

A time-frequency technique for blind separation and localization of pure delayed sources

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We present a time-frequency technique for the **blind separation and localization** of several sources, where a single scaled and delayed version of each source contributes to each sensor recording. The separation is performed in the time-frequency domain via an Alternating Least Squares (ALS) algorithm coupled with a Vandermonde structure enforcing strategy. The Time Differences Of Arrival (TDOAs) estimates are then exploited to localize the sources individually.

Problem Formulation

- **Parameters and propagation model:**
 - N : nb. of sources $s_n(t)$, $n = 1, \dots, N$.
 - $M \geq N$: nb. of sensors; received signals $r_m(t)$, $m = 1, \dots, M$.
 - a_{mn} : attenuation factor between n th source and m th sensor.
 - τ_{mn} : Time Of Arrival (TOA), in seconds, between n th source and m th sensor.
 - Linear time-shift mixing model: line of sight propagation, no reflections [1].

- **Time-shift model:**

$$r_m(t) = \sum_{n=1}^N a_{mn} s_n(t - \tau_{mn}) \quad (1)$$

Time-frequency reformulation

- **Parameters:**
 - F : Length of each DFT frame, $f = 1, \dots, F$.
 - P : nb. of (possibly overlapping) frames, $p = 1, \dots, P$.
 - $r_m(p, f)$: (p, f) th time-frequency sample of the m th recording.
 - $s_n(p, f)$: (p, f) th time-frequency sample of the n th source.
 - D_{mn} : Time Of Arrival (TOA), in number of samples, between n th source and m th sensor.
 - $\omega = \exp(-2j\pi/F)$.

- **Time-Frequency discrete mixing model:**

- **Analytic model:**

$$r_m(p, f) \simeq \sum_{n=1}^N a_{mn} \omega^{(f-1)D_{mn}} s_n(p, f), \quad f = 1, \dots, F. \quad (2)$$

- **Matrix format:**

$$\mathbf{R}(f) \simeq \mathbf{H}(f) \cdot \mathbf{S}(f), \quad f = 1, \dots, F, \quad (3)$$

where

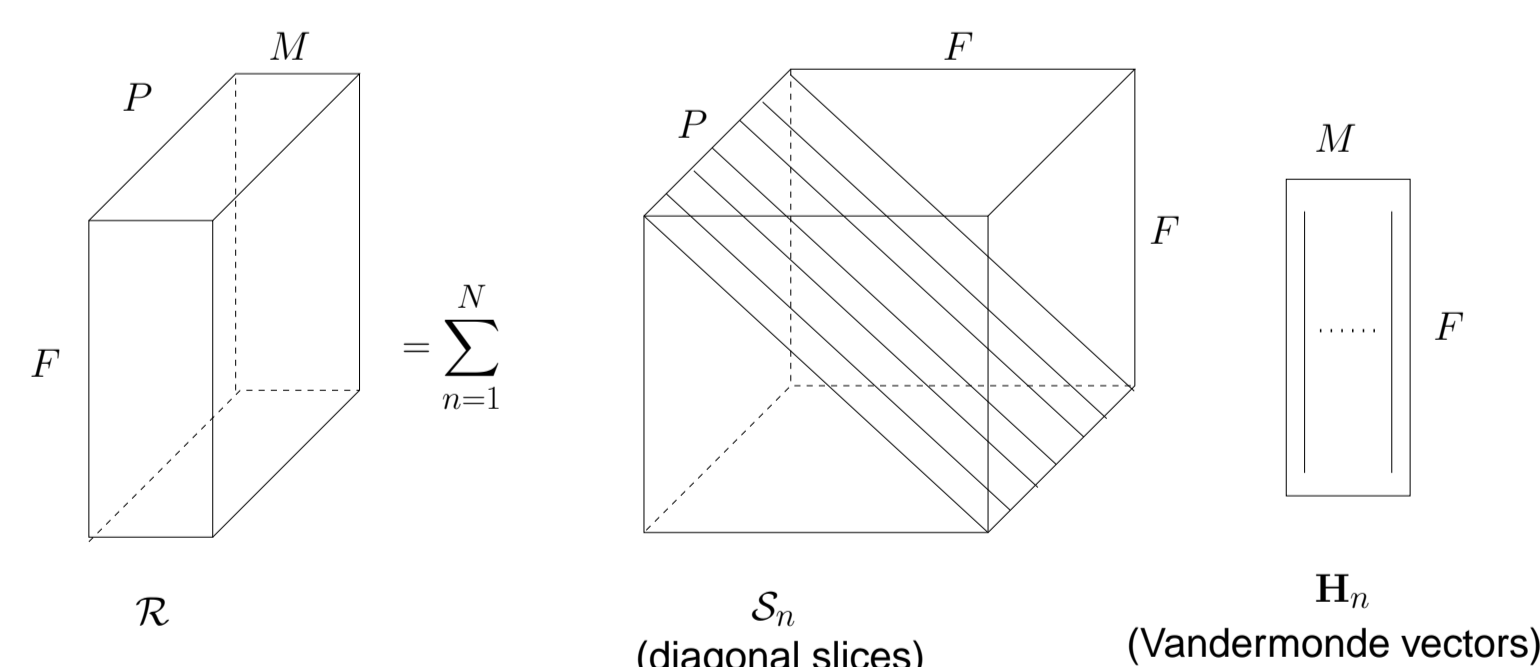
- * $[\mathbf{R}(f)]_{m,p} \stackrel{\text{def}}{=} r_m(p, f)$ is the $M \times P$ time-frequency observed matrix,
- * $[\mathbf{S}(f)]_{n,p} \stackrel{\text{def}}{=} s_n(p, f)$ is the $N \times P$ rank- N time-frequency source matrix,
- * $[\mathbf{H}(f)]_{m,n} \stackrel{\text{def}}{=} a_{mn} \omega^{(f-1)D_{mn}}$ is the $M \times N$ rank- N mixing matrix.

