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ORIGINAL ARTICLE

A novel technique for validating diagnosed respiratory noises in infants and children

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Abstract The goal of this paper is to develop a novel technique to validate diagnosed respiratory noises in infants and children with high accuracy and reduced time consumption. A large number of recorded lung sounds are acquired with varied cases of normal and abnormal respiratory sounds. Wavelet-based Dynamic Time Warping technique is utilized in the proposed approach and the recognition accuracy was found to be above 88% in average. All the sounds represent infants and children below 13 years old and collected from AUCH-Alexandria, Egypt.

1. Introduction

Respiratory noises are audible sounds associated with breathing that could be heard with or without a stethoscope. They can give important clues about the site and nature of underlying pathology. Respiratory noises are much more common in infants and children than in adults [1].

Most common encountered respiratory noises in clinical practice are "wheeze", "rattle", and "stridor [2].

Wheeze is described as a high-pitched, continuous and prolonged musical noise, which is usually associated with prolonged expiration. wheeze can be heard at any phase of the respiratory cycle but mainly heard during the expiratory phase. Wheeze originates from the lower respiratory airways including intra-thoracic trachea and the more distal airways up to the bronchioles [3].

When a pathology obstructs airflow in the large airways namely intra-thoracic trachea and major bronchi , the resultant noise is due to of turbulence of airflow at the point of narrowing. Thus, the wheeze is localized on auscultation, and is termed "monophonic" [4] as it has a single frequency [1].

In the presence of extensive small distal airway narrowing as in acute bronchiolitis or asthma attack, the resultant high pleural pressure compresses the large airways during expiration, producing generalized expiratory wheezing. Young infants are more prone to this mechanism because their large airways are more soft and compliant so they can easily collapse. So in this situation as 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 due to presence of excessive secretions in the large central airways; these secretions are in continuous movement with normal respiration so rattle may be heard in both phases of respiration [5].

Stridor is a harsh vibratory mainly inspiratory sound of variable pitch, it happens due to obstruction to airflow in the proximal airways down to the level of the thoracic inlet. In

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the case of severe obstruction, stridor can occur in both inspiration and expiration [6,7].

As described previously each type of respiratory noises originates from a specific anatomic site within the respiratory system. Therefore, by identifying the nature of each respiratory noise, localizing the site of obstruction, and identifying the underlying etiology will be much easier [8]. Unfortunately, in some situations it may be very difficult to discriminate between them even when heard by different clinicians [9].

Many studies were done for validation of different respiratory noises like respiratory questionnaires [10,11] or use of videos [12] and acoustic analysis [13].

Adult studies have showed problems with both accuracy and reliability of respiratory signs using a stethoscope [13]. So in young, uncooperative children, it is expected that these problems will be much more common [14].

In an attempt to improve, the utility of respiratory noises, computerized acoustic analysis has been evaluated. Most studies included adult population [13]. A small study of infants suggested the ability of acoustic analysis in differentiation between wheeze and rattle [13]. A recent study which assessed the validity and reliability of acoustic analysis of respiratory noises in infants younger than 18 months had disappointing results [15].

All above studies were performed on a very limited number of infants. However, in [16,17] a database of 492 noisy respiratory sounds and 100 normal breath sounds were recorded and studied. All sounds were collected from Alexandria University Children Hospital (AUCH), Egypt. The authors applied a new stethoscope having the ability to pair with computers through employing Bluetooth technology. They analyzed the recorded signal using Short Time Fourier Transform (STFT), used in [18], with Dynamic Time Warping (DTW).

In this paper the 592 sounds reported in [17] were analyzed by Wavelet Transform (WT), one of the future suggested extension in [17], and compared to STFT technique applied to them. It is established that the technique introduced in this paper outperforms the STFT used in [16,17].

The purpose of this paper was to analyze the recorded respiratory sounds in order to realize the following.

- Evaluate the role of proposed wavelet-based Dynamic Time Warping (WT-based DTW) approach in validating the established diagnosed respiratory sounds
- Compare the proposed approach to STFT that was used in validating respiratory noises on the same database [17].

This paper is structured as follows. The material and environment used are illustrated in Section 2. The proposed lung sounds analysis approach is presented in Section 3. The results and discussion are shown in Section 4. Finally, the paper is summarized in Section 5.

2. Material used

The aim of this paper is to propose a computerized clustering rule that is used to validate the pediatrician's judgment of pulmonary diseases. This clustering technique is based on Dynamic Time warping for sequences matching and wavelet analysis for feature extraction.

