Blind Source Separation for Convolutive Mixtures with Neural Networks

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***Abstract*—Blind source separation of convolutive mixtures is used as a preprocessing stage in many applications. The aim is to extract individual signals from their mixtures. In enclosed spaces, due to reverberation, audio signal mixtures are considered to be convolutive ones. Time domain algorithms (as neural network based blind source separation) are not suitable for signal recovery from convolutive mixtures, thus the need of frequency domain or subband processing arise. We propose a subband approach: first, the mixtures are split to several subbands, next time-domain blind source separation is carried out in each subband, finally the recovered sources are recomposed from the subbands. The major drawback of the subband approach is the unknown order of the recovered sources. Regardless of this undesired phenomenon the subband approach is faster and more stable than the simple time domain algorithm.**

***Index Terms*—blind source separation, neural networks, independent component analysis, subband analysis and synthesis.**

I. INTRODUCTION

The blind signal separation (BSS) has many potential exciting applications in wireless communications, non-invasive medical diagnosis (EEG, MEG, EKG, RMN) [1], geophysical exploration and image enhancement. BSS for speech or audio sources is based upon temporal or spatial diversity information contained in the observations of multiple channels [2]. There are two trends identified in the literature: the first is based on independent component analysis (ICA) [3], which aims to minimize the entropy between the separated signals; the second approach is a model based separation, where sources are identified by minimizing the probability of the source in the observed signal [4].

The BSS is widely applied in speech or audio signal processing. For example: the classical problems for signal separation is the so-called “cocktail-party problem”, where the source signals are individual speech signals and should be extracted from mixtures of multiple speakers audio signals [5]. Speech recognition should follow up the BSS process if two or more speakers are present [6]. The entertainment industry demands for better and better karaoke systems, where the singer voice should be extracted from a musical recording, thus the performer can sing it with the use of a microphone and a public addressing system. The use of source separation in audio stream coding could be an emerging trend, although the idea of transmitting the information of the surrounding first and the separated sources next is not entirely new [7].

The BSS is impaired by several real world effects, as reverberation. Early papers handled the multichannel signals processed by BSS as instantaneous mixtures [8]. Of course this is a gross approximation because the sound waves are reflected from the walls and ceiling of the enclosure and overlap with the original sound resulting in multipath propagation with large channel delay spread. Later the convolutive mixtures were introduced to describe frequency dependent effects as reverberations in enclosed spaces. As a consequence the early BSS solutions based on instantaneous domain algorithms (time-domain BSS) were replaced by the frequency domain algorithms (frequency-domain BSS) [9].

Our work is related to many audio signal processing applications as acoustic reverberators, acoustic echo control (AEC), evaluations of enclosed spaces and BSS. Although many reverberation algorithms can be found in the literature, very few design hints are given. The paper [10] includes a detailed design of the improved reverberators. The pursuit of this topic led to the performance analysis of different reverberation algorithms [11] and their digital implementations [12]. These reverberation models were used in the investigations regarding echo cancellation. AEC is a typical system identification problem, where the acoustic path is intended to be modeled. Least mean square (LMS) algorithms were deployed for system identification [13]. The simple LMS algorithm is well behaved, but the adaptation is slow. In order to improve adaptation time sub-band analysis can be carried out [14]. The performance of the subband analysis depends on the filter banks structure, number of bands, and even on the subband filter design method [15]. Further improvement in the adaptation process is achieved by the application of control algorithms as double talk detection [16]. Better performance for AEC can be achieved only if the system identification process is assisted by the acoustic map of the enclosure [17].

An emerging solution to the BSS problem is the combination of subband processing with ICA. An important advantage of subband BSS over the conventional frequency domain BSS is the computational effort. The subband processing reduces the sampling rate for the BSS core, while frequency domain BSS is done at the sampling rate. Reference [18] reports an online BSS algorithm where subband processing is applied to the mixtures.

The paper is organized as follows. In Section II the BSS based on neural network is presented. Its first part is dedicated to the time-domain BSS, followed by the second part where the subband analysis and synthesis filter banks are introduced and formulas for subband BSS are given. Simulation results are presented for both types of BSS in Section III. The unknown order of the separated output causes erroneous recovery at the synthesis filter banks. This

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aspect is discussed in Section IV. Finally conclusions are drawn in Section V.

