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Blind source extraction of heart sound signals from lung sound recordings exploiting periodicity of the heart sound

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BLIND SOURCE EXTRACTION OF HEART SOUND SIGNALS FROM LUNG SOUND RECORDINGS EXPLOITING PERIODICITY OF THE HEART SOUND

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ABSTRACT

A novel approach for separating heart sound signals (HSSs) from lung sound recordings is presented. The approach is based on blind source extraction (BSE) with second-order statistics (SOS), which exploits the quasi-periodicity of the HSSs. The method is evaluated on both synthetic periodic signals of known period mixed with temporally white Gaussian noise (WGN) as well as on real quasi periodic HSSs mixed with lung sound signals (LSSs). Qualitative evaluation involving comparison of the power spectral densities (PSDs) of the extracted signals, by the proposed method and by the *JADE* algorithm, and that of the original signal is performed for the case of real data. Separation results confirm the utility of the proposed approach, although departure from strict periodicity may impact performance.

Index Terms— Blind source extraction, second order statistics, periodicity, nonstationarity, heart sound signal and lung sound recordings.

1. INTRODUCTION

LSSs are produced in the airways of a human being during inhilation and expiration cycles [1]. The LSSs propagate through lung tissues in the parenchyma and can be recorded over the chest wall using a digital stethoscope. The tissue acts as a spatial frequency filter-like structure whose characteristics can vary according to pathological and indeed physiological changes [1]. Besides the fact that normal and abnormal lung sounds are mixed in the airways, which poses a problem in terms of their potential use for classification of respiratory diseases; quasi-periodic HSS, from heart beat activity, invariably interferes with the LSS and therefore masks or inhibits clinical interpretation of LSS particularly over low frequency ranges. The main frequency components of HSS are in the range $20-100$ Hz and this is the range in which LSS has major components [2]. Therefore, since HSS and LSS overlap in frequency and, they are somewhat statistically non-stationary, the major problem being faced in separating HSS from LSS is, doing so, without degrading the main characteristic features of the LSS. Traditional band-pass filtering with cut off frequencies of 70 and 100 Hz [3], results in an inefficient performance since LSS has major components in this region especially at low flow rates and there is still spectral overlap with HSS components. In [2], researchers have therefore used adaptive filtering with a pre-processing stage comprising a variable amplifier gain. Other groups used an adaptive filter based on the least mean square (LMS) algorithm to remove HS interferences [4]. In both of these cases, researchers used HSS recorded from close to the patient's heart location as the reference signal for the adaptive system, which of course are not completely free of LSS. Along the same lines, researchers in [5] have used an adaptive system with the ECG signal information as the reference signal. The discrepancy with this approach is the considerably high number of filter coefficients required which results in slow convergence. Efforts have been made to eliminate the use of a reference signal when performing adaptive filtering. In [6], a single recording technique based on a modified version of the adaptive LMS algorithm was proposed, wherein, a lowpass filter with a cut off frequency of 250Hz was added in the error signal path. More recently, in [7], a recursive least squares (RLS)-based adaptive noise cancellation (ANC) filtering technique was proposed to separate or reduce the HSS within the LSS. In their approach a bandpass filtered version of the recorded LSS was used as the reference signal. Although experimental results were promising, the method suffers from high computational load. Time-frequency (TF) filtering techniques have also been proposed for HSS reduction in LSS [8] and [9], of which the technique employed in [9] is computationally efficient [9] but the results are unconvincing. Recently, for the case of only a single measurement sensor, an adaptive line enhancer was employed to mitigate the HSS in LSS, which yielded promising results [10].

In this paper, blind source extraction (BSE) by second order statistics (SOS) based on the approximate joint diagonalization (AJD) algorithm [11], is used for the first time to mitigate HSS in LSS recordings with the assumption that multi sensor recordings are available. The motivation is to exploit the temporal correlation structure with the LSS and HSS signals together with the quasi-stationarity within the HSS signals.

