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A COMPRESSED SENSING APPROACH TO THE SIMULTANEOUS RECORDING OF MULTIPLE ROOM IMPULSE RESPONSES

Alexis Benichoux
Université Rennes 1, IRISA - UMR6074
Campus de Beaulieu 35042 Rennes, FR
alexis.benichoux@irisa.fr

Emmanuel Vincent, Rémi Gribonval
INRIA, Centre de Rennes - Bretagne Atlantique
Campus de Beaulieu 35042 Rennes, FR
{emmanuel.vincent, remi.gribonval}@inria.fr

ABSTRACT

We consider the estimation of multiple room impulse responses from the simultaneous recording of several known sources. Existing techniques are restricted to the case where the number of sources is at most equal to the number of sensors. We relax this assumption in the context of convolutive source separation [3]. To this aim, we propose statistical models of the filters associated with convex log-likelihoods, and we propose a convex optimization algorithm to solve the inverse problem with the resulting penalties. We provide a comparison between penalties via a set of experiments which shows that our method allows to speed up the recording process with a controlled quality tradeoff.

Index Terms— Room impulse response recording, convex optimization, compressed sensing

1. INTRODUCTION

We focus on the recording of multiple room impulse responses. Up to now this is typically achieved by activating each loudspeaker or source in turn, with a silent interval equal to the desired duration of the impulse response in between [1]. The total recording duration is then \( N(D + K - 1) \) where \( N \) is the number of sources, \( D \) the chirp duration and \( K \) the impulse response length in samples. An improvement [2] is to use time-overlapping but time-frequency disjoint chirps, which reduces the recording duration down to \( NK + D - 1 \) when the system is linear. These techniques remain time-consuming e.g. in the context of the calibration of high-end 3D audio systems or the collection of binaural room impulse responses involving hundreds of loudspeakers. We investigate here possible improvements using state-of-the-art system inversion tools. This problem is equivalent to the estimation of the mixing filters in the context of convolutive source separation [3].

The techniques in [4] and [3] for mixing filter estimation assume each source to be active alone in a certain time interval. This time interval has been localized, the corresponding filters are estimated using a subspace method [4], or convex optimization [3]. Alternative Convolutive Independent Component Analysis techniques [5] assume the number of sources to be at most equal to the number of sensors. Our work is to our knowledge the first to get rid of these two assumptions. We propose to take advantage of the a priori temporal structure of the filters to improve the iterative inversion of the linear system. In addition to the sparse prior introduced in [6] for single-source blind channel identification, we propose four new priors and a new multi-source inversion algorithm. Our approach is an example of compressed sensing [7][8], that is an emerging general approach to the recovery of structured signals from a smaller number of measurements. We show theoretically that white noise sources provide the most convenient system for inversion.

The structure of the paper is as follows. The formalization of the problem is described section 2. Section 3 corresponds to the study of the a priori structure of the filters. The implementation of the algorithm is detailed Section 4. The results shown in Section 5 show the potential of the proposed method.

2. APPROACH

The problem is formalized as follows: we represent the \( N \) sources of length \( T \) by the matrix \( S \in \mathbb{R}^{N \times T} \), the filters of length \( K \) by the three dimensional array \( A \in \mathbb{R}^{M \times N \times K} \) and the \( M \) observations by \( X \in \mathbb{R}^{M \times (T+K-1)} \). Assuming that the loudspeakers are linear, the convolutive matrix product \( \star \) allows us to write

\[
X = A \star S = \left( \sum_{n \leq N} A_{mn} \star S_n \right)_{m \leq M}.
\]

Earlier work [9] used convex optimization tools to recover \( S \) when \( A \) is known, using a sparsity prior on the sources.

We adapt the method in [9] to estimate \( A \) when \( S \) is known, by estimating \( \lim_{\lambda \to 0} A_{\lambda} \) where

\[
A_{\lambda} = \arg \min_A \left\{ \frac{1}{2} \| X - A \star S \|^2_2 + \lambda \mathcal{P}(A) \right\}.
\]

This limit is the solution of the constrained minimization problem

\[
\min_A \mathcal{P}(A) \quad \text{s.t.} \quad \| X - A \star S \|^2_2 = 0.
\]

We choose for \( \mathcal{P} \) the negative log-likelihood of a distribution suggested by the statistical analysis of a large family of filters.

