to physiology, sex and age of the patient, and parameters of the measurement system. In the study, prior to the feature extraction process, the amplitude of the HS signal is adjusted so that the power spectrum of one period of the signal is normalized.

2.3. Feature extraction method

In this study, HS signals are sampled at 5512.5 frequency and analyzed within windows that contain 4096 discrete data.

The spectrum of the HS signal is divided into sub-bands to extract the discriminating information from the normal and abnormal HSs. Because HS signals are non-stationary, discrete

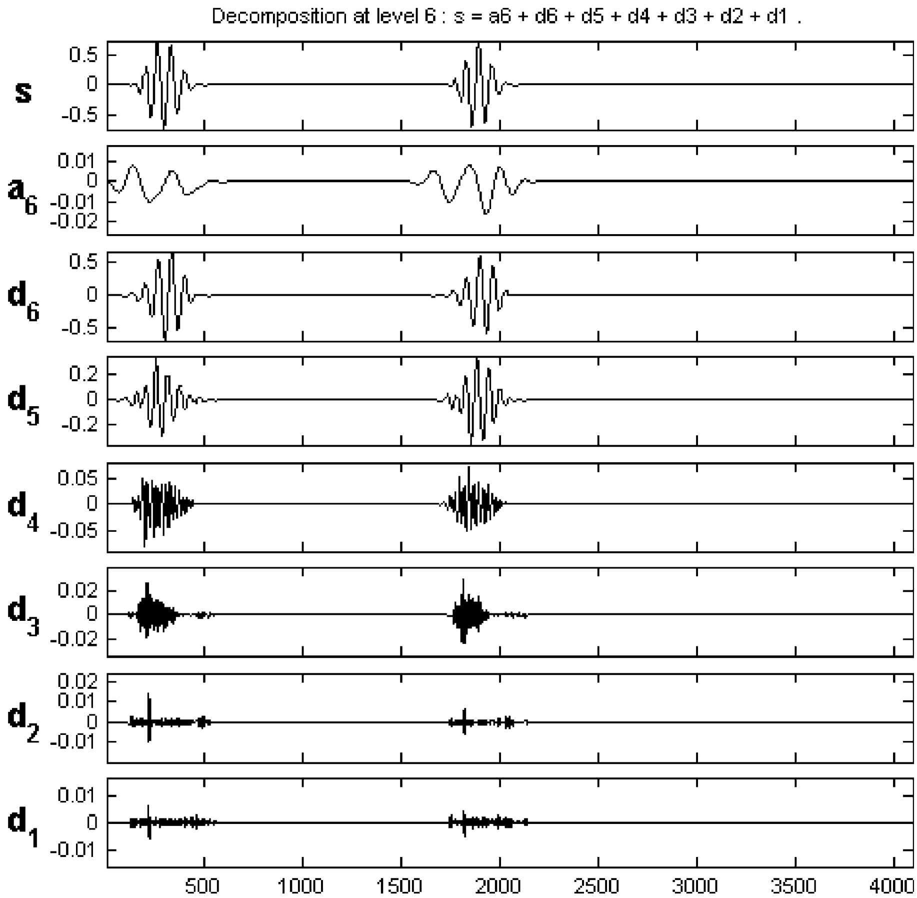

Fig. 2. Wavelet detail coefficients at the first-six decomposition levels (d^1–d^6) and wavelet approximation coefficients at the sixth level (a^6) for a normal subject. ***s*** is the original HS signal.

