On Analysis of Suitable Wavelet Family for Processing of Cough Signals

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Abstract. This paper presents an analysis on preprocessing of cough sound signals using continuous wavelet transform (CWT) and discrete wavelet transform (DWT) wavelet filter banks. The purpose of this analysis is to determine the suitable filter banks among CWT and DWT. The analysis of these filter banks includes a choice of requisite wavelet family and level of decomposition of cough signals for noise suppression. The performance comparison in the analysis has been validated using the signal-to-noise ratio (SNR) parameter.

Keywords: Cough signals · CWT · DWT · SNR · Wavelet

1 Introduction

It has been reported that the cough is one of the major symptoms of all childhood respiratory diseases such as pneumonia and asthma which are the major cause of childhood deaths [1]. Various techniques have been proposed to diagnose the cough sound signals for different respiratory diseases. However, cough sound signals analysis is done using sensors in which sensors are attached in contact with the patients and this technique requires trained personnel to acquire the cough sound signals [2–5]. In the previous few decades, authors have been proposed different techniques for the preprocessing of cough sound signals. Using Fourier transform (FT) and short-time Fourier transform (STFT), cough signals have been analyzed. But FT transform represents the signals only in frequency. So, all the information is not captured in the frequency domain [6]. When STFT is applied on 1D signals then due to its fixed window size, the analysis is done in a fixed range [7]. So, it is necessary to analyze the cough sound signals in time–frequency domain and wavelet transform (WT) decomposes the cough sounds signals using different values of its dilation and translation parameters. WT analyzes the cough sound signals in time as well as frequency domain so that the analysis could be more accurate [8]. In this paper, CWT and DWT are used for the time–frequency domain analysis, and different wavelet families are used to find out the best wavelet family among them and the suitable decomposition level for the cough sound signals. Following paper is categorized into four sections as: Sect. 2

S. C. Satapathy et al. (eds.), *Frontiers in Intelligent Computing: Theory and Applications*, Advances in Intelligent Systems and Computing 1014,
https://doi.org/10.1007/978-981-13-9920-6_20

contains a brief description on WT. Section 3 contains the proposed filtering technique using CWT and DWT. Section 4 concludes the overall cough sound signals analysis.

2 Overview on Wavelet Transform

When WT is applied on 1D signal, they are decomposed and are analyzed in the time–frequency scale plane [9]. The noise present in the cough sound signals is not suppressed easily by using the combination of filters. In WT, different types of wavelets are generated from a single basic wavelet $\psi(t)$, generally referred to as mother wavelet (or shift) factor τ. The translated and scaled types of the wavelet are shown below as [10]:

$$\psi_{s,\tau} = \frac{1}{\sqrt{|s|}}\psi\left(\frac{t-\tau}{s}\right) \tag{1}$$

A signal $x(t)$ can be represented as a function of mother wavelet $\psi(t)$ as:

$$T(s,\tau) = \int_{-\infty}^{\infty} x(t)\psi^{*}\left(\frac{t-\tau}{s}\right)\mathrm{d}t \tag{2}$$

Where the symbol $*$ represents the complex conjugate of ψ [11].

2.1 Continuous Wavelet Transform (CWT)

CWT is an approach, which is used to pull off the resolution problem that exists in STFT. CWT is a very efficient tool which is used to provide the directional WT. CWT is a rapid tool in audio analysis and also provides better result of practical implementation. CWT analysis is similar as the STFT analysis, but CWT analyzes the cough sound signals in time–frequency. The CWT of 1D sound signals is shown below as [12]:

$$\mathrm{CWT}(x,\psi)(s,\tau) = \int_{-\infty}^{+\infty} x(t)\psi^{*}\left(\frac{t-\tau}{s}\right)\mathrm{d}t \tag{3}$$

2.2 Discrete Wavelet Transform

The cough signals are analyzed using DWT into sub-bands at different frequencies which decompose the cough signals into approximation and detailed coefficients. The family of a DWT is given as:

$$\psi_{m,n}(t) = 2^{-m/2}\psi(2^{-m}t-n) \tag{4}$$

where m and n belong to integers for indices [11]. When DWT is applied on the cough signals at different levels, the cough sound signals get decomposed into approximation and detailed coefficients.

