Towards Validating Diagnosed Respiratory Sounds Using Dynamic Time Warping at Alexandria University Children Hospital (AUCH) – Egypt

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Abstract: The aim of this paper is to illustrate a new method that is suggested in order to validate the diagnosis of pulmonary diseases, in infants and children, within high accuracy. A very large database is constructed containing 500 adventitious respiratory sounds of 3 different categories, namely wheezes, stridor and rattle, in addition to 100 normal breath sounds. Sounds were collected from infants and young children till the age of 12 years old. All samples were acquired from AUCH-Egypt. Dynamic Time Warping using Short Time Fourier Transform is employed in the proposed technique, and the validation results were found to be over 85%.

[Nader A. Fasseeh, Doaa A. Heiba, Mohamed M. Abougabal, Bassem S. Abdel Meguid and Mohamed Rizk M. Rizk. **Towards Validating Diagnosed Respiratory Sounds Using Dynamic Time Warping at Alexandria University Children Hospital (AUCH)–Egypt.** *Life Sci J* 2015;12(3s):12-23]. (ISSN:1097-8135). http://www.lifesciencesite.com. 3

Keywords*:* Dynamic Time Warping, Wheezes, Stridor, Rattle, Short-time Fourier Transform

1. Introduction

Respiratory noises are audible sounds associated with breathing that can provide important diagnostic information on the site and nature of respiratory diseases. As the parents of infants and young children will attest, ‘‘noisy breathing’’ is extremely common in this age group [1].

Whereas a multitude of different noises have been described in the literature, the most frequently used terms are “wheeze”, “rattle”, “stridor”, “snore” and “nasal snuffle/sniffle” [2].

Wheeze is a high-pitched, continuous and prolonged musical noise, often associated with prolonged expiration. While predominantly heard in the expiratory phase, wheeze can occur throughout the respiratory cycle. Wheeze originates from the intrathoracic airways, and can be produced by pathology either in the large, central airways, or the small peripheral airways [3].

When a structural lesion obstructs airflow in the large airways (intrathoracic trachea and major bronchi), the resultant noise is a result of turbulent airflow at the point of narrowing. Thus, the wheeze may be quite localized on auscultation, and is termed “monophonic” [4] when it contains a single frequency [1]**.**

In the presence of extensive small airway narrowing, the resultant high pleural pressure can cause compression of the large airways during expiration, producing generalized expiratory wheezing. The very young are particularly prone to this, because their large airways are relatively soft and more prone to collapse. Because the specific site of the large airway obstruction is variable, the noise then contains several frequencies and is termed “polyphonic” [4].

Rattle is a coarse irregular sound as a result of excessive secretions in the large airways, which are presumably moving with normal respiration. Rattles may be heard in either, or both, inspiration and expiration [5].

Stridor is a harsh vibratory sound of variable pitch predominantly inspiratory, and indicates obstruction to airflow in the upper airways down to the level of the thoracic inlet and mainly in the larynx. However stridor can occur in both phases of respiration, particularly when the obstruction is severe [6, 7].

Snoring is an inspiratory noise of irregular quality produced by increase in the resistance to airflow through the upper airways, predominantly in the region of the nasopharynx and oropharynx. Although snoring is generally more obvious in inspiration, the noise is frequently audible throughout the respiratory cycle [8].

The terms ‘‘snuffles’’ and ‘‘sniffles’’ are used to describe respiratory noises emanating from the nasal passages. Snuffle has also been used to describe any discharge from the nasal passages, and is sometimes used to describe a minor viral upper respiratory tract infection. These nasal noises are frequently audible in both inspiration and expiration, and often associated with visible secretions from the nares [9].

Grunt is an expiratory sound that is classically heard in the presence of extensive alveolar pathology and is considered a sign of serious disease [10].

These noises originate from specific anatomic sites within the respiratory system. Thus, correctly identifying these noises is of major clinical relevance, in terms of localizing both the site of obstruction, and the most likely underlying cause [11]. However distinguishing these noises from each other may be very difficult, even when heard by different clinicians [12].

Many studies were done for getting clinical benefit of respiratory noises like validation of respiratory questionnaire [13, 14] or use of videos [15], and also acoustic analysis [16]. Adult studies have highlighted problems with both accuracy and reliability of respiratory signs using a stethoscope [16].

Given the increased difficulty of examining young, uncooperative children, the assumption is that errors will be substantially greater in pediatric practice [17].

In an attempt to improve the utility of respiratory noises, computerized acoustic analysis has been evaluated. Most studies have been in adults and the published data in children are limited [16]. A small study of infants suggested a potential role for acoustic analysis. In particular, the ability of acoustic analysis to clearly distinguish wheeze from rattle [16]. Unfortunately, in a more recent study acoustic analysis proved to be disappointing. This study assessed the validity and reliability of acoustic analysis of respiratory noises in infants younger than 18 months [18].

All above studies were performed on a very limited number of infants. In this paper, a database of 500 adventitious lung sounds and 100 normal breath sounds were recorded and studied. All sounds were collected from Alexandria University Children Hospital (AUCH), Egypt. A modern stethoscope having the capability to pair with computers employing Bluetooth technology was utilized. The aim of the study was to acoustically analyze the recorded signals in order to achieve the following.

- Evaluate the clinical significance of different respiratory noises.
- Objectively characterize the acoustic properties of the most common audible respiratory noises of early childhood namely stridor, wheeze, and rattles.
- Establish a reliable categorized database of different respiratory noises used for future validation of diagnosed noises, and training on sounds.

The remaining part of the paper is organized as follows. Materials and Methods are discussed in section 2. Results and discussions are detailed in section 3. The paper is concluded in section 4, along with suggestions for some future extensions of the work.

