An Integrated Computerized Cough Analysis by Using Wavelet for Pneumonia Diagnosis

Roshan S. Hande
Department of Electronics & Telecommunication Engineering, Smt. Kashibai Navale College of Engineering, Vadgaon Bk. Pune.
roshan9028037541@gmail.com

Pallavi S. Deshpande
Depaartment of Electronics & Telecommunication Engineering.Smt.Kashibai Navle College of Engineering ,Vadgaon Bk.Pune.
pallavisd@rediffmail.com

Abstract-Respiratory diseases such as pneumonia, bronchitis leading causes of child death in the word .out of this pneumonia are causing the million children death each year around the word. One of the challenged faced in consistent diagnosis of childhood pneumonia in secluded area is difficulties arising from field deployable, laboratory facilities and trained healthcare worker. Such issue we address in this paper and to categorize the pneumonia using the geometrical analysis of cough sound. We used the wavelet-based mathematical tool which is a useful work for crackle detection in lung sound analysis. Such feature can be added among new mathematical feature and to develop the automated classifier to distinguish the pneumonia with other respiratory diseases. In our project uses feed forward neural network classifier to increase the classification performance with having sensitivity 90%, specificity 98.7% and accuracy 97%.Cough and crackle sound are sign of pneumonia. Cough sounds permit us for pneumonia diagnosis with adequate sensitivity and specificity.

Keywords:- Slant Wavelet Transform, Neural Network, Pneumonia Cough Sample Sound.

I. INTRODUCTION

Cough is a justification system to the body which clears the respiratory tract from outside materials which are inhale accidentally and create internally by infections. It is a common symptom appearing in respiratory diseases such as pneumonia, the foremost of death is occouring in children which is less than five years of age. It has been estimate that pneumonia shall causes over 1.5 million deaths in each year, with more Than 96% of cases occurring in the well developing countries. Main reason behind them is the facility which is available having low cost instrument, field-deployable and diagnostic technology is most challenges key in struggle pneumonia Mortality. Currently does not have special method or standard is an available for pneumonia diagnosis even in hospitals. [1], The process which is available is not simple, but rather a grouping of clinical, radiological, and laboratory diagnostics that is often difficult to get to much of the population affected by the disease. Address such issue then developing an automated cough sound analysis method to diagnose pneumonia. This Will possible to develop the system which has inexpensive, noncontact, way of testing pneumonia cases without the help for widespread training in the field. aim to build a higher [1].specificity and maintain sensitivity at >90%.That study is a combination of several geometrical features, few of which are widely used in speech signal processing, such as [4],formant frequencies (FF) and Mel Frequency Cepstral Coefficients (MFCC). Work shown in this paper we intend the different class of features inspired by the adventitious lung sounds known as crackles, which is normally found in pneumonia and regularly observed more in the chest musculature using stethoscopes. We recorded cough sound signal with sound proof room in free-air outside the mouth and analyzed the (wavelet decomposition), targeting crackle-like components. We then combined the two feature sets and developed pattern recognition technology to diagnose childhood pneumonia.

[5].Wavelets transform can provide a best way of resolve the nonstationary signals such as the crackle sound in both time and frequency domains. Wavelet having the capability to attention on restricted signal structures with a zooming procedure is efficient in detect singularities between signals, and a powerful multiresolution analysis tool to detain changes in frequency characteristics at any instant in time. The diagnosis of childhood pneumonia using cough sound analysis is a like new research area. Our aim to explain the wavelets can be very effective in decomposing cough sounds and developing features definite to pneumonia.

II. OBJECTIVES

The Objective of this project listed below

- Extract the feature of cough sound using the wavelet for diagnosis of pneumonia
- To archive more accuracy of system
- To make system more flexible and robust

III. LITERATURE SURVEY

[1]The paper by U. R. Abeyratne in this research paper explains the cough sound analysis can be used to diagnose the child hood pneumonia. In this method the computerized study of cough signal and respiratory sound can be collected using microphone that does not require any direct contact with subject. Then segmentation had done using the manually from this find out mathematical feature, Such as non gaussianity and mel cepstra from cough sound. In this method differtiation of pneumonia and non pneumonia sound can done using logistic regression classifier

[6]The paper by F. Ayari works going on in this paper show that lung sounds analysis can done using wavelet transform The objective of this paper for lung sounds analysis can be done using adaptive filtering and wavelets show with one desertion moment can successfully detect .the pathological changes of the lung which produce sounds with measurable regularities. Local regularity can allows us to detect some important components of adventitious sounds which are difficult to detect by the physician ears due to their short duration. to analyze lung sound it can uses the mathematical tool lipschitz continuity function which can detect the maxima position and minima position regular lung sound waveform pattern. Numerical results show that normal lung sound is not regular than as compare to the crackle lung sound

[13]The paper by M. Du work going on this paper explain that Crackle sound classification and detection will based on matched wavelet analysis This is new method for crackle detection which is depends upon the ‘matched’ wavelet transform. Based on the Crackles sound can be detected using the envelope of the signal at optimal scale, and it can be classified based on energy distribution with scale.

