Combination of Wavelets and Hard Thresholding for Analysis of Cough Signals

Ahmad Taquee[1]
taquee.ahmad7@gmail.com

Vikrant Bhateja[1]
bhateja.vikrant@gmail.com

Adya Shankar[1]
adya.shankar5@gmail.com

Agam Srivastava[1]
agams47@gmail.com

[1]*Department of Electronics & Communication Engineering, Shri Ramswaroop Memorial Group of Professional Colleges (SRMGPC), Faizabad Road, Lucknow-226028 (U.P.), India.*

***Abstract*—Cough signals are fundamental symptom of respiratory diseases. During the acquisition of the cough signals via microphone, it gets contaminated due to the noise present in the surroundings or certain other reasons. It is a tough task to remove this noise from contaminated cough sound signals. This call for mathematical analysis of cough signals to aid in diagnosis of respiratory diseases. This paper consists of combination of hard thresholding and Discrete Wavelet Transform (DWT) for eliminating the noise present in the acquired cough sound signals. An improved result of noise filtering has been demonstrated in the result analysis with 'Sym4' wavelet family. This has been supported with better values of Signal-to-Noise Ratio (SNR) of the acquired cough signals**.

Keywords—Cough signals, DWT, Hard thresholding, Noise filtering, SNR.

I. INTRODUCTION

Cough has been one of the most recurrent indication of almost all type of respiratory diseases in the childhood. It has been a common symptom in initial and medium stages of respiratory diseases such as asthma, bronchiolitis, pneumonia, bronchitis, croup, cyanosis, etc. [1]. Cough signals are fundamental symptom of pneumonia, but the mathematical analysis of cough signals have never been used in diagnosing the disease. Further, it has been reported that cough signals fetch essential information on the lower respiratory tract of the lung which allows to identify diseases [2]. When the cough signals are acquired for the analysis of different types of diseases, it gets contaminated due to various types of noises. So, the noise filtering of the acquired cough signals plays a major role in the signal analysis. In the previous two decades, several techniques have been presented to recover the original cough signals from the noisy signals [3]. The conventional filtering approaches for cough signals denoising includes low pass filters [4], different types of filter banks such as linear phase and orthogonal filters [5,6], different modelling techniques have been proposed such as Mean Shift Algorithm [7], Kalman Filters [8], Empirical Mode Decomposition [9,10] and State Vectors with time delay [11]. But, these techniques are only useful when the cough signals are contaminated with one more than one type of noises. Earlier, denoising based on the wavelet of such signals using thresholding was done by Donoho and Johnstone [12]. With the development of different types of transforms, various approaches have been suggested for denoising of the cough signals such as Fourier Transform (FT) and Short Time Fourier Transforms (STFT) and Gabor Transform. Since, the FT represents the cough signals in frequency domain only. So, it is not possible to analyze the cough signals in the time domain. Hence, FT is not suitable for the time-varying signal and it also unable to preserve the sharpness of the signal [13]. STFT uses a small window for the analysis of the cough signals and the resolution in STFT is limited. The cough signal is analyzed in different window sizes and if the window size is big then it will provide better resolution of frequency but adverse resolution of time and if the window is narrow then it will provide better time resolution but the frequency resolution is not very good [13]. FT is the method of choice to remove noise but the most widely used method is the wavelet transform [14]. In this paper, it has been presented a threshold-based technique using Wavelet Transforms (WT) for noise reduction. Wavelet transform is a better implement for multiresolution cough signals analysis. Wavelet can be easily applicable by using convolution-based algorithm. The WT based technique using soft thresholding has been proposed in the [15]. But, the soft thresholding technique may not effective in filtering of the cough sound signals. So, a hard thresholding technique using DWT of cough signals has been proposed. Further, this paper is categorized into following sections: Section II gives the description of the proposed filtering methodology. Section III consists of the results and discussions whereas Section IV includes the conclusion of the proposed work.

