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### Learning Based Direction of Arrival Estimation of Multiple Targets

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### Abstract

We develop a deep learning framework for DOA estimation. The sparse power spectrum inspires us, and the first shows that the columns of the array covariance matrix can be formulated as under-sampled linear measurements of the spatial spectrum. Secondly, we introduce a DNN that learns potential inverse transformation from large training dataset. Our proposed DNN-based framework provides a larger aperture with a small number of antennas. Moreover, we reduce the hardware complexity and allow reconfigurability of the receiver channels. Our solution is able to estimate a number of closely spaced targets larger than the number of receiver channels.

### **Learning Strategy**

#### **Learning Phase:**

The stage collects vectors from RF chains and the desired vectors from the analog array. In this way, the DNN can learn the inherent mapping behavior in both original physical chains and analog chains.

#### Validation Phase:

The data set verifies the source localization of different signals by recovering sparse spatial spectrum, using the training network acquired in the learning phase.





### **Signal Model**

Receiver data	$y(t) = \sum_{k=1}^{K} a(\phi_k) \bar{s}_k(t) + n(t), \ t = 1, 2, \cdots, T,$
Covariance matrix	$\boldsymbol{R} = \mathbb{E}\left[\boldsymbol{y}(t)\boldsymbol{y}^{\mathrm{H}}(t)\right] = \sum_{k=1}^{K} \eta_k \boldsymbol{a}(\phi_k) \boldsymbol{a}^{\mathrm{H}}(\phi_k) + \sigma_n^2 \boldsymbol{I}_M,$
Vectorized	$\begin{aligned} \boldsymbol{c} &= \operatorname{vec}(\boldsymbol{R}) = \begin{bmatrix} \boldsymbol{c}_{1}^{\mathrm{T}}, \boldsymbol{c}_{2}^{\mathrm{T}}, \cdots, \boldsymbol{c}_{M}^{\mathrm{T}} \end{bmatrix}^{\mathrm{T}} \\ &= \begin{bmatrix} \boldsymbol{A}_{1}; \boldsymbol{A}_{2}; \cdots; \boldsymbol{A}_{M} \end{bmatrix} \boldsymbol{\eta} + \sigma_{n}^{2} \begin{bmatrix} \boldsymbol{e}_{1}; \boldsymbol{e}_{2}; \cdots; \boldsymbol{e}_{M}; \end{bmatrix} \\ &= \tilde{\boldsymbol{A}} \boldsymbol{\eta} + \sigma_{n}^{2} \vec{\boldsymbol{1}}_{n}. \end{aligned}$ $\tilde{\boldsymbol{A}} &= \boldsymbol{A}^{*} \odot \boldsymbol{A} = \begin{bmatrix} \boldsymbol{a}_{1}^{*} \otimes \boldsymbol{a}_{1}, \boldsymbol{a}_{2}^{*} \otimes \boldsymbol{a}_{2}, \cdots, \boldsymbol{a}_{K}^{*} \otimes \boldsymbol{a}_{K} \end{bmatrix}, \end{aligned}$

Spatial spectrum  $\eta \approx \tilde{A}^{H}c$ .

Data preprocessing

ng  $\hat{\boldsymbol{r}} = [\operatorname{real}(\tilde{\boldsymbol{r}}), \operatorname{imag}(\tilde{\boldsymbol{r}})],$ 

## Simulation







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