II. Blind Source Separation

A. *Neural Algorithm for BSS*

Our previous studies on BSS are materialized in several papers. The time domain solution based on neural algorithm was found in [19]. This approach is very similar to the ICA, but the process is interpreted from the viewpoint of neural networks. Aspects of digital implementation were studied in reference [20], where a Simulink model is proposed that serves as a register transfer level description for later HDL description and field programmable gate array implementation.

The neural approach deals with BSS where the signals are provided from channels without memory. In Figure 1 the block diagram for BSS is presented: the instantaneous mixture is achieved by matrix multiplication modeling the overlap of sound waves; next blind signal extraction is carried out in a neural network controlled by a learning algorithm.

We suppose that the signals are received by a sensor area and therefore they are mixtures of n audio source signals $s_j(t),\ j = 1, 2, \dots, n$. These signals are independent and unknown. At sensor outputs there are m observed zero-mean signals $x_i(t),\ i = 1, 2, \dots, m$, that are instantaneous linear combinations of the n unknown source signals. If the observed signals are noise-contaminated, we have:

$$x_i(t) = \sum_{j=1}^{n} h_{ij} \cdot s_j(t) + n_i(t),\ \ i = 1,2,\dots,m \qquad \text{or} \quad \mathbf{x}(t)=\mathbf{H}\cdot\mathbf{s}(t)+\mathbf{n}(t) \tag{1}$$

where $\mathbf{x}(t)=[x_1(t)\dots x_m(t)]^T$ is the sensors vector at moment t, $\mathbf{s}(t)=[s_1(t)\dots s_n(t)]^T$ is the sources signal vector, $\mathbf{n}(t)=[n_1(t)\dots n_m(t)]^T$ is the noise vector and $\mathbf{H}$ is an $m \times n$ unknown mixing matrix, intended to model the acoustic paths between sound sources and the sensor array.

The source signals can be recovered with the help of a separation neural network, having at its inputs the signals from the sensors area. The neural network can have a *feed-forward* or *recurrent* architecture [21].

Consider the feed-forward neural network from Figure 2. The separation process can be described by:

$$y_i(t) = \sum_{j=1}^{m} W_{ij}(t) \cdot x_j(t), i = 1,2,\dots,n \qquad \text{or} \quad \mathbf{y}(t)=\mathbf{W}\cdot\mathbf{x}(t) \tag{2}$$

where $\mathbf{y}(t)=[y_1(t),\dots,y_n(t)]^T$ is the estimation of the signals $\mathbf{s}(t)$ and $\mathbf{W}$ is the $n \times m$ separation matrix, with the elements called synaptic weights. In neural networks the synaptic weights vary in time according to the learning algorithm until the signals $\mathbf{y}(t)$ estimate in a good manner the original signals $\mathbf{s}(t)$. If $n=m$, the ideal solution for this problem is to find out the inverse matrix:

$$\mathbf{W} = \mathbf{H}^{-1} \tag{3}$$

Due to insufficient data about the original signals, this method cannot be used. A good solution is the use of a neural network controlled by a learning algorithm. Two ambiguities will appear even in the case of successful separations:

- the order of sources in matrix $\mathbf{s}(t)$ is not identical to the order of the separated signals in $\mathbf{y}(t)$ (i.e. $y_1(t)$ could estimate any source);
- the signal scaling is unknown.

Suppose that all variables are real, the sources number is equal to the number of sensors and the signals sources have zero-mean. All signals are sampled at discrete moments of time $t_k=kT$, where $k=0, 1, 2, \dots$ and T is the scaled sampling period ($T=1$). Most of the learning algorithms have been developed from heuristic considerations based on the minimization or maximization of a cost function. To obtain the learning algorithm one should consider the standard stochastic descent method [21]:

$$\mathbf{W}(k+1) = \mathbf{W}(k) + \eta(k)\left[\mathbf{I} - \mathbf{f}(\mathbf{y}(k))\cdot\mathbf{y}^T(k)\right]\cdot\mathbf{W}(k)\,, \tag{4}$$

where $\boldsymbol{\eta}(k)$ is the learning rate at time k and $\mathbf{f}(y)=[f_1(y_1),\dots,f_n(y_n)]^T$, $f_i(y_i)$ is:

$$f_i(y_i) = -\frac{d\log(q_i(y_i))}{dy_i} = -\frac{q_i'(y_i)}{q_i(y_i)}\,. \tag{5}$$

where $q_i(y_i)$ is the probability distribution. If the probability distributions of the sources $q_i(y_i)$ are known, then functions