II. PROPOSED FILTERING METHODOLOGY

A. Wavelet Transform

For the filtering of the static signals such as cough sound signals, WT has been applied to the cough signals. The decomposition of the cough sound signals takes place in the time frequency scale plane [16]. Residual noise and White Gaussian noise present in the cough sound signals are not easily eliminated by the simple combination of the filters. Therefore, WT is used for noise filtering of the cough sound signals [17]. The WT represents the signals in both frequency as well as time domain [16]. In WT, variants of wavelets are generated from a single category of fundamental wavelet $\psi(t)$. This fundamental wavelet is nomenclated as mother wavelet. The scale (or dilation) factor s and the translation (or shift) factor τ are described as the two important parameters of WT. The dilated and shifted types of the mother wavelet is shown below as:

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

Wavelet transforms of a signal *x(t)* can be represents as a function of mother wavelet $\psi(t)$ as:

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

Where, $*$ denotes the complex conjugate of ψ [18].

B. Discrete Wavelet Transform (DWT)

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

$$\psi_{m,n}(t) = 2^{-m/2}\psi\left(2^{-m}t - n\right) \tag{3}$$

Where, m and n $\in$ integers for indices [18]. When DWT is applied on the cough signals *x[n]* at different level, the cough signals decompose into approximation and detail coefficients. The approximation coefficients *a[n]* consists of high frequency noise whereas the detailed coefficients *d[n]* includes low frequency noise. Filters having different cut off frequencies are used to examine the cough signals at more than one level. The high pass filter H_0 provides detailed coefficients whereas the low pass filter L_0 provides approximation coefficients. If both the coefficients are combined beginning from the last level of decomposition to the first level, the original cough signal will be reconstructed. The following Fig. 1 shows the wavelet decomposition process at different levels and Fig. 2 shows the wavelet reconstruction process [19].

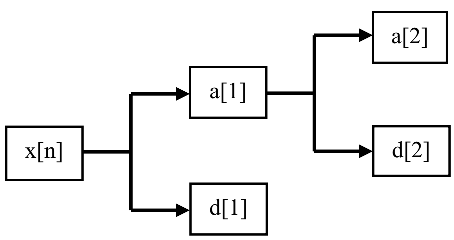


Fig. 1. Two Level Wavelet Decomposition [19].

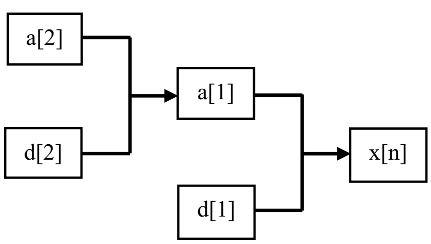


Fig. 2. Two Level Wavelet Reconstruction [19].

C. Proposed Filter for Pre-Processing of Cough Signals

The acquired cough sound signals are contaminated with various type of noise which are major issues in cough signals analysis. The pre-processing approach is used for removing the White Gaussian noise present in the cough sound signals [20]. In the presented work, a threshold-based noise filtering technique using discrete wavelet transform of cough signals has been proposed. The detail sub-bands obtained from the decomposition of cough sound signals deals with the residual noise which is difficult to eliminate through simple filtering processes [16]. Let the following model shows discrete noisy cough signals [21]:

$$y[n] = x[n] + e[n] \tag{4}$$

Where, *x[n]* is the original acquired cough signals, *e[n]* is amount of noise signal added and *y[n]* is the noisy cough signal. A threshold value λ is selected with the help of universal threshold given in [22]:

$$\lambda = \sqrt{2\log_2 N} \tag{5}$$

Where, N denotes the length of the cough signal and σ represents standard deviation. The value of σ can be calculated as [19]:

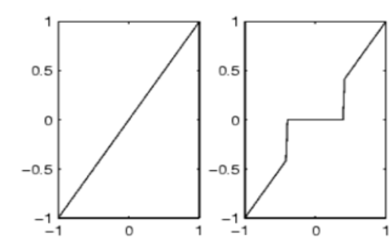
$$\sigma = \frac{MAD\left(d[n]\right)}{0.6745} \tag{6}$$

