A Novel Algorithm for Multichannel Deconvolutive based on $\alpha\beta$-Divergence

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ABSTRACT

We introduce a novel Algorithm for underdetermined convolutive mixture of source signals. Where the convolution is routinely approximated in the short-time Fourier transform (STFT) domain as linear instantaneous mixing in each frequency band. Each source STFT is given a model inspired from nonnegative matrix factorization (NMF) with the $\alpha\beta$-divergence, this divergence is a family of cost functions parameterized by a two tuning parameters (α and β), and smoothly connect the fundamental Alpha-, Beta- and Gamma-divergences. The proposed family of $\alpha\beta$-multiplicative NMF algorithms is shown to improve robustness separation with respect to noise and outliers. Our decomposition algorithm is applied to stereo audio source separation in various settings, covering blind and supervised separation, music and speech sources, synthetic instantaneous and convolutive mixtures.

General Terms

Algorithms for blind signal separation .

Keywords

Blind signal separation (BSS), Nonnegative matrix Factorization (NMF), $\alpha\beta$ -divergence, $\alpha\beta$ -NMF,ICA.

1. INTRODUCTION

Many convolutive BSS methods have been designed, typically; an instantaneous independent component analysis (ICA) algorithm is applied to data in each frequency subband, yielding a set of source subband estimates per frequency bin. This approach is usually referred to as frequency-domain ICA (FD-ICA) [18]. The source labels remain however unknown because of the ICA standard permutation indeterminacy, leading to the well-known FD-ICA permutation alignment problem, which cannot be solved without using additional a priori knowledge about the sources and/or about the mixing filters. In standard NMF only assume nonnegativity of factor matrices. Unlike blind source separation methods based on independent component analysis (ICA), here do not assume that the sources are independent.

NMF in its standard setting is only suited to single-channel data. Extensions to multichannel data have been considered, either by stacking up the spectrograms of each channel into a single matrix [16] or by considering nonnegative tensor factorization (NTF) where the channel spectrograms form the slices of a 3-valence tensor [11]. These approaches inherently assume that the original sources have been mixed instantaneously, which in modern music mixing is not realistic, and they require a posterior binding step so as to group the elementary components into instrumental sources. The aim of this work is to remedy these drawbacks so we formulate a multichannel NMF model that accounts for convolutive mixing and can see as a generalization for IS-NMF [14], also this algorithm is robust with respect to noise and/or outliers in multichannel convolution. The source spectrograms are modeled through NMF and the mixing filters serve to identify the elementary components pertaining to each source.

The remaining of this paper is organized as follows. The multichannel NMF model is introduced in section 2. Section 3 is devoted to the definition of $\alpha\beta$ -divergence. In section 4 the $\alpha\beta$ -NMF algorithm for multichannel is introduced. Section 5 presents the criteria that used to measure the performance of our algorithm. Section 6 presents the results of our algorithm to stereo source separation in various settings. Conclusions are drawn in section 7.

2. MULTICHANNEL NMF MODEL

Ozerov et al. [14] formulated an IS-NMF algorithm for convolutive and instantaneous mixing in which the sampled signals $x_i(t)(i=1,\dots,I,\quad t=1,\dots,T)$ generated as J convolutive noisy mixtures of point source signals $s_j(t)$ such that

$$x_i(t) = \sum_{j=1}^{J}\sum_{\tau=0}^{L-1} a_{ij}(\tau)s_j(t-\tau) + n_i(t) \qquad (1)$$

Where $a_{ij}(\tau)$ is the finite-impulse response of some filter and $n_i(t)$ is some additive noise. The time-domain mixing is given by (1) can be approximated in the short-time Fourier transform (STFT) domain as:

$$x_{i,fn} = \sum_{j=1}^{J} a_{ij,f}\, s_{j,fn} + n_{i,fn} \qquad (2)$$

where $x_{i,fn}$ and $s_{j,fn}$ are the complex-valued STFTs of the corresponding time signals, $a_{ij,f}$ is the complex-valued discrete Fourier transform of filter $a_{ij}(\tau)$, $f=1,\dots,F$ is a frequency bin index, n is a time frame index. In which the complex random variable $s_{j,fn}$ defined as:

$$s_{j,fn} = \sum_{k\in\mathrm{K}} c_{k,fn} \quad \text{with } c_{k,fn} \sim \mathbf{N}(0, w_{fk}h_{kn}) \qquad (3)$$

