An Alternative Respiratory Sounds Classification System Utilizing Artificial Neural Networks

Rami J. Oweis, Enas W. Abdulhay, Amer Khayal, Areen Awad

Background: Computerized lung sound analysis involves recording lung sound via an electronic device, followed by computer analysis and classification based on specific signal characteristics as non-linearity and nonstationarity caused by air turbulence. An automatic analysis is necessary to avoid dependence on expert skills.

Methods: This work revolves around exploiting autocorrelation in the feature extraction stage. All process stages were implemented in MATLAB. The classification process was performed comparatively using both artificial neural networks (ANNs) and adaptive neuro-fuzzy inference systems (ANFIS) toolboxes. The methods have been applied to 10 different respiratory sounds for classification.

Results: The ANN was superior to the ANFIS system and returned superior performance parameters. Its accuracy, specificity, and sensitivity were 98.6%, 100%, and 97.8%, respectively. The obtained parameters showed superiority to many recent approaches.

Conclusions: The promising proposed method is an efficient fast tool for the intended purpose as manifested in the performance parameters, specifically, accuracy, specificity, and sensitivity. Furthermore, it may be added that utilizing the autocorrelation function in the feature extraction in such applications results in enhanced performance and avoids undesired computation complexities compared to other techniques.

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Key words: adaptive neuro-fuzzy inference system, artificial neural network, classification, feature extraction, respiratory sounds

At a Glance Commentary

Scientific background of the subject

Respiratory sound (RS) is one of the most significant biosignals used to diagnose certain respiratory abnormalities. The RS analysis by conventional auscultation is highly dependent on the skills and experiences of the listener making it prone to human judgment and error. In contrast, modern computer technology provides the possibility to automate the process.

What this study adds to the field

This work addresses a new computerized technique for respiratory sound classification. It is believed that the main contribution of this study lies in the feature extraction stage, through which the desired features are calculated and acquired using auto-correlation in a completely automatic process without the need for complex calculations.

Respiratory sound (RS) is regarded one of the most significant biosignals used to diagnose certain respiratory abnormalities. It is established that breath sounds are created in the larger airways as a result of vibrations that are generated due to air velocity and turbulence. RSs are known to be highly non-stationary and non-linear due to variations in the airflow rate and airflow volumes during the respiratory cycle. The non-linearity of the RS stems mainly from the complex turbulent flow dynamics and its structural interaction with the larger airway walls.

RSs detected from the chest wall and mouth may be classified as normal and adventitious sounds. Owing to the presence of adventitious (abnormal) sounds, such signals convey valuable information pertaining to the underlying malfunctioning of the pulmonary system. On the other hand, normal sounds include those generated by healthy

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lungs and airways through normal spontaneous breathing. The method used for classification should take into account all the properties of RSs. Furthermore, it has to be robust due to the large inter-subject variability related to gender, age, weight, physiology, and recording conditions, as well as considerable intra-subject differences related to the evolution state of pathology.[1] Depending on the recording location, normal sounds can, in turn, be classified into tracheal–bronchial and vesicular.

The noise level is the first aspect to be taken into account by any proposed classification method. While normal RSs heard over the chest wall are characterized by low noise during inspiration and is hardly audible during expiration, normal RSs detected from the trachea are characterized by a broader spectrum of noise, audible during both inspiratory and expiratory phases.[2] In smaller bronchi, the gas velocity decreases and becomes less than the critical velocity needed to induce turbulence. Therefore, the airflow in smaller airways is believed to be laminar and silent.

The second essential requirement of the classification method is the frequency range. The noise coming from the larger airways has a wide frequency spectrum and is transmitted to the skin through lungs and chest wall that acoustically act as a low-pass filter. Therefore, the nominal breath sounds recorded over the lungs have their main frequency band up to 200-250 Hz. This frequency band also contains the components related to respiratory muscles and heart sounds. When recorded over the trachea, the sound is either less filtered or not filtered at all. Therefore, the frequency spectrum contains frequency components as high as 1200 Hz.[2,3]

Finally, the classification method should consider the energy issue as there is a rapid decline in energy when the frequency increases above 250 Hz.