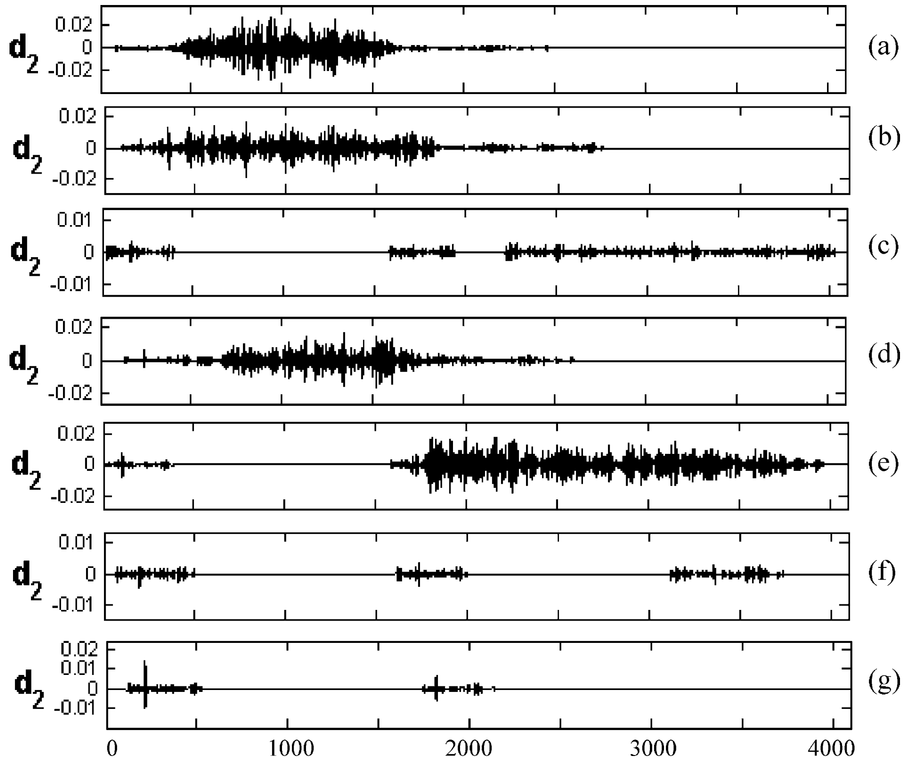

Fig. 3. Wavelet detail coefficients at the second decomposition level for (a) aortic stenosis, (b) mitral regurgitation, (c) mitral stenosis, (d) pulmonary stenosis, (e) aortic regurgitation, (f) summation gallop, and (g) normal HS.

wavelet transforms are involved for sub-band analysis. Wavelet coefficients are determined by using Daubechies-2 wavelets (Daubechies, 1994).

Fig. 2 shows wavelet detail coefficients at the first six decomposition levels, and wavelet approximation coefficients at the sixth level for a normal subject. These coefficients are obtained through a single period of HS signal. Fig. 3(a–g) show wavelet detail coefficients at the second decomposition level for aortic stenosis, mitral regurgitation, mitral stenosis, pulmonary stenosis, aortic regurgitation, summation gallop, and normal HS, respectively.

The signal formed by wavelet detail coefficients at the second decomposition level is splitted into 32 sub-windows that each contains 128 discrete

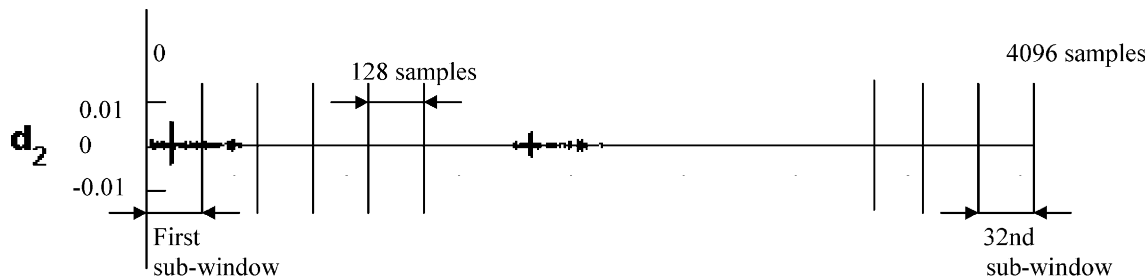

Fig. 4. 32 sub-windows on wavelet detail coefficients at the second decomposition level.