This paper is organized as follows; an overview of BSE by SOS including the extraction algorithm used is presented in Section 2. We consider the extraction of HSS from LSS exploiting periodicity in Section 3 and present experimental results; a summary and concluding remarks are given in Section 4

2. OVERVIEW OF BSE BASED ON SECOND ORDER STATISTICS

Consider the real valued signal generating model:

$$\mathbf{x}(t) = \mathbf{A}\mathbf{s}(t) + \mathbf{n}(t) \tag{1}$$

where $\mathbf{s}(t) = [s_1(t), s_2(t), ..., s_N(t)]^T$ is a column vector of N mutually uncorrelated zero-mean unknown source signals,
$\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, ..., \mathbf{a}_N]$ is an N x N invertible unknown mixing matrix,

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$\mathbf{x}(t) = [x_1(t), x_2(t), ..., x_N(t)]^T$ is column vector of N observed sensor signals, $\mathbf{n}(t) = [n_1(t), n_2(t), ..., n_N(t)]^T$ denotes a column vector of additive white Gaussian zero-mean interfering noise, $\mathbf{a}_i$ is the ith column of $\mathbf{A}$, $[.]^T$ and t denote respectively the vector transpose and the discrete time index. In the discussion that follows, the effect of noise is neglected as it can be easily assumed to be another source.
Based on the assumption that the sources are spatially uncorrelated, the time lagged autocorrelation matrix $\mathbf{R}_\tau$, is defined as

$$\mathbf{R}_\tau = E[\mathbf{x}(t)\mathbf{x}^T(t-\tau)] = \sum_{i=1}^{N} r_i(\tau)\mathbf{a}_i\mathbf{a}_i^T \tag{2}$$

for $\tau = 0, 1, ..., K$ where $r_i(\tau) = E[s_i(t)s_i(t-\tau)]$ is the temporal autocorrelation value of $s_i(t)$ at time lag τ, and $E[.]$ denotes the statistical expectation operator.
The goal of BSE is to find a vector $\mathbf{w}$ such that $y(t) = \mathbf{w}^T\mathbf{x}(t)$ and $y(t)$ is a non-zero scaled estimate of one of the source signals.
Observing that $\mathbf{x}(t)$ in equation (1) is a linear combination of the columns of matrix $\mathbf{A}$, the ith source can intuitively be extracted by projecting $\mathbf{x}(t)$ onto direction $\mathbf{a}_i$ which is a space, orthogonal to, denoted by $\perp$, $\{\mathbf{a}_1, ..., \mathbf{a}_{i-1}, \mathbf{a}_{i+1}, ..., \mathbf{a}_N\}$, all the columns of $\mathbf{A}$ except $\mathbf{a}_i$. Henceforth, by defining a vector $\mathbf{q} \perp \{\mathbf{a}_1, ..., \mathbf{a}_{i-1}, \mathbf{a}_{i+1}, ..., \mathbf{a}_N\}$ and setting $\mathbf{t} \equiv \mathbf{a}_i$ together with adopting oblique projector notation [12] gives

$$y(t)\mathbf{t} = E_{\mathbf{t}|\mathbf{q}^\perp}\mathbf{x}(t) \tag{3}$$

where $y(t)$ is an estimate of one source, $\mathbf{q}^\perp$ is the space spanned by $\{\mathbf{a}_1, ..., \mathbf{a}_{i-1}, \mathbf{a}_{i+1}, ..., \mathbf{a}_N\}$ orthogonal to $\mathbf{q}$, and $\mathbf{E}_{\mathbf{t}|\mathbf{q}^\perp} = (\mathbf{t}\mathbf{q}^T/\mathbf{q}^T\mathbf{t})$ is the oblique projection of $\mathbf{t}$ onto the space $\mathbf{q} \perp$.
By omitting the scalar $(1/\mathbf{q}^T\mathbf{t})$ and dropping $\mathbf{t}$ from both sides of equation (3) results in

$$y(t) = \mathbf{q}^T\mathbf{x}(t) \tag{4}$$

In BSE based on second-order statistics, both vectors $\mathbf{t}$ and $\mathbf{q}$ are not known. In order to extract one source, the following cost function has been proposed

$$[\hat{\mathbf{t}}, \hat{\mathbf{q}}, \hat{\mathbf{d}}] = \arg\min_{\mathbf{t},\mathbf{q},\mathbf{d}} J(\mathbf{t}, \mathbf{q}, \mathbf{d}) \tag{5}$$

where $J(\mathbf{t}, \mathbf{q}, \mathbf{d}) = \sum_{\tau=0}^{K} \|\mathbf{R}_\tau\mathbf{q} - d_\tau\mathbf{t}\|^2$, $\mathbf{d} = [d_0, d_1, ...d_K]^T$ is the column vector of unknown scalars, and $\|.\|$ denotes the Euclidean norm.
Minimization of the cost function (5) with respect to $\hat{\mathbf{q}}$ leads to the identification of vector $\mathbf{q}$ in equation (4) which can thereby be used to extract the estimate one of the sources.

