





One-Shot Near-Field Localization with Al-Optimized Hybrid Beamformer Design

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9th June 2025

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Introduction

- Is it possible to localize a user in the near-field with a hybrid beamformer?
- How many RF chains do we need to achieve reasonable localization accuracy?
- What is the performance gap compared to the fully-digital scheme?





Received signal:
$$\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$$



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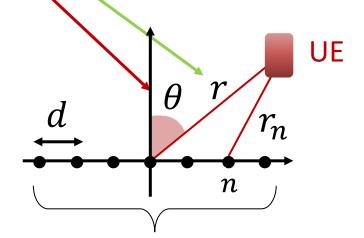
Received signal: $\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$ \downarrow Near-field array response vector $\mathbf{a}(\theta, r) = [e^{-j\frac{2\pi}{\lambda}(r_1-r)}, \dots, e^{-j\frac{2\pi}{\lambda}(r_N-r)}]^T$



Received signal: $\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$

$$\mathbf{a}(\theta, r) = [e^{-j\frac{2\pi}{\lambda}(r_1 - r)}, \dots, e^{-j\frac{2\pi}{\lambda}(r_N - r)}]^T$$

- γ Distance from the center of the array
- heta Angle from the center of the array





Received signal: $\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$ SNR Array response vector

- $\mathbf{a}(\theta, r) = [e^{-j\frac{2\pi}{\lambda}(r_1 r)}, \dots, e^{-j\frac{2\pi}{\lambda}(r_N r)}]^T$
 - $\frac{d}{n} = \sqrt{r^2 + \delta_n^2 d^2 2r \sin \theta \delta_n d}$

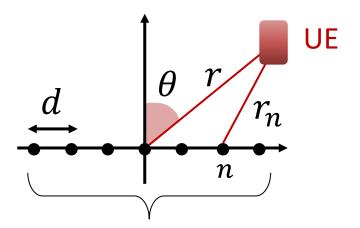
$$\gamma$$
 Distance from the center of the array

$$heta$$
 Angle from the center of the array

$$\gamma_n$$
 Angle from the *n*-th antenna element

Received signal: $\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$

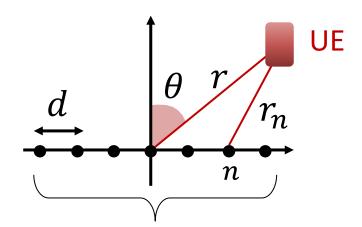
Combined signal: $\bar{\mathbf{y}} = \mathbf{V}\mathbf{y} = \sqrt{\rho}\mathbf{V}\mathbf{a}(\theta, r) + \mathbf{V}\mathbf{n}$

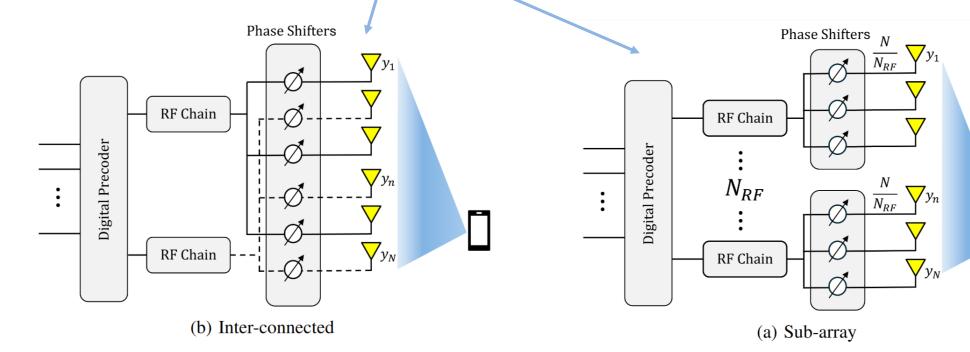




Received signal: $\mathbf{y} = \sqrt{\rho} \, \mathbf{a}(\theta, r) + \mathbf{n}$

Combined signal: $\bar{\mathbf{y}} = \mathbf{V}\mathbf{y} = \sqrt{\rho}\mathbf{V}\mathbf{a}(\theta, r) + \mathbf{V}\mathbf{n}$







Near-Field Localization with Hybrid Beamforming

Methodology

The analog combiner phase shifters are tuned through a set of **constrained** <u>learnable</u> <u>parameters</u>.

