Heart Sound Localization in Respiratory Sounds Based on Singular Spectrum Analysis and Frequency Features

Malihe Molaie and Mohammad Hassan Moradi

Heart sounds are the main obstacle in lung sound analysis. To tackle this obstacle, we propose a diagnosis algorithm that uses singular spectrum analysis (SSA) and frequency features of heart and lung sounds. In particular, we introduce a frequency coefficient that shows the frequency difference between heart and lung sounds. The proposed algorithm is applied to a synthetic mixture of heart and lung sounds. The results show that heart sounds can be extracted successfully and localizations for the first and second heart sounds are remarkably performed. An error analysis of the localization results shows that the proposed algorithm has fewer errors compared to the SSA method, which is one of the most powerful methods in the localization of heart sounds. The presented algorithm is also applied in the cases of recorded respiratory sounds from the chest walls of five healthy subjects. The efficiency of the algorithm in extracting heart sounds from the recorded breathing sounds is verified with power spectral density evaluations and listening. Most studies have used only normal respiratory sounds, whereas we additionally use abnormal breathing sounds to validate the strength of our achievements.

Keywords: Noise reduction, breath sounds, singular spectrum analysis, heart-sound-components identification, frequency features, SSA.

Manuscript received Dec. 23, 2014; revised Apr. 3, 2015; accepted Apr. 15, 2015.

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I. Introduction

Respiratory sounds recorded from the chest wall of a subject depend on the subject's lung tissue structures. Due to the fact that different diseases can have different effects on a person's lung tissue and respiratory sounds, such sounds can be used in the diagnosis of airway and lung diseases. However, when lung sounds are recorded from the chest wall of a subject, sounds from both the subject's heart and the subject's immediate environment are mixed and picked up. As such, these particular sounds will affect the accuracy of any attempted disease diagnosis and should therefore be removed. The main frequency components of heart and lung sounds lie in the ranges of 20 Hz to 150 Hz and 60 Hz to 2,000 Hz, respectively.

Heart-sound reduction has been accomplished through many methods, such as adaptive filters [1], independent component analysis [2]–[3], time-frequency filtering [4], wavelet denoising [5], entropy-based methods [6], and recurrence time and nonlinear prediction [7]. Some of these methods set apart lung sounds and heart sounds. Some of the aforementioned methods localize both the first and the second heart sound time segments from a lung sound recording before removing such segments and substituting them with a zero segment. After this, the omitted segments, which are now assumed to be free of any heart sounds, are predicted using the remaining parts of the lung sound recording.

In [8], a comparison of the aforementioned methods is carried out using the methods' false-positive and false-negative errors in the localizations of heart sounds; standard deviations; resolutions; speeds; sensitivities to window sizes; and modes

http://dx.doi.org/10.4218/etrij.15.0114.1447

(that is, whether a method is classed as automatic or manual, as in a method may require some manual adjustment of parameters for different subjects). This comparison demonstrated that entropy-based and wavelet methods have a greater efficiency over the other methods in the localization of heart sounds.

In [9], a singular spectrum analysis (SSA)–based method is introduced. The realized results with this method are better than those of the entropy-based and wavelet methods in a medium flow rate in terms of false-positive and false-negative errors and correlations between extracted heart sounds and their original sounds. Furthermore, the SSA- and entropy-based methods have equal results in low flow rates for the given dataset used in [9]. This study revealed that the SSA-based method has a minimum error when it comes to the localization of heart sounds. Therefore, in this paper, a new algorithm based on SSA and frequency features of heart sounds is presented to localize heart sounds in recordings that feature a mixture of lung sounds and heart sounds.

The rest of this paper is organized as follows. In Section II, the SSA method and proposed algorithm, along with the data used in this paper, are introduced. Subsequently, in Section III, simulation results and a comparison with the SSA-based method of [9] are presented; and finally, Section IV is devoted to discussion and conclusion.

II. Methodology

1. Diagnostic Algorithm

In this section, the proposed diagnostic algorithm for heart sound localization and environment noise reduction from respiratory sound is explained. A block diagram of this algorithm is shown in Fig. 1.

