EMPIRICAL WAVELET TRANSFORM BASED LUNG SOUND REMOVAL FROM PHONOCARDIOGRAM SIGNAL FOR HEART SOUND SEGMENTATION

K. Ajay Babu, Barathram. Ramkumar, and M. Sabarimalai Manikandan

School of Electrical Sciences, Indian Institute of Technology Bhubaneswar, Odisha-752050, India

ABSTRACT

Automatic removal of lung sounds from a phonocardiogram (PCG) signal is most essential for accurately detecting and recognizing the fundamental heart sounds such as the first heart sound (S1) and second heart sound (S2). In this paper, we propose an automated lung sound removal method using the empirical wavelet transform (EWT). The proposed method consists of three major stages: the EWT based signal decomposition; the frequency based mode selection; and the signal reconstruction. The proposed method is evaluated by synthetically adding the different lung sounds available in Littmann lung sound library with the real-time recorded PCG signals from 20 volunteers. The quality of the reconstructed signals is assessed by using both objective quality assessment metrics and subjective quality test such as mean opinion score (MOS). For the performance comparison, two lung sound removal methods have been implemented based on the ensemble empirical mode decomposition (EEMD) and frequency selective filtering techniques. The objective and subjective evaluation results and the heart sound segmentation results demonstrate that the EWT based lung sound removal method outperforms the other methods. The proposed method based heart sound segmentation scheme achieves an average sensitivity (Se) of 100%, positive predictivity (P_p) of 99.22%, and overall accuracy (OA) of 99.22%.

Index Terms— Phonocardiogram (PCG), Empirical wavelet transform (EWT), Lung sounds

1. INTRODUCTION

Cardiac auscultation based diagnosis is becoming popular due to the revolutionary adaptation of technology in the design of stethoscope. Generally, the phonocardiogram (PCG) consists of events like S1 and S2 heart sounds for the healthy adults [1]. The S3 and S4 sounds also can be heard in healthy elder people and children [1]. The abnormality of any person can be heard as murmurs and splits in PCG. The presence of S3 and S4 sounds in adults indicate that there may be abnormality in the functioning of the heart [1]. The detection of all these major events of PCG plays a key role in the diagnosis of heart. The detection of S1/S2 heart sounds is the essential step. These sounds are often corrupted with the lung sounds. Thus a removal of lung sound from PCG signal is most important for accurately recognizing the S1 and S2 sounds.

In [2] adaptive line enhancement (ALE) technique is used in which wheeze sounds and heart sounds are applied to adaptive line enhancer for separation of heart sounds and lung sounds. In [3] heart sounds are localized by using Shannon entropy of lung sounds. A new entropy bound based heart sound localization in respiratory sound is presented in [4]. In [5] the spectrum estimation along with independent component analysis (ICA) is utilized to separate the lung sounds and heart sounds. A modified non-negative matrix factorization (NMF) approach which recovers the cardiac sounds is described in [6]. Time-frequency filtering based approach and singular spectrum analysis (SSA) based methods for separation of heart sounds and lung sounds are presented in [7]-[8]. Statistical signal processing methods to localize the heart sounds are presented in [9]-[10]. Hidden Markov model (HMM) based reconstruction of heart sounds is presented in [11]. Non-stationary signal decomposition techniques such as empirical mode decomposition (EMD), and ensemble empirical mode decomposition (EEMD) are used to segment the heart sounds in presence of lung sounds [12]-[13].

In the existing works, temporal feature based approaches are not robust to the noise and hence may not capable to retain the time duration information of S1 and S2 sounds. Though the spectral estimation along with lung sounds rejection criterion based approaches are effectively reconstructing the heart sounds, there is limitation with computational complexity. The time-frequency feature based techniques are not capable to retain the morphology of the S1 and S2 sounds due to the lack of adaptation in filter bank. Non-stationary decomposition based methods suffers with the stopping criterion and mode mixing problem. Hence in this study an effective and robust algorithm is presented to remove the different lung sounds interfere with fundamental S1 and S2 heart sounds.

With the motivation of the effective heart sound segmentation and murmurs classification study presented in [14], in this work a unified framework has been established to remove the different lung sounds from the S1 and S2 heart sounds.

