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Low-altitude UAV swarm ISAC: new opportunities and challenges

Hongqi MIN[1], Dingbang YANG[1], Chenhao QI[1], Yong ZENG[1,2]✉

[1]*National Mobile Communications Research Laboratory, Southeast University, Nanjing 210096, China*

[2]*Purple Mountain Laboratories, Nanjing 211111, China*

Abstract: With the rapid development of the low-altitude economy, low-altitude unmanned aerial vehicle (UAV) swarms are emerging as important components of sixth-generation (6G) mobile communication networks, facilitating "full coverage" and "Internet of Intelligence." Integrated sensing and communication (ISAC) deeply integrates sensing functionality into wireless communication networks by sharing wireless infrastructures and resources such as base stations, antennas, radio frequency chains, and signal waveforms, thereby significantly improving the performance of low-altitude UAV swarms. This paper reviews the research status of low-altitude UAV swarm ISAC systems, analyzes the new challenges arising from key features of UAV swarms, including low–slow–small characteristics, high density, large quantity, complex low-altitude environments, and high swarm coordination requirements, presents a vision for future deployment, and proposes the so-called "Ten Ones" performance metrics tailored to low-altitude UAV swarm ISAC. To realize these ambitious key performance indicators for future UAV swarm ISAC, several promising technologies are discussed, such as new array architectures, including extremely-large multiple-input multiple-output (XL-MIMO), sparse XL-MIMO, and reconfigurable antenna arrays, sparse time–frequency resource allocation, and channel knowledge maps. Furthermore, the potential of exploiting UAV swarms as airborne ISAC platforms is discussed. Finally, future research directions are outlined, offering a guideline for the design and development of low-altitude UAV swarm ISAC systems.

Key words: Unmanned aerial vehicle (UAV) swarm; Integrated sensing and communication (ISAC); Sparse extremely-large multiple-input multiple-output (XL-MIMO); Reconfigurable antenna arrays; Sparse time–frequency resource allocation; Channel knowledge maps (CKMs)

1 Introduction

With the low-altitude economy being identified as a major strategic emerging industry, low-altitude aircraft, particularly unmanned aerial vehicles (UAVs), have achieved remarkable progress and widespread applications (Zeng Y et al., 2019). However, with the continuous expansion of UAV applications and the increasing complexity of their operating environments, the limitations of a single UAV are becoming increasingly evident. UAV swarms are expected to become a critical component of the future low-altitude economy. A UAV swarm is a distributed group system composed of multiple UAVs that achieves task planning and collaborative cooperation via inter-UAV data transmission and sharing, thereby completing complex tasks that a single UAV cannot accomplish. UAV swarms can provide more powerful technical support in fields such as urban logistics, traffic control, emergency rescue, patrol and inspection, agricultural and forestry protection, geographical surveying and mapping, and military security (Alqudsi and Makaraci, 2025).

The 3$^{\text{rd}}$ Generation Partnership Project (3GPP) released the 5G New Radio (NR) technical specifications supporting UAVs in 3GPP TR 21.918, validating the feasibility of supporting UAVs through terrestrial cellular networks, and also pointing out the required enhancements to remote control and data transmission-related technical indicators. On one hand, among various available wireless technologies supporting low-altitude UAV applications, mobile communication networks are considered the most effective way to achieve large-scale UAV swarm deployment and beyond line-of-sight (LoS) UAV operations (Song et al., 2025). On the other hand, space–air–ground–sea integrated infrastructures constructed based

✉ Yong ZENG, yong_zeng@seu.edu.cn
Hongqi MIN, https://orcid.org/0009-0001-2901-0718
Dingbang YANG, https://orcid.org/0009-0001-0989-9011
Chenhao QI, https://orcid.org/0000-0002-7360-939X
Yong ZENG, https://orcid.org/0000-0002-3670-0434

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on UAV development are expected to help sixth-generation (6G) mobile communication networks achieve the vision of "full coverage" and "Internet of Intelligence," accelerating the deep integration of low-altitude networks and economy (Qi et al., 2024; Zhang RY et al., 2025).

