

A SLIDE-SAVE BASED FRAMEWORK FOR MULTI-SOURCE DOA EXTRACTION WITH CLOSELY SPACED SOURCES



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Abstract

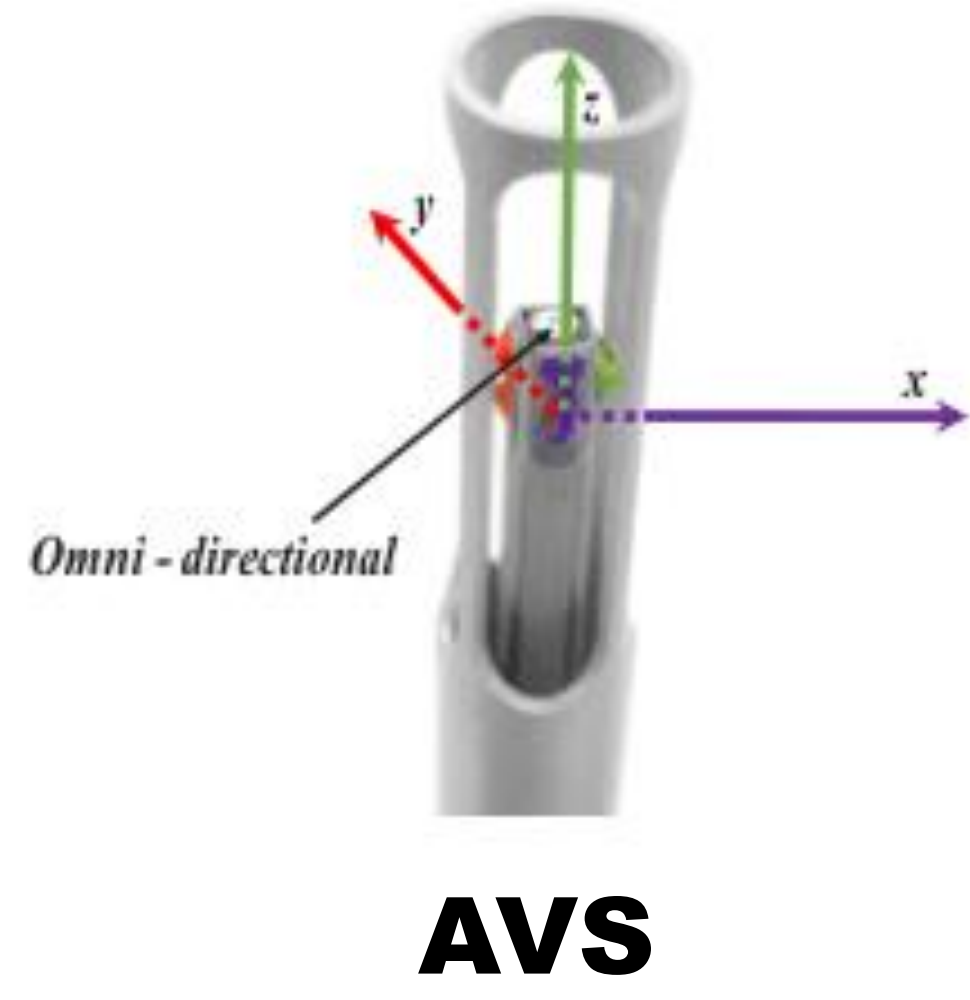
We propose a slide-save based framework to address the problem of extracting multi-source DOAs for closely spaced sources. The basic idea is to identify the DOA estimates corresponding to the locally most dominant source within a sliding time-frequency (TF) window. Three different schemes are introduced to determine the critical DOA estimates in each TF window. The final DOAs are extracted using the retained DOA estimates by extending multi-source DOA extraction methods. In addition, other intensity-based algorithms can also be incorporated into the proposed framework. Simulation results show that the proposed framework is effective to estimate multi-source DOAs in adjacent sources scenarios.