As Fig. 1 shows, to localize heart sounds in respiratory sound, firstly, a recorded signal is high-pass filtered with 20 Hz cutoff frequency. Then, using the SSA method, the filtered signal is decomposed into its components; the noise components are then are removed from the filtered sound. After this, the proposed algorithm is then able to identify heart sound components. Finally, the heart sound components are separated

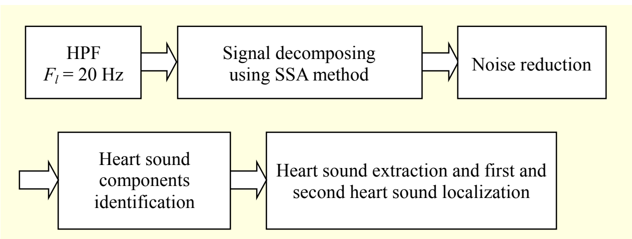

Fig. 1. Block diagram of proposed diagnostic algorithm.

from the respiratory sound and the first and second heart sounds are localized.

Since the presented algorithm is a modification of the SSA-based method of [9], we now take the time to introduce the related SSA algorithm as follows.

2. SSA Method

To reconstruct an attractor in a phase space, one must overcome the problems of selection of the best lag and embedding dimension in noisy data. The SSA method reconstructs signals in a k-dimensional phase space with time delay equal to one unit. The method is more sophisticated than the time delay method of [10], but it has the potential of providing more information. In the SSA method, after reconstructing a signal in a phase space, the signal is decomposed into several components. Then, these components are divided into groups, each of which is of a different dynamic. The number of groups depends on the complexity of the signal and any special requirements of the problem of separation. Based on different features, each component is assigned to a group, such as slowly varying trends, oscillatory components, quasi-periodic components, and random noise [11]. In the following, the SSA method is briefly described.

The SSA method generally consists of four steps. These are as follows. The first step is the reconstruction of the trajectory matrix and phase space. Let us assume that $\mathbf{x}$ is a time series of length N; that is,

$$\mathbf{x} = [x_1, x_2, \ldots, x_N]. \tag{1}$$

Then, using a window length of L ($2 \le L \le N/2$), we set $L = 300$ (to provide a fair decomposition and avoid a high computational cost) and $K = N - L + 1$; trajectory matrix $\mathbf{Z}$ is then reconstructed as

$$\mathbf{Z} = [z_{ij}] = \begin{bmatrix} x_1 & x_2 & x_3 & & x_k \\ x_2 & x_3 & x_4 & \cdots & x_{k+1} \\ x_3 & x_4 & x_5 & & x_{k+2} \\ & \vdots & & \ddots & \vdots \\ x_L & x_{L+1} & x_{L+2} & \cdots & x_N \end{bmatrix}, \tag{2}$$

where $\mathbf{Z}$ is a Hankel matrix (that is, it has equal elements along all of its diagonals; $i + j$ = constant). After this step and reconstruction of the trajectory matrix, the second step is the singular value decomposition (SVD) of $\mathbf{Z}^{\mathrm{T}}\mathbf{Z}$. In this step, L eigenvalues ($\lambda_1 \ge \ldots \ge \lambda_L \ge 0$) are produced in descending order of the amplitude (corresponding to L eigenvectors ($U_1, \ldots, U_L$)). The SVD of the trajectory matrix is

$$\mathbf{Z} = \mathbf{Z}_1 + \mathbf{Z}_2 + \ldots + \mathbf{Z}_d. \tag{3}$$

Likewise, $d = \mathrm{argmax}_i\ \{\lambda_i > 0\}$ and Z_i is the projection of Z in the direction of U_i.

Grouping is the third step of the SSA method. In this step, the set of indices $\{1, 2, \ldots, d\}$ is divided into several groups. The sum of the time series according to the indices in each group is a dynamic of a system that generates the considered signals.

In the extraction of heart sounds from respiratory sounds, there are three (behavior) dynamics that can be found in the recordings of such sounds — heart sound, lung sound, and environment noise. So, in the grouping step, there are three groups. In this paper, we introduce a modified SSA algorithm to identify those indices in each group that correspond to heart and lung sounds.

The final step in the SSA method is diagonal averaging. In this step, each group is transformed into a new time series using averaging over the diagonals $i + j =$ constant [11]–[12].

To extract the heart sounds from the lung sounds and environment noise, three time series corresponding to each of the three groups are extracted. In following, we introduce how to identify the components of each group.

