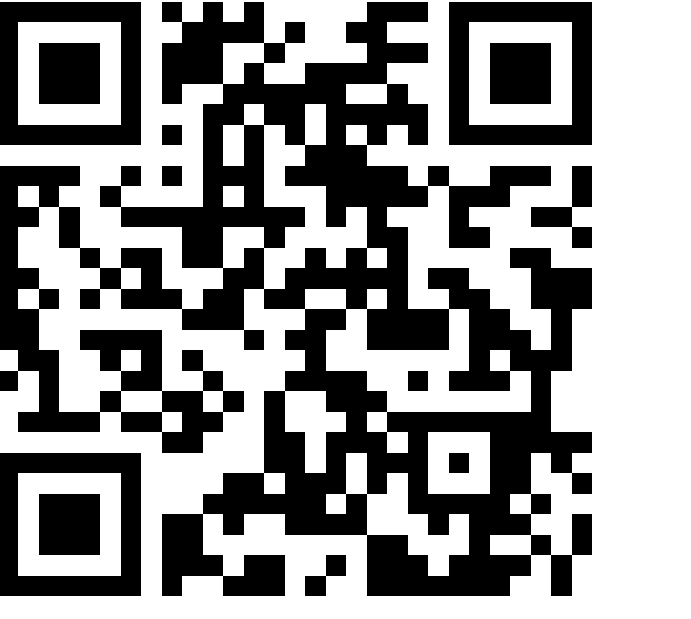


RaLU-Net: Deep Unfolded Radar Localization of Humans for Precise Multi-Person Non-Contact Vital Signs Monitoring

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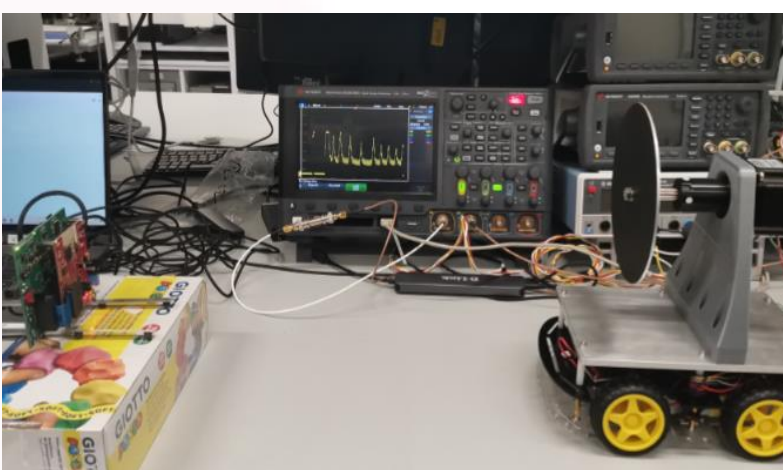


Motivation and Contributions

- SIMO FMCW radars enable multi-object localization, which is crucial for multi-person NCVSM. However, detecting and positioning humans in crowded scenarios is challenging and highly affected by resolution limitations
- This work first provides an iterative localization method (RaLU-JSR) which exploits joint sparsity and cardiopulmonary properties
- Then, it is unfolded into a neural network (RaLU-Net) that utilizes the unique structure of the data to enhance accuracy and reduce computational cost
- Simulations containing real-world data showed the network's superior performance in detecting and positioning multiple humans in thousands of close proximity scenarios outperforming existing techniques via key metrics

❖ Example of extracted thoracic motions of two adjacent humans. As the beamforming deviation increases, the vital information becomes distorted due to deflection noise and mutual interference

❖ Hardware phantom for monitoring both static and moving people



Iterative and Deep Unfolding Strategies

- Estimating $\{\mathbf{X}_l\}_{l=1}^L$ by promoting joint sparsity via the 3D $l_{2,1}$ LS problem:

$$\hat{\mathbf{X}} = \arg \min_{\mathbf{X} \in \mathbb{C}^{M \times P \times L}} \frac{1}{2L} \sum_{l=1}^L \|\mathbf{Y}_l - \mathbf{A}\mathbf{X}_l\mathbf{B}\|_F^2 + \gamma \|\mathbf{X}\|_{2,1}$$

