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Heart sound classification using wavelet transform and incremental self-organizing map

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ABSTRACT

Determination of heart condition by heart auscultation is a difficult task and requires special training of medical staff. Computerized techniques suggest objective and more accurate results in a fast and easy manner. Hence, in this study it is aimed to perform computer-aided heart sound analysis to give support to medical doctors in decision making. In this study, a novel method is presented for the classification of heart sounds (HSs). Discrete wavelet transform is applied to windowed one cycle of HS. Wavelet transform is used both for the segmentation of S1–S2 sounds and determination of the features. Based on the third, fourth and the fifth decomposition-level detail coefficients, the timings of S1–S2 sounds are determined by an adaptive peak-detector. For the feature extraction, powers of detail coefficients in all five sub-bands are utilized. In the classification stage, Kohonen's SOM network and an incremental self-organizing map (ISOM) are examined comparatively. In order to increase the performance of heart sound classification, an incremental neural network is proposed in this study. It is observed that ISOM successfully classifies the HSs even in noisy environment.

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 the 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.

In the literature, it is observed that time–frequency/scale methods have been applied to characterize heart sounds [1,2]. In previous publications, the authors have discussed the characterization of heart murmurs using time–frequency methods over a number of cardiac cycles [3,4].

The acoustic signals from the heart contain information which cannot be analyzed by the human ear [5]. The sensitivity of the ear in regard to frequency follows a logarithmic scale. The ear hears changes in frequency better than changes in intensity. Sounds with higher frequencies are perceived as being louder than those with lower frequencies of same intensity. Changes in frequency may be interpreted as changes in intensity. In the presence of high-frequency sounds, the ear may be

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unable to detect low-frequency ones which follow immediately [6]. Recent advances in data recording technology and digital signal processing have made it possible to record and analyze the sound signals from the heart. However, for computer analysis of the acoustic signals from the heart, it is essential that different components of heart cycle can be timed and separated [7].

Recent advances in information technology systems, in digital electronic stethoscopes, in acoustic signal processing and in pattern recognition methods have inspired the design of systems based on electronic stethoscopes and computers [8,9]. In the last decade, many research activities were conducted concerning automated and semi-automated heart sound diagnosis, regarding it as a challenging and promising subject. Many researchers have conducted research on the segmentation of the heart sound into heart cycles [10–12], the discrimination of the first from the second heart sound [13], the analysis of the first and the second heart sounds and the heart murmurs [14–17], and also on feature extraction and classification of heart sounds and murmurs [18–23].

In the literature, it is observed that wavelet transforms have been frequently used to extract features from heart sounds [20–23]. Andrisevic et al. determined the features of heart sounds by using wavelet transform and principle component analysis [20]. The heart sounds were classified into two categories by a neural network with a specificity of 70.5% and a sensitivity of 64.7%. Gupta et al. determined the features of heart sounds by using wavelet transform [21]. Heart sounds were classified into three categories by Grow and Learn network with a total performance of 96%. Uguz et al. determined the features of heart sounds by using wavelet transform and short-time Fourier transform [22]. The heart sounds were classified into two categories by a hidden Markov model with a specificity of 92% and a sensitivity of 97%. Comak et al. analyzed the Doppler signals of heart valves by using wavelet transform and short-time Fourier transform [23]. The heart sounds were classified into two categories by the least-squares support vector machine with a specificity of 94.5% and a sensitivity of 90%.

In the literature, it is also observed that wavelet transform is frequently used to classify biological signals [12,14,18,20, 24–28]. In this study, wavelet transform is used both for the segmentation of the S1–S2 sounds (the first and the second heart sounds) and determination of the features. In order to increase the performance of heart sound classification, an incremental neural network is proposed.

2. Methods

The decision-making process comprises of three main stages. At the first stage, S1–S2 sounds are segmented, i.e. their timings are determined. S1–S2 sounds are used to extract the features of the heart sounds [25]. At the second stage, feature vector elements are formed by using the wavelet plane [25]. At the last stage, classification process is realized by an artificial neural network. Fig. 1 shows the stages used in the decision-making process.

