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Study of Adventitious Lung Sounds of Paediatric Population using Artificial Neural Network Approach

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ABSTRACT

Objectives: Human lung sounds are important indicators of underlying lung pathology. The prime objective of this work is to classify normal and adventitious lung sounds in paediatric population using spectral features and artificial neural networks.

Material and Method: 3M Littmann 3200 electronic stethoscope was used to record the lung sounds. After pre-processing ten spectral features were extracted. For classification, comparative performance of different artificial neural networks is studied and GFF neural network with calculated optimum parameters is selected.

Results: For testing data Out of 49 normal subjects 48 were classified successfully and out of 52 pathological subjects 48 were classified successfully. The classification sensitivity and specificity obtained is 92.30% and 97.95% respectively.

Conclusion: Early diagnosis of lung disorder is important especially in childhood so that further progress of the disease could be prevented. New approach to detect adventitious lung sounds is being proposed utilizing electronic stethoscope as a recording device. Combination of spectral features and artificial neural networks has provided classification accuracy of 95.12%.

Key Words: Lung disease, Adventitious lung sounds, Spectral features, Artificial neural networks

INTRODUCTION

Human lung sounds play an important role in diagnosis of underlying respiratory pathology. Traditionally medical doctors used to auscultate the lung sounds with the conventional stethoscope. This approach is quite common, but is subjected to some concerns like, for the novice doctors it is difficult to distinguish between different categories of adventitious lung sounds due to unavailability of any objective reference. Moreover, the misdiagnosed adventitious lung sounds of paediatric population may lead to adulthood repository disease such as COPD.

Respiratory disorders, if diagnosed early in childhood, could be cured with proper antibiotics. To sum it up, it is very important to diagnose adventitious lung sounds in the paediatrics population due to their inability to communicate effectively about their health problems and lack of research in this category. This problem is more severe in the developing countries like India where majority (70%) of the population resides in the rural regions where appropriate medical facilities are not easily available due to distant geography and due to the shortage of trained medical practitioners.

There are estimated 6.4 million deaths [1] due to lung disease globally and in India it accounts for 11% of all the deaths [2]. Respiratory disorders are the second most cause of mortality in India after Heart related disease. The aim of this study is to address the issue by employing signal processing techniques in analysis of paediatric lung sounds to categorize them in normal and adventitious category. Now-a-days commercialization of electronic stethoscope with various inbuilt features opens a wide opportunity for the researchers in the biomedical field. Littmann is most trusted brand in the stethoscope market since many years. 3M Littmann traditional models were the most popular amongst the doctors especially amongst the pulmonologists and cardiologists. 3M Littmann 3200 Electronic stethoscope is used to record the lung sounds of subjects which was not utilized for lung sound recording and analysis purpose by previous researchers.

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The paper has been organized into four sections. The second section presents review of some research done in past. Section three describes materials and method which includes data acquisition, feature extraction and classification. Finally Section four presents results and fifth describes conclusion.

LITERATURE REVIEW

Table A provides some of the research work done in the past for automated objective analysis of lung sounds.

