A NEW TIME DOMAIN CONVOLUTIVE BSS OF HEART AND LUNG SOUNDS

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***Abstract*—In this paper the objective is to separate nonstationary heart and lung sounds from their convolutive mixtures in time domain. In order to separate the sources an orthogonal source model and a gradient based optimization have been used to best model the mixing system and best estimate the parameters respectively. Having diagonal or quasi diagonal covariance matrices for different source segments and also having independent profiles/envelops for different sources (which implies nonstationarity of the sources) are the requirements for our convolutive method. We applied the method to synthetically mixed real heart and lung sound signals. Compared to the other methods, the results show the high capability of the method for separating nonstationary heart and lung sound signals.**

***Index Terms*—Blind Source Separation, Heart-Lung Sounds, Convolutive Mixture, Orthogonal Model.**

I. Introduction

In many of the conventional statistical signal processing methods the signals are treated as they are statistically stationary. That means it is assumed that the parameters of the underlying physical mechanisms which generate the signals do not vary with time. But for most of the signals from man-made systems such as those encountered in physical and physiological systems, mechanical systems and communication, radar and sonar systems, some parameters and statistical properties vary with time. This imposes nonstationarity (or in some cases cyclostationarity) of the data. Among them auscultation of heart and lung sounds involves complicated variation of mixing medium with time which makes a nonlinear or nonstationary convolutive mixing of the two sounds recorded by each stethoscope. Cardiac pulsation and blood flow in the body are the major sources of a class of physiological artifacts in most of biomedical recordings. These artifacts are directly related to the heart activity and depending on the acquisition technology interfere with the underlying signals in different forms. Heart sounds are caused by flow of blood into and out of heart through valves and also heart tissue movements [1]. By placing a stethoscope over the chest, close to heart location, four basic heart sounds can be identified which are referred to as S1, S2, S3, and S4. The first and second heart sounds (S1 and S2) are the most fundamental heart sounds. S1 is caused by closure of the mitral and tricuspid valves at the beginning of ventricular contraction. During this contraction cycle the blood is pumped from heart to body. S2 is caused by closure of the aortic and pulmonic valves at the beginning of ventricular relaxation. The third heart sound (S3), when audible, occurs early in ventricular filling and the fourth heart sound (S4), when audible, is caused by vibration of the ventricular wall during atrial contraction. Both S3 and S4 do not have significant amplitude and mostly are not audible in healthy subjects. These components of heart sound are ignored in most of heart sound processing applications. Main frequency components of the heart sound are concentrated in the range of 20-150Hz. Removing heart sound signals from respiratory signals has been studied in many research works so far. The easiest way to cancel heart sound is to highpass filter the respiratory signals. However, due to temporal, spatial, and spectral overlaps of the heart and lung sounds, part of the useful signal information may be lost. Different methods based on adaptive filtering [2][3], Wavelet denoising [4][5], time-frequency filtering [6][7], and modulation filtering [6] have been proposed to overcome this problem. In [8] and [7] blind source separation methods have been used to separate heart and lung sounds from multichannel recordings. Due to the complex nature of the mixing system common blind source separation (BSS) methods, however, do not result in accurate separation in this problem. Therefore, the proposed approach here is meant for separation of convolutive nonstationary mixtures of heart and lung sounds blindly.

BSS is a technique to estimate unknown source signals from their mixtures without any prior knowledge about the sources or the medium. In some applications, signals are mixed through a convolutive model and this makes the BSS a difficult problem. A number of convolutive BSS (CBSS) methods as addressed in [9], have been published recently. There are three major approaches for solving the convolutive BSS problem; (i) time domain BSS, (ii) frequency domain BSS, where the convolutive problem is transferred to frequency domain whereby, the convolution operation changes to multiplication, and (iii) the approach which uses time-frequency domain in the sense of doing adaptation in both time and frequency domains which because of switching between the two domains is computationally expensive [10]. Some time-domain CBSS methods assume that the source samples are not temporally correlated. These types of methods are called multichannel blind deconvolution (MBD) methods. Consequently, if the original sources are not white, their time structures will be lost and this will cause distortion in the recovered signals. Hence, additional information from temporal structure of the sources is needed to preserve their temporal information. The method proposed in [11], so-called MBD-MFD, after applying MBD in its first stage tries to recover the temporal information of the sources using minimal filter distortion (MFD) concept. This method has shown good results for separation of speech signals. On the other hand, the time frequency methods, such as the method proposed in [12] by Parra as an extension of the second order blind identification (SOBI) algorithm, has been used for joint diagonalization of the spectral covariance matrices for all the time blocks. This method, similar to the other frequency based methods, suffers from permutation ambiguity and mitigating this problem can have strong effect on its results.