Where , $\mathbf{N}(0, w_{fk}, h_{kn})$ is the proper complex Gaussian distribution [14,18] and $\{\mathrm{K}_j\}_{j=1}^{J}$ be a nontrivial partition of $k=\{1,\dots,\mathrm{K}\}$, where $K \ge J$ [16,10]. Equation (2) can be rewritten in matrix form:

$$\mathbf{x}_{fn} = \mathbf{A}_f \mathbf{s}_{fn} + \mathbf{n}_{fn} \qquad (4)$$

where $\mathbf{x}_{fn} = [x_{1,fn},...,x_{I,fn}]^T$, $\mathbf{s}_{fn} = [s_{1,fn},...,s_{J,fn}]^T$, $\mathbf{n}_{fn} = [n_{1,fn},...,n_{I,fn}]^T$ and $\mathbf{A}_f = [a_{ij,f}]_{ij} \in C^{I\times J}$.

NMF is used to model the $F \times N$ power spectrogram $|\mathbf{S}_j|^2 = [|s_{j,fn}|^2]_{fn}$ of source j as a product of two nonnegative matrices $\mathbf{W}_j$ and $\mathbf{H}_j$, such that

$$\mathbf{S}_j^2 \approx \mathbf{W}_j \mathbf{H}_j \qquad (5)$$

We are interested in estimating the source spectrogram factors $\{\mathbf{W}_j, \mathbf{H}_j\}_j$ and the mixing system $\{\mathbf{A}_f\}_f$ based on the observed mixture STFTs, $\mathbf{X} = \{x_{i,fn}\}_{i,fn}$, as illustrated in Figure1.

3. $\alpha\beta$ -DIVERGENCE

The $\alpha\beta$-divergence [5] can be defined as :

$$D(\mathbf{X}\|\mathbf{Q}) = \frac{-1}{\alpha\beta}\sum_{it}\left(x_{it}^{\alpha} q_{it}^{\beta} - \frac{\alpha}{\alpha+\beta} x_{it}^{\alpha+\beta} - \frac{\beta}{\alpha+\beta} q_{it}^{\alpha+\beta}\right) \qquad (6)$$

Where $\alpha, \beta, \alpha+\beta \neq 0$ and $\mathbf{Q} = \hat{\mathbf{X}} = [\mathbf{AS}]$, this divergence can be by suitable choice of the (α, β) parameters simplifies into some existing divergences, including the well-known Alpha- and Beta-divergences. For example when $\alpha + \beta = 1$ the $\alpha\beta$-divergence reduces to the Alpha-divergence [1,8]:

$$D^{(\alpha,1-\alpha)}(\mathbf{X}\|\mathbf{Q}) = \begin{cases} \sum_{it} x_{it} \ln \frac{x_{it}}{q_{it}} - x_{it} + q_{it} & for\ \ \alpha = 1, \\ \frac{1}{\alpha(\alpha-1)} \sum (x_{it}^{\alpha} q_{it}^{1-\alpha} - \alpha x_{it} - (\alpha-1) q_{it}) & \forall \alpha \neq 0,1. \end{cases} \qquad (7)$$

On the other hand, when $\alpha = 1$ it reduces to the Beta-divergenc.

$$D^{(1,\beta)}(\mathbf{X}\|\mathbf{Q}) = \begin{cases} \sum_{it} \ln \frac{q_{it}}{x_{it}} - \left(\frac{q_{it}}{x_{it}}\right)^{-1} - 1 & \forall\ \beta = -1, \\ \frac{-1}{\beta} \sum_{it} (x_{it} q_{it}^{\beta} - \frac{1}{1+\beta} x_{it}^{1+\beta} - \frac{\beta}{1+\beta} q_{it}^{1+\beta}) & \forall \beta, \neq 0, -1. \end{cases} \qquad (8)$$

Also $\alpha\beta$-divergence reduces to the standard Itakura-Saito divergence for $\alpha = 1$ and $\beta = -1$ [6,10].