Table A: Literature Review

Researchers	Sensor type	Dataset	Method
K. J. Hong et.al.[3]	Stethoscope sensor	17	EMD, RMS value and Kurtosis
A. Rizal et.al. [4]	R.A.L.E data set	81	Spectrograms first order Statistics with KNN
D. Chamberlain et.al. [5]	Microphone embedded with stethoscope	284	STFT and SVM
M. Chekhovych et.al. [6]	Complex phonospirographic computer	77	Higher order spectral statistics
K. Kosasih et.al. [7]	Electret microphone	91	Wavelet and MFCC
N. Sengupta et.al. [8]	R.A.L.E data set	3	Optimized MFCC
N. S. Ambatkar and S. D. Chede [9]	Microphone embedded with stethoscope	36	Wavelet packet transform and ANN
S. Umeki et.al. [10]	Electronic stethoscope	106	HMM
Y. Amrulloh et.al. [11]	Low noise microphone	18	MFCC ,Shannon entropy and ANN
S. Ulukaya et.al. [12]	Electret microphone	40	AR model and GMM
J.V. Mankar and P.K. Malviya [13]	Simulated	01	STFT
A.Poreva et.al. [14]	Complex Phonospirog-raphic computer	120	Higher order spectral features
A.Parkhi and M.Pawar [15]	Online resources	03	STFT
P. J. M. Fard et.al. [16]	Electret microphone	80	Spectral randomness indices
K. W. Becker et.al. [17]	Pneumotrace piezoelectric belt	60	Spectral features with ANN
B. Wang et.al. [18]	Piezoelectric microphone with Labview	4	MFCC
X. Liu et.al. [19]	Online sources	45	Entropy features and threshold 2D
S. Matsutake et.al. [20]	Electronic stethoscope	80	HMM
S. A. Taplidou et.al.[21]	Electret microphones	21	Wavelets higher order spectral features
S.A. Taplidou, and L.J. Hadjileontiadis et.al.[22]	5 electret microphone (ECM-77B, Sony)	13	Time- frequency analysis of wheeze sound
Sonia Charleston-Villalobos et.al.[23]	5*5 sensor arrays of electrets microphone	02	Empirical mode decomposition
L. Xiaoguang, and B. Mohammed [24]	Electret microphones	18	Wavelet packet transform for de-noise. FD analysis
H.E. Elphick et.al.[25]	Acoustic analysis –sensor (Siemens EMT 25C)	102	Validity and reliability using k-statistic
A. Homs-Corberan et.al. [26]	Piezo-electric phonopneumograph sensor (PPG)	31	Spectral power peaks and mean spectral entropy
L. Hadjileontiadis [27]	Electret microphone	16	Wavelet based de-noising and higher order Discriminant analysis
Y.P. Kahya et.al.[28]	4 Electret microphone	41	Fast Fourier transform
M. Oud [29]	NA	10	PCA and ANN
L.J. Hadjileontia-dis. et.al.[30]	Teaching Tapes	24	Normalized bispectrum (Bicoherence)
Y. P. Kahya et.al. [31]	4 Electret microphone	68	AR model and k-NN

From table 1, it is noted that lot of research is done and still going on relating the automatic/computerized analysis of adventitious lung sounds and many signal processing techniques have been employed. The majority of the research carried out was for the adult population and vast non-uniformity is observed in the data acquisition methods, Some researchers have utilized lung sound training tapes where as some of them have used data from online resources. In spite of this, majority of the researchers have used the data which was acquired using microphones, microphones embedded with stethoscope or sensor jackets. There are in fact, very few researchers who have used data recorded from paediatric population. Also no one till date has utilized the electronic stethoscope model 3200 by 3M Littmann with the feature of ambient noise reduction. So there exists tremendous scope to study the lung sounds of paediatric population for objective analysis and for classification.

MATARIALS AND METHODS

A] Data Acquisition

For data acquisition, 3M Littmann 3200 electronic stethoscope was used .3M Littmann electronic stethoscope is been chosen because of its ambient noise reduction capability, larger bandwidth (0-2000 Hz) and facility to record in extended mode which provides maximum bandwidth as compared to traditional stethoscope which provides only two modes i.e. Bell and Diaphragm. Also 3M Littmann is most popular and trusted brand among medical practitioners. Also its fidelity for heart sound recording has been tested in our precious study [32].

The stethoscope has the Bluetooth connectivity with PC with the help of 'StethAssist' software provided by Littmann. One complete recoding of 60 sec is transmitted to PC simultaneously during auscultation through Bluetooth interface. The file is then exported in '.wav' format (16 bit PCM sampled at 4000 Hz). Recordings were made on PC running Windows 8 operating system with AMD quad core processor with 4 GB ram. The recording setup is shown in figure 1.

All lung sound recordings were made after obtaining approval from concerned authorities and in accordance with medical ethics. The mean age of children selected for recording is 2 years ± 1 year, with almost equal gender distribution. The recordings were carried out at renowned child hospitals having Paediatrician with more than 15 years of experience in Nagpur city and in the towns of Pusad and Digras (Vidharbha region of Maharashtra State India).