According to their acoustic properties, RSs can be divided into several categories. Dukor presents a good detailed account of such categories that include bronchial, bronchovesicular, vesicular, crackles, wheeze, stridor, grunting, squawk, and friction rub sounds.[3]

It is known that RS analysis by conventional auscultation is highly dependent on the skills and experiences of the listener, making it prone to human judgment and error. In contrast, modern computer technology offers great advantages in terms of acquisition, storage, and analysis of biosignals and provides the possibility to automate the process.[4-10] Computerized lung sound analysis involves recording the patient lung sound via an electronic device, followed by computer analysis and classification of lung sounds based on specific signal characteristics.[2,11] Gurung *et al*. conducted a review and an in-depth analysis of relevant classification studies using a computerized lung sound analysis in which the overall sensitivity and specificity of implemented algorithms were estimated.[12] Nowadays, the use of computerized diagnostic tools enjoys wide popularity in the healthcare facilities.[13,14]

The present study aims at introducing a novel, fully automated, accurate, and easy-to-use RS classification system that helps physicians to perform diagnosis without the need for invasive medical imaging techniques. The feature extraction is initiated with an autocorrelation function. Since this study deals with a non-stationary data set (RSs), autocorrelation function was performed to make the Fast Fourier Transform (FFT) tool applicable. In an attempt to avoid the complexities that are normally associated with the necessity to specify the window size or the mother wavelet function when using wavelet transform, this study implemented the autocorrelation function as an alternative approach. The system is capable of distinguishing between three normal and seven abnormal lung sounds quickly with a high accuracy level.

METHODS

In this study, the analysis of RS is performed in several stages, i.e. normalization, filtration, feature extraction, and classification, using both artificial neural networks (ANNs) and adaptive neuro-fuzzy inference system (ANFIS) on a comparative basis. The sequence of the whole process is schematically illustrated in Figure 1. Ten different RS categories, namely, bronchovesicular (BV), normal bronchial (NB), abnormal bronchial (AB), crackles (C), wheezes (W), stridor (S), normal bronchophony (NBP), bronchophony by consolidation (BC), normal egophony (NE), and abnormal egophony (E), were considered. Figure 2 shows the signal waveform for each RS category indicated above. All classification stages were implemented on 6.00 GB, 2.20 GHz PC with 64-bit operating system equipped with MATLAB 7.8.0.

The database for this particular study was constructed from real RSs obtained from two CDs with the titles Auscultation Skills: Breath and Heart Sounds, and Understanding Lung Sounds, respectively. No patient information was given due to privacy issues. Both these sets were recorded on tape from the chest of patients with a microphone.[15,16] Sound recordings were performed in sitting position, at rest, and during spontaneous breathing (healthy subjects and patients). The database contained 28 different patient records. Two different sets of signals were used for training and testing. Each class in the training set and test set consisted of two records from different patients, except for crackles and wheezes where the data were taken from six patients for each. The sampling frequency of the acquired recordings was 44.1 kHz.

The following sections report in detail on each of the stages of the RS analysis process.

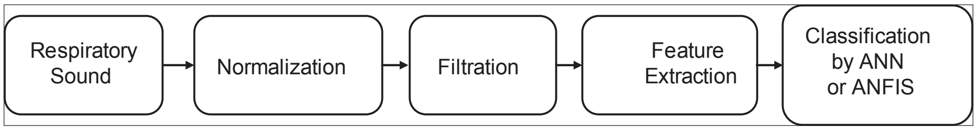

Figure 1: The block diagram of the processing stages used for RS classification.

Normalization process

In general, sharp or sudden changes in a physiological signal can represent abrupt faults. Therefore, normalization is a process that is intended to remove differences among signals acquired from different subjects at different time points from the same location. The process is considered complete when all signals are individually divided by the maximum data value for that particular signal that serves as a reference value.