$$D^{(1,-1)}(\mathbf{X}\|\mathbf{Q}) = \sum_{it} \ln \frac{q_{it}}{x_{it}} + \frac{x_{it}}{q_{it}} - 1 \qquad (9)$$

Figure2 show $\alpha\beta$-divergence $d(x\|y)$ as a function of y (with $x = 1$). The subfigures illustrate the regimes of the $\alpha\beta$-divergence for its characteristic ranges of values of α and β. We used $\alpha\beta$-divergence for many reasons that found in [5], in which it illustrated the role of the hyperparameters α and β on the robustness of the $\alpha\beta$-divergence with respect to errors and noises, and it compare the behavior of the $\alpha\beta$-divergence with the standard Kullback-Liebler divergence.Also by scaling arguments of the $\alpha\beta$-divergence by a positive scaling factor $c = 0$, it yields the following relation

$$D^{(\alpha,\beta)}(c\boldsymbol{X}||c\boldsymbol{Q}) = c^{\alpha+\beta} D(\boldsymbol{X}||\boldsymbol{Q}) \qquad (10)$$

These basic properties imply that whenever $\alpha \neq 0$, we can rewrite the $\alpha\beta$-divergence in terms of a $\left(\frac{\beta}{\alpha}\right)$-order Beta divergence combined with an α-zoom of its arguments as

$$D^{(\alpha,\beta)}(c\boldsymbol{X}||c\boldsymbol{Q}) = \frac{1}{\alpha^2} D_{\beta}^{\left(\frac{\beta}{\alpha}\right)}(\boldsymbol{X}||\boldsymbol{Q}) \qquad (11)$$

4. ESTIMATION OF THE PARAMETERS

In order to use $\alpha\beta$-divergence so our objective function is:

$$O(\boldsymbol{\theta}) = \sum_{ifn} d_{\alpha\beta}(|x_{i,fn}|^2 \| \hat{x}_{i,fn}) \qquad (12)$$

Where $\hat{x}_{i,fn}$ is th [structure defined by[14]:

$$\hat{x}_{i,fn} = \sum_{j} \mathrm{q}_{ij,f} \sum_{k\in} \mathrm{w}_{fk} \mathrm{h}_{kn} \qquad (13)$$

$q_{ij,f} = a_{ij,f}^2$ and, for a fixed channel i , $\hat{x}_{i,fn}$ is basically the sum of the source variances modulated by the mixing weights. Our objective function (12) may also be read as the ML criterion corresponding to the model where the contributions of each source for each channel would be different and independent realizations of the same Gaussian process, as opposed to the same realization. In other words, this assumption amounts to changing our observation and source models given by (2) and (5) to [15,5].

$$x_{i,fn} = \sum_{j=1}^{J} a_{ij,f} \mathrm{s}_{j,fn}^{i} + \mathrm{n}_{i,fn} \qquad (14)$$

where $\mathrm{s}_{j,fn}^{i}$ denotes the contribution of source to channel i , and these contributions are assumed independent over channels . Let $\boldsymbol{\theta}$ be a scalar parameter of the set $\{\mathbf{W}, \mathbf{H}, \mathbf{Q}\}$. The derivative of $O(\boldsymbol{\theta})$ w.r.t $\boldsymbol{\theta}$:

$$\nabla_{\theta} D(\mathbf{X}\|\hat{\mathbf{X}}) = \sum (\nabla_{\theta} x_{i,fn}) d'_{\alpha\beta}(x_{i,fn} \| \hat{x}_{i,fn}) \qquad (15)$$

where $d'_{\alpha\beta}(x||\hat{x})$ is the derivative of $d_{\alpha\beta}(x\|\hat{x})$ w.r.t. $\hat{x}$ given by

$$d'_{\alpha\beta}(x\|\hat{x}) = \frac{1}{\alpha}\left(\hat{x}^{\alpha+\beta-1} - x^{\alpha} \hat{x}^{\beta-1}\right) \qquad (16)$$