❖ RaLU-JSR (ISTA)

$$\begin{cases} \mathbf{G}_l^{(i)} = \frac{1}{L_f} \mathbf{A}^H \mathbf{Y}_l \mathbf{B}^H - \frac{1}{L_f} \mathbf{A}^H \mathbf{A} \mathbf{X}_l^{(i)} \mathbf{B} \mathbf{B}^H + \mathbf{X}_l^{(i)}, l=1, \dots, L \\ \{\mathbf{X}_l^{(i)}\}_{l=1}^L = \mathcal{T}_{\gamma^{(3D)}} \left(\{\mathbf{G}_l^{(i)}\}_{l=1}^L \right) \end{cases}$$

❖ Deep Unfolding

$$\begin{cases} \mathbf{G}_l^{(i)} = \mathbf{W}_1^{(i)} \mathbf{Y}_l \mathbf{W}_2^{(i)} + \mathbf{W}_3^{(i)} \mathbf{X}_l^{(i)} \mathbf{W}_4^{(i)} + \mathbf{X}_l^{(i)}, l=1, \dots, L \\ \{\mathbf{X}_l^{(i)}\}_{l=1}^L = \mathcal{T}_{\gamma^{(3D)}} \left(\{\mathbf{G}_l^{(i)}\}_{l=1}^L \right) \end{cases}$$

➡ Incorporating knowledge for multi-person NCVSM

❖ RaLU-Net

$$\begin{cases} \mathbf{G}_l^{(i)} = \mathbf{W}_1^{(i)} \mathbf{Y}_l \mathbf{W}_2^{(i)} + \mathbf{Z}_l^{(i)} \mathbf{W}_4^{(i)} + \mathbf{X}_l^{(i)}, l=1, \dots, L \\ \{\mathbf{X}_l^{(i)}\}_{l=1}^L = \mathcal{T}_{\gamma^{(3D)}} \left(\{\mathbf{G}_l^{(i)}\}_{l=1}^L \right) \\ \mathbf{Z}_l^{(i+1)} = \mathbf{X}_l^{(i)} + \rho^{(i)} \left(\mathbf{X}_l^{(i)} - \mathbf{X}_l^{(i-1)} \right), l=1, \dots, L \end{cases}$$

Learnable parameters:

$$\Theta = \{\{\mathbf{W}_1^{(i)}, \mathbf{W}_2^{(i)}, \mathbf{W}_4^{(i)}, \gamma^{(i)}, \rho^{(i)}\}_{i=1}^L, \Pi\}$$