In this paper in order to skip the frequncey domain problems, we have developed a time-domain approach. Unlike MBD-MFD method, we do not apply blind deconvolution. Therefore, we do not need any post processing algorithm to recover the sources and similar to all other BSS methods we assume that the sources are independent or more specifically the covariance matrix of the source signals and all their reasonable size segments are diagonal. Let's consider the following instantaneous mixing system:

$$x_i(t) = \sum_{j=1}^{N_s} a_{ij} s_j(t) + v_i(t), \qquad i = 1, \cdots, N_x \tag{1}$$

where N_s and N_x are respectively the number of sources and sensors, a_{ij} are the elements of mixing matrix $\mathbf{A}$, and $x_i(t)$, $s_j(t)$, and $v_i(t)$

are ith sensor, jth source, and ith noise signals at time instant t. Using matrix notations the above formulation can be represented as follows:

$$\mathbf{X} = \mathbf{S}\mathbf{A}^T + \mathbf{V} \tag{2}$$

where $\mathbf{X} \in \mathbb{R}^{N \times N_x}$, $\mathbf{S} \in \mathbb{R}^{N \times N_s}$, and $\mathbf{V} \in \mathbb{R}^{N \times N_x}$ denote respectively the matrices of observed signals, source signals, and noise. $\mathbf{A} \in \mathbb{R}^{N_x \times N_s}$ is the mixing matrix. Recovering the sources from the acquired mixtures has been investigated by incorporating different assumptions about the sources or mixing systems. The approach proposed here relies on orthogonality of the sources in different time segments. A simple temporal segmentation procedure has been developed to divide the signals $\mathbf{X}$ and $\mathbf{S}$ to K segments without overlap and with segment sizes as N_k. So, after temporal segmentation of $\mathbf{X}$ the main model changes to:

$$\begin{aligned} &\mathbf{X}_k = \mathbf{S}_k\mathbf{A}^T + \mathbf{V}_k \\ &subject\ to\ \ \mathbf{S}_k^T\mathbf{S}_k = \mathbf{D}_k^2;\ \ \forall\ k = 1, \ldots, K \end{aligned} \tag{3}$$

where $\mathbf{X}_k \in \mathbb{R}^{N_k \times N_x}$ and $\mathbf{S}_k \in \mathbb{R}^{N_k \times N_s}$ are respectively the mixture and the source signals and $\mathbf{D}_k$ is diagonal/semi-diagonal for each segment k. For simplicity, we ignore the noise term $\mathbf{V}_k$ and, also based on orthogonality of $\mathbf{S}_k$, each orthogonal $\mathbf{S}_k$ can be decomposed into one orthonormal matrix $\mathbf{P}_k$ and one diagonal matrix $\mathbf{D}_k$, which absorbs the norm of different sources at each segment k. In this decomposition, the diagonal elements of $\mathbf{D}_k$s can be either positive or negative and also their sign can be absorbed in their respective column of $\mathbf{P}_k$. When $\mathbf{D}_k$ diagonal elements are nonnegative, the proposed orthogonal decomposition $\mathbf{S}_k = \mathbf{P}_k\mathbf{D}_k$ also can be equal to the polar decomposition of orthogonal $\mathbf{S}_k$ where $\mathbf{P}_k$ is the orthonormal part and the diagonal/semi-diagonal $\mathbf{D}_k$ is the positive-semidefinite (PSD) part of decomposition [13]. So, based on the above decomposition the source model can be rewritten as:

