

Ray-Space-Based Multichannel Nonnegative Matrix Factorization for Audio Source Separation

[10.1109/LSP.2021.3055463](https://doi.org/10.1109/LSP.2021.3055463)

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Abstract

Nonnegative matrix factorization (NMF) has been traditionally considered a promising approach for audio source separation. While standard NMF is only suited for single-channel mixtures, extensions to consider multi-channel data have been also proposed. Among the most popular alternatives, multichannel NMF (MNMF) and further derivations based on constrained spatial covariance models have been successfully employed to separate multi-microphone convolutive mixtures. This letter proposes a MNMF extension by considering a mixture model with Ray-Space-transformed signals, where magnitude data successfully encodes source locations as frequency-independent linear patterns. We show that the MNMF algorithm can be seamlessly adapted to consider Ray-Space-transformed data, providing competitive results with recent state-of-the-art MNMF algorithms in a number of configurations using real recordings.

1. Related Works

Multichannel NMF model (MNMF)

- We consider a uniform linear array (ULA) of I channel acquiring the mixture of J acoustic sources.
- Under the local Gaussian model MNMF describes the mixture at the i th channel as

$$y_i(\omega, n) \sim \mathcal{N}_{\mathbb{C}} \left(0, \sum_{j=1}^J \mathbf{G}_j(\omega) \sum_k w_{j,k}(\omega) h_{j,k}(n) \right)$$

- $\mathbf{G}_j \in \mathbb{C}^{I \times I}$ is the spatial covariance matrix of the j th source
- $w_{j,k}(\omega), h_{j,k}(n)$ are the basis functions and the activation modeling the source PSD $p_j(\omega, n)$.

Ray Space Transform (RST)

RST [1] is a linear operator $\Psi \in \mathbb{C}^{I \times LD}$ that maps the signals of a ULA onto the Ray Space

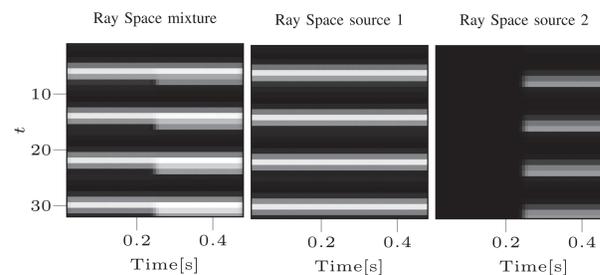
$$\mathbf{Z}(\omega, n) = \Psi^H(\omega) \mathbf{y}(\omega, n).$$

Array signals can be recovered using the inverse RST $\tilde{\Psi} = (\Psi\Psi^H)^{-1}\Psi$

$$\mathbf{y}(\omega, n) \approx \tilde{\Psi}(\omega) \mathbf{Z}(\omega, n).$$

GOAL:

exploit RS representation of source's position as input domain for MNMF separation



- $[\Psi]_{i,t} = e^{-j\omega \frac{d\mu_w}{c\sqrt{1+\mu_w^2}}(i-1)} \psi_{t,i}^*$, $t = 1, \dots, LD$ is the ray space index spanning D directions in L locations of the ULA
- Ray Space consists in the parametrization of line equation $z = \mu x + v$ as a function of slope μ and intercept v
- Main feature:** acoustic rays emitted by **point sources** are **mapped** onto **lines** in the Ray Space encoding their **location**.

2. The Ray Space MNMF (RS-MNMF)

In presence of J sources the Ray Space data is modelled as

$$\mathbf{Z}_t(\omega, n) = \sum_{j=1}^J r_{t,j} s_j(\omega, n) + b_t(\omega, n),$$

- $r_{t,j}$ describes the j th source contribution at t th Ray Space element.
- We employ a general β -divergence cost function

$$C_{RS}(\Theta) = \sum_{t,\omega,n} d_{\beta}(|Z_t(\omega, n)|^2 \hat{y}_t(\omega, n))$$

- $\hat{y}_t(\omega, n) = \sum_j g_{t,j} \sum_{k \in K_j} w_k(\omega) h_k(n)$ is the square magnitude of the ray space modeled using NMF
- Similarly to instantaneous algorithm in [2] the components are estimated using MU method.