Then, a localizing network maps the features into range and angle.

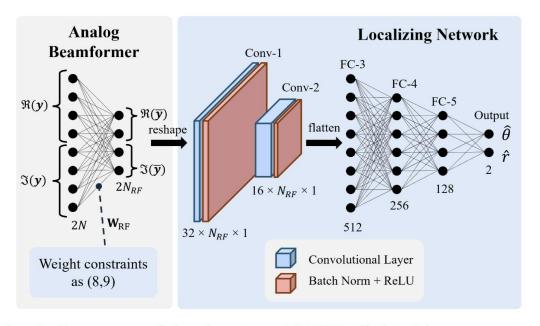


Fig. 2: Structure of the developed DNN, divided into two parts: analog beamformer and localizing function.

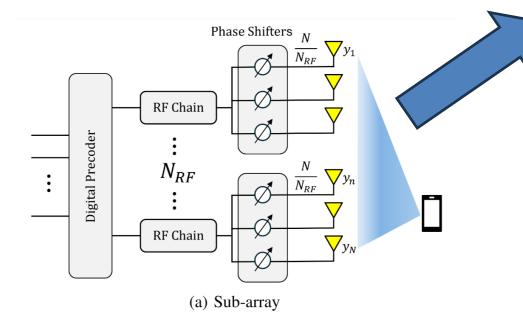


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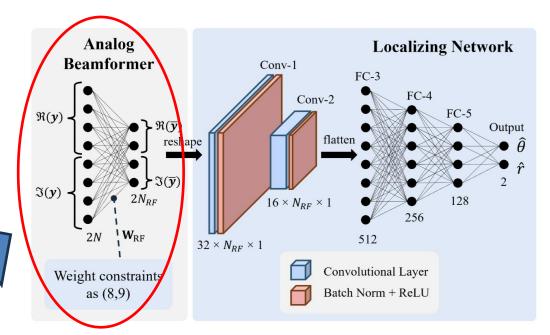


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Near-Field Localization with Hybrid Beamforming

Objective function: find the optimal weights and biases to minimize the position error.

$$(\widetilde{\mathbf{W}}, \widetilde{\mathbf{b}}) = \arg\min_{\mathbf{W}, \mathbf{b}} \mathbb{E} \left\{ \left\| \boldsymbol{\gamma}^{(i)} - f^{(\text{train})}(\mathbf{y}^{(i)}) \right\|_{2}^{2} \right\}$$

Weight constraints ensure consistency with the hybrid beamforming structure.

$$f^{(\text{train})}(\mathbf{y}^{(i)}) = f^{(\text{out})}(\dots(f^{(1)}(\mathbf{b}^{(\text{in})} + \mathbf{W}^{(\text{in})}\mathcal{F}(\mathbf{y}^{(i)})))),$$

$$\mathbf{W}^{(\text{in})} = \begin{bmatrix} \mathbf{W}_{1}^{(\text{in})} - \mathbf{W}_{2}^{(\text{in})} \\ \mathbf{W}_{2}^{(\text{in})} \mathbf{W}_{1}^{(\text{in})} \end{bmatrix}$$

$$\left(\begin{bmatrix} \mathbf{W}_{1}^{(\text{in})} \end{bmatrix}_{m,n} \right)^{2} + \left(\begin{bmatrix} \mathbf{W}_{2}^{(\text{in})} \end{bmatrix}_{m,n} \right)^{2} = \frac{1}{N},$$
 (9)
$$\forall n \in \{1, \dots, N\}, \forall m \in \{1, \dots, M\}$$

