RCoD-AoANet: Residual Covariance Denoising for AoA Estimation in ISAC-OTFS Vehicular Systems

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***Abstract*—Integrated sensing and communication (ISAC) is emerging as a key technology for intelligent transportation systems by enabling simultaneous sensing and data transmission over a shared wireless platform. In vehicular environments, orthogonal time-frequency space (OTFS) modulation is particularly attractive because of its robustness to Doppler effects. However, accurate angle-of-arrival (AoA) estimation remains challenging in ISAC-OTFS systems, since noise and multipath propagation distort the received spatial covariance matrix and degrade conventional covariance-based estimators. In this work, we present RCoD-AoANet, a residual covariance denoising network for robust AoA estimation in an ISAC-OTFS vehicular framework. By learning the residual mapping between noisy and clean covariance matrices using attenuation- and phase-related features, the proposed method enhances covariance quality prior to eigen-analysis and phase-difference-based AoA recovery. Simulation results demonstrate competitive root-mean-square error performance, improved robustness across signal-to-noise ratios and snapshot conditions, and lower processing time than conventional subspace-based methods.**

***Index Terms*—Angle-of-arrival (AoA), covariance denoising, deep learning, integrated sensing and communication (ISAC), orthogonal time-frequency space (OTFS).**

I. Introduction

Integrated sensing and communication (ISAC) has emerged as a cornerstone technology for sixth-generation (6G) wireless communication systems [1]. Unlike conventional communication frameworks, where sensing and data transmission operate independently, ISAC integrates both functionalities within a unified spectrum and signal processing architecture. ISAC improves spectral efficiency, reduces hardware redundancy, and enables wireless systems to simultaneously support high-rate data transmission and environmental sensing. ISAC capabilities play a crucial role in emerging applications such as autonomous driving, where dependable gigabit-level communication and real-time situational awareness are required to support safe and intelligent transportation systems (ITS) [2].

Conventional vehicular communication technologies, such as fifth-generation (5G) new radio vehicle-to-everything (NR-V2X) systems designed for ITS, are primarily optimized for reliable data exchange among vehicles, infrastructure, and pedestrians [3]. Environmental sensing in such systems is typically achieved through independent sensing platforms or camera-based systems, operating separately from the communication infrastructure [4]. In highly dynamic vehicular environments, characterized by rapid channel variations, high Doppler shifts, and stringent latency requirements, these limitations restrict the ability of existing architectures to simultaneously support reliable connectivity and accurate environmental awareness. Such challenges highlight the need for more integrated wireless system designs capable of jointly supporting communication and sensing functionalities in future intelligent vehicular networks [5].

In the ISAC-based systems, accurate estimation of the angle-of-arrival (AoA) of received signals from surrounding vehicles is a fundamental requirement for reliable environmental sensing [6]. AoA information serves as a key parameter for estimating sensing attributes such as vehicle speed, acceleration, and spatial position. Precise AoA estimation enables accurate situational awareness at the current time instant while also facilitating efficient beamforming and resource allocation for subsequent transmissions [7]. However, even subtle inaccuracies in AoA estimation can significantly affect the reliability of vehicular ISAC networks. In ISAC system, the error in AoA estimation propagate through the trigonometric relationships used in sensing algorithms, leading to inaccurate vehicle position and velocity estimates. Consequently, inaccurate AoA estimation can impair cooperative perception, introduce beam misalignment in vehicular links, and reduce the reliability of safety-critical vehicular communication networks [8].

The AoA estimation for sensing in ISAC-based vehicular systems has attracted significant research attention in recent literature. The authors in [9] proposed a maximum likelihood (ML) estimator integrated with a message passing algorithm (MPA)-based receivers for reliable sensing and data detection. The authors in [10] combined the ML estimation technique with matched filter to improve estimation accuracy. To reduce the computational burden of exhaustive grid search in ML estimation, the authors in [11] proposed a Fibonacci search-based method to reduce computations. In [12], the authors proposed an improved multiple signal classification (MUSIC)-based framework to mitigate interference within the sensing region. Existing approaches have demonstrated promising performance in AoA estimation; however, they generally depend on accurate channel state information and continuous-valued signal models, which limit their practical implementation. Moreover, subspace-based techniques such

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as MUSIC tend to suffer performance degradation in highly correlated propagation environments, as commonly observed in vehicular networks [13].