The gradient of the $\alpha\beta$-divergence can be expressed in a compact form (for any $\alpha, \beta \in R$) in terms of a deformed logarithm [5].By using (15), we obtain the following derivatives:

$$\nabla_{qij,f} D_{\alpha\beta}(\mathbf{X}\|\hat{\mathbf{X}}) = \sum_{n} p_{j,fn} d'_{\alpha\beta}(x_{i,fn} \| \hat{x}_{i,fn}) = \frac{1}{\alpha}\sum_{n} p_{j,fn}\left(\hat{x}_{i,fn}^{.[\alpha+\beta-1]} - x_{i,fn}^{.[\alpha]} \hat{x}_{i,fn}^{.[\beta-1]}\right) \qquad (17)$$

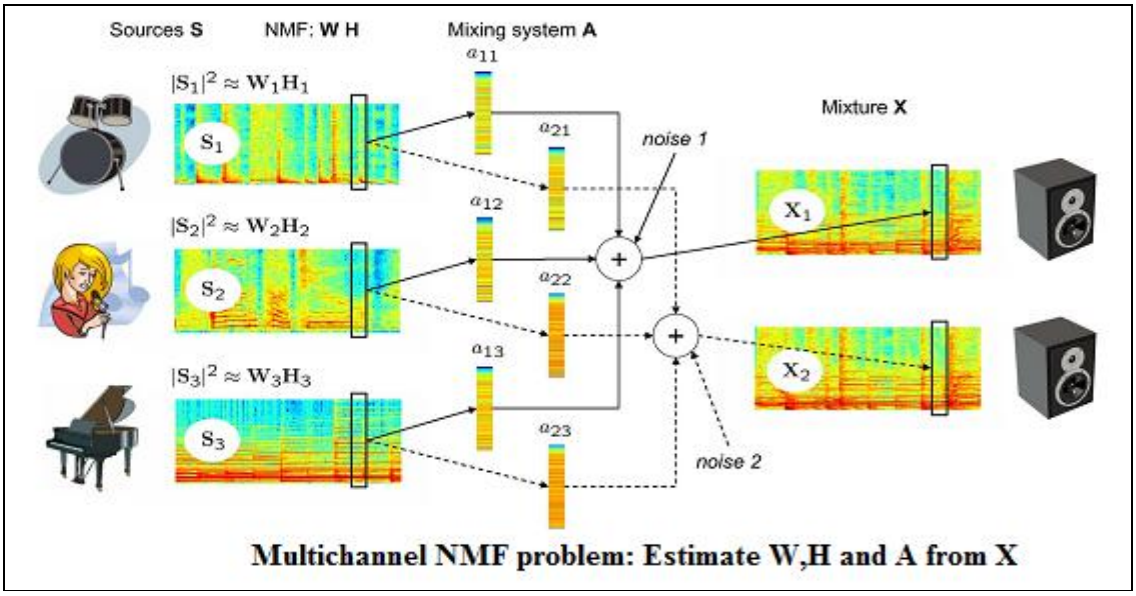

Fig1: Representation of convolutive mixing system and formulation of Multichannel NMF problem[6].