Filtration

Acoustic auscultation is generally limited by poor signal transmission due to noise, tubular resonance effect, ambient or internal organ sounds, and greater attenuation of higher-frequency sounds. Lung sounds used in this work were filtered with a band-pass filter of 100 Hz and 2000 Hz cut-off frequencies, canceling out undesired frequencies such as those coming from heart sounds.[2,15]

Feature extraction

Correlation is a function that shows how similar two signals are and for how long they remain similar when one is shifted with respect to the other. It should be noted that one respiratory cycle contained sufficient information to accomplish the intended function. The outcome of the application of the FFT was used to come up with the power spectrum (PS) of the data set. It turned out that the PS contained an excessive number of data points (1950 points) such that it called for examining the morphology of the PS of each signal that was utilized to distinguish between different signals. Consequently, it was chosen to divide the PS of each signal into 32 segments for which the individual averaged PS was calculated. These averaged values (32 values) made up the elements of the feature matrix (vector), which served to provide a coarse view (morphology) of the PS that allows for the effective differentiation among the 10 signals. In this work, a total of 10 such vectors were obtained that were to be fed as the input to the ANN.

Classification

Classification is the stage that immediately follows feature extraction. There are two phases to construct ANN and ANFIS classifiers. The first one is the training phase where each RS class is represented using a training data and then a discriminate is established to delimit these classes. The second phase is the test phase in which the unknown sound is analyzed and the best matching model is selected. The training procedure should be repeated until an acceptable error rate is achieved or a certain number of iterations are completed using training examples.

Classification is completely based on how representative the extracted features are. If inappropriate features were chosen, classification performance would decay. The ANN approach was deemed the best solution for such an obstacle. In this work, pattern recognition performances of ANN and ANFIS were comparatively studied for the classification of RSs, as they both have supervised learning schemes.

The classification performance of the classifier in both techniques used here is evaluated in terms of its ability to identify true positives (sick people correctly diagnosed as sick) and true negatives (healthy people correctly diagnosed as healthy), as well as to reject false positives (healthy people incorrectly identified as sick) and false negatives (sick people incorrectly diagnosed as healthy). The true-positive ratio (TPR) and the false-positive ratio (FPR) are given by the following equations:

$$TPR = TP/(TP + FN)$$

$$FPR = FP/(TN + FP)$$

Where TP, FN, FP, and TN are, respectively, the number of true-positive, false-negative, false-positive, and true-negative cases. Moreover, the performance of the classifiers was measured by standard parameters. Sensitivity is defined as the ratio of the number of pathological subjects classified correctly to the total number of pathological subjects (TPR). Specificity is defined as the ratio of the number of healthy subjects classified correctly to the total number of healthy subjects and equals (1-FPR). Finally, accuracy is defined as the ratio of the number of subjects correctly classified to the total number of subjects. The automatic evaluation has been achieved as follows. Every positive in the result vector has been attributed the number 1 and every negative has been attributed the number 0. The same has been applied to the target vector. Accordingly, the couples (1, 1), (1, 0), (0, 0), and (0, 1) were considered as TP, FP, TN, and FN, respectively.

Artificial neural networks

This work utilized ANN as a major component of the software module of the lung sound diagnosis system and aims at achieving very high accuracy. Such networks deduce the prevalent pattern and are able to respond correctly to any input information within the range of the training