[4]The paper by vinayak swarnkar “In this paper Automatic segmentation of pneumonia cough and non-contact sound recordings done in pediatric wards’’ In this paper developed a method which can differentiate non pneumonia and pneumonia cough segments automatically during the pediatric sound recordings. Method is based on extracting statistical features such as non-Gaussianity, Shannon entropy, and mel frequency cepstral coefficients to describe cough characteristics. These features then used to train a time delay artificial neural network classifier to detect coughs segment in the sound recordings. From this proposed method achieve the sensitivity, specificity of 93%, 98%, respectively.

[5]The paper by Yosuf Amrulloh, Rina Triasih in this research paper show that Pneumonia and asthma can be differtiate in pediatric Population based on cough sound analysis.This paper explains that Pneumonia and asthma are the common diseases in pediatric population. The diseases showing few similarities of symptoms that Cough is the major symptom of pneumonia and asthma. The audio of cough sounds may carry vital information which correlated with the diseases. This technique obtains the sound features such as Shannon entropy, mel frequency cepestral coefficient, bispectrum score and kurtosis. This features then used to develop artificial neural network classifiers. [4].Using this classifier achieved specificity, Kappa and sensitivity of 100%, 0.89 and 89% respectively. The physical examination findings show that more than 50% of asthma subjects had respiratory rate higher than threshold and 30% of them had sub-costal retraction. Study in suggested adding fever to improve the specificity of pneumonia diagnosis. However, 44.4% of asthma subjects had fever. The physical examinations also show that crackles sounds is not specific to pneumonia.

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IV. BACKGROUND

A. Continuous Wavelet Transform

The continuous wavelet transform uses signal and an analyzing function .it is different approach for simultaneous find out time and frequency signal. Wavelet has the advantage That it allows superior perceptible localization of frequency component to analyzed signal than commonly used short time Fourier transforms (STFT). Wavelet analysis allows to use long time windows function when we need the more specific low frequency signal. It can produce the exact representation for nonstationary signals with discontinuities like cough and crackle sounds. [4].The continues wavelet transform is given by

$$\mathbf{CWTxi\ (a,\ b) = xi,\ \psi\ a,b = \int xi\psi a,bdt}$$

Where a is the dilation parameter and b is the translation.

The Dilation parameter is alike to the scale, which determines the timescale resolution of the resulting CWT operation. By analyzing xi over a different range of scales, CWT offers multiresolution frequency filtering capability to target specific frequency bands. This change to dissimilar crackle types (coarse and fine) based on two cycle duration (2CD) of the detected crackles. Fig. 2 shows a time-domain example of an infant expiratory crackle in comparison with various wavelets such as [1]. Du,morlet , Mexican Hat,Daubechies and Paul. It can be observed that crackle waveform has some similarity to the basic shape of the various wavelets.

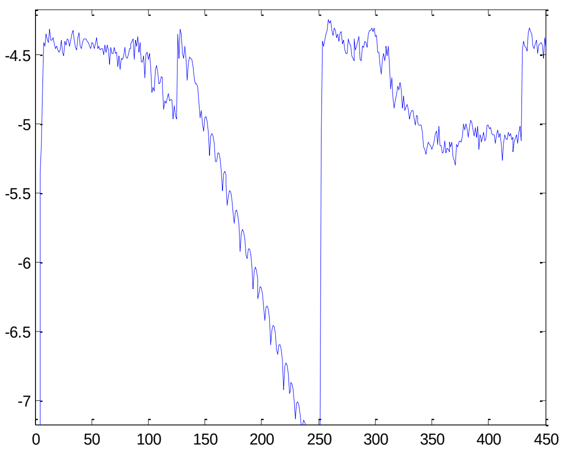

Figure 1: MFCC Plot of Pneumonia Signal.