- **Additional structure: Vandermonde vectors**

$$\mathbf{h}_{mn} = [\mathbf{H}_{mn}(1), \mathbf{H}_{mn}(2), \dots, \mathbf{H}_{mn}(F)]^T = [a_{mn}, a_{mn}\omega^{D_{mn}}, \dots, a_{mn}\omega^{(F-1)D_{mn}}]^T \quad (4)$$

- **Tensor format:**

$$\mathcal{R} = \sum_{n=1}^N \mathcal{S}_n \bullet_2 \mathbf{H}_n^T. \quad (5)$$



- **Model ambiguities:**

$$\mathcal{R} = \sum_{n=1}^N (\mathcal{S}_n \bullet_2 \mathbf{Z}_n^{-1}) \bullet_2 (\mathbf{H}_n^T \cdot \mathbf{Z}_n). \quad (6)$$

- To preserve the whole structure, \mathbf{Z}_n has to be diagonal and $\mathbf{u}_n \stackrel{\text{def}}{=} \text{diag}(\mathbf{Z}_n)$ has to be a Vandermonde vector:

$$\hat{\mathbf{H}}_n = \text{diag}([\alpha_n, \alpha_n \omega^{\phi_n}, \dots, \alpha_n \omega^{(F-1)\phi_n}]) \mathbf{H}_n, \quad (7)$$

with unknown arbitrary scaling factor α_n and phase factor ϕ_n .

- In case of perfect separation, we get the estimates: $\hat{a}_{mn} \stackrel{\text{def}}{=} a_{mn} \alpha_n$ and $\hat{D}_{mn} \stackrel{\text{def}}{=} D_{mn} + \phi_n$.

- The ambiguities $\{\alpha_n, \phi_n\}$ only depend on the source and can be removed by choosing a reference sensor, say \tilde{M} , and work with the relative attenuation factor $a_{mn}^{(rel)} \stackrel{\text{def}}{=} \frac{\hat{a}_{mn}}{\hat{a}_{\tilde{M}n}} = \frac{a_{mn}}{a_{\tilde{M}n}}$ and the relative Time Difference Of Arrival (TDOA) $D_{mn}^{(rel)} \stackrel{\text{def}}{=} \hat{D}_{mn} - \hat{D}_{\tilde{M}n} = D_{mn} - D_{\tilde{M}n}$.

ALS algorithm with Vandermonde structure

- **Cost function and optimization problem**

$$\gamma \stackrel{\text{def}}{=} \sum_{f=1}^F \|\mathbf{R}(f) - \mathbf{H}(f) \cdot \mathbf{S}(f)\|^2. \quad (8)$$

$$\min_{\{\mathbf{H}(f), \mathbf{S}(f)\}_{f=1}^F} \gamma$$

s.t. \mathbf{h}_{mn} defined in (4) is a Vandermonde vector, $\forall m, \forall n$,

STEP 1: Time-frequency computation

Build $\mathbf{R}(f) \in \mathbb{C}^{M \times P}$, $f = 1, \dots, F$ from FFT of P overlapping windowed frames of recorded signals. (Typical parameters: $F = 2048$, Hanning window, 50% overlap).

STEP 2: Blind separation

— Initialization —

stop=0, $k = 1$, K_{max} (e.g., $K_{max} = 200$) and ϵ (e.g., $\epsilon = 10^{-6}$). Randomly generate $\hat{\mathbf{S}}(f) \in \mathbb{C}^{N \times P}$, $f = 1, \dots, F$. Possibly try several random starting points.

— Start alternating updates —

while stop=0

$k = k + 1$

(2.a) $\hat{\mathbf{H}}^{(LS)}(f) = \mathbf{R}(f) \cdot \hat{\mathbf{S}}(f)^\dagger$, $f = 1, \dots, F$.

(2.b) $\{\hat{D}_{mn}, \hat{a}_{mn}\} \leftarrow \text{periodogram}(\hat{\mathbf{h}}_{mn}^{(LS)})$, $m = 1, \dots, M$, $n = 1, \dots, N$, see [2].