1.1. Contribution

An in-house developed PCG acquisition system is used for acquiring the real-time database. The obtained real-time signal is synthetically added with different lung sounds taken from Littmann lung sounds library [15]. The frequency spectrum of normal heart sounds mixed with different lung sounds (such as healthy bronchophony, abnormal bronchophony, monophonic wheezes, rhonchi low pitched wheezes, bronchovesicular, pleural rubs, crackles fine rales, crackles coarse rales, egophony, and vesicular normal) are analyzed. Without using any lung sounds removal techniques, the S1 and S2 heart sounds mixed with various lung sounds are reconstructed by incorporating the dominant frequency range of S1 and S2 heart sounds in the empirical wavelet transform (EWT) based decomposition.

The rest of the paper is organized as follows: Section II presents the proposed EWT based decomposition approach for detection of S1 and S2 heart sounds. Section III presents simulation results and discussion. Section IV presents the conclusion and future work.

2. PROPOSED METHODOLOGY

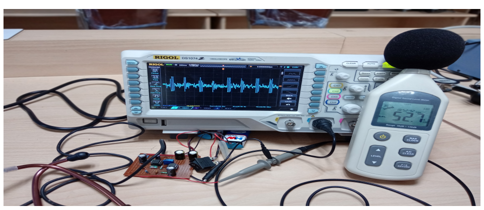

Fig. 1: Illustrates the real-time PCG acquisition.

In this section the proposed EWT based decomposition approach for the removal of lung sounds from the heart sounds is presented. The real-time PCG signal is acquired from the in-house developed PCG acquisition system which is shown in Fig. 1. Microphone (ABM 713 RC) is placed into the one of ear-tips of the stethoscope to acquire the PCG signal. The PCG acquisition system consists of different stages like high pass filter (5 Hz cut-off frequency), amplifier (gain of 100), and analog to digital converter (ADC). Arduino-Uno with 1200 Hz as sampling frequency is used in order to get the digitized PCG signal.

The acquired PCG signal is synthetically added with lung sounds. The mixed signal is pre-processed to remove the mean and normalize the amplitude. The spectrum of the normal PCG, abnormal PCG, and PCG mixed with lung sounds are shown in Fig. 2. From the spectrum, it is clear that the most of the energy of the S1 and S2 sounds are concentric between the 10-70 Hz whereas lung sounds are concentric between the 100-500 Hz. With this spectral information, EWT based decomposition is used for reconstruction of S1 and S2 heart sounds by automatically removing the lung sounds. EWT based decomposition is used in applications like seismic data analysis [16], electroencephalogram (EEG) seizure detection [17], and power quality analysis [18]. A brief description of EWT is presented in the next subsection and the EWT based decomposition for reconstruction and Shannon entropy envelogram (SEE) based detection of S1 and S2 heart sounds in presence of lung sounds is presented in the subsequent subsection.

2.1. Empirical wavelet transform

In this subsection a brief description of EWT is presented and the detailed description can be found in [19]. EWT builds an adaptive filter banks for the effective decomposition of the input signal. EWT comprises of estimating the spectrum components, accurately segmenting the spectrum, determining the boundaries of the Fourier spectrum, and defining the filter banks. The scaling function ϕ_1 and empirical wavelets ψ_i in the frequency domain are expressed as [19],

$$\phi_1(\omega) = \begin{cases} 1, \ \textit{if} \ |\omega| \leqslant (1-\gamma)\Omega_1 \\ \cos(\frac{\pi}{2}\beta(\gamma,\Omega_1)), \ \textit{if} \ (1-\gamma)\Omega_1 \leqslant |\omega| \leqslant (1+\gamma)\Omega_1 \\ 0, \ \textit{otherwise} \end{cases} \tag{1}$$