2.1. Segmentation of S1–S2 sounds

The size of rectangular window is determined so that one cycle of HS is contained in this window. The dependence of the segmentation method on the offset and the peak-to-peak magnitude of the signal are decreased by normalization. After the normalization, heart sounds are filtered by wavelet transform for the magnification of the two components of HSs: S1–S2. Lastly, timings of the S1–S2 sounds are determined by an adaptive peak-detector. Fig. 2 shows the blocks of segmentation process for HSs [25].

2.1.1. Normalization

As the spectrum of the HS signals contains a band of frequencies in the range of 5–500 Hz, it is sufficient to set the sampling frequency of HSs to 2000 Hz for computerized analysis. First, a window which is formed by 1700 discrete data is selected, so that it contains one cycle of HS. Then, mean value of the HS signal and peak-to-peak magnitudes of the windowed HS signal are normalized to 0 and 1 V, respectively.

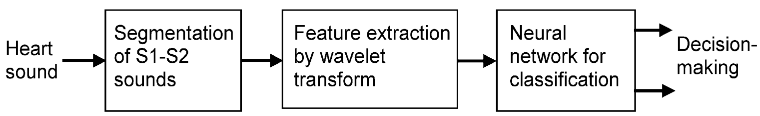

Fig. 1. Stages used in the decision making process.

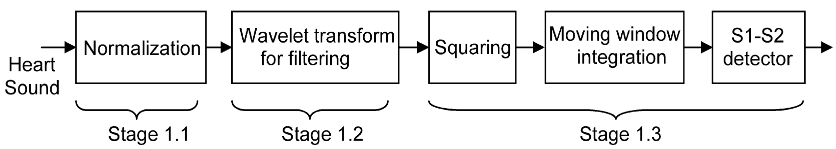

Fig. 2. Stages of the segmentation process for HSs.

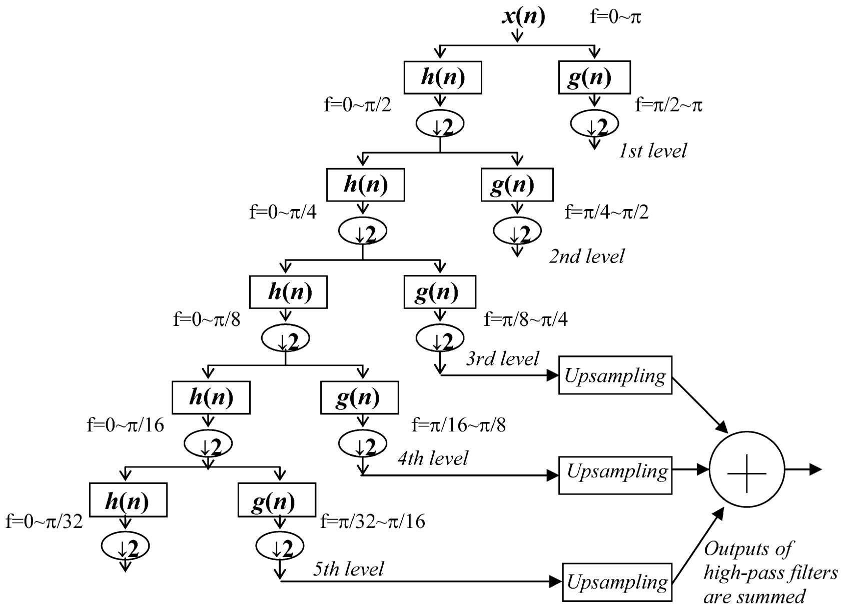

Fig. 3. Sub-bands used for the magnification of S1–S2 sounds on the wavelet tree. $g(n)$ and $h(n)$ represent half-band high-pass and low-pass filters, respectively [25].

2.1.2. Filtering of heart sounds by using wavelet transform

The spectrum of S1 and S2 components consists of frequencies in the range of 20–200 Hz. Considering the 2000 Hz sampling frequency, sub-bands which represent the third, the fourth and the fifth decomposition-level detail coefficients are summed. The spectrum of the summed sub-band corresponds to approximately a band of 20–200 Hz. S1 and S2 sounds are amplified by selecting these three sub-bands. Fig. 3 shows the sub-bands used for the magnification of S1–S2 sounds on the wavelet tree.

