

A two-stage ISAC framework for low-altitude economy based on 5G NR signals

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Abstract The evolution of next-generation wireless networks has accelerated the development of the low-altitude economy (LAE). To support this emerging paradigm while maintaining compatibility with existing network architectures, integrated sensing and communication (ISAC) based on 5G New Radio (NR) signals has been regarded as a promising solution. However, the direct use of standard 5G NR signals, such as the Synchronization Signal and PBCH Block (SSB), suffers from inherent limitations in sensing resolution. To address this challenge, this paper proposes a two-stage coarse-to-fine sensing framework for high-precision unmanned aerial vehicle (UAV) sensing, which exploits standard 5G NR initial access signals augmented with a custom-designed sparse pilot structure (SPS). In Stage I, information from the SSB, Type0-PDCCH, and System Information Block 1 (SIB1) is jointly fused to enable robust target detection. In Stage II, a refined estimation algorithm is developed to overcome the resolution limitations of these standard signals. Inspired by sparse array theory, this stage introduces a novel SPS inserted into selected resource blocks (RBs) within the CORESET#0 bandwidth. To accurately estimate off-grid range and velocity parameters from the sparse pilots, we further develop a high-resolution algorithm based on the weighted unwrapped phase (WUP) technique and a RELAX-based iterative method. Finally, the Density-Based Spatial Clustering of Applications with Noise (DBSCAN) algorithm is employed to eliminate redundant detections caused by beam overlap. Comprehensive simulation results demonstrate that the proposed framework achieves superior estimation accuracy and computational efficiency compared with existing techniques.

Keywords Integrated sensing and communication (ISAC); 5G New Radio (5G NR); MIMO-OFDM; low-altitude economy (LAE)

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1 Introduction

The evolution of future sixth-generation (6G) wireless networks is driven by the demands of emerging applications, with the low-altitude economy (LAE) at the forefront [1]. As a new economic form, the LAE utilizes low-altitude airspace to conduct diverse flying activities, which promises to deliver revolutionary productivity advancements in sectors such as logistics delivery, environmental monitoring, and intelligent inspection [2, 3]. As this large-scale economic activity is expected to involve millions of aircraft [4], the supporting network needs to provide a dual capability: massive, real-time data exchange for communication and continuous, high-precision sensing for safe and uniform regulation [5, 6].

To address these converging requirements, integrated sensing and communication (ISAC) has emerged as a critical enabling technology [7, 8]. By multiplexing 5G-Advanced (5G-A) or future 6G communication signals, ISAC can simultaneously support high-speed data transmission for unmanned aerial vehicles (UAVs) and provide effective flight supervision. Specifically, the seamless coverage provided by the communication network is leveraged for the effective perception, localization, and surveillance of UAVs. This capability, in turn, assists in UAV navigation, path planning, and airspace management, which is essential for the prosperity of the LAE [1, 4].

Building on this motivation, considerable research has focused on the sensing of UAVs utilizing terrestrial base stations (BSs) to support the LAE. In monostatic scenarios, for example, the authors of [9] proposed a practical ISAC framework for cluttered environments and addressed the power allocation between communication and sensing beams. In addition, the authors of [10] introduced an efficient algorithm for jointly angle, velocity, and range estimation in the orthogonal frequency-division multiplexing (OFDM)-based ISAC system, which includes a pruning algorithm for redundant target points. In multistatic scenarios, [11] investigated the UAV parameter estimation by employing the tensor decomposition technique and proposed a minimum spanning tree (MST)-based multi-BS data association scheme. Moreover,

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an extended Kalman filter (EKF) framework was introduced in [12] to predict the UAV's movement and developed a corresponding handover strategy.

Notably, the aforementioned research often operates without considering the practical constraints of standardized protocols like 5G New Radio (5G NR) [13–16] or Wi-Fi [17], focusing instead on theoretical aspects such as beamforming or parameter extraction. To foster practical deployment, both academia and industry have begun to focus on implementing sensing within these protocol frameworks, and the investigations generally fall into two categories: data-based and pilot-based sensing.

In monostatic data-based sensing scenarios, BS's *a priori* knowledge of transmitted data can be used to estimate UAV parameter estimation via techniques such as matched filtering and data cancellation, while beamforming can steer energy toward potential targets [18]. This principle can be applied within the 5G NR standard, where several downlink channels serve as potential signals of opportunity for wireless sensing. Early studies have explored the feasibility of using data-centric channels, such as the Physical Downlink Control Channel (PDCCH), the Physical Downlink Shared Channel (PDSCH), and the associated Demodulation Reference Signals (DMRS) [18]. For instance, the theoretical ambiguity functions of PDCCH and PDSCH were analyzed in [19]. However, such approaches are fundamentally dependent on active downlink data transmissions, rendering the sensing capability opportunistic rather than persistent. In addition, leveraging user-centric data channels like PDSCH for sensing poses significant privacy risks, as sensitive user information could be exposed to malicious eavesdroppers.

To overcome the reliance on user data and the associated privacy concerns, research has shifted towards dedicated reference signals that are independent of communication traffic. The Positioning Reference Signal (PRS) and the Channel State Information Reference Signal (CSI-RS) are potential candidates, as they are specifically designed for positioning and channel estimation. The work in [20] investigated the application of the PRS for radar sensing by proposing a multi-frame estimation scheme and deriving its Cramér-Rao lower bounds. In addition, [21] introduced a novel irregular resource pattern to suppress the inherent range-velocity ambiguities of the comb-like PRS structure. Despite the advantages, the dedicated signals like PRS and CSI-RS are typically transmitted only upon specific network configuration and are not always-on in most operational networks, which limits their ubiquitous applicability for persistent sensing.

In contrast, the Synchronization Signal and Physical

Broadcast Channel (PBCH) Block (SSB) is a fundamental component of the 5G NR frame structure that is broadcast periodically, which enables it an ideal and highly reliable signal of opportunity. Consequently, SSB-based sensing has been extensively investigated [22–27]. For instance, the authors of [22] leveraged the beam-sweeping nature of the SSB, utilizing reference signal received power (RSRP) measurements at the user equipment (UE) to achieve spatial environment mapping. Similarly, [23] exploited the periodicity of the SSB for passive coherent location (PCL). However, the study also highlighted that the maximum unambiguous velocity of PCL is severely constrained by the SSB's long transmission periodicity (e.g., 10 ms minimum). While the study in [24] addressed UAV detection using the SSB, its performance was limited: angular resolution is constrained by the wide beamwidth of the SSB, and velocity estimation accuracy is limited by the short duration of the per-beam OFDM transmission. To further address these limitations, the work in [28] proposed to combine the SSB with downlink control information (DCI) and System Information Block 1 (SIB1) signals to mitigate the radar ambiguity problem. Notably, while the 5G NR standard allocates a downlink bandwidth part (DL BWP) of $N_{RB}^{DL,BWP}$ resource blocks (RBs) for PDSCH carrying SIB1, the PDSCH itself often occupies only a fraction of this potential bandwidth [14–16, 28]. Since the PDSCH frequency allocation is mandated to use Downlink Resource Allocation Type 1 (i.e., a contiguous set of RBs), the requirement creates an opportunity to insert auxiliary pilots into the unused portions of the $N_{RB}^{DL,BWP}$ RBs [16]. These pilots can, in turn, further enhance sensing performance and assist the DMRS within the PDSCH for more effective channel estimation.^①

The design of the aforementioned auxiliary pilots is closely related to the placement of pilot or reference signals (RSs) in OFDM systems, which is essential for improving ISAC performance [29]. To optimize RS utilization, existing research has primarily evolved along two directions: dynamic resource allocation and geometric pattern design. In resource allocation, recent studies have investigated sensing-oriented adaptive schemes for OFDM-ISAC systems to balance delay-Doppler resolution, sidelobe suppression, sensing signal-to-noise ratio (SNR), and communication quality of service (QoS) [30]. In the domain of pattern design, early work primarily focused on the optimization of uniformly spaced pilot patterns [31]. However, equidistant placement inherently limits the maximum unambiguous range and velocity. To

^① The use of auxiliary pilots for enhanced channel estimation is beyond the scope of this paper, which primarily focuses on their benefit to sensing performance.

mitigate the ambiguity induced by sparse and periodic sampling, more advanced RS patterns have subsequently been developed. For example, [32] introduced a sensing pattern composed of multiple comb-type RS structures, in which the comb sizes of the constituent structures are coprime. Following a similar principle, [33] employed coprime intervals between RSs to resolve ambiguity. In addition, [34] proposed insertion criteria for OFDM RS patterns to maximize the extended ambiguity property (EAP), and this principle was further incorporated into super-resolution methods, such as two-dimensional multiple signal classification (2D-MUSIC) [35] and two-dimensional iterative adaptive approach (2D-IAA) [36, 37]. Nevertheless, these studies mainly focused on enlarging the interference-free detection region, whereas the practical accuracy of range and velocity estimation was not directly evaluated.

More recently, the pattern design has also been investigated from the perspective of array design. Along this direction, [38] first reformulated the design of RS pattern as a two-dimensional array design problem and developed an ISAC frame structure that reduces sensing overhead while maintaining comparable sensing performance. Building on this idea, [39] further proposed a multi-tier structured array-based sensing pilot design, in which the resulting sparse pilot scheme achieves the same unambiguous range and peak side-lobe level (PSL) as those of uniform pilot placement while substantially reducing the number of required resource elements (REs). However, existing sparse or non-uniform ISAC frame designs are still mainly developed at a generic OFDM-ISAC level, rather than being embedded into practical and standard-compliant 5G NR communication systems. In particular, the integration of sparse or non-uniform sensing resources with concrete NR initial-access structures, such as the SSB, Type0-PDCCH, SIB1, and control resource set (CORESET)#0, as well as the associated constraints on resource mapping, signaling compatibility, and range-velocity estimation, remains insufficiently explored.

Motivated by the above findings, this paper proposes a novel two-stage coarse-to-fine estimation framework^① to leverage 5G NR broadcast signals and newly designed sparse pilots for high-precision UAV sensing. Specifically, this framework is designed to operate within the constraints of the 5G NR protocol while overcoming the inherent limitations of standard signals. The main contributions of this paper are summarized as follows:

- First, we establish a coarse estimation stage (Stage I) that fuses information from multiple 5G NR initial access signals. By combining the range-Doppler maps (RDMs) derived from the SSB and SIB1 with the high-resolution range profile from the Type#0-PDCCH, this stage provides robust initial target detection by utilizing the area-based combination constant false-alarm rate (ABC-CFAR) algorithm.
- Second, to overcome the resolution limitations of standard signals, we design a novel sparse pilot structure (SPS) inspired by sparse array theory. The SPS is strategically inserted into the CORESET#0 bandwidth. We then develop a corresponding high-resolution refinement algorithm (Stage II), which employs the weighted unwrapped phase (WUP) estimator and a RELAX-based iterative method to accurately extract off-grid range and velocity parameters from these sparse pilots.
- Furthermore, we introduce a density-based spatial clustering of applications with noise (DBSCAN)-based algorithm that operates in the joint range-velocity-angle domain. This method effectively identifies and prunes redundant detections of a single target that arise from the intentional overlap of adjacent beams during the SSB/SIB1 sweep.
- Finally, comprehensive simulation results are presented to validate the effectiveness of the proposed framework. The results demonstrate that our two-stage approach achieves superior estimation accuracy. Notably, the proposed WUP-based refinement algorithm significantly outperforms conventional benchmark methods, including two-dimensional fast Fourier transform (2D-FFT), 2D-MUSIC, and two-dimensional compressed-sensing atomic norm (2D CS-AN), particularly under the challenging conditions imposed by the sparse pilot configuration.

Notations: Lowercase letters, boldface lowercase letters, boldface uppercase letters, and calligraphy letters denote the scalars, vectors, matrices, and sets, respectively, i.e., a , $\mathbf{a}$, $\mathbf{A}$, and $\mathcal{A}$. The operators $(\cdot)^T$ and $(\cdot)^H$ represent the transpose and Hermitian transpose, respectively. The operator $\odot$ denotes the Hadamard (element-wise) product. $\mathbb{R}$ and $\mathbb{C}$ denote the sets of real and complex numbers. $[\mathbf{A}]_{i,l}$ denotes the element in the i -th row and l -th column of matrix $\mathbf{A}$. $|\cdot|$ represents the absolute value of a scalar or the cardinality of a set. $\angle(\cdot)$ denotes the angle of a complex number. $\text{Diag}(\cdot)$ returns a diagonal matrix. $\text{vecl}(\cdot)$ stacks the strict lower triangular elements of a matrix into a vector. $\text{round}(\cdot)$ rounds to the nearest integer. $\cup$ denotes the set union operation.

^① The source code and simulation data are publicly available at <https://github.com/OnePieceofCakeforYou/A-Two-Stage-ISAC-Framework-for-Low-Altitude-Economy-Based-on-5G-NR-Signals>.

2 SYSTEM MODEL

In this paper, we consider a mono-static multiple-input multiple-output (MIMO)-OFDM ISAC system designed for simultaneous downlink communication and radar parameter estimation. The BS is equipped with separate uniform linear arrays (ULAs), consisting of N_t transmit and N_r receive antennas, respectively.^① As illustrated in Fig. 1, the BS first transmits SSB beams to scan the coverage area, immediately followed by Type#0-PDCCH and SIB1 signals with the same beam pattern. According to the prior studies [19, 28], these broadcast signals are utilized for a dual role. On one hand, they deliver the information necessary for uplink random access channel (RACH) procedures. On the flip side, they are adopted as sensing signals.