A. Random Noise Reduction

In assuming that the environment noise is random, we note that this implicitly implies that a random signal has low variance in all directions. Therefore, the directions of eigenvectors corresponding to small eigenvalues are due to the noise; hence, it is these eigenvectors that should be removed. To implement this, the eigenvalues that are approximately equal to zero are selected in proportion to the noise. To identify the *noise eigenvalues*, we consider the graph of the eigenvalue amplitudes (see Fig. 2). From this graph, we select the point where the slope begins to level off; that is, at the 52nd eigenvalue number (beyond this value, the normalized eigenvalues are less than 0.004, which then acts as an upper bound). The eigenvalues smaller than this eigenvalue number are then assumed to be caused by noise. We use the following conditions to select this eigenvalue number:

$$\frac{\lambda_{m-1} - \lambda_m}{(\lambda_m - \lambda_d)/(d-m)} > 10, \tag{4}$$

$$\lambda_m < 0.005 \qquad (L \geq m > d).$$

In this equation, λ is a normalized eigenvalue. All eigenvectors corresponding to eigenvalues lower than λ_m are related to the noise and must be removed. Therefore, the SVD of the denoised trajectory matrix is

$$\mathbf{Z}_d = \mathbf{Z}_1 + \mathbf{Z}_2 + \ldots + \mathbf{Z}_m, \tag{5}$$

where $\mathbf{Z}_m$ is the projection of the trajectory matrix (of the original signal before denoising) onto the direction of the eigenvector related to λ_m.

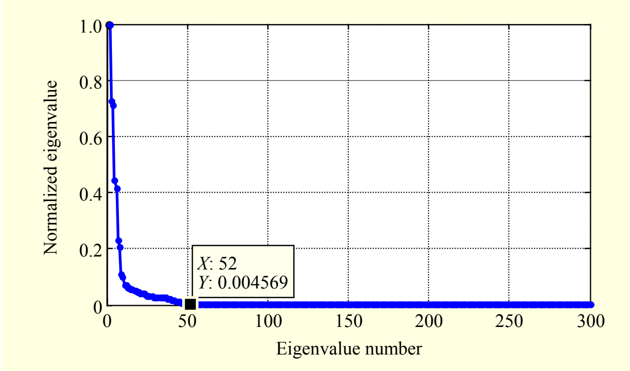

Fig. 2. Eigenvalues lower than 52nd eigenvalue number are assumed to equal zero and correspond to random noise.

In Fig. 2, eigenvalues larger than the extracted eigenvalue number (52) are related to the random environment noise for a typical noisy signal. After noise reduction, a further step is to then remove the heart sound. In the following, we introduce our proposed algorithm, which is used to identify heart sound components.

B. Identification of Heart Sound Components

In [9], using the SSA method, the heart sound is localized in the recorded respiratory sound. In the method of [9], it is assumed that the components of the heart sound have larger eigenvalues in low and medium flow rates. Therefore, from those eigenvalues corresponding to the periodic components, the six largest eigenvalues were selected to represent the components of the heart sound. However, this hypothesis is not true for all medium flow rates. In fact, for some medium flow rates, only two or four of the largest eigenvalues are proportional to the heart sound, and other larger eigenvalues correspond instead to components of the lung sound. Therefore, this assumption can reduce the accuracy of heart sound localization. As mentioned in [9], this hypothesis is not true for respiratory sound in high flow rates. To solve this problem and select more accurate eigenvalues corresponding to heart sound components, in this paper, the frequency properties of a heart sound are used.

We identified heart sound eigenvalues based on the fact that the principal frequency component of a heart sound is in the range 20 Hz to 150 Hz, whereas a respiratory sound's bandwidth lies in the range 60 Hz to 2,000 Hz. To use these properties for each eigenvalue and its corresponding component, each eigenvector is transformed to the frequency domain, and the energy percentage of the spectrum is calculated by dividing the energy of an eigenvector in the range of 20 Hz to 150 Hz by the energy of the eigenvector in the

ETRI Journal, Volume 37, Number 4, August 2015
http://dx.doi.org/10.4218/etrij.15.0114.1447

range of 20 Hz to 2,000 Hz. Since the heart sound components have the highest energy in the range 20 Hz to 150 Hz, such a ratio for them is very small. We assume for the heart sound components that this ratio is less than 0.3 and that each component having energy less than 0.3 in the ranges of 150 Hz to 2,000 Hz and 20 Hz to 2,000 Hz corresponds to a heart sound, which means

$$E_{\mathrm{f}(150\,\mathrm{Hz}-2{,}000\,\mathrm{Hz})} \Big/ E_{\mathrm{f}(20\,\mathrm{Hz}-2{,}000\,\mathrm{Hz})} < 0.3. \tag{6}$$

In (6), $E_{\mathrm{f}(150\,\mathrm{Hz}-2{,}000\,\mathrm{Hz})}$ is the energy of a component in the frequency range of 150 Hz to 2,000 Hz and $E_{\mathrm{f}(20\,\mathrm{Hz}-2{,}000\,\mathrm{Hz})}$ is the energy of a component in the frequency range of 20 Hz to 2,000 Hz.