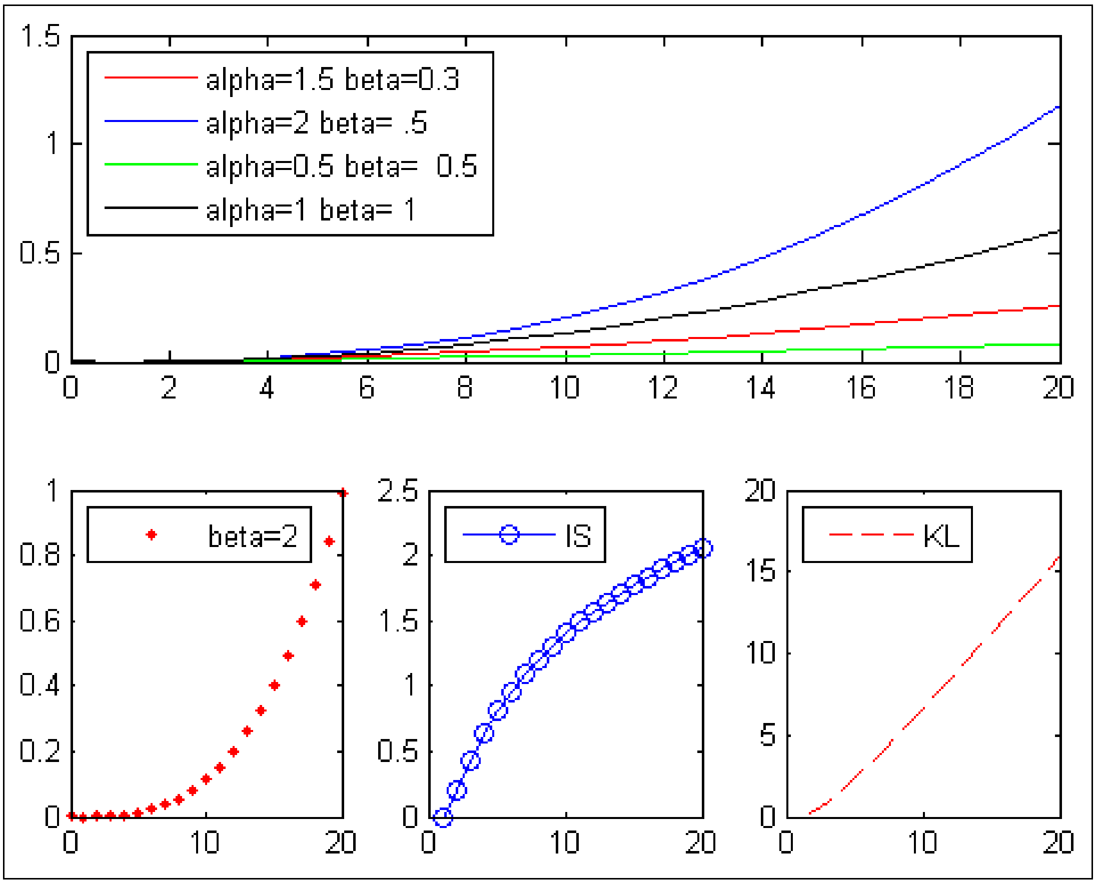

Fig2 : $\alpha\beta$-Divergence with various value for α and β.

$$\nabla_{wj,fk} D_{\alpha\beta}(\mathbf{X} \| \hat{\mathbf{X}}) = \sum_{i=1}^{I} \sum_{n=1}^{N} q_{ij,f} h_{j,kn} d'_{\alpha\beta}(x_{i,fn} \| \hat{x}_{i,fn}) = \frac{1}{\alpha} \sum_{i=1}^{I} \sum_{n=1}^{N} q_{ij,f} h_{j,kn} \left(\hat{x}_{i,fn}^{.[\alpha+\beta-1]} - x_{i,fn}^{.[\alpha]} \hat{x}_{i,fn}^{.[\beta-1]} \right) \quad (18)$$

$$\nabla_{hjkn} D_{\alpha\beta}(\mathbf{X} \| \hat{\mathbf{X}}) = \sum_{i=1}^{I} \sum_{f=1}^{F} q_{ij,f} w_{j,fk} d'_{\alpha\beta}(x_{i,fn} \| \hat{x}_{i,fn}) = \frac{1}{\alpha} \sum_{i=1}^{I} \sum_{f=1}^{F} q_{ij,f} w_{j,fk} \left(\hat{x}_{i,fn}^{.[\alpha+\beta-1]} - x_{i,fn}^{.[\alpha]} \hat{x}_{i,fn}^{.[\beta-1]} \right) \quad (19)$$

where $p_{i,fn} = \sum_{k \in K} w_{fk} h_{kn}$ .The previous equations can be written in the following matrix form:

$$\nabla_{q_{ij}} D_{\alpha\beta}(X\|\hat{X}) = \frac{1}{\alpha}\left(\left(\hat{X}_i^{\alpha+\beta-1} - X_i^{\alpha}\hat{X}_i^{\beta-1}\right) P_j\right) 1_{N\times 1} \quad (20)$$

$$\nabla_{W_j} D_{\alpha\beta}(X\|\hat{X}) = \frac{1}{\alpha}\sum_i diag(q_{ij})\left(\hat{X}_i^{\alpha+\beta-1} - X_i^{\alpha}\hat{X}_i^{\beta-1}\right) H_j^T \quad (21)$$

$$\nabla_{H_j} D_{\alpha\beta}(X\|\hat{X}) = \frac{1}{\alpha}\sum_i \left(diag(q_{ij}) W_j\right)^T \left(\hat{X}^{\alpha+\beta-1} - X^{\alpha}\hat{X}^{\beta-1}\right) \quad (22)$$