Motivated by the limitations of conventional subspace-based AoA estimators in vehicular ISAC-orthogonal time-frequency space (OTFS) scenarios, in this work, we propose a residual covariance denoising network (RCoD-AoANet) for reliable AoA estimation. In contrast to MUSIC, whose performance depends on accurate covariance estimation and clear separation between signal and noise subspaces, the proposed framework first refines the received covariance matrix using a residual deep neural network and then performs eigenvector-based AoA extraction. The proposed method is particularly suitable for vehicular networks, where low signal-to-noise ratio (SNR) operation, rapidly varying propagation conditions, and correlated multipath components often degrade the reliability of classical subspace methods. By preserving the intrinsic signal-subspace structure while suppressing noise and covariance perturbations, the proposed method enables robust multi-target AoA estimation without explicit channel estimation. The main contributions of this work are summarized as follows.

- We propose a residual covariance denoising network, RCoD-AoANet, for AoA estimation in ISAC-OTFS systems operating over realistic clustered-delay-line (CDL) channel-based vehicular channels. Unlike conventional estimation techniques, which can be sensitive to low-SNR conditions and correlated multipath, the proposed framework learns to refine the received covariance matrix prior to angle extraction, thereby improving robustness in challenging vehicular propagation environments.
- We develop a covariance-domain AoA estimation framework that integrates learned covariance denoising with eigenvector-based angle extraction. By explicitly preserving the underlying signal-subspace structure, the proposed method remains well suited to vehicular scenarios.
- We conduct extensive simulations to assess the proposed RCoD-AoANet from three perspectives: estimation error, computational time, and robustness with respect to the number of snapshots under low-SNR and highly correlated CDL vehicular channels.

The remainder of this paper is organized as follows. Section II presents the system model. Section III describes the proposed method. Section IV provides numerical results, and Section V concludes the paper.

II. System Model

We consider an active monostatic ISAC-OTFS vehicular communication system consisting of q vehicles and a roadside unit (RSU), as shown in Fig. 1. The RSU employs N_t transmit antennas and N_r receive antennas configured as a uniform linear array (ULA). In the simulation setup, we consider a single transmit antenna at the RSU for simplicity, the proposed framework can be extended to multiple-input multiple-output (MIMO) scenarios. The road is assumed to lie along the x-axis, with vehicles traveling in both positive and negative directions. According to this geometric arrangement and the parallel placement of the RSU antenna elements, the AoA of the received signal is equal to the angle of departure (AoD).

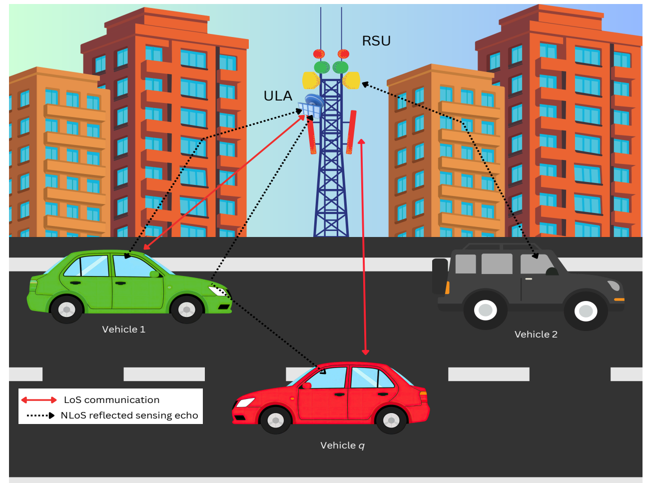

Fig. 1. Illustration of the considered ISAC-OTFS vehicular communication system, where an RSU equipped with a ULA communicates with multiple vehicles through LoS paths and senses vehicle targets via reflected multi paths.

Each vehicle is equipped with a single transmit antenna and communicates directly with the RSU. To jointly perform communication and sensing, the RSU employs ISAC waveforms modulated using OTFS over an $M \times N$ delay-Doppler (DD) grid, where $l \in \{0, 1, \ldots, M-1\}$ and $k \in \{0, 1, \ldots, N-1\}$ denote the delay and Doppler bin indices, respectively. The DD-domain symbols are mapped onto the time-frequency (TF) domain through the inverse symplectic finite Fourier transform (ISFFT). The TF-domain signal corresponding to the q-th vehicle is given as

$$X_q[m, n] = \sum_{k=0}^{N-1} \sum_{l=0}^{M-1} X_{DD}^q[l, k] \exp\left(j2\pi\left(\frac{nk}{N} - \frac{ml}{M}\right)\right), \tag{1}$$