Background

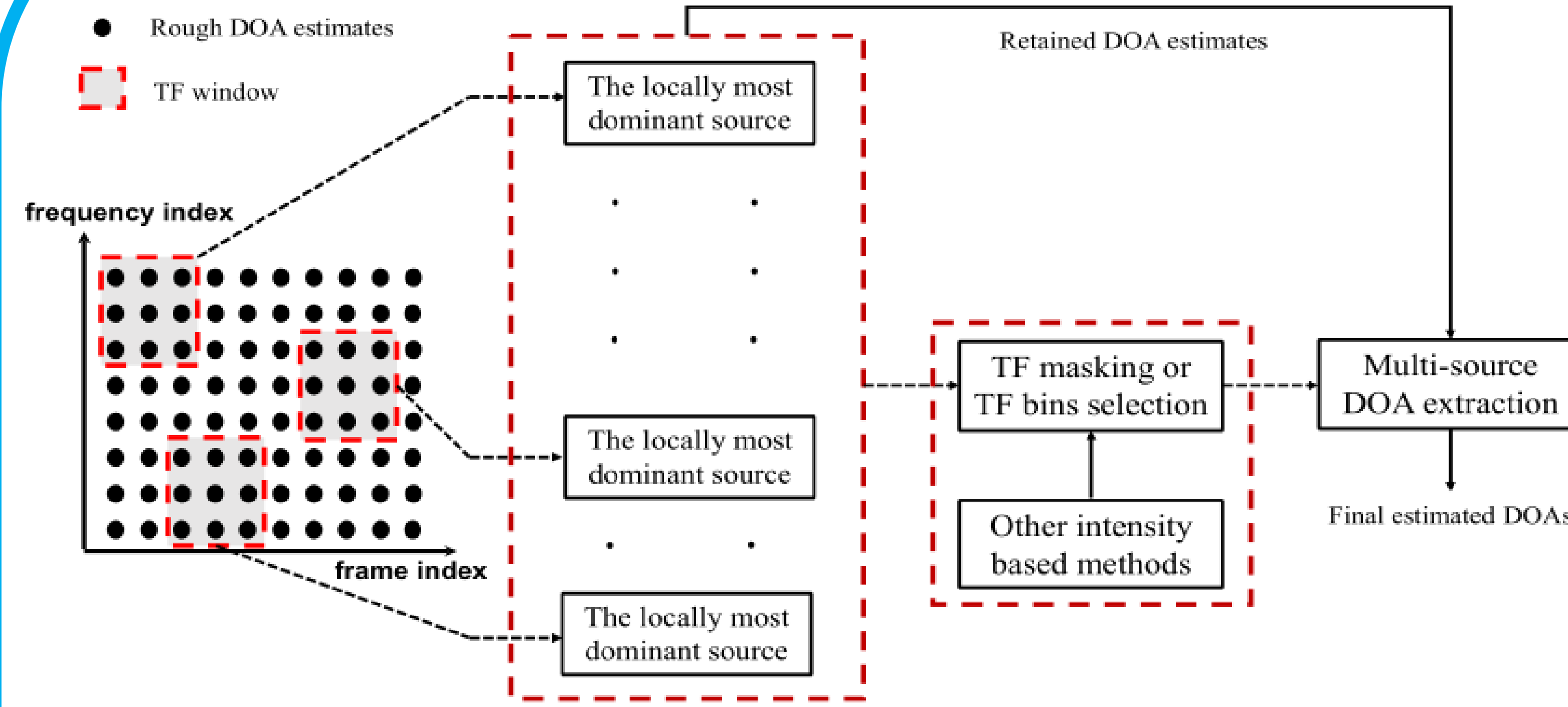
The instantaneous active intensity vector in the time-frequency (TF) domain is defined as

$$\mathbf{I}(k, l) = \mathcal{R} \left\{ x_p^*(k, l) \begin{bmatrix} x_{v_x}(k, l) \\ x_{v_y}(k, l) \\ x_{v_z}(k, l) \end{bmatrix} \right\}$$

The direction of $\mathbf{I}(k, l)$ denotes an estimated DOA at the TF bin (k, l) .



The proposed framework



- Saving the DOA estimates corresponding to the locally most dominant source within a sliding TF window.
- Extracting final DOAs from the set of retained DOA estimates.
- Other intensity-based algorithms can also be incorporated into the proposed framework.

The set of DOA estimates close to the core direction is defined as

$$\mathcal{D}(d_{ci}, \mathcal{W}_i) = \{d(t, f) | \angle\{d(t, f), d_{ci}\} \leq \theta, (t, f) \in \mathcal{W}_i\}$$

The core set of critical DOA estimates corresponding to all the locally most dominant sources can be obtained by

$$\Lambda = \mathcal{D}(d_{c1}, \mathcal{W}_1) \cup \mathcal{D}(d_{c2}, \mathcal{W}_2) \cup \dots \cup \mathcal{D}(d_{cM}, \mathcal{W}_M).$$

Based on clustering :

$$d_{ci} = (\psi_k, \phi_k)$$

$$k = \arg \max_k \{Card(\mathcal{C}_1), \dots, Card(\mathcal{C}_k), \dots, Card(\mathcal{C}_J)\}$$