2.1 Transmitted Signal Model

Let $l \in \{0, 1, \dots, N_s - 1\}$ and $i \in \{0, 1, \dots, N_c - 1\}$ denote the indices of the OFDM symbols and subcarriers, respectively. Under the frequency-flat assumption, the signal vector transmitted during the l -th symbol on the i -th subcarrier is modeled as^②

$$[\mathbf{X}]_{i,l} = \mathbf{w}[l][\mathbf{S}]_{i,l}, \quad (1)$$

where $\mathbf{S} \in \mathbb{C}^{N_c \times N_s}$ is the transmitted symbol matrix, and $\mathbf{w}[l] \in \mathbb{C}^{N_t}$ is the precoding vector for the l -th symbol. Specifically, the vector $\mathbf{w}[l]$ is selected from a predefined codebook $\mathcal{W}$ to steer the transmitted signal toward a specific direction. This codebook is constructed from an oversampled discrete Fourier transform (DFT) grid to achieve fine-grained angular coverage. In particular, given an integer oversampling factor O , the codebook is defined as $\mathcal{W} = \{\mathbf{w}_q\}_{q=0}^{N_{cb}-1}$, where $N_{cb} = ON_t$, and the q -th beamforming vector is given by

$$\mathbf{w}_q = \frac{1}{\sqrt{N_t}} \left[e^{j2\pi mq/N_{cb}} \right]_{m=0}^{N_t-1}. \quad (2)$$

Subsequently, after the inverse fast Fourier transform (IFFT) operation at the transmitter, the time-domain baseband OFDM signal is expressed as

$$\mathbf{x}(t) = \sum_{l=0}^{N_s-1} \sum_{i=0}^{N_c-1} [\mathbf{X}]_{i,l} e^{j2\pi i \Delta f t} r(t - lT) \in \mathbb{C}^{N_t}, \quad (3)$$

where Δf is the subcarrier spacing, $r(t)$ denotes the rectangular pulse, and $T = T_c + T_{cp}$ is the total duration of an OFDM symbol. Here, T_c is the duration of the OFDM symbol, and T_{cp} is the duration of the cyclic prefix (CP).

① We assume that the BS operates under an advanced full-duplex regime, where self-interference (SI) at the receive antennas is effectively canceled.

② Following [40], the signal bandwidth in this work is assumed to be confined to a single subband. Consequently, a common precoding vector is applied across all subcarriers for each OFDM symbol.

2.2 Sensing Signal Model

Let $\mathbf{y}(t) \in \mathbb{C}^{N_r \times 1}$ denote the received echoes from N_{target} unknown targets. The received signal model can be written as

$$\mathbf{y}(t) = \sum_{n=1}^{N_{\text{target}}} \beta_n e^{j2\pi f_{D,n} t} \mathbf{b}_r(\theta_n) \mathbf{a}_t^H(\theta_n) \mathbf{x}(t - \tau_n) + \mathbf{z}(t), \quad (4)$$

where the components are defined as follows:

- $\mathbf{y}(t) = [\tilde{y}(1, t), \dots, \tilde{y}(N_r, t)]^T \in \mathbb{C}^{N_r}$ is the received signal vector at the N_r receive antennas.
- $\tau_n = 2R_n/c$ is the round-trip propagation delay for the n -th target.
- $\mathbf{x}(t) \in \mathbb{C}^{N_t \times 1}$ is the vector of transmitted baseband signals from the N_t transmit antennas.
- $\mathbf{a}_t(\theta_n) \in \mathbb{C}^{N_t \times 1}$ is the transmit array steering vector towards the direction θ_n , with $[\mathbf{a}_t(\theta_n)]_m = e^{-j2\pi(m-1)d_t \sin(\theta_n)/\lambda_c}$.
- $\mathbf{b}_r(\theta_n) \in \mathbb{C}^{N_r \times 1}$ is the receive array steering vector for the direction θ_n , with $[\mathbf{b}_r(\theta_n)]_m = e^{-j2\pi(m-1)d_r \sin(\theta_n)/\lambda_c}$.
- $\mathbf{z}(t) = [z(1, t), \dots, z(N_r, t)]^T \in \mathbb{C}^{N_r}$ is the additive white Gaussian noise (AWGN) vector.

After the analog-to-digital conversion (ADC) with a sampling frequency of F_s and the subsequent CP removal, the discrete echo signal vector for the l -th symbol $\mathbf{y}(j, l) \in \mathbb{C}^{N_r \times 1}$ is obtained as

$$\mathbf{y}(j, l) \triangleq \mathbf{y}(lT + j/F_s + T_{cp}). \quad (5)$$

Subsequently, following serial-to-parallel conversion, an N_c -point FFT is applied to $\mathbf{y}(j, l)$ along the sample index dimension. As derived in Appendix A, the resulting frequency-domain OFDM symbol $\mathbf{y}(i, l)$ is given by^③

$$\mathbf{y}(i, l) = \sum_{n=1}^{N_{\text{target}}} \beta_n \mathbf{a}_t^H(\theta_n) [\mathbf{X}]_{i,l} e^{j i \omega_r(R_n)} e^{j l \omega_v(v_n)} \mathbf{b}_r(\theta_n) + \mathbf{z}(i, l), \quad (6)$$

where $\omega_r(R_n) \triangleq -4\pi \Delta f R_n/c$ and $\omega_v(v_n) \triangleq 2\pi f_{D,n} T$ are the normalized frequencies corresponding to the range and velocity of the n -th target, respectively. The notation $\mathbf{z}(i, l)$ denotes the noise term, which is approximated as AWGN [10, 43].

③ This frequency-domain model assumes circular convolution after CP removal. Hence, the maximum round-trip delay should satisfy $\tau_{\max} \leq T_{cp, \min}$, where $T_{cp, \min}$ is the shortest CP duration among the sensing OFDM symbols. For the monostatic case, this gives the conservative CP-limited range $R_{CP}^{\max} = cT_{cp, \min}/2$. Otherwise, insufficient CP induces ISI/ICI and requires explicit modeling or compensation [41, 42].

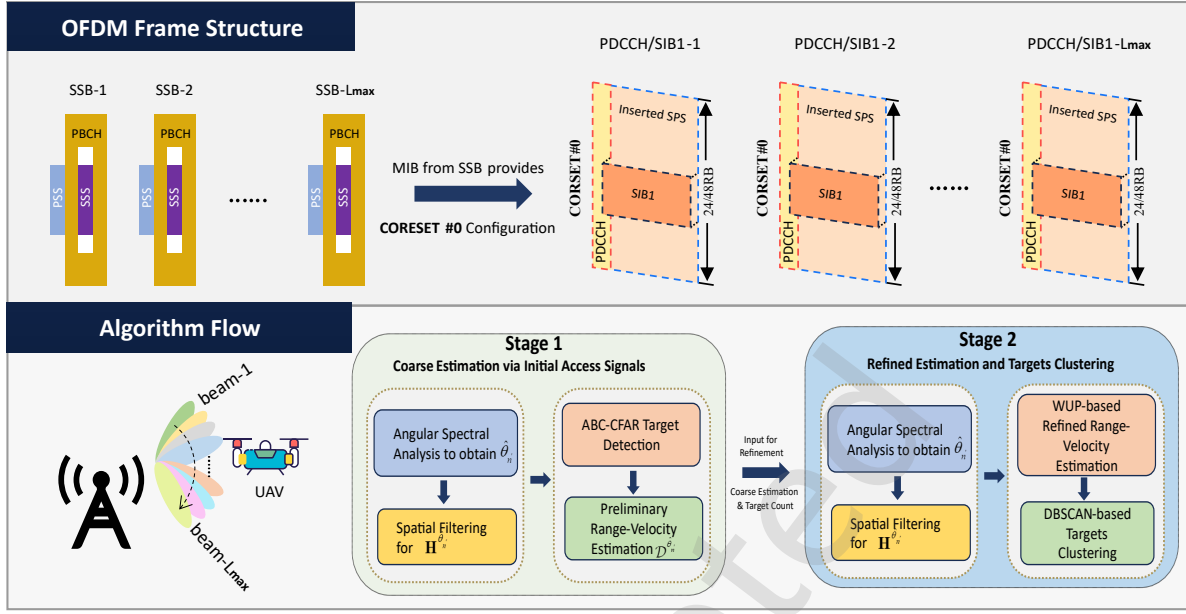


Fig. 1 Frame structure and algorithm flow for the proposed two-stage sensing framework.

3 Stage I: Coarse Target Detection and Parameter Estimation

In this section, we elaborate on the utilization of the SSB signal for target detection and coarse parameter estimation. Specifically, each SSB block occupies 20 RBs and four consecutive OFDM symbols in the time-frequency domain and is broadcast periodically, as illustrated in Fig. 1. We exploit the inherent beam-sweeping nature of SSB to obtain coarse estimates of the target's angular, range, and velocity parameters.

3.1 Angular Spectral Analysis

We begin by addressing the angular estimation. To perform Direction of Arrival (DoA) estimation for targets within the k -th SSB beam centered at θ_k , we employ the high-resolution MUSIC algorithm [10]. Firstly, we average the outer product of $\mathbf{y}(i, l)$ across all available subcarriers and OFDM symbols

$$\hat{\mathbf{R}} = \frac{1}{|\mathcal{R}_{k, \text{SSB}}|} \sum_{\{(i, l)\} \in \mathcal{R}_{k, \text{SSB}}} \mathbf{y}(i, l) \mathbf{y}(i, l)^H, \quad (7)$$

where $\mathcal{R}_{k, \text{SSB}}$ is the set of REs for the k -th SSB beam and $|\mathcal{R}_{k, \text{SSB}}|$ denotes the cardinality of this set.

Then, we perform the eigenvalue decomposition as

$$\hat{\mathbf{R}} = \mathbf{U} \mathbf{U}^H, \quad (8)$$

where $\mathbf{U} = [\mathbf{u}_1, \dots, \mathbf{u}_{N_r}]$ is the matrix of eigenvectors and $\mathbf{\Lambda} = \text{Diag}(\lambda_1 \geq \lambda_2 \geq \dots \geq \lambda_{N_r})$ is the diagonal matrix containing the corresponding eigenvalues, sorted in descending order.

Based on the auto-correlation coefficient matrix algorithm [44], the number of potential UAVs N_{θ_k} can be effectively determined^①. Once N_{θ_k} is estimated, the noise subspace matrix $\bar{\mathbf{U}}$ is constructed as $\bar{\mathbf{U}} = [\mathbf{u}_{N_{\theta_k}+1}, \dots, \mathbf{u}_{N_r}]$. Then, by exploiting the orthogonality between the array steering vectors and the noise subspace, the DoA of the potential UAVs in the current beam is given by

$$\{\hat{\theta}_n\}_{n=1}^{N_{\theta_k}} = \text{argpeak}_{\theta} \left(\frac{1}{\mathbf{b}_r^H(\theta) \bar{\mathbf{U}} \bar{\mathbf{U}}^H \mathbf{b}_r(\theta)}, N_{\theta_k} \right), \quad (9)$$

where the search window $\theta \in [\theta_k - \Delta\theta, \theta_k + \Delta\theta]$, with $\Delta\theta \approx 85^\circ / (N_t \cos(\theta_k))$ denoting the approximate half-beamwidth of the ULA at the suppression level -10 dB [46]^②. The operator $\text{argpeak}(\cdot, N)$ finds the locations of the N largest peaks.

3.2 Spatial Filtering

For each estimated DoA $\hat{\theta}_{n'} \in \{\hat{\theta}_n\}_{n=1}^{N_{\theta_k}}$ obtained from the preceding angular spectral analysis, we first perform the spatial filtering and remove the signal-dependent coefficients $\mathbf{a}_t^H(\hat{\theta}_{n'})[\mathbf{X}]_{i,l}$ [47]. The resulting 2D channel response $[\mathbf{H}^{\hat{\theta}_{n'}}]_{i,l}$ is given in (10), which is shown at the top of this page. In this model, $\mathcal{K}_{n'}$ represents the index set of targets

① Unlike the ideal assumption in [10, 11], the limited samples per SSB beam cause information-theoretic criteria to perform poorly; minimum description length (MDL) [45] becomes inaccurate while the Akaike information criterion (AIC) tends to overestimate. We therefore employ the more robust auto-correlation coefficient matrix method. The interested reader is referred to [44] for further details.

② The overlap between the half-power beamwidths of adjacent SSB beams may cause a single target to be detected multiple times. However, the clustering method is introduced in Section 5.4 to prune redundant detections and enhance the overall estimation accuracy.

whose DoAs are clustered around the estimated angle $\hat{\theta}_{n'}$.

Due to the SNR gains introduced by the spatial filter, both the interference from other target clusters ($n \notin \mathcal{K}_{n'}$) and the noise term are significantly suppressed. Thus, the model in (10) can be approximated by its dominant signal components

$$[\mathbf{H}^{\hat{\theta}_{n'}}]_{i,l} \approx \sum_{k \in \mathcal{K}_{n'}} \alpha_k e^{j i \omega_r(R_k)} e^{j l \omega_v(v_k)}, \quad (11)$$

where $\alpha_k = G_{n',k} \beta_k$ is the effective complex amplitude of the k -th target within $\mathcal{K}_{n'}$.

Remark1: In practical systems, the half-power beamwidths of adjacent beams overlap to ensure effective user coverage. Consequently, the resource set for estimation can be expanded, e.g., $\mathcal{R}_{k,\text{SSB}}^{\text{ext}} = \mathcal{R}_{k-1,\text{SSB}} \cup \mathcal{R}_{k,\text{SSB}} \cup \mathcal{R}_{k+1,\text{SSB}}$. The expansion introduces a trade-off: a larger resource set provides more samples but suffers from lower beamforming gain at the periphery. The reduced beamforming gain $\mathbf{a}_t^H(\hat{\theta}_{n'})[\mathbf{X}]_{i,l}$ increases the relative power of the interference and the noise terms in (10). Therefore, the estimation window must be judiciously configured to balance the number of samples against the degradation in effective signal to interference plus noise ratio (SINR).^①

3.3 Preliminary Range and Velocity Estimation

Before detailing our estimation algorithm, we first clarify two primary limitations inherent to the SSB's structure.