B] Sorting and Pre-processing

The recordings were labelled according to the disease and sorted according to the quality. Here quality means the absence of hospital noise. The noise in the data was mainly due to crying and movement of child subjects. So after sorting, almost 50% of the data was discarded due to high amount of noise content. Total 540 recording were recorded out of which only 253 recording were selected of which 127 include adventitious lung sounds such as wheezing, crackles, grunting, crepitations and harsh breath sounds. For categorizing normal lung sounds, 126 recordings were selected including the lung sounds of the subjects having common acute cough and cold.

The pre-processing stage involves filtering, DC removal, segmentation and normalization. Below 100 Hz the auscultation sounds are dominated by heart sounds, it is necessary to remove this unwanted signals by means of suitable filtering which will not only remove the noise but will also preserve the basic nature of lung sounds for higher frequencies. Different digital filters were designed and tested by varying order of filter and window types, and finally 7th order Chebyshev type I IIR filter with cut-off frequency of 100 Hz is selected after observing time and frequency domain characteristics of filtered signal. Filter designing is done using MATLAB 2008b licensed version. After successful filtering of all the recordings, two breath cycles from each recording is extracted manually using WAVEDIT software. Each segmented recording is relabelled and saved for analysis. Segmented sounds are then amplitude normalized in the range of ±1.These pre-processed sounds was then used for feature extraction and classification.

C] Feature Extraction:

By observing time and frequency domain description (spectrum) of all the cases of normal and adventitious lung sounds, it was observed that time domain analysis would not help good classification because of similarity in shape of time domain statistical parameters. The previous studies related to time domain analysis of lung sounds also do not reflect encouraging results in terms of accuracy. So, frequency domain analysis is carried out using spectral features which were extensively used in automatic speech recognition systems [33-34]. Total ten spectral features were extracted consisting of Spectral centroid, Spectral crest, Spectral decrease, Spectral flatness, Spectral flux, Spectral roll off, Spectral skewness, Spectral kurtosis, Spectral Slope and Spectral spread.

Brief definition of spectral features is given below

1. *Spectral Centroid*

It is the centre of gravity of spectrum. It is defined as

$$SC = \frac{\sum_{k=1}^{L} kX(k)}{\sum_{k=1}^{L} X(k)} \tag{1}$$

Spectral centroid basically represents the location of concentration of spectral energy. Low values of spectral centroid indicate presence of lower frequency components and vice versa.

2. *Spectral Crest Factor*

It is a measure of tonalness of the signal. It is the ratio of maximum of the magnitude spectrum to the sum of all bins in the magnitude spectrum. It is defined as

$$S.Cr(n) = \frac{\max\limits_{0 \le k \le k/2-1} |X(k,n)|}{\sum_{k=0}^{k/2-1} |X(k,n)|} \quad (2)$$

Where *n* is the block length. In this study the complete segmented signal (two breath cycles) were considered as single block. Low values of spectral crest factor indicates flat spectrum where as high values indicates a sinusoidal. Spectral crest factor is zero for the blocks having zero energy (silence).

3. Spectral Decrease

The spectral decrease measures the steepness of the decrease in the spectral envelope over frequency. It is defined as

$$S.Dec = \frac{\sum_{k=1}^{k/2-1} \frac{1}{k}\left(|X(k)| - |X(0)|\right)}{\sum_{k=1}^{k/2-1} |X(k)|} \quad (3)$$

The value of spectral decrease is a value S.Dec≤1. A lower value of spectral decrease indicates concentration of the spectral energy at bin 0.

4. Spectral Flatness

The spectral flatness is the ratio of geometric mean and arithmetic mean of the magnitude spectrum, it is defined as

$$S.F = \frac{\sqrt{\prod_{k=0}^{k/2-1} |X(k)|}}{2/k.\sum_{k=0}^{k/2-1} |X(k)|} \quad (4)$$

The value of spectral flatness is greater than 0.The upper value depends on the maximum spectral magnitude. Non-flat spectrum tends to have lower values of *S.F* where as flat spectrums results in higher values of *S.F.*

5. Spectral Flux

The spectral flux measures the amount of change in spectral shape. It is defined as the average difference between successive STFT frames

$$S.F(n) = \frac{\sqrt{\sum_{k=0}^{k/2-1} \left(|X(k,n)| - |X(k,n-1|\right)^2}}{k/2} \quad (5)$$

The value of spectral flux lies in the range $0 \le S.F \le A$ with *A* representing maximum possible spectral magnitude. Low values of A represents steady input signals.