where $m \in \{0, 1, \ldots, M-1\}$ and $n \in \{0, 1, \ldots, N-1\}$ represent the time slot and subcarrier indices, respectively. The time-frequency symbols $X_q[m, n]$ are converted into a continuous-time transmit signal using the Heisenberg transform, and the resulting time-domain signal $s_q(t)$ is given as

$$s_q(t) = \sum_{n=0}^{N-1} \sum_{m=0}^{M-1} X_q[m, n]\, g_{tx}(t - nT)\, e^{j2\pi m\Delta f(t-nT)}, \tag{2}$$

where $g_{tx}(t)$ denotes the transmit pulse shaping function, T represents the symbol duration, and Δf denotes the frequency spacing. The RSU transmits the signals corresponding to all q vehicles as a multi-beam ISAC signal. Accordingly, the transmitted signal vector is given as

$$\mathbf{s}(t) = [s_1(t), s_2(t), \cdots, s_q(t)]^T. \tag{3}$$

The received sensing signal at the RSU is expressed as

$$r(t) = \sum_{q=1}^{Q} \beta_q \mathbf{a}_r(\theta_q)\mathbf{a}_t^H(\theta_q)s(t - \tau_q)e^{j2\pi f_{D,q}t} + w(t), \tag{4}$$

where β_q, τ_q, and $f_{D,q}$ denote the radar cross-section, propagation delay, and Doppler frequency corresponding to the q-th vehicle, respectively, and $w(t)$ represents the additive white Gaussian noise. The vectors $\mathbf{a}_t(\theta_q)$ and $\mathbf{a}_r(\theta_q)$ denote the transmit and receive array responses associated with the angle θ_q, and are expressed as

$$\mathbf{a}_t(\theta_q) = \left[1, e^{j\pi \sin\theta_q}, \ldots, e^{j(N_t-1)\pi \sin\theta_q}\right]^T \tag{5}$$

$$\mathbf{a}_r(\theta_q) = \left[1, e^{j\pi \sin\theta_q}, \ldots, e^{j(N_r-1)\pi \sin\theta_q}\right]^T. \tag{6}$$

The wireless propagation environment is modeled using the CDL channel as specified by the third generation partnership project (3GPP) TR 38.901 [14], which captures realistic multipath propagation characteristics in vehicular environments through clustered scattering, delay dispersion, and Doppler spread. An accurate estimation of the angular parameter θ_q is essential, as it directly contributes to the accurate determination of vehicle position, speed, and velocity. Hence, the joint characterization of angular, delay, and Doppler parameters forms a key foundation of the proposed system model and is critical to achieving reliable sensing and communication performance in the ISAC-OTFS framework considered.

III. RCoD-AoANet: A Residual Covariance Denoising Network for Robust AoA Estimation

Accurate AoA estimation plays a fundamental role in ISAC-OTFS vehicular sensing framework, as the angular information directly governs the estimation of target position, motion direction, and velocity. The estimated AoA is based on geometric relationships used for localization and Doppler-based motion characterization, hence even a small angular mismatch can propagate into noticeable sensing errors. Therefore, robust AoA estimation is essential for achieving reliable spatial sensing performance, particularly in high-mobility vehicular environments. For the i-th vehicle, the estimated propagation delay determines the target range as

$$\hat{\mathbf{s}}_i = \begin{bmatrix} \hat{p}_{x,i} \\ \hat{p}_{y,i} \\ \hat{v}_i \end{bmatrix} = \begin{bmatrix} P_{x,\text{RSU}} + \dfrac{c\,\hat{\gamma}_i}{2}\sin\hat{\theta}_i \\ P_{y,\text{RSU}} + \dfrac{c\,\hat{\gamma}_i}{2}\cos\hat{\theta}_i \\ \dfrac{c\,\hat{\omega}_i}{f_c\cos\hat{\theta}_i} \end{bmatrix}, \tag{7}$$

where $\hat{p}_{x,i}$ and $\hat{p}_{y,i}$ denote the estimated position coordinates of the i-th vehicle, $\hat{v}_i$ is the estimated velocity, and $\hat{\gamma}_i$, $\hat{\theta}_i$, and $\hat{\omega}_i$ represent the estimated delay, AoA, and Doppler, respectively. To estimate the AoA, the received observations collected across the antenna array are first arranged into the received signal matrix given as

$$\mathbf{R}_{\text{noisy}} = \frac{1}{L}\mathbf{X}\mathbf{X}^H, \tag{8}$$

where $\mathbf{X} \in \mathbb{C}^{N_r \times L}$ is the received signal matrix formed from the array observations, L denotes the number of available snapshots, and $(\cdot)^H$ represents the Hermitian transpose. Based on the sample covariance matrix $\mathbf{R}_{\text{noisy}}$, the AoA is estimated