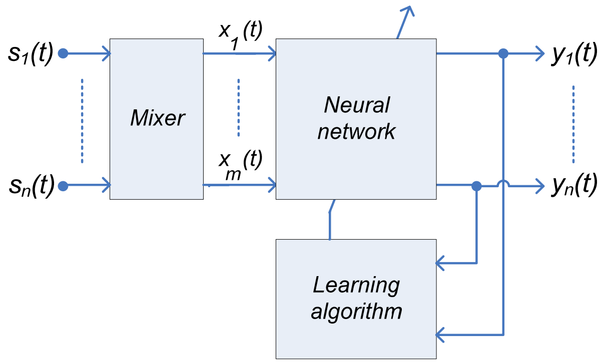

FIGURE 1. BLOCK DIAGRAM FOR BLIND SIGNAL SEPARATION.

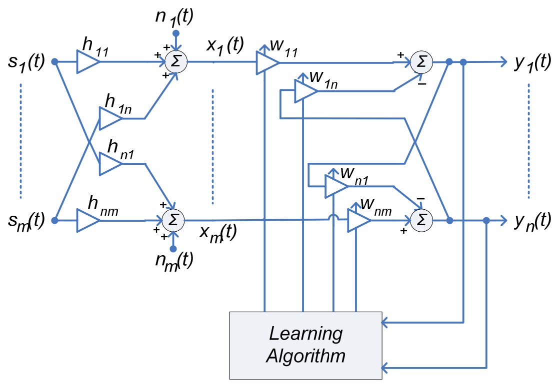

Figure 2. Feed-forward neural network

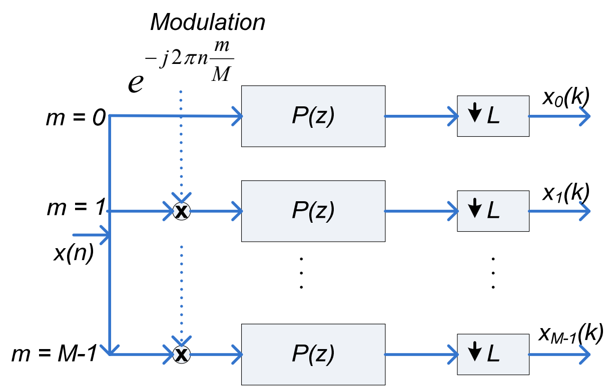

Figure 3. The analysis filter bank

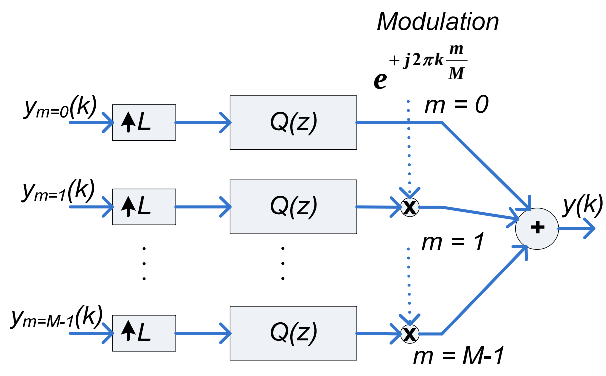

Figure 4. Synthesis filter bank

$f_i(y_i)$ can be computed according to (5.). If not, nonlinear non-optimal functions still allow the algorithm to perform separation. For sub-Gaussian sources with negative kurtosis the function could be selected as follows:

$$f_i(y_i) = \alpha y_i + y_i |y_i|^2 , \qquad (6)$$

and for super-Gaussian sources with positive kurtosis:

$$f_i(y_i) = \alpha y_i + \tanh(\gamma y_i) , \qquad (7)$$

where $\alpha \geq 0$ and $\gamma \geq 2$ are positive constants [21]. When $\mathbf{x}(t)$ contains mixtures of both sub- and super-Gaussian sources, additional techniques are required to enable the system to adapt properly.

