

PRISM: Platform for Reflective Imaging using SDR-Based mmWave Compressed Sensing

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Abstract—This paper presents PRISM, a 28 GHz near-field bistatic millimeter-wave (mmWave) compressed sensing (CS) imaging platform implemented on software-defined radio (SDR) hardware. To address practical constraints such as finite phase resolution, limited aperture size, bistatic geometry, and near-field propagation, PRISM integrates spherical-wave phase compensation, bistatic parallax search, virtual aperture expansion, and sparse reconstruction. Three sparse reconstruction methods, namely fast iterative shrinkage-thresholding algorithm (FISTA), CVX, and learned approximate message passing (LAMP), are compared under the same sensing model and measurement setup. Experimental results show reliable image reconstruction with only 3.4 % sampling, demonstrating the feasibility of low-sampling near-field mmWave imaging using practical SDR hardware.¹

Index Terms—millimeter-wave (mmWave) imaging, compressed sensing (CS), software-defined radio (SDR), near-field phase compensation, bistatic radar, FISTA, LAMP

I. INTRODUCTION

Millimeter-wave (mmWave) imaging has attracted attention for applications such as non-destructive inspection and wireless sensing due to its high spatial resolution and penetration capability. Conventional high-resolution mmWave imaging systems often rely on dense antenna sampling, large-scale phased arrays, or mechanical scanning, leading to high hardware cost, acquisition time, and complexity. Recently, compressed sensing (CS) has emerged as a promising solution by exploiting scene sparsity to reduce measurement overhead [1]. Recent studies have extended CS from synthetic aperture radar (SAR) to near-field mmWave imaging [2], [3], demonstrating the potential for sub-Nyquist sampling and lower complexity.

Despite these advances, most existing CS imaging studies rely on simplified sensing assumptions or simulation-based evaluations, while practical SDR-based near-field implementations remain largely underexplored. In particular, it is still unclear whether physically meaningful target geometries can be reconstructed from a few hundred real measurements under realistic hardware constraints. This challenge is particularly severe in bistatic near-field systems, where multiple propagation and hardware impairments deviate from idealized CS imaging models. Near-field spherical-wave propagation invalidates conventional far-field steering models based solely on angular information, while the spatial separation between the

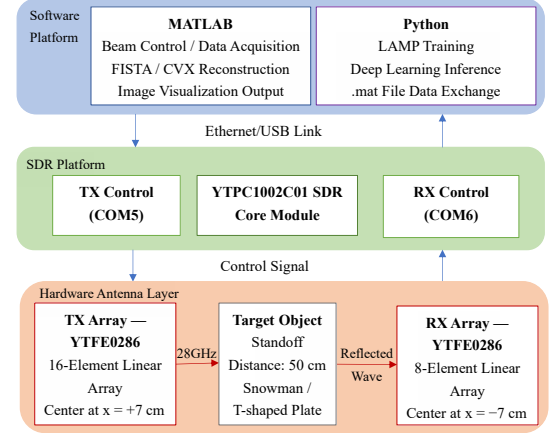


Fig. 1: PRISM platform and its system architecture for the near-field imaging.

transmitter (TX) and receiver (RX) arrays introduces bistatic parallax and geometric mismatch. Practical SDR platforms further suffer from finite 6-bit phase resolution, calibration errors, limited aperture size, and environmental multipath interference. Consequently, idealized CS imaging models [2], [3] become unreliable unless the actual hardware geometry and non-ideal effects are explicitly incorporated.

Motivated by these challenges, this paper investigates low-sampling near-field imaging on an SDR-based bistatic mmWave platform. We develop a hardware-aware imaging that integrates spherical-wave phase compensation, RX parallax search, virtual aperture expansion, and sparse reconstruction. The proposed method reconstructs a 6561-pixel image from only 225 SDR measurements, corresponding to an effective sampling rate (SR) of 3.4 %. We also compare three sparse reconstruction methods, fast iterative shrinkage-thresholding algorithm (FISTA) [4], CVX [5], and learned approximate message passing (LAMP) [6], under a common sensing model and hardware setup. This comparison provides insights into iterative, convex-optimization-based, and deep-unfolded reconstruction methods for practical near-field imaging.