This proposed technique applied to 592 respiratory sounds collected in [16,17]. All used lung sounds were acquired from the Emergency Department of El-Shatby Alexandria University Children's Hospital (AUCH), Egypt [17] through using the 3 M™ LITTMANN® Electronic Stethoscope M3200 [19] to record all sounds. Zargis StethAssist™ software [20] was used for pairing, and to export the sound signals to (.wav) files. A core i7, 8 GB PC was employed. All the used data are presented in Table 1. This dataset represents a large database specialized in children respiratory cases in Alexandria, Egypt.

The study focused on stridor, rattle and wheeze respiratory noises. Infants and children with any other lung sounds, or a combination of sounds were excluded from the study.

From 592, there are 100 normal infants and children of matched age and sex with normal quiet breath. They were recruited as a control group and used as a reference for offline validation of respiratory noises.

Respiratory sounds are clustered into 4 groups according to their similarity. The, dataset was separated into1 normal cluster and 3 clusters of respiratory noises which are Stridor, Rattle and Wheezes.

Applying MATLAB® R2015a (from The Mathworks™), all the recorded sounds were decomposed by Discrete Wavelet Transform (WT) and then the extracted wavelet coefficients are utilized by the dynamic time warping (DTW) to find the similarity matrix of each cluster as clarified in the following section.

Although one of the advantage of this stethoscope is the surrounding noise reduction [19], its program manual (Zargis StethAssist™) clearly clarified that the enclosing environment should be noiseless [21]. However, the noises were evident in the LITTMANN® children recordings, as illustrated in Fig. 1. Fig. 1 represents the decomposition of lung signal in different subands using wavelet decomposition, which will be explained in details in the following section. As shown in Fig. 1, noise in low frequency band (0–63 Hz) is the dominant signal in all type of lung sounds. Thus, preprocessing and denoising [22–23] of lung sounds, to remove these noises, is a necessary step before clustering.

3. The proposed sound analysis approach

3.1. Discrete wavelet transform (WT)

One of the famous signal analysis techniques is the Short Time Fourier Transform (STFT). STFT is mainly used to overcome the changes of non-stationary signals by segmenting the signal in time domain using a single fixed window which results in constant time resolution in all frequencies [24]. However, lung sounds are complicated non-stationary signals, where there

Table 1 Recorded lung Sound Signals.

Sound type	Number of signals
Normal	100
Stridor	98
Wheezes	321
Rattle	73
Total	592