In the previous study [25], for fourteen different heart sounds, different mother wavelets and sub-bands which enable the magnification of the S1–S2 sounds were examined. It was observed that when the eighteenth-order 'symlet' mother wavelet was used, filters representing the detail coefficients at the third, fourth and fifth levels amplified the magnitudes of S1–S2 sounds better, and suppressed the other sounds except from S1–S2 sounds.

2.1.3. Determination of S1–S2 locations in the heart sound

The outputs of the sub-bands are up-sampled and summed. Then, the summed output is squared ($\mathrm{HS}_{\mathrm{SS}}$). The squared output is smoothed by the moving window integration as follows:

$$\mathrm{HS}_{\mathrm{MSS}}(k) = \frac{1}{2M+1} \cdot \sum_{i=-M}^{M} \mathrm{HS}_{\mathrm{SS}}(k+i), \tag{1}$$

where HS represents any type of heart sound, $\mathrm{HS}_{\mathrm{SS}}$ represents the squared output, $\mathrm{HS}_{\mathrm{MSS}}$ represents the smoothed output. M is empirically selected as 150. Hills corresponding to the locations of the S1–S2 sounds become apparent after the smoothing operation.

First of all, the peaks of the hills are found by a simple peak detector. Then, the locations of S1 and S2 sounds are determined by analyzing the time intervals between the peaks [25].

2.2. Feature extraction by using wavelet transform

In this study, wavelet transform is used both for the segmentation of the S1–S2 sounds, and the determination of the features. For the feature extraction, the first five sub-bands are utilized.

Abnormalities or murmurs in heart sounds can appear either in systolic or diastolic phases or in both. Each phase; systolic and diastolic, are divided into five equal-duration segments. Powers of the detail coefficients in each segment are computed. The elements of the feature vectors are formed by the ten power values of each sub-band in the five decomposition levels. So, the dimension of the feature vectors is determined as 50 (5×10). Fig. 4 shows the locations of the features (powers) on each of five sub-bands of one cycle of HS in aortic regurgitation [25].

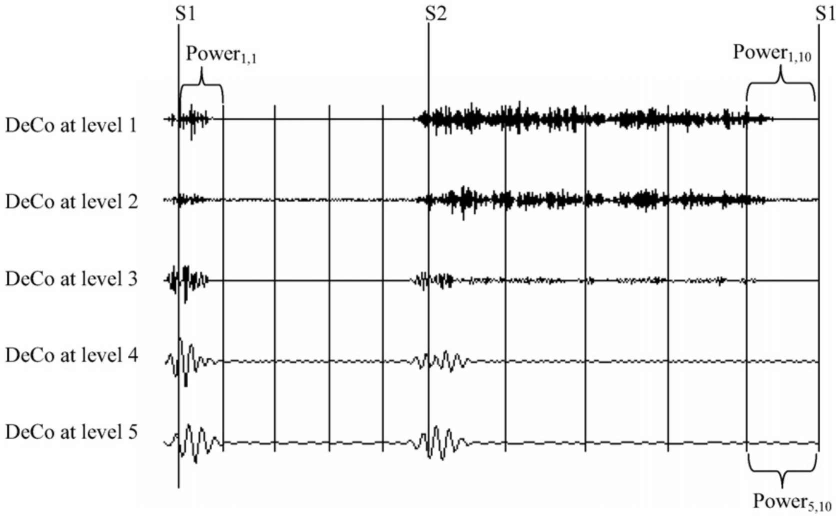

Fig. 4. Locations of the features (powers of the segments of filtered HS) on each of five sub-bands of one period of HS in aortic regurgitation (DeCo: detail coefficients).

2.3. The classification process

The formulation of a proper data representation is a common problem in segmentation/classification systems design. In order to construct realistic classifiers, the features that are sufficiently representative of the physical process must be found. If the right features are not chosen, classification performance will decrease. In this case, the solution of the problem has to be searched in the classifier structures, and artificial neural networks (ANNs) are used as classifiers to successfully overcome this problem.

It is observed that the Kohonen's SOM (self-organizing map) network is widely used in pattern recognition tasks. In this study, the incremental self-organizing map (ISOM) and the Kohonen network are compared for the classification of heart sounds as both of them are trained by unsupervised learning schemes, and have similar structures.

3. Artificial neural networks for the classification process

There are four reasons to use an ANN as a classifier: (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.

