Analysis of Cough Sound for Pneumonia Detection Using Wavelet Transform and Statistical Parameters

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Abstract— **Pneumonia is cause of death of millions of children under 5 years every year. Pneumonia is contagious disease which easily spread through air. In-spite of its severity the conventional methods used for diagnosis of pneumonia are costly and not easily available in resource poor regions. This paper presents a simple tool for diagnosis of pneumonia using cough sound analysis. Pneumonia patient's cough sound is collected, wavelet decomposition of the sound is performed and then statistical parameters are found out to divide the cough into pneumonia or non-pneumonia. In this paper, a crackle signal is analysed using different scales and different wavelets in CWT. For pneumonia cough samples the same steps are applied. FFT of the signal gives the frequency in required range. Then statistical parameters are calculated for original cough segments and also for CWT coefficients. Power spectral density of original signal as well as CWT coefficients is performed, in which, CWT coefficients gives required results. Threshold values of skewness and kurtosis are used to divide cough signals into pneumonia or non-pneumonia.**

Index Terms— Continuous wavelet transform, statistical parameters, power spectral density, etc.

I. INTRODUCTION

Pneumonia is a lower respiratory lung infection that causes inflammation in one or both lungs. Pneumonia is contagious; most of the cases are airborne usually caused by infection with viruses or bacteria.

India carries the highest burden of pneumonia deaths in children, the latest report of John Hopkins Bloomberg School of Public Health has said. The report stated that India accounts for one out of five child deaths due to the disease. In 2015, a projected 2.97 lakh pneumonia and diarrheoa deaths are estimated in children aged less than five in the country. Of the projected 5.9 million deaths of children aged less than five in 2015 across the world, pneumonia was the top killer at 16 per cent. The study was conducted in 15 countries that have reported more cases of pneumonia and diarrheoa [11].

The conventional methods normally employed for the diagnosis of pneumonia in the hospital by physicians are medical and physical history, physical examination, laboratory tests like blood or sputum tests, chest X-rays and other imaging techniques, etc. All existing methods require specialized equipment, therefore the tests are costly and also not always available in poor countries and resource constrained regions where death due to pneumonia is a common occurrence[1].

The World Health Organization (WHO) has therefore, developed a simple clinical algorithm to classify pneumonia based on the existence of symptoms like cough, breathing difficulty, chest-in-drawing, breathing rate. The WHO algorithm has un- acceptably low specificity (16-47 %) in diagnosing pneumonia, which is harmful to the patient and the society. Automated cough sound analysis is used to diagnose pneumonia which is low-cost, non-contact, non-invasive way of testing potential pneumonia cases without the need of any training in the field. Features of crackle will be analysed in cough sound analysis for accurate determination of pneumonia[1].

Section II describes the methodology used. Details of signal analysis and discussion is given in section III. Conclusions obtained are mentioned in section IV. Section V gives detail information about future work.

II. METHODOLOGY

The scope is defined for pneumonia detection of children of age 6 months to 15 years old. Collection of cough sample is the major task. Using a mobile phone voice recorder cough sounds will be collected. Distance from the microphone to the patients mouth varies from 15 to 30 cm, taking into account patient's movement on the bed. Manual segmentation is done to identify the cough samples in the recordings by listening. The segmented samples include the 100 ms of recordings prior to and after each cough which covers the possibility of crackles occurring in those brief moments[1]. Fig.1 shows the block diagram of the complete signal analysis. The programming is done in MATLAB R2010a.

Fourier Transform (FT): Often times, the information that cannot be readily seen in the time-domain can be seen in the frequency domain. FT is a reversible transform, that is, it allows to go back and forward between the raw and processed (transformed) signals. However, only either of them is available at any given time. That is, no frequency information is available in the time-domain signal, and no time information is available

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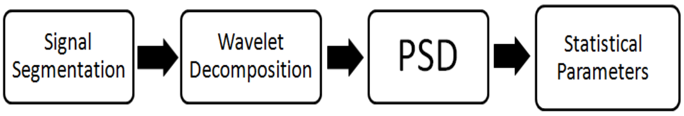

Fig.1: Steps carried-out in signal analysis

in the Fourier transformed signal. The FT gives the frequency information of the signal. But it does not tell us when in time these frequency components exist. This information is not required when the signal is stationary. As our crackle signal is transient and non-stationary in nature, FT only gives the information about which frequencies are present in the signal. This information will be used as a feature in the our analysis.