II. SYSTEM DESCRIPTION OF PRISM

A. Hardware Configuration

In Fig. 1, the transmitter (TX) and receiver (RX) use 16-element and 8-element linear arrays with element spacing $d = \lambda/2$, respectively. The system is operated at 28 GHz

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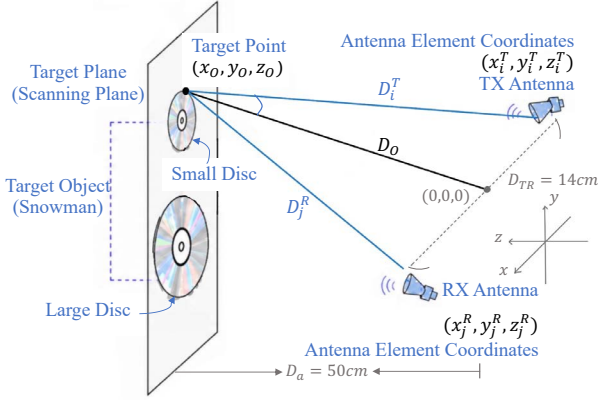


Fig. 2: Near-field coordinate geometry of the bistatic imaging system.

in a bistatic configuration, controlled by an SDR platform. Beam directions are parameterized by azimuth angle θ_x and elevation angle θ_y . The target region of interest spans $\theta_x, \theta_y \in [-\Theta_T, \Theta_T]$ at a standoff distance D_a from the array.

B. Near-Field Scattering Model

The phased array used in this system incorporates a built-in self-calibration mechanism that automatically compensates for internal phase errors; accordingly, hardware-induced phase errors are not considered. The Cartesian coordinate of this system is illustrated in Fig. 2. Let (x_i^T, y_i^T, z_i^T) and (x_j^R, y_j^R, z_j^R) denote the positions of the i -th TX antenna element and the j -th RX antenna element, respectively, while (x_O, y_O, z_O) is the target position. The parameter D_O denotes the distance from the midpoint of the TX–RX baseline to the target point, D_a denotes the distance from the origin to the target plane, and D_{TR} denotes the horizontal separation between the TX and RX arrays.

Following the near-field phased-array model in [2], [7], the received signal steered toward direction $\theta = (\theta_x, \theta_y)$ with element-wise phase offsets $\phi = (\phi_i, \phi_j)$ can be expressed as

$$s_{\theta, \phi} = \iiint_{\mathcal{V}} g(x, y, z) \sum_{i,j} \frac{e^{-jk(D_i^T + D_j^R)}}{D_i^T D_j^R} e^{-j(\phi_i + \phi_j)} dx dy dz, \quad (1)$$

where $\mathcal{V}$ is the imaging volume, $g(x, y, z)$ is the target scattering coefficient (i.e., the 3-D reflectivity map to be reconstructed), D_i^T and D_j^R are the distances from the i -th TX and j -th RX element to the target point, $k = 2\pi/\lambda$ is the wavenumber, and ϕ_i, ϕ_j are the phase compensation values applied to the TX and RX elements. This model explicitly captures the element-dependent path-length variations inherent to near-field propagation.

III. PROPOSED METHODS AND DESIGN

A. System Calibration and Hardware Constraint Modeling

1) *Near-Field Path-Phase Compensation*: To compensate for the phase distortions caused by near-field propagation, a

three-step calibration procedure is employed.

Step 1 — Coordinate conversion. Given the azimuth and elevation angles of the target $\theta = (\theta_x, \theta_y)$, the Cartesian coordinates are obtained as

$$x_O = D_O \sin \theta_x \cos \theta_y; \quad (2)$$

$$y_O = D_O \sin \theta_y; \quad (3)$$

$$z_O = D_O \cos \theta_x \cos \theta_y. \quad (4)$$

Step 2 — Element-wise path-length computation. The exact propagation distances from the target point (x_O, y_O, z_O) to the i -th TX and j -th RX elements are computed as:

$$D_O = \sqrt{x_O^2 + y_O^2 + z_O^2}; \quad (5)$$

$$D_i^T = \sqrt{(x_O - x_i^T)^2 + (y_O - y_i^T)^2 + z_O^2}; \quad (6)$$

$$D_j^R = \sqrt{(x_O - x_j^R)^2 + (y_O - y_j^R)^2 + z_O^2}. \quad (7)$$

Step 3 — Path difference to phase command. The path-length differences relative to the array reference distance D_O are converted into phase compensation commands via