Where, *MAD* is Median Absolute Deviation. The calculated value of λ from the Eq. 5 is applied to all the coefficients of the cough signals. 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) [23]:

$$s_j = \begin{cases} \left[sign\left(C_j\right)\left(\left|C_j\right| - \lambda\right)\right], & \left|C_j\right| > \lambda \\ 0, & \left|C_j\right| < \lambda \end{cases} \tag{7}$$

$$H_j = \begin{cases} C_j, & \left|C_j\right| > \lambda \\ 0, & \left|C_j\right| < \lambda \end{cases} \tag{8}$$

Where, C_j is the coefficients and λ is the threshold value. In the presented work, hard thresholding technique is preferred over soft thresholding because in soft thresholding the *SNR* of reconstructed cough signals are less than that of hard thresholding. The coefficients are obtained through hard thresholding; the threshold value λ set to zero and thresholds all the coefficients if the value of the coefficients is more than threshold value λ. The following figures show the hard thresholding of a signal [14]:



(a) (b)

Fig. 3. (a) Original Signal, (b) Hard Threshold Signal [14].

Fig. 3(a) shows the original signal and Fig. 3(b) shows the hard threshold signal. The block schematic of pre-processing of acquired cough signals is shown below in Fig. 4:

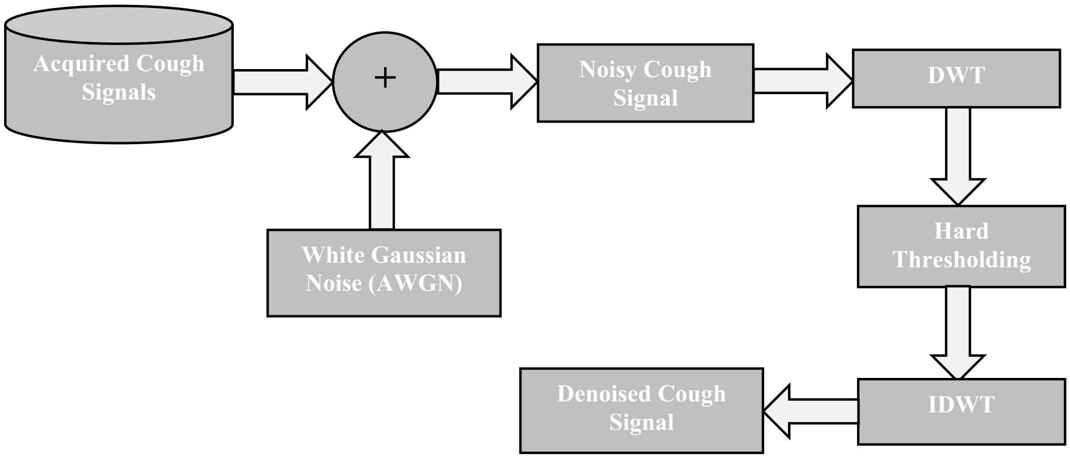


Fig. 4. Block Schematic of Pre-Processing of Acquired Cough Sound Signals [24].

The following *SNR* formula will help in checking the performance of the overall analysis of the cough sound signals [19]:

$$SNR(dB) = 10\log_{10} \frac{\sum_{i=1}^{N} \left(x_{dn}[n]\right)^2}{\sum_{i=1}^{N} \left(x[n] - x_{dn}[n]\right)^2} \tag{9}$$

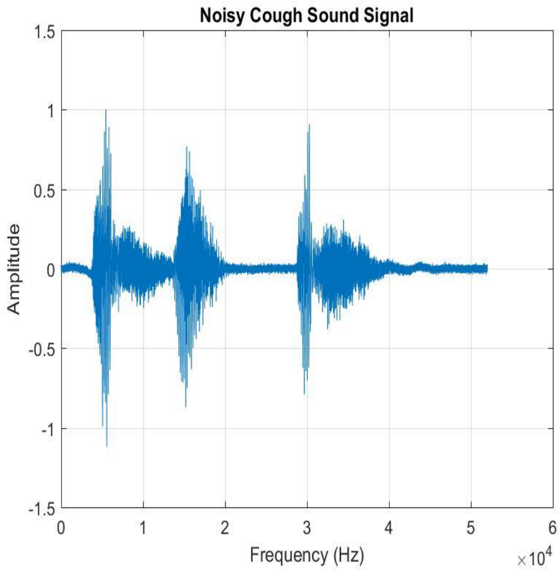
Where, $x_{dn}[n]$ denotes denoised cough signals and $x[n]$ is the original cough signals.