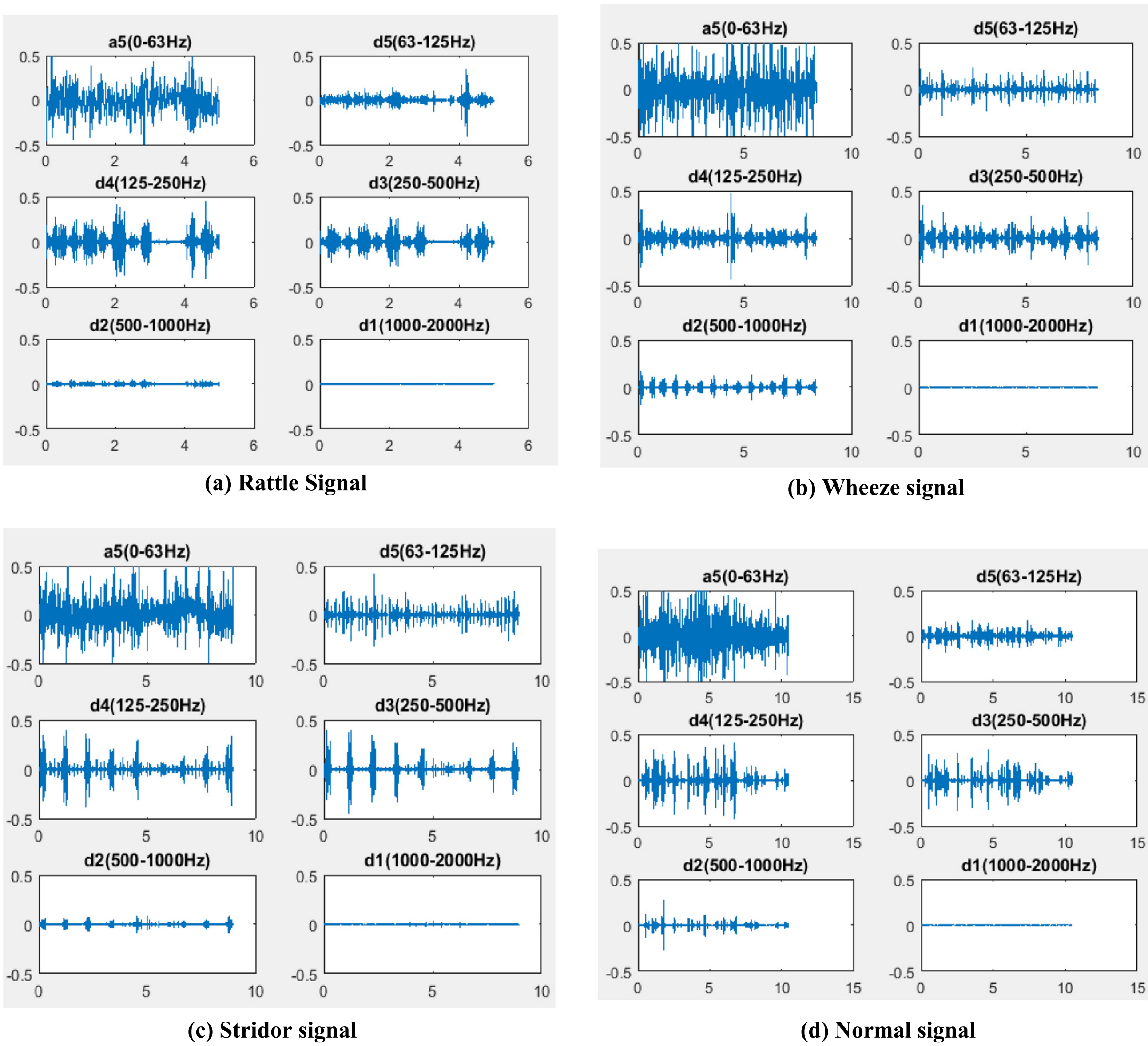

Fig. 1 WT decomposition of different signals.

may be many frequency components in a given time interval and the interval itself is very small. Consequently, the fixed window method of STFT is inadequate [25].

Wavelet Transform (WT) represents an analysis tool with inconstant time and frequency resolution, where every frequency is not disbanded equally as was the situation in the STFT [26]. Changeable window size is mainly the distinctive feature of WT analysis [27]. For this, WT analysis can detect more attributes about the signal than STFT [28]. The discrete WT is special version of WT that represents the signal in time and frequency domains with lower complexity and redundancy. In discrete WT, a signal is resolved into low frequency components (approximated coefficient CA) and high frequency components (detailed coefficient CD). Moreover, in multi-resolution analysis low spectral component is further decomposed by the discrete WT technique. Discrete WT decomposition is practically implemented by repeatedly applying high-pass and low-pass filters to the time domain signal as shown in Fig. 2 and is determined by the following equation [28,29]:

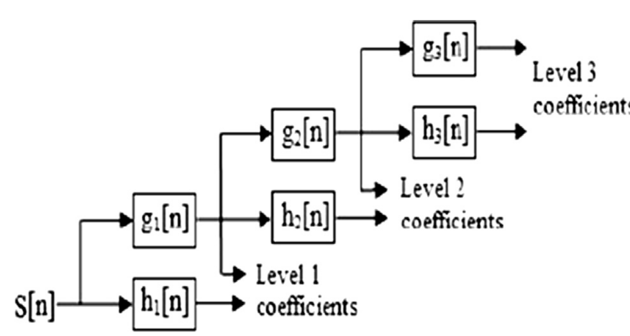

Fig. 2 DWT structure.

$$y_{high}[k] = \sum_n x[n] \cdot g[2k - n]. \tag{1a}$$

$$y_{low}[k] = \sum x[n] \cdot h[2k - n]. \tag{1b}$$

where Y_{high} [k], Y_{low} [k] are the outputs of the highpass (g) and lowpass (h) filters, shown in Fig. 2 respectively, after subsampling by 2 [29]. The calculated WT coefficients carry information about the signal in both time and frequency domains.

3.2. Dynamic time warping algorithm (DTW)

Dynamic time warping algorithm matches 2 real signals to find the degree of similarity between them by using signal discriminative features [30]. The similarity degree is zero if the 2 signals are identical and has a considerable value if they are dissimilar. Accurate recognition of similarity/dissimilarity depends on the features selected to identify the signal.

In this paper, the discrete WT coefficients of a signal are utilized as the discriminative features [31]. DTW relies on finding the best alignment between 2 time sequences where the sequences are warped in a dynamic way to resemble each other.

3.3. The proposed wavelet-based DTW approach

The proposed approach is illustrated in the following procedures and summarized in Fig. 3.