- 1) **Limited Velocity Estimation Fidelity:** The achievable velocity resolution is fundamentally limited by the short observation interval, as a UAV target is typically illuminated by only a few four-symbol SSB blocks.
- 2) **Limited Bandwidth and Range Resolution:** The spectral bandwidth of the SSB is confined to 240 subcarriers. This restricted bandwidth inherently limits the achievable range resolution.

To address these limitations, we further leverage the Type#0-PDCCH and SIB1 broadcasting signals, which offer a more extended observation interval and wider bandwidth than SSB, to enhance velocity estimation and range resolution. Firstly, the RDM of the SSB is generated by performing 2D-FFT on the approximated channel matrix $\mathbf{H}^{\hat{\theta}_{n'}}$ as

$$[\mathbf{R}_{\text{SSB}}^{\hat{\theta}_{n'}}]_{p,q} = \left| \sum_{(i,l) \in \mathcal{R}_{k,\text{SSB}}^{\text{ext}}} [\mathbf{H}]_{i,l}^{\hat{\theta}_{n'}} e^{-j \frac{2\pi p i}{N_r}} e^{-j \frac{2\pi q l}{N_d}} \right|, \quad (12)$$

where N_r and N_d are the FFT points for the range and doppler dimensions, respectively, with zero-padding applied

^① Due to the beam sweeping of the SSB, a target is only coherently illuminated during a subset of OFDM symbols. Processing the entire set of symbols would incorporate noise from irrelevant time instances where the beam was pointing elsewhere, thereby degrading the effective SNR.

to improve resolution. Similarly, we obtain the RDM of SIB1 as $\mathbf{R}_{\text{SIB1}}^{\hat{\theta}_{n'}}$. The wider-bandwidth PDCCH, in turn, yields a high-resolution range profile, defined as the vector $\mathbf{p}_{\text{PDCCH}}^{\hat{\theta}_{n'}}$. These components are then fused to form the combined RDM as

$$\mathbf{R}_{\text{comb}}^{\hat{\theta}_{n'}} = \mathbf{R}_{\text{SSB}}^{\hat{\theta}_{n'}} \odot \mathbf{R}_{\text{SIB1}}^{\hat{\theta}_{n'}} \odot \mathbf{p}_{\text{PDCCH}}^{\hat{\theta}_{n'}}, \quad (13)$$

where $\mathbf{p}_{\text{PDCCH}}^{\hat{\theta}_{n'}} = \mathbf{p}_{\text{PDCCH}}^{\hat{\theta}_{n'}} \mathbf{1}_{N_d}^T$, with $\mathbf{1}_{N_d}^T$ denoting a row vector of N_d ones. To visualize the combined RDM, Fig. 2 illustrates the combined RDM obtained with different numbers of beams used for angular estimation. It is clear that the 3-beam combination (Fig. 2b) achieves superior resolution over the single-beam case (Fig. 2a), while avoiding the noise-floor degradation apparent in the 5-beam scenario (Fig. 2c). Additionally, inaccuracies in the initial angle estimation often cause the energy of a point-based UAV target to disperse across a certain area in the RDM. Therefore, rather than a cell-average CFAR detector, we employ the ABC-CFAR framework [48] for target detection. The resulting set of estimated ranges and velocities for the detected targets can be expressed as

$$\mathcal{D}^{\hat{\theta}_{n'}} = \{(\hat{R}_m, \hat{v}_m, \hat{\theta}_{n'})\}_{m=1}^{N_{\text{det}}}, \quad (14)$$

where N_{det} is the total number of detected targets and $(\hat{R}_m, \hat{v}_m, \hat{\theta}_{n'})$ represents the estimated range-velocity-angle pair for the m -th target.

4 Sparse Pilot Structure for Refined Estimation

In this section, we present the necessary definitions and common structures of the SPS. The design of this SPS is directly motivated by Third Generation Partnership Project (3GPP) specifications [13–16] and [28], which indicate that the PDSCH carrying SIB1 typically occupies only a portion of the CORESET#0 bandwidth. This characteristic, combined with inspiration from 1D sparse array theory [49], leads to our phase-tracking reference signal (PT-RS)-like SPS configuration where pilots are sparsely arranged in the frequency domain. The approach yields two key advantages: i) spanning a wide effective bandwidth to improve range resolution; ii) multiplexing communication pilots to facilitate initial access. We now introduce the necessary definitions for this SPS.

4.1 Pilots Signal Structure

We first introduce the structure of the pilots, which are sparsely arranged in the frequency domain as illustrated in

$$\begin{aligned}
[\mathbf{H}^{\hat{\theta}_{n'}}]_{i,l} &= \frac{\mathbf{b}_r^H(\hat{\theta}_{n'})\mathbf{y}(i,l)}{\mathbf{a}_t^H(\hat{\theta}_{n'})[\mathbf{X}]_{i,l}} \\
&= \frac{\mathbf{b}_r^H(\hat{\theta}_{n'}) \left(\sum_{n=1}^{N_{\text{target}}} \beta_n \mathbf{a}_t^H(\theta_n) [\mathbf{X}]_{i,l} e^{j\omega_r(R_n)} e^{j\omega_v(v_n)} \mathbf{b}_r(\theta_n) + \mathbf{z}(i,l) \right)}{\mathbf{a}_t^H(\hat{\theta}_{n'}) [\mathbf{X}]_{i,l}} \\
&= \underbrace{\sum_{k \in \mathcal{K}_{n'}} G_{n',k} \beta_k e^{j\omega_r(R_k)} e^{j\omega_v(v_k)}}_{\text{Desired Signals from Target Cluster}} + \underbrace{\sum_{n \notin \mathcal{K}_{n'}} \beta_n \frac{\mathbf{a}_t^H(\theta_n) [\mathbf{X}]_{i,l}}{\mathbf{a}_t^H(\hat{\theta}_{n'}) [\mathbf{X}]_{i,l}} \left(\mathbf{b}_r^H(\hat{\theta}_{n'}) \mathbf{b}_r(\theta_n) \right) e^{j\omega_r(R_n)} e^{j\omega_v(v_n)}}_{\text{Interference from Other Targets}} + \underbrace{\frac{\mathbf{b}_r^H(\hat{\theta}_{n'}) \mathbf{z}(i,l)}{\mathbf{a}_t^H(\hat{\theta}_{n'}) [\mathbf{X}]_{i,l}}}_{\text{Noise}}
\end{aligned} \tag{10}$$

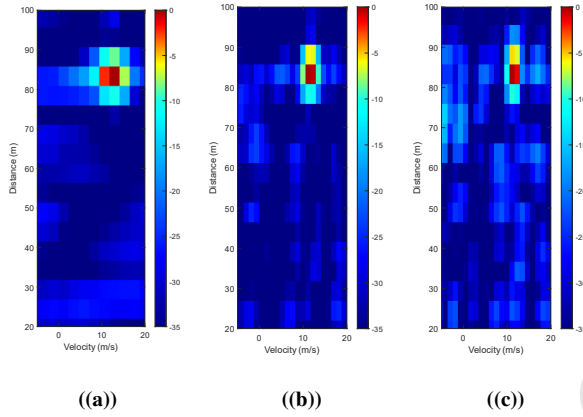


Fig. 2 RDMs with different numbers of beams: (a) 1 beams, (b) 3 beams, and (c) 5 beams.

Fig. 3.^②

Definition 1 (Frequency-Domain Sparse Pilot Structure):

For a set $\mathcal{S}_f$ of subcarrier indices where pilots are placed, let $\mathcal{D}_f$ denote the corresponding Difference Co-spectrum (DCS); $\mathcal{U}_f$ denote the virtual uniform spectrum and $\mathcal{C}(k)$ denote all pilot pairs contributing to the frequency lag k ,

$$\begin{aligned}
\mathcal{S}_f &= \{p_1, p_2, \dots, p_{N_p}\}, \\
\mathcal{D}_f &= \{p_i - p_j \mid p_i, p_j \in \mathcal{S}_f\}, \\
\mathcal{U}_f &= [-L_u, \dots, L_u] \subseteq \mathcal{D}_f, \\
\mathcal{C}_f(k) &= \{(p_i, p_j) \mid p_i - p_j = k; p_i, p_j \in \mathcal{S}_f\}.
\end{aligned} \tag{15}$$

Here, each $p_m \in \mathcal{S}_f$, $m = 1, \dots, N_p$, represents an individual subcarrier index, and L_u is the maximum one-sided lag of the DCS $\mathcal{U}_f$. Then, $|\mathcal{D}_f|$, $2L_u + 1$, and $|\mathcal{C}_f(k)|$ are referred to the degrees of freedom (DoF), the uniform DoF (uDoF), and the weight function $w(k)$ w.r.t. the $\mathcal{S}_f$ respectively. Similar to their roles in the DoA estimation problem, it will be shown in the subsequent analysis that the DoF, uDoF, and

^② According to the 3GPP TS-38 series specifications, for a 120 kHz subcarrier spacing (SCS), CORESET#0 can be configured with a bandwidth of either 24 or 48 RBs, corresponding to 288 or 576 subcarriers, respectively. For illustrative purposes, this figure depicts a case where 11 subcarriers are occupied for sensing.

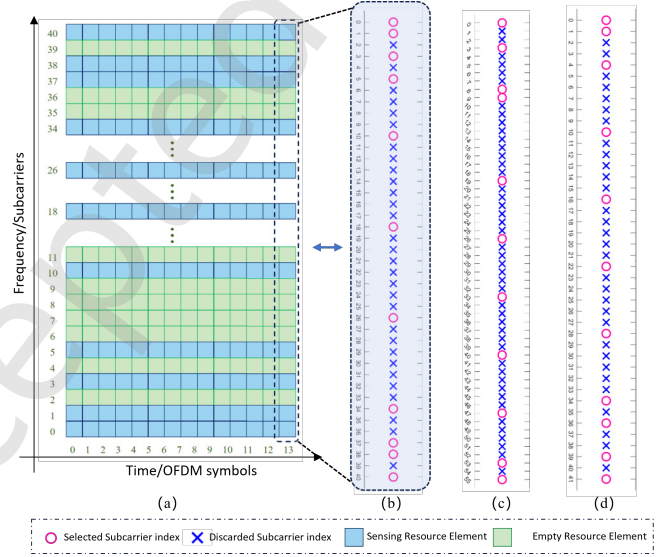


Fig. 3 Example of the Sparse Pilot Structure.

weight function of our sparse sensing scheme are instrumental in the performance of time-delay estimation.

Definition 2 (Augmented Nested Array with two levels and two-sided extensions (ANAI-2) Sparse Pilot Structure) [50]: For a given total of N sensors, the ANAI-2 structure is defined by the set of sensor positions $\mathcal{S}$. First, the intermediate parameters L and M are determined from N as

$$L = \text{round}(N/6), \quad M = N - 4L. \tag{16}$$

The set $\mathcal{S}$ is then constructed as the union of the following five sub-sets, $\mathcal{S} = \mathcal{S}_{L11} \cup \mathcal{S}_{L12} \cup \mathcal{S}_M \cup \mathcal{S}_{R21} \cup \mathcal{S}_{R22}$, where each sub-set is explicitly defined by

$$\begin{aligned}
\mathcal{S}_M &= \{2L^2 + L + 4Li \mid l \in \{0, \dots, M\}\}, \\
\mathcal{S}_{L12} &= \{2L^2 + L - (2L + 1)l \mid l \in \{0, \dots, L - 1\}\}, \\
\mathcal{S}_{L11} &= \{2L + 1 - l \mid l \in \{0, 2, \dots, 2L\} \cup \{2L + 1\}\}, \\
\mathcal{S}_{R21} &= \{2L^2 + L + 4LM + (2L - 1)l \mid l \in \{0, \dots, L - 1\}\}, \\
\mathcal{S}_{R22} &= \left\{ 4L^2 - 2L + 1 + 4LM + l \mid l \in \{0\} \cup \{1, 3, \dots, 2L - 1\} \right\}.
\end{aligned} \tag{17}$$

The resulting set $\mathcal{S}$ is normalized such that its minimum ele-

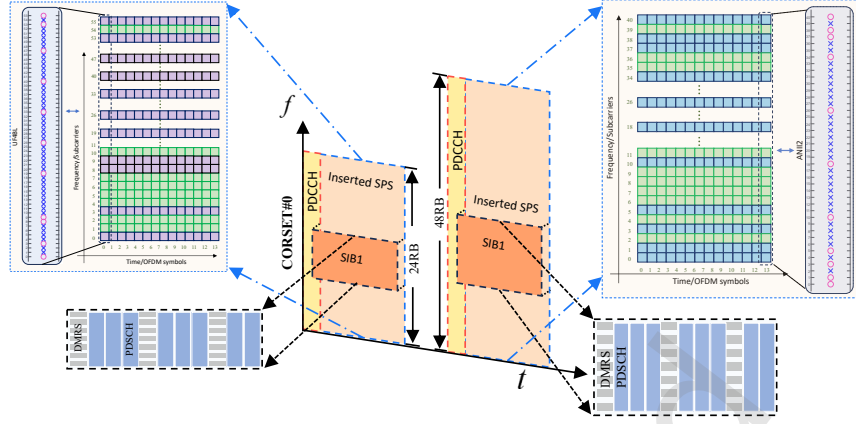


Fig. 4 Integration of SPS and SIB1.

ment is 0.