Based on histogram :

$$d_{ci} = \arg \max_{(\psi, \phi)} \mathbf{C}_{si}(\psi, \phi)$$

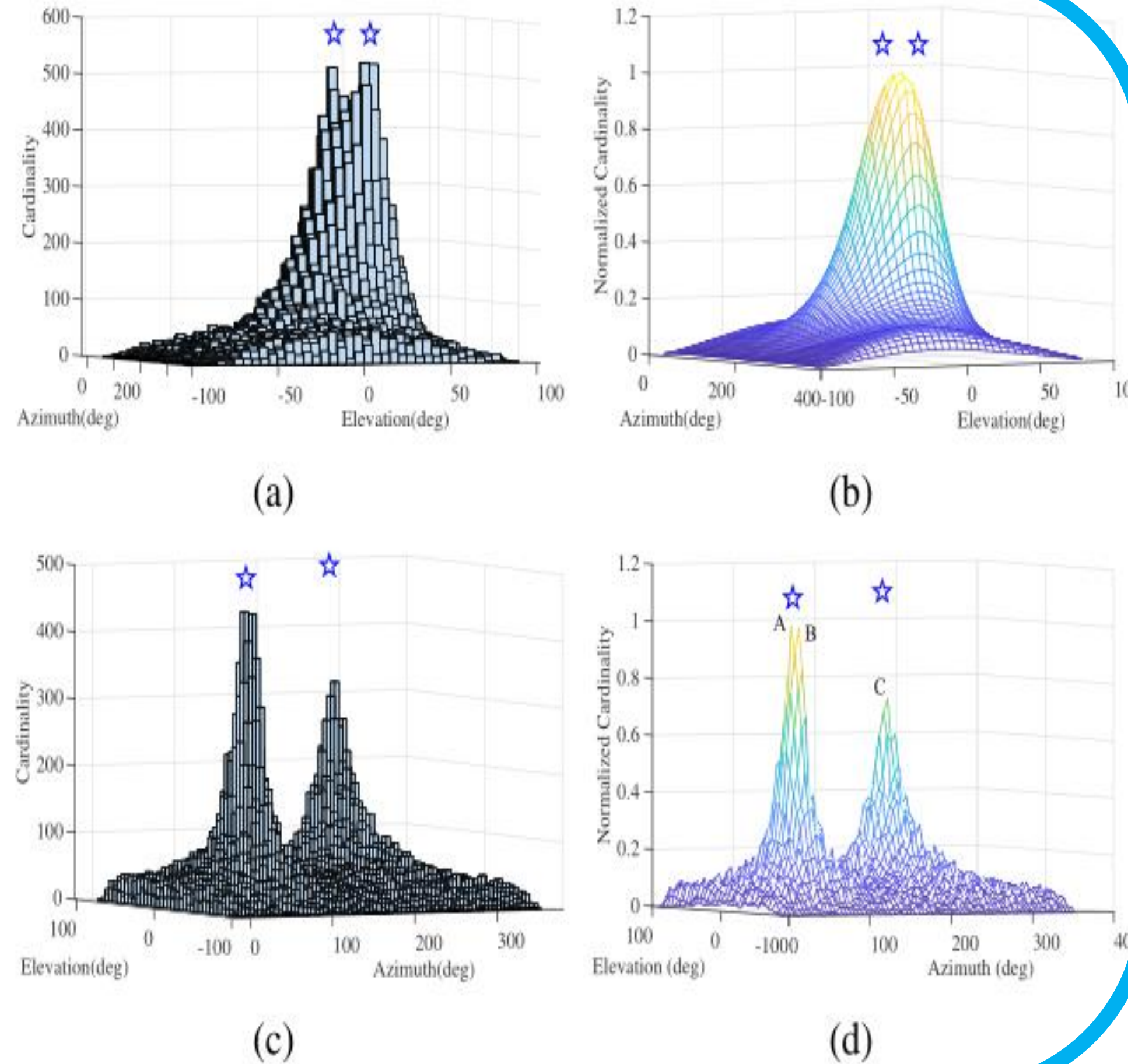
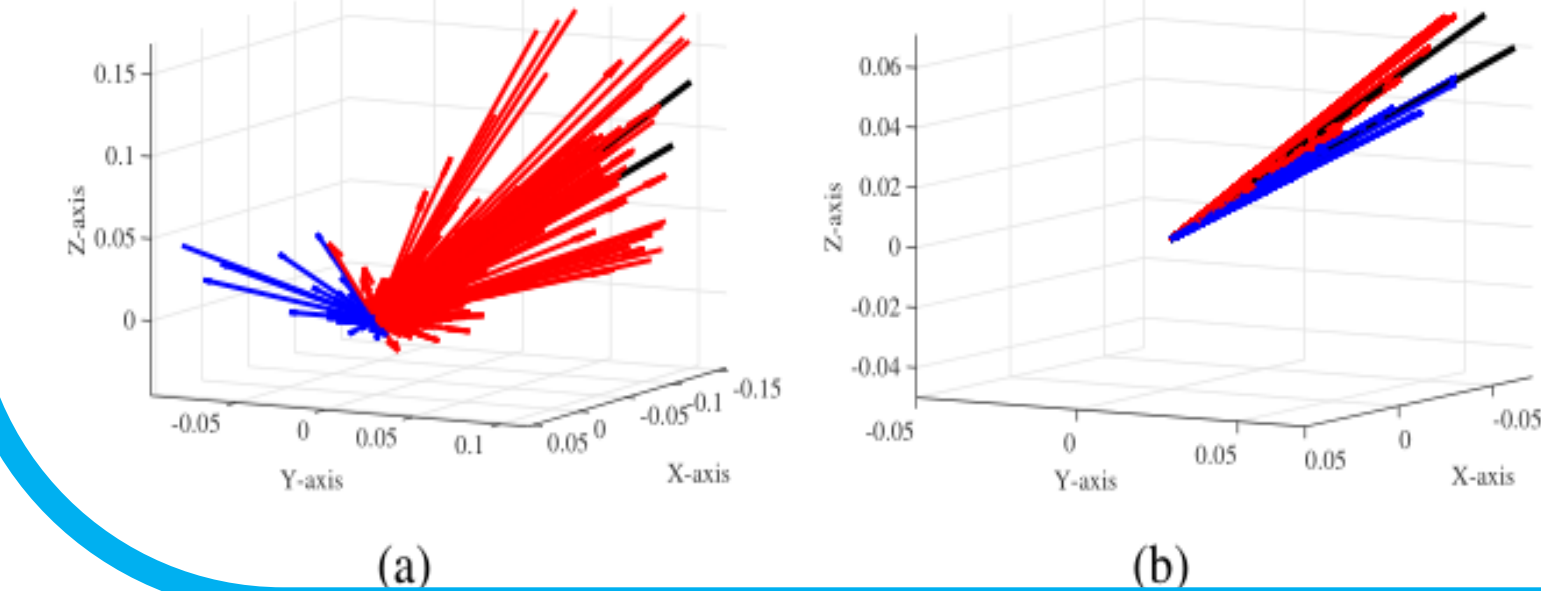
Based on GMM :

