A NEW EM ALGORITHM FOR UNDERDETERMINED CONVOLUTIVE BLIND SOURCE SEPARATION

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ABSTRACT

This paper presents a new statistical method for separating more than two sound sources from a two channels recording. It is based on the probabilistic model of the Interchannel Level/Phase Difference presented in [1] and an Expectation-Maximization algorithm for finding the maximum likelihood parameters of that model. Source separation is performed by soft time-frequency masking of the observation. These masks are derived from the estimated source position model. Algorithm performance is evaluated on the real and synthetic convolutive mixtures data of the first audio source evaluation campaign [2] as well as the Signal Separation Evaluation campaign (SiSEC) [10]. Promising results are obtained when comparing to the other methods presented in these two campaigns.

1. INTRODUCTION

Blind Source Separation (BSS) is a widely used technique that aims at recovering a set of N original sources based only on their M observed mixtures. This task is more difficult when the mixing model is not instantaneous but convolutive and gets even harder in the underdetermined case ($N > M$). Indeed, when N is larger than M, no algebraic linear solution can be found to separate the sources, even if the mixing matrix is identified. Still, with the source sparseness assumption, researchers have found a way to build non linear masks for the separation task.

Most of the BSS methods that consider the sparseness assumption deal with the two channels observation case from which cues or features like Interchannel Level/Phase Difference (ILD/IPD) are used. In [3] a KMeans algorithm classifies these features in clusters and binary separating masks are estimated. In [4], rather than clustering the observed (ILD/IPD), the authors propose to model these features as Gaussian variables with the assumption of a dominant path. Then, after estimating the parameters model, soft separating masks have been derived. Nevertheless, in real-world situations, the underlying linear phase assumption deriving from the dominant path hypothesis is found to be not applicable due to early reflections and reverberation. Also, the proposed Gaussian model is ad-hoc to which no theoretical background explanation was given.

In this paper a Model Based Underdetermined (blind) Source Separation (MBUSS) is considered. In our previous work [1] a theoretical distribution model for the (log(ILD)/IPD) feature is presented, but no separation algorithm based on this model have been explicitly provided. This paper, shows how to estimate this theoretical distribution parameter by an Expectation-Maximization procedure where the Maximization step is speeded-up by a Quasi-Newton algorithm. Unlike [3], probabilistic soft masks are computed instead of binary ones, thus less distortion and

artifact are heard in the extracted sources. Unlike [4], separation is performed independently in each frequency band, therefore no linear phase assumption is made and wide band sources can be extracted even with the presence of frequency aliasing. Of course separating independently in each frequency band has the traditional permutation problem drawback. This permutation alignment is corrected using the ratio envelope of the extracted sources as in [5].

2. MODEL BASED SOURCE SEPARATION

We describe here briefly the (log(ILD)/IPD) probabilistic model that will be used in the separation task. For more detailed analysis, please refer to [1]. Consider the convolutive two channels mixture model:

$$x_j(t) = \sum_{i=1}^{N} x_j^{(i)}(t) = \sum_{i=1}^{N} \sum_k a_{ji}(k) s_i(t-k) \qquad (1)$$

where $x_j^{(i)}(t)$ is the contribution of the ith source to the jth sensor. $s_i(t), i = 1, .., N$ are the sources and $a_{ji}(k)$ is the impulse response of the reverbarating channel separating source i from microphone j with $j = 1, 2$. The time-domain observed signals $x_j(t)$ are converted into frequency-domain time-series signals using the Short-Time Fourier Transform (STFT):

$$X_j(t, \omega) = \sum_{k=0}^{L-1} w(k) x_j(t+k) e^{-j\omega k} = \sum_{i=1}^{N} X_j^{(i)}(t, \omega) \qquad (2)$$

where $w(k)$ is a window (e.g. Hanning) and $X_j^{(i)}(t, \omega)$ is the STFT of $x_j^{(i)}(t)$. Sparseness of the sources in the Time Frequency (TF) domain is the key assumption in solving the underdetermined separation problem. More precisely, it is the window disjoint orthogonality assumption between the sources TF supports that has been used [3]. Consequently, for each TF slot, there can be at most one dominant source. If q is the index of this dominant source at (t, ω), then the jth observation in eq.(2) can be approximated to $X_j(t, \omega) \approx X_j^{(q)}(t, \omega)$ and the ratio between the two observations at (t, ω) will then be:

$$R(t, \omega) = \frac{X_1(t, \omega)}{X_2(t, \omega)} = \frac{\sum_{i=1}^{N} X_1^{(i)}(t, \omega)}{\sum_{i=1}^{N} X_2^{(i)}(t, \omega)} \approx \frac{X_1^{(q)}(t, \omega)}{X_2^{(q)}(t, \omega)}. \qquad (3)$$