Kurtosis is a measure of the deformation of the stochastic variable probability distribution in comparison with a normal probability distribution. For normal distribution kurtosis has the value 3. For distributions wider than the normal one the kurtosis is larger than 3 and for less disperse smaller than 3. Comprehensive study has been made in [22] about the capability, convergence and stability of the algorithm. A MATLAB program was developed using floating point variables and operations to simulate the behavior of the algorithm.

B. Subband BSS

Multirate processing [23] proved to be very useful in diverse applications. In this paper we propose the multirate processing of the convolutive mixture. The width of each subband being smaller than the convolutive mixture band, the sampling frequency for each neural network can be lowered by inserting down-sampling (L↓) and up-sampling (L↑) between the analysis and synthesis filter banks. This leads to a significant reduction of computational complexity in comparison to the frequency-domain BSS.

The *analysis* filter bank is presented in Figure 3. The analysis filter design problem reduces to the design of a single prototype non-recursive filter *P(z)*, the other filters being the modulated versions of the prototype. This design method is known in the literature as the modulated filter bank design. Ideal analysis filters are band-pass filters with normalized center frequencies $\omega_m = 2\pi\ m/M$, $m=0,\dots,\ M-1$, and with bandwidth equal to $2\pi/M$.

The ideal filters have unit magnitude and zero-phase in the pass-band while the stop-band magnitude is zero. While zero phase filters involve non causality, the requirements need to be relaxed by using linear phase filters. The choice is to use FIR filters with linear phase, but not ideal magnitude requirements. This approximation leads to aliasing effects.

The design of *synthesis* filter banks (Figure 4) reduces also to the design of a single synthesis prototype filter *Q(z)*. In the design the focus is on the performance of the analysis-synthesis filter bank as a whole.

Achieving zero residual error requires the subband filters and subband models to have an infinite tap size. Since we always use FIR subband filters and subband models, residual errors are unavoidable. This implies that in the

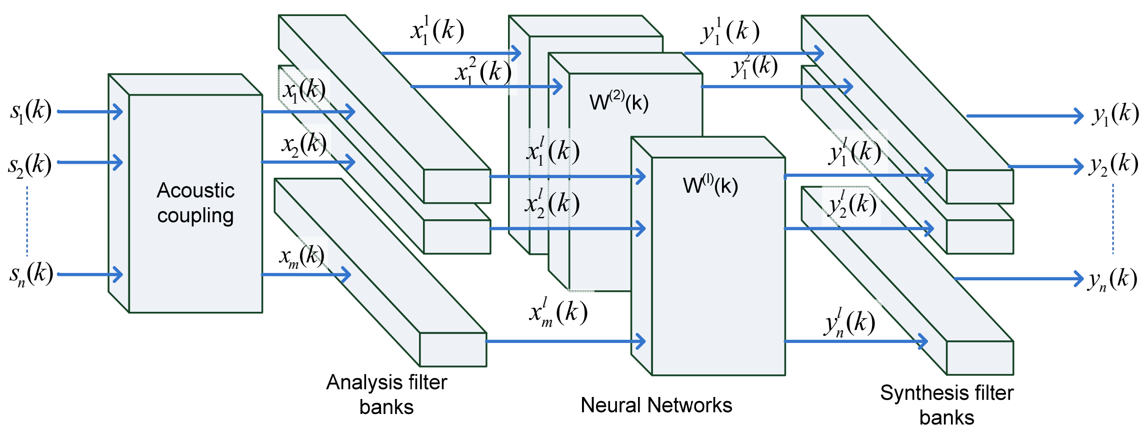

Figure 5. BSS with subband analysis

design of a subband BSS system, there is a tradeoff between asymptotic residual error and computational cost.

The neural algorithm approach operates on memoryless channels, but in real world application this is not a standing assumption. To include the frequency dependent behavior of the acoustic path the convolutive signal model is considered in the discrete domain:

$$x_i(k) = \sum_{j=1}^{n} p_{ij}(k) * s_j(k) + n_i(k),\;\; i = 1,2,...,m \qquad (8)$$

where * is the convolution operator, $p_{ij}(k)$ is the unknown impulse response of the acoustic path between source j and sensor i, the matrix P is an $m \times n$ sized matrix, a collection of impulse responses, describing the acoustic coupling of the enclosure.