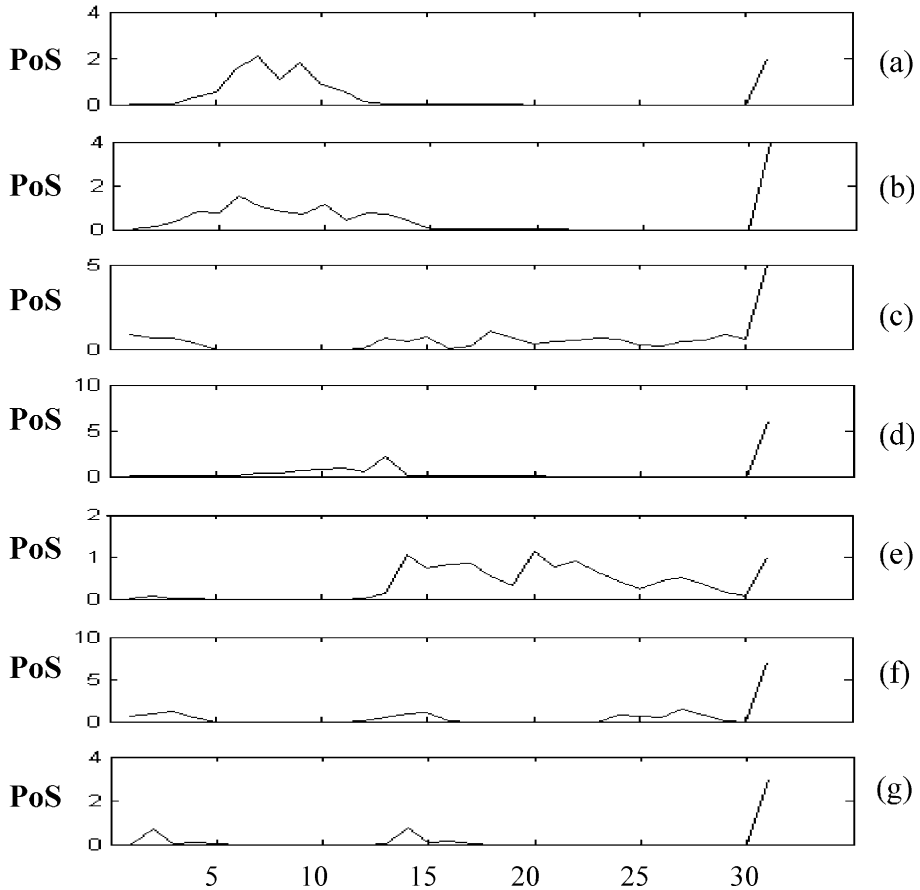

Fig. 5. Feature vector belonging to (a) aortic stenosis, (b) mitral regurgitation, (c) mitral stenosis, (d) pulmonary stenosis, (e) aortic regurgitation, (f) summation gallop, and (g) normal HS. (PoS: power of signal).

data. Fig. 4 shows the sub-windows on wavelet detail coefficients at the second decomposition level. The elements of the feature vectors are formed by the powers of the signals within these sub-windows. Fig. 5(a–g) show feature vectors for aortic stenosis, mitral regurgitation, mitral stenosis, pulmonary stenosis, aortic regurgitation, summation gallop, and normal HS, respectively.

3. Artificial neural networks

MLP (Lippmann, 1987) is frequently used in biomedical signal processing (Miller et al., 1992; Leung et al., 2000; Ölmez et al., 1998; Dokur and Ölmez, 2001; Dokur et al., 1998). It is observed that MLP has three disadvantages: (i) back-propagation algorithm takes too long time during the learning, (ii) the number of nodes in the hidden layers must be defined before the training (the structure is not automatically determined by the training algorithm), (iii) back-propagation algorithm may be caught by local minima, which decreases network performance. We observed these disadvantages in the previous studies (Ölmez et al., 1998; Dokur and Ölmez, 2001; Dokur et al., 1998). Especially, the number of nodes in the hidden layers could be defined after many trials, which took too long time. Moreover, the classification performance was not satisfactory. Therefore, in this study, MLP is not used in the comparisons with other networks.

We observed in previous studies (Ölmez et al., 1998; Alpaydın, 1990) that GAL network has advantages of fast training, implementation simplicity, and better performance over MLP. And also, the number of nodes of the GAL network is automatically determined during the training. Therefore, GAL network is proposed to classify the HSs in this study.

3.1. GAL network

Fig. 6 shows the structure of the GAL network. The network grows when it learns category definitions. The network has a dynamic structure; nodes and their connections (weights) are added during learning when necessary. The basic advantage of GAL network is its fast learning.

The GAL network is an incremental network for supervised learning. The output nodes of the GAL network are formed by choosing vectors from the training set. All vectors in the training set have their own classes. The procedure for the learning algorithm of the GAL network is as follows:

Step 1. Initially choose a number of vectors randomly from the training set as many as the number of classes. Each vector represents only one class. Initialize each chosen vector as an output node of the GAL. Initialize the iteration number to zero value.

Step 2. Increase the iteration number. If the iteration number is equal to the chosen maximum value, terminate the algorithm. Otherwise, go to step 3.

Step 3. Choose one vector denoted by x_i randomly from the training set. Compute the distances between each output node of the GAL and the input vector, and find the minimum distance as follows:

$$d_o = \sum_{j=1}^{N} (x_j - w_{oj})^2 \qquad d_m = \min_o (d_o) \tag{1}$$

where x_j is the jth element of the input vector $\boldsymbol{X}$, w_{oj} is the jth element of the oth node of the GAL, and N is the present number of input nodes. Compare the classes of the input vector and the mth node nearest to the input vector. If their classes are the same, go to Step 2. Otherwise go to Step 4.

Step 4. Include the input vector in the GAL network as a new output node. The elements of the input vector are assigned as the associated weights of the new output node of the GAL. Go to step 2.