3.1. Kohonen's SOM network

There are many types of self-organizing networks applicable to a wide area of problems. One of the most basic schemes is competitive learning. The Kohonen's SOM network can be seen as an extension to the competitive learning network [29].

In the Kohonen network, output nodes are ordered often in a two-dimensional grid, although this is application-dependent. The ordering which is chosen by the user, determines which output nodes are neighbors. When vectors are presented to the network, the weights to the output nodes are thus adapted such that the order present in the input space is represented in the output.

Three basic problems encountered during the training of the network are: (i) The number of output nodes is not known a priori, (ii) iteration number and how to change the parameter values during the training are not known, and (iii) too many nodes are used to represent the distribution.

3.2. Incremental self-organizing map

The ISOM is a two-layer network. Fig. 5 shows the structure of the ISOM. The nodes in the first layer of the ISOM are formed by the feature vectors. The number of nodes in the first layer is automatically determined by the learning algorithm. The *winner-takes-all* guarantees that there will be only one node activated. Each output node represents a unique class. The labels of the output nodes are saved in the second layer, which is called the class *layer*.

The ISOM has incremental structure for unsupervised learning. Its learning algorithm computes the Euclidean distances between the first-layer nodes of the ISOM and the input feature vector to determine the winner node (the node which is the nearest to the input vector). The minimum distance between the winner node and the input vector is compared with a

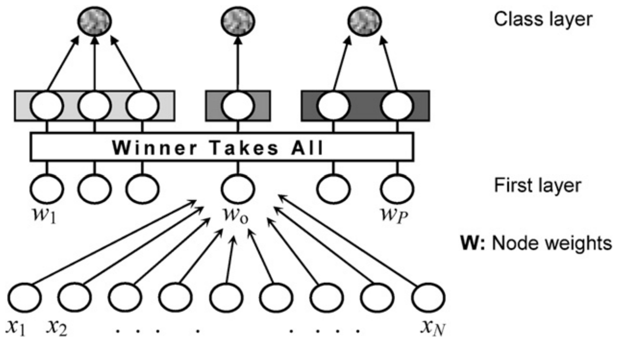

Fig. 5. Structure of ISOM, N is feature space dimension.

threshold to decide whether the input feature vector is a candidate to be a new node of the network or not. If the minimum distance is lower than the threshold value, the weights of the winner node are modified as follows:

$$w_{oj}(k+1) = w_{oj}(k) + \mu \cdot \big(x_j(k) - w_{oj}(k)\big), \tag{2}$$

where w_{oj} is the jth weight of the oth node nearest to the input vector (w_o is the winner node), x_j is the jth element of the input (feature) vector X, k is the iteration number, and μ is the learning rate. Otherwise, a new node is included into the network, and its weights are determined by the elements of the input feature vector. The index counter is incremented by one, and the value in the counter is assigned as the index (label) of the new node. In the study, the learning rate μ is set to 0.05 value and kept constant during the training.

The threshold value is automatically determined in a simple manner by computing the function in Eq. (3) before starting the self-organization stage. By using the automatic threshold (*AT*) function, a standard calculation method is provided to ensure the robustness of the algorithm. ISOM's automatic threshold value is defined as follows:

$$AT = \sqrt{\frac{1}{M}\sum_{i=1}^{M}\sum_{j=1}^{N}(x_{ij} - m_j)^2}, \quad m_j = \sum_{i=1}^{M} x_{ij}. \tag{3}$$

In Eq. (3), X is the feature vector matrix of size $M \times N$. Each row of the matrix is constituted by the elements of the feature vectors, hence, X holds N-dimensional M feature vectors. m_j denotes the mean value of the features on column j.

In fact, *AT* value represents the distribution of feature vectors in multi-dimensional feature space. Although *AT* function is simply defined, it shows high performance in generating proper threshold values depending on the number of features (dimension of vectors) and distribution in the feature space. It has been observed that the proposed function is capable of generating a reference value for the threshold.

The procedure for the learning algorithm of the ISOM is as follows:

Step 1: Take a feature vector from the training set in an order.
Step 2: Compute the distances between the input feature vector and the nodes in the first layer, and find the winner node with the minimum distance.
Step 3: If the minimum distance is higher than the threshold, include the feature vector into the ISOM as a new node, increment the index counter by one, and assign the value in the counter as the index (label) of the new node. Otherwise, modify the weights of the winner node according to Eq. (2) and increase the *usage counter* of the node by one to form a histogram.
Step 4: Go to Step 1 until all the vectors in the training set are exhausted.

