Separation of Heart Sound Artifact from Respiratory Signals Using
Singular Spectrum based Advanced Line Enhancer

Shinto Sebastian & Rathnakara S
Department of Instrumentation Technology, SJCE, Mysore
E-mail : shinseb@gmail.com, ratnakara_s@yahoo.com

Abstract – Both the heart sound and lung sound are produced within the almost same region of the human body. Heart sound makes severe interference while hearing the lung sound for the diagnosis purpose. So the separation of these sounds is very important for an accurate diagnosis. A special Advanced Line Enhancer (ALE), employing the strength of Singular Spectrum Analysis (SSA) is used in this paper. The SSA based ALE is comparatively a new filtering technique which have the advantage of adaptive selection of useful Eigen triples in the reconstruction stage of the normal SSA. Synthetically mixed and real respiratory signals are used to evaluate this method. The result of the proposed method is compared with the conventional ALE method. The performance of the proposed method is better than the conventional ALE in terms of output signal to noise ratio and correlation coefficient.

Keywords – Singular Spectrum Analysis (SSA), Advanced Line Enhancer (ALE).

I. INTRODUCTION

Auscultation is the process of listening to sounds that are produced in the body. Pulmonary auscultation is the auscultation of both sides of the chest with the objective of ascertaining the state of the lungs and air passages. Points observed are the rhythm and depth of breathing, quality of the breath sounds and the size and disposition of the area over which they can be heard. Auscultation is the most important and effective clinical technique for evaluating a patient’s respiratory function.

The sources of biomedical signals are always intractable among one another. To separate unwanted signal from the required one is a challenging task in the pre-processing step.

Auscultation is the most common way of physical examination of a patient by a physician. Recently, in order to develop automated home care system [1] and to assist physician getting better auscultation results; electronic stethoscope and computer analysis have become an inevitable trend. Lung sounds are always contaminated by heart sound interference [2]. HS are unavoidable and sometimes represent severe disturbing interference. Therefore, for better lung sound analysis we need a pre-processing step, which can separate lung sound from heart sound.

LSs are produced either by rapid fluctuations of gas pressure or by the oscillations of solid tissues. These signals exhibit wideband power spectrum; however, most of the energy is concentrated in frequencies below 200 Hz. On the other hand HS has four basic time components. The first two components (called S1 and S2) are the most fundamental ones. The other two components (called S3 and S4) do not have significant amplitudes and are mostly inaudible in healthy subjects. The main frequency components of the HS are found in the range of 20–150 Hz. Peak frequencies of HSs are shown to be lower than those of LSs.

Separating HS signals from respiratory signals have been studied in many research works so far. Methods such as high pass filtering, adaptive filtering [3],[4], wavelet denoising [5],[6], time frequency filtering [7], modulation filtering, blind noise filtering and singular spectrum analysis have been proposed to solve this problem. The SSA method is the latest method and has the advantages such as less false positives, better correlation with underlying HS and lower execution time compared to the classical methods. The main disadvantage is computational complexity and need of accurate setting of SSA parameters [2].

An adaptive line enhancer (ALE) based on singular spectrum analysis (SSA) is proposed here to solve the
problem[8]. By assuming the noise signal is uncorrelated and narrow band, the adaptive line enhancer (ALE) is used widely for the enhancement of signal. However, the auscultation signals are not additive i.e. correlated and wide band in nature so normal ALE fails to remove the unwanted HS signals.

Although the ALE is an effective tool for single channel signal denoising, it uses (second) order statistics of the data within its minimization criterion. On the other hand, its application is limited to narrowband signals and Gaussian noise. Therefore, it is not applicable in important situations where the noise is not white Gaussian or the artifact signals are other temporally correlated components.

On the other hand, SSA [9] is becoming an effective and powerful tool for time series analysis where short and long, 1-D and multidimensional, stationary and no stationary, almost deterministic and noisy time series are to be analyzed. This concept is exploited in designing a new high performance SSA based ALE.

In SSA based ALE method, in the reconstruction stage of SSA, the Eigen triples are adaptively selected (filtered) using the delayed version of the data. Unlike the conventional ALE where (second) order statistics are taken into account, here the full eigen-spectrum of the embedding matrix is exploited. Consequently, the system works for non-Gaussian noise and wideband periodic signals [2]. Hence, this method can be useful for separating LS from HS since it contains wideband spectrum.

II. METHODOLOGY

The basic SSA method consists of two complementary stages: decomposition and reconstruction; each stage comprises of two separate sub stages. In the first stage the series is decomposed and in the second stage the original series is reconstructed and used for further analysis. The main concept in studying the properties of SSA is separability, which characterizes how well different source signals can be separated from their single channel mixtures.

A brief description of the two SSA stages together with the corresponding mathematics is given in the following sections.

A. Decomposition

This stage includes an embedding operation followed by singular value decomposition (SVD). The embedding operation maps a 1-D time series f of length r into an l x k matrix (Trajectory matrix) with rows of length k and columns of length l, where k = r − 1 + 1, l is the window length (1 ≤ l ≤ r), which is a Hankel matrix X.