The estimate of the j th source image in the Ray Space is given in terms of MMSE as

$$\tilde{s}_j^{(t)\text{im}}(\omega, n) = \frac{g_{t,j} p_j(\omega, n)}{\hat{y}_t(\omega, n)} Z_t(\omega, n)$$

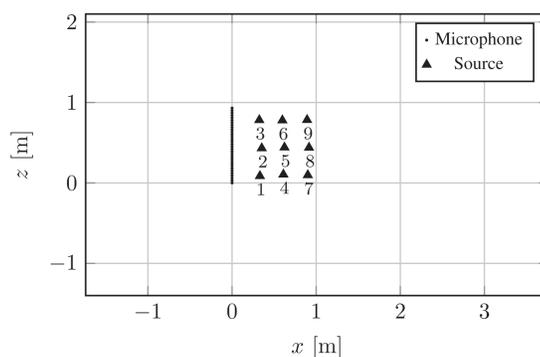
Estimate of the j th sources at the microphones is obtained using the inverse RST:

$$\hat{s}_j^{\text{im}}(\omega, n) = \tilde{\Psi}(\omega, n) \tilde{s}_j^{\text{im}}(\omega, n)$$

3. Results

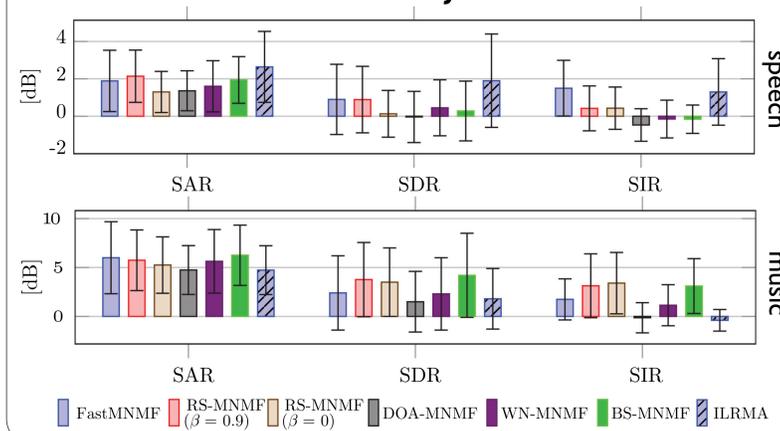
Setup and metrics

- 5.5m×3.4m×3.3m Room with $T60 \approx 0.4s$
- ULA of $I = 32$ microphones and 9 source locations
- Mixtures with $J = \{2,3\}$ sources with 3s signals of male/female speech and music
- Results compared with BS-MNMF[2,], FastMNMF[3], DOA-MNMF[4], WN-MNMF[5] and ILRMA[6].
- Performance is evaluated in terms of :
 - Signal-to-artifacts ratio (SAR),
 - Signal-to-distortion ratio (SDR),
 - Signal-to-interference ratio (SIR).

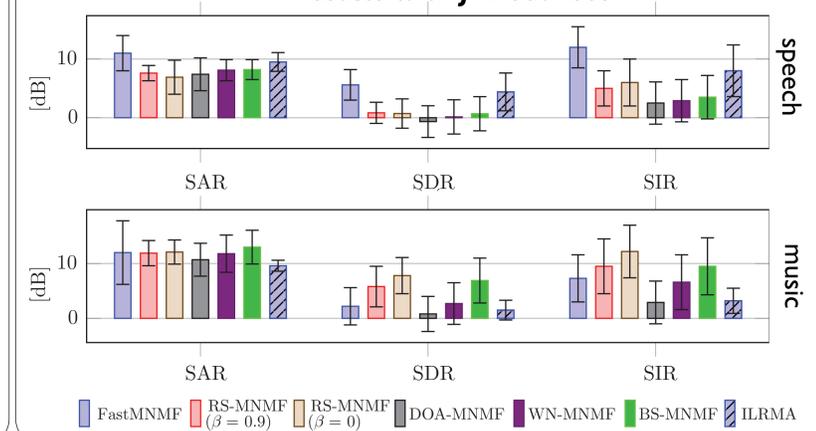


<https://github.com/polimi-ispl/rs-mnmf>

Results with J=3 sources



Results with J=2 sources



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