3 Proposed Filtering Technique

The acquired cough sound signals are contaminated with different types of noise which are main issues in cough sound signals analysis. The preprocessing approach is used for suppressing the white Gaussian noise present in the cough sound signals [13]. In the presented work, a threshold-based noise filtering technique using DWT of cough signals has been presented. The detail sub-bands obtained from the cough sound signals decomposition deals with the noise residue which is difficult to suppress through simple filtering processes [9]. There are two types of thresholding techniques presented which are hard thresholding and soft thresholding. The following equations show the hard thresholding (H_j) and soft thresholding (s_j) [14]:

$$s_j = \begin{cases} \left[\operatorname{sign}(C_j)\left(\left|C_j\right| - \lambda\right)\right], & \left|C_j\right| > \lambda \\ 0, & \left|C_j\right| < \lambda \end{cases} \tag{5}$$

$$H_j = \begin{cases} C_j, & \left|C_j\right| > \lambda \\ 0, & \left|C_j\right| < \lambda \end{cases} \tag{6}$$

where C_j denotes the coefficients, and λ denotes the threshold value. Figure 1 shows the different thresholding techniques [15].

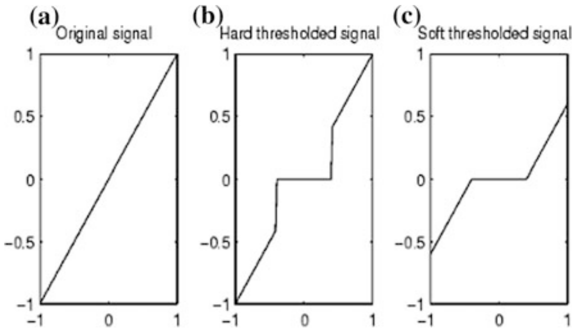

Fig. 1. **a** Original signal. **b** Hard threshold signal. **c** Soft threshold signal [16]

The above Eqs. 5 and 6 are for the calculation of soft thresholding and hard thresholding, respectively [15]. Signal-to-noise ratio (SNR) is used to measure the quality of the audio signal over the channel. When the signal-to-noise ratio is greater, easier to identify and estimate the source of the noise. SNR formula given below will help in checking the completion of the analysis [16]:

$$\mathrm{SNR}(\mathrm{d}B) = 10\log_{10}\frac{\sum_{i=1}^{N}\left(x_{\mathrm{d}n}[n]\right)^2}{\sum_{i=1}^{N}\left(x[n]-x_{\mathrm{d}n}[n]\right)^2} \tag{7}$$

where $x_{\mathrm{d}n}[n]$ denotes denoised cough signals, and $x[n]$ is the original cough signals.

3.1 Analysis of Cough Sound Signals Using CWT

In this analysis, CWT is used for the processing of cough sound signals. The cough sound signals are taken from ICBHI 2017 Respiratory Sound Database [17]. These cough signals are analyzed for the selection of the most appropriate wavelet family and best level of decomposition depending upon the respective SNR values. The SNR value calculated for the normalized cough signal is −13.3592 dB. Table 1 shows the analysis for the different wavelet families such as Haar, Daubechies, Symlets, and Coiflets. Each time different SNR value is obtained for the cough sound signal and now if we compare the table, then the best SNR value (−12.6729 dB) is obtained for the db2 which is shown in Table 1.

Table 1. Selection of requisite wavelet family to be used in filter banks

Normalized signal SNR(dB)	−13.3592			
Wavelet family	haar	db2	sym2	coif1
Reconstructed signal SNR (dB)	−13.6439	−12.6729	−12.6714	−12.6234

The cough sound signal for the best wavelet family (db2) is shows in Fig. 2.

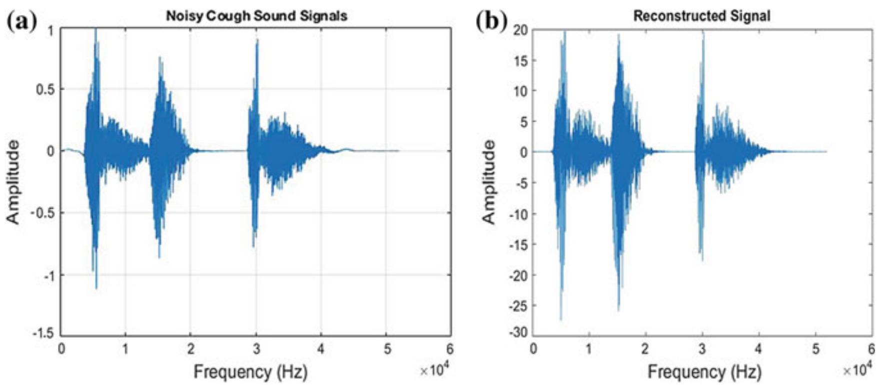

Fig. 2. **a** Noisy cough sound signals. **b** Filtered cough sound signals using CWT

Now, further analysis is done by analyzing the cough sound signals for the selection of the best level of decomposition which is shown in following Table 2 and the best level is obtained at level 2, and the SNR value obtained is −12.6715 dB.