Applying the subband decomposition for the processed mixture one can obtain the structure in Figure 5. The mixture signals $x_i(k)$ are decomposed to L subbands each denoted with $x_i^s(k)$, where $s=1, 2, ... l$. The s^{th} subband vector $\left[x_1^s(k), x_2^s(k), ... x_m^s(k)\right]$ undergoes the BSS process presented in the previous section. The inputs of the synthesis filter banks are $\left[y_i^1(k), y_i^2(k), ... y_i^l(k)\right]$, obtaining the recovered signal $y_i(k)$, $i=1, 2, ..., n$.

The convolution operation in equation (8) turns into a multiplication if the mixtures and the collection of impulse responses are converted to the frequency domain:

$$X_i(k) = \sum_{j=1}^{n} P_{ij}(k) \cdot S_j(k) + N_i(k),\;\; i = 1,2,...,m \qquad (9)$$

where $P_{ij}(k)$, $S_j(k)$ and $N_i(k)$ are the discrete Fourier transforms of $p_{ij}(k)$, $s_j(k)$, respectively $n_i(k)$. According to reference [24] the output of the BSS core in the s^{th} subband is:

$$\mathbf{Y}^s(k) = \mathbf{W}^s \cdot \mathbf{X}^s(k) \qquad (10)$$

where $\mathbf{Y}^s(k) = \left[y_1^s(k), y_2^s(k), ... y_n^s(k)\right]$, $\mathbf{X}^s(k) = [x_1^s(k), ... x_2^s(k), ... x_m^s(k)]$ and $\mathbf{W}^s$ is the demixing matrix in the s^{th} subband and the adaptation is governed by the stochastic descent algorithm:

$$\begin{aligned} &\mathbf{W}^s(k+1) = \mathbf{W}^s(k) + \\ &+\eta(k)\left[\mathbf{I} - \mathbf{f}(\mathbf{Y}^s(k)) \cdot \mathbf{Y}^s(k)^T\right] \cdot \mathbf{W}^s(k) \end{aligned} . \qquad (11)$$