$$\psi_i(\omega) = \begin{cases} 1, \ \textit{if} \ (1+\gamma)\Omega_i \leqslant |\omega| \leqslant (1-\gamma)\Omega_{i+1} \\ \cos(\frac{\pi}{2}\beta(\gamma,\Omega_{i+1})), \ \textit{if} \ (1-\gamma)\Omega_{i+1} \leqslant |\omega| \leqslant (1+\gamma)\Omega_{i+1} \\ \sin(\frac{\pi}{2}\beta(\gamma,\Omega_i)), \ \textit{if} \ (1-\gamma)\Omega_i \leqslant |\omega| \leqslant (1+\gamma)\Omega_i \\ 0, \ \textit{otherwise} \end{cases} \tag{2}$$

where γ is a overlap controlling parameter, $\beta(\gamma,\Omega_i) = \beta(\frac{1}{2}\gamma\Omega_i(|\omega| - (1-\gamma)\Omega_i))$. Ω_i is the boundaries given by [19],

$$\Omega_i = \frac{\omega_i + \omega_{i+1}}{2} \ \textit{for} \ 1 \leqslant i \leqslant N-1 \tag{3}$$

where ω_i, ω_{i+1} are the frequencies, and N is the number of segments.

The approximation and detailed coefficients denoted as I and D are obtained by inner dot product of input signal $p(t)$ with scaling and empirical wavelet functions respectively which is basically inverse fast Fourier transform (IFFT) and are given by [19],

$$I = \int p(\tau)\phi_1(\tau - t)d\tau = IFFT(P(\omega) \times \phi_1(\omega)) \tag{4}$$

$$D = \int p(\tau)\psi_i(\tau - t)d\tau = IFFT(P(\omega) \times \psi_i(\omega)) \tag{5}$$

Hence it is clear that the EWT approach is effective in analyzing the real-time signal consists of multiple frequency components. The study made in [19] demonstrates that the EWT has better frequency resolution than EMD. The heart sounds analysis using EWT presented in [14] gives a promising approach for removal of physiological interference from heart sounds. In the next subsection the effectiveness of the EWT decomposition based lung sounds separation from the heart sounds is presented.

2.2. EWT decomposition based lung sounds separation from heart sounds

The steps involved in the EWT based decomposition and separation of lung sounds from the heart sounds is as follows:

- *Step B.0:* Acquire the real-time PCG signal and add lung sounds synthetically
- *Step B.1:* Estimate the spectrum of the mixture signal
- *Step B.2:* Determine the frequency span where the S1 and S2 sounds are dominant
- *Step B.3:* Segment the band where the S1 and S2 heart sounds gets the local maximum in the spectrum
- *Step B.4:* Keep the spectrum components other than the dominant S1 and S2 sounds as residual signal
- *Step B.5:* Compute the boundaries using (3)
- *Step B.6:* Build the scaling function and wavelet filter bank in frequency domain using (1) and (2)
- *Step B.7:* Get back the reconstructed PCG with only S1 and S2 heart sounds using (4) and (5)

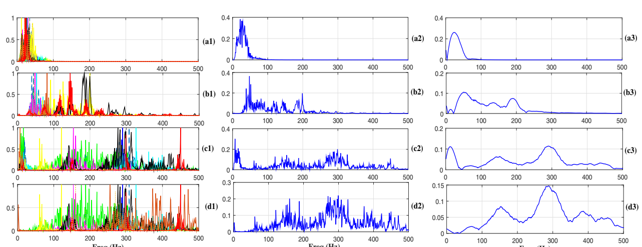

Fig. 2: Illustrates the spectrum of heart sounds mixed with different lung sounds. (a1)-(a3) Frequency spectrum of fundamental heart sounds. (b1)-(b3) Frequency spectrum of abnormal heart sounds. (c1)-(c3) Frequency spectrum of Heart sounds with different lung sounds. (d1)-(d3) Frequency spectrum of different lung sounds.

An example of an effective reconstruction and detection of S1 and S2 sounds using EWT is shown in Fig. 3. The wheezes sound is synthetically added to heart sounds and is shown in Fig. 3.(a3). As per the spectral information in Fig. 2, in the EWT based decomposition the boundaries of the spectrum are selected between 10-70 Hz and the decomposed output signal within this range of frequencies is shown in Fig. 3.(a4). From Fig. 3.(a4), it is observed that the S1 and S2 heart sounds are effectively reconstructed. To show the other frequency components in the mixed signal, the residual signal is shown in Fig. 3(a5). From Fig. 3(a5), it is understood that the lung sound signals are reconstructed. So it is observed that the EWT based decomposition not only useful to remove the lung sounds from heart sounds but also useful for the lung sound analysis.