Table 2. Selection of appropriate level of decomposition using CWT

Normalized signal SNR (dB)	−13.3592			
Level	1	2	3	4
SNR of reconstructed signal (dB)	−12.6713	−12.6715	−12.6731	−12.6746

3.2 Analysis of Cough Sound Signals Using DWT

In this analysis, DWT is used for processing the cough sound signal; as in previous analysis, the signal is now being analyzed using different wavelet families like Haar, Daubechies, Symlets, and Coiflets. The SNR value for normalized cough sound signal is −13.3592 dB. Table 3 shows the entire analysis, and different SNR values are observed for different wavelet families and from which the best result is selected as Symlets (sym4) having SNR value −13.3589 dB.

Table 3. Selection of requisite wavelet families to be used in filter banks

Normalized signal SNR (dB)	−13.3592			
Wavelet family	haar	db4	sym4	coif4
Reconstructed signal SNR (dB)	−13.3213	−13.3232	−13.3589	−13.3585

The cough sound signal for the best wavelet family (sym4) is shows in Fig. 3.

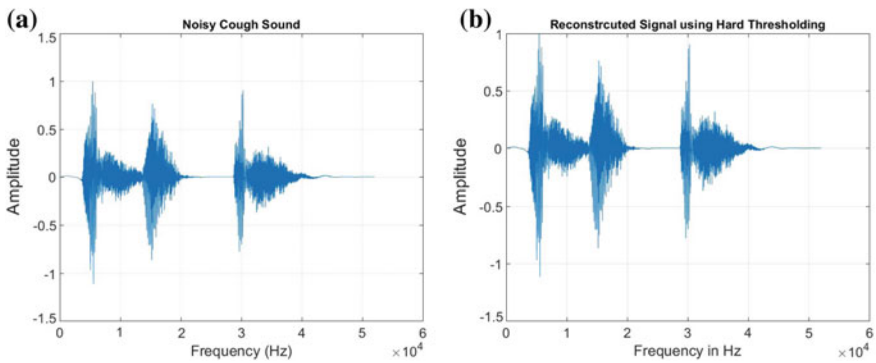

Fig. 3. **a** Noisy cough sound signals. **b** Filtered cough sound signals using DWT

Now, for the selection of best decomposition level, the signal is analyzed at different levels of decomposition and the best result is selected which is shown by the following Table 4 and the best SNR value is obtained at level 8 which is −13.3596 dB, and the signal decomposed at level 8 is shown.

Table 4. Selection of appropriate level of decomposition using DWT

Normalized signal SNR (dB)	−13.3592			
Level	5	6	7	8
SNR of reconstructed signal (dB)	−13.3244	−13.3537	−13.3574	−13.3596

4 Inferences and Recommendations

For the analysis of cough sound signals, the preprocessing of the cough sound signals has been done in the presented paper using CWT and DWT. The results obtained from both the analyses are shown in tabulated form in this paper. The performance parameter that has been used for validation is the signal-to-noise ratio (SNR). The inferences of the presented analytical work are listed below:

- For the CWT analysis, the cough sound signals are analyzed firstly for the selection of suitable wavelet family to be used for CWT filter bank. The wavelet families that have been used are Haar, Daubechies, Symlets, and Coiflets. The best wavelet family depending upon the SNR value is db2 (Daubechies).
- In CWT analysis, for the selection of an appropriate level of decomposition of cough sound signals. The cough signals are decomposed using different levels, and the best result for the level of decomposition is level 2.
- Similarly, for the DWT analysis, the requisite wavelet family that came out to be used for the DWT filter bank is sym4 (Symlets) and the most appropriate level of decomposition is level 8.
- The obtained SNR values in DWT analysis have been improved in comparison with CWT analysis. Other wavelet transforms such as stationary wavelet transform (SWT) and maximal overlap discrete wavelet transform (MODWT) can also be employed for the same purpose.

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