Mixing Matrix Estimation of Audio Signals By Independent Component Analysis

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Abstract - *Traditional signal acquisition is based on the Nyquist sampling theorem, which shows that the sampling rate must be no less than twice the maximum frequency component of the signal. When the signal frequency increases, the sampling rate becomes faster and faster, which presents a huge challenge to sampling devices as well as in data storage and transfer. Compressive sensing (CS) shows that, when a signal is sparse or compressible with respect to some basis, a small number of compressive measurements of the original signal can be sufficient for approximate recovery. . The underlying method for mixing matrix estimation reconstructs the mixtures by a DCS approach first and then estimates the mixing matrix from the recovered mixtures. The reconstruction step takes considerable time and also introduces errors into the estimation step. This paper proposes a novel method that estimates the mixing matrix directly from the compressive observations without reconstructing the mixtures. ICA (Independent Component Analysis Theory) is one of the most popular Approaches in the BSS (Blind Source Separation) field to solve the mixing signals problems.*

***Key Words*: Audio signals, distributed compressive sensing(DCS), independent component analysis (ICA) mixingmatrix estimation.**

1.INTRODUCTION

the audio source acquisition on a spaceship or space station, although the frequencies and sampling rates of these signals are not high, the source signals are recorded for a very long time, such as several weeks on a spaceship or several months on a space station, which will produce a huge set of data. Recovering mixing parameters and source signals only from the mixed observations without having prior information on both source signals and the mixing process is often referred to as blind source separation (BSS).Blind mixing matrix estimation is one of the most important steps in BSS, which significantly affects the recovery accuracy of the source signals. Independent component analysis (ICA) is one of the most popular methods for solving BSS problems.

1.1 Mixing Signal Model

The original signals are assumed to be independent of each other. The mixing process of source signals in BSS problems can be sorted into several models, such as the convolved mixture model, the instantaneous linear mixture model, or the nonlinear mixture model. In this paper, we consider only the instantaneous linear mixture model.

1.2 Compressive Sensing

CS theory indicates that, if a signal is sparse or compressive in some basis, it can be exactly recovered by a small number of measurements. Let $x = [x(1), x(2)\ldots, x(N)]^T$ be a K sparse signal with length N ($K << N$). The sparse basis is ψ, an $N \times N$ matrix, with a sparse coefficient vector $\eta \in R^N$ The signal can be denoted as follows:

$$x = \psi \eta$$

Let ϕ be the $M \times N$ measurement matrix, where $M < N$.
The observation vector 'y' consists of M linear projections of' x', such that $y=\phi x=\phi\psi \eta=\Theta\eta$, *Where* $\Theta=\phi\psi$ is called the sensing matrix.

2. PROPOSED ALGORITHM

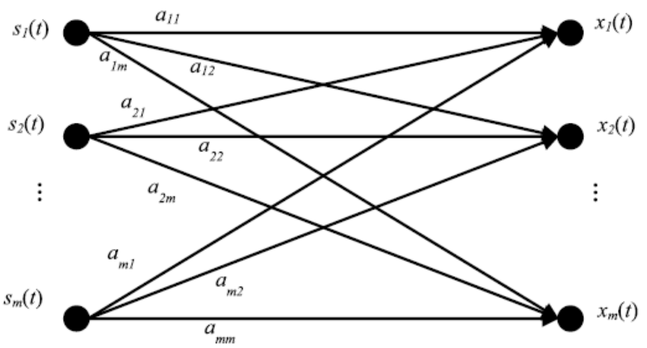
As observed in Fig. 3, the recovery of the mixing signals is a necessary step in the underlying framework, and it takes a great deal of time. However, what we are interested in are the mixing matrix and the source signals, but not the mixtures. As mentioned in [9], in some signal processing problems, the reconstruction of the signals is not a necessary step. Instead, it is possible to estimate and/or extract attributes of the signal directly from the compressive measurements. To take advantage of this idea, we try to estimate the mixing matrix **A** directly from the compressive measurements of the mixtures without recovering the mixing signals. Because it is unnecessary to reconstruct the mixtures, omitting that process will greatly reduce the complexity of computation and improve the estimation speed. The compressive observation of each mixture is denoted as follows:

$$y_i=\phi x_i(t)$$

$$=\phi \sum_{j=1}^{m} a_{ji}\, s_j(t) = \sum_{j=1}^{m} a_{ji}(\phi s_j(t)) = \sum_{j=1}^{m} a_{ji} y_{sj}$$

Where $y_{sj}=\phi s_j(t)$ can be regarded as the compressive measurement of the source $s_j(t)$.

Fig. 1. Instantaneous linear mixture model.



Then, the compressive observation set can be denoted as follows:

$$\mathbf{y} = [y_1, \ldots, y_m]$$

$$= [y_{s1}, \ldots y_{sm}] \begin{bmatrix} a_{11} & \ldots & a_{1m} \\ . & . & . \\ . & . & . \\ . & . & . \\ a_{m1} & \ldots & a_{mm} \end{bmatrix}$$

Where $y_s = \phi \mathbf{s}$ is the compressive measurement of the original source set **s**. The value y_i is the compressive measurement of the mixing signal $x_i(t)$, and it is also the mixture of all the y_{sj} $(j = 1, 2, \ldots, m)$, which is the compressive measurement of the source signal $s_j(t)$.