Integrated sensing and communication (ISAC) has been identified by the International Telecommunication Union Radiocommunication Sector as one of the six key usage scenarios for International Mobile Telecommunications 2030 (IMT-2030) (Kaushik et al., 2024). ISAC is also regarded as a key enabling technology for enhancing the efficiency of low-altitude UAV applications. ISAC integrates sensing functions into existing communication networks by sharing resources such as antennas, radio frequency (RF) chains, and signal waveforms, without adding additional UAV payloads, to enhance network functionality and environmental sensing capabilities (Liu F et al., 2022). ISAC is expected to have two typical paradigms in future low-altitude UAV swarm scenarios. The first paradigm is ISAC for low-altitude UAV swarms, which aims to realize UAV detection, localization, classification, and tracking, requiring wireless networks to sense non-cooperative UAVs or UAV swarms. This is driven by a series of issues for the large-scale deployment of low-altitude applications, such as flight risks and aircraft supervision (Song et al., 2025). The second paradigm is ISAC based on low-altitude UAV swarms, where UAV swarms are leveraged as airborne ISAC platforms, acting as communication and sensing nodes of the wireless network, thereby expanding the field of view of the network from two to three dimensions to enhance communication and sensing performance (Zeng Y et al., 2019).

Individual UAVs in the low-altitude space exhibit typical characteristics of being low, slow, and small. In contrast, low-altitude UAV swarms have new features of high density, large quantity, complex low-altitude environments, and stringent requirements for swarm coordination. These features introduce challenges and requirements for ISAC systems (Wang QX et al., 2025). Based on this background, this paper first analyzes the research status of low-altitude UAV swarm ISAC and summarizes its new opportunities and challenges. Then, a future vision of low-altitude UAV swarm ISAC is conceived, and new approaches for addressing the aforementioned challenges and realizing the conceived vision are elaborated with novel array architectures, sparse time–frequency resource allocation, and channel knowledge maps (CKMs) as entry points.

2 Research status of low-altitude UAV swarm ISAC

The earlier development of UAV technologies primarily focused on single-platform operations (Liu BY et al., 2022). Compared with conventional ground-based stations or users, UAVs operate at higher altitudes, providing three-dimensional (3D) low-altitude coverage (Li YM et al., 2024) and green communication (Hua et al., 2020, 2021). This aerial deployment offers distinct air–ground channel characteristics with a higher likelihood of LoS links, thereby improving communication capacity and reliability. It also creates new dimensions for communication scheduling and resource allocation even though it introduces challenges such as air–ground interference and security concerns (Khuwaja et al., 2019). Effective UAV control requires highly reliable data links and precise positioning. Early payload communications employed point-to-point wireless links using cooperative, multiband, short-packet transmissions, hybrid automatic repeat request protocols (Raut et al., 2021; Dalai et al., 2025), or task-oriented semantics-aware technologies (Xu YJ et al., 2023) to improve reliable communications. UAV positioning relying on integrated global navigation satellites and inertial navigation systems suffers from accumulating errors. As mission complexity increases, a single UAV faces limitations in energy, endurance, size, and functionality, motivating the shift toward low-altitude UAV swarm systems (El-Malek et al., 2023; Alqudsi and Makaraci, 2025).

UAV swarms offer significant advantages over a single platform. Individual swarm units are smaller and more cost-effective; however, through collaboration, they achieve greater overall payload capacity, mission efficiency, and enhanced 3D coverage (El-Malek et al., 2023). Collaborative mechanisms also improve robustness, because tasks from a failed unit can be reassigned to nearby operational UAVs. UAV swarm research is extensive. In military fields, UAV swarms are used for reconnaissance, surveillance, strike, and electronic warfare, creating asymmetric advantages; they can also be deployed defensively in counter-swarm operations. In civilian domains, swarms support emergency communication networks, air quality monitoring, smart city management, and aerial displays (Masaracchia et al., 2021).

The growing low–altitude economy will lead to more ubiquitous and complex unmanned missions, placing unprecedented demands on swarm navigation, high–speed communication, environmental sensing, and collaborative control. The development of low-altitude ISAC systems is crucial to meet these demands. Such systems are key to supporting airspace development, accelerating economic growth, and advancing mobile networks from two-dimensional (2D) planes to integrated 3D communication–sensing spaces. There is ongoing research on UAV ISAC. For beamforming design, previous studies have explored communication–sensing trade-offs, such as joint UAV maneuver and beamforming design (Lyu et al., 2023), hybrid beamforming for ground–UAV integrated systems (Qi et al., 2022), CKM-assisted beamforming against blockage (Zeng SQ et al., 2023), and extensions to wideband scenarios (Guo and Qi, 2025). Regarding trajectory design and resource management, previous studies have investigated subcarrier and power allocation (Yang B et al., 2025), Internet of Things-oriented sensing and data collection (Liu ZC et al., 2024), energy-constrained trajectory, and resource allocation (Jing et al., 2024). At the signal design level, frame structure design (Meng et al., 2024) and waveform design under jamming (Shu et al., 2025; Mao et al., 2026) have been investigated to strike a balance between sensing and communication performance. The integration of reconfigurable intelligent surfaces (RISs) has also been widely studied, e.g., RIS-aided beam training and target detection (Chen KJ et al., 2024b), beamforming optimization (Zhang JM et al., 2026), joint RIS and transmission strategy optimization (Huroon et al., 2024, 2025, 2026), and secure beamforming for obstructed targets (Yang S et al., 2025). Moreover, movable antennas (MAs) implemented as UAV-mounted platforms offer additional degrees of freedom