III. Results And Discussions

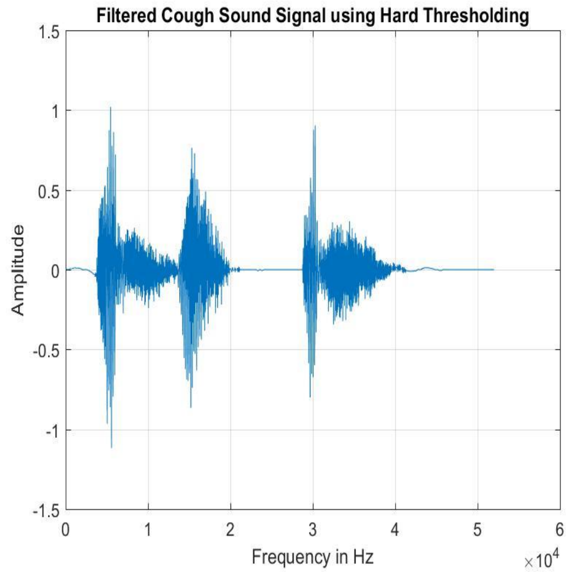
The cough signals are acquired with the help of microphone. White Gaussian noise is introduced to the original cough sound signals, the cough signals becomes noisy. Fig. 5(a) and 5(c) shows the noisy cough sound signals sample 1 and sample 2 whose *SNR* is calculated with the help of Eq. 9. The DWT is applied at different level and with different wavelet families on the noisy cough signals and a threshold value λ is calculated with the help of Eq. 5. The hard thresholding is done by applying threshold value λ to all the coefficients of the decomposed noisy cough signals. The best level of decomposition at level 8 and the best wavelet family Symlets (sym4) are chosen because at this, the *SNR* of the filtered cough signals are nearly to the original cough signals. High values of *SNR* are obtained by Symlets (sym4) wavelet family which represents better noise elimination as compared to other various types of wavelet families [16]. Fig. 5(b) and 5(d) shows the filtered cough signals at level 8 using sym4 wavelet family. Thus, an improved result of noise filtering using hard thresholding and DWT has been derived. The reconstruction of the cough signals is done from the new threshold coefficients with the help of inverse discrete wavelet transform (IDWT). The essential data present in the reconstructed cough sound signals are saved without disturbing the characteristic information present in the cough signals [16].

IV. Conclusion

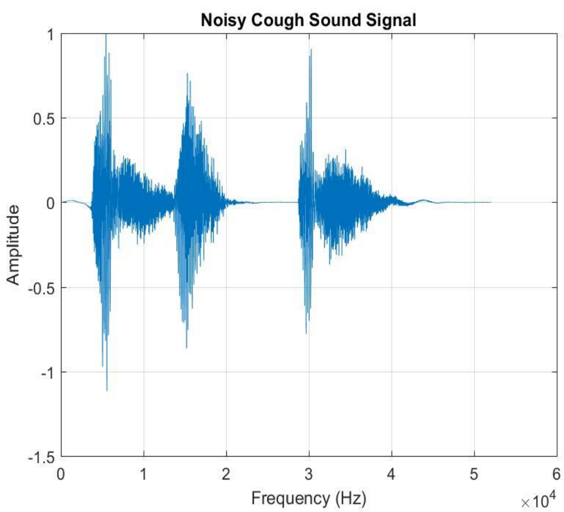
In the presented work, the analysis of the acquired cough sound signals has been done by applying a filtering technique using hard thresholding and DWT. A threshold value is selected for the process of thresholding of cough sound signals to remove the noise and to keep the cough signals smooth and distortion free. It is found with the entire analysis that the hard thresholding technique improves the *SNR* of the acquired cough signals.