$$\phi_i = \frac{D_O - D_i^T}{\lambda} \times 360^\circ; \quad (8)$$

$$\phi_j = \frac{D_O - D_j^R}{\lambda} \times 360^\circ. \quad (9)$$

The resulting phase terms, ϕ_i and ϕ_j , are applied to the TX and RX elements, respectively, to compensate for near-field phase variations and ensure coherent signal focusing at the desired target location.

2) *Hardware Phase Quantization and Physical Constraint Analysis*: After the near-field phase compensation is computed, the physical limitations of the SDR platform must be considered. The phase shifters employed in this system provide 6-bit quantization resolution, with a minimum phase step of $360^\circ/2^6 = 5.625^\circ$. As a result, the applied phase may deviate from the ideal compensation value by up to $\pm 2.8^\circ$ due to quantization. A geometric analysis conducted in this work shows that, at a typical imaging distance D_a , the maximum phase quantization error corresponds to a spatial localization error of approximately 0.08 mm. Compared with the decimeter-scale targets considered here, such an error is negligible and has an insignificant effect on image reconstruction accuracy. Furthermore, sparse recovery algorithms inherently suppress quantization noise through ℓ_1 -norm regularization, thereby providing additional robustness against hardware imperfections [4]–[6].

B. Bistatic Parallax Compensation

Due to the horizontal separation between the TX and RX arrays, the target is observed from different viewing angles, resulting in a bistatic parallax effect. For a TX–RX separation of D_{TR} and an imaging distance of D_a , the corresponding parallax angle is

$$\alpha = \arctan(D_{TR}/D_a), \quad (10)$$

which causes a mismatch between the TX illumination direction and the RX observation direction. To mitigate this effect, an adaptive RX angular search mechanism based on a two-level loop structure is employed:

$$s(\boldsymbol{\theta}, \boldsymbol{\phi}^*) = \max_{\Delta\theta_{\text{RX}} \in \mathcal{D}} s(\boldsymbol{\theta}, \boldsymbol{\phi}^*, \Delta\theta_{\text{RX}}), \quad (11)$$

where $s(\boldsymbol{\theta}, \boldsymbol{\phi}^*, \Delta\theta_{\text{RX}})$ denotes the received signal power when the TX beam is steered to $\boldsymbol{\theta}$ using phase weights $\boldsymbol{\phi}^*$ from (8)–(9). The RX beam simultaneously searches over discrete candidate angles $\mathcal{D}$, which covers the angular range $[-\Theta_R, +\Theta_R]$ with offset angles $\Delta\theta_{\text{RX}}$.

C. High-Resolution Software Dictionary Construction with Virtual Aperture Expansion

The physical SDR array has a limited effective aperture in the elevation direction because only a small number of vertical rows are equipped. Consequently, the elevation-domain point-spread function (PSF) is broad, reducing the separability of vertically adjacent scatterers. Importantly, the proposed virtual aperture expansion does not generate additional RF measurements. The measurement vector ($\mathbf{s}$) remains unchanged and is acquired solely from the physical SDR system. Instead, following the over-complete dictionary framework in sparse radar imaging [8], the aperture expansion is introduced during dictionary construction. Specifically, PRISM constructs a virtual phase-center set $\mathcal{A}^v = \{(x_a^v, y_b^v, z_0) \mid a = 1, \dots, A_{nx}, b = 1, \dots, A_{ny}\}$, which can be interpreted as a model-based virtual antenna array used solely for sensing-dictionary generation. Here, A_{nx} and A_{ny} denote the numbers of virtual phase centers along the horizontal and vertical directions, respectively. The constant $z_0 = 0$ places the virtual phase centers co-planar with the physical antenna arrays. The horizontal and vertical coordinates are uniformly spaced by $\lambda/2$ and centered at the array midpoint:

$$x_a^v = \left(a - \frac{A_{nx} + 1}{2}\right) \frac{\lambda}{2}, \quad a = 1, \dots, A_{nx}, \quad (12)$$

$$y_b^v = \left(b - \frac{A_{ny} + 1}{2}\right) \frac{\lambda}{2}, \quad b = 1, \dots, A_{ny}. \quad (13)$$