In our algorithm, the amplitude of eigenvalues is not important and does not affect identification of heart sound components. Therefore, flow rate and heart sound intensity in the recorded sound are not important in the identification of heart sound components.

Assuming that $\lambda_{I_1}, \lambda_{I_2}, \ldots, \lambda_{I_p}$, are the identified eigenvalues of the heart sound, the SVD of the heart sound trajectory matrix is then

$$\mathbf{Z}_h = \mathbf{Z}_{I_1} + \mathbf{Z}_{I_2} + \ldots + \mathbf{Z}_{I_m}, \tag{7}$$

where $\mathbf{Z}_h$ is the trajectory matrix of the heart sound. Other eigenvalues are related to the respiratory sound. We expect that this algorithm identifies the heart sound components more accurately and localizes the heart sound with smaller error. The results have verified this. The locations of the first and second heart sounds are identified in the extracted heart sound using an adaptive threshold defined as ($\mu + \sigma$), where μ and σ are the mean and the standard deviation of the envelope of the extracted heart sound, respectively [9].

C. Data

In this paper, both the proposed algorithm and the SSA method in [9] are performed for three different datasets. The first dataset is the heart and lung sounds used in [9]. By applying these algorithms to these data, we can correctly compare our proposed algorithm with the SSA method introduced in [9]. The second dataset is obtained from [13]–[14]. This dataset contains normal and abnormal respiratory sounds, and recorded and simulated heart sounds. Using various mixtures of these sounds, we can produce recordings consisting of both lung and heart sounds. To mix the heart and lung sounds in a complex manner, the sounds are first normalized within the interval [−1, 1]. They are then passed through two randomly generated finite impulse response filters of length four and added together [9]. Both the proposed algorithm and the SSA method are performed for these synthesized data, and components of the heart sounds are identified in both methods. In the extracted heart sounds, the first and second heart sounds are localized. Finally, the percentage of false-negative and false-positive errors in localizations of the heart sounds for these methods are compared. The third dataset is recorded from five healthy subjects aged between 17 years and 25 years old. These data are recorded in the 2nd intercostal distance by an ECM44 Sony microphone in low and medium flow rates. This microphone is air-coupled and its frequency response is in the range of 40 Hz to 15,000 Hz [15], which is appropriate to record the respiratory sounds. The sampling rate was 40 kHz, which was later down-sampled to 5 kHz. Based on the fact that the heart and lung sounds' frequency bandwidths are higher than 20 Hz, the recorded signal is passed from a high-pass filter with 20 Hz cutoff frequency.

III. Results

In this section, the results for the SSA method and proposed algorithm on the aforementioned three different datasets are expressed. For each dataset, the typical extracted heart and lung sounds are shown and the two methods (SSA and proposed) are compared based on false-positive and false-negative errors in the localization of the first and second heart sounds.

1. First Dataset

To compare the proposed algorithm with the SSA method proposed in [9] (which has had the best efficiency in the localization of heart sounds), both algorithms are executed on the data used in [9]. Figure 3 demonstrates the typical heart and lung sounds, and their mixture, for a medium flow rate. The extracted heart and lung sounds obtained by using the two aforementioned methods are shown in Figs. 4 and 5. Similarly, the mean and standard deviation of the false-negative and false-positive errors in the localization of the first and second heart

Table 1. Mean and standard deviation of false-positive and false-negative errors for SSA and proposed algorithms in low and medium flow rates for 100 different mixtures of first dataset.

Flow rate	Low		Medium	
Error	False positive (%)	False negative (%)	False positive (%)	False negative (%)
SSA method	0.0 ± 0.0	0.0 ± 0.0	1.32 ± 1.43	0.54 ± 1.03
Proposed algorithm	0.0 ± 0.0	0.0 ± 0.0	0.18 ± 0.69	0.02 ± 0.14

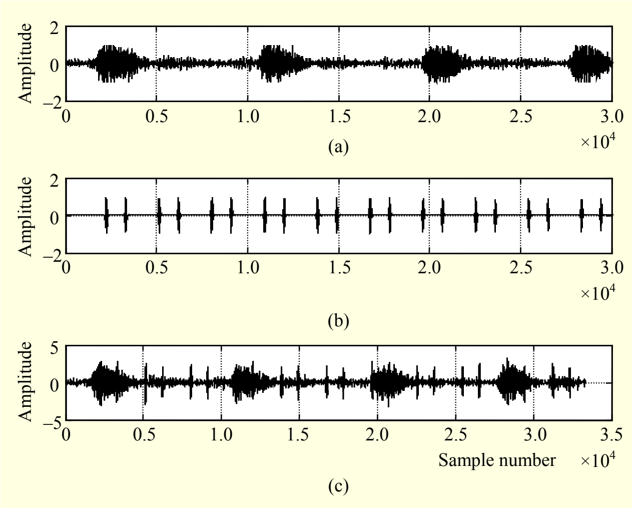

Fig. 3. Lung sound (a), heart sound (b), and their mixture (c).