(DoFs) by jointly optimizing 3D location and orientation to simultaneously reshape and align sensing and communication channels (Wang PL et al., 2025). Multi-base station (BS) cooperative ISAC architectures (Ma et al., 2025) have also been investigated to improve system-level performance.

Recent studies have introduced near-field sparse extremely-large multiple-input multiple-output (XL-MIMO) bistatic orthogonal frequency division multiplexing ISAC for swarm systems (Min et al., 2025b), employing a hybrid-domain framework that employs physical and virtual arrays for communication and sensing, respectively (Min et al., 2025a). This approach improves both the communication rate and sensing resolution while mitigating near-field phase coupling effects. In addition, other studies have proposed high-resolution and low-cost ISAC solutions tailored to low-altitude UAV swarms (Zhou ZW et al., 2025; Xu JR et al., 2026). However, existing achievements are insufficient for low-altitude UAV swarm ISAC systems, highlighting the need for further development in the field. Table 1 summarizes existing studies on UAV ISAC, the majority of which focused on UAVs acting as non-terrestrial ISAC platforms for ground users or targets, with a limited number addressing the emerging paradigm of UAV swarms. The transition to low-altitude UAV swarms introduces challenges, as detailed in Section 3, necessitating the development of novel technologies to enhance the communication and sensing capabilities of ISAC systems. This study addresses these needs by focusing on advanced array architectures and time–frequency resource allocation schemes to achieve super-resolution sensing and higher data rates. Furthermore, we investigate how to leverage prior environmental information and multi-UAV cooperation to improve performance and enable non-LoS (NLoS) sensing.

3 New challenges for low-altitude UAV swarm ISAC

Future low-altitude UAV swarms will be characterized not only by the widely recognized low–slow–small attributes but also by emerging features such as high density, large UAV quantity, operation in complex low-altitude environments, and higher swarm coordination requirements.

1. Low altitude: Future UAV swarms for low-altitude economy are expected to primarily operate in low-altitude or ultra-low-altitude airspace, generally below 1 km.

2. Low speed: Low-altitude UAVs typically move at low speeds below 200 km/h and operate in hovering states (Masaracchia et al., 2021).

3. Small size: Individual UAVs within a swarm are small, with radar cross sections (RCSs) typically under 0.1 m^2 (Tsai et al., 2016). In radar detection, such small targets yield weak echo signals that are easily masked by clutter and noise, significantly reducing the detection probability and increasing false alarm rates.

4. High swarm density: During mission execution, UAV swarms typically exhibit high spatial density, with extremely small inter-UAV spacing. This makes it difficult for conventional sensing systems to resolve individual targets and complicates multitarget tracking due to challenges in data association and frequent track crossings.

5. Large UAV quantity: Swarms typically comprise dozens to hundreds of small UAVs. This scale imposes higher demands on the sensing DoFs and low signal processing complexity of sensing systems for effective detection, localization, and tracking. Sensing DoF refers to the number of independent signal parameters, such as angles, delays, or Doppler shift, which can be resolved or estimated from received data.

6. Complex low-altitude environment: Typical low-altitude operational areas, such as dense urban or mountainous forested regions, present challenges such as signal blockage, severe multipath, and strong clutter. These conditions result in coverage gaps, weak echoes, and frequent NLoS sensing scenarios.