Algorithm 1 RCoD-AoANet-Based AoA Estimation

Input: $\mathbf{X}_{\text{noisy}} \in \mathbb{C}^{N_r \times L}$, trained RCoD-AoANet
Output: $\hat{\theta}$
Compute noisy sample covariance matrix
    $\mathbf{R}_n \leftarrow \frac{1}{L}\mathbf{X}_{\text{noisy}}\mathbf{X}_{\text{noisy}}^H$
Normalize covariance matrix
    $\mathbf{R}_n \leftarrow \mathbf{R}_n / \|\mathbf{R}_n\|_F$
Form network input feature
    $\mathbf{f} \leftarrow [\Re\{\mathbf{R}_n\}, \Im\{\mathbf{R}_n\}]$
Recover denoised covariance matrix
    $\mathbf{R}_d \leftarrow \text{RCoD-AoANet}(\mathbf{f})$
Enforce Hermitian structure
    $\mathbf{R}_d \leftarrow \frac{1}{2}\left(\mathbf{R}_d + \mathbf{R}_d^H\right)$
Perform eigenvalue decomposition
    $[\mathbf{U}, \mathbf{\Lambda}] \leftarrow \text{eig}(\mathbf{R}_d)$
Extract principal eigenvector
    $\mathbf{u} \leftarrow \mathbf{U}(:, \arg\max \text{diag}(\mathbf{\Lambda}))$
Compute adjacent-element phase increment
    $\phi \leftarrow \sum_{i=1}^{N_r-1} \angle\left(\dfrac{u_{i+1}}{u_i}\right)$
Estimate AoA
    $\hat{\theta}_i \leftarrow \sin^{-1}\left(\frac{\lambda}{2\pi d}\phi\right)$
return $\hat{\theta}$

by exploiting the spatial correlation structure across the receive antenna array. First, eigenvalue decomposition is performed as

$$\mathbf{R}_{\text{noisy}} = \mathbf{U}\mathbf{\Lambda}\mathbf{U}^H, \tag{9}$$

where $\mathbf{\Lambda}$ denotes the diagonal matrix of eigenvalues and $\mathbf{U}$ contains the corresponding eigenvectors. The dominant eigenvector, corresponding to the largest eigenvalue, represents the principal direction of arrival embedded in the received observations. For the considered ULA, the AoA can then be recovered from the phase difference between adjacent elements of this dominant eigenvector, which is given by

$$\hat{\theta}_i = \sin^{-1}\left(\frac{\lambda}{2\pi d}\,\phi\right), \tag{10}$$

where $\mathbf{u} = [u_1, u_2, \ldots, u_{N_r}]^T$ is the principal eigenvector of $\mathbf{R}_{\text{noisy}}$, u_m and u_{m+1} are two adjacent entries, λ is the carrier wavelength, and d is the inter-element spacing. In conventional subspace-based AoA estimation, angular information is extracted from the dominant spatial subspace of the covariance matrix. To improve robustness under noise, the proposed RCoD-AoANet refines $\mathbf{R}_{\text{noisy}}$ before AoA recovery by learning the residual mapping between noisy and clean covariance matrices using its attenuation and phase features as input to the RCoD-AoANet.

Algorithm 1 outlines the proposed RCoD-AoANet-based AoA estimation framework. The received noisy array observations are first converted into a sample covariance matrix, followed by normalization to improve numerical stability. The real and imaginary parts of this covariance matrix are then used as input to RCoD-AoANet, which learns to refine the noisy