The approximation $X_j^{(i)}(t, \omega) \approx A_{ji}(\omega) S_i(t, \omega)$, with $A_{ji}(\omega)$ as the Fourier transform of $a_{ji}(k)$, can be found in most of the TF source separation methods. It derives from the fact that convolution in time is transformed to product in

the frequency domain. With it, the last term in (3) can be reduced to a constant in each frequency band ω and thus:

$$R(t,\omega) = \frac{X_1(t,\omega)}{X_2(t,\omega)} \approx \frac{X_1^{(q)}(t,\omega)}{X_2^{(q)}(t,\omega)} \approx \frac{A_{1q}(\omega)}{A_{2q}(\omega)}. \quad (4)$$

Being frequency and source dependent (but time independent), this ratio has been widely used as dominant source indicator in the TF binary masks approach. In [3], the modulus and argument of $R(t,\omega)$, no other than the traditional Interchannel Level Difference (ILD) and Interchannel Phase Difference (IPD), has been clustered by a KMeans algorithm. The cluster members define the binary separating mask and the cluster centers gives an estimation of $A_{1q}(\omega)/A_{2q}(\omega)$. But does the above approximation (4) holds when dealing with a long tap impulse response, i.e reverberating environment?

2.1 One source Ratio STFT distribution model

To simplify the notations in this section, we will omit the ω parameter. From now, we implicitly work at a fix frequency band ω. It has been demonstrated in [1] that, even if one source is observed, $R(t)$ is not constant in time. Fig.1 plots the real and imaginary part of $R(t)$ for a 10-sec speech source placed in a moderate reverberant conditions ($T_{60} = 250$ms). Noting this variation, we propose to model the one source observed log ratio, $\log R^{(q)}(t) = \log[X_1^{(q)}(t,\omega)/X_2^{(q)}(t,\omega)]$, as a random variable and estimate the joint density of its real and imaginary part (x,y) where:

$$
\begin{aligned}
x &= \Re[\log R^{(q)}(t)] = \log|R^{(q)}(t)| = \log \mathrm{ILD}_q \\
y &= \Im[\log R^{(q)}(t)] = \arg R^{(q)}(t) = \mathrm{IPD}_q
\end{aligned}
$$

with ILD_q and IPD_q as the ILD and IPD of s_q. Note that we did not model the traditional feature $R^{(q)}(t)$ because it admits an infinite variance (see [1]). To estimate the joint density of (x,y), we assume that L is large enough so that, by the Central Limit Theorem, the pair $X_1^{(q)}(t)$ and $X_2^{(q)}(t)$ can be considered as Gaussian (complex circular) [1] with variance $\sigma_{1,q}^2(t)$ and $\sigma_{2,q}^2(t)$ and complex cross correlation β_q. It has been demonstrated in [1] that the variance ratio $\sigma_{1,q}/\sigma_{2,q}$ and β_q does not vary in time and thus may be used to model $\log R^{(q)}(t)$. Based on the complex gaussian circular assumption,the variables couple (x,y) will admits the following joint density [1]:

$$
\begin{aligned}
&p\left(x,y|r_q,\rho_q\right) = \\
&\frac{1}{4\pi} \frac{1-\rho_q^2}{\left[\cosh\left(x - \log|r_q|\right)\right) - \rho\cos\left(y - \arg r_q\right)\right]^2}. \quad (5)
\end{aligned}
$$

