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AN INTELLIGENT PATTERN RECOGNITION SYSTEM BASED ON NEURAL NETWORKS AND WAVELET DECOMPOSITION FOR INTERPRETATION OF LUNG SOUNDS

ABSTRACT

In this study, a new automated pattern recognition system for interpretation of lung sound signals based on wavelet decomposition of signals and classification using neural network is developed. Inputs to the system are the lung sound signals acquired by a stethoscope in a noiseless environment. Features for the objective concise representation of lung sound signals are generated by means of wavelet decomposition. Classification of the features is performed using a back propagation neural network with adaptive learning rate. Ten different types of lung sound signals are analysed. Fifty-one record windows obtained from young humans are studied. Thirty of the record windows in database are selected to be used for training phase of the neural network. The results show that the intelligent pattern recognition system used to interpret ten different types of lung sound are acquired a high success.

Keywords: Lung Sounds, Wavelet Decomposition, Neural Networks, Pattern Recognition.

AKCİĞER SESLERİNİ DEĞERLENDİRMEK İÇİN DALGACIK AYIRIŞIMI VE SİNİR AĞLARI TABANLI AKILLI ÖRÜNTÜ TANIMA SİSTEMİ

ÖZET

Bu çalışmada, akciğer seslerini değerlendirmek için işaretlerin dalgacık ayrışımı ve sinir ağları kullanılarak yeni bir otomatik örüntü tanıma sistemi geliştirildi. Sistemin girişleri, gürültüsüz bir ortamda steteskop ile alınan akciğer ses işaretleridir. Akciğer ses işaretlerinin özelliklerini çıkarmak için dalgacık ayrışımı kullanıldı. Bu özelliklerin sınıflandırılması, uyarlamalı öğrenme oranlı geri yayınım sinir ağı kullanılarak gerçekleştirildi. Akciğer ses işaretlerinin 10 farklı türü incelendi. Genç kişilerden elde edilen 51 kayıt penceresi çalışma için derlendi. Yapay sinir ağını eğitmek için ise bu veri tabanından 30 kayıt penceresi seçildi. Geliştirilen akıllı örüntü tanıma sisteminin başarımını değerlendirmek için 10 farklı akçiğer ses türü kullanılarak, yüksek bir başarıya ulaşıldı.

Anahtar Kelimeler: Akciğer Sesleri, Dalgacık Ayrışımı, Sinir Ağları, Örüntü Tanıma.

1.INTRODUCTION (GİRİŞ)

In many countries roughly five percent of the population suffer from asthma and other related pulmonary disorders [1]. For this reason, early detection of lung diseases is one of the most important medical research areas. Pulmonary diagnosis is often based on analysis of acoustical pulmonary signals [2]. The auscultation of the human lung sound is still one of the standard procedures used by physicians. The specific lung sound patterns can be easily listened by a stethoscope. Although such analysis has been proved to be effective, it has the disadvantage of being subjective, relying on the individual's experience and skill. Many attempts have been undertaken to automatically classify those signals using pattern recognition [3, 4, 5, 6 and 7]. Automatic classification using advanced pattern recognition methods so far has been applied partly to lung sound [8, 9 and 10].

This investigation is performed by use of eleven recognition features extracted from the wavelet decomposition of ten various lung sounds (Table 1). The results showed that the correct classification rate of the neural network classifier is 98.4% (Table 2). The intelligent system used in the present study includes following units:

1.1. Pattern Recognition (Örüntü Tanıma)

Pattern recognition process is the classification of the patterns [11]. A popular schematic of the pattern recognition process is shown in Figure 1 [12]. The sensors measure some physical process, which may be in one of many possible states of nature at a given time. The following block performs the important task of dimensionality reduction in one of two possible ways, depending on the application. Extraction involves a mathematical mapping from all the available measurements to a lower dimension feature space. On the other hand, selection entails choosing features among available measurements, without any functional mapping. Those measurements with discriminatory information are retained and those with redundant or irrelevant information are discarded. Finally, the role of classifier is to categorize the features of the recorded pattern into the appropriate class. The focus of works is on the feature extractor unit [13].

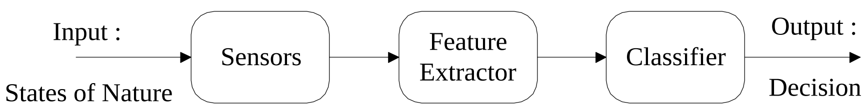

Figure 1. A pattern recognition system.
(Şekil 1. Bir örüntü tanıma sistemi)

1.2. Wavelet Decomposition (Dalgacık Ayrışımı)

Wavelet transforms are rapidly surfacing in fields as diverse as telecommunications and biology. Because of their suitability for analysing non-stationary signals, they have become a powerful alternative to the Fourier methods in many medical applications, where such signals abound [14, 15 and 16].