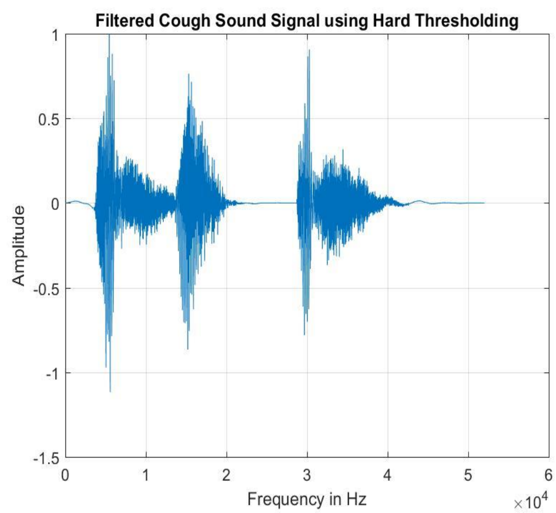
(a) Noisy Cough Signals Sample 1.
SNR = -13.3256 dB.



(b) Filtered Cough Signals Sample 1.
SNR = -13.2355 dB.



(c) Noisy Cough Signals Sample 2.
SNR = -13.3582 dB.



(d) Filtered Cough Signals Sample 2.
SNR = -13.3590 dB.

Fig. 5. (a) Noisy Cough Signal Sample 1, (b) Filtered Cough Signal Sample 1, (c) Noisy Cough Signal Sample 2, (d) Filtered Cough Signal Sample 2.

References

[1] Y. A. Amrulloh, U. R. Abeyratne, V. Swarnkar, R. Triasih and A. Setyati, "Automatic Cough Segmentation from Non-Contact Sound Recordings in Pediatric Wards," Biomedical Signal Processing and Control, Vol. 21, pp. 126-136, August 2015.

[2] U. R. Abeyratne, V. Swarnkar, A. Setyati and R. Triasih, "Cough Sound Analysis can Rapidly Diagnose Childhood Pneumonia," Annals of Biomedical Engineering, Vol. 41, No. 11, pp. 2448–2462, November 2013.

[3] R. Aggarwal, J. K. Singh, V. K. Gupta, S. Rathore, M. Tiwari and A. Khare, "Noise Reduction of Speech Signal using Wavelet Transform with Modified Universal Threshold," International Journal of Computer Application, Vol. 20. Issue 5, pp. 14-19, April 2011.

[4] T. Slonim, MA Slonim and EA Ovsyscher, "The Use of Simple FIR Filters for Filtering of ECG Signals and a New Method for Post-Filter Signal Reconstruction," Proc. of Computers in Cardiology Conference, London, UK, pp. 871-873, September, 1993.

[5] V. X. Afonso, W. J. Tompkins, T. Q. Nguyen, S. Trautmann and S. Luo, "Filter bank-based Processing of the Stress ECG," Proc. 17th International Conference of the Engineering in Medicine and Biology Society, Montreal, Canada, pp. 887-888, September 1995.

[6] Y. Wu, R. M. Rangyaan, Y. Zhou and S. Ng, "Filtering Electrocardiographic Signals using An Unbiased and Normalized Adaptive Noise Reduction System," Medical Engineering & Physics, Vol. 31, Issue 1, pp. 17-26, March 2008.

[7] J. Yan, Y. Lu, J. Liu, X. Wu and Y. Xu, "Self-Adaptive Model-based ECG Denoising using Features Extracted by Mean Shift Algorithm, Biomedical Signal Processing and Control, Vol. 5, Issue 2, pp. 103-113, April 2010.