Definition 3 (Uniform Fitting 4-Block-Level (UF-4BL) Sparse Pilot Structure) [51]: For a total of N sensors, the UF-4BL structure is defined by the set of sensor positions $\mathcal{S}$. The structure is determined by two intermediate parameters, N_b and N_u , which are derived from N as:

$$N_b = \lfloor (N - 8)/8 \rfloor, \quad N_u = N - 4N_b - 6. \quad (18)$$

For compact notation, let $\mathcal{I}_b = \{0, 1, \dots, N_b - 1\}$, $\mathcal{I}_u = \{0, 1, \dots, N_u - 1\}$, and $A = 4N_uN_b + 7N_u$. Then, the final set of frequency positions $\mathcal{S}$ is constructed as the union of eight distinct sub-ULAs, $\mathcal{S} = \bigcup_{i=1}^8 \mathcal{S}_i$, where each sub-array is explicitly defined by (19).

$$\begin{aligned} \mathcal{S}_1 &= \{3l \mid l \in \{0, 1\}\}, \\ \mathcal{S}_2 &= \{7 + 4l \mid l \in \mathcal{I}_b\}, \\ \mathcal{S}_3 &= \{4N_b + 8 + l \mid l \in \{0, 1\}\}, \\ \mathcal{S}_4 &= \{4N_b + 15 + 4l \mid l \in \mathcal{I}_b\}, \\ \mathcal{S}_5 &= \{8N_b + 19 + (4N_b + 7)l \mid l \in \mathcal{I}_u\}, \\ \mathcal{S}_6 &= \{A + 4N_b + 19 + 4l \mid l \in \mathcal{I}_b\}, \\ \mathcal{S}_7 &= \{A + 8N_b + 18 + 2l \mid l \in \{0, 1\}\}, \\ \mathcal{S}_8 &= \{A + 8N_b + 25 + 4l \mid l \in \mathcal{I}_b\}. \end{aligned} \quad (19)$$

Table 1 Comparison of Weight Functions and uDoF for Different Arrays

Array Type	$w(1)$	$w(2)$	$w(3)$	uDoF
ANAI-2 [50]	2	$N/3$	2	$\mathcal{O}(2N^2/3)$
MISC [52]	1	$2\lfloor N/4 \rfloor - 2$	$1/2$	$\mathcal{O}(N^2/2 + 3N)$
TSENA [53]	$N_1 - 6$	$N_1 - 8$	$N_1 - 9$	$\mathcal{O}(N^2/2 + 3.5N)$
UF-3BL [51]	1	1	$3N_b - 1$	$\mathcal{O}(N^2/2 + 2N)$
UF-4BL [51]	1	1	2	$\mathcal{O}(N^2/2 + 2N)$

Note: For the TS-ENA array, the parameter $N_1 = 2\lfloor (N + 3)/4 \rfloor$. For UF-3BL, the parameter $N_b = \lfloor (N - 5)/6 \rfloor$.

Based on the comparison in Table 1, the SPS selection should not be interpreted as a purely empirical choice. In-

stead, the adopted pattern should jointly optimize *local estimation efficiency* and *global ambiguity control*. From this perspective, the UF-4BL structure is preferred for the 24RB configuration, whereas ANAI-2 is selected for the 48RB configuration. The underlying estimation-theoretic rationale is discussed next.

4.2 An Estimation-Theoretic Perspective on SPS Design

To connect the sparse-array metrics in Table 1 with range-estimation performance more explicitly, we briefly examine the single-target range Cramér-Rao lower bound (CRLB) induced by the sparse frequency allocation. Let $\mathcal{S}_{f,\text{combined}} = \{p_1, \dots, p_N\}$ denote the selected subcarrier indices, where $N = |\mathcal{S}_{f,\text{combined}}|$. For a target at range R_k , the corresponding delay steering vector can be written as

$$\mathbf{a}_r(R_k) = \bar{\alpha}_k \left[e^{jp_1\omega_r(R_k)}, \dots, e^{jp_N\omega_r(R_k)} \right]^T,$$

where $\omega_r(R_k) = -4\pi\Delta f R_k/c$. Differentiating $\mathbf{a}_r(R_k)$ with respect to R_k and substituting the result into the scalar CRLB expression yields

$$\text{CRLB}(R_k) = \frac{\sigma_z^2 c^2}{32\pi^2 \Delta f^2 |\bar{\alpha}_k|^2 N \text{var}(\mathbf{p})},$$

where σ_z^2 denotes the noise variance and

$$\text{var}(\mathbf{p}) = \frac{1}{N} \sum_{n=1}^N p_n^2 - \left(\frac{1}{N} \sum_{n=1}^N p_n \right)^2$$

is the variance of the selected subcarrier indices. This result shows that a larger effective aperture and a more widely spread index set improve the local estimation bound through the factor $N \text{var}(\mathbf{p})$.

However, minimizing the CRLB alone is insufficient for SPS design. It is noted that optimizing solely for $N \text{var}(\mathbf{p})$ tends to push the selected pilots toward the band edges.

While such edge-spread allocations enlarge the effective aperture, they introduce large spectral gaps and sparse lag structures, which restrict the ambiguity-free range and elevate sidelobes. Consequently, UF-4BL and ANAI-2 are selected as they provide the optimal trade-off between these competing objectives under their respective resource budgets. In the 24-RB case, UF-4BL preserves a competitive effective aperture while maintaining light short-lag coupling, striking a favorable balance between CRLB reduction and sidelobe control. In the 48-RB case, ANAI-2 yields a substantially longer contiguous virtual spectrum, where the gains in identifiability and ambiguity suppression outweigh the increased low-order coupling. Ultimately, these adopted SPS patterns represent a principled trade-off between local estimation efficiency and global ambiguity suppression.

4.3 Integration of Sensing Pilots and SIB1

In this subsection, we describe how the proposed SPS is integrated into the SIB1 block. Let $\mathbf{S}_{\text{SIB1}}, \mathbf{S}_{\text{sen}} \in \mathbb{C}^{N_{c,\text{SIB1}} \times N_{s,\text{SIB1}}}$ denote the SIB1 data symbol matrix and the sparse sensing pilot matrix, respectively. Their physical resource allocations are governed by the respective binary masks $\mathcal{L}_{k,\text{SIB1}}, \mathcal{L}_{k,\text{sen}} \in \{0, 1\}^{N_{c,\text{SIB1}} \times N_{s,\text{SIB1}}}$. For the sensing pilot mask $\mathcal{L}_{k,\text{sen}}$, we adopt a configuration analogous to the PT-RS in 5G NR. Specifically, the sensing pilots span all OFDM symbols within the SIB1 block but are restricted to a sparse set of subcarrier indices $\mathcal{S}_f$, as detailed in Section 4.1.

To ensure communication reliability, SIB1 symbols are prioritized over sensing pilots on any overlapping REs. Consequently, the final transmitted signal matrix $\mathbf{S}_{\text{tx}} \in \mathbb{C}^{N_{c,\text{SIB1}} \times N_{s,\text{SIB1}}}$ is synthesized as

$$\mathbf{S}_{\text{tx}} = \mathbf{S}_{\text{SIB1}} + \mathbf{S}_{\text{sen}} \odot (\mathbf{J} - \mathcal{L}_{k,\text{SIB1}}), \quad (20)$$

where $\mathbf{J} \in \mathbb{C}^{N_{c,\text{SIB1}} \times N_{s,\text{SIB1}}}$ is an all-ones matrix. This priority-based insertion mechanism, where SIB1 symbols strictly supersede sensing pilots, is illustrated in Fig. 4.

Remark 2: Equation (20) should be interpreted as a priority-based orthogonal insertion rule rather than a literal symbol superposition. The SIB1/PDSCH allocation is determined first, and the SPS is then mapped only onto the remaining communication-idle REs within the same CORESET#0 span, so the SIB1 payload and its associated DMRS remain untouched. Moreover, under the monostatic architecture, the BS knows the complete transmitted waveform *a priori*; hence, the SIB1-occupied REs also remain valid sensing observations. Therefore, increasing the SIB1 occupancy only changes the ratio between sparse pilots and known data symbols, without reducing the total number of valid sensing

observations. In the sequel, $\mathcal{S}_{f,\text{combined}}$ denotes the union of all subcarrier indices whose transmitted symbols are known at the BS and jointly utilized for the refined sensing stage.

5 Stage II: Refined Parameter Estimation with Sparse Pilot Symbols

To alleviate the off-grid errors induced by the finite grid resolution and the active-RE mask in Stage I, we introduce a refinement stage based on a proposed RELAX-based WUP algorithm. Inspired by the phase-unwrapping refinement method for non-uniform sensing resources in [29], WUP exploits the continuous phase variations across active REs to refine the coarse estimates beyond the FFT grid. The RELAX framework [54, 55] is further incorporated to iteratively decouple multi-target components and refine their individual parameters. Subsequently, the refined range and velocity estimates are paired to identify the most probable target associations, followed by DBSCAN-based clustering to remove redundant and spurious detections. Finally, the clustered estimates are regarded as the high-resolution target estimates.

5.1 WUP Velocity Estimation

Let $N_s \triangleq N_{s,\text{SIB1}}$ and fix a subcarrier index $i \in \mathcal{S}_{f,\text{combined}}$. For the angle bin $\hat{\theta}_{n'}$, we assume that the corresponding channel response is dominated by the k -th target. The Doppler-domain row response can be written as

$$\mathbf{h}_{i,k} \triangleq [\mathbf{H}^{\hat{\theta}_{n'}}]_{i,:} = \bar{\alpha}_k \mathbf{a}_D(\omega_k), \quad (21)$$

where $\omega_k \triangleq \omega_v(v_k)$ and $\mathbf{a}_D(\omega) \triangleq [1, e^{j\omega}, \dots, e^{j(N_s-1)\omega}]$. The Doppler correlation matrix associated with this response is

$$\begin{aligned} \mathbf{R}_{i,k}^{f_D} &= \mathbf{h}_{i,k}^H \mathbf{h}_{i,k} \\ &= |\bar{\alpha}_k|^2 \mathbf{a}_D^H(\omega_k) \mathbf{a}_D(\omega_k), \end{aligned} \quad (22)$$

with its (p, q) -th entry $[\mathbf{R}_{i,k}^{f_D}]_{p,q} = |\bar{\alpha}_k|^2 e^{j(q-p)\omega_k}$, $1 \leq p, q \leq N_s$.

To remove the diagonal entries and retain only the positive Doppler lags, we define $\text{vec}_u(\cdot)$ as the row-wise vectorization of the strictly upper triangular part of a matrix. The Doppler correlation vector is then constructed as

$$\mathbf{r}_{i,k}^{f_D} = \text{vec}_u(\mathbf{R}_{i,k}^{f_D}) \in \mathbb{C}^{N_{\text{vec}} \times 1}, \quad (23)$$

where $N_{\text{vec}} = N_s(N_s - 1)/2$. Let (p_n, q_n) , $1 \leq p_n < q_n \leq N_s$, denote the index pair associated with the n -th entry of $\mathbf{r}_{i,k}^{f_D}$ under the row-wise upper-triangular ordering. The corresponding Doppler lag is defined as $d_n \triangleq q_n - p_n$. Then,

$$[\mathbf{r}_{i,k}^{f_D}]_n = |\bar{\alpha}_k|^2 e^{jd_n \omega_k}, \quad n = 1, \dots, N_{\text{vec}}. \quad (24)$$



Accordingly, the wrapped phase vector is defined as $\mathbf{p}_{i,k} \triangleq \angle \mathbf{r}_{i,k}^{fD} \in \mathbb{R}^{N_{\text{vec}} \times 1}$, whose n -th entry satisfies $[\mathbf{p}_{i,k}]_n = \text{wrap}_{2\pi}(d_n \omega_k)$. Based on the coarse velocity estimate v_{FFT} obtained in Section 3, we construct the reference unwrapped phase vector $\mathbf{p}_{\text{FFT}} \in \mathbb{R}^{N_{\text{vec}} \times 1}$, with $[\mathbf{p}_{\text{FFT}}]_n = d_n \omega_v(v_{\text{FFT}})$. The integer wrap vector κ is then estimated as

$$\kappa = \text{round} \left(\frac{\mathbf{p}_{\text{FFT}} - \mathbf{p}_{i,k}}{2\pi} \right), \quad (25)$$

where $\text{round}(\cdot)$ is applied element-wise. The unwrapped phase vector is recovered as

$$\tilde{\mathbf{p}}_{i,k} = \mathbf{p}_{i,k} + 2\pi\kappa. \quad (26)$$

Finally, the Doppler angular frequency is estimated by fitting the unwrapped phases to the Doppler lags. In the WUP estimator, each unwrapped phase observation is weighted by its corresponding Doppler lag d_n , yielding

$$\hat{\omega}_v(v_k) = \frac{\sum_{n=1}^{N_{\text{vec}}} d_n [\tilde{\mathbf{p}}_{i,k}]_n}{\sum_{n=1}^{N_{\text{vec}}} d_n^2}. \quad (27)$$

Remark 3: Observing (22), we note an analogy between the phase differences captured by the cross-correlation operation and the virtual difference co-arrays exploited in DoA estimation [50, 55]. As depicted in Fig. 3, the considered PT-RS style reference signal structure, which is dense across OFDM symbols, is analogous to the ULA. Furthermore, the weighted unwrapped estimator in (27) inherently assigns higher weights to phase differences corresponding to larger effective time separations (i.e., larger Doppler lags d_n), as these generally provide finer velocity resolution. This weighting strategy aligns conceptually with the objectives in the non-ULA design, which often aims for higher DoF and lower mutual coupling.