2. Material and Methods

Study Design

The purpose of this study is to test a new proposed technique, that is used to validate the primary diagnosis of pulmonary diseases by pediatricians, within high range of accuracy for infants and children of ages from 0 to12 years old. This technique depends on Dynamic Time Warping using Short Time Fourier Transform.

In this paper, the term *infant* will point to the group of subjects whose ages range from zero to 11 months, while the term *children* will point to those whose ages range from 1 year to 12 years.

All subjects were recruited from the Emergency Department, outpatient clinics, and inpatient wards of El-Shatby Alexandria University Children's Hospital (AUCH), Egypt. All selected subjects were recorded after obtaining their consent.

The study emphasizes on wheezes, stridor and rattle subjects. Only infants and children with clear auscultatory characteristics of wheeze, stridor or coarse rattling sounds will be selected. Infants and children with any other lung sounds, or a combination of sounds will be excluded from the study.

One hundred apparently normal infants and children of matched age and sex with normal quiet breath were recruited as a control group. They could be used as a reference for offline validation of non-normal sounds and for training purposes as mentioned below.

Ethical approval for the study was obtained from Ethical Committee of Alexandria Faculty of Medicine.

Study Dataset

A large dataset of adventitious respiratory noises was acquired from 500 patients whose ages range from zero to 12 years old and 100 sound signals of normal breath sound, all obtained from AUCH, as mentioned above. The overall statistics of the acquired sound signals are illustrated in Table 1.

A large library was established using those acquired sounds, and it was uploaded to a server that could be used for training purposes, and also could be used for future work in this field of computerized respiratory sound analysis.

The main advantage of this dataset is that it's collected from real data at the AUCH, and it studies the environment of infants and children in Alexandria, Egypt.

In this work, monophonic wheezes sounds, in addition to some signals that were found to be very noisy, were excluded from the study. The monophonic sounds were excluded because their number was very few. Similar sounds were grouped together to form a reliable categorized database of sounds. Thus, the Database was divided into 4 diagnosed clusters; polyphonic wheezes, stridor, rattle and normal sounds.

Table 1 : Overall Statistics of Acquired Sound Signals

		Total No. of Signals	Percentage of Total Sounds (%)	Infants/Disease Type (%)	Children/Disease Type (%)
Wheezes	**Polyphonic**	321	64.20%	59.81%	40.19%
	Monophonic	4	0.80%	50.00%	50.00%
Stridor		98	19.60%	86.73%	13.27%
Rattle		73	14.60%	87.67%	12.33%
Noisy Signals		4	0.80%		
Total Sounds		**500**	**100%**		

Clinical Assessment

All selected cases were subjected to the following.

1. Thorough history taking stressing on onset, character, timing of respiratory noises.
2. Clinical examination by 2 consultant clinicians stressing on.
   - Auscultation of the chest.
   - Detection of respiratory noises.
3. Recording of respiratory noises using electronic stethoscope with Bluetooth technology.
4. Final clinical diagnosis of the cases with respiratory noises is confirmed using various imaging procedures, flexible fiber-optic bronchoscopy, and/or other investigations according to the history and clinical findings, if required.

To evaluate clinical significance of different respiratory noises, patients with each studied respiratory noise is categorized according to the underlying cause.

Signal Acquisition

Figure 1: 3M™ Littmann® M3200 paired to a Laptop (running Zargis StethAssist software) using Bluetooth technology

Using the advanced technology available nowadays, the 3M™ LITTMANN® Electronic Stethoscope M3200 [19] was used to record all the sounds and then paired to a PC (running Windows 7, Intel processor of Core i7 vPro/2.57 GHz, 8 GB of RAM) via Bluetooth® technology. Zargis StethAssist™ software [20] was used for pairing, and to export the sound signals to (.wav) files for the ease of use in processing. The environment is illustrated in Figure above.

The LITTMANN® M3200 generates sound files having a sampling frequency of 4 KHz (4,000 samples/sec.).

Using MATLAB® R2014a (from The Mathworks™), all the collected sounds were analyzed using Dynamic Time Warping algorithm by using their Short-time Fourier Transform (STFT) as features to calculate the similarity between all the sounds, and that will be illustrated in the next section.

Although this stethoscope features a technology of Ambient Noise Reduction, which cancels 85% of the background noise [19], yet the manual of the accompanied software (Zargis StethAssist™) stated clearly that the environment shouldn't be noisy, and should be as quiet as possible [21]. This was impractical with infants and children, in particular at the AUCH. The noises were evident in the LITTMANN® recordings, as depicted in the figures of the results section. Also heart beats sounds are heard sometimes. Thus de-noising, of the acquired sounds, was a must. This was done by employing filtering techniques which will be illustrated in the next section.

The Proposed Sound Analysis Technique

The proposed technique depends on Dynamic Time Warping (DTW) and Short-time Fourier Transform (STFT). This is in view of the below discussion.

The function of the Dynamic Time Warping is to compare similarity between 2 signals depending on a quantity (a metric) which is calculated. Ideally, the quantity may tend to zero if the 2 signals are identical and large if the 2 signals are dissimilar. The comparison is conducted according to some features. Those features are defined as the characteristic and distinctive attributes that could identify the signal.

Dynamic Time Warping is based on dynamic programming. It is a pattern matching algorithm with non-linear time normalization effect. It is found to be very useful in aligning two time sequences in order to measure the similarity between them using non-linear temporal alignment [22]. It has been used widely in the field of speech recognition. Respiratory noises are similar to speech patterns in having non-stationary characteristics and having inconsistency of frame length. In DTW algorithm, the fluctuation in time is modeled approximately by a non-linear warping function with some carefully specified properties. Thus, DTW algorithm perfectly fits the problem of concern in processing and analyzing the respiratory noises signals.