Hence, by using these derivatives we form our algorithm that called $\alpha\beta$-NMF algorithm (and it illustrated in algorithm $\alpha\beta$-NMF) , this algorithm is a natural extension of many existing algorithms for NMF, including the ISRA, EMML, Lee-Seung algorithms and Alpha- and Beta-multiplicative NMF algorithms [7, 4]. For example, by selecting $\alpha + \beta = 1$, we obtain the Alpha-NMF algoa Betam, for $\alpha = 1$, we have Beta-NMF algorithms, for $\alpha = \beta \neq 0$ we obtain a family of multiplicative NMF algorithms based on the extended Itakura-Saito distance [6, 10]. Furthermore, for $\alpha = 1$ and $\beta = 1$, we obtain the ISRA algorithm and for $\alpha = 1$ and $\beta = 0$ we obtain the EMML algorithm.

For reconstruction of the source images: consider the MMSE estimate of the image $s_{j,fn}^{(i)im}$ of source j in channel i ,given $(\mathbf{x}_{fn};\boldsymbol{\theta})$ that defined as [14]:

$$s_{j,fn}^{(i)im} = \frac{q_{ij,f}\ p_{i,fn}}{\hat{x}_{i,fn}} x_{i,fn} \quad (23)$$

Algorithm $\alpha\beta$ -NMF

Input : $X \in R_+^{I\times T}$:input data,

ω : Window length (50%), and K .

Output: A, W and H such that cost function (12) is minimized.

1.**begin**

2. Initializationn for A, W and H

3. X =STFT(X, ω, K)

4. **Repeat**

5. **update** **Q**

$$q_{ij} \leftarrow q_{ij} \otimes \frac{\left(x_i^{\alpha}\hat{x}_i^{\beta-1} P_j\right) 1_{N\times 1}}{\left(\hat{x}_i^{\alpha+\beta-1} P_j\right) 1_{N\times 1}}$$

6. **update** **W**

$$W_j \leftarrow W_j \otimes \frac{\sum_{i=1}^{I} diag(q_{ij})\left(x_i^{\alpha}\hat{x}_i^{\beta-1}\right) H_j^T}{\sum_{i=1}^{I} diag(q_{ij})\left(\hat{x}_i^{\alpha+\beta-1}\right) H_j^T}$$

7. **update** **H**

$$H_j \leftarrow H_j \otimes \frac{\sum_{i=1}^{I} diag(q_{ij}) W_j^T\left(x_i^{\alpha}\hat{x}_i^{\beta-1}\right)}{\sum_{i=1}^{I} diag(q_{ij}) W_j^T\left(\hat{x}_i^{\alpha+\beta-1}\right)}$$

8. **until** a stopping criterion is met /* convergence condition */

9.**End**

5. SOURCE SEPARATION EVALUATION CRITERIA

In order to evaluate our multichannel NMF algorithms in terms of audio source separation we use the signal-to-distortion ratio (SDR) numerical criterion defined in [19], which essentially compares the reconstructed source images with the original ones and it define as:

$$SDR = 10\log_{10}\frac{\|\hat{s}_{target}\|^2}{\|e_{interf} + e_{noise} + e_{artif}\|^2} \quad (24)$$

$$SIR = 10\log_{10}\frac{\|\hat{s}_{target}\|^2}{\|e_{interf}\|^2} \quad (25)$$

where $\hat{s}_{target}$ is the desired target signal e_{interf} is the sum of interfering signals, e_{noise} is the known noise signal .

Before going to the experiments section we mention important note about K, is how can determine it. We can use any method of clustering such as Model-Based Clustering or Finding Clusters [5], so the problem of partitioning can be viewed as a clustering problem with unknown number of clusters, which is a typical machine learning problem.

6. RESULTS AND ANALYSIS

6.1 Experiment Setup

Several experimental simulations under different conditions have been designed to investigate the efficacy of the proposed method. To generate mixed signal, we have analyzed a 10s synthetic (instantaneous and convolutive) and live-recorded (convolutive) stereo mixtures of speech and music sources.