Continuous Wavelet Transform (CWT): CWT is an alternative approach to the STFT, which was developed to overcome the resolution problem. The analysis technique is similar in wavelet analysis and STFT analysis. The technique involves that the signal is multiplied with a function i.e. wavelet function, and the transform is computed separately for different segments of the time-domain signal.

The continuous wavelet transform is defined as follows,

$$CWT_x^{\psi}(T,s) = \psi_x^{\psi}(T,s) = \frac{1}{\sqrt{|s|}} \int x(t)\psi^*(\frac{t-T}{s})dt$$

Wavelet transforms allow time-frequency localisation. Wavelet means small wave. Wavelets used in this paper are Morlet, Db3 and Mexican Hat. Specifically these wavelets are used because they have shape similar to that of crackle signal.

Mean: Mean is determined by adding all the values in a signal and then dividing by total number of values. The resulting number is known as the mean or the average. The statistical mean refers to the mean or average that is used to derive the central tendency of the data in question.

Variance: Variance is the expectation of the squared deviation of a random variable from its mean, and it informally measures how far a set of (random) numbers are spread out from their mean.

Skewness: Skewness is a measure of the asymmetry of the probability distribution of a real-valued random variable about its mean. The skewness value can be positive or negative, or even undefined.

Kurtosis: The kurtosis is a measure of the peakedness associated with a probability distribution of segment or the sharpness of the peak of a frequency-distribution curve.

Power Spectral Density (PSD): Power Spectral Estimation method is to obtain an approximate estimation

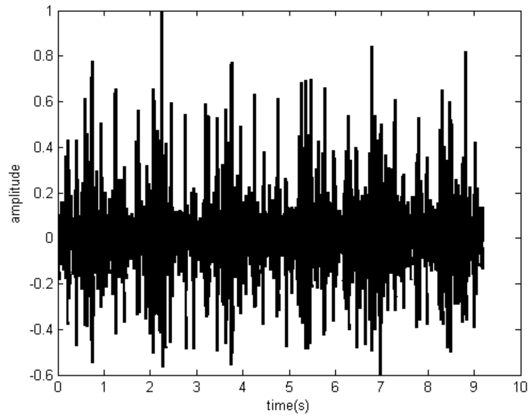

Fig.2 : Crackle signal taken from online database[2]

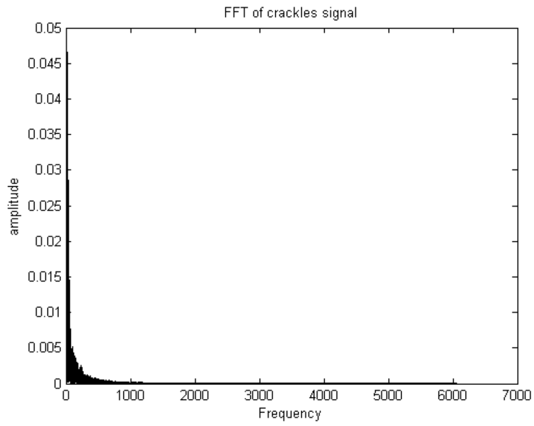

Fig.3 : FFT plot of Crackle signal

of the power spectral density of a given real random process. The method consists of dividing the time series data into possibly over- lapping segments, computing a modified periodogram of each segment, and then averaging the PSD estimates. Each segment is windowed with a Hamming window that is the same length as the segment.

III. ANALYSIS AND DISCUSSION

The filtered crackle signal is taken from database available at [2]. The signal is plotted in Matlab as shown in Fig.2. FFT of the signal is taken. Fig.3 shows the FFT plot, which indicates that, the rackle signal has frequency less than 1 kHz. The frequency range of crackles is between 150 to 2000 Hz [3]. Continuous wavelet transform is used to decompose the crackle signal. Different scales are used with same wavelet Morlet so as to separate each crackle distinguishably as shown in Fig.4. The results are good with scale 32 as well as 64, but the final scale selected is 32. With scale 128 the results are not good to separate each crackle. The scale depends on the frequency content of the signal. The results of different wavelets like Db3, Morlet and Mexican Hat wavelets are compared as shown in Fig.5. The wavelets are used because they have basic shape approximately equal to crackle signal [1]. The crackles are separated very well by Morlet wavelet than Db3 and