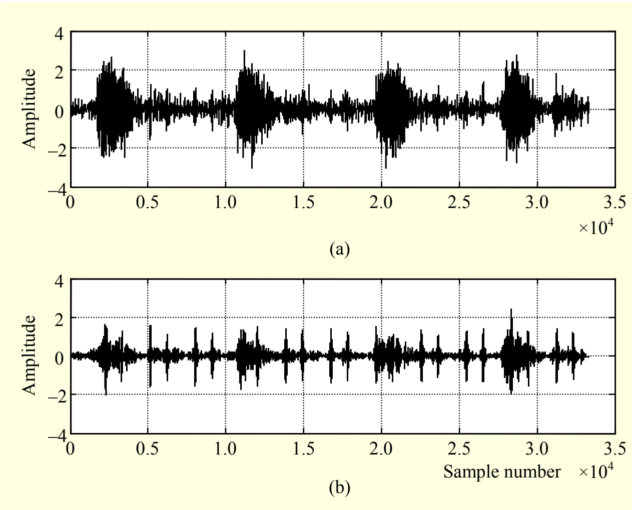

Fig. 4. Extracted lung sound (a) and heart sound (b) using SSA method.

sounds for 100 different mixtures of heart and lung sounds in low and medium flow rates are reported in Table 1. As shown in Table 1, false errors for both methods are equal to zero in the low flow rates, and the proposed algorithm has less false-positive and false-negative errors than the SSA method in the medium flow rates.

Figures 4 and 5 show that the proposed algorithm is able to extract heart and lung sounds more accurately than the SSA method.

2. Second Dataset

In this subsection, the results of the proposed algorithm and SSA method are shown for the mixture data obtained from [13]–[14]. One hundred different mixtures of these heart and

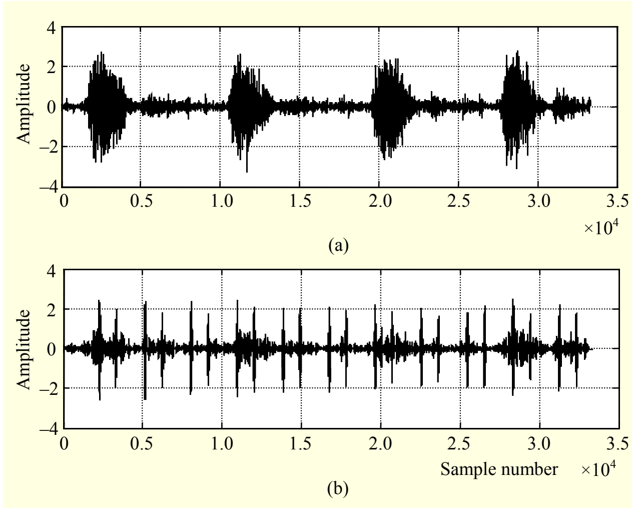

Fig. 5. Extracted lung sound (a) and heart sound (b) using proposed algorithm.

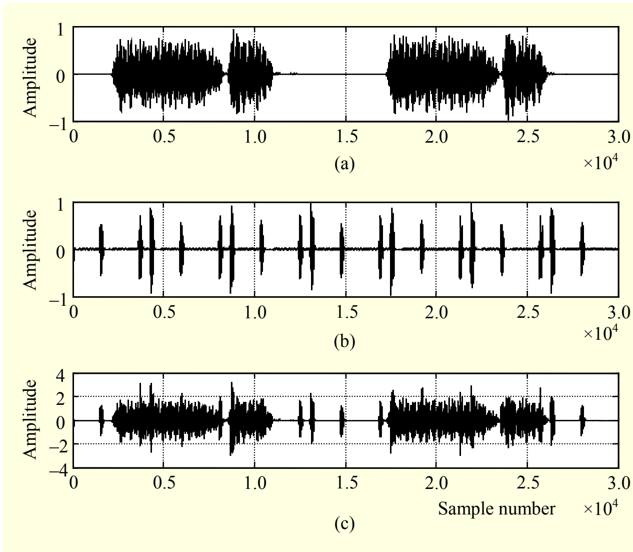

Fig. 6. Lung (a) and heart (b) sounds achieved from second dataset and their mixture (c).

lung sounds are produced in low and medium flow rates. A typical mixture of these sounds is shown in Fig. 6. Likewise, the extracted heart and lung sounds using the two aforementioned methods are depicted in Fig. 7. The power spectrums of the original lung sound and extracted lung sounds via the SSA and proposed methods are exhibited in Fig. 8. The mean and standard deviation of false-negative and false-positive errors for 100 different mixtures are reported in Table 2.