The mixed signal is sampled at 16–kHz sampling rate ,in which these signals are selected from the [9] database. The instantaneous mixing is characterized by static positive gains. The synthetic convolutive filters were generated with the Roomsim toolbox [3]. In all cases, the sources are mixed with equal average power over the duration of the signals. The TF representation is computed by normalizing the time-domain signal to unit power and computing the STFT using 2048 point Hanning window FFT with 50% overlap. We have evaluated our separation performance in terms of the SDR and SIR which are forms of perceptual measure. MATLAB routines for computing these criteria are obtained from the SiSEC'08 webpage [12].Also to determine the number of partitions K we used ***k–means*** algorithm and We can use the ***cophenetic correlation coefficient*** or ***silhouette statistic*** as a measure of estimating the number of groups in a data set.

6.2 Example 1

In this example we compare our algorithm $\alpha\beta$-NMF with IS-NMF.The audio source separation results are shown. In particular, Figures 3 and 4 show the separated sources in terms of spectrogram and time-domain representation, respectively. Panels (G)–(L) in both Figures 3 and 4 clearly show that better source separation results. In the case of IS-NMF factorization [e.g., (D)-(F)], the factorization still contains the mixed components (as indicated by the red box marked area).

The overall comparison results between $\alpha\beta$-NMF and IS-NMF have been summarized in Table1.According to the table, first in the convolutive case: $\alpha\beta$-NMF tends to yield better result than the IS-NMF. We may summarize the average performance improvement of our method against the IS-NMF: 1) For Live recording, the improvement per source in terms of the SDR is 1.8 dB, and SIR 2.2 dB. 2) For Synthconv, the improvement per source in terms of SDR is 2 dB, SIR 1.1 dB. 3) For male4, SDR is 0.7dB and SIR is 0.5dB.

Second in the instantaneous case: also $\alpha\beta$-NMF is better than IS-NMF in which SDR and SIR for $\alpha\beta$-NMF is higher than SDR and SIR for IS-NMF as illustrated in the second part of Table 1

Table 1: Comparison between IS-NMF and $\alpha\beta$-NMF in Convolution case.

	Source	SDR		SIR	
		$\alpha\beta$-NMF	IS-NMF	$\alpha\beta$-NMF	IS- NMF
Convolution	Live	11.945	10.142	11.6	9.4
	Synthconv	9.145	7.255	9.5	7.4
		8.438	6.517	9.8	7.1
	male4	6.316	5.649	8.1	7.8
		6.094	5.198	7.3	6.8
Instantaneous	female4	12.072	6.732	10.2	8.2
		7.221	5.598	10.8	9.5
	Sunrise	15.326	10.009	11.0	9.0
		11.012	8.732	8.5	7.0
	Nodrums	12.6884	9.7613	9.8	8.8
		13.6523	11.7545	12.9	10.3