5.2 RELAX-Based Multi-Target Velocity Estimation

We now extend the estimation framework to the multi-target scenario, where multiple targets may share the same angle bin $\hat{\theta}_{n'}$. In this case, the i -th row of the channel response matrix is the superposition of $|\mathcal{K}_{n'}|$ signals :

$$[\mathbf{H}^{\hat{\theta}_{n'}}]_{i,:} = \sum_{k=1}^{|\mathcal{K}_{n'}|} \alpha_k \mathbf{a}_D(\omega_v(v_k)). \quad (28)$$

To estimate the parameters of each target individually, we adopt the estimate-subtract strategy inspired by the RELAX algorithm [54, 55]. This iterative method estimates the parameters of one target at a time while treating the others as interference. Specifically, assuming that the parameters of $Q - 1$ targets have already been estimated in $\mathbf{H}^{\hat{\theta}_{n'}}$, the signal component corresponding to the k -th target ($k \leq Q$) is

Algorithm 1 RELAX-Based Iterative Velocity Estimation

```

1: Input:  $\mathbf{s}_{fD} = [\mathbf{H}^{\hat{\theta}_{n'}}]_{i,:}$ ,  $|\mathcal{K}_{n'}|$ ,  $\varepsilon_{\text{relax}}$ .
2: Initialization: Obtain initial estimates  $\{\hat{\omega}_v(v_k)\}_{k=1}^{|\mathcal{K}_{n'}|}$ ,  $\{\hat{\alpha}_k\}_{k=1}^{|\mathcal{K}_{n'}|}$ ,
    $\Delta = \infty$ ,  $\mathbf{y}_1 = \mathbf{s}_{fD}$ .
3: for  $Q = 1$  to  $|\mathcal{K}_{n'}|$  do
4:   Estimate  $\hat{\omega}_v(v_Q)$  from  $\mathbf{y}_Q$  using the WUP estimator in (27).
5:   Estimate  $\hat{\alpha}_Q$  from  $\mathbf{y}_Q$  and  $\hat{\omega}_v(v_Q)$  according to (30).
6:   Reset convergence check  $\Delta = \infty$ .
7:   while  $\Delta \geq \varepsilon_{\text{relax}}$  do
8:      $J_{\text{prev}} = \left\| \mathbf{s}_{fD} - \sum_{k=1}^Q \hat{\alpha}_k \mathbf{a}_D(\hat{\omega}_v(v_k)) \right\|_2^2$ 
9:     for  $k = 1$  to  $Q$  do
10:       $\mathbf{y}_k^{\text{refine}} = \mathbf{s}_{fD} - \sum_{\bar{k}=1, \bar{k} \neq k}^Q \hat{\alpha}_{\bar{k}} \mathbf{a}_D(\hat{\omega}_v(v_{\bar{k}}))$ 
11:       $J_{\text{old}} = \left\| \mathbf{y}_k^{\text{refine}} - \hat{\alpha}_k \mathbf{a}_D(\hat{\omega}_v(v_k)) \right\|_2^2$ 
12:      Estimate candidate  $\hat{\omega}_v(v_k)$  from  $\mathbf{y}_k^{\text{refine}}$  using the WUP
        estimator in (27).
13:      Estimate candidate  $\hat{\alpha}_k$  from  $\mathbf{y}_k^{\text{refine}}$  and  $\hat{\omega}_v(v_k)$  according to
        (30).
14:       $J_{\text{cand}} = \left\| \mathbf{y}_k^{\text{refine}} - \hat{\alpha}_k \mathbf{a}_D(\hat{\omega}_v(v_k)) \right\|_2^2$ 
15:      if  $J_{\text{cand}} < J_{\text{old}}$  then
16:        Accept update:  $\hat{\omega}_v(v_k) \leftarrow \hat{\omega}_v(v_k)$ ,  $\hat{\alpha}_k \leftarrow \hat{\alpha}_k$ 
17:      end if
18:    end for
19:     $J_{\text{curr}} = \left\| \mathbf{s}_{fD} - \sum_{k=1}^Q \hat{\alpha}_k \mathbf{a}_D(\hat{\omega}_v(v_k)) \right\|_2^2$ 
20:     $\Delta = |J_{\text{prev}} - J_{\text{curr}}| / J_{\text{prev}}$ 
21:  end while
22:  Prepare residual for the next target's initial estimation
23:   $\mathbf{y}_{Q+1} = \mathbf{s}_{fD} - \sum_{k=1}^Q \hat{\alpha}_k \mathbf{a}_D(\hat{\omega}_v(v_k))$ 
24: end for
25: Output: Estimated velocities  $\{\hat{\omega}_v(v_k)\}_{k=1}^{|\mathcal{K}_{n'}|}$ .

```

extracted as

$$\mathbf{s}_{fD}^{(k)} = [\mathbf{H}^{\hat{\theta}_{n'}}]_{i,:} - \sum_{\bar{k} \in \mathcal{Q} \setminus \{k\}} \hat{\alpha}_{\bar{k}} \mathbf{a}_D(\hat{\omega}_v(v_{\bar{k}})). \quad (29)$$

where $\mathcal{Q} = \{1, \dots, Q\}$ denotes the current target index set, and $\hat{\alpha}_{\bar{k}}$ and $\hat{\omega}_v(v_{\bar{k}})$ are the current estimates for the other targets. The Doppler frequency $\hat{\omega}_v(v_k)$ is then estimated from $\mathbf{s}_{fD}^{(k)}$ using the WUP method described previously. Subsequently, the complex amplitude α_k can be estimated as

$$\hat{\alpha}_k = \frac{\mathbf{a}_D(\hat{\omega}_v(v_k))^* \mathbf{s}_{fD}^{(k)}}{N_s}. \quad (30)$$

where $\mathbf{a}_D(\hat{\omega}_v(v_k))$ is the estimated Doppler vector for the k -th target's Doppler frequency. This process is iterated, refining the estimates for all targets until all $Q = |\mathcal{K}_{n'}|$ targets have been identified. The final algorithm is summarized in Algorithm 1.

Remark 4: Convergence Behavior and Local Minima Risks. The proposed RELAX-based refinement operates as a coordinate-wise estimate-and-subtract procedure. By holding the parameters of the remaining $Q - 1$ targets fixed, each inner iteration reoptimizes the current target based on its corresponding residual signal, thereby directly reducing the local residual cost. Consequently, the overall residual energy forms a monotonically non-increasing sequence across the it-

erations and, being lower-bounded by zero, is guaranteed to converge. Nevertheless, due to the highly non-convex nature of the joint multi-target estimation problem, an inadequate initialization or insufficient target separation may still trap the algorithm in a local minimum. Therefore, the quality of the Stage-I initialization is crucial, and its practical impact is numerically evaluated in Section 6.3.

5.3 Range Estimation and Parameter Pairing

Drawing inspiration from research in the non-ULA design, we adopt the SPS for the pilots, as detailed in Section 4. Let $\mathcal{S}_{f,\text{combined}} = \{p_1, \dots, p_{|\mathcal{S}_{f,\text{combined}}|}\}$ denote this sparse set of subcarrier indices. Assuming a single target k , we define the delay vector $\mathbf{a}_\tau(R_k) \in \mathbb{C}^{|\mathcal{S}_{f,\text{combined}}| \times 1}$ by extracting the channel response at the sparse subcarrier indices over a specific OFDM symbol l

$$\mathbf{a}_\tau(R_k) \approx \bar{\alpha}_k [e^{jp_1\omega_r(R_k)}, \dots, e^{jp_{|\mathcal{S}_{f,\text{combined}}|}\omega_r(R_k)}]^T. \quad (31)$$

Following the WUP estimator framework proposed in Sections 5.1 and 5.2, the delay covariance vector $\mathbf{r}^\tau$ is constructed as

$$\mathbf{r}^\tau = \text{vecl}(\mathbf{a}_\tau(R_k)\mathbf{a}_\tau(R_k)^H). \quad (32)$$

Then, the corresponding unwrapped phase vector $\tilde{\mathbf{p}}^\tau$ can be expressed as

$$\tilde{\mathbf{p}}^\tau = \text{vecl}(\mathbf{R}_\tau)\omega_r(R_k), \quad (33)$$

where $[\mathbf{R}_\tau]_{i,j} = p_i - p_j$, with p_i and p_j being the i -th and j -th frequency indices from $\mathcal{S}_{f,\text{combined}}$, respectively. Notably, the vector $\text{vecl}(\mathbf{R}_\tau)$ contains the frequency index differences corresponding to the DCS, which is detailed in Definition 1. The subsequent steps for $\omega_r(R_k)$ proceed analogously to the velocity estimation.

Using the above range and velocity estimators, we obtain the sets of estimated normalized range frequencies $\{\hat{\omega}_r(R_k)\}_{k=1}^{|\mathcal{K}_{n'}|}$ and Doppler frequencies $\{\hat{\omega}_v(v_k)\}_{k=1}^{|\mathcal{K}_{n'}|}$. Parameter pairing is then performed to associate the correct range and velocity estimates for each target. To this end, we first construct Γ containing all possible $|\mathcal{K}_{n'}|^2$ range-velocity pairings

$$\Gamma = \{(\hat{\omega}_r(R_i), \hat{\omega}_v(v_j))\}_{i,j=1}^{|\mathcal{K}_{n'}|}, \quad (34)$$

where for each pair $(\hat{\omega}_r(R_i), \hat{\omega}_v(v_j)) \in \Gamma$, the matching score is calculated as

$$S_{\hat{\omega}_r(R_i), \hat{\omega}_v(v_j)}^{\hat{\theta}_{n'}} = \left| \mathbf{a}_\tau(\hat{R}_i)^H \mathbf{H}^{\hat{\theta}_{n'}} \mathbf{a}_D(\hat{v}_j) \right|. \quad (35)$$

Subsequently, by identifying the $|\mathcal{K}_{n'}|$ pairs in Γ that yield the highest matching scores, the final set $\Xi^{\hat{\theta}_{n'}}$ of paired range

and velocity parameters for the $|\mathcal{K}_{n'}|$ targets is given by

$$\Xi^{\hat{\theta}_{n'}} = \{(\hat{R}_k, \hat{v}_k)\}_{k=1}^{|\mathcal{K}_{n'}|}. \quad (36)$$

5.4 DBSCAN-based Repeated Targets Pruning

In order to maintain continuous energy coverage, the half-power beamwidths of adjacent beams typically overlap during SSB and SIB1 beam sweeping. Consequently, a single UAV target may be detected by multiple beams. To address this redundancy, we employ the DBSCAN algorithm [56] to cluster the detected targets in the range-velocity-angle space. To mitigate the impact of spurious noise detections, the minimum number of points $N_{\min}$ in a cluster is set to 2.

As a prerequisite for clustering, we define the detected targets set Ξ across all detected angles $\{\hat{\theta}_{n'}\}$ as

$$\Xi = \bigcup_{\hat{\theta}_{n'}} \{(\hat{R}_k, \hat{v}_k, \hat{\theta}_{n'}) \mid (\hat{R}_k, \hat{v}_k) \in \Xi^{\hat{\theta}_{n'}}\}, \quad (37)$$

where each element $\mathbf{s} \in \Xi$ is a tuple $\mathbf{s} = (\hat{R}, \hat{v}, \hat{\theta})$. Next, we define the weighting matrix $\mathbf{W} = \text{Diag}(w_R, w_v, w_\theta)$, where the weights reflect the inverse squared resolutions: $w_R = (2N_{c,\text{SIB1}}\Delta f/c)^2$, $w_v = (2N_{s,\text{SIB1}}T_{\text{sym}}/\lambda)^2$ and $w_\theta \propto N_R^2$. Then, the weighted distance $d(\mathbf{s}_1, \mathbf{s}_2)$ between two points $\mathbf{s}_1, \mathbf{s}_2 \in \Xi$ is calculated as

$$d(\mathbf{s}_1, \mathbf{s}_2) = ((\mathbf{s}_1 - \mathbf{s}_2)^T \mathbf{W} (\mathbf{s}_1 - \mathbf{s}_2))^{1/2}, \quad (38)$$

where $(\mathbf{s}_1 - \mathbf{s}_2)$ represents the element-wise difference vector.

Following the classical density-based clustering practice, the neighborhood radius $d_{\min}$ (i.e., ϵ in standard DBSCAN terminology) can be selected with the aid of a sorted nearest-neighbor-distance graph [56], where the neighbor order is denoted by ζ , rather than being chosen solely by trial and error. Related hierarchical density-based clustering methods also exploit the density structure of the point cloud to improve robustness under varying local densities [57]. After applying DBSCAN with the weighted distance metric and the selected radius $d_{\min}$, the algorithm groups the points in Ξ into clusters. Each resulting cluster ideally corresponds to multiple detections of a single, unique UAV target, while points classified as noise by DBSCAN are discarded. Specifically for each cluster $\mathcal{C}_m$ identified by DBSCAN, the final estimate $(\hat{R}_m^{\text{final}}, \hat{v}_m^{\text{final}}, \hat{\theta}_m^{\text{final}})$ for the m -th target is obtained as

$$(\hat{R}_m^{\text{final}}, \hat{v}_m^{\text{final}}, \hat{\theta}_m^{\text{final}}) = \frac{\sum_{\mathbf{s} \in \mathcal{C}_m} S_{\hat{\omega}_r(R), \hat{\omega}_v(v)}^{\hat{\theta}} \cdot \mathbf{s}}{\sum_{\mathbf{s} \in \mathcal{C}_m} S_{\hat{\omega}_r(R), \hat{\omega}_v(v)}^{\hat{\theta}}}, \quad (39)$$

where the summation and division are performed element-wise for the tuple $\mathbf{s} = (\hat{R}, \hat{v}, \hat{\theta})$. This process yields the final pruned set of detected UAV parameters.

