Classification Of Normal and Abnormal Lung Sounds Using Neural Network and Support Vector Machines

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Abstract: *This work proposes feature extraction of lung sounds using wavelet coefficients and their classification by neural network and support vector machines. The lung sounds were classified into 6 classes. The results stated the advantages of a support vector machines for the classification of normal and abnormal lung sounds, and indicated that SVMs are a highly successful classifier with accuracy about 93.51 - 100 for classification of lung sounds.*

Keywords: Lung Sounds, Wavelet Transform, Neural Network, Support Vector Machines.

1. Introduction

The history of utilizing the stethoscope for the chest auscultation was presented by French Laénnec physician about 200 years ago. He discovered the relationship between auscultation to respiratory lung sounds and detection of human pulmonary disorders. Ausculation of respiratory lung sounds with a stethoscope furnished physicians to find respiratory disorders signs of their patients and enabled them to diagnose some of the pulmonary diseases. In the past, the conventional method for auscultation to respiratory lung sounds was performed by a conventional stethoscope. Today, the effectual diagnostic information can be provided by electronic stethoscopes for physicians. This procedure is reliable and effective for evaluation of lung sounds. The digital recording of lung sound signals are accomplished by using an electronic stethoscope and readily performed by a computer. Nowadays, computers are used for the clinical applications. Using computers for analysis of organic body signals like heart sounds, bowel sounds, lung sounds provides countless virtues in order to help the physician for diagnose and treat the disease. Adventitious sounds or abnormal sounds ordinarily demonstrate certain respiratory disturbances. Lung sound signals are non-stationary in their nature and this non-stationarity is extreme with respect to abnormal subjects. Therefore, we need to exert a wavelet transform to furnish the signals in two dimensions. A lot of the clinical information can be obtained from lung sounds frequency distribution. Wavelet transform is a beneficial procedure for furnishing time-frequency distribution of lung sound signals.

Some different articles in the medical fields, were published for diagnosis or therapy of lung disease. Pourazad et al. offered a new heart noise (HN) cancellation method. This algorithm used an image processing technique to detect HN segments in the spectrogram of the recorded lung sound signal [1]. J. Hadjileontiadis et al. designed an automatic technique for wheeze detection and monitoring using spectral analysis [2]. Bahoura and Lu introduced an integrated automated system for crackles recognition [3]. Aboofazeli and Moussavi developed an automated and objective method to separate swallowing sounds from breath sounds [4]. Gnitecki et al. described recursive least squares (RLS) adaptive noise cancellation (ANC) filtering for heart sounds reduction using lung sounds [5]. Charbonneau et al. described a detailed discussion and guidelines for the application of basic analysis techniques to respiratory sounds [6]. Marshall and Boussakta described the feasibility of an automatic stethoscope for particular screening and monitoring algorithms for clinical applicability [7]. Yeginer and Kahya used wavelet to parameterize and quantify pulmonary crackles with an aim to depict the waveform with a small set of meaningful parameters [8]. They also introduced a new automatic method for the elimination of background vasicular sound from crackle signal with a view to introduce minimum distortion to crackle parameters [9]. Hashemi et al. analyzed wheeze sounds and classified them as monophonic and polyphonic types [10]. Potdar and Haider implemented a virtual instrument which could detect and separate out the heart sound segments from lung sound [11]. Rajeshwari and Vaithiyanathan combined fuzzy modeling and artificial Neural Network architecture that aids to diabetolgist as a support for classification and more analysis [12]. Güler, et al. designed two-stage classification of respiratory sound patterns [13]. Subasi et al. developed feed forward error backpropagation artificial neural networks and wavelet neural networks based classifiers [14]. Ayari et al. used a classification scheme to classify crackles based on waveform features and frequency domain features [15]. Gnitecki et al. classified lung sounds acquired from children during bronchial provocation using waveform fractal dimensions [16].

In this study, the design of feed forward and PNN neural network was provided for classification based on the symptoms, for identifying adventitious sounds from normal sound. The support vector machine (SVM) was used for classifying and investigating the result. SVM provided better results for classification of lung adventitious sounds from normal sounds. This method for analysis of lung sound signals was implemented using wavelet transform, neural network, and support vector machine technique for better divorcing adventitious sounds from normal ones.

2. Material and Methods

2.1 Adventitious Sounds

The Breath sounds can be classified into two categories: normal sounds and adventitious sounds. Breath sounds originate in the large airways where air velocity and turbulence induce vibrations in the airway wall. These vibrations are then transmitted through the lung tissue and thoracic wall to the surface where they may be heard readily with the aid of a stethoscope. Lung sounds are produced by vertical and turbulent flow within lung airways during inspiration and expiration of air [11]. A wheeze is a continuous, coarse, whistling sound produced in the respiratory airways during breathing. For wheezes to occur, some part of the respiratory tree must be narrowed or obstructed, or airflow velocity within the respiratory tree must be heightened. Wheezing is commonly experienced by persons with a lung disease; the most common cause of recurrent wheezing is asthma attacks, though it can also be a symptom of lung cancer. A special type of wheeze is stridor. Stridor is a harsh, high-pitched, vibrating sound that is heard in respiratory tract obstruction. Stridor in the inspiratory phase is usually heard with obstruction in the upper airways, such as the trachea, epiglottis, or larynx; because a block here means that no air may reach either lung, this condition is a medical emergency. Stridor is a physical sign which is produced by narrowed or obstructed airway path. It can be indicative of serious airway obstruction from severe conditions such as epiglottitis, a foreign body lodged in the airway, or a laryngeal tumor. Crackles, crepitations, or rales are the clicking, rattling, or crackling noises that may be made by one or both lungs of a human with a respiratory disease during inhalation. Crackles are caused by explosive opening of small airways and are discontinuous, nonmusical, and brief. Crackles are much more common during the inspiratory than the expiratory phase of breathing, but they may be heard during the expiratory phase. Crackles are often associated with inflammation or infection of the small bronchi, bronchioles, and alveoli. Rhonchi is the coarse rattling sound somewhat like snoring, usually caused by secretion in bronchial airways. It is an abnormal or adventitious sound heard when listening to the chest as the person breathes. These are low pitched, continuous sounds that are similar to wheezes. Rhonchi can be heard in patients with chronic obstructive pulmonary disease (COPD) and acute or severe bronchitis. Squawks or short wheezes are brief "squeaky" sounds that are also referred to as squeaks. Their waveforms show a sinusoidal pattern with duration 10 to 100 ms and a frequency between 200 and 800 Hz [17]. There are some more groups of lung sounds like whispered pectoriloquy, egophony, death rattle, pleural friction rub, etc. These groups of lung sounds were not investigated in this paper. Lung sound signals available on the internet sites were used in this study [18-19]. The advantage of lung sound classification and distinguishing the characteristic of adventitious sound will assist the physician in diagnosis and treatment of respiratory diseases.