$$\begin{aligned} &\mathbf{S}_k = \mathbf{P}_k\mathbf{D}_k \\ &subject\ to\ \ \mathbf{P}_k^T\mathbf{P}_k = \mathbf{I}_{N_s};\ \ \forall\ k = 1, \ldots, K \end{aligned} \tag{4}$$

where $\mathbf{I}_{N_s} \in \mathbb{R}^{N_s \times N_s}$ is an identity matrix. Actually the above formulation tries to define a structured model for the source signals $\mathbf{S}_k$. Above source model is independent of the mixing system and is valid for convolutive mixing systems as well. In this work this source model has been used to define a structured model for convolutive mixture signals and ultimately separation of the sources and estimation of the mixing channels for different lags. The remainder of the paper is structured as follows. In Section II our model and its problem formulation is described. In Section III estimation of the model parameters is provided. In Section IV the results of applying the method to synthetically mixed real data are provided. Finally Section V concludes the paper.

II. Convolutive mixing model and problem formulation

Consider the convoltive BSS problem based on the orthogonal model (4). In many practical situations the signals and their reflections reach the sensors with different time delays. The corresponding delay between source j and sensor i, in terms of numbers of samples, is directly proportional to the sampling frequency and conversely to the speed of sound in the medium, i.e. $a_{ij} \propto d_{ij} \times f_s/c$, where d_{ij}, f_s, and c are respectively, the distance between source j and sensor i, the sampling frequency, and the speed of sound. A general formulation of the CBSS for each time segment of k (ignoring the noise part) can be written as:

$$x_{ki}(t) = \sum_{j=1}^{N_s}\sum_{\tau=0}^{M-1} s_{kj}(t-\tau)a_{ij}(\tau); \forall\ i = 1, \ldots, N_x \tag{5}$$

where $a_{ij}(\tau)$ are the elements of mixing matrix $\mathbf{A}_\tau$ at different time lags τ and M is the maximum number of lags. Above convolutive mixing model can be formulated using matrix notations as follows:

$$\mathbf{X}_k = \sum_{\tau=0}^{M-1} \mathbf{\Xi}_\tau\mathbf{S}_k A_\tau^T; \forall\ k = 1, \ldots, K \tag{6}$$

where $\mathbf{\Xi}_\tau = [\mathbf{0}_{M-\tau}, \mathbf{I}_{N_k}, \mathbf{0}_\tau]$ denotes a shift matrix which represents a shift operator for $\mathbf{S}_k \in \mathbb{R}^{(N_k+M) \times N_s}$ and $\mathbf{0}_n \in \mathbb{R}^{N_k \times n}$ is a zero matrix [14]. Regarding (4) and after substituting $\mathbf{S}_k$ with its orthogonal model the final convolutive model of the mixture signals $\mathbf{X}_k$ can be shown as:

$$\begin{aligned} &\mathbf{X}_k = \sum_{\tau=0}^{M-1} \mathbf{\Xi}_\tau\mathbf{P}_k\mathbf{D}_k\mathbf{A}_\tau^T \\ &subject\ to\ \ \mathbf{P}_k^T\mathbf{P}_k = \mathbf{I}_{N_s};\ \ \forall\ k = 1, \ldots, K \end{aligned} \tag{7}$$

Define the overall cost function J for our optimization problem as:

$$\begin{aligned} &J(\mathbf{P}_k, \mathbf{D}_k, \mathbf{A}_\tau) = \sum_{k=1}^{K} ||\mathbf{X}_k - \sum_{\tau=0}^{M-1} \mathbf{\Xi}_\tau\mathbf{P}_k\mathbf{D}_k\mathbf{A}_\tau^T||_F^2 \\ &subject\ to\ \ \mathbf{P}_k^T\mathbf{P}_k = I_{N_s};\ \ \forall\ k = 1, \ldots, K \end{aligned} \tag{8}$$