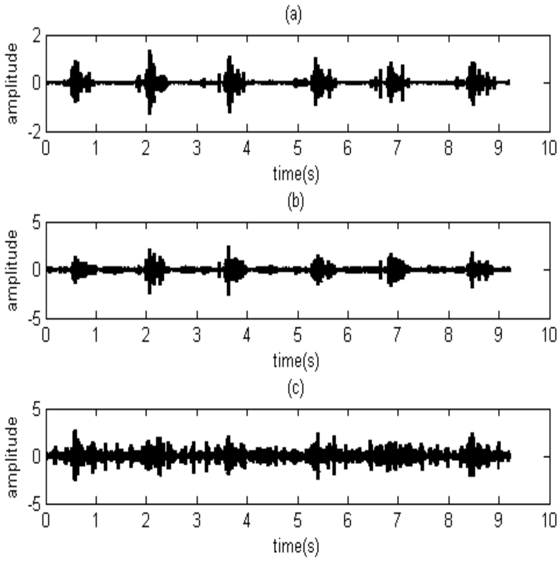

Fig.4: Comparison of wavelet decomposition results of wavelet as Morlet and different scales (a)32, (b) 64, (c) 128

Mexican Hat wavelet. Hence for further analysis Morlet wavelet is used.

Fig.6 shows the plot of actual cough signal recorded from pneumonia patient two and half years old. The signal is of duration around 8 seconds. The sampling frequency used is 18100 Hz. The signal is divided into different segments, each of duration 400 ms. The segment duration is such that it will contain crackle. Four segments extracted from the signal and their respective FFTs are as shown in Fig.7. The wavelet decomposition of each segment is done using Morlet wavelet and scale as 32 as shown in Fig.8. Depending on the CWT coefficients further analysis will be done. Further again, FFT of CWT coefficients is taken to confirm the frequency range of crackle signal as shown in Fig.9. Fig.9 is actually a filtered version of Fig.7.

Mean, variance, skewness and kurtosis of each segment is calculated before CWT decomposition and after CWT decomposition. These values did not define any threshold. Hence further signal analysis is done using PSD. PSD is applied to original cough segments and also to CWT coefficients, results of CWT coefficients are better than original cough segments. For PSD, welch method is used because small segments of sample are taken with some overlapping. Skewness and kurtosis calculated after PSD of CWT coefficients gives the required threshold values. After the signal analysis, threshold will be applied to divide the signal into pneumonia or non-pneumonia.

Analysis of 22 signals (17 pneumonia and 5 nonpneumonia) is carried out. The values of skewness and kurtosis for these signals are as given in table I. These are the

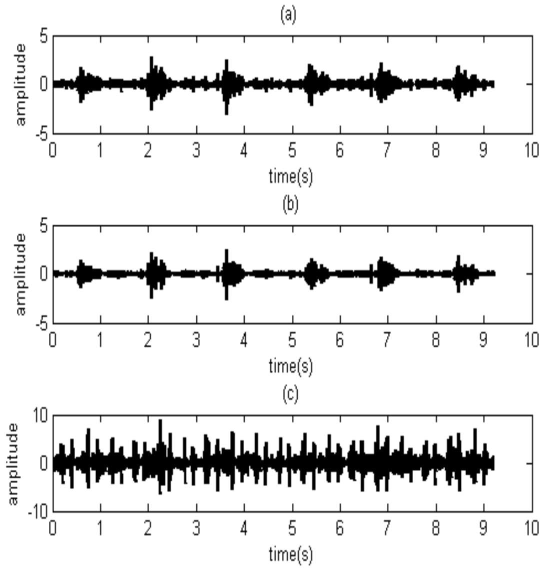

Fig.5: Comparison of wavelet decomposition results for (a)Db3, (b)Morlet, (c)Mexican Hat wavelets at constant scale 64