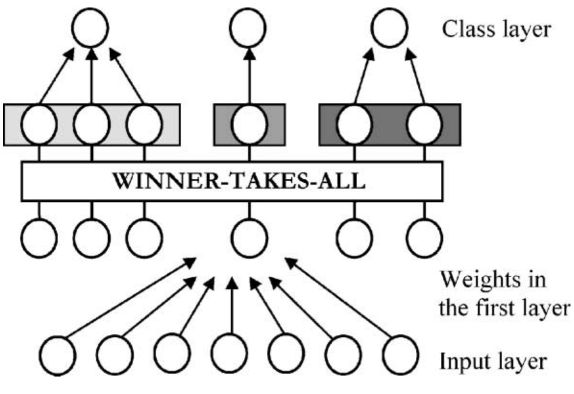

Fig. 6. Structure of the GAL network.

During the learning with GAL, nodes generated depend on the order of the input vectors. A node previously stored may become useless when another node nearer to the class boundary is generated. When a useless node is eliminated from the GAL network, the classification performance of the network does not change. In order to decrease the network size, these nodes are extracted from the GAL by the forgetting algorithm given below.

Step 1. Select the maximum iteration number as the number of output nodes in the GAL. Initialize the iteration number as zero.

Step 2. Increase the iteration number. If the iteration number is equal to the maximum value, terminate the algorithm. Otherwise, go to Step 3.

Step 3. Choose the next node from the GAL in an order. This node is extracted from the network and is given as an input vector to the GAL network.

Step 4. Compute Eq. (1). Compare the classes of the input vector and the mth node of the GAL. If their classes are not the same, go to Step 5. Otherwise, go to Step 3.
Step 5. Include the input vector again in the GAL. Go to 2.

4. Computer simulations

In this study, HSs are categorized into seven classes: aortic stenosis, mitral regurgitation, mitral stenosis, pulmonary stenosis, aortic regurgitation, summation gallop, and normal. 28 subjects, each four subjects having the same type of HSs, are involved in the study. Therefore, there are 28 (4×7) records for the analysis of the HSs. Each record contains 12 periods of HSs. Training set contains 336 (28×12) feature vectors, 48 ($28 \times 12/7 = 48$) feature vectors belonging to each class. Test set is formed in the same way involving different subjects. It also contains 336 feature vectors, and is different from the training set.

Fig. 7(a–g) show the HSs of aortic stenosis, mitral regurgitation, mitral stenosis, pulmonary stenosis, aortic regurgitation, summation gallop, and normal, respectively. Each HS signal in Fig. 7 contains 4096 discrete data. HS signals are sampled at 5512.5 frequency and analyzed within subwindows of 128 discrete data long.

Table 1 shows the classification performance, the number of nodes and the training time of each