- The LITTMANN® M3200 generates sound files having a sampling frequency of 4 KHz (4000 samples/s.).
- After that, the wave file is sampled by sampling frequency of 4000 Hz and saved as time sequence signal. The sampled signal was then down-sampled by 6. Down-sampling was essential as the length of sampled lung signal is very large where the time of sound file 10 s in average and the sampling rate is 0.25 ms which leads to high number of samples up to 40,000 samples. This huge number of samples increases the computational time and complexity of DTW algorithm. For this reason, down-sampling was implemented.
- Fig. 1 shows the discrete WT decomposition of different lung sounds. The used level of decomposition was five. Note that, a5 and (d1 to d5) represents the constructed approximated and detailed signals respectively from the wavelet coefficients. The Figure illustrates that the signal noise is concentrated in the in the approximation part of the signal (a5). This was the situation of all lung cases due to the heart sounds present in this low frequency band [23]. As a result, signal preprocessing and denoising were essential steps.
- At low frequencies, heart sound interference was removed by applying DWT denoising [22,23], through discarding the subband of lung sound that includes heart sound. This denoising mechanism results in a lung signal absolutely free of heart beat interference. The denoising effect is obvious by studying Figs. 4.1–7.2 as an indication. In case of rattle and stridor, 6th order low-pass Butterworth filter is applied with 500 Hz cut off frequency [16] and 1000 Hz respectively [7].
- After preprocessing, the signal was reconstructed and Discrete WT decomposition was performed one more time on each denoised signal by using equation 1. The number of decomposition level was selected according to the signal's main spectral components and the used sampling frequency [32]. Since the respiratory signal does not have any valuable spectral information below 60 Hz and the dominant signal in this frequency band is the noise as shown in Fig. 1. The number of decomposition level was selected to be 5, where minimum frequency band is (0–63 Hz) and maximum band (1000–2000 Hz). Hence the signal is analyzed into the detailed coefficients CD1-CD5 and one approximated coefficients (CA5). The frequency bands of the detailed and approximated coefficients are displayed in Table 2. The WT family applied for decomposition is Daubechies of order 8 (db8) which highly suites the analysis of lung sounds [32].
- DTW algorithm was applied to detect similarity between 2 signals using the WT coefficients as the signals identification metric. DTW works by finding the distance matrix between

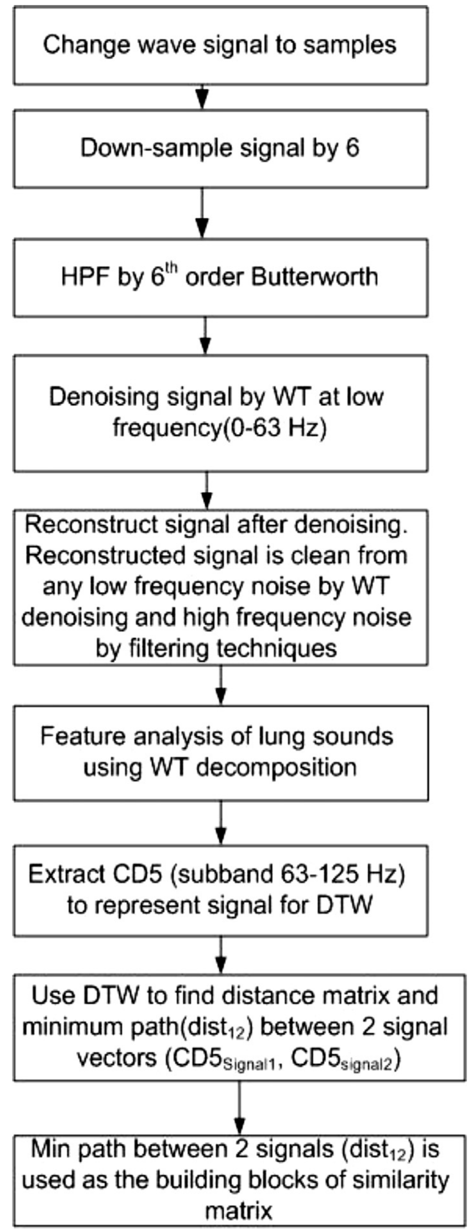

Fig. 3 Schematic representation of proposed approach.

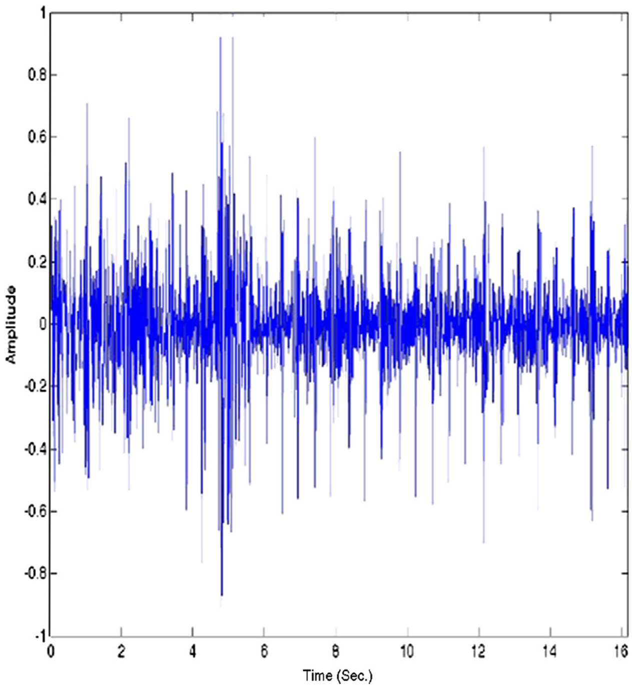

Fig. 4.1 Noisy Wheeze 2 signal.