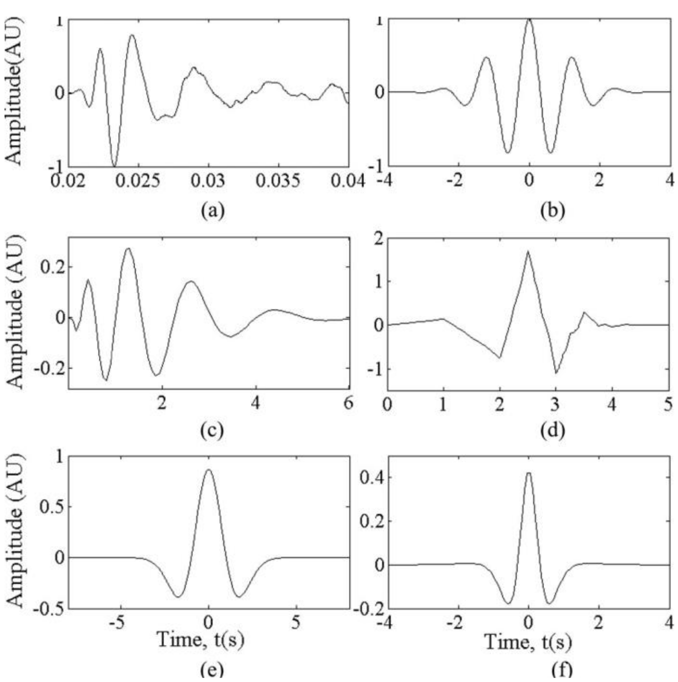

Figure 2: Side-By-Side Comparison of (A) Example Infant Expiratory Crackle. With Various Wavelets: (B) Morlet , (C) Du, (D) Daubechies3, (E) Mexican Hat, (F) Paul.

Wavelet feature of cough sound can be extracted is given by The process will applied for slant wavelet transform following computation is used to calculation of CWT.[1]

Computation of CWT:

- Let x denote an RMS normalized cough sample.
- Apply CWT on scales. Let ci represent wavelet representation of x on the ith scale, where i = 1, 2, 3,etc.
- Segment each ci to equal non overlapping sub segments and calculate the energy concentration by sum of absoluteValues in each segment, cij , where j = 1,2,3, . . . ,etc Eachcough sample, ci
- For each ci , calculate the slopes for each cij along the timeAxis. For the first segment, it is the ratio of cij : $ci(j+1)$.
- For segments 2–11, it is the ratio of $ci(j-1)$: $ci(j+1)$. For The last segment, it is the ratio of $ci(j-1)$: cij .
- Repeat for each ci for all cough samples

V. EXPERIMENTAL SETUP

The cough sound can be collected from Datta Hospital Sangamner.most of the patients showing symptom of pneumonia. The recording setup contains of high reliability recordings from one bedside microphone having the model NT1 RODE. Software NUEND04 used for recording purpose. The distance between the microphone and subject is near about 1 foot. distance may be vary depend upon movement of the subject .we keep the sampling rate 48Khz sampling/s and 16 bit resolution to obtain the best quality of sound. File format for speech format is .wav.the total recording sample 300 collected from this study and split into the training and testing data set.

VI. SYSTEM ARCHITECTURE

A. Choice of Scale

The selection of scale used for direct conversion of its 2 cycle duration to frequency. Selection of scale in wavelets is like that of window sizes in short time Fourier transform which determine the frequency resolution of cough sounds which is directly affects the shapes of the output of the signal.

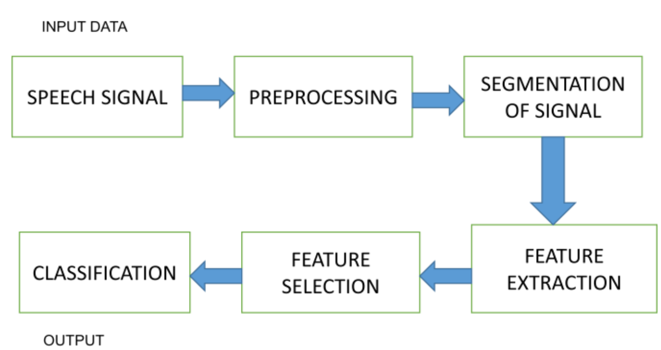

Figure 3: Block Diagram of Proposed System.

B. Data Acquisition

In this step from collection of cough sample training model data set will be created for pneumonia classification process. in this project we uses the feed forward neural network classifier .criteria is to choose feed forward neural network classifier is depends upon it should cover all types of cough sound. It can be learn the characteristic of cough sound from this it can be differtiate non cough sound and cough sound.

a). Preprocessing

In this step noise can removed by using the high pass filter .high pass filter having the capability to reduce the small variation in sound intensity. we design the butter worth high pass filter having fourth order with cut off frequency is 10Hz.if any local noise is present then it is removed by using the selection of cough selection feature matrix.

b). Calculate the Feature Selection Matrix

In this step after the normalization of cough sample signal wavelet feature can be calculated using the classifier. We uses the slant wavelet for computing the feature of each cough sample computed process is explain section III.same process will repeated for each cough sample. Slanted transform is very useful technique especially in piecewise linear data. slanted wavelet transform show the orthogonality property with 2 zero moment with time localization. It also retains the basic characteristic of octave filter bank with dilation factor of two.

c). Feature Extraction

To describe the feature of sound signal by using the rectangular window having length (N=960 sample equal to the 40ms) to the filtered signal. From that we create the data signal sub block and obtain feature of each sub block. Then Following feature will computed each sub block.