6. Spectral Kurtosis

The *Kurtosis* is referred to the ratio of fourth central movement of a variable to the fourth power of standard deviation. The spectral kurtosis measures how much the distribution of spectral magnitude resembles the Gaussian distribution. It is defined as

$$S.K = \frac{2\sum_{k=0}^{k/2-1}(|X(k)| - \mu\,|\,x\,|)^2}{k\sigma^4\,|\,x\,|} - 3 \quad (5)$$

Spectral kurtosis represents peakedness of the signal. For spectrum having peaks, its value will be higher. Again one complete segmented signal is used as input to calculate spectral kurtosis.

7. Spectral Roll off

It is the measure of concentration of spectrum. It is defined as the frequency below which certain percentage (In this study 95%) of the magnitude distribution of the spectrum is concentrated. If m^{th} DFT coefficient corresponds to the spectral roll off of the i^{th} frame then

$$\sum_{k=1}^{m} X_i(k) = C\sum_{k=1}^{F_L} X_i(k) \quad (7)$$

C is the adapted percentage which is 95% in our case. To normalize spectral roll off frequency it is divided by the F_L (total length of the band). So it will have values between 0 and 1, where 1 corresponds to the maximum frequency of signal (*fs/*2).This parameter actually describes the distribution and shape of the spectrum i.e. narrower spectrum yields lower values where as wider spectrum results in higher values of spectral roll off.

8. Spectral Skewness

The Spectral skewness is a measure of symmetry of distribution of the spectral magnitude around their arithmetic mean. It is defined as

$$S.Skw = \frac{2\sum_{k=0}^{k/2-1}(|X(k)| - \mu\,|\,x\,|)^3}{k\sigma^3\,|\,x\,|} \quad (8)$$

It indicates the amount of non similarities between spectral magnitudes i.e. for flat like spectrums it has a very low value, where as for fluctuating spectrum its value is high.

9. Spectral Slope

The spectral slope is similar to the spectral decrease which measures the slope of the spectral shape. It is calculated using a linear approximation of the magnitude spectrum. In the presented form, the linear function is modelled from the magnitude spectrum. It is calculated with the following equation

$$S.Slp = \frac{\sum_{k=0}^{k/2-1}(k-\mu_k)(|X(k)|-\mu\,|\,x\,|)}{\sum_{k=0}^{k/2-1}(k-\mu_k)^2} \tag{9}$$

10. *Spectral Spread*

It is defined as the second central moment of the spectrum. To calculate it deviation from the spectral centroid is taken

$$S \;= \frac{\sum_{k=1}^{L}(k-C)^2 X(k)}{\sum_{k=1}^{f_L} X(k)} \tag{10}$$

To normalize *SS* in the range [0,1], it is divided by the factor ($f_s/2$) ,where 1 corresponds to maximum frequency of signal ($f_s/2$).

All ten spectral features are calculated for each segmented recording. The calculations were performed in Matlab R2008b Licensed version using toolbox available [34]. For 126 normal subjects the dimension of feature matrix is 126*10 and for 127 Pathological subjects the feature matrix dimension is 127*10. By observing both the feature matrices it is concluded that they are not linearly separable, so classification based of artificial neural network has been employed.

C] Classification:

Neurosolutions (Neuro Dimension Inc.USA) 5.07 was used to implement different NN based classifiers on lung sound recordings which are represented by feature vector containing 10 different elements. This paper explores the Multilayer Perceptron (MLP), Generalized feed forward (GFF) and Modular Neural networks for classification purpose.