$$d_{ci} = \mu_k$$

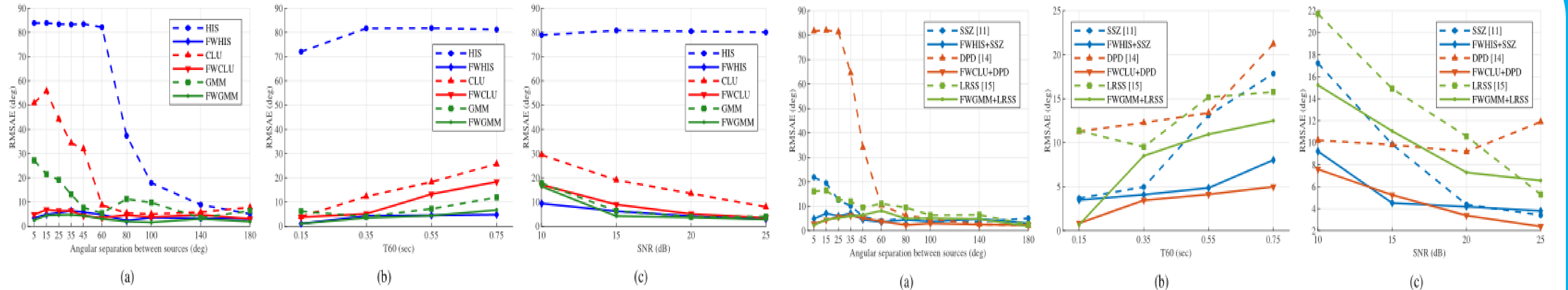
$$k = \arg \max_j \left\{ \frac{w_1}{\sqrt{2\pi}\sigma_1}, \dots, \frac{w_j}{\sqrt{2\pi}\sigma_j}, \dots, \frac{w_J}{\sqrt{2\pi}\sigma_J} \right\}$$

Challenges

For histogram-based approaches, a strong smoothing may merge close peaks in adjacent sources scenarios. A weak smoothing may result in irregular peaks corresponding to one source being identified as multiple sources. For clustering-based approaches, classifying rough DOA estimates by directions may merge two adjacent sources into one.



Performance



- ✓ The proposed method is accurate, even in adjacent sources scenario.
- ✓ The proposed method is robust to T60 and SNR.

- Average angular error $e = \frac{1}{J} \sum_{i=1}^J \angle\{d_i, (\psi_i, \phi_i)\}$.
- Root-mean-square angular error (RMSAE) $\sqrt{\mathbb{E}\{e^2\}}$.