The concept of DTW was used in 2005 to recognize ECG changes in heart rhythm disturbances and it revealed very good results [23]. However, it was not used to date in computerized respiratory sound analysis.

Short-time Fourier Transform (STFT) reflects the power distribution of the frequencies along different time slots. Thus, STFT coefficients of each respiratory noise sound signal were calculated to represent the features of each signal in the Dynamic Time Warping algorithm. Short-time Fourier Transform produce the spectrogram of the signal, which is a graph having two geometric dimensions: the horizontal axis represents time, the vertical axis is frequency; a third dimension indicating the amplitude of a particular frequency at a particular time .This can be illustrated as in Figure 2 below.

The proposed technique is simplified in the following steps.

- Signal acquisition using the Littmann M3200 where the recorded sound signal is transferred to the processing computer via Bluetooth using Zargis StethAssist software.
- The Zargis StethAssist software was then used to playback the signal in order to check the quality of the signal, and also to export the recorded sound signal into Wave (.wav) file.

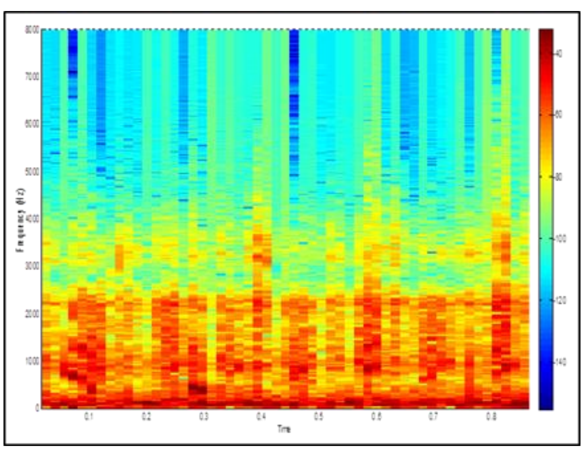

Figure 2: Spectrogram of a Sound Signal acquired Using the Littmann Stethoscope

- The previous 2 steps were repeated through the whole experiment for all the subjects.
- Using MATLAB, filtering was applied to all sounds in order to eliminate heart beats. Heart sounds range from 20 Hz to 100 Hz [1], but the lung sounds spectrum falls within 100 Hz. Therefore, high pass butterworth filters of 6th order with cutoff frequency at 80 Hz were employed [24].If the recorded sound was diagnosed either as stridor or rattle, it is passed through another low pass 6th order butterworth filter with cutoff frequency 1000 Hz [25], or 600 Hz [16], respectively. Since wheezes spectrum range from 80 Hz to 1600Hz [11] and sometimes up to 2500 Hz [1][26], no low pass filters were applied to wheezes sound samples. This is in view of the fact that the stethoscope maximum output frequency is 2,000 Hz.
- Short-time Fourier Transform on each signal $s(t)$can be calculated using equation 1, as follows:

$$F_{STFT}(\tau, f) = \int_{-\infty}^{\infty} s(t).h^{*}(t-\tau)\, e^{-j2\pi ft}\, dt \ldots$$
(1),

where $F_{STFT}(\tau, f)$ and $h^{*}(t-\tau)$ present the complex distribution function, and the conjugate of the spectral window used as a Time-Frequency kernel. The STFT was estimated [27], using 512-point Hamming windowed signal with 50% overlap and a discrete Fourier transform length of 2048 points.

- The difference (distance), between the calculated features of each 2 signals, is measured using the cosine distance between these two signals given by equation 2,

$$cos(\theta) = \frac{A.B}{\|A\|\|B\|} \ldots (2).$$

A , B are the two Spectrogram matrices of Signal 1 and Signal 2, respectively. $Cos\theta$ is the measure of similarity (measured metric) between the 2 signals and it is a matrix which is called the Distance matrix.

- Next, DTW is applied using the dynamic programming to calculate the best path (minimal distance) between each two signals.
- The total cost/distance between each 2 sounds is calculated depending on the best path chosen by the DTW algorithm.

The above steps are represented by the simplified flow chart depicted in Figure 3.

Similarity Matrices Generation

In this work, 4 clusters have been constructed, as mentioned above, from the previously acquired data. Those 4 clusters are polyphonic wheezes, stridor, rattle and normal sounds.

For each cluster, a Similarity Matrix (SM) is generated [28], where both the rows and columns correspond to the same objects (sound signals), i.e. the first row and the first column corresponds to the first sound signal, and the second row and second column corresponds to the second sound signal, and so on…, thus, 4 Similarity Matrices are constructed.

The data stored in a SM represent a collection of elements $d(i,j)$. Each $d(i,j)$ represents the total cost/distance between the 2 sound signals i and j , respectively. The Similarity Matrix is an (n x n) symmetric matrix with zero diagonal elements as shown in equation 3. This is in view of the fact that the rows and columns correspond to the same objects, and the element(i, i) represents the same sound signal.