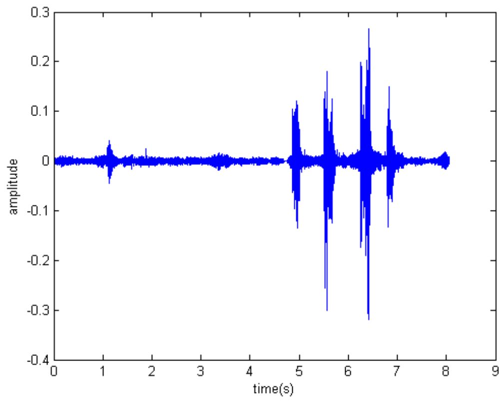

Fig.6: Original signal 1

values calculated after calculating PSD of CWT coefficients for different cough segments. Statistical parameters are found out for original cough segments directly, then after PSD of original cough segments. Statistical parameters are found out for CWT coefficients also, but no satisfactory results are achieved. The final threshold values of skewness and kurtosis are found out after applying PSD to CWT coefficients and using Welch method as observed in table I. In table I, signal 16, 21 and 22 defines the threshold values for normal non-pneumonia cough. Skewness values 7 or below 7 and kurtosis values 54.5 or below that define cough as non-pneumonia (normal cough) and above these values are pneumonia cough. The method is not 100 % accurate hence some exceptions are observed in table I i.e. signal 18 and 20. But by analysing more and more signals, results can be validated and accuracy can be increased.

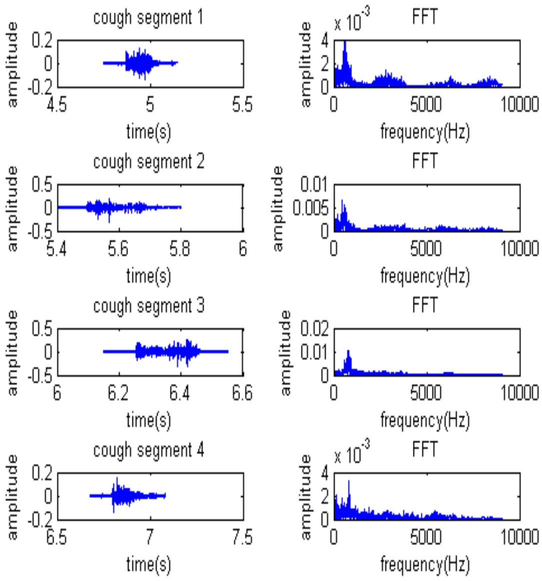

Fig.7: Segments of signal and Their FFTs

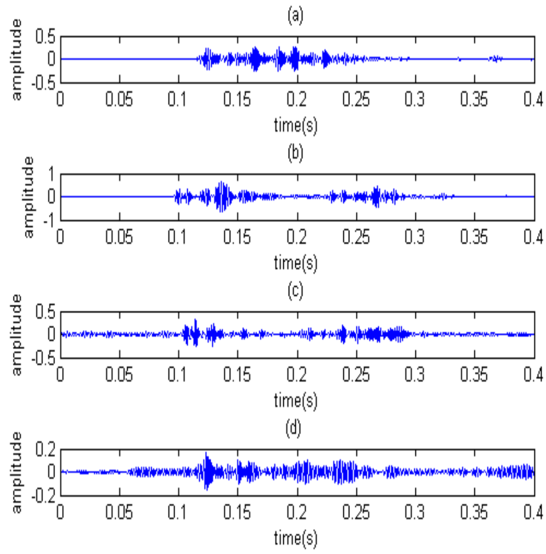

Fig.8: CWTs of segments of signal with wavelet as Morlet and scale as 32 (a)segment 1 CWT (b)segment 2 CWT (c)segment 3 CWT (d)segment 4 CWT

IV. CONCLUSION

In this paper, analysis of crackle signal is performed using wavelet transform. Crackle signal is having frequency less than 1000 Hz. After wavelet decomposition using different scales and different wavelets, scale as 32 and Morlet wavelet is finalised for further signal analysis. For pneumonia cough signal, different segments are found out each of duration 400/450 ms which will have probability of crackle in it. The wavelet analysis of these segments using Morlet wavelet and scale 32 gives good separation of crackles. Statistical parameters are calculated of original cough segments and of CWT coefficients. Also after applying PSD to original cough segments and CWT coefficients. The results are better after applying PSD to CWT coefficients and then calculating statistical parameters. Skewness and kurtosis threshold values divide the signal into pneumonia and non-pneumonia. This is a low cost, non-contact, noninvasive, screening test method for detection of pneumonia in rural health camps.