Wavelet decomposition uses the fact that it is possible to resolve high frequency components within a small time window, and 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 stage. The wavelet decomposition function of x(t) signal at level m and time location t_m can be expressed as Equation (1):

$$d_m(t_m) = \left|x(t)\right| * \Psi_m\left(\frac{t - t_m}{2^m}\right) \qquad (1)$$

where Ψ_m is the decomposition filter at frequency level m. The effect of the decomposition filter is scaled by the factor 2^m at stage m, but otherwise the shape is the same at all stages. This wavelet decomposition function is sampled at different rates at every stage to produce the wavelet decomposition coefficients. The sampling rate at stage m output is $F_s/2^m$. The level m coefficients are denoted as $d_m[k_m]$, where k_m is an integer such that $k_m=t/\Delta t_m$. The synthesis of the signal from its time-frequency coefficients given in Equation (2) can be rewritten to express the composition of the signal x[n] from its wavelet coefficients [17],

$$\begin{aligned} d[n] &= x[n] * h[n] \\ c[n] &= x[n] * g[n] \end{aligned} \qquad (2)$$

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

1.3. Neural Networks (Sinir Ağları)

Artificial neural networks are systems that are deliberately constructed to make use of some organizational principles resembling those of a human brain. They represent the promising new generation of information processing systems. Neural Networks are good at tasks such as pattern matching and classification, function approximation, optimisation and data clustering, while traditional statistical methods, because of their architecture, are inefficient at these tasks, especially pattern-matching tasks [13].

The multi layer feed-forward neural networks are a parallel-distributed information processing structure with the following characteristics:

- It is a neural inspired mathematical model.
- It consists of a large number of highly interconnected processing elements.
- A processing element can dynamically respond to its input stimulus, and the response completely depends on its local information.
- It has the ability to learn, recall, and generalize from training data by assigning or adjusting the connection weights.
- Its connections hold the knowledge.
- Its collective behaviour demonstrates the computational power, and no single neuron carries specific information.

Because of these characteristics, multi layer feed forward neural networks are commonly used in the large area [18].

2. METHODOLOGY (YÖNTEM)

Figure 2 shows the automated identification system we developed. It consists of three parts: a) Data acquisition and preprocessing, b) Feature Extraction, c) Classification.

2.1. Data Acquisition and Preprocessing (Veri Alma ve Önişlem)

Lung sounds are sampled at 5 Khz using the sound card which has 16-bit Analog to digital conversion resolution and 44.1 Khz maximum sampling frequency. Software used to implement the system was developed under MATLAB programming environment. The type and the average period of each of these lung sounds are shown in Table 1. It has been observed that the duration of each lung sound is approximately 5 seconds, and thus lung sounds are divided into windows having 25,000 samples.

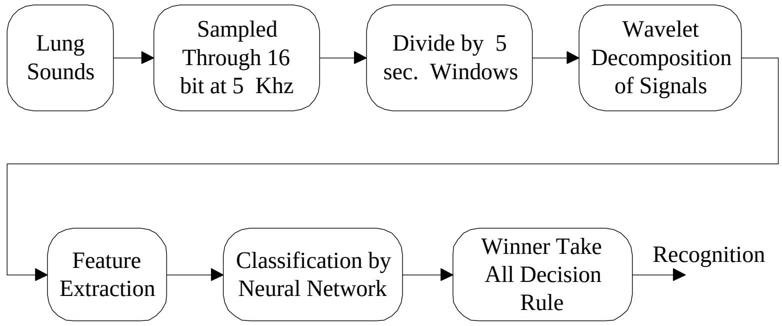

Figure 2. Block diagram of the lung sound identification system.
(Şekil 2. Akciğer seslerini tanıyan sistemin blok diyagramı)

Table 1. Type of lunc sounds
(Tablo 1. Akciğer seslerinin türleri)

No.	Type	Auscultation area	APOW (sec)
1	Normal tracheal sound	Trachea interscapular	4
2	Normal vesicular sound	Right/Left lower lobe	5
3	Fine crackles with deciduous bronchial sound	Right middle lobe	2
4	Coarse crackles	Right lower lobe	2
5	Bronchial sound	Left lower lobe	2
6	Inspiratory stridor	Trachea	3.4
7	Rhonchus	Right lower lobe	1.6
8	Wheezing	Left lower lobe	2.2
9	Fine crackles	Lung basis	3
10	Pleural Friction	Right middle lobe	2

APOW: Average period of waveform

2.2. Feature Extraction Using Wavelet Decomposition (Dalgacık Ayrışımı Kullanılarak Özellik Çıkarmak)

Feature extraction is the key to pattern recognition. Figure 3 shows the feature extraction structure, which is performed using wavelet coefficients of the wavelet decomposition at ten levels. Wavelet decomposition is obtained using the Daubechies 4-coefficient wavelet filters [19]. For example, the wavelet decomposition at ten-levels of the bronchial sound signal in a window is shown in Figure 4.