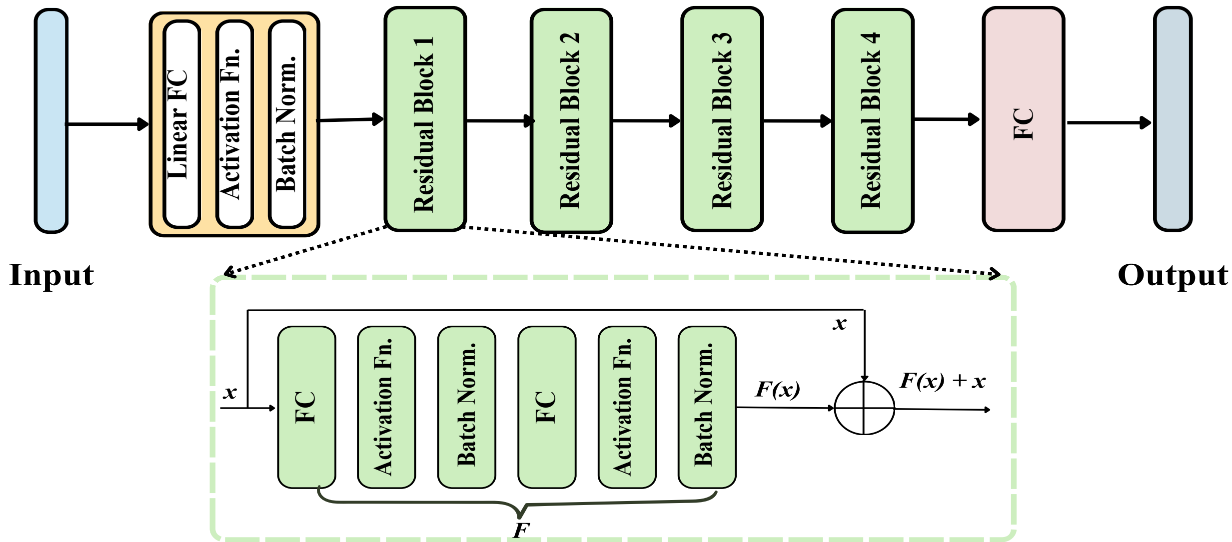

Fig. 2. Architecture of the proposed RCoD-AoANet, comprising an input fully connected (FC) layer followed by activation function (fn.) and batch normalization (norm.), four stacked residual blocks, and an output FC layer.

covariance representation and recover a cleaner spatial correlation structure. The refined covariance matrix is subsequently constrained to satisfy the Hermitian property, ensuring a valid physical covariance form. Next, eigenvalue decomposition is applied, and the dominant eigenvector is extracted to capture the principal spatial signature of the impinging signal. The final AoA estimate is obtained from the phase progression between adjacent entries of this eigenvector. By embedding covariance refinement prior to eigen space-based angle extraction, the proposed algorithm enhances robustness against noise corruption and yields more accurate AoA estimate.

The proposed RCoD-AoANet architecture, shown in Fig. 2, comprises of an input fully connected layer, four lightweight residual blocks, and a final fully connected output layer for covariance reconstruction. The input feature vector is derived from the covariance representation, and the network is designed to learn the residual distortion between the noisy and clean covariance matrices rather than directly estimating the clean covariance matrix itself. Each residual block consists of fully connected transformations followed by ReLU activation and batch normalization, along with an identity skip connection that facilitates gradient propagation, alleviates vanishing-gradient effects, and preserves the structural information embedded in the covariance features. This residual learning strategy enables the network to suppress noise-induced distortions while retaining the dominant spatial characteristics required for accurate AoA estimation. The reconstructed covariance matrix is subsequently processed through phase-difference-based AoA recovery, thereby improving estimation robustness under noisy vehicular propagation conditions. Overall, the network contains 10 weight layers and is trained using the mean square error (MSE) loss function and Adam optimizer with a batch size of 256 over 200 epochs. The proposed design enables efficient denoising, which is required for accurate and reliable estimation of AoA in vehicular networks.

TABLE I
SIMULATION PARAMETERS FOR DATA GENERATION

Parameter	**Value**
Number of transmit antennas, N_t	1
Number of receive antennas, N_r	8
Number of time slots, M	4
Number of subcarriers, N	16
AoA distribution	CDL-A
AoA range, θ	$[-60°, 60°]$
SNR (dB)	$[-10, 20]$
Number of training samples	30000
Number of test samples per SNR	600
Total number of test samples	9600

IV. NUMERICAL RESULTS

In this section, we present the simulation results of the proposed RCoD-AoANet and compare it with the conventional estimation algorithms. The simulation parameters for the considered ISAC-OTFS transmission system are summarized in Table I. To evaluate the effectiveness of the proposed framework, we perform Monte Carlo simulations under the same system model with CDL-A channel framework, and the estimation performance is measured in terms of error, computation time, and number of snapshots.