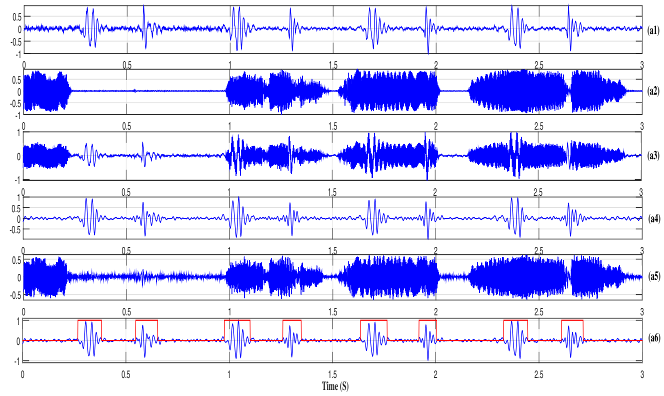

Fig. 3: Illustrates the EWT based effective reconstruction and detection of S1 and S2 heart sounds. (a1) Normal heart sounds. (a2) lung sound. (a3) mixed heart sound and lung sound. (a4) EWT decomposed based reconstructed S1 and S2 heart sounds. (a5) Residual signal. (a6) SSEE based S1 and S2 detection.

2.3. Detection of S1 and S2 heart sounds using Shannon entropy envelogram (SEE)

The reconstructed S1 and S2 heart sound signal $\hat{P}_{S1,S2}[n]$, is subjected to a non-linear amplitude transformation to emphasize the informative amplitude content present in the signal. In this work, Shannon entropy is considered for non-linear transformation. Shannon entropy is chosen because it enhances the informative low amplitude segments of the heart sound. Since this feature will also enhance the low amplitude noise, $\hat{P}_{S1,S2}[n]$ is subjected to a fixed threshold to suppress the noise. The threshold signal $\hat{P}_{th}[n]$ is given as,

$$\hat{P}_{th}[n] = \begin{cases} \hat{P}_{S1,S2}[n], & \textit{if } \hat{P}_{S1,S2}[n] > \gamma_{th} \\ 0, & \textit{otherwise} \end{cases} \tag{6}$$

The value of γ_{th} is chosen as 0.1 by considering the $S1$ and $S2$ amplitude levels. The Shannon entropy envelope (SEE) is computed as,

$$P_{Sh}[n] = -|\hat{P}_{th}[n]| \log|(\hat{P}_{th}[n])| \tag{7}$$

The smoothen Shannon entropy envelope (SSEE) is obtained by smoothening $P_{Sh}[n]$ using a zero phase forward and reverse filter (for filtering, a rectangular window of length 50 ms with overlap of 1 ms is used). Then the gated signal is computed as follows:

$$\hat{P}_g[n] = \begin{cases} 1, & \text{if } \hat{P}_{Sh}[n] > \gamma_{sh} \\ 0, & \text{otherwise} \end{cases} \tag{8}$$

where γ_{sh} is chosen as the mean value of $\hat{P}_{Sh}[n]$.

The gated signal computed from the SSEE is shown in Fig. 3.(a6).

3. RESULTS AND DISCUSSION

The performance of the proposed algorithm is analyzed using MATLAB 2014 software simulations. For performance analysis, both real time PCG signals and standard lung sound signals from Littmann lung sounds library are considered. For real time PCG recording, in-house developed PCG acquisition system shown in Fig. 1. is used. 20 male subjects of the age ranging between 18-35 years are voluntarily participated to give their database. While recording (30 Seconds of duration) the data, the subject is in sitting position and the recording environment is free from the external sound disturbances. All the recordings are carried out under the observation of experienced medical practitioner.