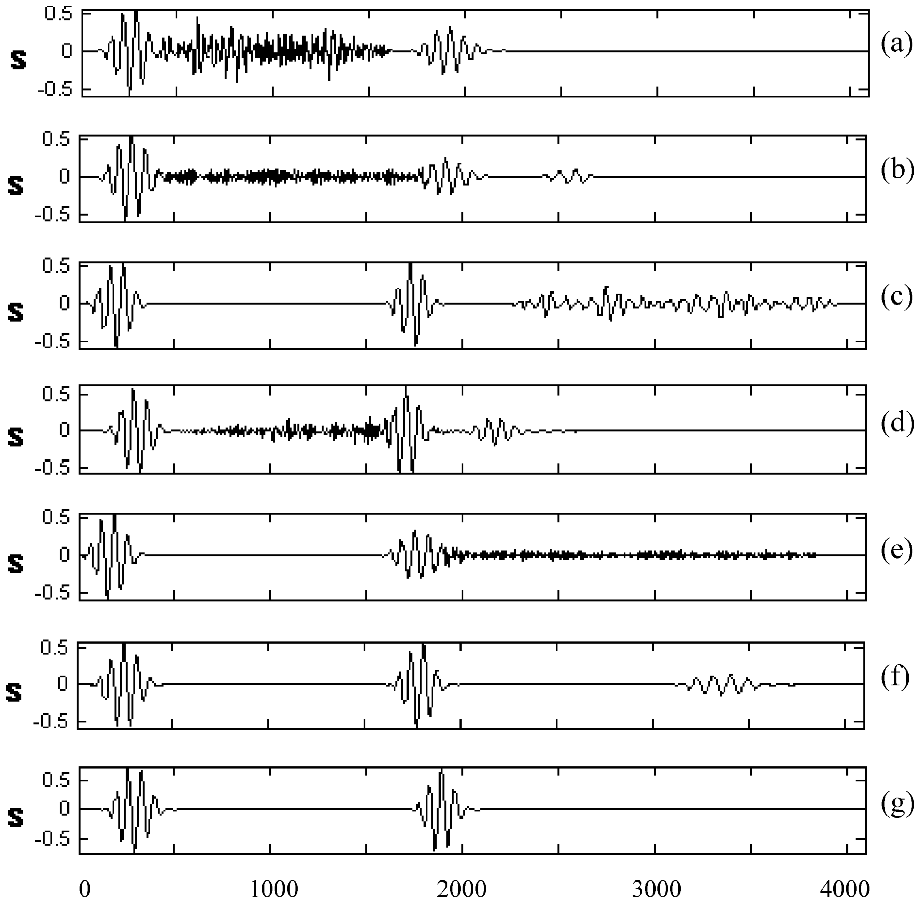

Fig. 7. (a) Aortic stenosis, (b) mitral regurgitation, (c) mitral stenosis, (d) pulmonary stenosis, (e) aortic regurgitation, (f) summation gallop, and (g) normal HS.

Table 1
Performances obtained by using the GAL and the LVQ networks

Performances	GAL network	LVQ network
Number of nodes	8	16
Training time	4.3 s	5.1 s
Classification of aortic stenosis	47/48	44/48
Classification of mitral regurgitation	48/48	46/48
Classification of mitral stenosis	48/48	47/48
Classification of pulmonary stenosis	47/48	46/48
Classification of aortic regurgitation	48/48	46/48
Classification of summation gallop	48/48	48/48
Classification of normal heart sound	48/48	47/48

network. For learning process of both networks, iteration number is selected as 3500. Iteration number for pruning process of the GAL is selected as the number of output nodes found during learning. The results presented in the table demonstrate that GAL network outperforms LVQ in terms of number of nodes, and classification performance for seven different HSs.

Fig. 8(a–g) show wavelet detail coefficients at the sixth decomposition level for aortic stenosis, mitral regurgitation, mitral stenosis, pulmonary stenosis, aortic regurgitation, summation gallop, and normal signal, respectively.

The signal formed by the wavelet detail coefficients at the second decomposition level is splitted into 32 sub-windows of 128 discrete data long. The elements of the feature vectors are formed by the powers of the signals within these sub-windows. The number of the sub-windows determines the dimension of the feature vectors, and affects the distribution of the vectors in the feature space. In order to increase the dimension of the feature vector, the signal formed by the wavelet detail coefficients at the second decomposition level may be splitted into more than 32 sub-windows. In this case, classification performances of the HSs will increase. However, this will lead to increase the overall computational time.

The best features are searched by applying divergence analysis (Cohen, 1986) to the training set of 336 vectors. Divergence analysis enables to determine the best features (from a given number of features) which increase the classification performance, and it gives information to determine the dimension of the feature vectors. From the calculated 32 features (power values) a subset of the best 16 features is searched by using dynamic programming (Cohen, 1986) according to the divergence values. The ordering of the first sixteen elements in each feature vector is as follows:

1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16
r_{28}	r_6	r_8	r_{11}	r_{10}	r_7	r_{24}	r_{25}	r_{27}	r_{30}	r_1	r_{18}	r_{19}	r_{29}	r_{20}	r_{16}

$$\boldsymbol{R} = [r_{28} \quad r_6 \quad r_8 \quad r_{11} \quad r_{10} \quad r_7 \quad r_{24} \quad r_{25} \quad r_{27} \quad r_{30} \quad r_1 \quad r_{18} \quad r_{19} \quad r_{29} \quad r_{20} \quad r_{16}] \tag{2}$$

where r_i is the power of the ith sub-window, and $\boldsymbol{R}$ represents the new ordering of the first 16 elements of the new feature vectors. Fig. 9 shows the divergence values according to the dimension of the feature vectors. In an other analysis, the elements of the new feature vectors are formed by the best