2.1. Signal Extraction Algorithm

By employing the sequential approximate diagonalisation algorithm (SDA) proposed in [11], the cost function (5) is minimized by adjusting its parameters alternatively as follows:

- Stage 1 : Freeze both $\mathbf{t}$ and $\mathbf{d}$ and adjust $\mathbf{q}$ to yield the optimal $\mathbf{q}$:

$$\mathbf{q} \leftarrow \mathbf{H}\Big(\sum_{\tau=0}^{K} \mathbf{d}_\tau\mathbf{R}_\tau\Big)\mathbf{t} \tag{6}$$

  where $\mathbf{H} = [\sum_{\tau=0}^{K} \mathbf{R}_\tau^2]^{-1}$, and $e \leftarrow f$ denotes replacing e by f.

- Stage 2: Freeze both $\mathbf{t}$ and $\mathbf{q}$ and consider the Lagrange function

$$J_{\lambda_d} = J + \lambda_d\Big(\sum_{\tau=0}^{K} d_\tau^2 - 1\Big) \tag{7}$$

  where λ_d is the Lagrange multiplier, to obtain the optimal $\mathbf{d}$

$$\mathbf{d} \leftarrow \frac{\mathbf{d}}{\|\mathbf{d}\|} \tag{8}$$

  where $\mathbf{d} = [\mathbf{r}_0^T\mathbf{t}, \mathbf{r}_1^T\mathbf{t}, ..., \mathbf{r}_K^T\mathbf{t}]^T$.

- Stage 3: Freeze both $\mathbf{q}$ and $\mathbf{d}$ and adjust $\mathbf{t}$ and consider the Lagrange function

$$J_{\lambda_t} = J + \lambda_t(\mathbf{t}^T\mathbf{t} - 1) \tag{9}$$

  to obtain the optimal adjustment for $\mathbf{t}$

$$\mathbf{t} \leftarrow \frac{\mathbf{v}}{\|\mathbf{v}\|} \tag{10}$$

  where $\mathbf{v} = \sum_{\tau=0}^{K} d_\tau\mathbf{r}_\tau$.

These three stages are repeated until the cost function (5) converges, and one source can be extracted according to equation (4). Typically, five iterations are sufficient and no problem with ill-convergence has been experienced.
After extracting one source a deflation procedure is employed to remove it from the mixture as follows [13]

$$\mathbf{x}_{i+1}(t) = \mathbf{Z}^T\mathbf{x}_i(t) \tag{11}$$

where $\mathbf{x}_i(t) = \mathbf{x}(t)$ in equation (1) and

$$\mathbf{Z} = \mathbf{I} - \frac{\mathbf{R}_{\tau(i)}\mathbf{w}\mathbf{w}^T}{\sigma_y^2} \tag{12}$$

$\mathbf{R}_{\tau(i)} = E[\mathbf{x}_i(t)\mathbf{x}_i^T(t-\tau)]$ and $\mathbf{I}$ is the identity matrix.
The autocorrelation matrix is then updated as

$$\mathbf{R}_{\tau(i+1)} = \mathbf{Z}^T\mathbf{R}_{\tau(i)}\mathbf{Z} \tag{13}$$

before another source can be extracted following the same procedure, equations (6-13).
This extraction is computationally simple when compared with other AJD algorithms [14].

3. EXTRACTION OF HSS FROM LSS EXPLOITING PERIODICITY

Successful minimization of the cost function (5) in concert with equation (4) leads to the extraction of any one source. It is not possible to extract the source of interest (SoI) unless some additional information about this is known *a priori*. The source of interest in our case is the HSS. If the fundamental period, or its approximation, of the SoI is known, then the algorithm can be made to focus only on this specific source. This is based on the fact that if the fundamental period is, say, M samples, then its autocorrelation matrix will have the same value at time lag cM, where c is any integer. Hence, the autocorrelation matrices $\mathbf{R}_\tau s$ can jointly be diagonalized at time lags $\tau = 0, M, ..., KM$ along with constraint $d_0 = d_1 = ... = d_K$.
To this end, we exploit knowledge of the HSS periodicity in order to extract it from the LSS. By using techniques such as the one