$\hat{\mathbf{H}}_{mn}^{(VDM)} \leftarrow [\hat{a}_{mn}, \hat{a}_{mn}\omega^{\hat{D}_{mn}}, \dots, \hat{a}_{mn}\omega^{(F-1)\hat{D}_{mn}}]$, $m = 1, \dots, M$, $n = 1, \dots, N$.

(2.c) $\hat{\mathbf{S}}(f) = \hat{\mathbf{H}}^{(VDM)}(f)^\dagger \cdot \mathbf{R}(f)$, $f = 1, \dots, F$.

if $(k = K_{max})$ or $(|\gamma^{(k)} - \gamma^{(k-1)}| \leq \epsilon)$; stop=1; end

end

STEP 3: Blind localization

- Choose ref. sensor \tilde{M} and compute TDOAs $\hat{D}_{mn}^{(rel)} = \hat{D}_{mn} - \hat{D}_{\tilde{M}n}$.

- Each source is localized individually on the basis of its TDOAs; its x and y coordinates can be estimated in the least squares sense, see [3,4].

Numerical experiments

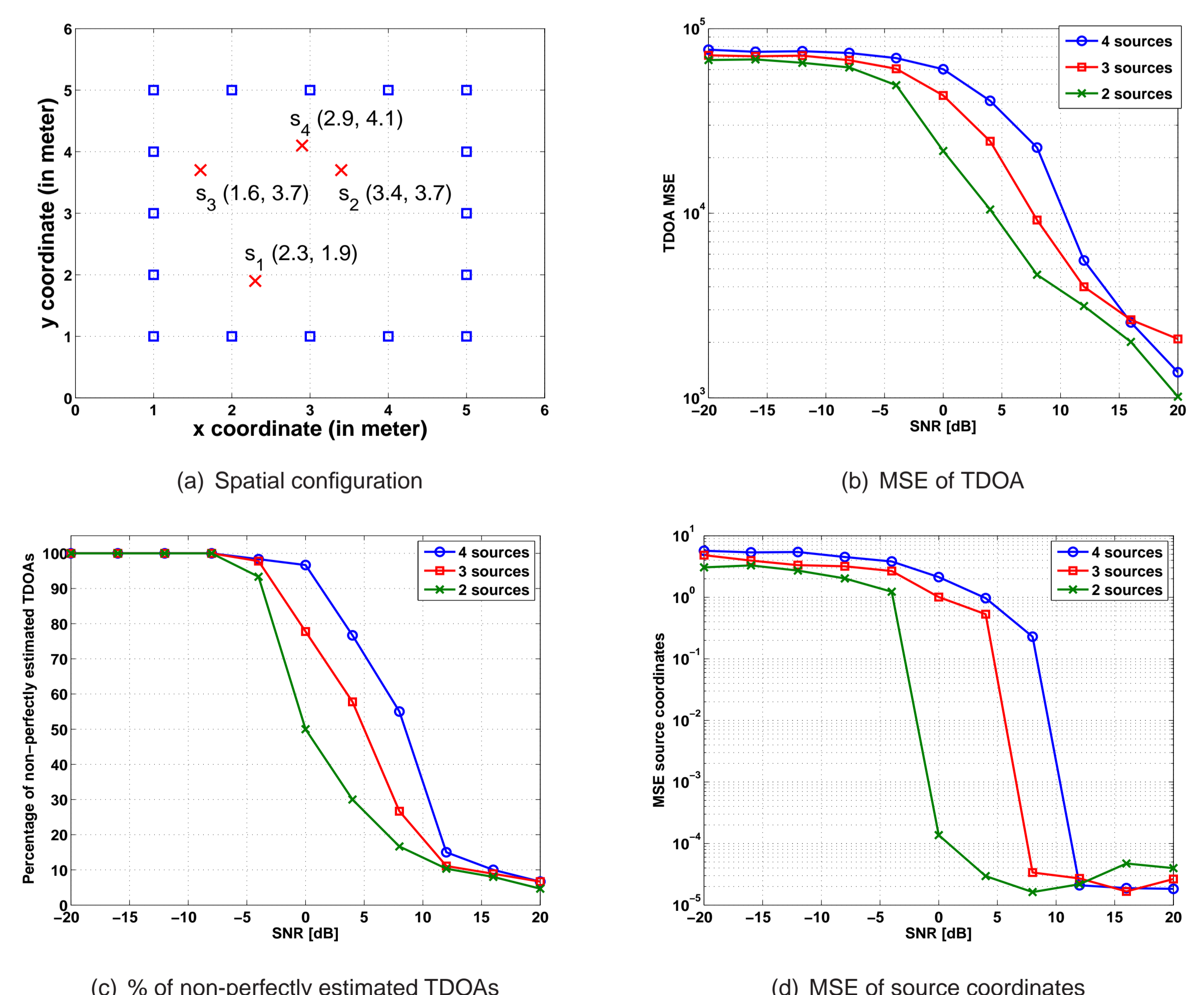


Figure 1: Spatial configuration and results of Monte-Carlo experiments.

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