where $||.||_F$ is Frobenius norm. Two sets of parameters $(\mathbf{P}_1, ..., \mathbf{P}_K)$ and $(\mathbf{D}_1, ..., \mathbf{D}_K)$ vary for different ks however, $(\mathbf{A}_0, \mathbf{A}_1, ..., \mathbf{A}_\tau)$ are fixed for all ks. In order to approach an unique solution (subject to estimation of the filtered version of sources and permutation ambiguities) to the above problem one extra constraint is imposed on those parameters which are not fixed for all segments. Orthogonality of source profiles is a constraint that is imposed on $\mathbf{D}_k$s along the segments. This constraint physically means that the activities of the sources are relatively sparse along the segments rather than being sparse for each time sample. In this work no constraint is imposed on the mixing channels $\mathbf{A}_\tau$. However, having fixed $\mathbf{A}_\tau$s for all segments can be considered as a weak constraint on $\mathbf{A}_\tau$s. In order to fit the model of mixtures (7), alternating optimization, are developed for estimation of the three sets of parameters $(\mathbf{A}_0, \mathbf{A}_1, ..., \mathbf{A}_\tau)$ and $(\mathbf{P}_1, ..., \mathbf{P}_K)$, $(\mathbf{D}_1, ..., \mathbf{D}_K)$ separately. The next section introduces the process to estimate all the parameters of the above optimization problem.

III. Estimation of the model parameters

The parameters in (8) can be estimated using three alternating minimizations for estimation of the three sets of existing parameters separately. The following procedures introduce the minimizing processes for estimation of $(\mathbf{A}_0, ..., \mathbf{A}_\tau)$ and each set of $(\mathbf{D}_1, ..., \mathbf{D}_K)$ and $(\mathbf{P}_1, ..., \mathbf{P}_K)$ parameters.

A. Estimation of $\mathbf{A}_\tau$s

Assume $\mathbf{P}_k$ and $\mathbf{D}_k$ for $k = 1, \ldots, K$ are known. Then, to estimate $\mathbf{A}_\tau$ the sum in (7) can be converted to matrix multiplication as follows:

$$\mathbf{X}_k = [\Xi_0\mathbf{P}_k\mathbf{D}_k, \mathbf{\Xi}_1\mathbf{P}_k\mathbf{D}_k, \cdots, \mathbf{\Xi}_{M-1}\mathbf{P}_k\mathbf{D}_k] \begin{bmatrix} \mathbf{A}_0^T \\ \mathbf{A}_1^T \\ \vdots \\ \mathbf{A}_{M-1}^T \end{bmatrix} \tag{9}$$

After defining new variables $\mathbf{Z}_k$ and $\breve{\mathbf{A}}$ as:

$$\begin{aligned} &\mathbf{Z}_k = [\mathbf{\Xi}_0\mathbf{P}_k\mathbf{D}_k, \mathbf{\Xi}_1\mathbf{P}_k\mathbf{D}_k, \cdots, \mathbf{\Xi}_{M-1}\mathbf{P}_k\mathbf{D}_k] \\ &\breve{\mathbf{A}} = \begin{bmatrix} \mathbf{A}_0^T \\ \mathbf{A}_1^T \\ \vdots \\ \mathbf{A}_{M-1}^T \end{bmatrix} \end{aligned} \tag{10}$$

every $\mathbf{X}_k$ can be modelled as $\mathbf{X}_k = \mathbf{Z}_k\breve{\mathbf{A}}$.

By stacking $\mathbf{X}_1, \ldots, \mathbf{X}_K$ and $\mathbf{Z}_1, \ldots, \mathbf{Z}_K$ in two new matrices we have a set of linear equations. The mixing hyper matrix for different lags, $\breve{\mathbf{A}}$, can be estimated as follows:

$$\breve{\mathbf{A}} = \begin{pmatrix} \mathbf{Z}_1 \\ \mathbf{Z}_2 \\ \vdots \\ \mathbf{Z}_K \end{pmatrix}^{\dagger} \begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \\ \vdots \\ \mathbf{X}_K \end{pmatrix} \tag{11}$$

where † refers to the pseudo-inverse operation. After rearranging $\breve{\mathbf{A}}$, estimation of $\mathbf{A}_\tau$ for each τ will be available.