d). Mel-Frequency Cepstral Coefficient(MFCC)

MFCC is mostly useful tool in speech recognisation process. it is very useful for cough analysis.MFCC involve the estimation of short time power spectra. Mapped to the mel frequency scale and to compute cepstral coefficient.

e). Formant Frequency(FF)

In speech signal analysis formant frequency explain the resonance of vocal tract. In cough, it is reasonable to expect that resonances of the overall airway will be represented in the formant structure. Formant frequency can be calculated using linear predictive coding. in our work we calculate the three formant frequency for each sub block.

f). Shannon Entropy

Cough sound is complex signal which represent the different structure of vocal tract. A structure display component is like pseudo-periodic type, while others have a random stochastic character. in this work we capture the such feature by using the Shannon entropy

g). Zero Crossing Rate(ZCR)

Zero crossing rate defined in total duration time signal crosses the zero axis. it is mostly used to detect the periodic nature of the signal. it may show that the glottis vibration can be used to separate the voiced and unvoiced signal

C. Design of Optimal Classification Model

in this step we automatically classified the pneumonia sample signal and non pneumonia sample signal. description of this process given as follow

a). Design of Neural Network Classifier

in our work project we use the feed forward neural network classifier for the separation of the pneumonia sample signal and non pneumonia sample signal. It is biologically inspired classification algorithm .feed forward neural network having the Capability to know the different types of the cough sound. It consists of a number of simple neurons like processing unit organized in layer. Every unit in layer is connected with all the units in previous layer. It having the advantages that it can be classifies the data using the linear decision boundaries.

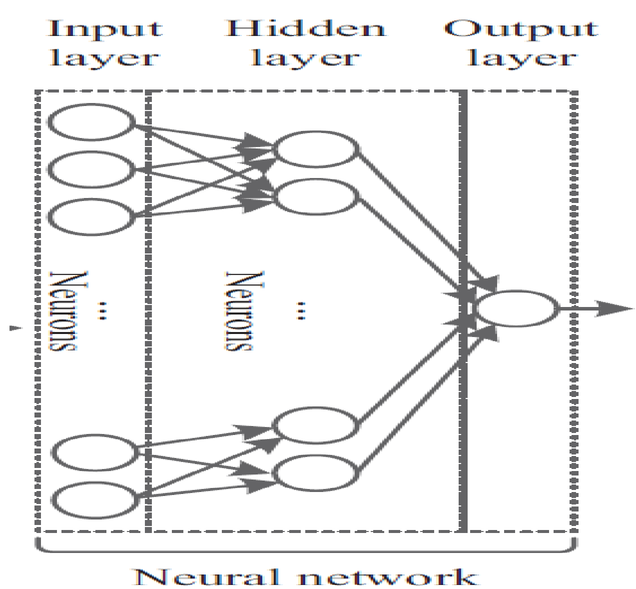

Figure 4: Feed Forward Neural Network Classifier

VII. IMPLEMENTATION RESULTS

For classification purpose we uses the feed forward neural network classifier.inour study we collect the sample of pneumonia age between 1-15 years old patients during the study we analyze the total 250 sample. Out of which we use 150 samples for training data set And 100 sample for testing data set.

Correct classification of pneumonia of infected person cough sample sound and normal person cough sample sound can be measured in terms of specificity, sensitivity and accuracy the following confusion matrix gives the output accuracy of proposed system

VIII. CONFUSION MATRIX

	NORMAL PAITENTS	PNEUMONIA INFECTED PAITENTS
NORMAL PAITENTS	18	2
PNEUMONIA INFECTED PAITENTS	1	79

Figure 5: Final Result with Confusion Matrix.

Manual calculation given below

Positive (P) =20
Negative (N) =80

$$\textbf{Accuracy}=\frac{TP+TN}{P+N} = \frac{18+79}{20+80} = 97\%$$

$$\textbf{Sensitivity (TPR)} = \frac{\mathrm{TP}}{\mathrm{P}} = \frac{18}{20} = 90\%$$

$$\textbf{Specificity (TNR)} = \frac{\mathrm{FN}}{\mathrm{N}} = \frac{79}{80} = 98.7\%$$

Where True positive (TP) = Number of pneumonia cough sound is classified as pneumonia cough sound, False negative (FN) = Number of pneumonia cough sound is classified as normal cough sound, True negative (TN) = Number of normal cough sound is classified as normal cough sound False positive (FP) = Number of normal cough sound is classified as pneumonia cough sound .

IX. CONCLUSION

In proposed method it is easily possible to classify the pneumonia using cough sound. Using this method we achieve the accuracy of 97%, sensitivity of 90% and specificity of 98.7%.in addition that wavelet transform can extract cough sound feature with higher accuracy so it is possible to increase classification performance.

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