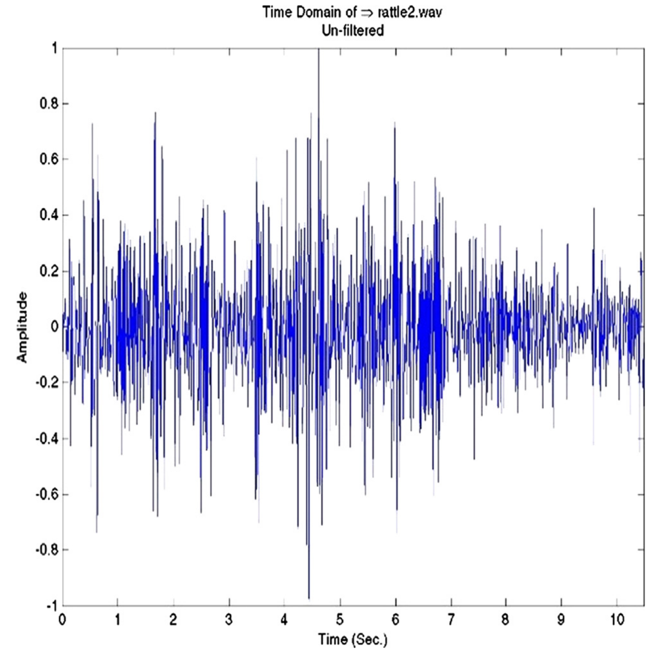

Fig. 5.1 Noisy rattle 34 signal.

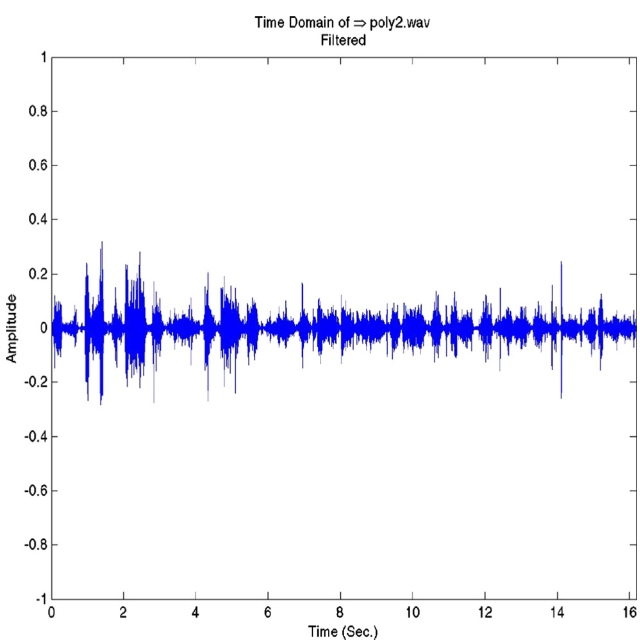

Fig. 4.2 Denoised Wheeze signal.

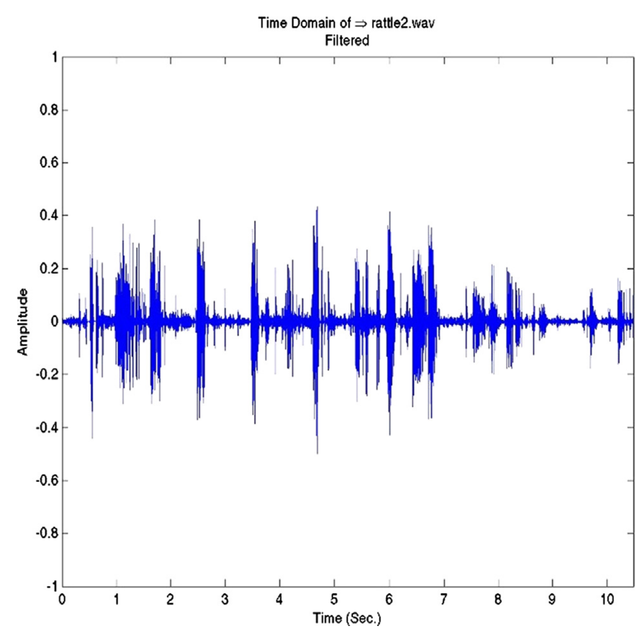

Fig. 5.2 Denoised rattle 34 signal.

the sequences of $signal_1$ (length k) and $signal_2$ (length n) resulting a distance matrix of size [k*n], then the DTW locates the shortest path between the 2 signals from this distance matrix. However, the main problem of the traditional DTW is the tremendous computational complexity as the length of the signal increments. DTW complexity is O (N^2) where N is the length of the longest input sequence [31].