3. STATISTICAL ANALYSIS OF A FAMILY OF FILTERS

The statistical theory of room acoustics [10] treats each filter as a random i.i.d. signal whose amplitude envelope \( \rho(t) \) decays exponentially according to

\[
\rho(t) = \sigma \sin^{-\frac{1}{4}} \frac{1}{t_{\text{IR}}},
\]

where \( t_{\text{IR}} \) is the room reverberation time in samples, and \( \sigma \) a scaling factor. This theory assumes that a filter \( A \in \mathbb{R}^K \) follows a Gaussian distribution. In other work [6], \( A(t) \) is instead assumed to have a constant amplitude envelope and to be sparse, as it is formed by
of both the envelope model and the sparsity model, we consider the
echoes at distinct instants. In order to evaluate the respective impact
of generated filters for a reverberation time of 250 ms.

Figure 1 compares the average negative log-likelihoods of these
four models over a set of 10 000 filters simulated by the image
method [11] for one source and one microphone at random positions
spaced by 1 m, in a rectangular room of dimensions 10 × 8 × 4 m
with t_{R} = 250 ms. For each model, the scaling factor \sigma is set in
the maximum likelihood sense. Envelope modeling appears to be
crucial: the likelihood of models \( P_{1} \) and \( P_{4} \) is much larger than
that of \( P_{1} \) and \( P_{2} \) for large \( t \). Sparsity has a weaker impact: the
likelihood of \( P_{2} \) (and to a lesser extent that of \( P_{2} \)) is larger than that
of \( P_{2} \) for \( t \leq 60 \) ms, but becomes similar for \( t > 60 \) ms. These
observations lead us to propose a fifth hybrid model

\[
P_{5}(t) = \begin{cases} P_{1}(t) & \text{if } t \leq 60 \text{ ms} \\
0 & \text{if } t > 60 \text{ ms.} \end{cases}
\]

Assuming Gaussian white additive noise, maximum
\textit{a posteriori} estimation of the filters is equivalent to (2) with
\( P_{i} = - \log P_{i} \).

4. ALGORITHM

To solve (2), we use the FISTA (Fast Iterative Shrinkage-
Thresholding) algorithm [12], which exploits the differentiability
of the data fidelity term

\[
\mathcal{L} : A \mapsto \| X - A * S \|^2_{2},
\]

and the convexity and semicontinuity of \( P_{i} \). So-called proximity
operators are employed to overcome the non-differentiability of \( P_{i} \).

**Definition 1** For \( P : E \mapsto \mathbb{R} \) semicontinuous and convex the proximity operator associated with \( P \) is the function

\[
\text{prox}_{P} : x \in E \mapsto \arg\min_{y \in E} \left\{ P(y) + \frac{1}{2} \| x - y \|^2 \right\}
\]

The general steps of FISTA are described in Algorithm 1. It relies
on the computation of the gradient of \( \mathcal{L} \), its Lipschitz constant \( L \),
and the proximity operator of the scaled penalty \( \alpha P \).

**Algorithm 1 FISTA**

1. \( A^{0} \in \mathbb{R}^{M \times N \times K} , \tau^{0} = 1 \)
2. for \( k \leq k_{\text{max}} \) do
   \[ \hat{A}^{k} = \text{prox}_{\alpha P} \left( \frac{A^{k-1}}{\tau} - \nabla \mathcal{L}(A^{k-1}) \right) \]
   \[ \tau^{k} = \frac{1 + \sqrt{1 + 4(\alpha/\tau^{k})^2}}{2} \]
   \[ A^{k} = \hat{A}^{k} + \frac{\tau^{k-1} - \tau^{k}}{\tau^{k}} (\hat{A}^{k} - \hat{A}^{k-1}) \]
3. end for

The computation of the gradient of \( \mathcal{L} \) requires the introduction of the adjoint of the linear operator \( A \mapsto A * S \). Denoting by \( S_{m} \in \mathbb{R}^{T} \) the time reversal of \( S_{m} \), i.e. for \( t \leq T \), \( S_{m}(t) = S_{m}(T-t+1) \), the adjoint operator is expressed using \( S^{*} = (S_{1}, \ldots, S_{N}) \) as

\[
X \mapsto X * S^{*} := \left( (S_{m} * X_{m})(t) \right)_{m \leq M, n \leq N, 1 \leq t \leq K}.
\]

One may then write the gradient as

\[
\nabla \mathcal{L}(A) = (X - A * S) * S^{*}.
\]

The Lipschitz constant of \( \nabla \mathcal{L} \) is the greatest eigenvalue of the operator \( A \mapsto A * S * S^{*} \). We obtain this value using the power iteration algorithm as in [9, Algorithm 5].