In the first stage all the network classifiers were tested for different topologies i.e. by varying number of hidden layers and processing elements (PEs) and by changing transfer function and learning rules. Performance measures such as mean square error (MSE), minimum absolute error, maximum absolute error, mean absolute error (MAE), correlation coefficient and classification accuracy were calculated for different classifiers. After observing performances of all the possible combination of transfer functions and learning rules with varying processing elements in hidden layers, it was decided to use network having one hidden layer with six processing elements in it.

Table I provides comparative performances in terms of minimum MSE for MLP, GFF and MNN, where as table II provides their performance in terms of minimum absolute error, maximum absolute error, correlation coefficient and classification accuracy on testing data.

From tables I and II it is concluded that GFF outperforms MLP and MNN in terms of performance measures. The classification accuracy attained by GFF for normal and adventitious lung sound is 90.90% and 91.22% respectively. So in order to optimize GFF for improved accuracy, network is trained by different combinations of transfer functions and learning rules. Table III and IV illustrates the comparative performance of the network for various combinations of transfer functions and learning rule

From the table III it is observed that *tanh*, which is a non linear transfer function performs better than other transfer functions. This might be due to high degree of non linear separability in the data. So in the next stage of network development, different learning rules such as *Step*, *Momentum*, *Conjugate gradient* (CG), *Levenberg Marquardt* (LM), *Quickprop* (QP), *Delta bar delta* (DBD) were used along with *Tanh* as a transfer function. Table IV shows comparative performances in terms of Mean square error (MSE), Mean absolute error (MAE), Correlation coefficient and classification accuracy for different learning rules.

Maximum classification accuracy and correlation coefficient value was obtained by the tanh- CG combination. The computed value of MSE and MAE is also minimum for this combination. All the performances were calculated for testing data.

From Table III and IV it is evident that GFF with *tanh* as transfer function with *Conjugate gradient* as a learning rule performs better than other transfer function-learning rule combinations. The final specifications of the network after carrying out trials can now be defined as follows:

1. Network: *Generalized feed forward NN*
2. Stopping condition: *3000 Epochs*
3. Conscience rule: *L2 Norm*
4. Number of hidden layer: *01*
5. Number of PEs in hidden layer: *06*
6. Hidden Layer Transfer function: *Tanh*
7. Hidden layer learning rule: *Conjugate gradient*
8. Output layer: Transfer function: *Tanh*
9. Output layer Learning Rule: *Conjugate gradient*

RESULTS

Table IV shows the results using GFF neural network in terms of performance measures such as MSE, MAE, Correlation coefficients and classification accuracy. The sensitivity of neural network for all the ten features is shown in figure 2. For testing data of 49 subjects belonging to normal category, 48 were classified successfully and for Subjects belonging to pathological category out of 52, 48 were successfully classified. The sensitivity and specificity for conducted study is 92.30% and 97.95% respectively leading to the overall accuracy of 95.12%.

CONCLUSIONS

A new approach to preliminary detect adventitious lung sounds in paediatric population has been proposed in this study. Features representing spectral characteristics were calculated for each recording and subsequently different artificial neural network topologies involving MLP, GFF and MNN have been tested by varying number of hidden layers, PEs, transfer functions and learning rules. It has been concluded that GFF with one hidden layer and with 6 PEs in it incorporating *tanh* as transfer function with Conjugate gradient as learning rule is the most optimum neural network for this application. The overall accuracy obtained is 95.12%. The work can be further extended to classify different categories of adventitious lung sounds for detecting specific disease after suitable increase in the subjects recordings pertaining to each disease.

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Abbreviation

Chronic Obstructive Pulmonary Disease (COPD)
Infinite Impulse Response filter (IIR-Filter)
Spectral centroid (SC)
Spectral crest factor (SCr)
Spectral decrease (S.Dec)
Spectral flatness (SF)
Spectral flux (SFx)
Spectral roll off (S.Roff)
Spectral skewness (S.Skw)
Spectral kurtosis (SK)
Spectral Slope (S.Slp)
Spectral spread.(SS)
Multilayer Perceptron (MLP)
Generalized feed forward (GFF)
Modular neural network (MNN)
Sigmoid (SIG)
Linear Tanh (LT)
Linear Sigmoid (LS)
Soft max (SM)
Conjugate gradient (CG)
Momentum (MOM)
Conjugate gradient (CG)
Levenberg Marquardt (LM)
Quickprop (QP)
Delta bar delta (DBD)
Mean square error (MSE)
Mean absolute error (MAE)