Independent Component Analysis Theory

ICA is one of the most popular approaches in the BSS field to solve the mixing signals problems. It takes advantage of the high-order statistical properties of signals to estimate the mixing matrix and/or to retrieve the source signals without resorting to any *a priori* information about the mixing matrix. It exploits only the information carried by the observations of the mixing signals themselves. When using ICA, the source signals must satisfy two important properties:

1) all of the signals are independent of each other
2) at most, one of the signals is Gaussian

Basically, signals $s_1(t), s_2(t), \ldots, s_m(t)$ are considered to be independent if information on the value of $s_i(t)$ does not give any information on the value of $s_j(t)$ for $i \neq j$. The mixture of two independent Gaussian signals is also a Gaussian signal whose probability density function only contains the second-order statistical property, without higher order statistical properties. Thus, if more than one signal is Gaussian, the signals cannot be separated by ICA methods. To evaluate the accuracy of the proposed algorithm, generalized cross talking error (GCE) is used to compare the mixture matrix **A** with the estimated matrix is given by

$$\mathrm{GCE} = \min_{\mathbf{B}\in\prod} \left\| \mathbf{A} - \hat{\mathbf{A}} \right\|$$

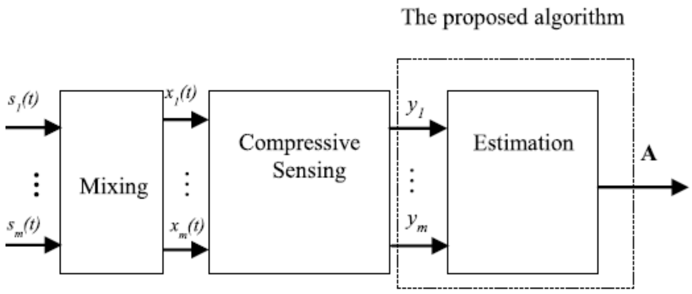


Fig.2. Framework of estimating A using the proposed algorithm

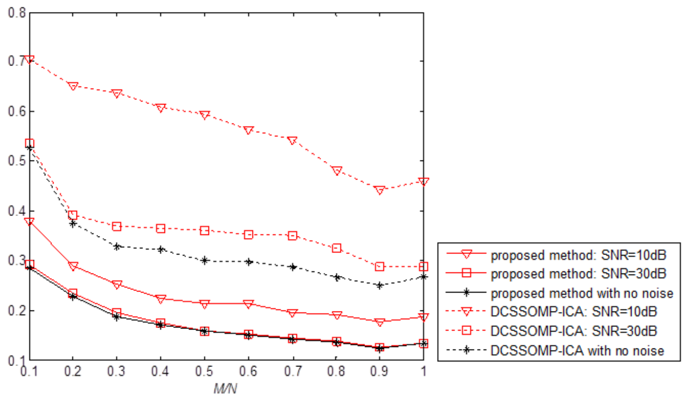


Fig -1: Average GCE generated by proposed algorithm.

3. CONCLUSIONS

In this paper, we considered the blind mixing matrix estimation of audio signals in the compressive measurement domain, where mixing signals are sampled under the compressive sensing framework. Compared to the underlying method, the proposed method could estimate the mixing matrix directly without recovering the mixtures. The experimental results demonstrated that the proposed method outperforms the underlying algorithm with better estimation speed and accuracy.

REFERENCES

[1] Hongwei Xu, Ning Fu, "Compressive blind mixing matrix estimation of audio signals," *IEEE Trans.*Instrumentation and Measurement.,vol.63,no.5, pp.1253-1261,May 2014.

[2] D. Baron, M. F. Duarte, S. Sarvotham, M. B. Wakin, and R. G. Baraniuk, "An information-theoretic approach to distributed compressed sensing,"

[3] Y. Wu, Y. Chi, and R. Calderbank, “Compressive blind source separation,” in *Proc. IEEE 17th Int. Conf. Image Process.*, Hong Kong, Sep. 2010, pp. 89–92.

[4] R. Der,“Blind signal separation,” Dept. Electr. Comput. Eng., McGillUniv., Montreal, QC, Canada, Tech. Rep. 1, pp. 1–9, 2001.

[5] . M. Shen, Q. Zhang, D. Li, J. Yang, and B. Li, “Adaptive sparse representation beamformer for high-frame-rate ultrasound imaging instrument,” *IEEE Trans. Instrum. Meas.*, vol. 61, no. 5, pp. 1323–1333, May 2012.

[6] I.W.Selesnick,“Overcomplete discrete wavelet transforms with rational dilation factors,” *IEEE Trans. Signal Process.*, vol. 57, no. 1, pp. 131–145, Jan. 2009.