The recorded databases are synthetically added with the 12 various lung sounds collected from the Littmann lung sound library. The proposed EWT based decomposition method is compared with the singular spectrum analysis (SSA), and ensemble empirical mode decomposition (EEMD) methods. The effectiveness of the EWT based decomposition is shown in Fig. 4. In all these methods, the reconstructed signals are further processed for detecting the S1 and S2 heart sounds. The performance of the methods are summarized in Table 1 in terms of standard benchmark performance metrics such as Sensitivity (Se), positive predictivity (P_p), and overall accuracy (OA) are calculated by,

$$Se. = \frac{TP}{TP+FN} \times 100 \tag{9}$$

$$P_p = \frac{TP}{TP+FP} \times 100 \tag{10}$$

$$OA = \frac{TP}{TP+FP+FN} \times 100 \tag{11}$$

where 'TP' indicates the true positive, 'FP' indicates the false positive and 'FN' indicates the false negative. The proposed EWT based method has 100 % sensitivity, 99.22 % of positive predictivity as well as accuracy. The signal reconstruction quality parameters such as root mean square error (RMSE), maximum error (ME), signal to noise ratio (SNR in dB) are presented in Table 2. The performance metrics in Table 1 infers that the proposed EWT based decomposition method has great ability of resolution in frequency domain for detecting the S1 and S2 heart sounds in presence of lung sounds.

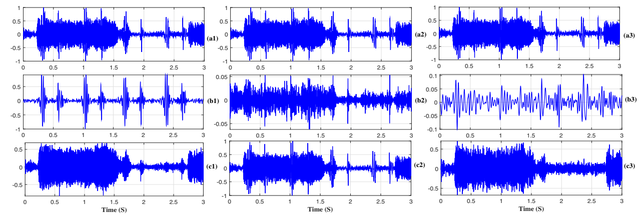

Fig. 4: Illustrates the effectiveness of EWT decomposition. (a1), (a2), and (a3) Heart sounds signal which is mixed with stridor lung sound. (b1), (b2), and (b3) decomposed signals using EWT, SSA, and EEMD. (c1), (c2), and (c3) residuals obtained using three different methods.

Table 1: Performance metrics of the fundamental S1 and S2 heart sound reconstruction with three different methods.

Method	Seg.	TP	FP	FN	Se(%)	P_p(%)	OA(%)
EWT+SEE+A.Th (Proposed)	1920	1920	15	0	100	99.22	99.22
EEMD+SEE+A.Th	1920	1907	122	13	99.32	93.99	93.40
SSA+SEE+A.Th	1920	1882	334	38	98.02	84.96	83.54

Table 2: Quality parameters.

Rec.	SSA			EEMD			Proposed (EWT)		
	RMSE	ME	SNR	RMSE	ME	SNR	RMSE	ME	SNR
1	0.16	0.80	3.74	0.16	0.84	3.74	0.07	0.58	17.94
2	0.19	0.98	0.08	0.15	0.80	4.79	0.07	0.59	17.89
3	0.19	0.99	-0.04	0.13	0.71	6.75	0.07	0.58	18.09
4	0.19	1.05	-0.20	0.15	0.81	4.31	0.08	0.59	17.49
5	0.19	0.98	0.17	0.15	0.83	5.06	0.08	0.59	17.48
Avg.	0.18	0.96	0.75	0.14	0.79	4.93	0.07	0.58	17.77

4. CONCLUSION

This paper presents an automated EWT based method for removal of lung sound from PCG signal. For performance comparison, the two lung sound removal methods are implemented based on the singular spectrum analysis (SSA) and EEMD techniques. The performance of the methods are evaluated using both synthetically generated PCG signals corrupted with lung sounds and the real-time PCG signals. The evaluation results show that the proposed method outperforms the SSA and EEMD based methods in terms of achieving better objective quality metrics and segmentation performance. The proposed method had an average accuracy of 99.22% in detecting the S1 and S2 sounds in presence of lung sounds whereas EEMD method and SSA methods had 93.40% and 83.54% respectively.

5. REFERENCES

[1] Rangaraj M. Rangayyan, Biomedical Signal Analysis. New York: Wiley, 2002.

[2] Thato Tsalaile, and Saeid Sanei, "Separation of heart sound signal from lung sound signal by adaptive line enhancement," *EURASIP,* pp. 1231-1235, Sept. 2007.