7. High requirements for swarm coordination: In conventional UAV systems, communication and sensing functions are typically handled by independent hardware modules, allowing UAVs to serve as high-mobility user terminals or aerial relays to enhance coverage. However, in low-altitude UAV swarm ISAC systems, the close spatial spacings and concurrent operation of numerous UAVs result in strong

Table 1 Comparison of existing magazine/survey papers on UAV ISAC

Reference	System model			Communication and sensing enhancement				
	UAV swarm	ISAC for UAVs	ISAC based on UAVs	Array architecture	Time–frequency resource allocation	Prior information	NLoS	Cooperative
Cui YP et al. (2023)	×	✓	✓	×	×	×	×	✓
Fei et al. (2023)	×	×	✓	×	×	×	×	✓
Mu et al. (2023)	✓	✓	✓	×	×	×	×	✓
Meng et al. (2024)	×	×	✓	✓	✓	×	✓	✓
Zhang YB et al. (2024)	✓	×	✓	×	×	✓	×	✓
Xu JL et al. (2024)	×	×	✓	×	×	×	✓	×
Song et al. (2025)	✓	✓	✓	×	×	✓	✓	✓
Wang XY et al. (2025)	×	✓	✓	×	✓	×	✓	✓
Mao et al. (2026)	×	×	✓	✓	×	×	×	✓
Zhao YJ et al. (2026)	×	×	✓	✓	×	×	✓	×
Luo et al. (2026)	×	✓	×	×	×	✓	✓	✓
This paper	✓	✓	✓	✓	✓	✓	✓	✓

intra-swarm mutual interference in both communication and sensing channels. Furthermore, the altitude and motion dynamics of each UAV simultaneously affect the performance of both functions. These factors necessitate high-precision synchronization, high-reliability hardware, and precise control technologies to effectively manage interference and swarm coordination.

Despite the above challenges, with their advantages of high mobility, easy deployment, and low cost, low-altitude UAV swarms play an important role in achieving the vision of 6G "full coverage" and "Internet of Intelligence" in low-altitude intelligent networking (Fig. 1) and have extensive research opportunities (Wang J et al., 2021).

4 Vision and performance metrics for low-altitude UAV swarm ISAC

3GPP has defined 5G-Advanced (5G-A) sensing services in 3GPP TR 22.837, listing 32 typical use cases, four of which are related to UAVs: UAV flight trajectory tracing, network-assisted sensing to avoid UAV collision, UAV intrusion detection, and UAV detection near smart grid equipment. Taking sensing performance requirements in intrusion detection as an example, within the coverage area of BSs, the horizontal positioning error $\leq$ 10 m, vertical error $\leq$ 5 m, range resolution = 10 m, velocity resolution = 5 m/s, sensing latency $\leq$1000 ms, and false alarm rate $\leq$ 5%. In addition, the typical UAV size described in the smart grid use case is 1.6 m $\times$ 1.5 m $\times$ 10.7 m, with the number of UAVs $\leq$ 25.

Compared with the aforementioned 5G-A sensing service requirements, the typical key performance indicators (KPIs) for communication and sensing in low-altitude economy scenarios are summarized in a white paper (Wei et al., 2023). For communication, a communication coverage height of 300 m and an uplink edge rate of 5–25 Mb/s are defined. For sensing, the target RCS is in the range of 0.01–2 m^2, sensing height is 300 m, range and velocity resolutions are 10 m and 5 m/s, respectively, position accuracy (horizontal/vertical) is 10 m, and false alarm rate is 5%. However, the low-altitude scenarios in the white paper target medium and large UAVs used in low-altitude logistics, security, and sea surface monitoring.

Although the use cases defined by the 3GPP and white paper represent important steps toward integrating sensing capabilities into mobile networks, the associated performance requirements are primarily designed for conventional medium-to-large UAV operations rather than emerging low-altitude UAV swarm scenarios. Low-altitude UAV swarms are rapidly developing, with swarm UAVs characterized by miniaturization and low cost. Representative models such as the U.S. "Perdix" and "Coyote" may have maximum dimensions $\leq$ 0.165 m $\times$ 0.3 m, mission altitude $\leq$ 0.5 km, maximum speed $\leq$ 100 km/h, and swarm sizes $\geq$ 200 UAVs. In other words, UAV swarms are advancing toward miniaturization and large-scale, high-density, and complex low-altitude environments. Existing standards and performance metrics cannot fully characterize the actual requirements of future low-altitude UAV swarm ISAC (Alqudsi and Makaraci, 2025). Owing to their new characteristics of high density, large quantity, complex low-altitude environments, and stringent coordination, future low-altitude UAV swarms require more stringent communication and sensing capabilities. Therefore, to realize the low-altitude UAV swarm ISAC vision, a set of key performance metrics should be redefined.