- For the above reason, our approach used a modified DTW technique in which certain portion of the discrete WT coefficients is used to represent the signal [31,33]. Our main objective is to lower the DTW computational cost by reducing the length of the input signals. This is achieved by choosing appropriate subband to represent the signal without affecting the performance of DTW in locating the best path.
- In this paper, for any 2 signals in the same cluster, the 2 signals were analyzed by the discrete WT with decomposition level 5 as discussed previously. The coefficients of selected subband (CD5) of both signals were matched to find the shortest path (Dist (1, 2)). Although, this reduced the computational complexity of traditional DTW by $O\ (N^2/32)$

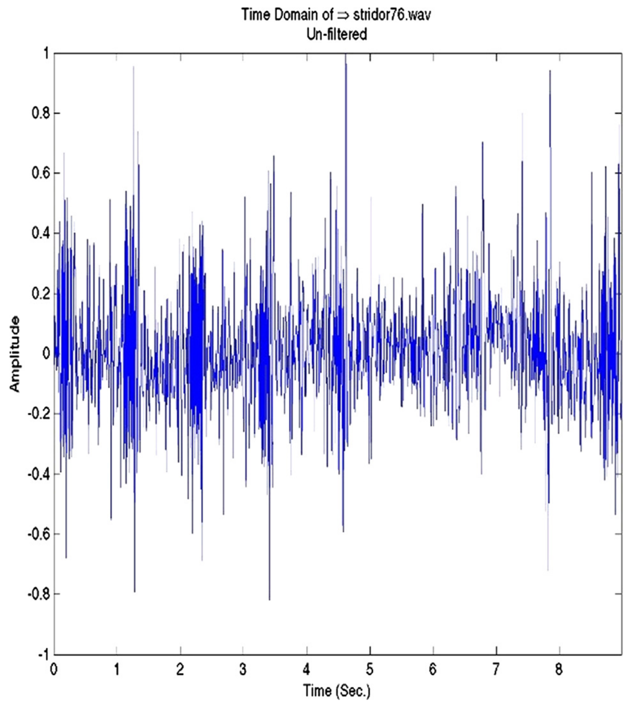

Fig. 6.1 Noisy Stridor 76 signal.

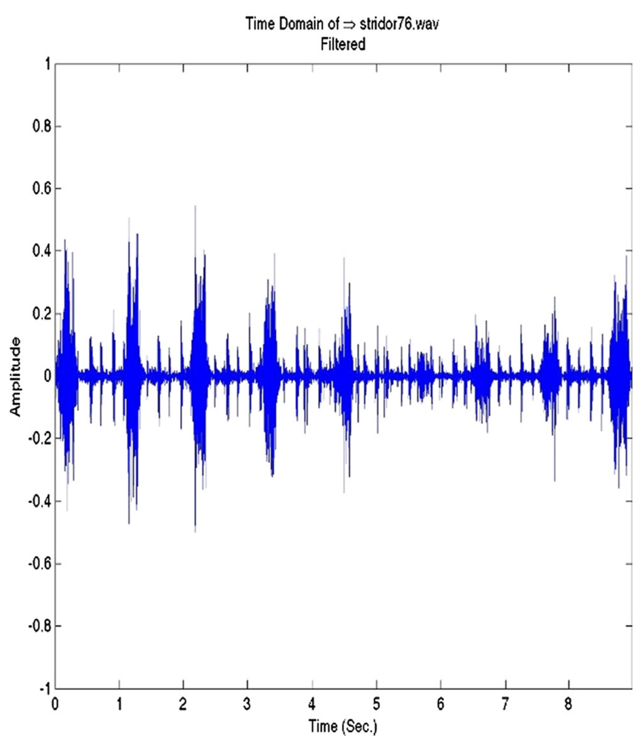

Fig. 6.2 Denoised Stridor 76 signal.

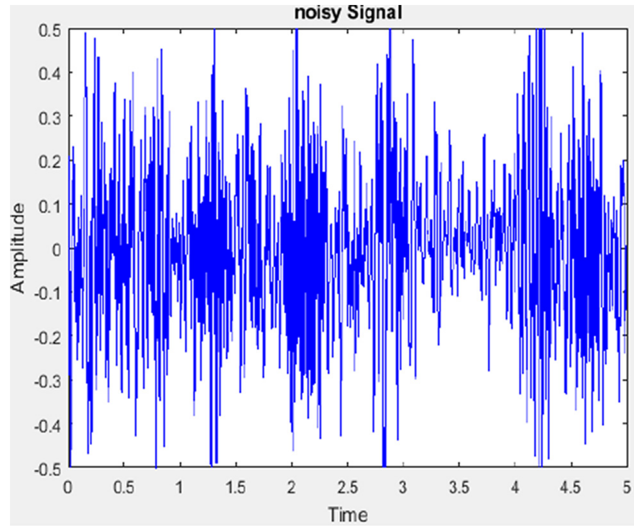

Fig. 7.1 Noisy Normal 3 signal.