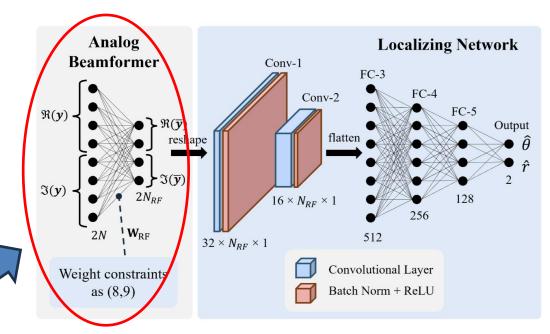


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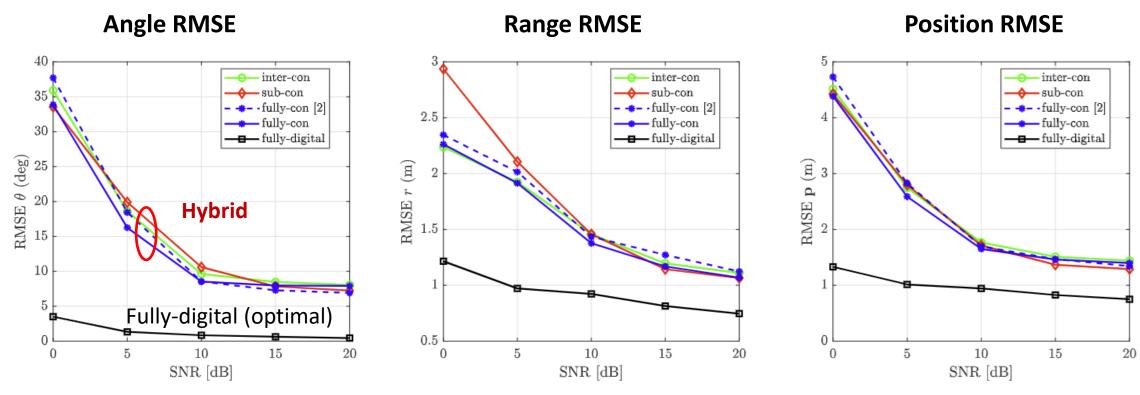
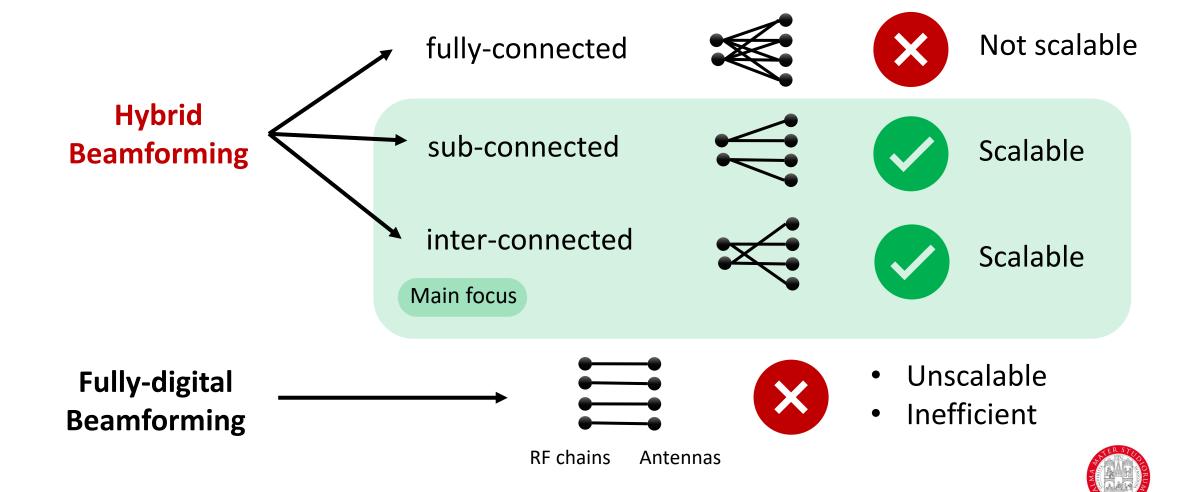


Fig. 3: RMSE of angle, range, and position versus SNR with different hybrid beamforming configurations, when M = 16 and N = 128.