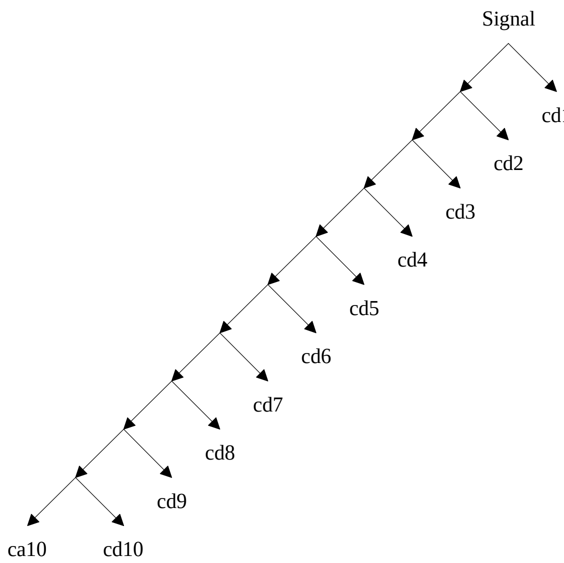

Figure 3. The wavelet coefficients of the wavelet decomposition at ten levels.
(Şekil 3. 10 seviyeli dalgacık ayrışımının dalgacık katsayıları)

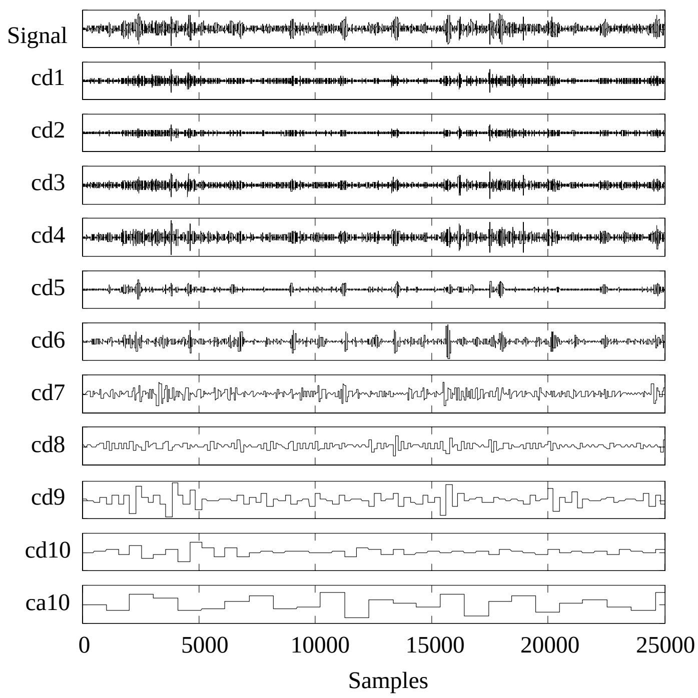

Figure 4. The wavelet decomposition at ten-levels of the bronchial sound signal in a window.
(Şekil 4. Bir pencerede bronşitli akciğer ses işaretinin 10 seviyeli dalgacık ayrışımı)

The features are extracted from wavelet decomposition components of the signals using Equation (3). Thus, the each component of signal is expressed with a single value,

$$a_j = \frac{\sum_{i=1}^{n} \left| c_{ji} \right|}{n} \tag{3}$$

where a_J is the average of j_{th} component of signal and the c_{ji} indicates the j_{th} component vector of wavelet decomposition of signal. n is the dimension of the signal in a window. Thus, the feature vector is defined by the wavelet decomposition of the signal analysed at ten levels as follow:

$$[cda_1, cda_2, cda_3, cda_4, cda_5, cda_6, cda_7, cda_8, cda_9, cda_{10}, caa_{10}] \tag{4}$$

For each record, these feature parameters are given as the input to the multi layer feed forward neural network classifier.

2.3. Classification Using Back-Propagation Neural Network (Geri Yayınım Sinir Ağını Kullanarak Sınıflama)

Recent developments in the field of artificial neural networks have made them a powerful tool as pattern classifiers. The application of neural networks has opened a new area for solving complex problems. It has been shown that they are more powerful methods compared with the traditional pattern classifying techniques. A number of neural network algorithms and their applications have been widely reported [20]. Among the many neural networks learning algorithms, the adaptive learning multi layer feed forward back propagation is considered as the most powerful learning algorithm.