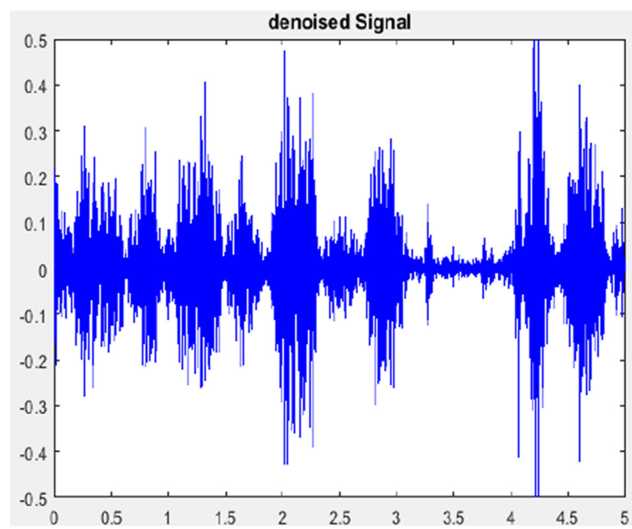

Fig. 7.2 Denoised Normal 3 signal.

Table 2 Frequency bands of used WT decomposition at level 5.

WT coefficients	Frequency bands
CA5	0–63 Hz
CD5	63–125 Hz
CD4	125–250 Hz
CD3	250–500 Hz
CD2	500–1000 Hz
CD1	1000–2000 Hz

[33], yet, it was shown experimentally, using the data under study, that the accuracy of the traditional DTW was maintained.

- The shortest path between $signal_1$ and $signal_2$ (Dist (1,2)), calculated by the modified DTW, was used as the building blocks of the similarity matrix (S) [34, pp 65–70] given below.
- As discussed previously, the respiratory sounds were categorized into four clusters (normal, rattle, wheezes, and stridor). For every cluster, a similarity matrix S was calculated. The building block of S is the element Dist (i,–j), where Dist (i, j) indicates the shortest path between the 2 sounds signal i and j respectively. The S size is square ($M*M$) where M indicates the number of sounds in each cluster. The value

of the diagonal of S matrix is always zero due to the reality that at i equal j the row and column of the diagonal element identify the same sound signal.

$$S = \begin{bmatrix} 0 & dist(1,2) & dist(1,3) & \dots & dist(1,M) \\ dist(2,1) & 0 & dist(2,3) & \dots & .. \\ dist(3,1) & dist(3,2) & 0 & \dots & .. \\ \dots & \dots & \dots & 0 & .. \\ dist(M,1) & dist(M,2) & \dots & \dots & 0 \end{bmatrix}$$

- The next 4 Indicators have to be calculated for every S-matrix:
  1) ***I1***: I1 is calculated for each sound. ***I1*** represents the average similarity of this sound and all other sounds within the cluster.
  2) ***I2***: ***I2*** is considered for each sound. ***I2*** represents the difference between ***I1*** of the concerned sound and all other sounds within the cluster (excluding the sound itself from calculation).
  3) ***I3: I3*** calculated for the whole cluster. It corresponds to the average similarity of all the sounds in the cluster (***I3*** is the average of all ***I1*** of the cluster***)***.
  4) ***I4: I4*** related to every cluster. It indicates the average of the difference between ***I1***of a sound and all other sounds within the cluster (***I4 is*** average of all ***I2*** of the cluster***)***

Any newly respiratory sound is categorized to fall within a specific cluster by evaluating its ***I1*** and shows that it satisfies equation (2) of the involved cluster. Equation (2) represents the recognition tool used for clustering and diagnosis of any newly pulmonary sound [16].

$$(I3 - I4)_{Cluster} \leqslant (I1)_{sound} \leqslant (I3 + I4)_{Cluster} \qquad (2)$$

However, for any sound, if Eq. (2) is not fulfilled as a clustering tool, the sound has to be checked by expert for final decision.