B. Estimation of $\mathbf{P}_k$s

At this section it is assumed that $\mathbf{A}_\tau$s and $\mathbf{D}_k$s are known for all k and τ and estimation of all $\mathbf{P}_k$s is required. Based on the model in (7) it is necessary to find orthonormal $\mathbf{P}_k$s to fit the model at each segment k. This problem can be solved for each k separately. So, after defining a new variable $\mathbf{G}_\tau = \mathbf{D}_k \mathbf{A}_\tau^T$ a local minimization problem for each k can be defined as:

$$\begin{gathered} J_k(\mathbf{P}_k) = ||\mathbf{X}_k - \sum_{\tau=0}^{M-1} \mathbf{\Xi}_\tau \mathbf{P}_k \mathbf{G}_\tau||_F^2 \\ \text{subject to } \mathbf{P}_k^T \mathbf{P}_k = I_{N_s} \end{gathered} \tag{12}$$

without having orthogonality constraint on $\mathbf{P}_k$ there is a closed solution for $\mathbf{P}_k$ as:

$$vec\,(\mathbf{P}_k) = \left(\sum_{\tau=0}^{M-1} \mathbf{G}_\tau^T \otimes \mathbf{\Xi}_\tau \right)^{\dagger} vec\,(\mathbf{X}_k) \tag{13}$$

where $vec(.)$ is matrix to vector converter operator and $\otimes$ denotes Kronecker product. Because of high dimensionality of $\mathbf{\Xi}_k$ this solution is computationally expensive and also does not support the orthogonality constraint of $\mathbf{P}_k$. Moreover, in our blind process, the exact $\mathbf{G}_\tau$ are not available and the above exact solution may force the algorithm towards a local minimum. In order to overcome these problems an iterative approach has been developed. One standard iterative solution for the unconstrained version of (12) is proposed in [15]. Using this iterative concept the solution of constrained problem can be proposed as:

$$\begin{aligned} \mathbf{Q}_k =& \mathbf{P}_k + \frac{\mu}{M} \left(\sum_{i=0}^{M-1} \mathbf{\Xi}_i^T \left(\mathbf{X_k} - \sum_{\tau=0}^{M-1} \mathbf{\Xi}_\tau \mathbf{P}_k \mathbf{G}_\tau \right) \mathbf{G}_i^T \right) \\ \mathbf{P}_k \leftarrow& \mathbf{U}_k \mathbf{V}_k^T \end{aligned} \tag{14}$$

where $\mathbf{U}_k$ and $\mathbf{V}_k$ include orthonormal left and right singular vectors of $\mathbf{Q}_k$ using singular value decomposition (SVD) as $\mathbf{Q}_k = \mathbf{U}_k \mathbf{\Sigma}_k \mathbf{V}_k^T$ and $\mu \leq \left(\sum_{\tau=0}^{M-1} ||\mathbf{G}_\tau||^2 \right)^{-1}$. In above formulation $\mathbf{Q}_k$ is the solution to the unconstrained version of (12) and it is computed iteratively by minimizing the gradient. However, updating $\mathbf{P}_k$ in (14) imposes the orthogonality constraint. There is another standard iterative solution for the above constrained problem using majorization concept which is computationally more intensive than the gradient based method [16][17].