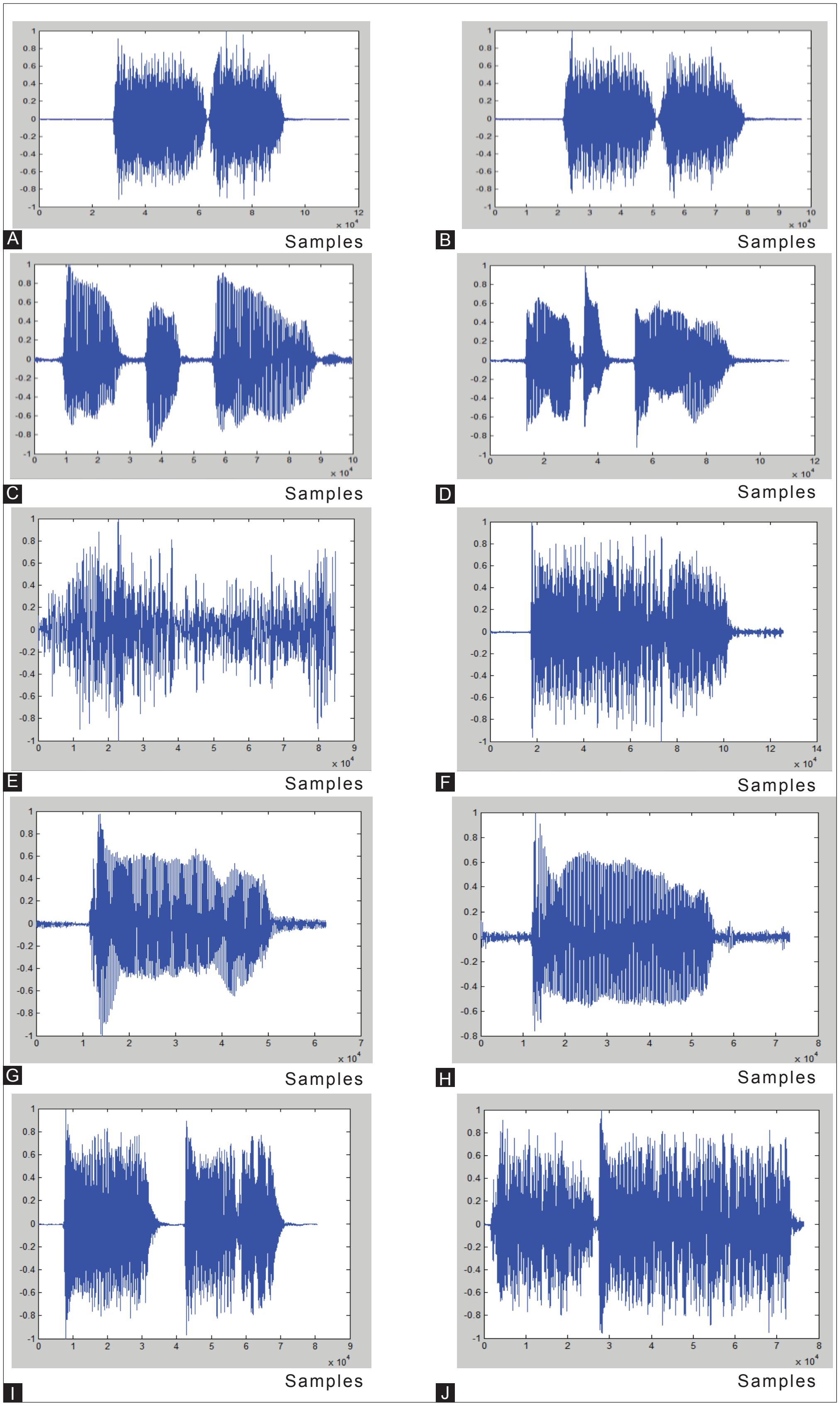

Figure 2: The 10 different RSs used in this work. (A) Bronchial normal. (B) Bronchial abnormal. (C) Bronchophony normal. (D) Bronchophony abnormal. (E) Bronchovesicular. (F) Crackles (G) Egophony-a. (H) Egophony-e .(I) Stridor. (J) Wheezes.

data set. Further, ANN is an adaptive system that changes its structure based on external or internal information that flows through the network during the learning phase. It is generally capable of giving high performance for any distribution of feature vectors. Here, it is noteworthy that 70% of the recorded signals of each category were used in the training phase while 15% were allocated for validation, leaving the remaining 15% for testing. The structure of the pattern recognition neural network used in this study is illustrated in Figure 3.

Adaptive neuro-fuzzy inference systems

A fuzzy neural network (FNN), also called a neuro-fuzzy system (NFS), is a learning machine that is capable of obtaining the parameters of a fuzzy system by exploiting the learning characteristic of the neural network. Working with ANFIS is very similar to working with ANN, except for the arrangement of the input and output data. Also, the training and testing sets are not automatically divided by the system. The structure of the generated ANFIS used in this work is shown in Figure 4. While the subtractive clustering Sugeno ANFIS model was generated using the default values of parameters (range of influence = 0.5, squash factor = 1.25, accept ratio = 0.5, reject ratio = 0.15), training was carried out with a hybrid of mean squared error optimization method. Also, error tolerance was set to zero due to the unpredictable behavior. Forty epochs were chosen because they gave higher accuracy. Five input membership functions were assigned to each of the 32 inputs, with five rules and five output membership functions. The output of the system is one element only. As shown in Figure 4, this element is rounded to an integer, which is the number of the RS category.