From Table 2, it is observed that for this dataset, in low and medium flow rates, false-negative and false-positive errors for the proposed algorithm are equal to zero and are less than those for the SSA method. This means that for this dataset, the

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Table 2. Mean and standard deviation of false-positive and false-negative errors in localization of heart sounds for second dataset.

Flow rate	Low		Medium	
Error	False positive (%)	False negative (%)	False positive (%)	False negative (%)
SSA method	0.05 ± 0.33	0.03 ± 0.17	1.8 ± 3.01	0.73 ± 1.7
Proposed algorithm	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0	0.0 ± 0.0

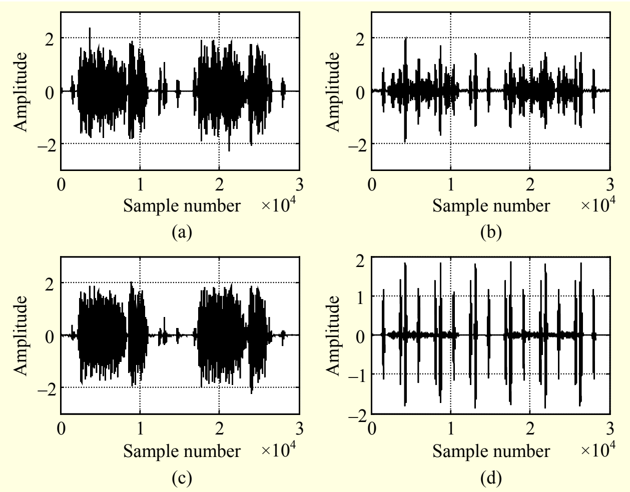

Fig. 7. Extracted heart and lung sounds using SSA ((a) and (b)) and proposed ((c) and (d)) methods.

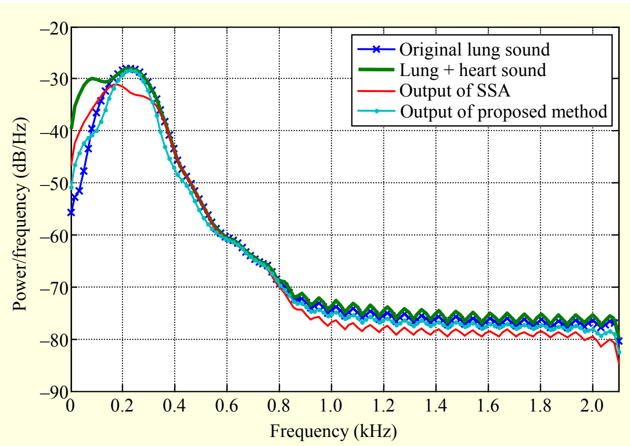

Fig. 8. Power spectral density of original lung sound; mixture of heart and lung sounds; and output lung sounds of SSA and proposed methods.

proposed algorithm identifies all of the locations of the heart sounds correctly.

From Fig. 7, it is known that the proposed algorithm can extract the heart sound components more accurately than the SSA method, because six higher eigenvalues in this dataset, with medium flow rates, are not corresponding to heart sounds. However, it is known that heart sounds are concentrated in lower frequencies than respiratory sounds despite the fact that both sounds share the same bandwidth. The power spectrums of the extracted lung sounds from the SSA and proposed methods in Fig. 8 show that the spectrum of the extracted lung sound from the proposed algorithm is more similar to that of the original lung sound.

Abnormal lung sounds. In [13], there are some different abnormal respiratory sounds. These sounds are mixed with the heart sounds achieved from [14]. The abnormal respiratory sounds used here consist of course and fine *crackles*, *wheezes*, and *stridors*. The SSA method could not extract heart sounds from these abnormal respiratory sounds and *signed* the first and second heart sounds correctly. The mean and standard deviation of false-positive and false-negative errors in the localization of the heart sounds using the proposed algorithm for 100 different mixtures of the heart and abnormal respiratory sounds in low and medium flow rates are reported in Table 3. A typical crackle sound and its mixture with heart sound are shown in Fig. 9. The extracted heart sound using the proposed algorithm is also shown in this figure, and the locations of the heart sounds are signed.