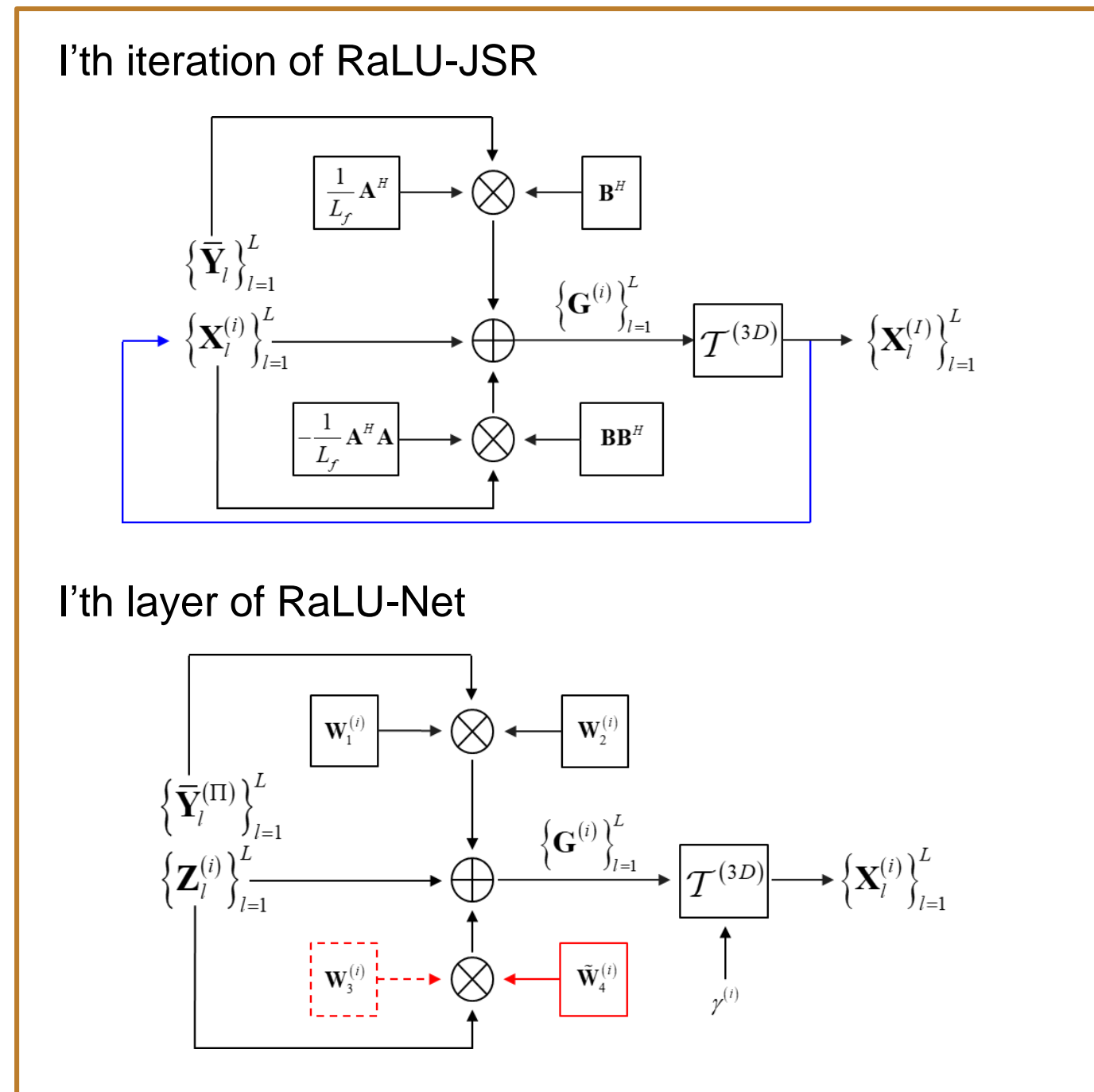
Mask loss:

$$\mathcal{L}_{\text{mask}}(\bar{\mathbf{X}}, \bar{\mathbf{X}}_{GT}) = \mathcal{L}_{\text{MSE}}^{(S)} + \mu \mathcal{L}_{\text{h}}^{(S)}$$

$$\mathcal{L}_{\text{MSE}}^{(S)} = \frac{1}{|S|} \sum_{(m,p) \in S} (\bar{\mathbf{X}}(m,p) - \bar{\mathbf{X}}_{GT}(m,p))^2$$

$$\mathcal{L}_{\text{h}}^{(S)} = \frac{1}{|S^{(r)}|} \sum_{(m,p) \in S^{(r)}} \|\bar{\mathbf{X}}(m,p)\|$$

$$\Rightarrow \mathcal{L}(\Theta) = \frac{1}{N_{\text{tr}}} \sum_{n_p=1}^{N_{\text{tr}}} \mathcal{L}_{\text{mask}} \left(f \left(\{\mathbf{Y}_l\}_{l=1}^L, \Theta \right), \bar{\mathbf{X}}_{GT, n_p} \right)$$



Signal Model

- We adopt the bilinear model of [1] for a SIMO FMCW radar signal

$$\mathbf{Y}_l = \mathbf{A}\mathbf{X}_l\mathbf{B} + \mathbf{N}_l, \quad l=1, \dots, L \text{ frames}$$

$$\mathbf{A} \in \mathbb{C}^{N \times M} : \mathbf{A}(n,m) \triangleq e^{j2\pi f_m n T_f} \text{ (range-related matrix)}$$

$$\mathbf{B} \in \mathbb{C}^{P \times K} : \mathbf{B}(p,k) \triangleq e^{j\theta_p[k]} \text{ (angle-related matrix)}$$

$$\mathbf{X}_l \in \mathbb{C}^{M \times P} : \mathbf{X}_l(m,p) \triangleq x_{m,p} e^{j\omega_{m,p}[l]} \text{ (complex amplitudes)}$$