RESULTS

The power spectra for one respiratory cycle for each RS, as mentioned in the section "Classification," are shown in Figure 5, while Figure 6 depicts the averaged spectrum power for two RS categories, namely, crackles and wheezes, selected to serve just as examples.

The remaining findings related to the two classifications techniques (ANN and ANFIS) are reported separately for clarity and convenience.

Artificial neural networks

The configuration setup shown in Figure 3 resulted in an accuracy of 98.6%, specificity of 100%, and sensitivity

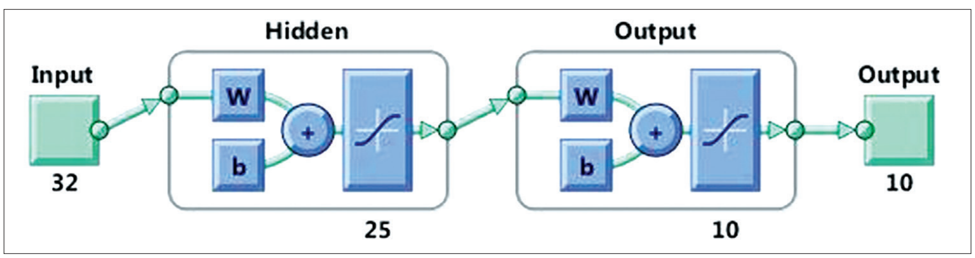

Figure 3: The structure of the pattern recognition neural network used in this study.

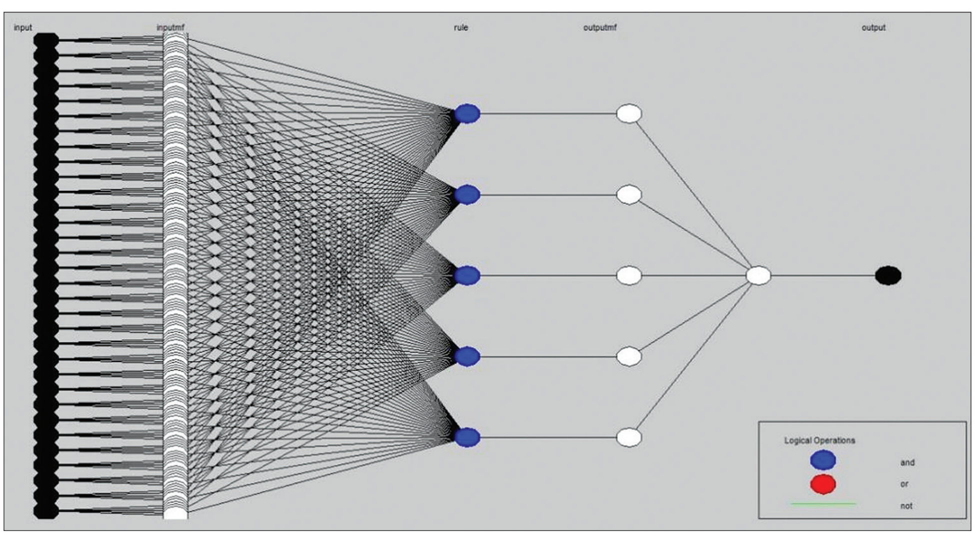

Figure 4: The structure of the generated ANFIS used in this study.