The labels of the nodes of ISOM are determined before the classification process. A *usage counter* is assigned for each node. During the training process, the usage counter of the winner node is increased by one. After the training, a histogram, which shows the usage frequency of nodes, is formed. If the content of the usage counter of the node is higher than a predefined threshold of the histogram (*TH*), a label is assigned to this node. The *TH* value is selected by the user, and it determines the number of labels (classes). Each node is labeled with a different label, and represents only one class. The nodes, having values lower than *TH* in their usage counters, are removed from the network.

4. Computer simulations and conclusions

In this study, fourteen different heart sounds are classified by artificial neural networks: Ventricular septal defect (VSD), mitral regurgitation (MRE), late systolic murmur (LAS), early systolic murmur (EAS), opening snap (OPS), diastolic rumble (DRU), Ebsteins anomaly (EBA), aortic regurgitation (ARE), aortic stenosis (AST), normal FCG (NFC), mitral stenosis (MST),

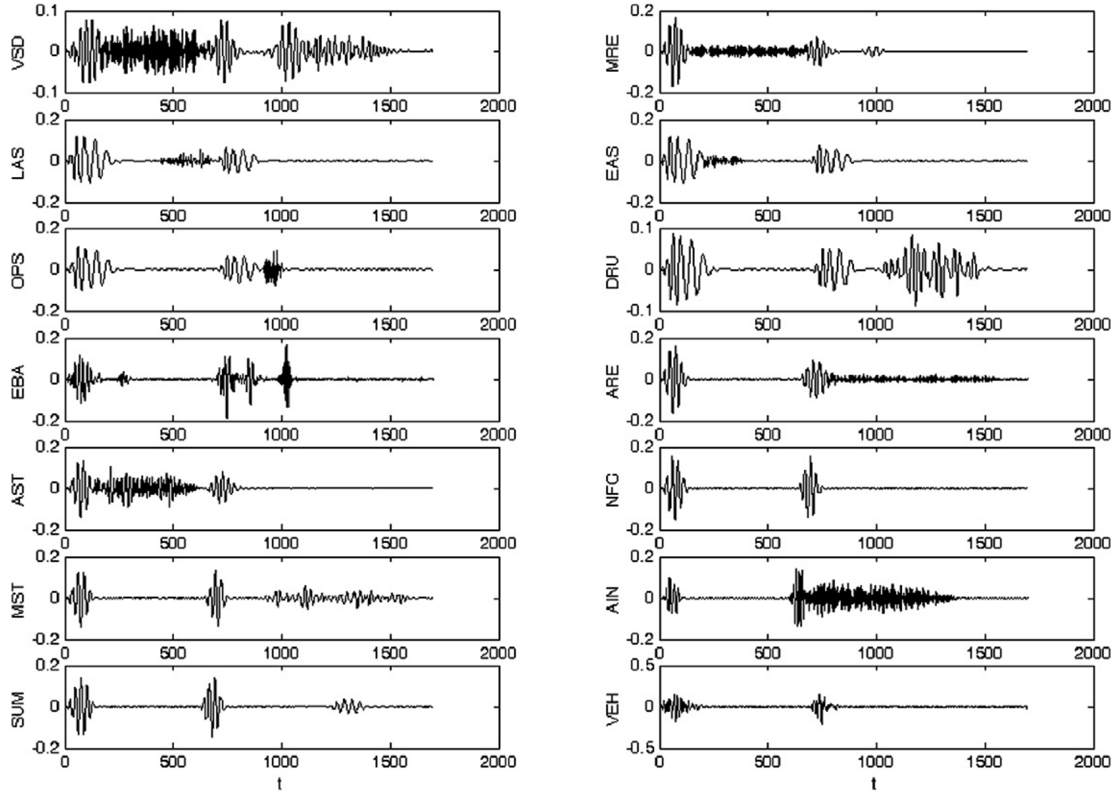

Fig. 6. One cycle of fourteen different heart sound categories.