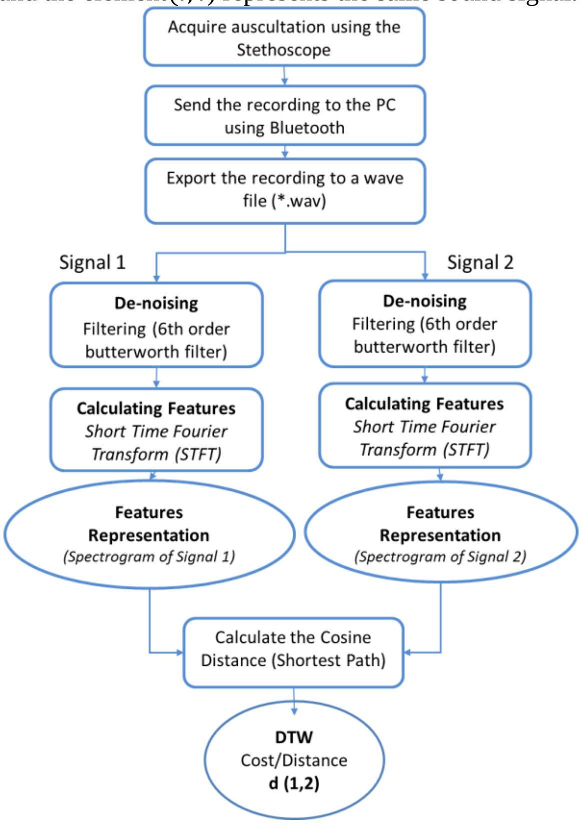

Figure 3: Flow Chart of the Proposed Technique

$$\begin{bmatrix} 0 & d(2,1) & d(1,3) & \dots & d(1,n) \\ d(2,1) & 0 & d(2,3) & \dots & \vdots \\ d(3,1) & d(3,2) & 0 & \dots & \vdots \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ d(n,1) & d(n,2) & \dots & \dots & 0 \end{bmatrix} \quad (3).$$

For each SM, the following parameters were evaluated:

1. parameter for each sound in the cluster which reflects the average similarity between this sound and all the other sounds within the cluster (P1);
2. parameter for each sound in the cluster which reflects the difference between the average similarity between this sound and all the other sounds within the cluster (P2);
3. parameter for the cluster which reflects the average similarity of all the sounds in the cluster ($P3$);
4. parameter for the cluster which reflects the difference between the average similarity of all the sounds in the cluster (3 above) and the average similarity of each specific sound within the cluster ($P4$);
5. parameter for each cluster which reflects the average of differences between the average similarities between each specific sound and all the other sounds within the cluster ($P5$);
6. finally, a parameter for each cluster, which reflects the difference between the average of differences between the average similarities between each specific sound and all the other sounds within the cluster ($P6$).

The Similarity Matrices, for the four clusters under study (wheeze, stridor, rattle and normal) along with the 6 evaluated parameters, are presented in appendix A.

Any newly diagnosed sound is validated to fall within the pertinent cluster by calculating its $P1$ and showing that it falls within ($P3 \pm P5$) of the concerned cluster. This condition is presented by equation 4

$$(P3 - P5)_{cluster} \leq (P1) \leq (P3 + P5)_{cluster} \quad \dots (4).$$

However, if equation 4 is not satisfied for validating the diagnosed sound, an expert opinion is needed.

3. Results and Discussion

Observed Statistics

It could be derived from Table 1, that in the environment of Alexandria, Egypt, infants represent 68.20% of subjects exposed to pulmonary diseases. Also, it may be observed from Table 1, that polyphonic wheezes are the most spread amongst infants and children, and presented 64.2% of the collected samples.

Results of de-noising the recorded sounds

De-noising was a very important step due to the presence of excessive noise, and some heart beats traces in most of the recorded sounds. The effect of the de-noising process using high pass and low pass butterworth filters is evident by studying Figures 4 through 7.

Validation of diagnosed sounds

The Similarity Matrices for all the 4 clusters wheezes, stridor, rattle and normal sounds were constructed for all the acquired signals. The Validation Parameters $P3$ and $P5$ for each cluster were calculated and are summarized as in Tables 2.1 to 2.4. The accuracy of validation entry, in each table, represents the percentage of signals of sounds satisfying the condition of equation 4 for each cluster. It is worthwhile mentioning that the accuracy of validation for all cases should have been 100%. This is in view of the fact that the clusters are reliably diagnosed as mentioned above. This confirms the above statement that *"**if equation 4 is not satisfied for validating the diagnosed sound, an expert opinion is needed**"*.

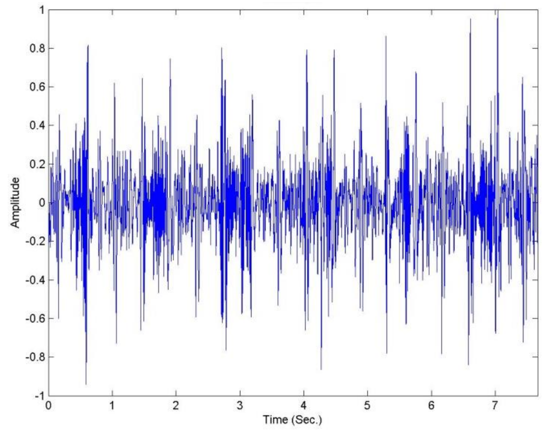

Figure 4.1: Time Domain Plot of Polyphonic Wheeze 9 (Un-filtered)

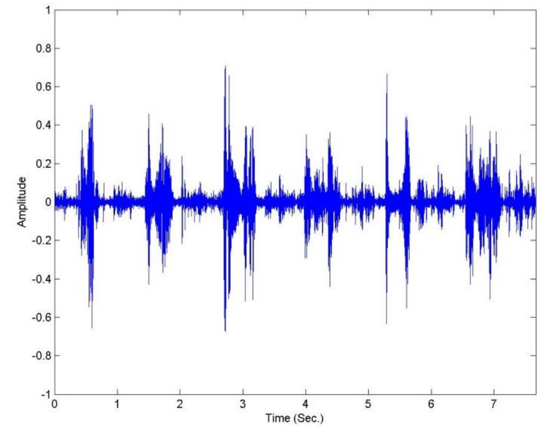

Figure 4.2: Time Domain Plot of Polyphonic Wheeze 9 (Filtered)