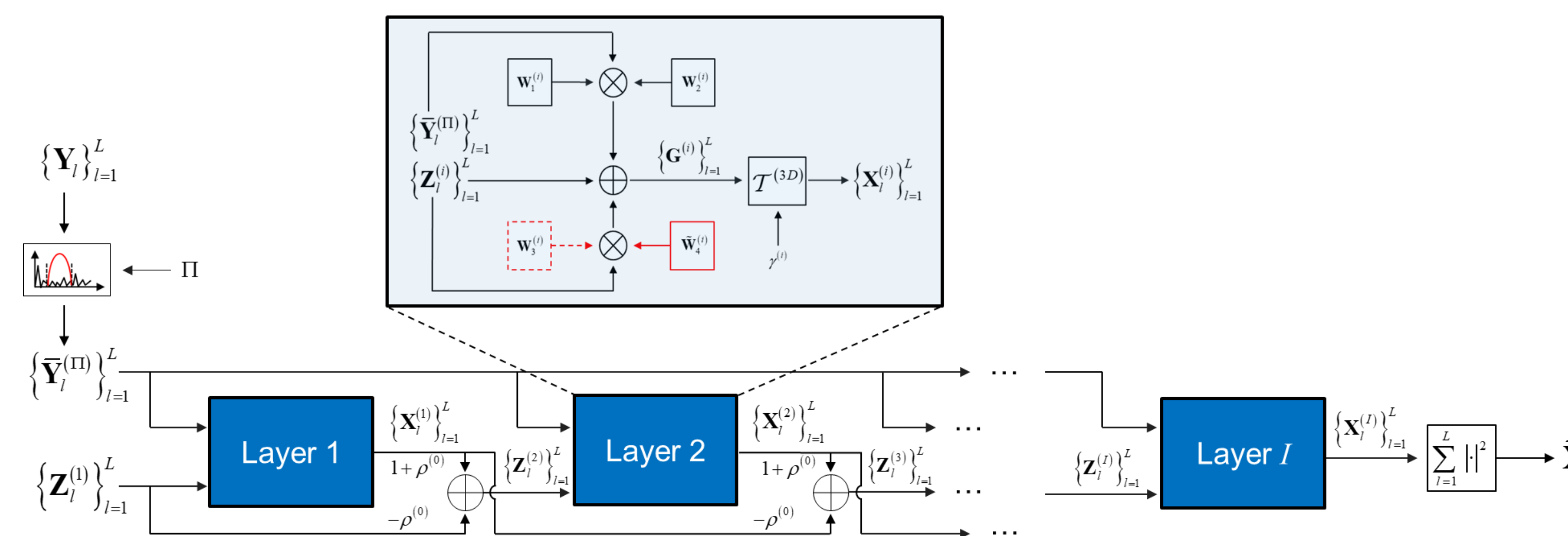
$$\mathbf{N}_l \in \mathbb{C}^{N \times K} : \mathbf{N}_l(n,k) \triangleq w[n,k,l] \text{ (noise matrix)}$$

- A-1: The humans are stationary. This means that the $\{m,p\}$ coordinates of $\{\mathbf{X}_l\}_{l=1}^L$, corresponding to the thoracic locations, are fixed and joint across all L frames.

- A-2: $U \ll MP$ objects, meaning that $\{\mathbf{X}_l\}_{l=1}^L$ are U-sparse matrices

- Goal: Estimate # of humans Z and their $\{d^{(z)}, \theta^{(z)}\}_{z=1}^Z$ coordinates