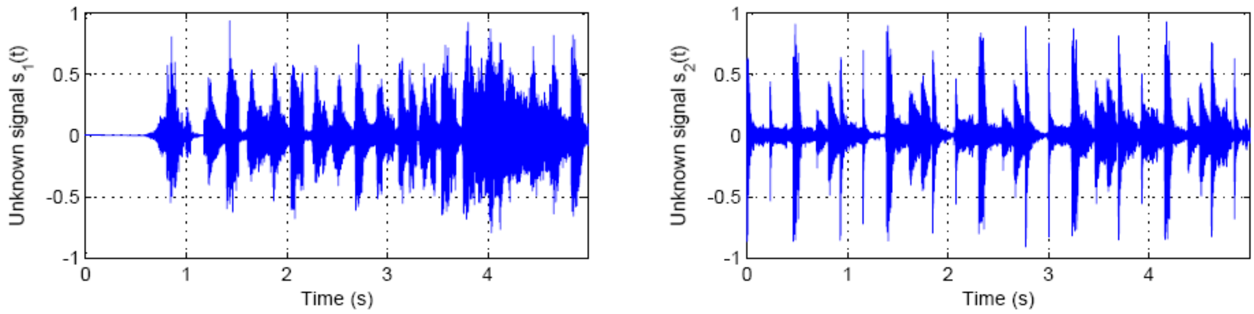

Figure 6. Sound sources $S_1(T)$ and $S_2(T)$

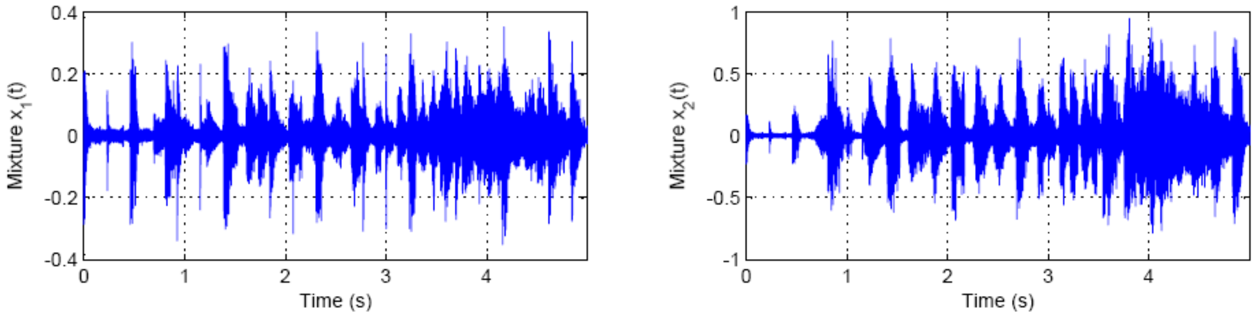

Figure 7. Mixtures signals $X_1(T)$ and $X_2(T)$

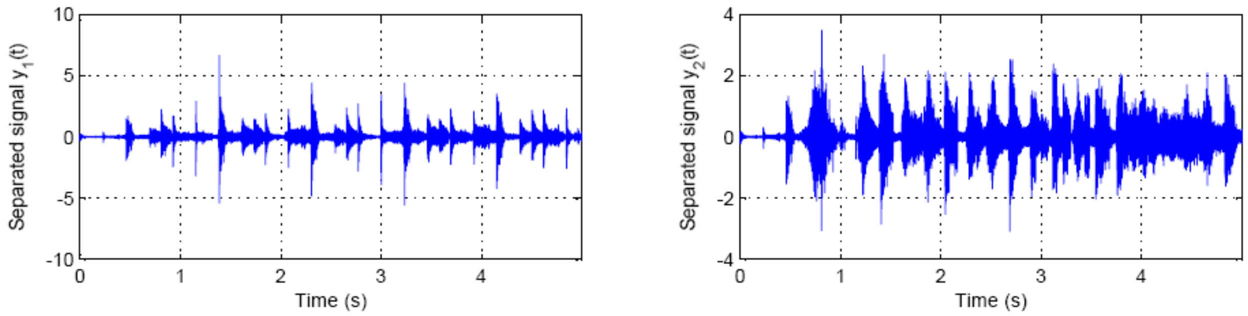

Figure 8. Estimated/separated signals $Y_1(T)$ and $Y_2(T)$

III. Simulation Results

We compared the time-domain BSS and subband BSS using the next test procedure prepared in MATLAB: the sources are wave files, that are read and mixed to provide the inputs for the BSS system and the outputs are converted in PCM format wave files. Simulations with two sources and two mixtures were considered ($m = n = 2$).

A. The Time-Domain BSS performance

Stages of the testing procedure are illustrated in the example below: the sound sources $s_1(t)$ and $s_2(t)$ are represented in Figure 6, the mixtures $x_1(t)$ and $x_2(t)$ in Figure 7 and the outputs of the BSS $y_1(t)$ and $y_2(t)$ in Figure 8. The mixtures are considered to be instantaneous due to a memoryless channel.

The input signals are sampled at f_s=*44100 Hz.* In Fig. 5 to 7 the first *5 s* signals are captured. About *0.5 s* are needed to start the adaptation process. The transition to an equilibrium state lasts about *0.25 s* to correct the output signal estimation. After *0.75 s* a good separation of the sources is achieved.

The shape of the time domain signals is not a measure of the performance. Paper [25] presents and defines numerous quantities that can characterize the BSS, as the source to distortion ratio, source to interference ratio, sources to noise ratio and sources to artifacts ratio. We adopted the signal to interference ratio (SIR) to evaluate the neural network. The SIR for the first source can be expressed [26]:

$$SIR(y_1(t)) = \left(\frac{E\{y_1(t) \cdot s_1(t)\}}{E\{y_1(t) \cdot s_2(t)\}} \right)^2, \qquad (12)$$

where $y_1(t)$ is the estimated source, $s_1(t)$ is the original source, $s_2(t)$ is the original interferer signal and E$\{x\}$ is the expectation of signal x. The formula can be interpreted as follows: the SIR is the ratio of the cross-correlation of estimated and original signals and the cross-correlation of estimated and original interferer signals. The SIR is depicted in Figure 9. When the value of the SIR is negative the sources are not separated. Large oscillations can be observed after the separation is achieved. The mean value of SIR is around 5 dB. Although this value seems to be low, for sound BSS it is an acceptable value.