6 Numerical Results

In this section, simulation results are presented to evaluate the performance of the proposed sensing framework. Firstly, we provide the simulation parameter settings. Next, we verify the practical communication compatibility of the proposed SPS insertion using a 5G NR link-level simulation. Then, we compare the performance of our proposed RELAX-based WUP algorithm with conventional techniques in a single-target scenario. Furthermore, we also evaluate the impact of SPS configurations. Finally, we compare our DBSCAN-based clustering algorithm with the benchmark pruning method in the multi-target scenario.

6.1 Simulation Settings

Unless otherwise specified, the default simulation parameters are set as follows. We consider a monostatic dual-function radar-communication (DFRC) base station (BS) operating at a carrier frequency of $f_c = 30$ GHz with a sub-carrier spacing of $\Delta f = 120$ kHz. The BS employs separate half-wavelength transmit and receive uniform linear arrays (ULAs) equipped with $N_t = 32$ and $N_r = 64$ antennas, respectively. For a normal CP configuration, the CP durations are $T_{cp} \approx 1.107 \mu s$ for the 0-th and 7-th OFDM symbols, and $T_{cp,min} \approx 0.586 \mu s$ for the remaining 12 symbols. For the 5G NR normal-CP numerology with $\Delta f = 120$ kHz, the minimum CP duration is $T_{cp,min} \approx 0.586 \mu s$. Under the echo-model validity condition $\tau_{max} \leq T_{cp,min}$ in Section 2.2, the monostatic round-trip delay imposes a CP-limited sensing range of $R_{max}^{CP} = cT_{cp,min}/2 \approx 87.9$ m. Accordingly, all simulated targets are placed within this range: the target range is set to 50 m in the single-target scenario, and all target ranges are below 85 m in the multi-target scenario. The radar cross section (RCS) of the target is set to $\sigma = 0.05$ m². The two-stage sequential sensing protocol first sweeps 64 SSB beams within the angular sector from -45° to 45° to perform coarse detection. Subsequently, it transmits SPS-augmented PDCCH and SIB1 signals to facilitate simultaneous access for the UE and refined parameter estimation. To evaluate the communication performance, a standard-compliant 5G NR initial-access link-level simulation is conducted. In this simulation, the SPS is exclusively mapped to communication-idle REs, whereas the REs allocated for SIB1 are preserved for data demodulation at the UE and inherently reused by the BS as known sensing waveforms. All the presented results are averaged over 200 Monte Carlo trials.

6.2 5G NR Link-Level Verification of the SPS Insertion

The detailed link-level settings used for Fig. 5 are summarized in Table 2.

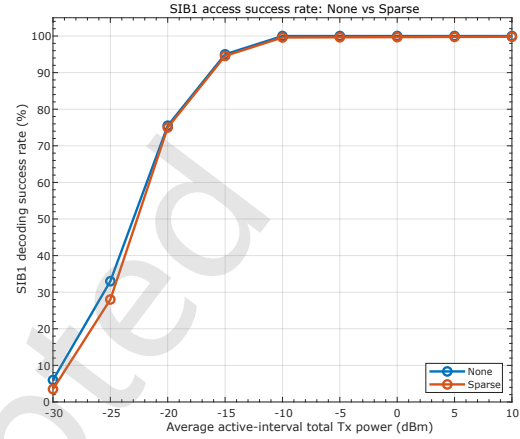


Fig. 5 SIB1 decoding success rate versus average active-interval total transmit power for the pure-communication baseline ('None') and the proposed SPS-assisted transmission ('Sparse').

Fig. 5 illustrates the success rate of SIB1 decoding versus the average transmit power. Here, 'None' represents the baseline of pure-communication initial access, whereas 'Sparse' denotes the proposed SPS-assisted transmission scheme. A trial is considered successful only if the BCH, DCI, and SIB1 are all decoded correctly. It is observed that the insertion of SPS impacts the access performance of SIB1 solely in the low-transmit-power regime (i.e., below -20 dBm), where a marginal degradation occurs. In contrast, within the practically relevant operating region above -20 dBm, the two curves are nearly indistinguishable. This demonstrates that the proposed SPS insertion does not compromise the reliability of the initial-access procedure under practical deployment conditions.

These results should be analyzed in conjunction with the monostatic signal model presented in Section 4.3. Because the BS has full knowledge of the transmitted waveform, the REs occupied by SIB1 can still be leveraged for sensing, even though they are unavailable for SPS placement. Consequently, variations in the occupancy of SIB1 do not reduce the number of effective observations in the frequency domain within the proposed framework. Rather, the practical role of the SPS is to expand the usable aperture in the frequency domain by occupying the communication-idle REs. This effectively improves the performance of range estimation without sacrificing the functionality of communication.

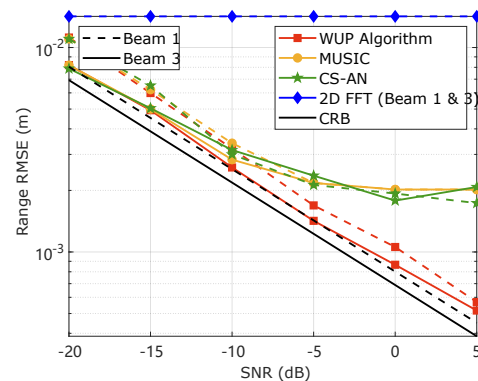
Table 2 Link-level simulation parameters for the 5G NR initial-access verification in Section 6.2.

Parameter	Setting
Carrier and waveform	$f_c = 30$ GHz, 100 MHz channel bandwidth, 120 kHz common SCS, SSB block pattern Case D
Initial-access resource region	CORESET#0 with 24 RBs; Type-0 common search space (CSS) with duration 2 OFDM symbols; PDCCH aggregation level 8
SIB1/PDSCH allocation	8 RBs, Mapping Type A with $(S, L, K_0) = (3, 11, 0)$
Modulation and DMRS	quadrature phase shift keying (QPSK), single layer, DMRS Type A, position 3, configuration type 1
Channel and propagation	3GPP urban micro line-of-sight (UMi-LOS) path loss and single-input single-output (SISO) tapped-delay-line D (TDL-D) fading channel with root-mean-square (RMS) delay spread 30 ns; shadow fading enabled with standard deviation 4 dB
Geometry and mobility	BS height 10 m, UE height 1.5 m, horizontal distance 20 m; UE speed 3.6 km/h with maximum Doppler about 83 Hz
Beam sweeping model	32-antenna BS panel with 0.5λ spacing; beam sweeping implemented through a time-varying sample-domain gain mask
Power sweep and averaging	Average active-interval total transmit power from -30 dBm to 10 dBm in steps of 5 dB, with 200 Monte Carlo trials per point
Receiver chain	primary synchronization signal (PSS)-based coarse carrier frequency offset (CFO) correction, timing synchronization, secondary synchronization signal (SSS) search, PBCH DMRS detection, broadcast channel/master information block (BCH/MIB) decoding, DCI blind decoding, and SIB1 PDSCH recovery
Success criterion	A trial is counted as successful only if BCH, DCI, and SIB1 are all decoded correctly

6.3 Estimation Accuracy and Computational Cost for Single Target

We first evaluate the performance of our proposed algorithm in the single-target scenario by comparing it against three benchmark methods: 2D-FFT [10], 2D-MUSIC [35], 2D CS-AN [58]. These benchmarks represent the periodogram, subspace-based and compressed sensing methods, respectively. It is noted that the benchmark methods, namely 2D-FFT, 2D-MUSIC, and 2D CS-AN, are applied directly to the SPS-augmented PDCCH/SIB1 resources, bypassing the SSB. This baseline setup is justified by the limited duration and bandwidth of the SSB, which restrict the achievable Doppler and range resolutions. In contrast, the proposed algorithm explicitly leverages the SSB for coarse target estimation before refining the parameters over the SPS-augmented PDCCH/SIB1 resources. For this simulation, the range, radial velocity, and angle of the single target are set to (50 m, 25 m/s, 15°).

Fig. 6 compares the range RMSE performance versus SNR for different algorithms. We can observe that the 2D-FFT method exhibits a nearly constant RMSE, limited by bandwidth resolution and unaffected by the number of beams. In contrast, both 2D-MUSIC and CS-AN show performance gains as SNR increases; however, their grid-based search leads to eventual error floors. Among these, CS-AN provides better range estimation than 2D-MUSIC. The proposed WUP algorithm significantly outperforms all benchmarks, achiev-

**Fig. 6** Root mean squared error (RMSE) of range estimation versus SNR.

ing the lowest RMSE and highlighting its effective off-grid estimation capability under challenging sparse pilot conditions.

Fig. 7 presents the velocity RMSE versus SNR for different algorithms. A key observation is that utilizing multiple beams significantly enhances velocity estimation accuracy for all algorithms by extending the effective observation interval and thus improving velocity resolution. Notably, this performance gain is markedly stronger than that observed for range estimation. In contrast to the range estimation results, it is noted that the 2D-MUSIC slightly outperforms CS-AN in velocity estimation under the sparse frequency configuration. Furthermore, the proposed WUP algorithm demonstrates superior performance, consistently achieving the lowest RMSE

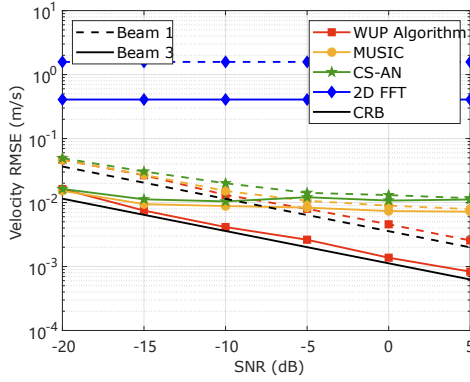


Fig. 7 RMSE of velocity estimation versus SNR.

across the entire simulated SNR range.

Table 3 summarizes the dominant asymptotic complexities of the evaluated algorithms in the single-target setting. In this context, $N_s \triangleq N_{s,\text{SIB1}}$ and $N_f \triangleq |\mathcal{S}_{f,\text{combined}}|$ denote the dimensions of the SPS-augmented resources. For the SSB signal, the corresponding symbol and subcarrier dimensions are given by $N_{s,\text{SSB}}$ and $N_{f,\text{SSB}}$, with their product defined as $N_{\text{SSB}} \triangleq N_{f,\text{SSB}}N_{s,\text{SSB}}$. Furthermore, γ_{os} represents the FFT oversampling factor for the coarse grid, and B denotes the number of processed beams. The complexity of the proposed algorithm stems from the oversampled SSB-based coarse estimation, followed by the WUP-based parameter refinement. In contrast, the benchmark algorithms operate directly on the SPS-augmented resources and bypass the SSB initialization entirely. Despite the initial coarse-estimation overhead, the proposed algorithm achieves a substantially lower overall complexity than 2D-MUSIC and 2D CS-AN, owing to the efficient WUP-based refinement.

Table 3 Asymptotic complexity comparison for the single-target refinement and benchmark algorithms.

Method	Dominant complexity
Proposed algorithm	$\mathcal{O}(\gamma_{\text{os}}^2 B N_{\text{SSB}} \log(\gamma_{\text{os}}^2 B N_{\text{SSB}}) + B N_f N_s)$
2D-FFT	$\mathcal{O}(B N_f N_s \log(B N_f N_s))$
2D-MUSIC	$\mathcal{O}(B[(N_f N_s)^3 + G_f G_s (N_f N_s)^2])$
2D CS-AN	$\mathcal{O}(B(N_f N_s)^{4.5})$

Fig. 8 demonstrates the average processing time of the proposed algorithm against benchmark methods under different beam configurations. The results reveal a clear computational hierarchy, with 2D-FFT exhibiting the lowest processing time and the proposed method following closely. In contrast, 2D-MUSIC incurs a noticeably higher computational burden, while 2D CS-AN is the most time-consuming method. Although the processing time increases with the

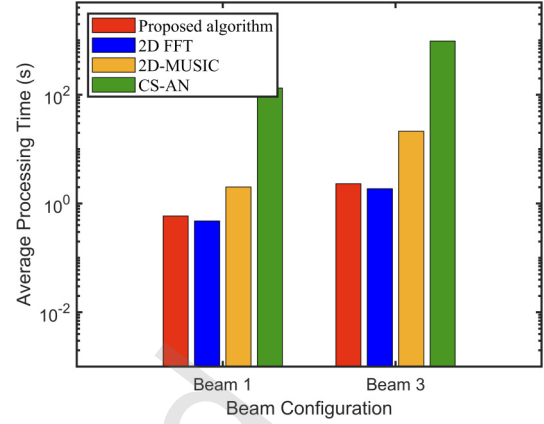


Fig. 8 Computational time comparison .

number of beams, the proposed algorithm maintains a low computational cost comparable to 2D-FFT and remains substantially more efficient than 2D-MUSIC and CS-AN. This advantage demonstrates its favorable scalability under different beam configurations.

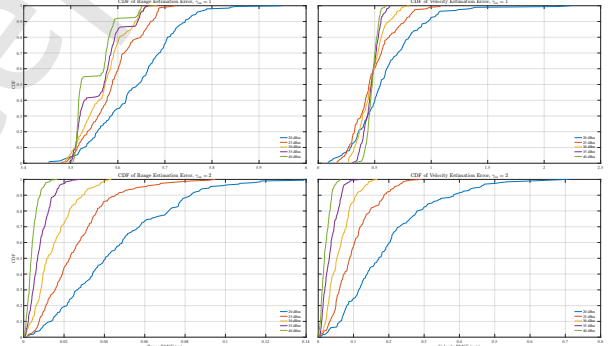


Fig. 9 Impact of the Stage-I oversampling factor on the robustness of the refined estimation.