V. FUTURE WORK

The results can be improved by collection of more data samples for results validation and also calculation of more statistical parameters to increase accuracy of method. Also automatic classifier and automatic segmentation for cough signal can be applied.

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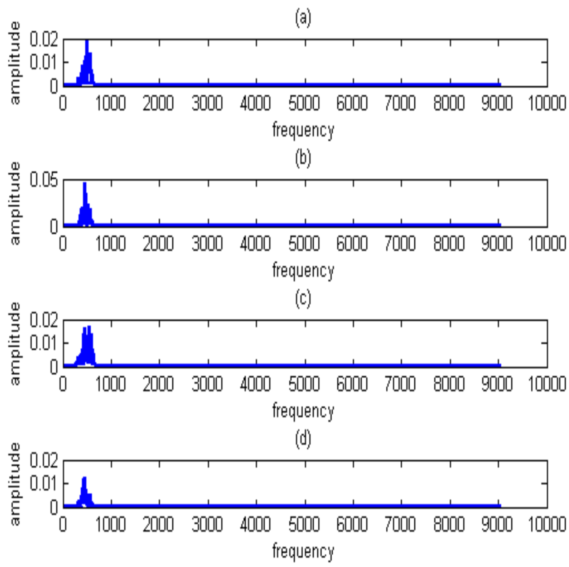

Fig.9: FFT of CWT coefficients of different segments (a)Segment 1 FFT (b)Segment 2 FFT (c)Segment 3 FFT (d)Segment 4 FFT

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TABLE I : ANALYSIS TABLE : SKEWNESS & KURTOSIS CALCULATIONS FOR CWT COEFFICIENTS AFTER WELCH PSD METHOD

signals	duration(ms)	skewness of CWT coefficients after welch				kurtosis of CWT coefficients after welch			
		seg1	*seg2*	*seg3*	*seg4*	*seg1*	*seg2*	*seg3*	*seg4*
1	400	10.5498	12.7003	8.2831	12.1423	131.7826	194.7924	78.3144	177.7787
2	450	8.2901	7.8147	11.375	12.0908	78.5077	69.0625	145.2774	189.6804
3	400	9.4715	15.8684	13.4358	8.5896	98.3622	279.1581	223.2241	87.5708
4	400	12.0849	8.2806	-	-	173.3441	79.5031	-	-
5	400	9.167	9.4756	8.4567	9.7759	101.8957	111.9924	86.5185	126.8551
6	450	8.3069	16.7201	9.5934	8.8457	83.643	342.3302	116.4661	88.3114
7	400	11.7595	14.4441	9.3099	9.2438	161.5334	239.574	100.1725	93.0101
8	400	7.5724	11.3998	5.7067	12.1659	72.271	160.8831	36.7678	176.4303
9	450	9.2019	7.0907	9.3423	12.853	111.6111	58.7302	98.5812	196.1772
10	400	11.9166	9.2745	16.6222	-	157.0132	96.9417	307.1567	-
11	400	9.1122	15.7238	17.2999	11.435	90.1605	271.4477	333.4967	143.1348
12	400	10.2859	12.066	7.4653	8.4584	126.3285	170.9226	64.9354	88.8029
13	450	12.3751	9.8106	12.282	15.7436	185.4567	117.9591	183.2582	278.471
14	400	12.5143	14.9706	8.2064	-	173.8505	255.9524	81.0488	-
15	400	16.755	8.1724	7.3648	8.3301	322.7121	74.4101	61.4532	76.8543
16 NC	450	6.1541	6.9537	-	-	44.0359	54.4252	-	-
17	450	9.7833	7.5186	15.0328	-	110.9906	64.3924	249.9585	-
18 NC	400	9.61725	-	-	-	114.789	-	-	-
19	400	7.015	12.6384	8.2864	-	59.2977	195.4245	77.8791	-
20 NC	450	9.523	13.0111	10.4252	11.0504	104.7598	190.4039	134.5048	141.8971
21 NC	400	5.7126	6.7078	-	-	36.7839	49.7187	-	-
22 NC	450	6.1942	5.9497	6.6303	-	48.8655	53.2262	46.5518	-