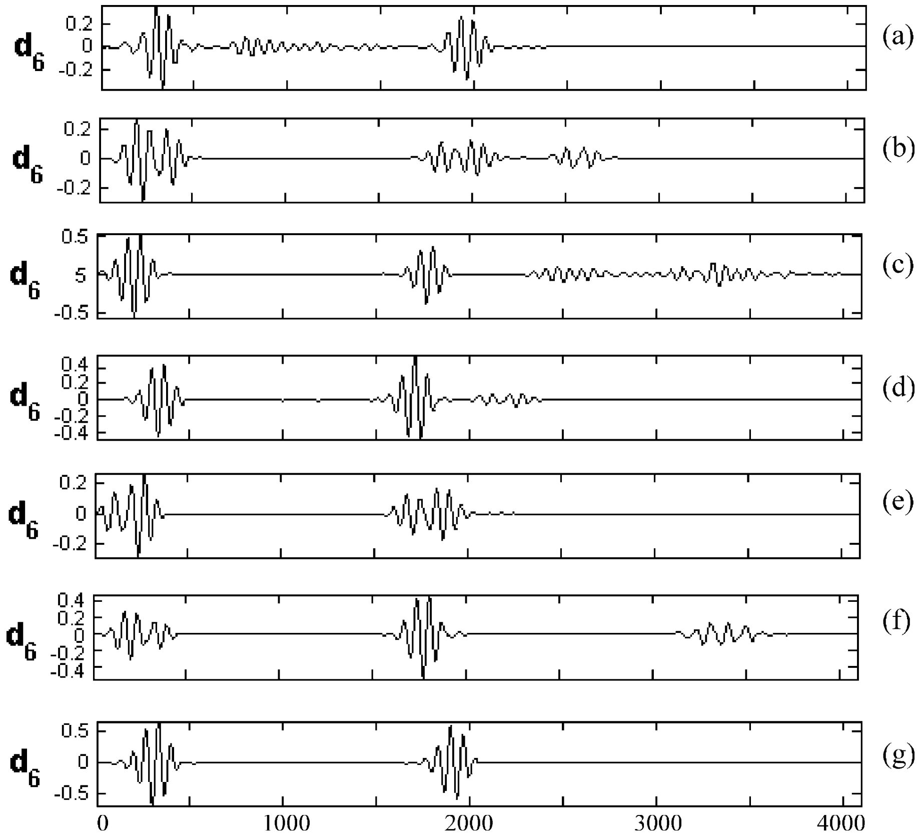

Fig. 8. Wavelet detail coefficients at the sixth decomposition level for (a) aortic stenosis, (b) mitral regurgitation, (c) mitral stenosis, (d) pulmonary stenosis, (e) aortic regurgitation, (f) summation gallop, and (g) normal HS.

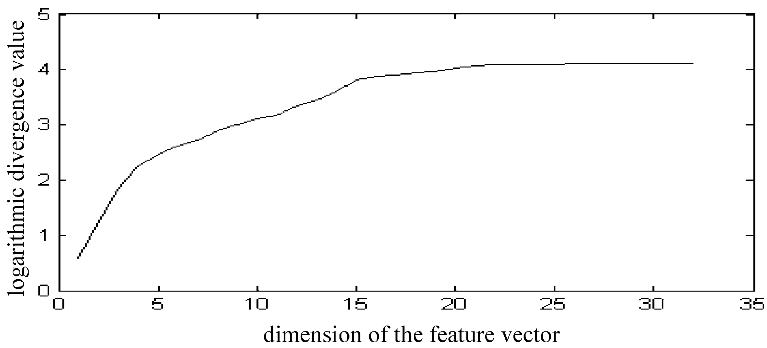

Fig. 9. Divergence change for different dimension values of the feature vectors.

16 features shown in the ***R*** vector. We obtained the same results in Table 1 except for the training time value. The training time decreased to half of the value presented in Table 1.

One reason of the incorrect identification is the high level interfering signals like speech, crying, or other ambient noise. Sometimes the sudden release of stethoscope from the patients for a short time during the recording of data has also resulted incorrect detection. It is observed that large murmurs that overlap S1 or S2 will make the correct identification impossible. And also, it has been found that the signal to noise ratio (SNR) of the phonocardiogram is crucial in the system performance. Poor SNR may lead to wrong identifications of systolic and diastolic regions, hence wrong features being extracted and eventually a wrong classification.

5. Conclusions

It is observed that four (Leung et al., 1999) and six (Leung et al., 2000) different HSs are classified by using time–frequency analysis. In the former study, fifteen features were extracted from the murmurs of four groups of patients. The features represented the energy distribution across the time–frequency plane. These features were used to train a two-dimensional SOM. However, satisfactory classification performances were not obtained. In the latter study, six different heart sounds were classified by a probability neural network. Training set consisted of a different group of 18 non-pathological and 37 pathological HSs. The input feature vector contained 54 features from systole, 25 features from diastole, and two features from the magnitudes of the systolic and diastolic signals which altogether summed up to 81 features. Since the number of features used in this study was high, the overall computational time increased.