The log-likelihood of the distributions introduced previously
correspond to the \( \ell_{1} \) and \( \ell_{2} \) norms, whose proximity operators are
well-known [9]. Denoting \( x^{+} := \max(x, 0) \) for \( x \in \mathbb{R} \), we obtain

\[
\text{prox}_{\alpha P_{1}}(A)_{m,n,t} = \frac{\rho(t)A_{m,n}(t)}{\rho(t)A_{m,n}(t)} \left( |A_{m,n}(t)| - \frac{\alpha}{\rho(t)} \right)^{+}
\]

(13)

\[
\text{prox}_{\alpha P_{2}}(A)_{m,n,t} = \frac{A_{m,n}(t)}{1 + \alpha/\rho^{2}}
\]

(14)

\[
\text{prox}_{\alpha P_{3}}(A)_{m,n,t} = \frac{A_{m,n}(t)}{\|A_{m,n}(t)\|} \left( \|A_{m,n}(t)\| - \alpha \right)^{+}
\]

(15)

\[
\text{prox}_{\alpha P_{4}}(A)_{m,n,t} = \frac{A_{m,n}(t)}{1 + \alpha}. \quad (16)
\]

Concerning the hybrid model (9), we use (13) or (14) depending on the value of \( t \).

We estimate the minima \( A_{*} \) for \( \lambda \in \{ 1, 10^{-1}, \ldots, 10^{-14} \} \),
initializing each FISTA step at the minimum obtained for the previous
value. We keep the last minimum obtained for \( \lambda = 10^{-14} \),
and consider it as an estimate of the limit \( \lim_{\lambda \to 0} A_{*} \), i.e. the solution of (3). Note that the \( \ell_{2} \) penalization \( P_{2} \) corresponds to the definition of the Moore-Penrose pseudo inversion.
Figure 2: Performance of the estimation of $\mathbf{A}$ with $N = 5$ white noise sources, depending on the duration of the signal.

5. EXPERIMENTAL RESULTS

The Matlab code allowing to reproduce the following experiments is available at the following address [13].

5.1. Role of the condition number

First we wish to study the contribution of the penalty depending on the invertibility of the problem. The system is composed of $M(T+K-1)$ equations for $MNK$ variables, therefore it is underdetermined if and only if the recording duration in samples satisfies

$$T + K - 1 < T_c := NK.$$  \hfill (17)

Note that $T_c$ is smaller than $NK + D - 1$ which is the length of the recording required in [2].

Performance does not depend on the number $M$ of microphones, in fact each microphone brings an independent problem.

The $MN$ filters are a solution of the linear system, for $m \leq M$

$$X_m = S_1 \ast A_{m1} + S_2 \ast A_{m2} + \ldots + S_N \ast A_{mN}.$$  \hfill (18)

In order to guide the choice of the source signals, we first show theoretically that the system is well conditioned if the sources are uncorrelated. To this aim we compute the condition number of the system.

The condition number of the system is detailed in the following lemma.

Lemma 1

For small $r$, the condition number of (18) obeys

$$1 \leq c \leq \frac{\max_n r_{nn}(0) + r(NK - 1)}{\min_n r_{nn}(0) - r(NK - 1)}. $$  \hfill (21)

Note that for white noises, $r$ is small, and $c$ is close to 1, leading to a well conditioned system.

5.2. Performance as a function of the recording duration

In previous work [14, fig.2], we used human voice recordings, and we observed a transitory regime for $T > T_c$ where the penalties still had an impact due to a large condition number. In this paper we want to choose the sources such that the system is well-conditioned, therefore we used white Gaussian noise, motivated by the above theoretical guarantees. We observed experimentally (results not shown here) that this choice remains experimentally valid for underdetermined systems.