The p -th beam-scan measurement corresponds to steering direction $\boldsymbol{\theta}_p = (\theta_{x,p}, \theta_{y,p})$ with hardware phase commands $\phi_{i,p}$ and $\phi_{j,p}$ from (8)–(9). For the p -th beam-scan measurement, the distance from the same virtual phase center to the focusing point $(x_p^{\text{foc}}, y_p^{\text{foc}}, z_p^{\text{foc}})$, is denoted by

$$D_{a,b,p}^{v,\text{foc}} = \sqrt{(x_p^{\text{foc}} - x_a^v)^2 + (y_p^{\text{foc}} - y_b^v)^2 + (z_p^{\text{foc}} - z_0)^2}. \quad (14)$$

The near-field distance from the virtual phase center (x_a^v, y_b^v, z_0) to the voxel position (x_n, y_n, z_n) is given as

$$D_{a,b,n}^v = \sqrt{(x_n - x_a^v)^2 + (y_n - y_b^v)^2 + (z_n - z_0)^2}. \quad (15)$$

The corresponding virtual dictionary $\mathbf{H} \in \mathbb{R}_+^{P \times N}$ (i.e., virtual near-field array response) is then established as

$$H_{p,n}^v = \left| \sum_{a=1}^{A_{nx}} \sum_{b=1}^{A_{ny}} \exp(j\Delta\varphi_{p,n}^v(a,b)) \right|^2, \quad (16)$$

where $H_{p,n}^v$ is the (p,n) -th entry of $\mathbf{H}$, and $\Delta\varphi_{p,n}^v(a,b) = k(D_{a,b,n}^v - D_{a,b,p}^{v,\text{foc}})$ is the residual phase mismatch between the focusing point and the candidate voxel. The virtual dictionary $\mathbf{H}$ is subsequently used in the sparse reconstruction formulation $\mathbf{s} = \mathbf{H}\mathbf{g}$. The measurement vector $\mathbf{s} \in \mathbb{R}_+^P$ is acquired from the physical SDR system after bistatic parallax compensation, i.e., $s(\boldsymbol{\theta}, \boldsymbol{\phi}^*)$ in (11). Moreover, $\mathbf{g} \in \mathbb{R}_+^N$ is the voxel reflectivity vector to be reconstructed. Accordingly, the SR is defined as P/N . Note that this method does not increase the number of independent measurements but rather imposes a physics-motivated near-field dictionary prior that improves sparse target separability under the assumed geometry.

D. Sparse Reconstruction Algorithms

Three sparse reconstruction algorithms, including FISTA, CVX, and LAMP, are implemented in the proposed PRISM to solve the ℓ_1 -regularized problem [2]:

$$\hat{\mathbf{g}} = \arg \min_{\mathbf{g}} \|\mathbf{H}\mathbf{g} - \mathbf{s}\|_2^2 + w\|\mathbf{g}\|_1, \quad (17)$$

where the first term enforces consistency with the measurements, while ℓ_1 -regularization promotes sparsity in the reconstructed scene. This formulation enables target sensing from sub-Nyquist measurements.

a) *FISTA* [4]: FISTA solves (17) by alternating a gradient descent step on the first data fidelity term, followed by a soft-thresholding operation that promotes sparsity:

$$\mathbf{g}^{(k)} = \mathcal{S}_{w/L} \left(\mathbf{z}^{(k)} - \frac{1}{L} \mathbf{H}^T (\mathbf{H}\mathbf{z}^{(k)} - \mathbf{s}) \right); \quad (18)$$

$$\mathcal{S}_\tau(\mathbf{u}) = \text{sign}(\mathbf{u}) \odot \max(|\mathbf{u}| - \tau, \mathbf{0}),$$

where L is the Lipschitz constant and w governs the sparsity-fidelity tradeoff. In addition, Nesterov momentum is used to accelerate convergence.

b) *CVX* [5]: CVX allows the optimization problem (17) to be stated directly in mathematical form and automatically selects an appropriate interior-point solver. It provides a theoretically optimal solution and serves as the reference benchmark for evaluating the reconstruction performance of FISTA and LAMP.