Let \( M=X^T \), and the Eigen values of \( M \) are denoted as \( \lambda_1, \ldots, \lambda_l \), in the descending order and \( u_1, u_2, \ldots, u_l \) are the corresponding Eigenvectors.

Set \( d=\max(i | \lambda_i > 0) = \text{rank}(X) \); if we denote \( v_i = X^T u_i / \sqrt{\lambda_i} \), where \( v_i \) is \( 1 \times l \). Then, the SVD of the trajectory matrix can be written as, \( X = X_1 + X_2 + \ldots + X_d \), where \( X_i = v_i, u_i, v_i \) are 3 values \( (\sqrt{\lambda_i}, u_i, v_i) \) is called as the \( i^{th} \) Eigen triple of the singular value decomposition.

B. Reconstruction

This stage also consist 2 steps: grouping and diagonal averaging. During grouping, the set of indices \((1,2,\ldots,d)\) divided into \( m \) disjoint subsets \( I_1, I_2, \ldots, I_m \). For every group \( I_j=\{i_{j1}, \ldots, i_{jd}\} \), then \( X_{ij}=X_{i1}+\ldots+X_{id} \).
Grouping the Eigen triples and expanding all matrices $X_i$, $X$ can be written as, $X = X_1 + \ldots + X_m$.

Grouping is an important stage. By a properly selected group, it can separate a signal from noise, in a mixed signal.

Then each group is transformed into a series of length $r$. The next step is diagonal averaging which is used to convert the reconstructed Hankel matrix into a time series. For a typical $l \times k$ matrix $Y$, the $q$th element of the resulted time series is calculated by averaging the matrix elements over the diagonals $i + j = q + 2$, where $i$ and $j$ are the row and column indices of $Y$, respectively.

C. SSA Based ALE

For the application of SSA for separation or denoising the signals, the corresponding subspace of the desired signal should be identified. This is the main disadvantage of basic SSA for single channel signal separation or denoising.

In case of periodic signals, given the signal period, the information can be used in a way similar to that used in ALE. A delayed (by one period) version of the signal is then used as a reference for adaptive reconstruction of the signal. Unlike for basic SSA, where the Eigen values of the desired signals have to be selected manually, here, the algorithm is adaptive and the signal periodicity is fully exploited (as for the ALE). A block diagram of the overall SSA-based ALE is depicted in Fig. 1.

Consider the Hankel matrix for the delayed signal $r(t) = s(t - \Delta)$ is $R$. At the reconstruction stage, the following function can be minimized in order to make sure the correct subgroup of Eigen triples is selected for reconstruction of the periodic signal

$$J(W) = \| R - U\Lambda^{1/2}V^T \|_F^2$$

where $\| \cdot \|_F$ denotes the Frobenius norm. $U$, $\Lambda$ (diagonal matrix of Eigen values), and $V$ are the SVD factors and $W$ is a $1 \times 1$ diagonal matrix of adaptive weights $w_{ij}$ . Its size is the same as $\Lambda$’s. By using a gradient approach for minimize the above function which leads to the following update equation:

$$W_{k+1} = W_k - \mu (U\Lambda^{1/2}V^T(R - U\Lambda^{1/2}V^T)$$

where $\mu$ is the iteration step size (which is often set manually but can be adapted to the convergence rate). The weights of the filter, $W$, are estimated using above equation. In the reconstruction process, $W$ is multiplied by $\Lambda^{1/2}$ and the desired signal is recovered during the SSA reconstruction process.

III. EXPERIMENTS

Different experiments were carried out using synthetic data, synthetically mixed real data and real respiratory sound signals. All the experiments were conducted using MATLAB on a PC with 3.2 GHz Core i3 Intel CPU and 4 GB of internal memory. MATLAB codes were written for the classic ALE separation and for the proposed SSA based ALE method.

A. Synthetic Data

To compare the new ALE with the original ALE, a number of experiments were carried out using mixtures of synthetic signals. For the synthetic data, a sinusoid i.e. a 1s, $N = 44100$ sample sinusoid of 1KHz and 1 volt amplitude were generated. Then the Gaussian noise were added to this sinusoid at different SNR’s. The input amplitude is kept constant and five different input noise levels were selected in order to examine the performance of the algorithm for input SNRs of $-10, -5, 0, 5,$ and $10$ dBs and both the original ALE and the new proposed SSA based ALE have been applied to the signals.

Fig. 2 presents the performance[10] of the two ALEs in terms of output SNR with respect to input SNR for noise. Table 1 shows the experimental results obtained when calculating the SNR. The output SNR is defined as

$$SNR_{out} = \frac{\sum_{t=1}^{N} \hat{x}^2(t)}{\sum_{t=1}^{N} (x(t) - \hat{x}(t))^2}$$

where $x(t)$ is the estimated desired signal. The output SNRs are 5 ~ 12 dB higher in SSA-ALE method than in ALE method for Gaussian noise. Fig. 3 shows the output waveforms for different input SNR signals.
Fig. 2: Output SNRs for different input SNRs for synthetic data for both original ALE and SSA-based ALE

Fig. 3: Comparison of SSA based ALE and normal ALE for the synthetic data

B. Synthetically Mixed Real Data

Segments of Heart sounds and Lung sounds can be downloaded from http://www.littmann.com. For the experimental purpose, 11 different pairs of 3 second data of heart sound and lung sound respectively were selected.