where $r_q = (\sigma_{1,q}/\sigma_{2,q})e^{i\arg\beta_q}$ and $\rho_q = |\beta_q|$. r_q and ρ_q are specific parameters to the source s_q position in space. Note that the source position is modeled and not the source it self. Thus, this "'space"' position model can be applied independently from the source model (gaussian, laplacian, ...). More in details, r_q corresponds to the mean of $\log R^{(q)}(t)$ and thus depends only on the source position in space where $|r_q|$ is equal to the ILD_q and $\arg(r_q)$ is equal to the IPD_q. As for ρ_q, it will stand for the reverberation degree of the acoustic path separating s_q from the set of microphones. This can be viewed from its definition as the modulus of the cross correlation between the two observations where high reverberation causes low cross correlation between microphones and vis versa. For example, in free field conditions, i.e anechoic environment, the cross correlation is maximum and $\rho_q = 1$.
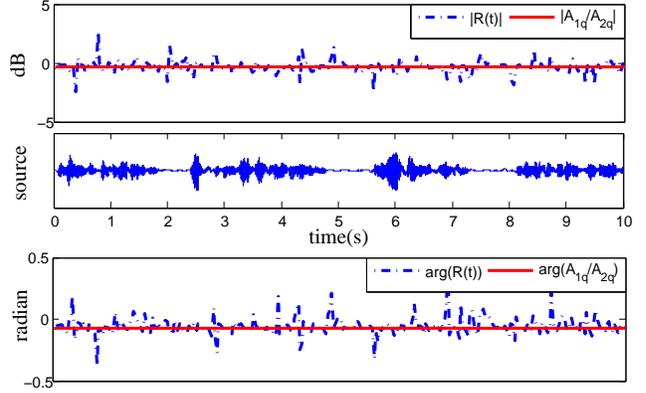

Figure 1: Ideal and observed (IPD,ILD) for one observed source at the frequency 100Hz

2.2 Mixture ratio STFT distribution model

Having the one source log ratio distribution model (5) and under the disjoint assumption, we are led to assume the following distribution model for the real and imaginary parts of the observed log ratio $\log[R(t,\omega)]$:

$$p\left(x,y|\boldsymbol{\rho},\boldsymbol{r},\boldsymbol{\mu}\right) = \sum_{i=1}^{N} \mu_i p_{\rho_i}\left\{x - \log|r_i|, y - \arg r_i\right\}. \quad (6)$$

This model is given at the frequency ω for the set of considered time points $t \in T$ with $\boldsymbol{\rho} = [\rho_1,..,\rho_N]$, $\boldsymbol{r} = [r_1,..,r_N]$ and $\boldsymbol{\mu} = [\mu_1,..,\mu_N]$ where μ_i is an added parameter that denotes the *a priori* probability of the ith source in the considered frequency band. Note that $\boldsymbol{\rho}$, $\boldsymbol{r}$ and $\boldsymbol{\mu}$ depend on frequency ω and will be the paremeter defining the source position model.

2.3 Soft mask separation

If somehow, the parameters of the probabilistic model given in (6) are estimated, the *a posteriori* probability that i^{th} source is dominant at the TF point (t,ω) can be obtained directly by the following:

$$\pi_i\left(t\right) = \frac{\mu_i p_{\rho_i}\left[\log|R_i(t)|, \arg R_i(t)\right]}{\sum_{q=1}^{N} \mu_q p_{\rho_q}\left[\log|R_q(t)|, \arg R_q(t)\right]} \quad (7)$$

where $R_i(t) = R(t)/r_i$. Then, source separation can be easily performed in each frequency band ω by applying these above probabilities to the observations. Note that sources are independently separated in each frequency band, thus permutation ambiguity remains and needs to be solved. In this paper, the correlation between the ratio envelope is used as in [5]. Note that other methods, based on linear phase assumption [6], can not be used due to reverberation. Fig. 2 shows the flow of the Model Based Source Separation approach where $M_i(t,\omega)$ refer to the masks that extract the ith source. $M_i(t,\omega)$ is constructed from the *a posteriori* probabilities (7) with $M_i(t,\omega) = \pi_{\Pi_\omega(i)}$ with $\Pi_\omega = [\Pi_\omega(1),\ldots,\Pi_\omega(N)]$ the permutation vector alignment solved by [5] in the frequency band ω.