As shown in Fig. 2, we propose the following so-called "Ten Ones" visionary performance metrics for low-altitude UAV swarm ISAC: Taking a ground-based (or low-height, tower-mounted) ISAC BS as the origin, for a hemispherical airspace with a radius of $R_{\rm r}$ = 1 km, the following metrics are established: flight altitude $\leq$ 1 km, UAV density within swarms = 1 unit/m^3, quantity $\geq$ 100 units, ISAC BS-side sensing achieving an angular resolution of $\Delta\theta \leq 0.1^\circ \approx 1.745 \times 10^{-3}$ rad, range resolution of $\Delta R \leq 1$ m, velocity resolution of $\Delta v \leq 1$ m/s, false alarm rate of $\leq$1%,

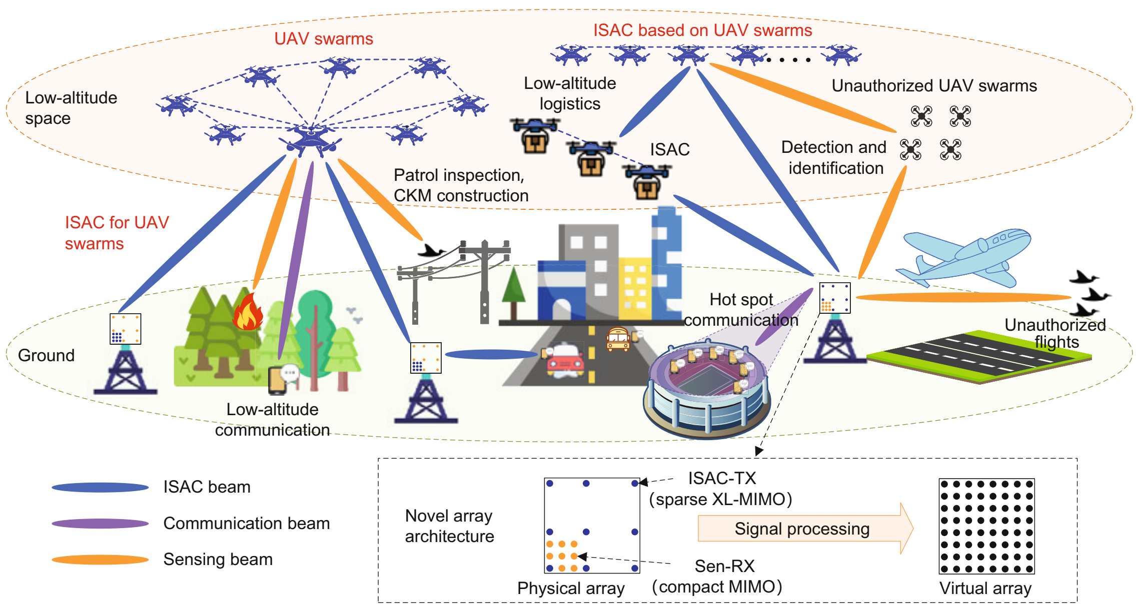

Fig. 1 Illustration of low-altitude UAV swarm ISAC

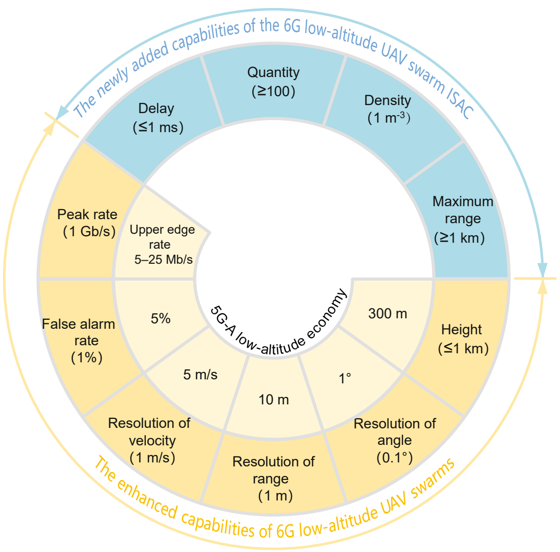

Fig. 2 "Ten Ones" performance metrics for low-altitude UAV swarm ISAC

communication peak rate of 1 Gb/s, and latency less than 1 ms. To realize these metrics, we consider a millimeter-wave system with carrier frequency $f_{\rm c}=28\,\text{GHz}$, which must satisfy bandwidth $B\geq c/(2\Delta R)=150$ MHz and coherent processing interval $T_{\rm cpi}\geq\lambda/(2\Delta v)=5.35$ ms unless super-resolution techniques are used, and a total number of elements at ISAC receiver (ISAC-RX) $M_{\rm R}\geq 2/\Delta\theta=1146$, where c represents the speed of light and $\lambda=c/f_{\rm c}$ denotes the signal wavelength. Moreover, to realize the false alarm rate requirement, the minimum signal-to-noise ratio (SNR) is in the range of $13-16\,\text{dB}$; thus, if SNR ≥ 15 dB is selected for simplicity (Zhou Y et al., 2025), based on the basic radar equation SNR $=\frac{P_{\rm T}G_{\rm T}G_{\rm R}\lambda^2\sigma\tau_{\rm p}}{(4\pi)^3R_{\rm T}^4kT_{\rm s}L}$, the transmit power is obtained as $P_{\rm T}\geq 26.6$ dBm, where the transmit pulse width is set as $\tau_{\rm p}=T_{\rm cpi}$, and k denotes the Boltzmann constant. Moreover, $G_{\rm T}=M_{\rm T}\times 10^{G/10}$ and $G_{\rm R}=M_{\rm R}\times 10^{G/10}$ denote the array gains of the ISAC transmitter (ISAC-TX) and ISAC-RX, respectively. Table 2 shows the system parameter configurations. The "Ten Ones" include enhancements to certain low-altitude UAV ISAC scenario metrics in existing white papers while additionally introducing metrics for latency, the number of sensing targets, and swarm density, to better guide the system design of future low-altitude UAV swarm ISAC.

5 ISAC for low-altitude UAV swarms

Fig. 1 shows the vision for low-altitude UAV swarm ISAC systems. To realize this vision, this section introduces key enabling technologies from aspects such as novel array architectures, sparse time–frequency resource selection, and CKM-based methods.

5.1 Novel array architectures