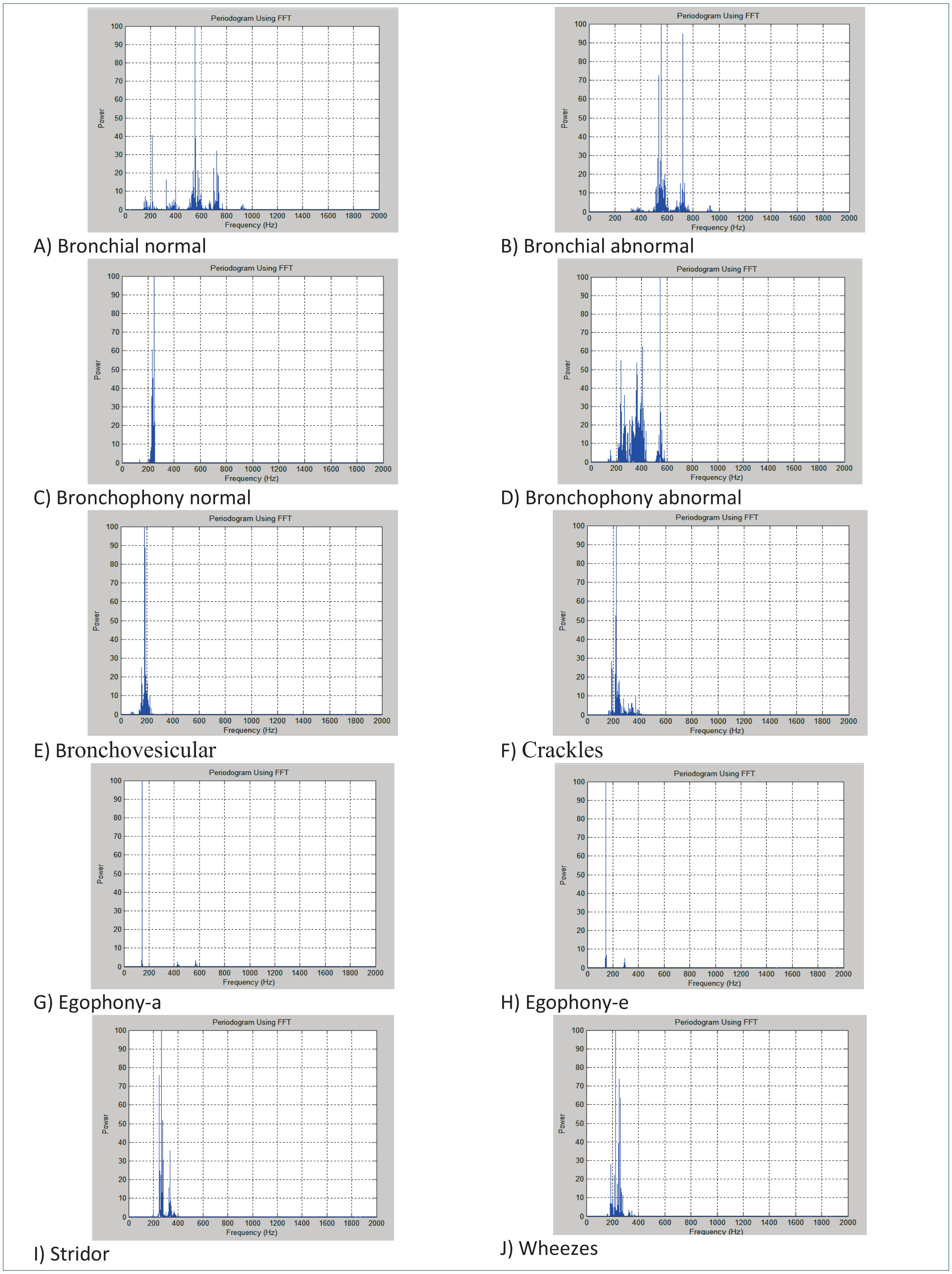

Figure 5: Power spectra of the 10 RSs shown in Figure 2.

of 97.8%. Moreover, the findings regarding the classification performance using the ANN are reported in Table 1. As for the number of hidden layers, for best accuracy, it turned out to be 25 after 195 iterations by MATLAB.