As said before, to construct the soft separating mask, the model parameters μ_i, r_i, and ρ_i need to be estimated for each source at each frequency band ω. To do so, we propose to use as criterion the maximum of the log-likelihood of the data $\{\log|R(t)|, \arg R(t)\}, t \in T$. Under the independence
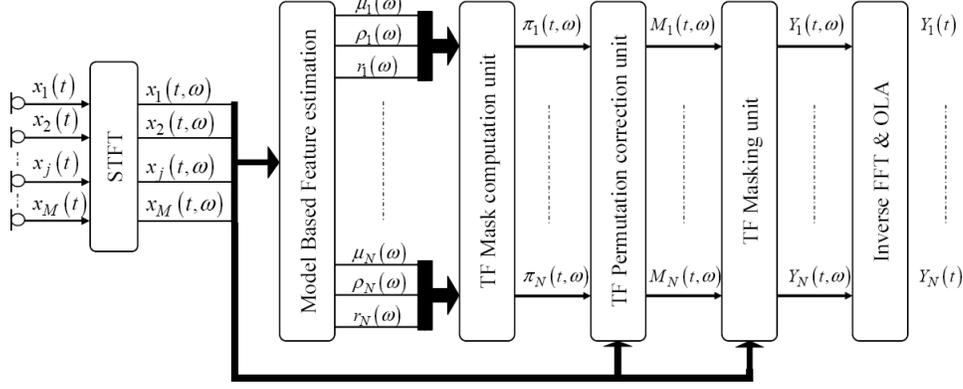
Figure 2: Basic scheme of Model Based Source Separation Approach

assumption between the time set of observations, it is given by:

$$L(\boldsymbol{\rho}, \boldsymbol{r}, \boldsymbol{\mu}) = \sum_{t \in T} \log \left\{ \sum_{i=1}^{N} \pi_i p_{\rho_i} [\log |R_i(t)|, \arg R_i(t)] \right\}. \quad (8)$$

The above log-likelihood is hard to maximize. However, it may be recasted as the log-likelihood for a model with missing observations or hidden variables. These variables are the indexes that indicate which source is dominant at each (t, ω) point (here ω is fixed and hence not displayed). In this context the log-likelihood can be maximized by the well known Expectation Maximization (EM) algorithm [7].

3. THE EM ALGORITHM

This algorithm operates in two steps as described below.

3.1 The E-step

This step computes the conditional expectation of the full log-likelihood given the data $\{\log |R(t)|, \arg R(t)\}, t \in T$. The expected log-likelihood will be computed at generic new parameters μ'_i, r'_i and ρ'_i and the conditional expectation is computed relatively to the model specified by the current old parameter μ_i, r_i and ρ_i. The result can be shown to be:

$$\sum_{t \in T} \sum_{i=1}^{N} \pi_i(t) \log \left\{ \mu'_i p_{\rho'_i} \left[\log \left| \frac{R(t)}{r'_i} \right|, \arg \frac{R(t)}{r'_i} \right] \right\} \quad (9)$$

where $\pi_i(t)$ is the *a posteriori* probability given in (7) and computed at the current old parameter μ_i, r_i and ρ_i.

3.2 The M-step

This step maximizes the above conditional expectation of the full log-likelihood with respect to the generic parameters μ'_i, r'_i and ρ'_i. The maximum point is then taken as the new parameter. It is easily seen that the maximization of (9) with respect to μ'_i (under the constraint $\sum_{i=1}^{N} \mu'_i = 1$) and with respect to the set (r'_i, ρ'_i) can be performed independently. The first maximization yields the new μ_i: $\mu_i = \sum_{t \in T} [\pi_i(t)]/|T|$ where $|T|$ denotes the number of points in T. The second one is reduced to the maximization of:

$$C(r'_i, \rho'_i) = \sum_{t \in T} \pi_i(t) \log p_{\rho'_i} \left[\log \left| \frac{R(t)}{r'_i} \right|, \arg \frac{R(t)}{r'_i} \right] \quad (10)$$

for each $i = 1, .., N$ with respect to r'_i and ρ'_i.