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Figure 1: Lung Recording Setup

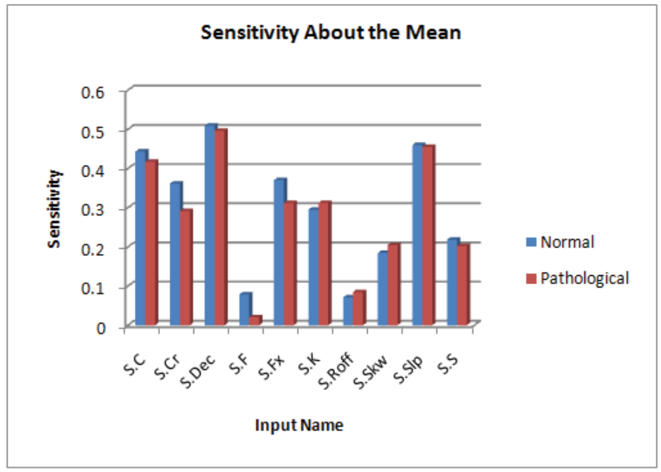

Figure 2: Sensitivity of GFF NN for ten spectral features

Table 1: Minimum MSE for MLP, GFF and MNN

Classifier	Training	Cross Validation	Testing
MLP	0.003737	0.210948	0.109380
GFF	0.023676	0.159846	0.088513
MNN	0.003737	0.210948	0.123582

Table 2: Comparative Performance of MLP, GFF and MNN

Classifier	Subjects	Min.AbsError	Max.AbsError	Correlation Coefficient	Classification Accuracy
MLP	Normal	0.00134	1.05044	0.75642	85.71429
	Pathological	0.00127	1.05090	0.76041	82.69231
GFF	Normal	0.00045	1.01837	0.80154	90.90909
	Pathological	0.00182	1.00296	0.80088	91.22807
MNN	Normal	0.00440	0.96908	0.72716	76.47059
	Pathological	0.00543	0.96590	0.72339	92.00000

Table 3: Comparative Performance of GFF for Different Transfer Functions on Testing Data

Transfer Function	MSE		MAE		Correlation Coefficient		Classification Accuracy	
	Normal	Advent.	Normal	Advent.	Normal	Advent.	Normal	Advent.
Tanh	0.06194	0.06394	0.15475	0.15673	0.86686	0.86194	94.54545	91.30435
SIG	0.18513	0.18969	0.35336	0.35528	0.52012	0.50582	82.97872	61.11111
LT	0.10889	0.10814	0.22250	0.22430	0.75669	0.75652	89.28571	80.00000
LS	0.12332	0.12734	0.27882	0.28480	0.71286	0.70081	82.35294	78.00000
SM	0.13747	0.13079	0.29548	0.28180	0.66627	0.68613	88.88889	76.78571
Bias	0.11584	0.12116	0.25120	0.26561	0.73296	0.71707	83.33333	83.01887

Table 4: Comparative Performance of GFF for Different Learning Rules with *Tanh* Transfer Function

Learning Rule	MSE		MAE		Correlation Coefficient		Classification Accuracy	
	Normal	Path.	Normal	Path.	Normal	Path.	Normal	Path.
MOM	0.06194	0.06394	0.15475	0.15673	0.86686	0.86194	94.54545	91.30435
CG	0.06297	0.05777	0.13309	0.13124	0.88170	0.88668	97.95918	92.30769
LM	0.17232	0.15896	0.23397	0.22066	0.71179	0.69668	98.00000	70.58824
QP	0.10610	0.11453	0.24320	0.25142	0.76021	0.73611	90.19608	74.00000
DBD	0.15864	0.15699	0.19756	0.19411	0.71856	0.73800	84.31373	88.00000
STEP	0.07099	0.07270	0.15435	0.15827	0.85081	0.84620	93.61702	85.18519