Then each pair of data were mixed at input SNRs of 0 ~ 3 dB and sampled at 44100 Hz. Thus obtained 11 synthetically mixed real data were applied to the proposed algorithm as well as the original ALE algorithm. The comparison of SNRs from results of separation using both original ALE and SSA-based ALE are illustrated in Fig. 4.

In addition, the output SNRs have been calculated for each case and depicted in Table II. Although the distribution of the lung sound can change and the lung sound signal is generally nonstationary, the performance of the SSA-based ALE is significantly better than that of the traditional ALE. The output SNRs are 5 ~ 7 dB higher in SSA-ALE method than in ALE method.

Table II: Output SNRs for different input SNRs of synthetically mixed real data

<table>
<thead>
<tr>
<th>Samples</th>
<th>Input SNR</th>
<th>Output SNR</th>
<th>Proposed Method</th>
<th>Original ALE</th>
</tr>
</thead>
<tbody>
<tr>
<td>0 ~ 3 dB</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>10.6928</td>
<td>5.7385</td>
<td></td>
<td></td>
</tr>
<tr>
<td>2</td>
<td>11.0740</td>
<td>5.3025</td>
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<td></td>
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<tr>
<td>3</td>
<td>10.9867</td>
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</tr>
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<td>4</td>
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<td>5</td>
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<td>11</td>
<td>11.6708</td>
<td>4.3695</td>
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</table>

Fig. 4: SNR Comparison between proposed method and original ALE method with synthetically mixed real data

C. Real Data

For acquiring real data, a Welch Allyn Tycos Digiscope® stethoscope was used. The respiratory signals recorded from eight healthy subjects (male, aged 28~36 years) with no known health problem. The subjects were reposed in a comfortable position and the stethoscope was fixed over the chest in the left midclavicular area, second intercostal space. The subjects were trained and asked to breath at a medium flow rate during each experiment. For each subject, the respiratory data were recorded for 1 minute, amplified, and digitized at 44100 Hz.

The proposed algorithm and original ALE algorithm were applied to each of the above signals. As per these algorithms, the nearly periodic signal (Heart Sound) is first extracted. Then, the Respiratory component is easily obtained by subtracting the estimated HS from the original recording. The results of separation using both original ALE and SSA-based ALE are illustrated in Fig. 5. While observing the output
waveforms, one can easily come to an assumption that the performance of the SSA-based ALE is significantly better than that of the traditional ALE.

Since the primary objective in separation is to have independency or non correlation between the output components, a quantitative or objective assessment for comparing these two methods has to be achieved. Here, the correlation coefficients of both normalized separated signals are calculated using the equation given below.

$$\xi = \frac{1}{N} \sum_{n=1}^{N} HS(f_i)LS(f_i) \quad (4)$$

The correlation coefficient is merely a digit in between 0 and 1. If the correlation coefficient is 1, the meaning is separation quality is very poor. If it is zero, the separation is perfect. The average values of correlation coefficient of 8 samples obtained after calculation using (4) is given in table 3. The values of this coefficient for the original ALE output is $\xi_{ALE} = 0.098$, whereas for the output of the SSA-based ALE this coefficient is negligible ($\xi_{SSA-ALE} = 0.0026$).

<table>
<thead>
<tr>
<th>Table 3</th>
<th>Correlation Coefficient (= MAX. VARIATION) BETWEEN THE ESTIMATED HS AND LS FOR 8 DATA SEGMENTS FROM 8 SUBJECTS USING BOTH ORIGINAL ALE AND THE SSA-BASED ALE</th>
</tr>
</thead>
<tbody>
<tr>
<td>SSA BASED ALE</td>
<td>ORIGINAL ALE</td>
</tr>
<tr>
<td>0.0026 ± 0.004</td>
<td>0.098 ± 0.032</td>
</tr>
</tbody>
</table>

The lower value of correlation coefficient indicates the objective of separation is more perfect in SSA based ALE. It means that the heart sounds are better separated out in the SSA based ALE method than the conventional ALE method.

IV. SUMMARY AND CONCLUSION

ALE based on SSA has been designed for the separation of the lung sound from heart sound. It outperforms original ALE as well as traditional SSA due to three major reasons: 1) Unlike in original SSA, the estimation of the filter coefficients is based on the full spectrum of SSA eigenvalues; 2) the noise doesn’t need to be stationary or Gaussian; and 3) the periodic signal can be wideband. Moreover, there is no need for accurate setting of the SSA parameters.

Both ALEs have been assessed against different noise levels. The proposed system is more robust than the original ALE. Real-world respiratory signals from eight different subjects recorded were also used to evaluate the methods. The results were almost similar to the results of synthetic signals.

V. REFERENCES