LVQ and ART can be seen as the most basic schemes of the competitive learning network. GAL is also a competitive learning network. Although GAL and ART2 are competitive learning networks, they differ from each other in some aspects. ART2 uses unsupervised learning scheme, and therefore does not need any pre-specified number of clusters. GAL is trained by a supervised learning scheme, and consists of only feed-forward connections. However, ART2 consists of both feed-forward and backward connections. ART2 also utilizes a vigilance value for the clustering of input patterns and for the generation of new clusters. There is no direct way for choosing appropriate vigilance value, and a trial-and error process is usually time-consuming. The problem may be solved by using 'slow learning mode'. The significant increase of time for learning and clustering may become a drawback when ART2 models with 'slow learning' or 'intermediate learning' are used in applications with stringent time constraints. With 'fast learning' mode, the learning and clustering speed of ART2 models may improve; however, the non-centroid computation sometimes causes problems on the clustering results (Chin-Der and Stelios, 1997). If appropriate vigilance value is not chosen, and the high level interfering signals like speech, crying, or other ambient noise are existed during the recording of data, ART2 will generate too many classes (more than seven classes in this study). Therefore, classification performances will decrease.

In the literature, there exist other neural network models for category perception (Basak et al., 1993; Chin-Der and Stelios, 1997). GAL forms categories and uses them as address book to learn the class or concept. Basak presented a connectionist model for category perception. In the work, the capability of the network was shown to learn and recognize multiple objects simultaneously under a noisy environment. It can be thought as an abnormal HS consisting of multiple objects, like S1, S2 and murmurs, under interfering signals (speech, crying, or other ambient noise). Connectionist model presented by Basak can be used to distinguish S1, S2 and murmurs from each other. However, the complex process of iterative loops in connectionist model increases the processing time for recognizing and learning. In a real-time decision making system for HSs, overall processing time (feature extraction + classification process) must be less than 0.8 (60/75; 1 min/normal heart rate) seconds. Since the overall processing time of GAL network is less than 0.2 s, it is possible to carry out HS classification in real-time.

In our previous studies (Ölmez et al., 1998; Dokur, 2002; Dokur and Ölmez, 2001), we have developed novel incremental neural networks for the classification of biomedical signals and images. Genetic algorithms were used to determine the topologies of these networks. We observed that training and classification time, and complexities of neural network structures are important parameters in the design of real-time classifiers. In the literature, growing neural Gas is widely used as an incremental neural network for self-organizing clustering and topology preserving. However, GCS generates too many nodes to represent the distribution of classes. As a consequence, both, the training and the classification time increase drastically with the maximum number of nodes that the network is allowed to allocate (Berlich and Kunze, 1997). Also, the training algorithm of the network adds and deletes nodes based on the 'resource' used in GCS. This introduces some complexity in its implementation. In this study, we prefer GAL network as a simple structured classifier in order to carry out HS classification in real-time. The proposed GAL network provides 99% classification performance for seven different heart sounds after a short training time. Since the overall processing time of GAL network is less than 0.2 s, it is possible to carry out heart sound classification in real-time.

In this study, seven HSs are successfully classified by utilizing the wavelet transform and GAL network together. It is observed that wavelet transform increases the classification performance. There exist more than seven HS categories in clinical area. Classification performance usually decreases as the number of categories increases. Since wavelet transform gives successful classification results, in a future study, wavelet transform can still be proposed for the classification of more than seven HS categories. Satisfactory classification performances will be obtained by utilizing wavelet transform and GAL network together.

References

Alpaydın, E., 1990. Neural models of incremental supervised and unsupervised learning. PhD Thesis, Ecole Polytechnique De Lausanne, Switzerland.

Barschdorff, D., Ester, S., Most, E., 1995. Phonocardiogram analysis of congenital and acquired heart diseases using artificial neural networks. Advances in Fuzzy Systems-Applications and Theory (3), Comparative approaches to medical reasoning, World Scientific Publishing Co., 271–288.

Basak, J., Murthy, C.A., Chaudhury, S., Majumder, D.D., 1993. A connectionist model for category perception: theory and implementation. IEEE Transactions on Neural Networks 4 (2), 257–269.

Bently, P.M., 1996. Time–frequency analysis of native and prosthetic heart valve sounds. PhD Thesis, Electrical and Electronics Department, University of Edinburgh.

Berlich, R., Kunze, M., Steffens, J., 1996. A comparison between the performance of feed forward neural networks and the supervised growing neural gas algorithm. In: 5th Artificial Intelligence in High Energy Physics Workshop, Lausanne, World Scientific.

Berlich, R., Kunze, M., 1997. A comparison between the performance of feed forward neural networks and the supervised growing neural Gas algorithm. Nuclear Instruments and Methods in Physics Research A 389, 274–277.