Table 3. Mean and standard deviation of false-positive and false-negative errors in localization of heart sounds in abnormal respiratory sounds using proposed algorithm.

Flow rate	Low		Medium	
Error	False positive (%)	False negative (%)	False positive (%)	False negative (%)
Proposed algorithm	0.0 ± 0.0	0.0 ± 0.0	0.32 ± 0.78	0.0 ± 0.0

Table 3 illustrates that the means of the false-negative and false-positive errors in low and medium flow rates are both equal to zero. These low mean errors illustrate that the proposed algorithm can separate heart sounds and localize them in abnormal breathing sounds efficiently. As Fig. 9 shows, the proposed algorithm can extract the heart sound components and localize the first and second heart sounds correctly.

3. Third Dataset

In this subsection, a typical result from performing the proposed algorithm on the recorded data from five healthy subjects is shown. To estimate the efficiency of the proposed algorithm in extracting heart sound components in the real recorded data from the chest wall, the extracted lung sounds are listened to and the power spectrum density and time shape of

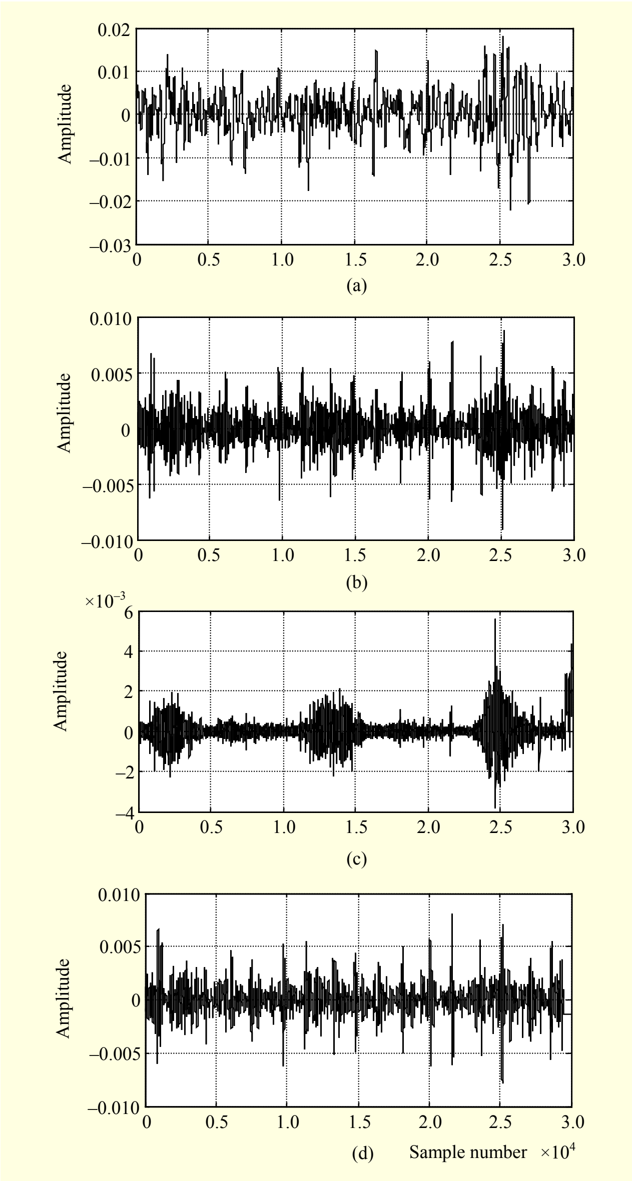

Fig. 9. Abnormal crackle sound (a), heart sound (b), their mixture (c), and extracted heart sound (d).

them are evaluated. Typical examples of the recorded sound and extracted heart and lung sounds are shown in Fig. 10, and their spectra are exhibited in Fig. 11.

As Figs. 10 and 11 show, the heart sounds are extracted from the recorded respiratory sounds. Extraction of heart and lung sounds is done better in medium flow rates as opposed to in low flow rates. In low flow rates, some audible heart sounds remain in the lung sound, but their intensity is reduced significantly. The output respiratory sounds are listened to, and the extractions of heart sounds in low and medium flow rates (and their subsequent removal) is verified. There are no audible heart sounds in the output respiratory sounds for medium flow rates.