We provide the performance analysis of the proposed RCoD-AoANet in Fig. 3, through three comparative plots with baseline AoA estimators. First, we present the AoA root mean square error (RMSE) of all methods, where AoA RMSE decreases with increasing SNR, indicating improved angular estimation reliability under cleaner observation conditions. Across the full SNR range, RCoD-AoANet shows a clear monotonic error reduction and maintains accuracy close to the stronger subspace-based baselines, while significantly outperforming

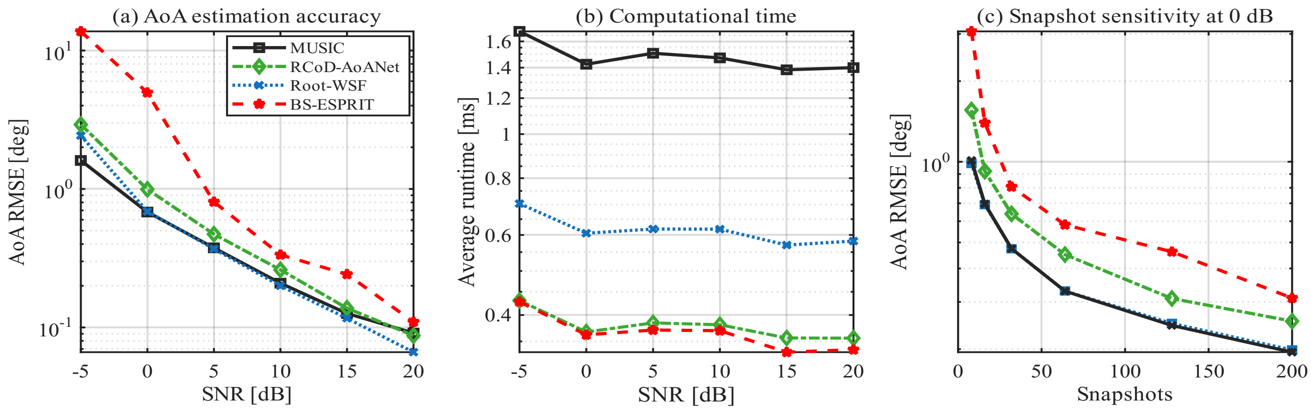

Fig. 3. Performance analysis of the proposed AoA estimator. The figure shows the variation of AoA RMSE with SNR, provides a comparative evaluation against conventional benchmark methods, and highlights the SNR-dependent estimation behavior of the proposed RCoD-AoANet.

beam space estimation of signal parameters via rotational invariance technique (BS-ESPRIT), particularly in the low-SNR region. Next, we compare the computational time, where RCoD-AoANet requires substantially lower average runtime than MUSIC and root-weighted subspace fitting (WSF), showing that the proposed network-assisted framework enables efficient inference without exhaustive grid search. Finally, we compare the robustness of the proposed technique with respect to the number of snapshots at 0 dB, showing that the estimation error decreases for all methods as more snapshots become available. Overall, Fig. 3 shows that, although MUSIC and Root-WSF achieve better RMSE, their higher computational cost and reliance on accurate subspace estimation limit practical feasibility. BS-ESPRIT reduces complexity, but its accuracy degrades significantly in noisy and limited-snapshot conditions. In contrast, RCoD-AoANet offers a more favorable accuracy–complexity trade-off, with competitive performance, low runtime, and limited sensitivity to snapshot count.

From a practical deployment perspective, the RCoD-AoANet is suitable for practical ISAC scenarios where both accuracy and latency are critical. The network training is performed offline using covariance samples, while real-time deployment only requires a forward denoising pass followed by conventional subspace-based AoA extraction. The offline training and online deployment separation keeps the online processing burden low and avoids repeated retraining during sensing operation. In terms of scalability, the framework can be adapted to different snapshot settings and array sizes by operating directly in the covariance domain.

V. Conclusion

In this work, we presented RCoD-AoANet, a residual covariance denoising framework for robust AoA estimation in active monostatic ISAC-OTFS vehicular systems. By refining the received spatial covariance matrix before angle recovery, the proposed method reduces noise- and multipath-induced covariance perturbations, improving the reliability of the signal subspace used for eigen-analysis and phase-difference-based estimation. The hybrid design combines learning-based covariance refinement with interpretable subspace processing, achieving competitive accuracy, robustness under varying signal-to-noise-ratio and snapshot conditions, and reduced computational burden.

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