As a measurement of the error between the estimated filters $\mathbf{A}_\Lambda$ and the true filters $\mathbf{A}$, we define the following ratio in decibels

$$\text{SNR}_{\mathbf{A}}(\mathbf{A}_\Lambda) = 10 \log_{10} \frac{\| \mathbf{A} \|_2}{\| \mathbf{A} - \mathbf{A}_\Lambda \|_2}.$$  \hfill (22)

When the solution is not unique, we expect to observe better results with the proposed regularizations : we then run the algorithm for several values of $T$.

The results shown in Figure 2 correspond to the case of $N = 5$ sources, $M = 2$ sensors, with filters of length $K = 2753$ (250 ms sampled at 11025 Hz) synthesized as in Section 2. For readability we express all the durations in ms. Therefore the system is overdetermined. We vary the length of the sources from $T = 45$ ms to $T = 1500$ ms.

We observe in Figure 2 a clear jump around the critical value $T_c = 1250$ ms beyond which the system is underdetermined. We vary the condition of the sources $T = 45$ ms to $T = 1250$ ms.

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5.3. Robustness to noise

We now add Gaussian white additive noise to the mixtures,

\[ X = A \cdot S + W. \]  

For each penalty \( P_s \) and each duration \( T + K - 1 \) of the recordings, six experiments were made for a signal-to-noise ratio of 30, 40, 50, 60, 70 and 80 dB. We observe in Figure 3 that the noise decreases the overall performance, but has a smaller impact on the \( \ell_1 \) re-scaled penalty \( P_s \) than on the common pseudo-inversion \( P_s \). Not surprisingly, the two penalties lead to the same result once the sources are long enough for the solution to be unique.

This experiment confirms the possibility to speedup the recordings even in the presence of noise. With an input SNR of 50 dB, the estimation fidelity SNR\textsubscript{out} is still 25 dB.

6. CONCLUSION

For the considered problem, the various a priori introduced as convex penalties provide better estimation of the filters than simple de-convolution using Moore-Penrose pseudo-inverse. The best results are achieved with the new proposed penalties based on a decaying envelope model. This method can speed up the recording, with a reasonable quality trade-off for noisy measurements. For large numbers of sources \( N \) in reverberant rooms, the expected speedup can be significant. Further experiments are needed to confirm the validity of the approach in such scenarios, by taking into account the nonlinearity of the loudspeakers, as well as other performance measures. Besides, we know that source separation informed by the nonlinearity of the loudspeakers, as well as other performance measures.

We derive from (18) the block matrix notation

\[
\Sigma_n := \begin{pmatrix}
S_n(1) & 0 & \cdots & 0 \\
\vdots & \ddots & \ddots & \vdots \\
0 & \cdots & S_n(T) & 0 \\
0 & \cdots & 0 & S_n(1)
\end{pmatrix} \in \mathbb{R}^{(T+K-1) \times N}.
\]

We then have

\[ (\Sigma_n^T \Sigma_n)_{n \leq N} = (\Sigma_n^T \Sigma_n^r)_{n,n' \leq N} (A_{mn})_{n \leq N}, \]  

and the correlation of the sources (19) appears since we have

\[ \Sigma_n^T \Sigma_n^r = \begin{pmatrix}
0_{n,n'}^{(K-1)} & \cdots & r_{n,n'}(0) \\
\vdots & \ddots & \vdots \\
r_{n,n'}(0) & \cdots & 0_{n,n'}^{(K-1)}
\end{pmatrix}. \]  

Now \( c \) is the condition number of the \( NK \times NK \) block matrix \( \mathbb{R} = (\Sigma_n^T \Sigma_n^r)_{n,n' \leq N} \), and the key is to choose the sources so that this matrix is highly diagonally dominant. Using Gerschgorin’s disc theorem [16], we control its eigenvalues. For \( \lambda \in \text{Sp}(\mathbb{R}) \),

\[
|\lambda - r_{nn}(0)| \leq \sum_{k=1}^{K-1} r_{nn}(k) + \sum_{k=0}^{K-1} r_{nn'} \leq r(NK - 1) - 1.
\]

Then if \( r(NK - 1) < \min_n r_{nn}(0) \) we can conclude that

\[
c = \left| \frac{\lambda_{\text{max}}}{\lambda_{\text{min}}} \right| \leq \frac{\max_n r_{nn}(0) + r(NK - 1)}{\min_n r_{nn}(0) - r(NK - 1)}. \]

7. REFERENCES