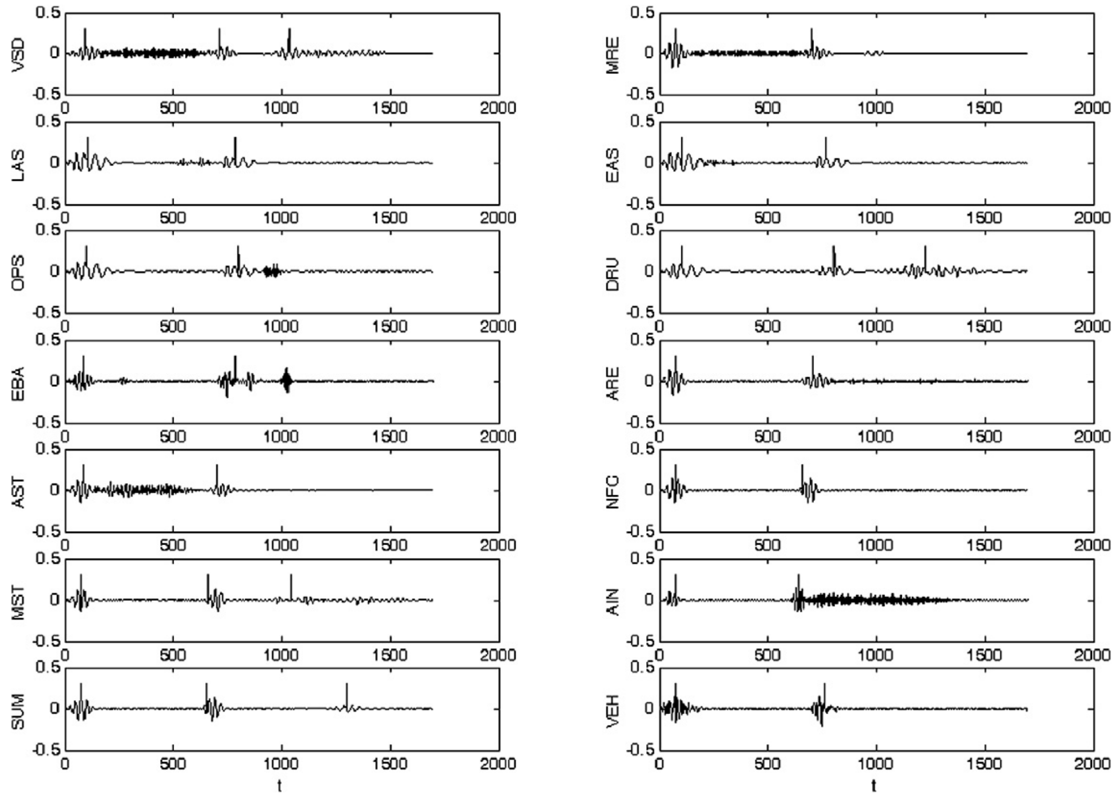

Fig. 7. Segmentation results of one pair of S1 and S2 sounds contained in one heart beat.

Table 1a
Classification performances by the ISOM

	VSD	MRE	LAS	EAS	OPS	DRU	EAB	ARE	AST	NFC	MST	AIN	SUM	VEH
VSD	10													
MRE		10												
LAS			10		2									
EAS				10										
OPS					8									
DRU						10								
EBA							10							
ARE								10						
AST									10					
NFC										9			2	
MST											10		2	
AIN												10		
SUM										1			6	
VEH														10

Table 1b
Classification performances by the Kohonen network

	VSD	MRE	LAS	EAS	OPS	DRU	EAB	ARE	AST	NFC	MST	AIN	SUM	VEH
VSD	10	3							8					
MRE		7						5	2					
LAS			7	1										
EAS				9										
OPS			3		10									
DRU						10								
EBA							10							
ARE								5						
AST											1			
NFC										10	9		10	
MST														
AIN												10		
SUM														
VEH														10

aort insufficiency (AIN), summation gallop (SUM), and venus hum (VEH). Fig. 6 shows the heart sounds examined in the study. Simulations were performed on 2.2 GHz PC by using MATLAB 6.0.

Each heart sound record of any category is formed by the signals acquired from two patients. Each record contains 20 cycles of heart sounds (10 cycles from each patient). Some of the heart sound records are formed by using an electronic stethoscope, and some of them are obtained from the internet [30] and the exercise CD of the book [31]. In the study, the training set is formed by 140 HS cycles of 14 different types. The sounds are recorded with 16 bit accuracy and 2000 Hz sampling frequency. No ECG equipment has been used.