To evaluate the sensitivity of the refinement stage to the initialization quality provided by Stage I, Fig. 9 compares the final estimation performance using the standard 2D-FFT initialization ($\gamma_{\text{os}} = 1$) versus the oversampled initialization adopted in this work ($\gamma_{\text{os}} = 2$). The oversampled approach yields a noticeably more concentrated error distribution and significantly mitigates severe estimation outliers, particularly in the low-to-moderate SNR regime. These results confirm that the zero-padded Stage-I RDM establishes a robust starting point for the subsequent RELAX-based WUP refinement.

Fig. 10 illustrates the performance of range estimation versus transmit power under different array layouts, where Fig. 10(a) and Fig. 10(b) correspond to the 24RB and 48RB CORESET#0 configurations, respectively. Since the frequency-domain pattern mainly affects the delay structure, only the ranging RMSE is evaluated. The observed ranking is consistent with the design rationale in Section 4.2. For the

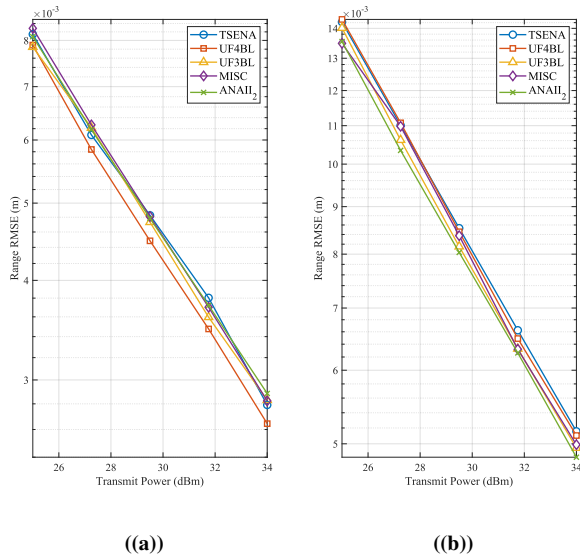


Fig. 10 RMSE of range estimation versus transmit power with different CORESET#0 configurations: (a) 24RBs, (b) 48RBs

24RB configuration, the UF-4BL scheme achieves the best performance because it preserves a sufficiently large effective aperture while keeping the short-lag weights and coupling relatively small, thereby providing a favorable trade-off between the CRLB term $N \text{var}(\mathbf{p})$ and sidelobe suppression. For the 48RB configuration, ANAII-2 provides the highest accuracy because its substantially larger contiguous uDoF improves identifiability and stabilizes the delay estimate, even though its low-order coupling is higher. Furthermore, for a given transmit power, increasing the bandwidth from 24RBs to 48RBs does not necessarily improve sensing performance, because the SNR per RE decreases as the total power is distributed over a larger number of REs.

6.4 Comparison with Existing Pilot Patterns

Recent ISAC sensing pilot designs are typically tightly coupled with specific estimators or tailored ambiguity-elimination mechanisms (e.g., the high-resolution MUSIC algorithm). However, the strict 20 ms SSB scanning cycle in our framework precludes the use of the computationally prohibitive subspace-based algorithms. Therefore, to ensure a fair and practically viable comparison, we evaluate representative pilot patterns under a unified, low-complexity receiver architecture. Specifically, all candidate schemes are forced to employ the identical two-stage estimator proposed in this work (Stage-I coarse estimation followed by WUP-based refinement), and the total BS transmit power budget is maintained strictly constant. We compare three schemes: the proposed SPS, a frequency-domain coprime pilot pattern [33], and a ‘Full’ baseline that activates all available REs within

the CORESET#0 frequency span.

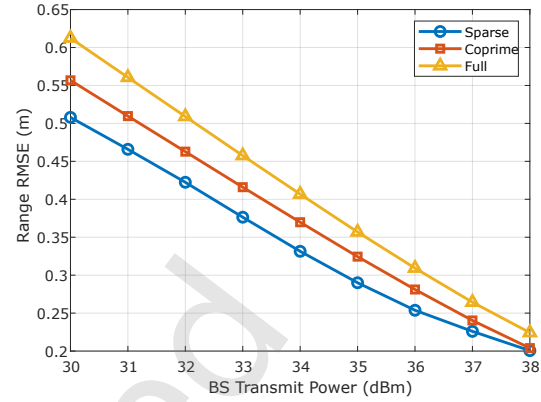


Fig. 11 Comparison of range estimation RMSE among different sensing pilot patterns under a constant total BS transmit power budget, utilizing the proposed two-stage estimator.

As illustrated in Fig. 11, the Full scheme exhibits the poorest range RMSE. This confirms that, under a fixed transmit power constraint, simply increasing the pilot density is counterproductive; the power allocated to each individual RE is severely diluted, leading to an inadequately low per-pilot SNR. By concentrating power on fewer REs, the coprime scheme [33] successfully mitigates this power dilution and outperforms the Full baseline, yet it remains inferior to the proposed SPS. The fundamental reason is that the coprime pattern was originally tailored for high-complexity algorithms like MUSIC. When evaluated using the WUP-based estimator dictated by the latency constraint, its specific RE placement becomes highly suboptimal for the phase unwrapping mechanism. In contrast, the proposed SPS strategically concentrates power on a carefully selected set of sparse REs that are co-designed with the WUP estimator. Consequently, it inherently maximizes the per-pilot SNR while optimally aligning with the phase unwrapping logic, thereby achieving the lowest range RMSE across all evaluated power levels under strict latency constraints.

6.5 Estimation Accuracy for Multiple Targets

To evaluate the multi-target performance, we employ the optimal sub-pattern assignment (OSPA) metric [10], which provides a unified performance assessment by jointly capturing both localization and cardinality errors (i.e., the difference between the true and estimated number of targets) in a single value.

Given the ground truth set of L target positions $P = \{p_1, \dots, p_L\}$, and the estimated set of $\hat{L}$ positions $\hat{P} = \{\hat{p}_1, \dots, \hat{p}_{\hat{L}}\}$, the distance between any true position p and

estimated position $\hat{p}$ is defined as

$$d(p, \hat{p}; \bar{c}) = \min\{\bar{c}, \|p - \hat{p}\|_2\}, \quad (40)$$

where $\bar{c} > 0$ is the cutoff parameter that determines how the metric penalizes cardinality error with respect to the localization error. For the case $L \leq \hat{L}$, the OSPA metric of order q is defined as [59]

$$\begin{aligned} \bar{d}_q(P, \hat{P}; \bar{c}) \\ = \left(\frac{1}{L} \left(\min_{\pi \in \Pi_{\hat{L}}} \sum_{l=1}^L (d(p_l, \hat{p}_{\pi(l)}; \bar{c}))^q + \bar{c}^q (\hat{L} - L) \right) \right)^{1/q}, \end{aligned} \quad (41)$$

where $\Pi_{\hat{L}}$ is the set of permutations of $\{1, 2, \dots, \hat{L}\}$ and $\pi(l)$ is the index of the estimated point in $\hat{P}$ assigned to the l -th true point p_l under a specific permutation $\pi \in \Pi_{\hat{L}}$. In particular, the metric is computed symmetrically as $\bar{d}_q(P, \hat{P}; \bar{c}) = \bar{d}_q(\hat{P}, P; \bar{c})$ if $L > \hat{L}$. Moreover, the order q determines the sensitivity to outliers, while the cutoff $\bar{c}$ balances the localization and cardinality error penalties. In our simulations, we follow the recommendations in [59] and set $q = 2$ and $\bar{c} = 10$ m to ensure a proper balance between these error components. Specifically, we consider $L = 5$ targets, whose parameters are randomly drawn from uniform distributions: ranges in $[5, 85]$ m, velocities in $[-35, 35]$ m/s, and angles in $[-35^\circ, 35^\circ]$. We employ this setup to validate the performance of our proposed two-stage detection scheme in a multi-target environment.

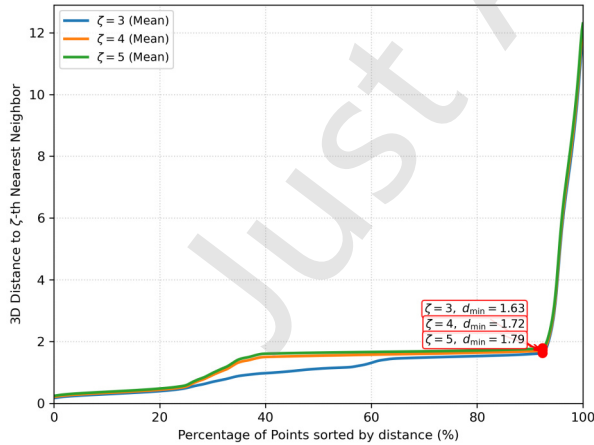


Fig. 12 Sorted 3D nearest-neighbor-distance statistics of the weighted point cloud used for DBSCAN-based fusion. The marked elbows indicate the candidate $d_{\min}$ values obtained for neighbor orders $\zeta = 3, 4, 5$. Here, ζ denotes the neighbor order, i.e., each point's ζ -distance is its weighted distance to the ζ -th nearest neighbor.

To complement the fixed-threshold analysis, Fig. 12 plots the sorted 3D nearest-neighbor-distance statistics under the adopted weighted metric. Following the standard DBSCAN

heuristic [56], the curves for $\zeta = 3, 4, 5$ exhibit a consistent elbow around $d_{\min} \approx 1.6$ – 1.8 . This indicates that repeated detections of the same UAV form compact local groups in the weighted space, providing a practical, data-driven guideline for threshold selection.

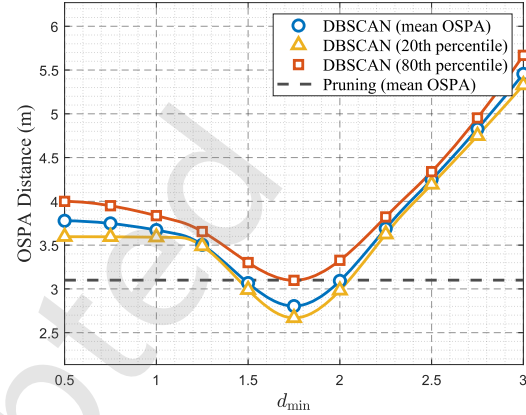


Fig. 13 Sensitivity of the OSPA distance to the DBSCAN minimum distance threshold $d_{\min}$.

Furthermore, Fig. 13 evaluates the sensitivity of the OSPA metric to $d_{\min}$. For comparison, the baseline Pruning algorithm [10] is configured with its optimal parameters $\epsilon_r = \Delta r$ and $\epsilon_v = 3\Delta v$, and its mean performance is plotted as the black dashed line. For the proposed method, the mean, 20th, and 80th percentile OSPA curves are reported. The curve exhibits a U-shaped trend, reflecting the trade-off between over- and under-segmentation. Specifically, an overly small $d_{\min}$ fails to merge detections of the same target across adjacent beams, thereby inflating the cardinality; conversely, an excessively large $d_{\min}$ incorrectly merges distinct nearby targets, degrading both localization and cardinality accuracy. The optimal performance is attained at $d_{\min} \approx 1.7$, which perfectly aligns with the nearest-neighbor-distance elbow in Fig. 12.

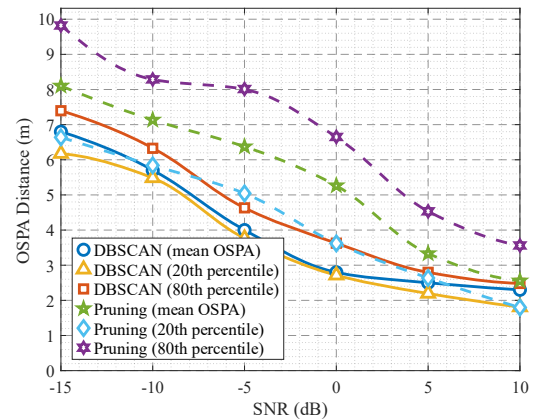


Fig. 14 OSPA distance versus SNR.

Fig. 14 depicts the OSPA distance versus SNR for the proposed DBSCAN-based fusion algorithm and the Pruning benchmark [10]. The proposed algorithm consistently achieves better accuracy and greater robustness across the entire SNR range. This improved robustness is reflected in the narrower spread between its 20th and 80th percentile curves around the mean. In contrast, the Pruning algorithm exhibits larger performance fluctuations, which can be attributed to its selection mechanism: it retains only the single target candidate with the maximum matching score. The clustering nature of DBSCAN, however, inherently suppresses such variability by aggregating the regional detections, resulting in more stable and reliable performance.

7 CONCLUSION

This paper proposed a two-stage ISAC framework designed to support the emerging LAE by leveraging 5G NR networks. Specifically, the framework addressed the fundamental sensing resolution limitations of standard broadcast signals. In Stage I, we first fused RDMs from the SSB, Type0-PDCCH, and SIB1 for robust initial detection. In Stage II, we employed the novel SPS, inspired by sparse array theory and inserted into unused SIB1 resources, to overcome the resolution limitations. To this end, a corresponding high-resolution algorithm based on the WUP estimator and the RELAX-based iterative method was developed to accurately extract off-grid range and velocity parameters from these sparse pilots. Finally, the DBSCAN-based clustering scheme was employed to prune redundant detections. Comprehensive simulation results demonstrated that the proposed framework achieves superior estimation accuracy at a significantly lower computational cost compared to conventional benchmark methods. In addition, the 5G NR link-level verification showed that the priority-based SPS insertion preserves the practical initial-access reliability, while the monostatic architecture ensures that the SIB1-occupied REs remain exploitable for sensing. Moreover, the controlled comparison against a representative coprime pilot pattern under the same BS transmit-power budget and the same two-stage estimator confirmed that the proposed SPS is better matched to the latency-constrained coarse-to-fine architecture than both the coprime and full-RE baselines. Future work will focus on investigating the framework's performance in more complex, dense multi-target scenarios and exploring further optimization of the SPS patterns in 5G NR.