C. Estimation of $\mathbf{D}_k$s

Estimating $\mathbf{D}_k$s as part of the main model can be performed for each k separately. The unconstrained estimation of diagonal elements of $\mathbf{D}_k$ stacked in vector $\mathbf{m}_k \in \mathbb{R}^{N_s \times 1}$ can be shown by:

$$\mathbf{m}_k = \left(\sum_{\tau=0}^{M-1} \mathbf{A}_\tau \odot \mathbf{\Xi}_\tau \mathbf{P}_k \right)^{\dagger} vec\,(\mathbf{X}_k) \tag{15}$$

where $\odot$ denotes Khatri-Rao product. Moreover, in order to have more robust estimations an orthogonality constraint is imposed between on vectors including the diagonal elements of all $\mathbf{D}_k$s. Figure 1 shows typical profiles (absolute value of diagonal elements of $\mathbf{D}_k$s) of sound signals. Actually, the orthogonality is applied to the source envelopes along the time segments called their profiles. For this, the transposed version of $\mathbf{m}_k$s for all $k = 1, ..., K$ must be stacked in matrix $\mathbf{C} \in \mathbb{R}^{K \times N_s}$ and then each row of the orthogonalized version of $\mathbf{C}$ will be the final estimation of diagonal elements of $\mathbf{D}_k$s as:

$$\mathbf{D}_k = diag(\mathbf{m}_k^T \mathbf{R} \mathbf{\Sigma}^{-1} \mathbf{R}^T) \tag{16}$$

where $diag(\mathbf{x})$ makes a diagonal matrix with diagonal elements equal to $\mathbf{x}$ elements and $\mathbf{R}$ and the diagonal $\mathbf{\Sigma}$ include the right singular vectors and singular values of $\mathbf{C}$ respectively.

By estimating the model parameters, both blind identification (by estimation of $\mathbf{A}_\tau$) and source separation (by estimation of all $\mathbf{S}_k$ as $\mathbf{S}_k = \mathbf{P}_k \mathbf{D}_k$) can be performed simultaneously. Alternating optimization is used to minimize $J(.)$ which has monotonical convergence property. The alternating optimization is robust to noise and at the presence of noise the minimum value of J is proportional to the noise variance. Therefore, in order to define a stopping criterion for the optimization we define $\sigma = \frac{J_{old} - J_{new}}{J_{old}}$. The final algorithm for alternating minimization process for estimation of all the parameters is shown in Algorithm 1. In the next section this algorithm will be applied for separation of heart and lung sound signals. These signals can be considered mutually orthogonal for certain segment sizes. Moreover, their profiles are normally independent of each other which provides orthogonality of profiles as the second requirement for the proposed method.

Algorithm 1 CBSS parameter estimation using alternating minimization

- **Step1** : Initialize all of the model parameters randomly.
- **Step2** : Estimate $\mathbf{P}_k$ using (14) for all $k = 1, ..., K$.
- **Step3** : Estimate $\mathbf{A}_\tau$s using (11).
- **Step4** : Estimate $\mathbf{D}_k$s using (15) and (16).
- **Step5** : Check the σ if $\sigma > \epsilon$, **go to Step2** till convergence

IV. SIMULATION RESULTS

In this section the proposed method is evaluated for separation of nonstationary heart and lung sources from their convolutive mixtures. The signals are chosen from sample signals provided in [18] to be mixed convolutively. Signals are sampled at 8000 Hz. In order to simulate the geometrical positions of the stethoscopes on chest the maximum number of lags to build up their convolutive mixtures is selected as 30 ($M = 30$) and the mixing matrices for different lags are randomly generated. To build up the segmented data from the mixtures a temporal segmentation scenario has been used with segment size of $N_k = 300$ without overlap. All parameters of the model are randomly initialized and the algorithm converged after 50 iterations. Due to blind processing of the data, the estimated mixing channels are not necessarily similar to the original ones. While, the estimated profiles $\mathbf{D}_k$s are very close to the original ones (because of the fact that filtering the data with a random vector does not have stong effect on power of the signal). The original and estimated profiles for different sources are shown in Figure 1. It can be seen that the estimated profiles have closely followed the original ones. Accordingly, the source separation performance was good. Also, we applied the MBD-MFD method and time-frequency Parra's method to compare our results with. Generally, the results for Parra's method were not as good as the two other methods. This may be due to common problems of frequency domain BSS methods. On the other hand, although in MBD-MFD method it is tried to compensate the blind deconvolution effects (estimating the separation filters to compensate the deconvolution effect), the results show that the proposed method has outperformed MBD-MFD method as well. The superiority of the proposed method is due to the fact that we have not transferred the time domain signals to any other domain and also the assumptions made for the algorithm were consistent with the heart and lung signals.