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introduced in [15], the cycle frequency of HSS may be estimated and hence its period. The method called heart instataneous frequency (HIF) was developed for the extraction of the instantaneous heart rate from non-stationary electrocardiagram (ECG) signals, the value of which varies over time due to pathological and physiological changes. The steps to extract HIF or cyclic frequency are summarized below:

- Obtain the signal to be analysed $s(t)$.
- Calculate the spectrogam $S(t,f)$ of $s(t)$.
- Find the frequency value at which $S(t,f)$ attains its maximum value in a given frequency interval $[\delta(t^-) - \gamma, \delta(t^-) + \gamma]$, where $\delta(t^-)$ is the value of the driver at the previous time, and the frequency range scanned is limited by γ.
- Divide the original signal $s(t)$ into signals $s_\Omega(t)$ with short time intervals Ω.
- Obtain signal $z_\Omega(t)$ by passing $s_\Omega(t)$ through a band-pass filter with center frequency $\delta\hat{(}t)$, which is the mean of $\delta(t)$.
- For each $z_\Omega(t)$, find the instantaneous frequency from $\omega(t) = \phi(t+1) - \phi(t)$, $\phi(t) = \tan^{-1}(-H[z_\Omega(t)]/z_\Omega(t))$, where $H[z_\Omega(t)]$ is the Hilbert transform of the signal $z_\Omega(t)$.
- From $f = 1/T$, compute T, where T is the signal period, this is rounded if necessary.

In practice, any lung sound recording performed invariably contains both HSS and LSS. However, if the recording transducer is placed closer to the person's heart location, then HSS spectral components would be more dominant in the recorded signal than LSS. The method outlined above can then be used to estimate the period of the HSS dominant signal.

3.1. Simulation Results

In this section, we demonstrate the ability of the BSE algorithm to mitigate HSS in the LSS recordings. Two examples are considered. In the first example we consider a deterministic periodic signal and the WGN that have been mixed by a mixing matrix **A** with elements drawn from a standardized Gaussian distribution, and the second example considers two real HSS and LSS measurement signals that have been mixed in the same manner. The HSS and LSS signals are obtained from R.A.L.E. data sets available at: *www.rale.ca/*. Qualitative evaluation is performed in the second example by comparing power spectral densities (PSDs) of the signals before and after mixing for our method and for the *JADE* algorithm, a benchmark BSS algorithm [16].

3.1.1. Blind source extraction of a periodic signal of known period

In this simulation we consider two source signals. One is the periodic pulsetrain signal and the other is the white Gaussian noise (WGN) signal, a portion of which is shown in Figure 1 (top subplot). The SoI is the periodic signal whose period is 50 samples. The two signals are mixed as shown in the same Figure (bottom subplot). By setting the period to 50 samples, and K, the number of autocorrelation matrices, to 30, the algorithm is run and the SoI is obtained as in Figure 2 (top subplot), confirming an accurate reconstruction. As seen from the same Figure (bottom subplot), when no information about the periodicity is incorporated in the algorithm, the algorithm locks onto the noise component.

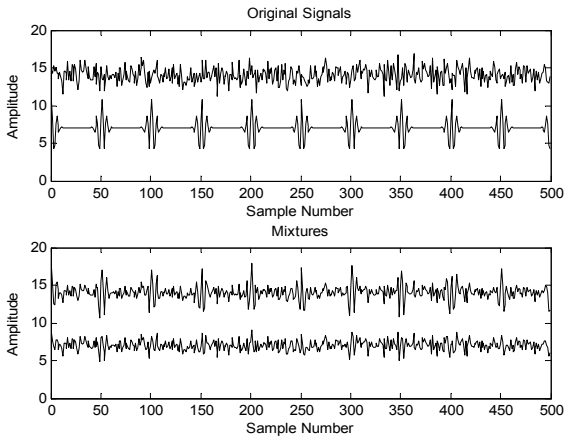


Fig. 1. Pulsetrain and noise before mixing (top), and the linera mixtures (bottom)