c) *LAMP* [6]: LAMP is a deep-unfolding approach that maps the iterations of the Approximate Message Passing (AMP) algorithm onto a neural network with $L = 8$ layers. Unlike conventional AMP, where the step sizes and threshold parameters are analytically determined from the sensing matrix and noise statistics, LAMP treats these quantities as trainable parameters. By learning them directly from data, LAMP adapts to the sensing environment and typically achieves accurate reconstruction with fewer iterations. For training, simulated measurement-scene pairs $(\mathbf{s}, \mathbf{g})$ are generated in MATLAB using a normalized sensing matrix $\mathbf{H}/|\mathbf{H}|_F$.

For the three algorithms, the non-negativity of $\mathbf{g}$ is enforced by clipping after convergence.

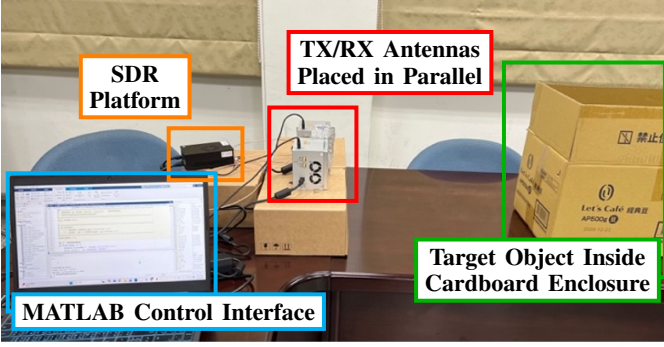


Fig. 3: Experiment configuration.

E. Image Visualization and Spatial Filtering

Sparse reconstruction inherently produces discrete point estimates rather than continuous target extents [9]. To restore spatial continuity, PSF convolution is applied to approximate the footprint of physical scatterers [10], followed by field-of-view masking to suppress out-of-region artifacts and sidelobes. These post-processing steps are applied to all reconstructed images.

IV. SIMULATION AND EXPERIMENT RESULTS

The proposed PRISM is evaluated via computer simulation and experiments. The system uses a 2×8 TX array and a 1×8 RX array operating at a carrier frequency of 28 GHz. The key parameters of FISTA and CVX are listed in Table I, while the training parameters of LAMP are shown in Table II. Simulations are conducted over a 10×10 cm² target region, discretized into $51 \times 51 = 2601$ voxels. The reconstruction performance is evaluated for SRs of 50%, 40%, 30%, and 20% under two scenarios: Sim-1 with a single point target at SNR= -30 dB and Sim-2 with a T-shaped metallic plate at SNR= -40 dB. The reconstruction quality is assessed using the peak signal-to-noise ratio (PSNR), enabling quantitative comparison among different reconstruction algorithms and SRs. Fig. 3 shows the experiment configuration. Based on the geometry locations in Fig. 2, the TX and RX arrays are centered at $(-7\text{cm}, 0, 0)$ and $(+7\text{cm}, 0, 0)$, respectively, yielding a bistatic separation of $D_{TR} = 14$ cm and a standoff distance of $D_a = 50$ cm. Substituting these values into (10) gives $\alpha = \arctan(14/50) \approx 15.64^\circ$. Rounding to the nearest beam-scan step of $\Delta\theta_{RX} = 3^\circ$ yields $\pm 15^\circ$, while the adjacent step $\pm 12^\circ$ is included as a robustness margin, resulting in $\mathcal{D} = \{-15^\circ, -12^\circ, +12^\circ, +15^\circ\}$. In the experiment, the TX beam sweep spans $[-\Theta_T, +\Theta_T]$ with $\Theta_T = 21^\circ$. A beam-scan step size of $\Delta\theta_{TX} = 3^\circ$ is adopted to balance acquisition time and measurement density, resulting in $M = 2\Theta_T/\Delta\theta_{TX} + 1 = 15$ scan directions per axis. For virtual aperture expansion, we set $A_{nx} = 8$ and $A_{ny} = 8$. Consequently, $15 \times 15 = 225$ beam-scan measurements are used to reconstruct an $81 \times 81 = 6561$ -pixel image, corresponding to a sampling ratio of $\text{SR} = P/N \approx 3.4\%$.