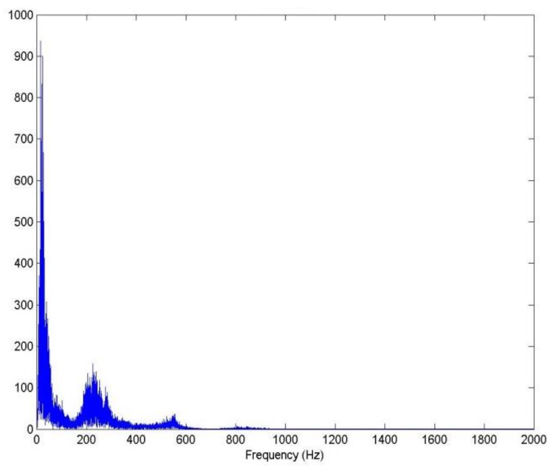

Figure 4.3: Frequency Domain Plot of Polyphonic Wheeze 9 (Un-filtered)

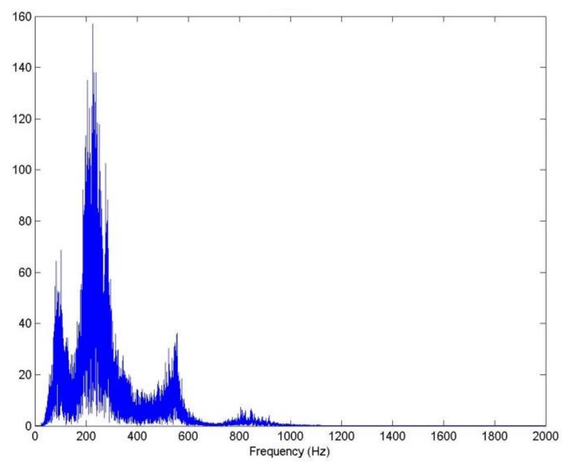

Figure 4.4: Frequency Domain Plot of Polyphonic Wheeze 9 (Filtered)

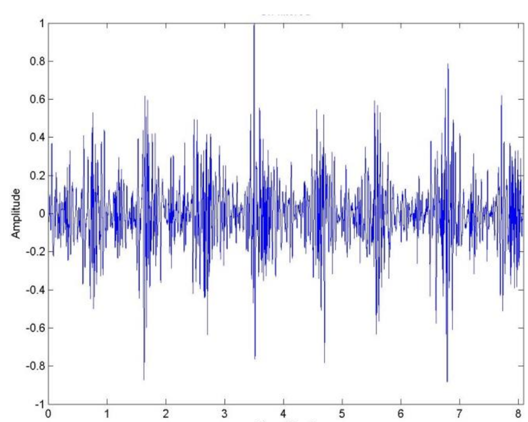

Figure 5.1: Time Domain Plot of Stridor 25 (Un-filtered)

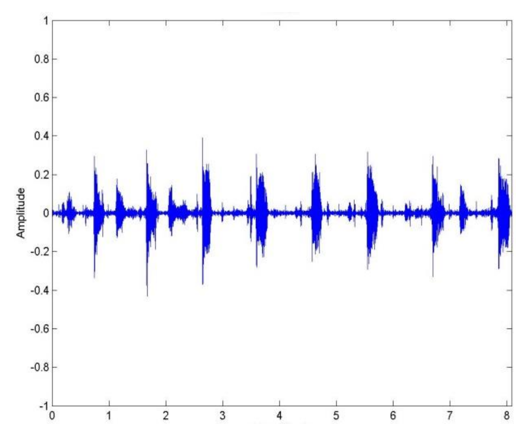

Figure 5.2: Time Domain Plot of Stridor 25 (Filtered)

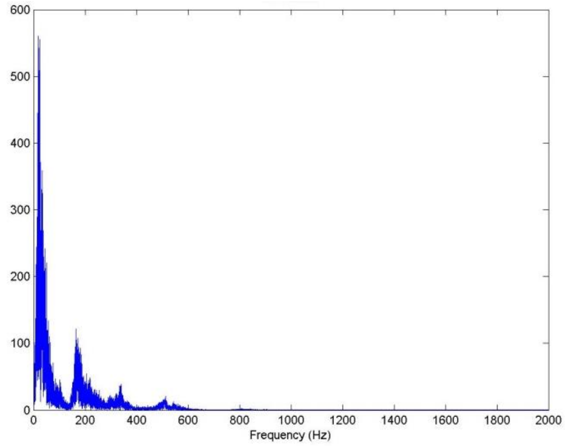

Figure 5.3: Frequency Domain Plot of Stridor 25 (Un-filtered)

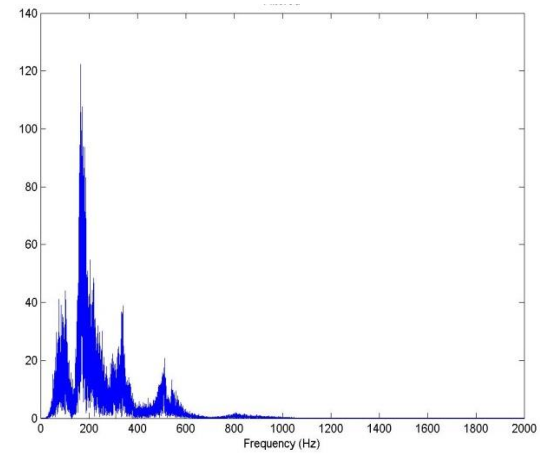

Figure 5.4: Frequency Domain Plot of Stridor 25 (Filtered)