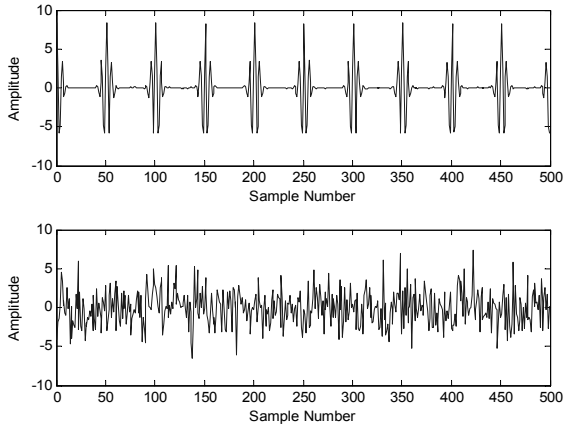


Fig. 2. Extracted signals: pulsetrain (top), and the noise (bottom)

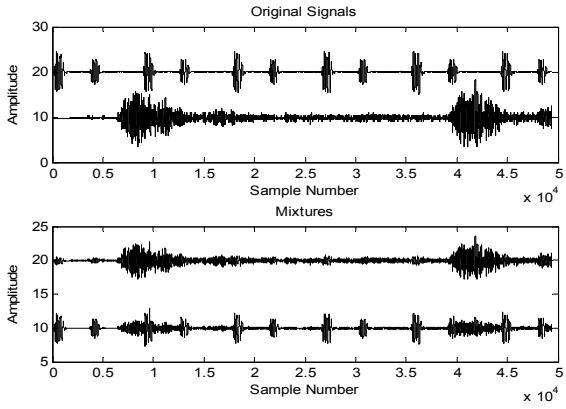


Fig. 3. HSS and LSS before mixing (top), and the linear mixtures (bottom)

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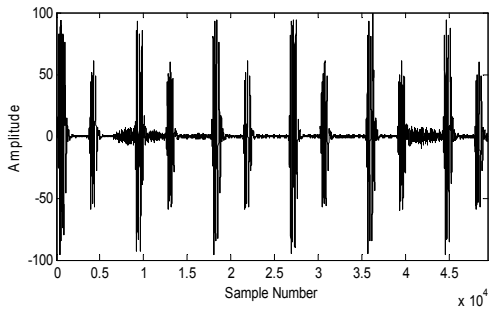


Fig. 4. Extracted HSS

3.1.2. Blind source extraction of the HSS

In this simulation, the two source signals are the HSS and the LSS signals, shown in Figure 3 (top subplot). The SoI in this case, is the HSS signal whose period can be estimated by the method outlined in Section 3. The two signals are mixed by a matrix **A** with random elements drawn from a standardized Gaussian distribution to yield the mixtures in Figure 3 (bottom subplot). Figure 4 shows the recovered HSS signal obtained after running the algorithm. As seen from Figure 4, the HSS has also been recovered from the mixture though it is slightly corrupted in the regions of low signal (HSS)-to-noise (LSS) ratio. The PSDs in Figure 5 show that the frequencies of the original HSS signal have been preserved in the recovered signal for both cases, although there is a change in magnitude of the extracted signal, but this is a result of scale ambiguity and can easily be mitigated. Moreover, the performance is as good as the full *JADE* blind source separation algorithm which extracts all the sources, but suffers from the problem of reliably estimating fourth order statistics.

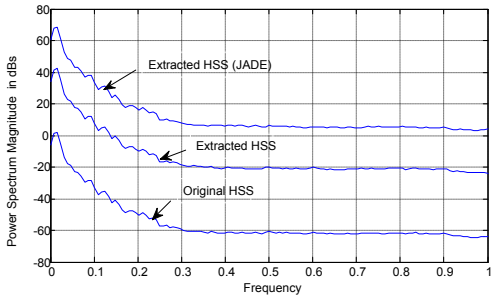


Fig. 5. Comparison of PSDs for: original HSS , extracted HSS by our method, and extracted HSS using the JADE algorithm

4. SUMMARY AND CONCLUSIONS

The performance of the BSE algorithm depends on *a prior* knowledge of the source signal. Knowledge of the period of the SoI helps to extract the source signal of interest from the mixture. From other investigations of the convergence of the algorithm, it appears that there is an optimum number of the autocorrelation matrices that have to be used such that the algorithm converges well. This subject and considering the effect of error in the period estimation given nonstationary HSS are the focus of on going research.

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