[8] O. Sayadi and M. B. Shamsollahi, "ECG Denoising and Compression Using a Modified Extended Kalman Filter Structure, IEEE Transactions on Biomedical Engineering, Vol. 55, Issue 9, pp. 2240-2248, September 2008.

[9] H. Liang, Q. Lin and J. D. Z. Chen, "Application of the Empirical Mode Decomposition to the Analysis of Esophageal Manometric Data in Gastroesophageal Reflux Disease," IEEE Transactions on Biomedical Engineering, Vol. 52, Issue 10, October 2005.

[10] H. Liang, Z. Lin and F. Yin, "Removal of ECG Contamination from Diaphragmatic EMG by Nonlinear Filtering," Nonlinear Analysis, Vol. 63, Issue 5-7, pp. 745-753, December 2015.

[11] M. B. Velasco, B. Weng and K. E. Barner, "ECG Signal Denoising and Baseline Wander Correction Based on the Empirical Mode Decomposition," Computers in Biology and Medicine, Vol. 38, Issue 1, pp. 1-13, January 2008.

[12] D. L. Donoho and I. M. Johnstone, "Adapting to Unknown Smoothness via Wavelet Shrinkage," Journal of the American Statistical Association, Vol. 90, Issue 432, pp. 1200-1224, February 2012.

[13] P. Arora and M. Bansal, "Comparative Analysis of Advanced Thresholding Methods for Speech-Signal Denoising," Vol. 59, Issue 16, pp. 28-32, December 2012.

[14] M. S. Chavan, M. N. Chavan and M. S. Gaikwad, "Studies on Implementation of Wavelet for Denoising Speech Signal," Vol. 3, Issue 2, pp. 1-7, June 2010.

[15] M. Alfaouri and K. Daqrouq, "ECG Signal Denoising By Wavelet Transform Thresholding," American Journal of Applied Sciences, Vol. 5, Issue 3, pp. 276-281, 2008.

[16] V. Bhateja, S. Urooj, R. Verma and R. Mehrotra, "A Novel Approach for Suppression of Powerline Interference and Impulse Noise in ECG Signals," Proc. of IMPACT-2013, Aligarh, India, pp.103-107, November, 2013.

[17] V. Bhateja, S. Urooj, R. Mehrotra, R. Verma, A. Lay-Ekuakille and V. D. Verma (2013), "A Composite Wavelets and Morphology Approach for ECG Noise Filtering," International Conference on Pattern Recognition and Machine Intelligence, pp. 361-366.

[18] S. Poungponsri and X. Yu, "An Adaptive Filtering Approach for Electrocardiogram (ECG) Signal Noise Reduction using Neural Networks," Neurocomputing, Vol. 117, pp. 206-213, February 2013.

[19] N. H. Narona, S. Mukherjee and V. Kumar, "Wavelet Based Non-Linear Thresholding Techniques for Pre-Processing ECG Signals," International Journal of Biomedical and Advance Research, Vol. 4, Issue 8, pp. 534-544, August 2013.

[20] V. Bhateja, A. Srivastava and D. K. Tiwari (2017), "An Approach for the Preprocessing of EMG Signals using Canonical Correlation Analys," Smart Computing and Informatics, pp. 201-208.

[21] B. N. Singh and A. K. Tiwari, "Optimal Selection of Wavelet Basis Function Applied to ECG Signal Denoising, Digital Signal Processing, Vol. 16, Issue 13, pp. 275-287, May 2006.

[22] D. L. Donoho, "De-noising by Soft-Thresholding," IEEE Transactions on Information Theory, Vol. 41, Issue 3, pp. 613-627, May 1995.

[23] H. A. R. Akkar, W. A. H. Hadi, I. H. Al-Dosari, "A Squared-Chebyshev Wavelet Thresholding Based 1D Signal Compression," Defence Technology, pp. 1-6, August 2018.

[24] M. T. Johnson, X. Yuan and Y. Ren, "Speech Signal Enhancement through Adaptive Wavelet Thresholding," Speech Communication, Vol. 49, Issue 2, pp. 123-133, February 2007.