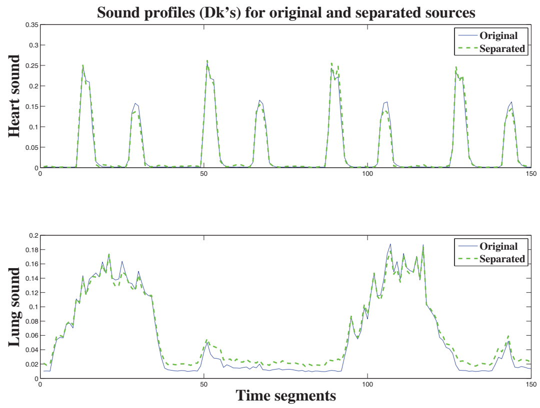

Fig. 1: Original and separated profiles ($\mathbf{D}_k$'s) of the source signals.

TABLE I: Measured SIR levels between original and separated signals using the both methods.

SIR (in dB)	Separated heart	Separated lung
Proposed method	**30.89**	**21.77**
MBD-MFD	21.26	14.81
Parra	12.091	9.32

The separated sources can be estimated by stacking $\hat{\mathbf{S}}_k = \mathbf{P}_k\mathbf{D}_k$ matrices. Because of blindly estimation of the channels $\mathbf{A}_\tau$s there are different scaling ambiguities for different lags and this causes the separated sources to be the filtered versions of the original sources. Figure 2 shows the normalized original signals, the normalized separated signals using both the MBD-MFD method and our proposed method, and the mixture signals. Because of having filtered version of the signals measuring the signal to interference ratio (SIR) has been done by using BSS EVAL toolbox [19]. Different combinations of the available heart and lung sounds in [18] are chosen and mixed with random FIR filters convolutivly. Table I shows the average measured SIR levels for the three methods over 10 experiments. Since the heart sound is more sparse in time domain, all the methods have shown better results for separation of heart sound and the proposed method has shown much better performance compared with the other methods (by at least 7dB increase in SIR).

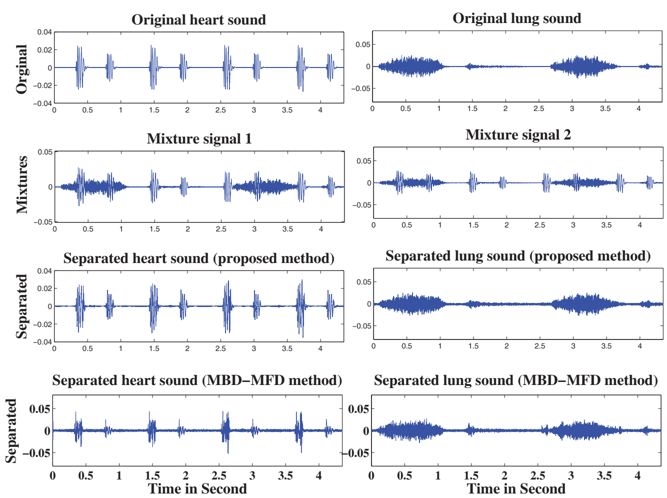

Fig. 2: Original signals on top, convolutive mixtures in the middle, and separated sources for both methods at the bottom plots.

V. Conclusions

In this paper an orthogonal signal model is defined for source signals and used to define a signal model for convolutive mixture signals. The blind source separation as the main objective of the paper is performed by estimating the parameters of the defined convolutive mixture model. The sources within each segment and consequently their profiles are considered orthogonal and the lagged mixing matrices fixed across segments. These assumptions lead to a unique and robust solution. This method solves the CBSS problem in time domain. The separated source signals by this method are filtered versions of the original sources. To evaluate the performance of the system some randomly generated mixing channels for different lags are used to mix the sound signals. The results show the high performance of the method compared to multichannel blind deconvolution based method (MBD-MFD) and also time-frequency based (Parra's) CBSS methods in achieving higher SIR levels for the separated heart and lung sounds.