3.3 Relaxing the M-step

Maximizing the above expression (10) is not easy and can not be done without using an iterative algorithm. In [8], we overcome this problem by replacing the theoretical density (5) in (10) with another similar and easier one to handle. Thus, we were able to maximize it analytically. In this work, as the theoretical density shall be used, we propose not to maximize the expected full log-likelihood (10) but to just make it *increase*. In fact, from the EM algorithm theory, *increasing* the expected likelihood (10) would be sufficient to increase, also, the marginal likelihood (8). Therefore, given the current *old* parameters r_i and ρ_i, we limit ourselves to finding the new parameters r'_i and ρ'_i that increases the objective function (10). Such new parameters can indeed be found *analytically* as described in the following basic step:

3.3.1 Basic step

It can be easily proved, by the Jensen's inequality, that $C(r'_i, \rho'_i) - C(r_i, \rho_i)$ can be bounded below by

$$-2\zeta \log \sum_t \frac{w_i(t) \{\cosh[\xi_i(t) - \lambda_i] - \rho'_i \cos[\phi_i(t) - \theta_i]\}}{\zeta (1 - \rho'^2_i)^{1/2}/(1 - \rho^2_i)^{1/2}} \quad (11)$$

where

$$w_i(t) = \frac{\pi_i(t)}{\cosh[\log |R_i(t)|] - \rho \cos[\arg R_i(t)]}$$
$$= \frac{2|R_i(t)|\pi_i(t)}{|R_i(t)|^2 + 1 - 2\rho \Re[R_i(t)]}$$

and $\zeta = \sum_u \pi_i(u)$, $\xi_i(t) = \log |R_i(t)|$, $\lambda_i = \log |r'_i/r_i|$, $\phi_i(t) = \arg R_i(t)$, $\theta_i = \arg(r'_i/r_i)$ and $\Re(z)$ is the real part of the complex number z. The maximum of the above equation (11), with respect to (r'_i, ρ'_i), is strictly larger than zero (because it is equal to zero when $(r'_i, \rho'_i) = (r_i, \rho_i)$). Thus, the new couple (r'_i, ρ'_i) that maximizes (11) will increase, at the same time, the objective function (10). Therefore, by a simple variable substitution, the problem of increasing the likelihood is now reduced to maximize (11) with respect to $\theta_i, \lambda_i, \rho'_i$. By developing the numerator terms $\cosh[\xi_i(t) - \lambda_i]$ and $\cos[\phi_i(t) - \theta_i]$, the maximum is obtained when

$$\lambda_i = \tanh^{-1} \frac{\sum_t w_i(t) \sinh \xi_i(t)}{\sum_t w_i(t) \cosh \xi_i(t)}$$

$$\theta_i = \arg \sum_t w_i(t) \text{sign} \{R_i(t)\}$$

$$\rho'^2_i = \frac{[\sum_t w_i(t) \cos \phi_i(t)]^2 + [\sum_t w_i(t) \sin \phi_i(t)]^2}{[\sum_t w_i(t) \cosh \xi_i(t)]^2 - [\sum_t w_i(t) \sinh \xi_i(t)]^2}$$

where sign of (z) is $z/|z| = e^{i \arg z}$. Finally, to increase (10), we are led to assume the following *one* iteration basic step:

$$r_i \leftarrow r_i \sqrt{a_i/b_i} \text{ sign } c_i, \qquad \rho_i \leftarrow |c_i|/\sqrt{a_i b_i}$$

where $a_i = \sum_t \chi_i(t)|R_i(t)|^2$, $b_i = \sum_t \chi_i(t)$, and $c_i = \sum_t \chi_i(t)R_i(t)$ with $\chi_i(t) = \frac{1}{2}w_i(t)/|R_i(t)|$.