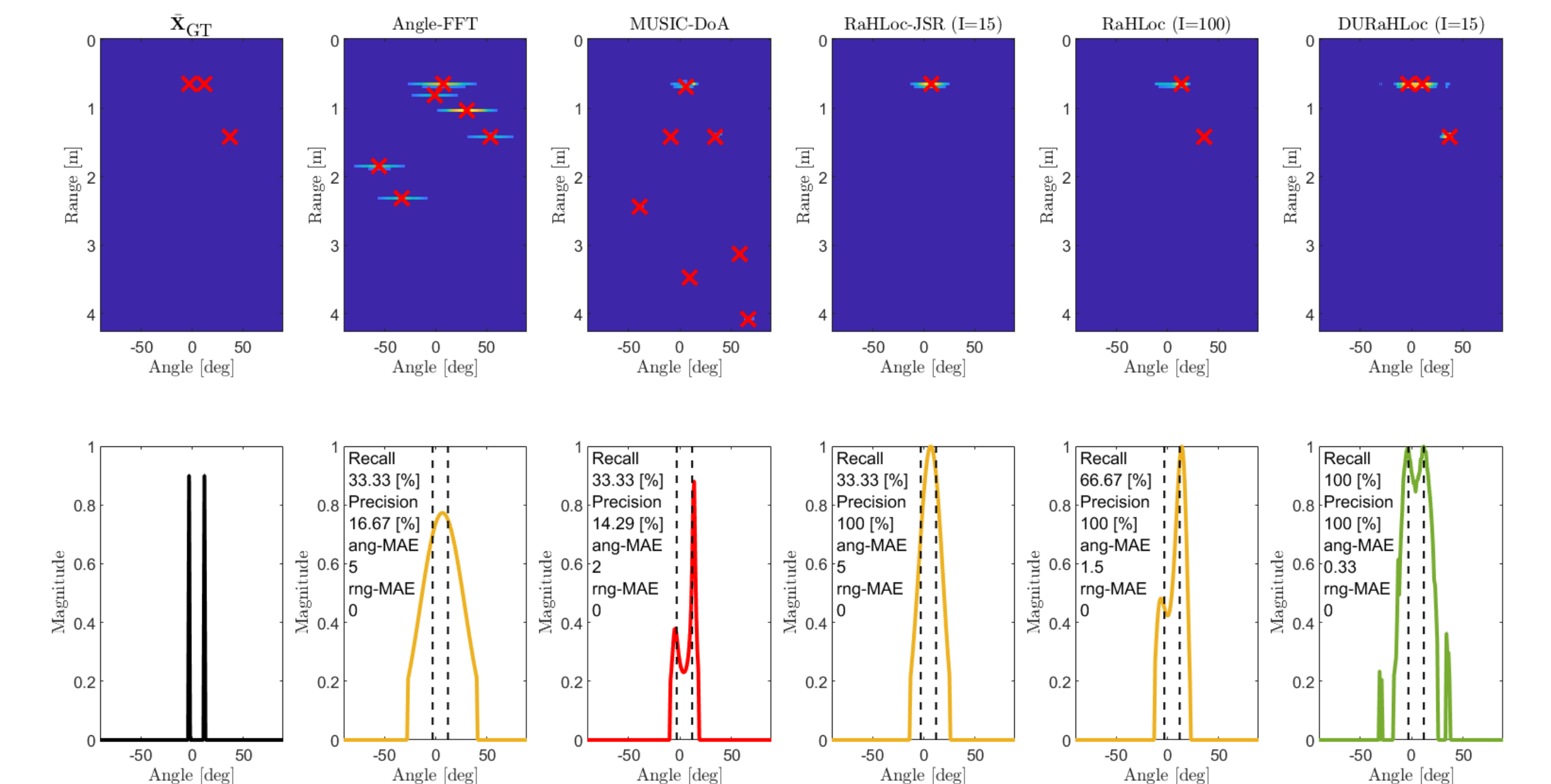
RaLU-Net Architecture



[1] Eder, Y., Zagoury, E., Savariego, S., Namer, M., Cohen, O., & Eldar, Y. C. (2025). Robust Phantom-Assisted Framework for Multi-Person Localization and Vital Signs Monitoring Using MIMO FMCW Radar. arXiv preprint