B. Subband BSS performance

The second simulation example is for the evaluation of the proposed subband BSS system. Instead of an instantaneous, a convolutive mixture is applied to the subband BSS. The filter bank splits the mixture signal into L=8 subbands. The time domain signals are similar to the ones obtained by neural network BSS; only the SIR is depicted in Figure 10. The proposed subband BSS system achieves further 5 dB improvement in the separated signal, the mean SIR taking values around 10 dB. Comparing the plots from Fig. 9 and Fig. 10 we can conclude that the subband BSS converges faster with almost *1 s* than the time-domain BSS and is more stable.

IV. Discussion

An identified drawback of the subband approach is the uncertainty of the separated source order. Depending on the inputs the neural networks in the subbands may output the separated source in different order causing erroneous recovery of individual sources in the synthesis filter bank. Up to this moment the proposed solutions are offline solutions. Paper [24] suggests a filter bank design method, by optimizing the correlations between adjacent subbands; this method reduces the number of permutations mainly in the lower subbands. This solution can be hardly adopted for online processing, because the filter bank should be redesigned if the type of the input signals are modified (the filter banks become suboptimal). Another solution based on sparsity of the source is presented in reference [4]. The paper presents a compensation method exploiting the sparsity assumption of sources in the time domain. This solution can compensate not only for the permutation but also for the unknown scaling of the signal, at the cost of high computational costs that inhibits real-time implementation. We consider that the best subband BSS method for online processing is based on the exploration of special diversity [27]. In this approach the sources are separated upon their direction of arrival (DOA), instead of their statistical properties. Recent results suggest to combine spatial and frequency diversity to increase the performance of BSS [28]. As a future challenge we identify the development of an algorithm to compensate for the scaling and source order uncertainty in real time.

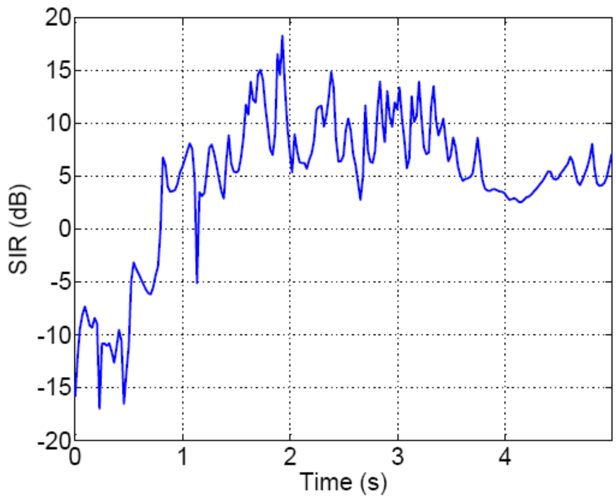

Figure 9. SIR of neural network BSS

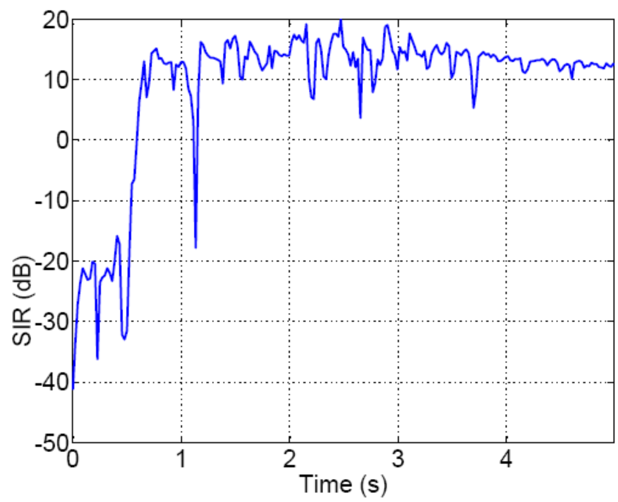

Figure 10. SIR of subband BSS

V. CONCLUSION

The paper gives an overview of our achievements in the field of BSS. Time domain BSS is suitable for instantaneous mixtures, but in real world applications, the mixtures are convolutive ones due to reverberations. Source separation from convolutive mixtures can be achieved with the use of subband processing.

MATLAB simulations showed the advantages of subband BSS. It achieves 5dB SIR improvement and has faster convergence than time domain BSS. The computational cost of subband BSS is moderate, thus enables real-time implementation.

These advantages are shadowed by the uncertainty of output order in the subband, a problem that is unavoidable for time-domain BSS too.

Further work consists in the development of a source separation platform (sensor array development) and implementation of the subband BSS on FPGA platform.

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