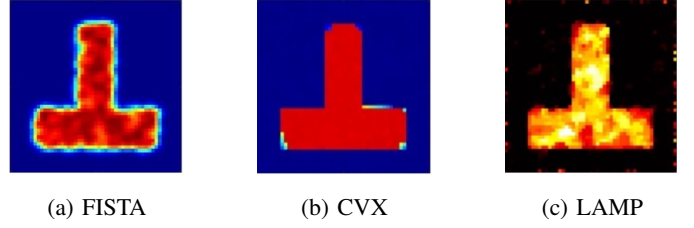


Fig. 4: Reconstruction results at SR=40%, Sim-2 T-shaped metallic plate. (a) FISTA. (b) CVX. (c) LAMP.

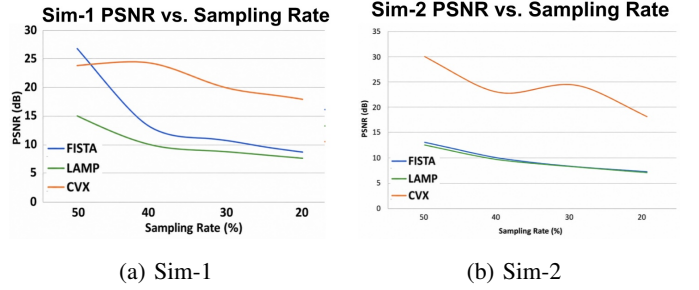


Fig. 5: PSNR vs. SR for (a) Sim-1 (single point target, SNR= -30 dB) and (b) Sim-2 (T-shaped metallic plate, SNR= -40 dB).

A. Simulation Results

Fig. 5 presents the reconstruction PSNR versus SR. As expected, the reconstruction quality generally degrades as the SR decreases due to the reduced amount of measurement available for image recovery. For Sim-1 in Fig. 5(a), FISTA achieves the highest PSNR at SR=50%, reaching 26.7 dB and outperforming CVX by 3.1 dB. However, its PSNR drops sharply to 13.1 dB when the SR is reduced to 40%, indicating a threshold effect in which a relatively small reduction in measurements results in a significant degradation in reconstruction quality. In contrast, LAMP exhibits gradual degradation, with PSNR decreasing from 15.2 dB to 7.8 dB as the SR decreases. CVX demonstrates the most stable performance, maintaining PSNR values between 17.9 dB and 23.9 dB across all SRs.

For Sim-2 in Fig. 5(b), CVX consistently achieves the highest reconstruction quality, attaining a peak PSNR of 30.2 dB at SR= 50%. Interestingly, its PSNR exhibits a non-monotonic trend, decreasing to 20.1 dB at SR= 40% and subsequently increasing to 24.7 dB at SR= 30%. This behavior may be attributed to variations in problem conditioning and the optimization trajectory of the interior-point solver, rather than the SR alone. In comparison, FISTA and LAMP achieve comparable PSNR performance across the tested SRs, indicating that the sparsity-promoting reconstruction strategy provides less advantage for geometrically extended targets than for isolated point-like targets.

For Sim-1, Fig. 6(a) shows that the convergence of LAMP, in terms of training loss, deteriorates as the SR decreases. The training loss converges within approximately 10 epochs for $\text{SR} \geq 40\%$, while mild fluctuation is observed at $\text{SR} = 30\%$.

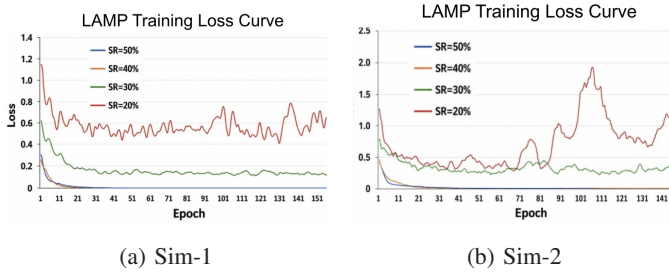


Fig. 6: LAMP training loss curves (SR = 20%–50%). (a) Sim-1 (single point target, SNR = −30 dB). (b) Sim-2 (T-shaped metallic plate, SNR = −40 dB).