Adaptive neuro-fuzzy inference systems

Implementing the structure in Figure 4 with the default values of the relevant parameters, the system accuracy was

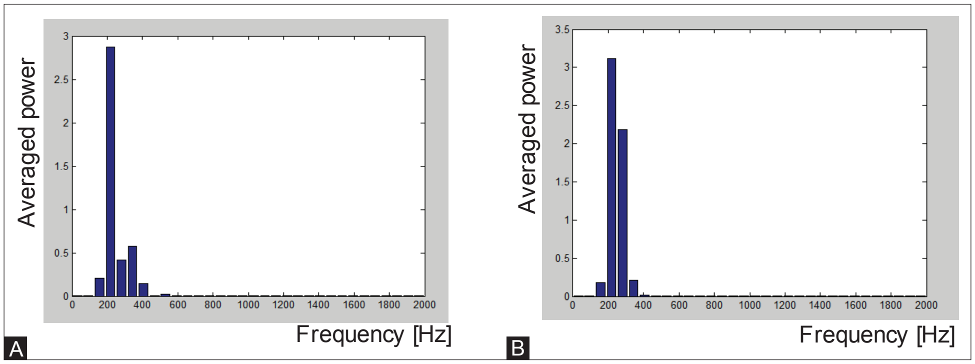

Figure 6: The averaged spectrum power for crackles and wheezes.

66.4%, specificity was 70.4%, and sensitivity was 56.9%. Similar to the ANN table, the classification performance of the ANFIS is reported in Table 2.

DISCUSSION

In an attempt to make more sense out of the data obtained in this work, it was chosen to compare the findings herein to those of a number of different related previous studies. Most studies reviewed here used a wide range of techniques for sound classification. Neural networks, in their various forms, were extensively used in RS classification. A comparison of neural network predictors in the classification of tracheal–bronchial breath sounds was shown by Folland *et al.*[17] They concluded that the constructive probabilistic neural network (CPNN) and radial basis function network (RBFN) were capable of attaining accuracies of 97.85% and 96.2%, respectively, which are lower values than those of the proposed method. Bahoura described recognition methods to classify RSs into normal and wheeze classes.[18] The study was based on Mel-frequency cepstral coefficient combined with Gaussian mixture models. Findings showed that this approach achieved a sensitivity of 97.2% and a specificity of 94.2%. However, it did not attain a superior performance than the suggested presented approach. Abbas and Fahim developed an automated auscultation diagnostic system that is capable of categorizing the abnormal sounds into crackles or wheezes.[19] The core of the technique relied on using FFT, power density spectrum (PDS), and time domain plots. The identification and diagnosis subsystem employed the neural networks method. Nonetheless, it is applied only to two RS categories and implies delicate windowing process. In a related study, Hashemi *et al*. made use of wavelet and neural networks to analyze wheeze sounds observed in asthma, chronic obstructive pulmonary disease (COPD), and bronchitis, and classified them as monophonic and polyphonic types.[20] A multilayer perceptron (MLP) neural network was used as a classifier, resulting in 89.3% accuracy.

On their part, Jin *et al*. conducted a study based on instantaneous frequency (IF) analysis, which produced a noise-resistant high-definition time–frequency representation of respiratory signals as compared to the conventional linear TF analysis methods.[21] However, an overall accuracy of 92.4% for the classification of RS recordings was obtained. Another study was carried out based on Hidden Markov models (HMMs) as a classification procedure.[22] The evaluation experiments demonstrated a 19.1% increase in accuracy of

Table 1: Classification performances for ANN

	C	W	AB	S	BV	NB	NBP	BC	NE	E
C	26	1								
W		29		3						
AB			27							
S				29						
BV					23					
NB						24				
NBP							25			
BC								27		
NE									35	
E										40

Abbreviations: ANN: Artificial neural networks; C: Crackles; W: Wheezes; AB: Abnormal bronchial; S: Stridor; BV: Bronchovesicular; NB: Normal bronchial; NBP: Normal bronchophony; BC: Bronchophony by consolidation; NE: Normal egophony; E: Egophony

Table 2: Classification performances for ANFIS

	C	W	AB	S	BV	NB	NBP	BC	NE	E
C	12	6	1							
W	6	8	5	2		1				
AB	8	13	16	6						
S		3	3	17	1	1				
BV			2	7	19	3				
NB					3	14				
NBP					5	24	4			
BC							1	16	4	
NE								4	28	2
E								3	3	38