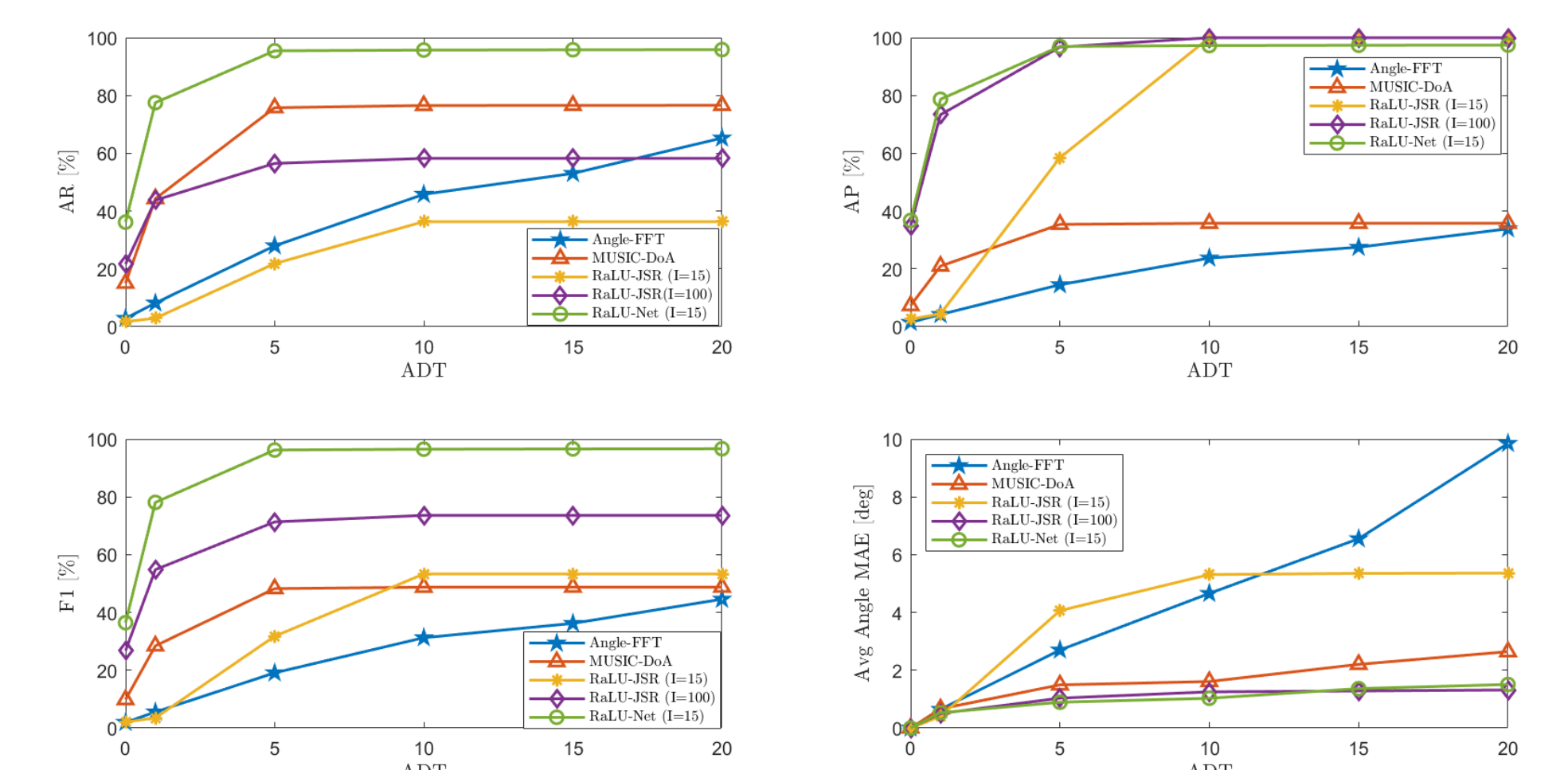
Results

- Validation example: predicted localization maps of all compared methods relative to ground-truth (GT) map for angle deviation threshold (ADT) of 5°
- The proposed RaLU-Net achieves the best performance:
 1. Detects exactly 3/3 humans (without any misses or false detections)
 2. Exhibits the most distinct separation by both power and angular pattern
 3. Positions the humans with the lowest average angle-MAE
 4. Reduced computational cost compared to the iterative RaLU-JSR



- Average scores for the entire validation set vs. ADT

1. F1 score of the RaLU-Net outperforms all other methods and passes 96% for any ADT above 5° (here the theoretical angle resolution is ~30°)
2. Both RaLU-JSR and RaLU-Net achieved a small average angle-MAE < 1.5° for every ADT. However, whereas the accelerated iterative method requires 100 iterations, the unfolded network employs about 7 times lower number of layers



Achieving high performance with minimal computation in thousands of close-proximity scenarios