Bruske, J., Sommer, G., 1995. Dynamic cell structure learns perfectly topology preserving map. Neural Computation 7 (4), 845–865.

Burzevski, V., Mohan, C.K., 1996. Hierarchical growing cell structures, In: ICNN96: Proceedings of the International Conference of the Neural Networks.

Carpenter, G.A., Grossberg, S., 1987. ART2: self-organizing of stable category recognition codes for analog input patterns. Applied Optics 26, 4919–4930.

Chin-Der, W., Stelios, C.A.T., 1997. A comparative study of self-organizing clustering algorithms Dignet and ATR2. Neural Networks 10 (4), 737–753.

Cohen, A., 1986. Biomedical Signal Processing, Vol. II, Boca Raton-Florida: CRC Press Inc., 75–79.

Daubechies, I., 1994. Ten Lectures on Wavelets. Capital City Press, Vermont.

Debjais, F., Durand, L.G., Ouo, Z., Guarlo, R., 1997. Time–frequency analysis of heart murmurs. Part II: optimisation of time–frequency representations and performance evaluation. Medical & Biological Engineering & Computing 35, 480–485.

Dokur, Z., Ölmez, T., Yazgan, E., 1998. Classification of MR and CT images using genetic algorithms. In: 20th Annual International Conference of the IEEE-EMBS, 20(3), Hong Kong, 1418–1421.

Dokur, Z., Ölmez, T., 2001. ECG beat classification by a novel hybrid neural network. Computer Methods & Programs in Biomedicine 66 (2–3), 167–181.

Dokur, Z., 2002. Segmentation of MR and CT images using a hybrid neural network trained by genetic algorithms. Neural Processing Letters 16 (3), in press.

Dokur, Z., Ölmez, T., 2002. Segmentation of ultrasound images by using a hybrid neural network. Pattern Recognition Letters 23 (14), 1825–1836.

Fritzke, B., 1994. A growing neural Gas network learns topology. In: G. Tesauro, D.S. Touetzky, T.K. Leen (Eds.), Advances in Neural Information Processing Systems, Vol. 7, Cambridge MA: MIT Press.

Fritzke, B., 1995. Growing cell structure—a self-organizing network for unsupervised and supervised learning. Neural Networks 7 (9), 1441–1460.

Huiying, L., Sakari, L., Liro, H., 1997. A heart sound segmentation using wavelet decomposition and reconstruction. In: Proceedings of the 19th Annual International Conference of the IEEE-EMBS, Chicago, 1630–1633.

Leung, T.S., White, P.R., Collis, W.B., Brown, E., Salmon, A.P., 1998. Acoustic diagnosis of heart diseases. In: Proceedings of the 3rd International Conference on Acoustical and Vibratory Surveillance Methods and Diagnostic Techniques, France, 389–398.

Leung, T.S., White, P.R., Collis, W.B., Brown, E., Salmon, A.P., 1999. Characterisation of paediatric heart murmurs using self-organising map. In: Proceedings of the 21st Annual International Conference of the IEEE-EMBS, Atlanta, 926.

Leung, T.S., White, P.R., Collis, W.B., Brown, E., Salmon, A.P., 2000. Classification of heart sounds using time–frequency method and artificial neural networks. In: Proceedings of the 22nd Annual International Conference of the IEEE-EMBS, Chicago, 988–991.

Liang, H., Hartimo, L., 1998. A heart sound feature extraction algorithm based on wavelet decomposition and reconstruction. In: Proceedings of the 20th Annual International Conference of the IEEE-EMBS, Hong Kong, 1539–1542.

Lippmann, R.P., 1987. An introduction to computing with neural nets. IEEE ASSP Magazine, 4–22.

Martinetz, T., Berkovich, S.G., Schulten, K., 1993. Neural-gas network for vector quantization and its application to time-series prediction. IEEE Transactions on Neural Networks 4 (4), 558–569.

Martinetz, T., Schulten, K., 1994. Topology representation networks. Neural Networks 7 (3), 507–522.

Miller, A.S., Blott, B.H., Hames, T.K., 1992. Review of neural network applications in medical imaging and signal processing. Medical & Biological Engineering & Computing 30, 449–464.

Ölmez, T., Dokur, Z., Yazgan, E., 1998. Classification of ECG waveforms using a novel neural network. In: 20th Annual International Conference of the IEEE-EMBS, 20(3), Hong Kong, 1616–1619.

Yoshida, H., Shine, H., Yana, K., 1997. Instantaneous frequency analysis of systolic murmur for phonocardiogram. In: Proceedings of the 19th Annual International Conference of the IEEE-EMBS, Chicago, 1645–1647.