The training characteristics and the structure of the neural network used in this study are as follow:

- *The Number of Layers: 3 (input, hidden, output)*
- *The number of neuron on the layers:11-input,30-hidden,10-output*
- *Adaptive learning rate (lr):lr_beginning:0.005,lr_increase:1.04, lr_decrease: -0.7*
- *Momentum coefficient: 0.98*
- *Sum-squared error: 0.005*
- *Activation Functions: Tangent Sigmoid*

The winner-take-all decision rule [12] used in this study means that the input pattern feature vector was set to the class belonging to the neural network output node whose value is the highest. In the training phase of neural network structure, the feature vectors of signal types shown in Figure 5 are used. The number of training samples is thirty record windows and three record windows are used for each lung sound sample.

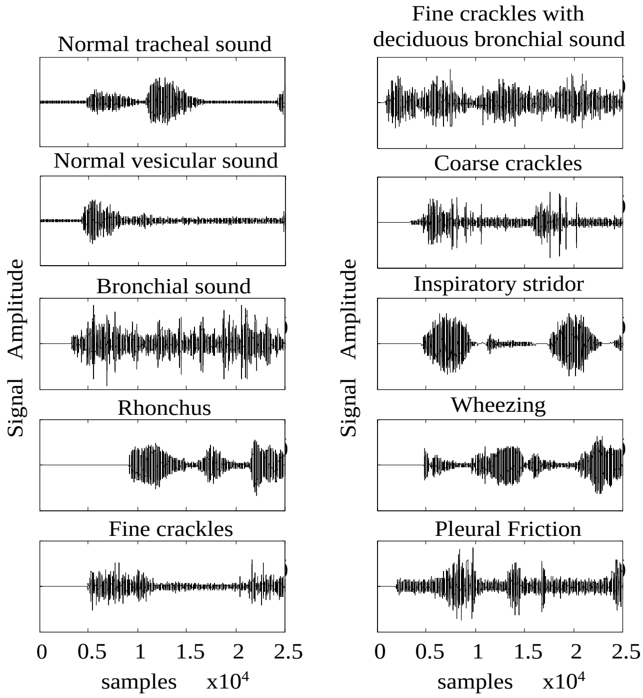

Figure 5. The one-window samples of the signal types of lung sound.
(Şekil 5. Akciğer ses işaret türlerinin bir pencerelik örnekleri)

3. RESULTS (SONUÇLAR)

Table II shows the classification results for each lung sound. Classification results of the test data set are given at correct form and incorrect form. The testing data set is used twenty-one record windows apart from training data set.

Table 2. Classification results
(Tablo 2. Sınıflama sonuçları)

Lung Sound Types	Correctly classified		Incorrectly classified	
	Number	ARP (%)	Number	ARP (%)
Normal tracheal sound	1	99.4	--	--
Normal vesicular sound	2	98.8	--	--
Fine crackles with deciduous bronchial sound	3	99.5	--	--
Coarse crackles	1	99.1	--	--
Bronchial sound	2	97.8	1	92.9
Inspiratory stridor	2	99.3	--	--
Rhonchus	2	99.2	--	--
Wheezing	1	99.5	--	--
Fine crackles	3	95	--	--
Pleural Friction	3	99	--	--
Total	20	98.4	1	92.9

The ARP is average recognised percent of lung sound type, and is defined as follow:

$$\text{ARP(Lung sound type)} = \frac{\text{Correctly classified}}{\sum \text{Lung sound}} \text{x}100 \qquad (5)$$

4. DISCUSSIONS AND CONCLUSIONS (TARTIŞMA VE SONUÇLAR)

The feature vectors obtained by the developed method were used as the input to the neural network classifier. The classifier consists of feed forward neural network using back propagation learning rule of adaptive learning rate to train the network. In this study, ten varieties of lung sounds were used on the contrary to the previous studies [8-10]. The training set, which included thirty data samples are used to train the network and the testing set, which included twenty-one data samples apart from training set are used to check the automatic pattern recognition performance. The best of these recognition results were obtained a 99.5% correct recognition rate. This recognition rate indicates the robustness of the developed feature extraction method by us. However, there is one incorrect classification. The misclassification rate might reduce with a larger train set. Our further work will continue in this direction.

The most important aspect of the intelligent pattern recognition system is the ability of self-organization of the neural network without requirements of programming and the immediate response of a trained net during real-time applications. These features make the intelligent pattern recognition system suitable for automatic classification in many acoustical signal applications like interpretation of lung sound. These results point out to the ability of design of a new intelligence medical assistance system.

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