References

[1] J. Gnitecki and Z. M. K. Moussavi, "Separating heart sounds from lung sounds - accurate diagnosis of respiratory disease depends on understanding noises," *Engineering in Medicine and Biology Magazine, IEEE*, vol. 26, no. 1, pp. 20 –29, Jan. 2007.

[2] L. J. Hadjileontiadis and S. M. Panas, "Adaptive reduction of heart sounds from lung sounds using fourth-order statistics.," *IEEE Trans Biomed Eng*, vol. 44, no. 7, pp. 642–8, 1997.

[3] T. Tsalaile and S. Sanei, "Separation of heart sound signal from lung sound signal by adaptive line enhancement," *15th European Signal Processing Conf. (EUSIPCO)*, pp. 1231–1235, 2007.

[4] L. J. Hadjileontiadis and S. M. Panas, "Separation of discontinuous adventitious sounds from vesicular sounds using a wavelet-based filter," *IEEE Trans. on Biomedical Engineering*, vol. 44, no. 12, pp. 1269 – 1281, Dec. 1997.

[5] I. Hossain and Z. Moussavi, "An overview of heart-noise reduction of lung sound using wavelet transform based filter," Sept. 2003.

[6] T. H. Falk and W. Y. Chan, "Modulation filtering for heart and lung sound separation from breath sound recordings," Aug. 2008.

[7] M. T. Pourazad, Z. Moussavi, F. Farahmand, and R.K. Ward, "Heart sounds separation from lung sounds using independent component analysis," Jan. 2005.

[8] F. Ghaderi, S. Sanei, B. Makkiabadi, V. Abolghasemi, and J. G. McWhirter, "Heart and lung sound separation using periodic source extraction method," Jul. 2009.

[9] M. S. Pedersen, J. Larsen, Kjems U., and L. C. Parra, "A survey of convolutive blind source separation methods," *Springer Handbook of Speech Processing*, 2007.

[10] S. Makino, H. Sawada, R. Makui, and S. Araki, "Blind source separation of convolutive mixtures of speech in frequency domain," *IEICE Trans. Fundamentals*, vol. 88, no. 7, pp. 16401654, 2005.

[11] K. Zhang and L. W. Chan, "Convolutive blind source separation by efficient blind deconvolution and minimal filter distortion," *Neurocomput.*, vol. 73, pp. 2580–2588, Aug. 2010.

[12] L. Parra and C. Spence, "Convolutive blind separation of non-stationary sources," *IEEE Trans. on Speech and Audio Processing*, vol. 8, no. 3, pp. 320–327, May 2000.

[13] G. H. Golub, V. Loan, and F. Charles, *Matrix computations*, Johns Hopkins University Press, Baltimore, 1983.

[14] L. K. Huang and A. Manikas, "Blind single-user array receiver for mai cancellation in multipath fading ds-cdma channels," *EUSIPCO Proc. of*, vol. 2, pp. 647–650, Sep. 2000.

[15] F. Ding and T. Chen, "Gradient based iterative algorithms for solving a class of matrix equations," *IEEE Trans. on Automatic Control*, vol. 50, no. 8, pp. 1216 – 1221, Aug. 2005.

[16] H. A. L. Kiers, "Setting up alternating least squares and iterative majorization algorithms for solving various matrix optimization problems," *Computational Statistics & Data Analysis*, vol. 41, no. 1, pp. 157–170, Nov. 2002.

[17] H. A. L. Kiers, "Majorization as a tool for optimizing a class of matrix functions," *Psychometrika*, vol. 55, no. 3, pp. 417–428, Sep. 1990.

[18] "solutions.3m.com," http://solutions.3m.com/wps/portal/3M/en$_US/3M-Littmann/stethoscope/littmann-learning-institute/heart-lung-sounds/$.

[19] *BSS Eval toolbox for performance measurement in (blind) source separation*, http://bass-db.gforge.inria.fr/bss$_eval/$.