Abbreviations: ANFIS: Adaptive neuro-fuzzy inference systems; C: Crackles; W: Wheezes; AB: Abnormal bronchial; S: Stridor; BV: Bronchovesicular; NB: Normal bronchial; NBP: Normal bronchophony; BC: Bronchophony by consolidation; NE: Normal egophony; E: Egophony the recall rate of abnormal RSs compared with the baseline method. In a similar study, Hitoshi Yamamoto *et al*. proposed the same classification procedure but used HMMs for acoustic spectral features, and Bigram models were used for occurrence of acoustic segments in each respiratory period.[1] The study outcomes revealed that the use of the segment Bigram was responsible for a 4.8% reduction in the error.

A comparative classification study was conducted by Dokur in which the classification performances of MLP, grow and learn (GAL) network, and incremental supervised neural network (ISNN) were compared.[3] Results indicated that the ISNN gave the highest classification performance (98%). Kahya *et al.* proposed a wavelet-detection technique of crackles in pulmonary sounds that proved to be adequate for the intended purpose.[23] It was concluded that the technique could effectively reduce the signal-to-noise ratio by applying nonlinear Teager and threshold operators. Similarly, Sello *et al*. proposed the application of the wavelet method combined with statistical power distribution method to characterize the frequency power distribution of the unsteady RS signals.[24] Analysis of the findings of this study showed the possibility of extracting useful statistics related to the energy content and its mean frequency distribution, giving quantitative characteristics of the respiratory pattern. Results showed that different power spectra patterns recognize normal from abnormal (unhealthy) patterns. In their study, and based on parameterizing by auto-regression, Alsmadi *et al*. compared the K-nearest neighbor (K-NN) and minimum distance classifier.[25] The K-NN–based classifier achieved better performance than that of the minimum distance classifier, giving an accuracy of 97.5%, sensitivity of 92%, and specificity of 100%.

In recent works, a new signal classification scheme known as empirical classification was developed for signal dimensional reduction.[26] Empirical classification is based on multi-scale principal component analysis (PCA) as a signal enhancement and feature extraction method. The accuracy of this method turned out to be 98.3%. Also, Himeshima proposed a novel method for discriminating between normal and adventitious RSs based on duration distribution.[27] Gaussian/gamma distribution was used to describe the duration of these sounds. The classification stage was performed using HMM for acoustic spectral features and the duration validity score acquired from the Gaussian/gamma distribution. This approach achieved a classification rate of 84.1%.

The work presented here addresses a new computerized automatic technique for RS classification. It is believed that the main contribution of this study lies in the feature extraction stage, through which the desired features are calculated and acquired in a completely automatic and accurate process, without the need for complex calculations, using MATLAB platform throughout the various stages of classification. In addition, compared to recent literature, the suggested method has been applied to a higher number of RSs and enjoys a fast response time with high accuracy. This work proposes a system that is capable of automatically processing, parameterizing, and eventually classifying RSs into 10 different classes. It should be noted that the system can perform with several RS cycles, but the use of a single RS cycle in this study was just to prove the efficiency and reliability of the system. The use of correlation function in the feature extraction stage is responsible for the major achievements in this work. In terms of the required hardware and time delay, the proposed system requires simple hardware and offers a significant drop in the time needed to perform RS classification, i.e. 6 s. Also, the accuracy of the proposed system (98.6%) is the highest compared to previous studies that dealt with a lower number of classes.

Conclusion

This work presents a new reliable RS classification method with the aim of discriminating normal healthy respiration from abnormal respiration containing adventitious sounds from patients. Based on the study findings, it may be concluded that the proposed method proved to be an efficient and effective tool for the intended purpose as manifested in the figures obtained for the performance parameters, specifically, accuracy, specificity, and sensitivity. Furthermore, it may added that utilizing the autocorrelation function in the feature extraction stage in such applications results in enhanced performance and avoids much undesired computation complexities compared to other techniques. A potential future contribution in this field could be in attempting to design a coherent fully diagnostic tool that encompasses both classification as well as diagnosis.

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