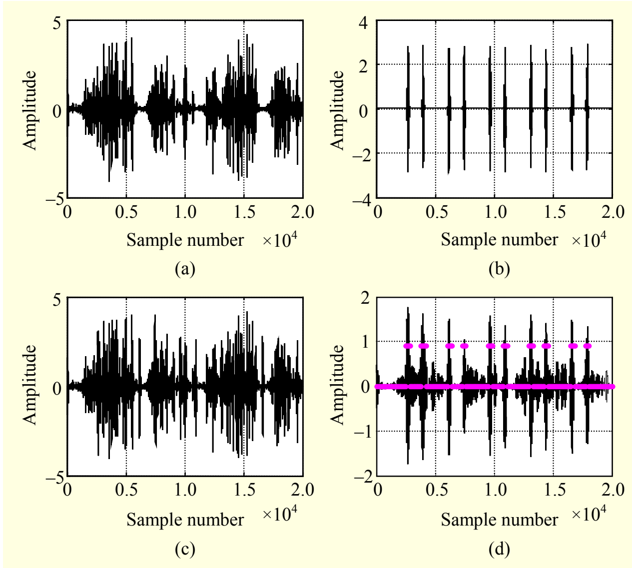

Fig. 10. Recorded respiratory sound from chest wall (a), filtered respiratory sound (b), extracted heart sound (c), and extracted lung sound (d).

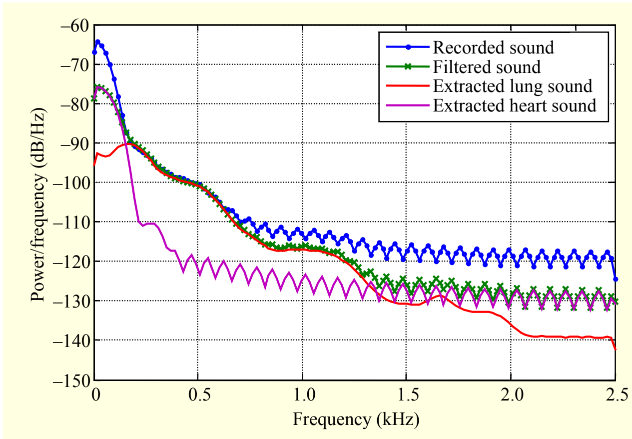

Fig. 11. Power spectral density of recorded lung sound; filtered lung sound; and extracted lung and heart sounds with proposed algorithm.

IV. Discussion and Conclusion

Recorded respiratory sounds from the chest wall consist of heart sounds and environment noises. Hence, in this paper, a modified algorithm has been introduced based on the SSA method and frequency properties of heart and respiratory sounds. The presented algorithm has been compared with the SSA method in the detection of heart sound. Comparisons of these methods are performed for two synthetic datasets, and the results are based on the false-positive and false-negative errors of localizations of heart sounds and power spectrum densities of extracted lung sounds.

We expected the proposed method to discover heart sounds more accurately than the SSA method, because in some medium flow rates the six highest eigenvalues do not correspond to heart sounds; only two or four of these are related to heart sounds. The proposed method achieves more accurate results because it is based on the fact that heart sounds have less energy in the range of 150 Hz to 2,000 Hz than respiratory sounds.

For the first dataset, the means of the false-positive and false-negative errors for the proposed method are 0.18 and 0.02, respectively, in medium flow rates and are zero in low flow rates. For the second data set, the means of the errors are zero in both low and medium flow rates. The results of the proposed method show better performances than the SSA method, as expected. The proposed algorithm is also performed to extract the heart sound and detect the location of the first and second heart sounds in a mixture of heart and abnormal respiratory sounds. For this dataset, the mean of the false-negative errors is zero in low and medium flow rates, whereas the mean of the false-positive errors is zero in low flow rates and 0.32 in medium flow rates. False-positive and false-negative errors have verified our algorithm's efficiency in extracting heart sounds from abnormal breathing sounds. On the contrary, the SSA method couldn't identify heart sound components correctly because in some abnormal breathing sounds, such as crackles, the highest eigenvalues are related to the breathing sound components.

Using the proposed algorithm for the recorded breathing sounds from the chest wall illustrates that the algorithm can extract lung and heart sounds as well. Results were confirmed by listening, and no audible heart sounds were heard in extracted lung sounds in medium flow rates. The intensity of heart sounds significantly decreases in low flow rates. Furthermore, the power spectrum of the extracted lung sounds verified that the heart sound components, which have lower frequency, were extracted from the recorded lung sounds.

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