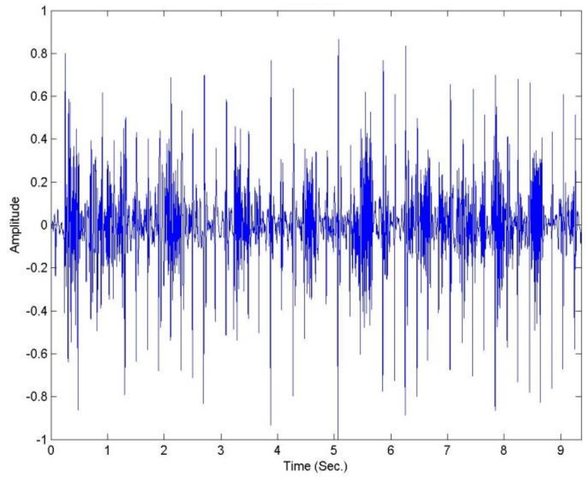

Figure 6.1: Time Domain Plot of Rattle 8 (Un-filtered)

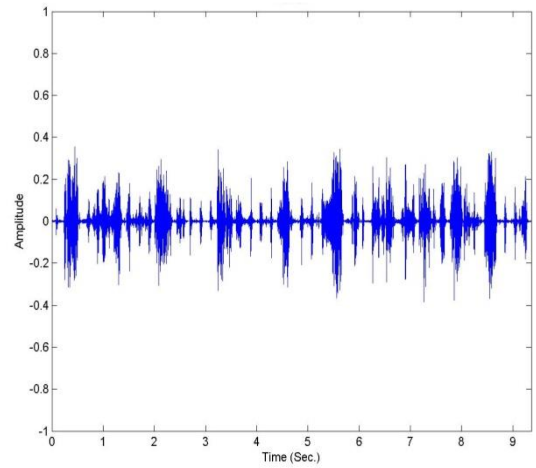

Figure 6.2: Time Domain Plot of Rattle 8 (Filtered)

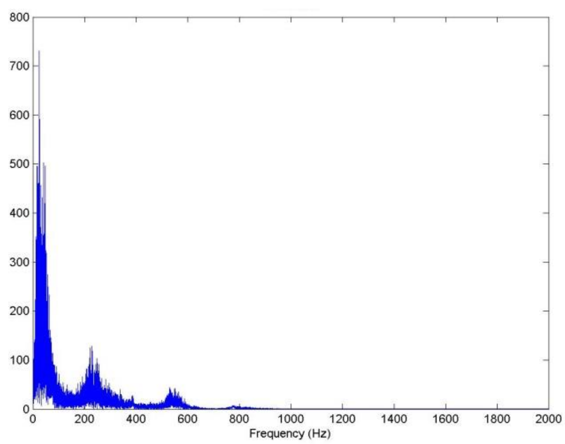

Figure 6.3: Frequency Domain Plot of Rattle 8 (Un-filtered)

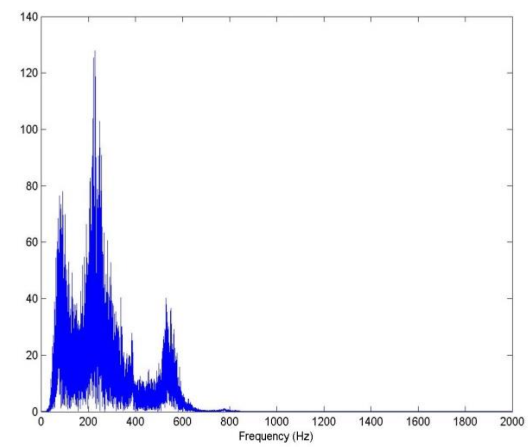

Figure 6.4: Frequency Domain Plot of Rattle 8 (Filtered)

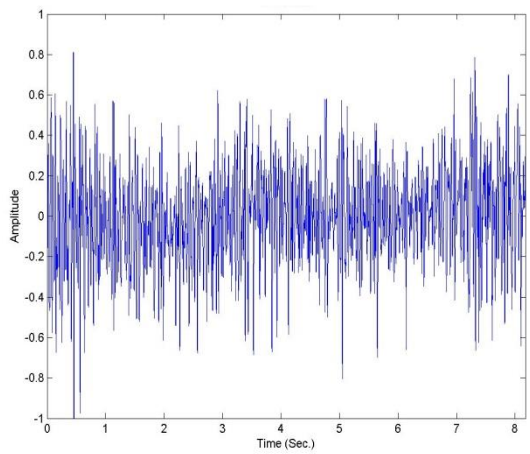

Figure 7.1: Time Domain Plot of Normal 27 (Un-filtered)

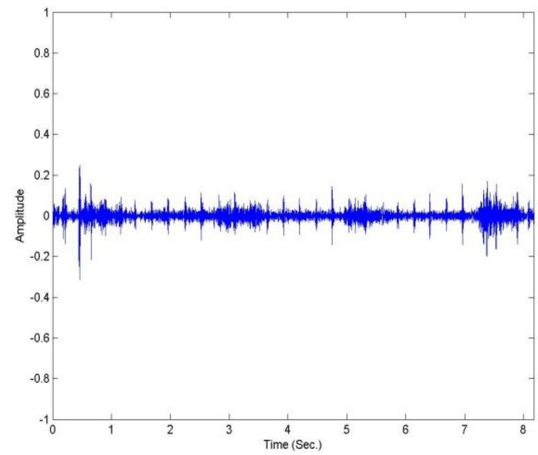

Figure 7.2: Time Domain Plot of Normal 27 (Filtered)