3.3.2 Combining with the Quasi Newton step

The basic step could lead to a slower convergence of the algorithm as the obtained increase of the expected log-likelihood (10) can be much less than the maximum achievable. To overcome this problem we will consider a Quasi-Newton (Q-N) algorithm. In fact, when the old parameter r_i and ρ_i are close to the maximum solution of (10), the Quasi-Newton algorithm would have a quadratic convergence to the point maximizing (10). Therefore, the algorithm should converge within one single Q-N iteration. However, in contrast to the basic step, the Q-N step does not guarantee the increase of the expected log-likelihood. It does not even guarantee the new ρ'_i to be in the interval (0,1). Thus, the following strategy is adopted in the M-step:

- Compute the new parameter ρ'_i and r'_i based on the basic step as in section 3.3.1
- Compute the other new estimation of $\hat{\rho}'_i$ of the Q-N step and test if it belongs to the interval (0,1)
- If not, adopt the new parameter ρ'_i and r'_i of the basic step, otherwise compute the other new parameter $\hat{r}'_i$ of the Q-N step and test if it and $\hat{\rho}'_i$ of the Q-N step lead to a larger increase of the expected log-likelihood than the basic step; if so, adopt these parameter $\hat{r}'_i$ and $\hat{\rho}'_i$ otherwise adopt those of the basic step ρ'_i and r'_i.

Computations (not detailed here) show that the Q-N step is given by:

$$\hat{\rho}'_i = \rho_i - \frac{\rho_i(a_i + b_i) - 2\Re(c_i)}{\sum_t \chi^2(t)\{[|R_i(t)|^2 + 1]^2 - 4\Re[R_i(t)]^2\}/\pi_i(t)}$$
$$\hat{r}'_i = r_i \exp[(3/2)(a_i + b_i)/(a_i - b_i)]\text{sign}[3c_i - \Re(c_i)]$$

Note that these formula involve the already computed quantities a_i, b_i, c_i.

3.4 EM Initialization and Stop Criteria

A simple way to initialize our algorithm is to choose randomly N times points $t_1, .., t_N$ and initialize r_i by $r_i = R(t_i)$, $i = 1..N$. The *a posteriori* probability $\pi_i(t)$ can be initialized by formula (7) using the density (5) with ρ_i set to one, leading to:

$$\pi_i(t) = \frac{d[R(t), r_i]}{\sum_{i=1}^{N} d[R(t), r_i]}$$

where $d[R(t), r_i] = \cosh \log [R(t)/r_i] - \cos \arg [R(t)/r_i]$. Since the log-likelihood increases monotonically at each EM iteration, the EM iteration process is stopped when the increase of log-likelihood becomes insignificant(e.g 10^{-6}).

4. EXPERIMENTS AND RESULTS

In order to evaluate our algorithm, we simulated speech and music mixtures in a reverberant noise-free environment by convolving speech and music samples with filter impulse responses coming from the first audio source separation campaign [2]. Also, it was recently tested in the Signal Separation Evaluation Campaign (SiSEC) [10] where results showed that our algorithm compares favorably with the others presented in this campaign in most of the real and synthetic convolutive situation. As these results can be accessed at [10], only the results for the first audio source separation

campaign will be presented. Signals are 16 kHz-sampled and have a 10s duration. Four types of mixtures were generated: 4 female speakers, 4 male speakers, 3 musics with one of them as drums and 3 other musics (no drums). Two different sets of source positions are used, one for speech and another from music mixtures. Angles and distances of these position are given in the Table 2. Our algorithm uses Hanning windowed 2048 samples frames, and reconstruction is achieved using the overlap and add method with 75% overlap.

	Speech Sources				Music Sources		
	S1	S2	S3	S4	M1	M2	M3
Distance (m)	1,2	1,1	1	0,8	1,1	0,9	1
Angle (deg)	50	-15	-45	15	45	-30	5

Table 2: Sources position from the set of microphone

4.1 Comparison Algorithm and performance measurement

The proposed algorithm is compared with two other algorithms: The first one is our previous method based on the same model-based EM approach, but with a simplifying probability distribution of the model [8]. The second one is the KMeans underdetermined source separation presented in [3], in which the ILD/IPD observations are grouped into N clusters using a KMeans algorithm: each cluster center gives an estimation of the mixing matrix and the cluster point sets give the binary TF separating masks. The separation performance was evaluated for each estimated source i by the same criteria used in SiSEC. That is, Signal to Interference Ratio (SIR_i), Image to Signal Ratio (ISR_i), Signal to Distortion Ratio (SDR_i) and Signal to Artifact Ratio (SAR_i). For a detailed analysis on how to compute the reader may refer to [10].