[3] Azadeh Yadollahi, and Zahra M. K. Moussavi, "A Robust method for heart sounds localization using lung sounds Entropy," *IEEE Trans. Biomed. Eng.,* vol. 53, no. 3, pp. 497-502, Mar. 2006.

[4] I. Yucel Ozbek, and Hamed Shamsi, "Heart sound localization in respiratory sound based on a new computationally efficient entropy bound," *IEEE J. Biomed. And Health Infor.,* vol. 21, no. 1, Jan. 2017.

[5] M. T. Pourazad, Z. Moussavi, F. Farahmand,"Heart sounds separation from lung sounds using independent component analysis," *IEEE. EMBS Conf. on Biomed. Eng. and Sci.,* Sept. 2005.

[6] Ghafoor Shah, Peter Koch, Constantinos B. Papadias, "On the blind recovery of cardiac and respiratory Sounds," *IEEE J. Biomed. And Health Infor.,* vol. 19, no. 1, pp. 151-157, Jan. 2015.

[7] M. T. Pourazad, Z. Moussavi, G. Thomas, "Heart sound cancellation from lung sound recordings using time-frequency filtering," *Med Biol Eng Comput.,* vol. 2, pp. 216-225, Mar. 2006.

[8] H. Liang, S. Lukkarinen, and I. Hartimo, "Localizing heart sounds in respiratory signals using singular spectrum analysis," *IEEE Trans. Biomed. Eng.,* vol. 58, no. 12, pp. 3360-3367, Dec. 2011.

[9] Hamed Shamsi, and I. Yucel Ozbek, "Robust heart sound detection in respiratory sound using LRT with maximum a posteriori based online parameter adaptation," *Med. Eng. & Phy.,* vol. 36, pp. 1277-1287, July 2014.

[10] Feng Jin, and Farook Sattar, "A multiscale mean shift localization approach for robust extraction of heart sounds in respiratory signals," *ICASSP.,* pp. 1291-1295, May 2013.

[11] Hamed Shamsi, and I. Yucel Ozbek, "Heart sound detection in respiratory sound using hidden Markov model," *EUSIPCO.,* pp. 1-5, Sept. 2013.

[12] Samit Ari, and Goutam Saha, "Classification of heart sounds using empirical mode decomposition based features," *Int. J. of Medical Engineering and Informatics*, vol. 1, no. 1, pp. 91-108, 2008.

[13] C. D. Papadanil and Leontios J. Hadjieontiadis, "Efficient heart sound segmentation and extraction using ensemble empirical mode decomposition and kurtosis features," *IEEE J. Biomed. And Health Infor.* vol. 18, no. 4, pp. 1138-1152, July 2014.

[14] V. Nivitha Varghees and K. I. Ramachandran, "Effective heart sound segmentation and murmur classification using empirical wavelet transform and instantaneous phase for electronic stethoscope," *IEEE Sensors J.* vol. 17, no. 12, pp. 3861-3872, June 2017.

[15] (Jan. 9, 2018) Littmann Lung Sounds database. [Online] Available: http://www.3m.com/healthcare/littmann/mmm-library.html.

[16] Wei Liu, Siyuan Cao, and Yangkang Chen, "Seismic timefrequency analysis via empirical wavelet transform," *IEEE Geosci. Remote Sens. Lett.,* vol. 13, no. 1, Jan. 2016.

[17] Abhijit Bhattacharyya, and Ram Bilas Pachori, "A multivariate approach for patient-specific EEG seizure detection using empirical wavelet transform," *IEEE Trans. Biomed. Eng.,* vol. 64, no. 9, pp. 2003-2015, Sept. 2017.

[18] Karthik Thirumala, Amod C. Umarikar, and Trapti Jain, "Estimation of single-phase and three-phase power-quality indices using empirical wavelet transform," *IEEE Trans. Power Del.,* vol. 30, no. 1, pp. 445-454, Feb. 2015.

[19] Jerome Gilles, "Empirical wavelet transform," *IEEE Trans. Signal Process.,* vol. 61, no. 16, pp. 3999-4010, Aug. 2013.