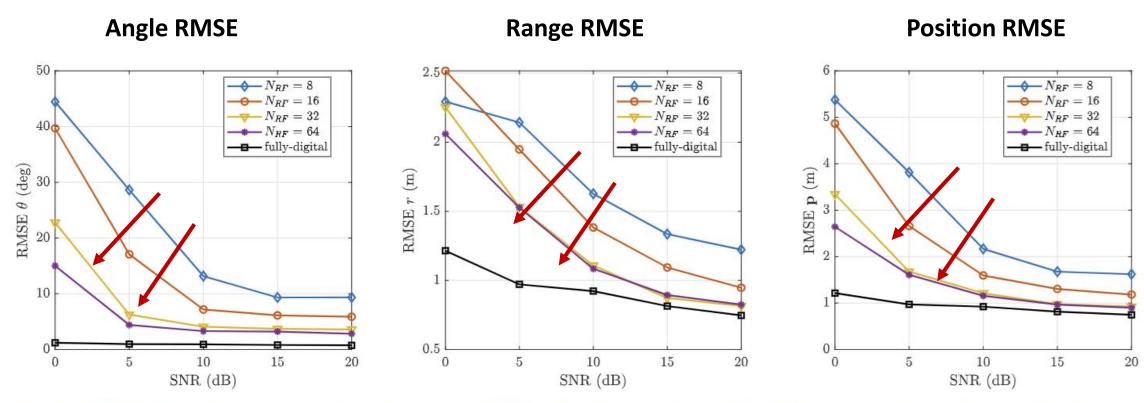


Fig. 4: RMSE of angle, range, and position versus SNR when the number of RF chains varies in a sub-array beamformer configuration with M=16 and N=128.



Is the proposed scheme robust to multipath effects?

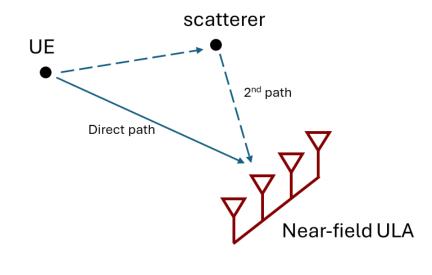
Hypothesis:

A point-like scatterer is randomly placed in the strong near-field region of the ULA

Objective:

Localize both the user and a scatterer in a single snapshot

$$\begin{cases} \mathbf{h}_{\text{LoS}} = \sqrt{\rho} \mathbf{a}(\theta, r) \\ \mathbf{h}_{\text{NLoS}} = \sum_{i=1}^{P} \sqrt{\rho_i} e^{j\phi_i} \mathbf{a}(\theta_i, r_i) \end{cases}$$



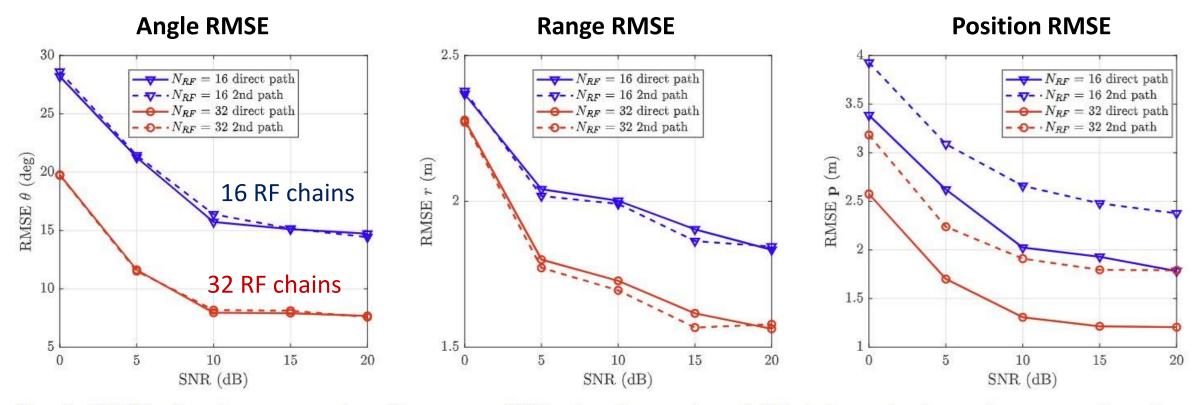


Fig. 5: RMSE of angle, range, and position versue SNR when the number of RF chains varies in a sub-array configuration with multipath.



Conclusions

- The proposed CNN-based framework achieves sub-meter localization accuracy from a single snapshot.
- It reduces phase shifter requirements by a factor of M compared to fully-connected architectures, improving scalability.
- Robustness against multipath effects.





Thanks for your attention!

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