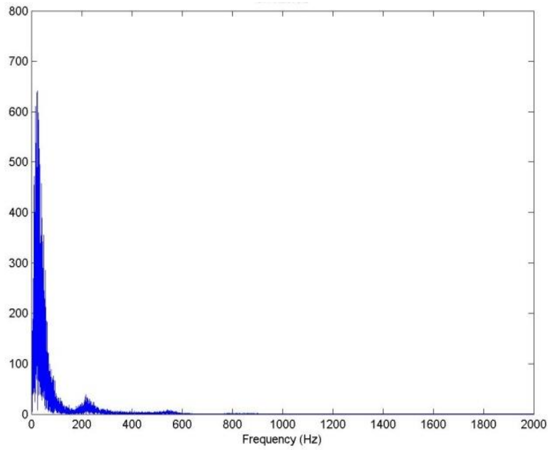

Figure 7.3: Frequency Domain Plot of Normal 27 (Un-filtered)

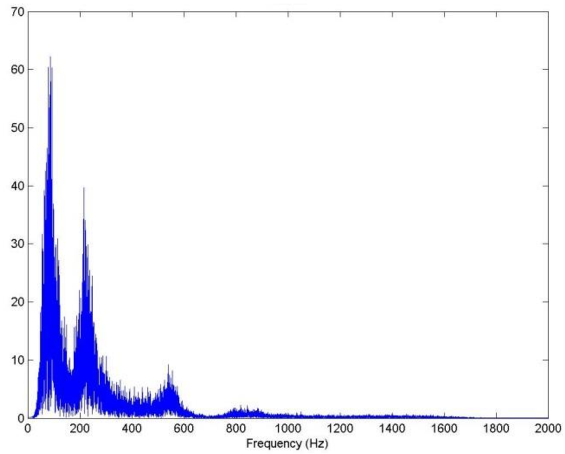

Figure 7.4: Frequency Domain Plot of Normal 27 (Filtered)

Close study of Tables 2.1 – 2.4 reveals, that categorization of the database by constructing two Similarity Matrices, one for infants and the other for children for each disease type, results in more accurate validation.

Overall discussion of results

It should be observed that the results reported in this paper are based on a large infants and children database acquired from a specific university hospital. This compares very favorably to all reported work which is based on much smaller sample of sounds [25,26,29,30] and most of them not acquired from a specific particular environment [31][32].

Therefore, this research lends itself very useful to the pediatric department at Alexandria University Children Hospital (AUCH), as it reflects real situation in Alexandria, Egypt. It may be used as an e-learning and e-diagnosis aid.

Table 2.1: Accuracy of Validation Attributes for Wheezes (M=Months)

Wheezes	**All Wheezes (321 Sounds)**	**< 12 M (192 Sounds)**	**≥ 12 M (129 Sounds)**
$P3$	42.12	41.95	41.03
$P5$	9.01	9.27	8.98
$P3 - P5$	33.11	32.68	32.05
$P3 + P5$	51.13	51.22	50.01
Accuracy of Validation	**81.93%**	**82.81%**	**89.15%**

Table 2.2: Accuracy of Validation Attributes for Stridor (M=Months)

Stridor	All Stridor (98 Sounds)	< 12 M (85 Sounds)	≥ 12 M (13 Sounds)
$P3$	53.56	53.46	50.19
$P5$	11.45	11.59	18.61
$P3 - P5$	42.12	41.88	31.58
$P3 + P5$	65.01	65.05	68.80
Accuracy of Validation	**86.73%**	**88.24%**	**92.31%**

Table 2.3: Accuracy of Validation Attributes for Rattle (M=Months)

Rattle	All Rattle (73 Sounds)	< 12 M (64 Sounds)	≥ 12 M (9 Sounds)
$P3$	43.80	42.68	44.34
$P5$	11.19	11.07	18.95
$P3 - P5$	32.61	31.61	25.39
$P3 + P5$	54.99	53.75	63.29
Accuracy of Validation	**87.67%**	**89.06%**	**100%**

Table 2.4: Accuracy of Validation Attributes for Normal (M=Months)

Normal	All Normal (100 Sounds)	< 12 M (26 Sounds)	≥ 12 M (74 Sounds)
$P3$	30.00	28.34	29.88
$P5$	6.70	7.78	6.92
$P3 - P5$	23.30	20.56	22.96
$P3 + P5$	36.70	36.12	36.80
Accuracy of Validation	**89.00%**	**96.15%**	**90.54%**

4. Conclusions and Future Extensions

A reliable categorized database of different respiratory noises was established and uploaded to a server. The Database contains 500 adventitious respiratory sounds and 100 normal sounds, all acquired from El-Shatby AUCH, Egypt. The studied age group was from 0 to 12 years. These were recorded using Littmann M3200, employing the techniques discussed in section 2 above.

This database may be used as an e-learning and e-diagnosis tool as follows.

- Offline training of junior residents/interns/5th year students on infants' chest sounds. Also validate their diagnosis when in practice as explained above.
- Used for future validation of diagnosed chest sounds. This is towards an attempt to spare infants/children from suffering from the procedures that are used to further diagnose the pulmonary diseases besides the stethoscope that is used as a primarily tool. It was found that the validation was over 85% accurate. However, a false validation doesn't mean false diagnosis. A second expert's opinion must be considered.

Also, the techniques used allow the recording of sounds, filtered signals and complete data of patients. Thus, allowing a second offline opinion for the diagnosed sound i.e. without the need of the re-auscultation process of the patient. This is equivalent to writing radiography reports using only the images, without the need for the presence of patients.

The presented work suggests the following future extensions.

- Apply the proposed technique on more samples of stridor and rattle sounds for children.
- Extract other metric features (other than the range given by eq.4) from respiratory sound samples which may result in better accuracy.
- Study the sensitivity of accuracy to the cutoff frequencies used in the low pass filters.
- The sounds library database may be published on the Internet with security measures to be accessed remotely and used according to a preset policy.
- Repeat the previous work using other signal analysis techniques, to mention Wavelet transform, and compare to the current results.
- Use the reliable categorized database (600 sounds) to train classifiers to be used in automatic diagnosis of sounds.
- Pediatricians may use the acquired realistic, reliable, categorized database (Time/Frequency domain signals plots and Audio sounds) in extracting

visual/acoustic characteristics of different pulmonary diseases. These characteristics may be used employing image/sound recognition techniques to automatically identify/diagnose different diseases. This seems to be a very interesting point for team work research.