4.2 Results

Detailed performance are given in Table 1 whereas the mean of each case and the overall performance (OVAP) are plotted in Figure 3. When looking to the OVAP, in terms of SDR which computes the global separation performance, the proposed MBUSS gives the best results as compared to the others. It shows a slight advantage for the new MBUSS 3.61dB compared to the old one 3.5dB and a more efficient compared to KMeans 3.42dB. Furthermore, the intermediate errors shows that the compromise operated by the algorithms is different.

Comparing the new MBUSS to the old one, results show that the proposed algorithm gives better results in terms of SAR (SAR=8.05 and 7.19 respectively) and, almost, the same in terms of SIR (SIR=7.04 and 7.27 respectively). We believe that using the theoretical distribution and not the approximated one as in [8] has caused this boost in the artifact distortion. Comparing the new MBUSS to the KMeans, Fig. 3 (a),(b) and (c) shows that the MBUSS method performances better for speech mixture than music one. It is caused by the nature of musics spectrogram that is more sharp than speech. Thus, hard masking would be more suitable for this type of mixture than soft ones. But, when looking to the OVAP at Fig. 3 (d), the KMeans algorithm favors weak interferences (SIR=8.34) to the cost of more degraded separated speech (SAR=7.22), in contrast to our method that presents stronger interference (SIR=7.04) but with a clearer separated speech signal (SAR=8.05).

These results are confirmed by informal listening tests: less audible artifact are noticed in the proposed MBUSS, at the expense of more interference, which reveals more pleasant to our auditory system which is highly sensitive to artifact (gurgling noise) than to interference. One explanation

		4 Men Speech					4 Women Speech					3 Music, No drums				3 Music, with drums				OVAP
		S1	S2	S3	S4	Mean	S1	S2	S3	S4	Mean	S1	S2	S3	Mean	S1	S2	S3	Mean	
new MBUSS	SDR	3,91	2,68	3,71	4,17	3,61	4,46	3,40	4,37	5,27	4,37	2,42	5,80	4,81	4,34	1,65	3,49	0,35	1,83	3,61
	ISR	6,17	5,99	6,52	6,87	6,39	6,58	7,28	7,07	7,52	7,11	4,27	8,61	8,61	7,16	1,76	6,38	0,40	2,85	6,00
	SIR	5,75	2,62	5,37	6,89	5,16	6,75	3,45	6,77	10,13	6,78	4,07	8,80	6,57	6,48	13,38	6,15	11,88	10,47	7,04
	SAR	6,21	5,52	6,19	6,08	6,00	7,78	7,44	6,82	7,72	7,44	5,50	11,24	8,96	8,56	15,90	9,73	7,56	11,06	8,05
old MBUSS [8]	SDR	3,25	1,97	3,69	4,11	3,25	4,43	3,84	4,44	5,50	4,55	1,69	5,87	5,19	4,25	1,64	3,02	0,34	1,67	3,50
	ISR	6,14	4,17	6,87	7,21	6,10	6,34	8,03	7,89	8,65	7,73	4,31	8,30	10,50	7,70	1,80	7,16	0,42	3,12	6,27
	SIR	3,73	2,21	5,20	6,27	4,35	8,45	5,35	7,24	9,53	7,64	3,15	9,78	7,15	6,69	14,85	6,94	11,94	11,24	7,27
	SAR	5,99	5,04	6,25	6,17	5,86	6,78	6,95	6,68	7,29	6,93	5,60	11,26	9,00	8,62	11,59	6,09	6,01	7,89	7,19
Kmeans [3]	SDR	3,50	2,24	3,16	3,57	3,12	4,03	3,10	3,77	5,22	4,03	1,82	5,58	5,15	4,19	1,72	4,62	0,36	2,23	3,42
	ISR	7,64	5,90	7,38	8,65	7,39	6,16	10,55	9,20	10,06	8,99	5,29	8,00	10,28	7,86	1,82	8,75	0,42	3,66	7,15
	SIR	7,01	4,62	6,36	7,08	6,27	12,51	5,52	8,04	9,81	8,97	4,13	8,49	7,05	6,55	14,73	7,77	13,68	12,06	8,34
	SAR	4,58	2,40	4,24	4,54	3,94	4,69	5,65	5,53	6,31	5,54	7,34	11,27	9,68	9,43	16,26	10,92	7,75	11,64	7,22