4. Results and discussion

Table 1 summarized all the studied cases. The respiratory signals collected in [17] were the used data signals in this research. The statistics of those cases indicate that 83% of the examined children experience respiratory noises. Wheeze is the most common noise in the tested children (54.2% of the studied objects). Four clusters were formed from the reported respiratory sounds, where those sounds were identified into normal, rattle, stridor and wheeze clusters. From those clusters, a clustering recognition rule, Eq. (2), had been estimated. This rule benefits in categorizing any new undiagnosed sounds in its appropriate cluster. Where, any new sound is clustered by calculating its ***I1*** and showing that it is involved in (***I3*** ± ***I4)*** of the intended cluster.

Tables 3.1–3.4 demonstrate the recognition indicator ***I3*** and ***I4*** of every cluster. The recognition accuracy is the parameter used to indicate that a sound is correctly clustered and diagnosed. Recognition accuracy corresponds to the percentage of lung sounds that fulfills the clustering rule in Eq. (2) for the concerned cluster. The best recognition accuracy is the one of 100% achievement.

As presented in Tables 3.5–3.8, Short Time Fourier Transform (STFT) and discrete WT are two different techniques implemented for feature extraction. As the recognition per-

Table 3.1 Wheezes Cluster Indicators and recognition accuracy using WT-based DTW.

Wheezes	All wheezes (321 sounds)
I3	50.3
I4	13.95
I3– I4	36.35
I 3+I 4	63.95
Accuracy of recognition	88.16%

Table 3.2 Rattles Cluster Indicators and recognition accuracy using WT-based DTW.

Rattle	All rattle (73 sounds)
I 3	38.73
I 4	9.6
I 3 – I 4	29.13
I 3 + I 4	48.33
Accuracy of recognition	87.6%

Table 3.3 Stridor Cluster Indicators and recognition accuracy using WT-based DTW.

Stridor	All stridor (98 sounds)
I 3	49.46
I 4	15.34
I 3 – I 4	34.12
I 3 + I 4	64.8
Accuracy of recognition	89.8%

Table 3.4 Normal Cluster Indicators and recognition accuracy using WT-based DTW.

Normal	All normal (100 sounds)
I 3	63.2
I 4	14.7
I 3 – I 4	48.7
I 3 + I 4	77.9
Accuracy of recognition	86%

Table 3.5 Discrete WT vs STFT recognition accuracy and speed in Wheezes sounds.

Wheezes sounds	Accuracy of recognition	Speed of recognition (s)
STFT + DTW	78.8%	3310
Discrete WT + DTW	88.16%	1739

Table 3.6 Discrete WT vs STFT recognition accuracy and speed in Rattle sounds.

Rattle sounds	Accuracy of recognition	Speed of recognition (s)
STFT + DTW	84.7%	202.5
Discrete WT + DTW	87.6%	100

Table 3.7 Discrete WT vs STFT recognition accuracy and speed in Stridor sounds.

Stridor sounds	Accuracy of recognition	Speed of recognition (s)
STFT + DTW	77.5%	415.168
Discrete WT + DTW	89.8%	210.22

Table 3.8 Discrete WT vs STFT recognition accuracy and speed in Normal sounds.

Normal sounds	Accuracy of recognition	Speed of recognition (s)
STFT + DTW	82%	293.12
Discrete WT + DTW	86%	154.64

centage demonstrates, the discrete WT has higher recognition accuracy due to its varying resolution in both time and frequency; leading to discrete WT detects more details about the signal than STFT. Consequently, discrete WT analysis gives more accurate diagnosis of lung sounds in comparison with STFT [16].

This paper utilized modified version of DTW along with the discrete WT to decrease the traditional DTW complexity since the complexity of DTW is O (N^2)., where N the length of largest input signal to the DTW algorithm. In the modified version, coefficients of a certain subband (CD5) are used to represent the matched signals without influences the reliability of the traditional DTW. As the results illustrated in Tables 3.5–3.8, the proposed WT-based DTW technique achieved high performance in terms of recognition accuracy and recognition speed. Recognition speed measures the time required to execute program and detect final clustering decision for each sound. The proposed WT-based DTW has recognition speed almost twice the STFT as the results indicates.

The environment detailed in Section 2 was employed throughout this study.

5. Conclusion

In this study, we applied discrete Wavelet Transform (WT) and modified Dynamic time warping for automatically clustering and validating diagnosis of respiratory sounds. Discrete WT was implemented as the signal feature extraction technique and a modified DTW algorithm was applied to find similarity matrix for every cluster. The modified DTW algorithm featured by less time consumption and higher performance than the traditional one. The proposed WT-based DTW achieved higher clustering recognition rate and recognition accuracy than STFT-DTW technique as the results illustrated. This work represents one of the future suggested extension in previous work. It was established that the technique introduced in this paper outperformed the previous STFT-DTW approach reported in [16,17].

This work can be extend through finding the best classifier and feature extraction techniques that results in the highest accuracy for diagnosing lung noises.

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