In the study, high performance is achieved by the proposed segmentation method. All S1 and S2 heart sounds in the training set are segmented successfully. Fig. 7 shows the segmentation results obtained for the S1 and S2 sounds within one heart beat.

In the previous study [25], the best features were examined for fourteen different heart sounds types. The best features were determined by dynamic programming (DP) according to the divergence value. Divergence analysis [32] gives information about the distribution of the class vectors in the feature space. As the class vectors arbitrarily scatter, the divergence value decreases. In this study, divergence analysis is used to reduce the dimension of the feature vectors from 50 to 10, and the vectors of fourteen different heart sounds types are formed by the features determined in the previous study [25].

After the training of both networks, the output nodes in the index layer of ISOM and the output nodes of the Kohonen network are labeled by using the training set. The classification performance of the ISOM for fourteen different heart sounds is obtained as 95% (the ratio of the true positives to the total vectors in the test set). Table 1a shows the classification performances by the ISOM for fourteen different heart sounds. *AT* and *TH* parameters for ISOM are set to 1300 and 1 values, respectively. The training algorithm of the ISOM generated 34 nodes. Table 1b shows the classification performances by the Kohonen network. In the training of the Kohonen network, learning rate and neighborhood values are set to 0.05 and 1, respectively. It is observed after many trials that the Kohonen network gives the best performance for 6×6 node structure. The classification performance of the Kohonen network for fourteen different heart sounds is obtained as 70% (the ratio of the true positives to the total vectors in the test set).

In order to examine the classification performances of the proposed methods for heart sounds in a noisy environment, noise is added artificially to the heart sounds in the test set (signal to noise ratio is 43.94 dB). Tables 2a and 2b show the classification performances by the ISOM and Kohonen network for heart sounds with noise, respectively.

Tables 1 and 2 show that ISOM gives higher performances compared to the Kohonen network, and classification performance of the proposed method was not affected for an SNR ratio of 43.94 dB.

Table 2a
Classification performances by the ISOM for noisy heart sounds, SNR = 43.94 dB

	VSD	MRE	LAS	EAS	OPS	DRU	EAB	ARE	AST	NFC	MST	AIN	SUM	VEH
VSD	10													
MRE		10							1					
LAS			10											
EAS				10										
OPS					10									
DRU						10								
EBA							10							
ARE								10			1			
AST									9					
NFC										10	2		5	
MST											6			
AIN												10		
SUM											1		5	
VEH														10

Table 2b
Classification performances by the Kohonen network for noisy heart sounds, SNR = 43.94 dB

	VSD	MRE	LAS	EAS	OPS	DRU	EAB	ARE	AST	NFC	MST	AIN	SUM	VEH
VSD	10													
MRE		6						2	1					
LAS			7		4									
EAS			3	10										
OPS					6									
DRU						10								
EBA							10							
ARE		4						8						
AST									9					
NFC										10	10		10	
MST											0			
AIN												10		
SUM													0	
VEH														10

Duration of one cycle of heart sound is approximately 0.85 seconds for a normal beat rate. The same processes are applied to the heart sounds for the segmentation of S1–S2 and the extraction of the features. Therefore, overall computational time for one cycle of heart sound is low due to the parallel processing. Overall computational time is the sum of the durations spent for the segmentation of S1–S2, feature extraction and classification processes. Overall computational time of the classification process for one cycle of heart sound by the proposed method is 1.95 s on a PC with 2.2 GHz CPU. The proposed method can be applied to real time data analysis by a digital signal processor.

Although Kohonen's SOM is a fast algorithm, it is not an incremental network. Also, the strategy of the learning algorithm of the Kohonen network makes the output nodes locate in the feature space homogeneously rather than concentrating on class boundaries. This strategy may require excessive number of nodes in the network. Network nodes may not be capable of representing the classes well enough if network parameters such as the neighborhood and learning rate are not properly set. The problem of determining optimum number of nodes and network topology is another disadvantage of the Kohonen network. Since ISOM is an incremental network, it automatically determines the proper number of nodes required for the segmentation.

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