Table 1: Results for synthetic recording with a 5 cm microphone spacing and two different types of sources: speech and music. the overall performance (OVAP) of the source separation is presented in the last column. SDR,ISR,SIR and SAR are given in dB
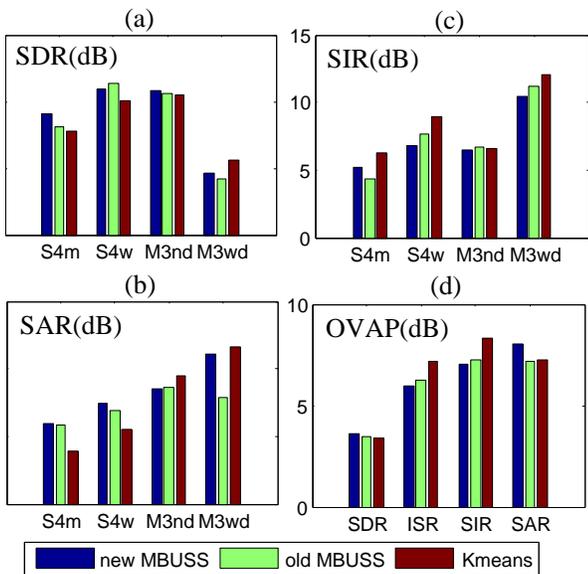

Figure 3: (a),(b),(c) presents respectively the SDR, SAR and SIR performance for each type of mixture; (d) presents the OVAP

(partially) lies in the nature of the mask: as compared to the binary mask used in the KMeans method, the soft mask slightly smooths the output, limiting the isolated errors (the artifact like musical noise), but favoring the presence of interference. Note that the mask is used "as is": we are inclined to think that some "wise" smoothing (linear or nonlinear) could give better objective and subjective results, reducing even more the artifact.

5. CONCLUSION

In this paper, a new method to solve the underdetermined blind separation of audio mixtures problem has been presented. It is based on the sparseness assumption and on a theoretical model for the interchannel cues (log(ILD),IPD) given in [1]. By an EM algorithm, we were able to estimate the parameters of this model and then build the time frequency separating masks. The algorithm demonstrated its ability to separate undetermined reverberant mixtures, in terms of objective criteria and to give the best results in terms of artifact and distortion. Nevertheless, more studies need to be done, especially on the robustness of the model over the source positions and room reverberation.

REFERENCES

[1] A. Pham, Z. El-Chami, C. Serviere, and A. Guerin, "Modeling the short time fourier transform ratio and application to underdetermined audio source separation,"in *ICA 2009*, Brazil.

[2] E. Vincent, H. Sawada, P. Bofill, S. Makino, and J.P. Rosca, "First stereo audio source separation evaluation campaign: data, algorithms and results,"*ICA 2007*, UK.

[3] S. Araki, H. Sawada and S. Makino (2007). "K-means Based Underdetermined Blind Speech Separation."In *Blind Speech Separation*: 243–270. S. Makino, Te-Won Lee and H. Sawada Editors, Springer: New-York.

[4] Michael I. Mandel, Daniel P. W. Ellis, "Em localization and separation using interaural level and phase cues," *WASPAA 2007*, Japan.

[5] H. Sawada, S. Araki, S. Makino, "Measuring Dependence of Bin-wise Separated Signals for Permutation Alignment in Frequency-domain BSS,"ISCAS 2007, USA

[6] F. Nesta, M. Omologo, and P. Svaizer, "A novel robust solution to the permutation problem based on a joint multiple tdoa estimation "*IWAENC 2008*, USA.

[7] A.P. Dempster, N.M. Laird, and D.B. Rubin, "Maximum likelihood from incomplete data via the em algorithm,"*Journal of the Royal Statistical Society. Series B*, vol. 39, no. 1, pp. 1–38, 1977.

[8] Z. El-Chami, D.-T. Pham, Ch. Servière and A. Guérin, "A New-Model Based Underdetermined Source Separation,"*IWAENC 2008*, USA.

[9] http://sassec.gforge.inria.fr/

[10] http://sisec.wiki.irisa.fr/tiki-index.php