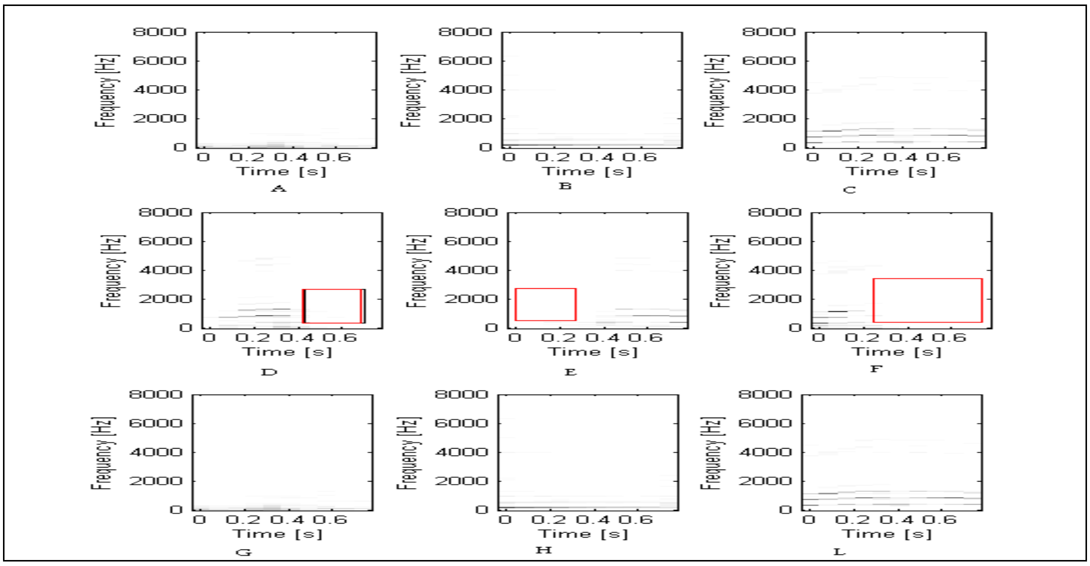

Fig 3: : Separated sources in terms of spectrogram representation for (1) $\alpha\beta$ -NMF(D,E,F) . (2) IS-NMF (G,H,L).

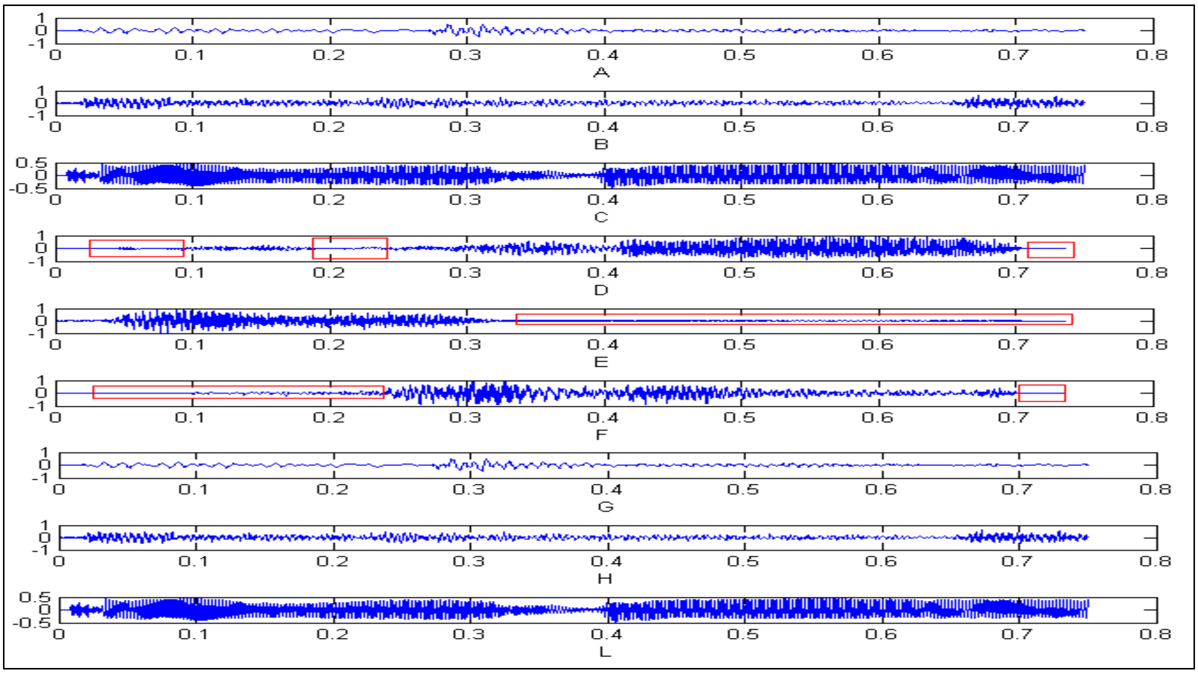

Fig 4 : Separated sources in terms of time-domain representation for (1) $\alpha\beta$ -NMF (D, E, F). (2) IS-NMF (G, H, L).

7. CONCLUSION

This paper has addressed a novel NMF algorithm based on $\alpha\beta$-divergence for the representation of underdetermine multichannel and noisy convolutive mixing assumptions signal ,since $\alpha\beta$-divergence has many properties that can deal with noise and outliers and also it may be consider as generalization for many divergences such as alpha, beta and Itakura-Saito. In final we applied our algorithm to source separation in various settings, covering blind and supervised separation, music and speech sources, synthetic instantaneous and convolutive mixtures. In which we compare our algorithm with IS-NMF and we show from the experimental that our algorithm is better than IS-NMF in various setting.

8. ACKNOWLEDGMENTS
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