2.2 Wavelet Transform

The wavelet transform is used for frequency investigation adoption of convenient wavelet and the number of levels of decomposition is essential for investigation and analysis of signals.

The best wavelet transform that could generate the minimum number of errors and express good results in this study was daubechies wavelet of order 8 (db8). The numbers of levels of decomposition were assigned appropriately with the quality of signals. In this work, the number of levels, were considered to be up to 7 [20]. The wavelet coefficients exhibit the distribution of signal energy. It was found out that the values of the coefficients are dreadfully near zero in D1, D2 and A7. The lung sound frequency spectrum is situated in frequency band of 50 to 1000 Hz. For this reason the coefficients proportionate to D1, D2 and A7 were eliminated, so the number of the extracted features declined [20]. The extracted features of signals are shown below: (1) the mean of the coefficients in any subband, (2) the mean of the power of the wavelet coefficients in any subband, (3) the standard deviation of the coefficients in any subband, (4) the ratio of the mean values in beside subbands [20]. The features one and two demonstrate the frequency distribution of the signal and the features three and four indicate the extent of changes in frequency distribution. These extracted features, calculated for the D3-D7 subbands were used for classification of the lung sound signals with the neural network and the support vector machines.

2.3 Artificial Neural Networks

An artificial neural network, now and then just called a neural network, is a mathematical model inspired by biological neural networks. A neural network contains an interconnected group of artificial neurons, and it processes information using a connectionist approach to computation.

In this paper, feed forward neural network was used. The number of input neurons was 19, equal to the number of input features. The number of the output layer neurons is 6 which equal to the number of output classes. The optimum number of neurons in the hidden layer was found equal to 40 neurons [20]. In this study, we used the neural network; furthermore we investigated the performance of the support vector machine and PNN network for classification. About 87% of the dataset is used as the training set and the remaining as the test set. In order to improve the confidence intervals on the performance estimates, 6-fold cross validation was performed.

2.4 Support Vector Machines

In machine learning, support vector machines (SVMs) are supervised learning models with associated learning algorithms that analyze data and recognize patterns, used for classification and regression analysis. The basic SVM gets a set of input data and predicts, for each one of given input, which of two possible classes forms the input, making it a non-probabilistic binary linear classifier [21]. Given a set of training examples, each marked is belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a demonstration of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped inside that same space and predicted to belong to a category based on which side of the gap they fall on [21].

SVM is originally designed for binary classification. The conventional way to extend it to multi-class is to decompose an M-class problem into a series of two-class problems, for which one-against-all is the earliest and one of the most widely used implementations. This paper used one-against-all method for separating of 6 classes.

Block diagram schematic of the proposed method is shown in Fig. 1.

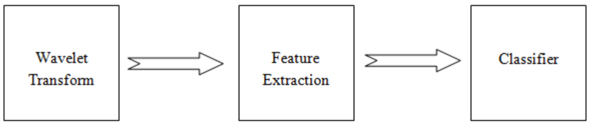

Fig. 1: Diagram of the classification method.

3. Results

The total number of 48 samples for train and test were used in this work and were divided into 6 classes. The extracted statistical features from the wavelet coefficients of signal were used as inputs for classification. The results were investigated using feed forward and PNN neural network and also with support vector machines. Neural network results are shown in TABLE I. We compared the simulated results for feed forward neural network with the results in other papers. As an innovative approach, the performance of the PNN neural network and support vector machine were investigated in this study. The eta1 is the classifier accuracy for the condition that total number of samples were used for training and then for test. The eta2 indicates classifier accuracy for the state in which 87% of the data were used for train and 13% for test. We used 6-fold cross validation and then the mean of eta2 were reported. For classification using the support vector machine the method of one versus the rest was used which means each time one class was dissociated and the results for divorce of each class are reported in TABLE II.

TABLE I: Performance of Neural Network

Classifier	Eta1	Eta2
Feed forward	100	94.44
Pnn	100	83.33

TABLE II: Performance of SVMs

Classifier	Eta
Class1	96.18
Class2	93.51
Class3	100
Class4	95.48

Class5	100
Class6	94.86

4. Conclusion

In this study, we present classification of lung sounds with neural network and support vector machines. For this purpose, at first we calculated the wavelet coefficients of the signal, then for each signal, the statistical features were extracted. These features were used for classification. The performance of the neural network and support vector machines were evaluated for classification. The results show that the support vector machine has a better performance.

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