A Frequency-Domain Signal Model Derivation

In this appendix, we derive the received frequency-domain signal model for a MIMO-OFDM system as presented in the main text. We begin with the continuous-time baseband signal models and proceed through the steps of sampling, CP-removal, and DFT.

Substituting (5) into (3), and assuming a sufficiently long CP such that ISI is eliminated, the sampled signal from the l -th transmitted symbol is

$$\mathbf{y}(j, l) \approx \sum_{n=1}^{N_{\text{target}}} \beta_n e^{j2\pi f_{D,n} t_{j,l}} \mathbf{b}_r(\theta_n) \mathbf{a}^H(\theta_n) \times \sum_{i=0}^{N_c-1} [\mathbf{X}]_{i,l} e^{j2\pi i \Delta f (t_{j,l} - \tau_n)}, \quad (42)$$

where $t_{j,l} = lT + j/F_s + T_{\text{CP}}$ and the noise term is omitted for clarity.

An N_c -point DFT is then applied to $\mathbf{y}(j, l)$ along the index j to obtain the frequency-domain signal $\mathbf{y}(k, l)$:

$$\begin{aligned} \mathbf{y}(k, l) &= \sum_{j=0}^{N_c-1} \mathbf{y}(j, l) e^{-j2\pi k j / N_c} \\ &\approx \sum_{j=0}^{N_c-1} \sum_{n=1}^{N_{\text{target}}} \beta_n e^{j2\pi f_{D,n} t_{j,l}} \mathbf{b}_r(\theta_n) \mathbf{a}^H(\theta_n) \\ &\quad \times \sum_{i=0}^{N_c-1} [\mathbf{X}]_{i,l} e^{j2\pi i \Delta f (t_{j,l} - \tau_n)} e^{-j2\pi k j / N_c}. \end{aligned} \quad (43)$$

By rearranging the summations and substituting the definition of $t_{j,l}$, (43) can be written as

$$\begin{aligned} \mathbf{y}(k, l) &\approx \sum_{n=1}^{N_{\text{target}}} \beta_n \mathbf{b}_r(\theta_n) \mathbf{a}^H(\theta_n) \sum_{i=0}^{N_c-1} [\mathbf{X}]_{i,l} e^{-j2\pi i \Delta f \tau_n} \\ &\quad \times \left(\sum_{j=0}^{N_c-1} e^{j2\pi (f_{D,n} + i \Delta f) t_{j,l}} e^{-j2\pi k j / N_c} \right). \end{aligned} \quad (44)$$

The summation over j can be simplified. First, we expand $t_{j,l}$ and factor out the term that is constant with respect to j :

$$\begin{aligned} &\sum_{j=0}^{N_c-1} e^{j2\pi (f_{D,n} + i \Delta f) (lT + T_{\text{CP}} + j/F_s)} e^{-j2\pi k j / N_c} \\ &= e^{j2\pi (f_{D,n} + i \Delta f) (lT + T_{\text{CP}})} \\ &\quad \times \sum_{j=0}^{N_c-1} e^{j2\pi (f_{D,n} + i \Delta f) (j/F_s)} e^{-j2\pi k j / N_c}. \end{aligned} \quad (45)$$

Using the standard OFDM relation $F_s = N_c \Delta f$, the summa-

tion term in (45) becomes

$$\sum_{j=0}^{N_c-1} e^{j2\pi \frac{j}{N_c} (i-k+f_{D,n}/\Delta f)}. \quad (46)$$

For scenarios where the Doppler shift is much smaller than the subcarrier spacing ($f_{D,n} \ll \Delta f$), we can approximate $f_{D,n}/\Delta f \approx 0$. This approximation neglects ICI. Under this condition, (46) simplifies to the delta function

$$\sum_{j=0}^{N_c-1} e^{j2\pi \frac{j}{N_c} (i-k)} = N_c \cdot \delta_{i,k}. \quad (47)$$

Substituting (47) back into (44) causes the summation over i to collapse to a single term where $i = k$:

$$\begin{aligned} \mathbf{y}(k, l) &\approx \sum_{n=1}^{N_{\text{target}}} \beta_n \mathbf{b}_r(\theta_n) \mathbf{a}^H(\theta_n) [\mathbf{X}]_{k,l} e^{-j2\pi k \Delta f \tau_n} \\ &\quad \times e^{j2\pi (f_{D,n} + k \Delta f) (lT + T_{CP})} \cdot N_c. \end{aligned} \quad (48)$$

After compensating for the known phase component $e^{j2\pi k \Delta f (lT + T_{CP})}$ and neglecting the negligible term $e^{j2\pi f_{D,n} T_{CP}}$ and the constant N_c , (48) simplifies to

$$\begin{aligned} \mathbf{y}(k, l) &= \sum_{n=1}^{N_{\text{target}}} \beta_n \mathbf{a}_t^H(\theta_n) [\mathbf{X}]_{k,l} e^{jk\omega_r(R_n)} e^{jl\omega_v(v_n)} \\ &\quad \times \mathbf{b}_r(\theta_n) + \mathbf{z}(k, l), \end{aligned} \quad (49)$$

where $\omega_r(R_n) \triangleq -4\pi \Delta f R_n / c$ and $\omega_v(v_n) \triangleq 2\pi f_{D,n} T$ respectively.

B CRLB Derivation for the MIMO-OFDM Signal Model

B.1 Stacking Order Convention

To facilitate the joint estimation of all target parameters, we aggregate the observations from all receive antennas. First, for each receive antenna p , we form a data vector $\mathbf{b}_p = \text{vec}(\mathbf{Y}_p) \in \mathbb{C}^{MN \times 1}$, where $[\mathbf{Y}_p]_{i,l} = [\mathbf{y}(i, l)]_p$. Then the total observation vector $\mathbf{b} \in \mathbb{C}^{N_r MN \times 1}$ is expressed as:

$$\mathbf{b} = \begin{bmatrix} \mathbf{b}_0 \\ \mathbf{b}_1 \\ \vdots \\ \mathbf{b}_{N_r-1} \end{bmatrix}. \quad (50)$$

B.2 Contribution of the n -th Target

For the n -th target, we define the time-frequency phase vector $\mathbf{s}_n \in \mathbb{C}^{MN \times 1}$ with elements arranged in column-major order as

$$\begin{aligned} [\mathbf{s}_n]_{i+lm} &= \mathbf{a}_t^H(\theta_n) [\mathbf{X}]_{i,l} e^{ji\omega_r(R_n)} e^{jl\omega_v(v_n)}, \\ 0 \leq i \leq M-1, \quad 0 \leq l \leq N-1. \end{aligned} \quad (51)$$

The contribution of the n -th target to the complete received vector is given by

$$\begin{aligned} \mathbf{y}_n &= \beta_n \mathbf{b}_r(\theta_n) \otimes \mathbf{s}_n \\ &= \beta_n \mathbf{b}_r(\theta_n) \otimes [\mathbf{T}^T \mathbf{a}_t^*(\theta_n) \\ &\quad \odot (\mathbf{a}_v(v_n) \otimes \mathbf{a}_r(R_n))] \end{aligned} \quad (52)$$

where $\mathbf{a}_r(R_n) = [1, e^{j\omega_r(R_n)}, \dots, e^{j(M-1)\omega_r(R_n)}]^T \in \mathbb{C}^{M \times 1}$, $\mathbf{a}_v(v_n) = [1, e^{j\omega_v(v_n)}, \dots, e^{j(N-1)\omega_v(v_n)}]^T \in \mathbb{C}^{N \times 1}$ and $\mathbf{T} \in \mathbb{C}^{N_t \times MN}$ is formed by stacking $[\mathbf{X}]_{i,l}$ in column-major order.

B.3 Complete Signal Model

The full received signal is the superposition of all target contributions plus noise

$$\begin{aligned} \mathbf{y} &= \sum_{n=1}^{N_{\text{target}}} \beta_n (\mathbf{b}_r(\theta_n) \otimes [\mathbf{T}^T \mathbf{a}_t^*(\theta_n) \\ &\quad \odot (\mathbf{a}_v(v_n) \otimes \mathbf{a}_r(R_n))]) + \mathbf{z}. \end{aligned} \quad (53)$$

Denoting the joint steering vector for the n -th target as

$$\begin{aligned} \mathbf{a}_n &= \mathbf{b}_r(\theta_n) \otimes [\mathbf{T}^T \mathbf{a}_t^*(\theta_n) \\ &\quad \odot (\mathbf{a}_v(v_n) \otimes \mathbf{a}_r(R_n))], \end{aligned} \quad (54)$$

the model can then be written in the matrix form

$$\mathbf{y} = \mathbf{A}\boldsymbol{\beta} + \mathbf{z}, \quad (55)$$

where $\mathbf{A} = [\mathbf{a}_1, \mathbf{a}_2, \dots, \mathbf{a}_{N_{\text{target}}}]$ and $\boldsymbol{\beta} = [\beta_1, \beta_2, \dots, \beta_{N_{\text{target}}}]^T$.

Substituting these results back, the final expression for the partial derivative of the joint steering vector with respect to the angle θ_n is:

$$\begin{aligned} \frac{\partial \mathbf{a}_n}{\partial \theta_n} &= (\mathbf{J}_{\text{br}} \mathbf{b}_r(\theta_n)) \otimes \mathbf{s}_n \\ &\quad - \mathbf{b}_r(\theta_n) \otimes [(\mathbf{T}^T \mathbf{J}_{\text{at}} \mathbf{a}_t^*(\theta_n)) \\ &\quad \odot (\mathbf{a}_v(v_n) \otimes \mathbf{a}_r(R_n))]. \end{aligned} \quad (56)$$

$$\begin{aligned} \frac{\partial \mathbf{a}_n}{\partial \omega_r(R_n)} &= \mathbf{b}_r(\theta_n) \otimes [(\mathbf{T}^T \mathbf{a}_t^*(\theta_n)) \\ &\quad \odot (\mathbf{a}_v(v_n) \otimes (\mathbf{J}_r \mathbf{a}_r(R_n)))], \end{aligned} \quad (57)$$

$$\begin{aligned} \frac{\partial \mathbf{a}_n}{\partial \omega_v(v_n)} &= \mathbf{b}_r(\theta_n) \otimes [(\mathbf{T}^T \mathbf{a}_t^*(\theta_n)) \\ &\quad \odot ((\mathbf{J}_v \mathbf{a}_v(v_n)) \otimes \mathbf{a}_r(R_n))]. \end{aligned} \quad (58)$$

where $\mathbf{J}_{\text{br}}$, $\mathbf{J}_{\text{at}}$, $\mathbf{J}_r$ and $\mathbf{J}_v$ are diagonal matrices. $[\mathbf{J}_{\text{br}}]_{i,i} = -j2\pi(i-1)d_r \cos \theta_n / \lambda_c$ and $[\mathbf{J}_{\text{at}}]_{i,i} = -j2\pi(i-1)d_t \cos \theta_n / \lambda_c$, $\mathbf{J}_r = j \cdot \text{diag}(0, 1, 2, \dots, M-1)$, and $\mathbf{J}_v = j \cdot \text{diag}(0, 1, 2, \dots, N-1)$.

Based on Theorem 1 in [60], the CRLB w.r.t. $\boldsymbol{\Theta} =$

$[\theta^T, \omega_r^T, \omega_v^T]^T$ can be given as

$$\text{CRLB}(\Theta) = \frac{\sigma_v^2}{2} [\text{Re} \{ \tilde{\mathbf{B}}^H (\bar{\mathbf{A}}^H \mathbf{P}_A^\perp \bar{\mathbf{A}}) \times \tilde{\mathbf{B}} \}]^{-1}, \quad (59)$$

where

$$\bar{\mathbf{A}} = \left[\left\{ \frac{\partial \mathbf{a}_n}{\partial \theta_n} \right\}_{n=1}^{N_{\text{target}}}, \left\{ \frac{\partial \mathbf{a}_n}{\partial \omega_r(R_n)} \right\}_{n=1}^{N_{\text{target}}}, \left\{ \frac{\partial \mathbf{a}_n}{\partial \omega_v(v_n)} \right\}_{n=1}^{N_{\text{target}}} \right], \quad (60)$$

$$\mathbf{P}_A^\perp = \mathbf{I} - \mathbf{A} (\mathbf{A}^H \mathbf{A})^{-1} \mathbf{A}^H, \quad (61)$$

and

$$\tilde{\mathbf{B}} = \mathbf{I}_3 \otimes \text{diag}(\beta). \quad (62)$$

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Author contributions

Haisu Wu contributed to conceptualization, methodology, software, validation, visualization, and writing—original draft. Hong Ren and Cunhua Pan contributed to conceptualization, supervision, funding acquisition, project administration, and writing—review and editing. Boshi Wang, Jun Tang, and Haoyang Weng contributed to investigation, validation, and writing—review and editing. Feng Shu and Jiangzhou Wang contributed to resources, supervision, and writing—review and editing. All authors read and approved the final manuscript.

Availability of data and materials

The source code and simulation data that support the findings of this study are publicly available at: <https://github.com/OnePieceofCakeforYou/A-Two-Stage-ISAC-Framework-for-Low-Altitude-Economy-Based-on-5G-NR-Signals>.

Declaration of competing interest

The authors have no competing interests to declare that are relevant to the content of this article.

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