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Appendix A
Similarity Matrices

In this appendix, the similarity matrices of only uncategorized sounds are presented. This is in view of lack of space.

Table A.1: Similarity Matrix of All Sounds of Wheezes

	'poly1.wav'	'poly2.wav'	'poly3wav'	'poly4.wav'	'poly5.wav'	…	'poly321.wav'	**Average ($P1$)**	**Standard Deviation ($P2$)**
'poly1.wav'	0.00	67.32	34.28	64.70	35.54	…	29.37	**35.63**	**8.96**
'poly2.wav'	67.32	0.00	74.55	80.17	66.29	…	67.03	**74.91**	**8.28**
'poly3.wav'	34.28	74.55	0.00	76.33	43.57	…	35.57	**45.61**	**9.81**
'poly4.wav'	64.70	80.17	76.33	0.00	61.18	…	65.40	**69.24**	**9.16**
'poly5.wav'	35.54	66.29	43.57	61.18	0.00	…	36.40	**43.74**	**7.70**
⋮	…	…	…	…	…	…	⋮	⋮	⋮
'poly321.wav'	29.37	67.03	35.57	65.40	36.40	…	0.00	**34.60**	**8.66**
						Average		**42.12 ($P3$)**	**9.01 ($P5$)**
						$(P3 - P5)_{cluster}$		**33.11**	
						$(P3 + P5)_{cluster}$		**51.13**	
						Accuracy of Validation		**81.93 %**	

Table A.2: Similarity Matrix of All Sounds of Stridor

	'stridor1.wav'	'stridor2.wav'	'stridor3wav'	'stridor4.wav'	'stridor5.wav'	…	'stridor98.wav'	**Average ($P1$)**	**Standard Deviation ($P2$)**
'stridor1.wav'	0.00	52.13	57.36	57.51	66.69	…	54.69	**63.10**	**9.99**
'stridor2.wav'	52.13	0.00	41.08	37.54	47.58	…	32.19	**42.18**	**11.02**
'stridor3.wav'	57.36	41.08	0.00	41.99	62.42	…	35.45	**49.68**	**11.35**
'stridor4.wav'	57.51	37.54	41.99	0.00	58.11	…	35.49	**47.57**	**10.31**
'stridor5.wav'	66.69	47.58	62.42	58.11	0.00	…	57.84	**61.51**	**10.95**
⋮	…	…	…	…	…	…	⋮	**⋮**	**⋮**
'stridor98.wav'	54.69	32.19	35.45	35.49	57.84	…	0.00		
						Average		**53.56 ($P3$)**	**11.45 ($P5$)**
						$(P3 - P5)_{cluster}$		**42.12**	
						$(P3 + P5)_{cluster}$		**65.01**	
						Accuracy of Validation		**86.73 %**	

Table A.3: Similarity Matrix of All Sounds of Rattle

	'rattle1.wav'	'rattle2.wav'	'rattle3wav'	'rattle4.wav'	'rattle5.wav'	…	'rattle73.wav'	**Average ($P1$)**	**Standard Deviation ($P2$)**
'rattle1.wav'	0.00	61.15	78.25	76.39	66.81	…	62.83	**67.32**	**10.48**
'rattle2.wav'	61.15	0.00	52.25	51.29	37.51	…	32.78	**41.97**	**10.03**
'rattle3.wav'	78.25	52.25	0.00	71.67	39.46	…	40.97	**48.61**	**11.17**
'rattle4.wav'	76.39	51.29	71.67	0.00	50.99	…	47.43	**55.53**	**14.26**
'rattle5.wav'	66.81	37.51	39.46	50.99	0.00	…	30.31	**39.01**	**10.06**
⋮	…	…	…	…	…	…	⋮	**⋮**	**⋮**
'rattle73.wav'	62.83	32.78	40.97	47.43	30.31	…	0.00	**35.07**	**11.03**
						Average		**43.80 ($P3$)**	**11.19 ($P5$)**
						$(P3 - P5)_{cluster}$		**32.61**	
						$(P3 + P5)_{cluster}$		**54.99**	
						Accuracy of Validation		**87.67 %**	

Table A.4: Similarity Matrix of All Sounds of Normal

	'normal1.wav'	'normal2.wav'	'normal3wav'	'normal4.wav'	'normal5.wav'	…	normal100.wav	**Average ($P1$)**	**Standard Deviation ($P2$)**
'normal1.wav'	0.00	47.04	54.55	47.48	47.08	…	54.77	**49.51**	**6.76**
'normal2.wav'	47.04	0.00	20.24	31.65	21.40	…	29.06	**27.00**	**6.19**
'normal3.wav'	54.55	20.24	0.00	36.94	21.97	…	31.79	**29.03**	**7.64**
'normal4.wav'	47.48	31.65	36.94	0.00	29.36	…	28.65	**31.55**	**6.80**
'normal5.wav'	47.08	21.40	21.97	29.36	0.00	…	31.31	**28.25**	**6.28**
⋮	…	…	…	…	…	…	⋮	**⋮**	**⋮**
'normal100.wav'	54.77	29.06	31.79	28.65	31.31	…	0.00	**28.10**	**7.81**
						Average		**30.00 ($P3$)**	**6.70 ($P5$)**
						$(P3 - P5)_{cluster}$		**23.30**	
						$(P3 + P5)_{cluster}$		**36.70**	
						Accuracy of Validation		**89.00 %**	