TABLE I: Experiment Parameters for FISTA and CVX

Parameter	FISTA	CVX
Dynamic range (caxis)	[−12, 0] dB	[−18, 0] dB
Sparsity weight	$0.2 \times \max \mathbf{H}^T \mathbf{s} $	$0.17 \times \max \mathbf{H}^T \mathbf{s} $
Reconstruction res.	$0.5^\circ/\text{pixel}$	$0.5^\circ/\text{pixel}$
Convergence criteria	Tol 1×10^{-5} , Max 200	Solver adaptive (IPM)
Spatial filtering (PSF)	Cubic B-Spline	2D Gaussian

TABLE II: LAMP Experiment and Training Parameters

Parameter	Value
Unfolded layers (Layers)	8
Training epochs	150
Initial step size (α)	0.8

At SR= 20%, the loss exhibits pronounced fluctuations. For Sim-2, Fig. 6(b) shows that convergence of LAMP becomes less stable at lower SRs, with larger loss fluctuations observed than in Sim-1. This indicates that the increased structural complexity of the T-shaped target makes learning more challenging under highly undersampled conditions.

B. Experiment Results

Fig. 7(a) shows the measured 15×15 raster scan, whose blocky appearance reflects the 3° beam-scanning quantization. Despite the coarse sampling, the dual-sphere snowman target is clearly identifiable in all reconstructions. FISTA in Fig. 7(b) produces a sparse, focused image that preserves the target shape, validating the proposed near-field phase compensation and bistatic parallax search. CVX in Fig. 7(c) accurately localizes the dominant scattering centers, while LAMP in Fig. 7(d) yields a smoother contour but exhibits increased diffusion in the upper sphere, likely due to mismatch between hardware measurements and simulated training data.

V. CONCLUSION

This paper presented PRISM, a near-field bistatic CS imaging framework for SDR-based mmWave systems. By integrating spherical-wave phase compensation, RX parallax search, virtual-aperture dictionary construction, and sparse reconstruction, PRISM successfully reconstructs target images with an SR of only 3.4%. Among the evaluated methods, CVX achieves the best reconstruction quality, FISTA offers

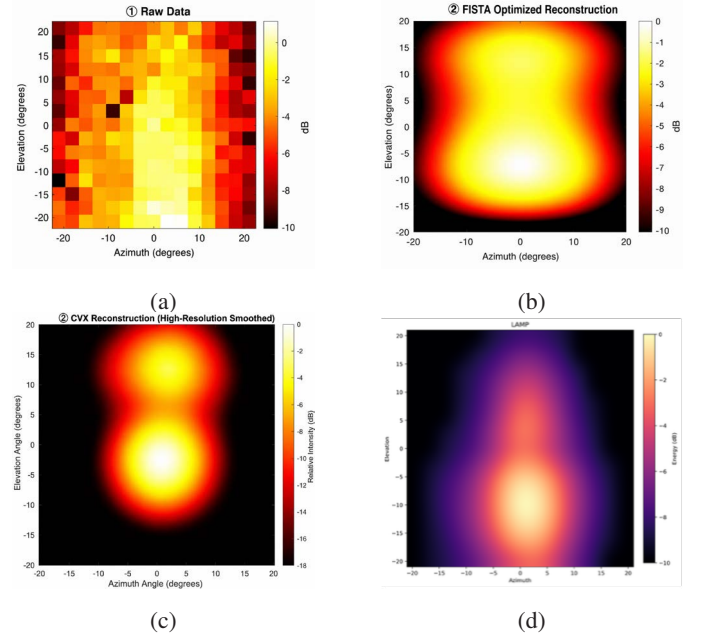


Fig. 7: Experimental results for a dual-sphere snowman structure (a) Raw scan (15×15 grids, 3° spacing), (b) FISTA, (c) CVX and (d) LAMP.

a favorable quality–complexity tradeoff, and LAMP provides the fastest inference speed but is more sensitive to distribution mismatch. The results demonstrate the feasibility of reliable near-field mmWave imaging at extremely low SRs. Future work will incorporate hardware impairments and more diverse training geometries to further improve robustness.

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