5.1.1 XL-MIMO

Taking the angular resolution of 0.1° in the "Ten Ones" vision as an example, the number of antennas required in the horizontal or elevation dimension must satisfy $M\geq 1146$. Although super-resolution algorithms such as multiple signal classification (MUSIC) can significantly reduce the number of antennas required (Cao et al., 2017), they will also introduce substantially increased computational complexity, which may not be practical for real-time processing in UAV swarm scenarios. To achieve simultaneous detection and localization of no less than 100 UAVs, based on the calculation formula for sensing DoFs $M-1$, the array scale must satisfy $M\geq 100$. Furthermore, considering UAV swarms for low-altitude airspace, it is necessary to expand arrays from one-dimensional (1D) linear arrays to 2D planar arrays to satisfy 3D communication and sensing requirements, potentially increasing the number of antennas in future ISAC systems dramatically. This implies that we need to significantly increase the current 5G NR antenna quantity configuration of $M=64$. In academia, arrays with $M\geq 256$ are generally called XL-MIMO. As a natural evolution of the current massive MIMO technology, XL-MIMO increases the number of antennas by at least one order of magnitude (reaching hundreds or even thousands of antennas), thereby enhancing the spectral efficiency and spatial resolution of wireless communication and sensing. Therefore, XL-MIMO is a key enabling technology for achieving multiple 6G KPIs (such as peak data rate, spectral efficiency, reliability, and positioning and sensing accuracy).

The evolution from massive MIMO to XL-MIMO is not simply an increase in the number or size of antennas but a fundamental transformation of channel characteristics. Specifically, this transformation is manifested in the transition from the conventional far-field uniform plane wave (UPW) propagation mode to a new non-uniform spherical wave (NUSW) propagation mode and from conventional spatial stationary characteristics to spatial non-stationary characteristics, providing new communication and sensing opportunities (Lu et al., 2024; Chen KJ et al., 2025c). The enhanced spatial resolution of XL-MIMO provides a new dimension for inter-user interference (IUI) suppression; i.e., IUI can be suppressed not only through angular separation in the traditional far-field UPW model but also through distance separation of users in the same direction (Zhang HY et al., 2022). For example, Lu and Zeng (2022) evaluated the signal-to-interference-plus-noise ratio performance of three typical beamforming schemes in multi-user near-field communication: maximum ratio combining,

Table 2 Low-altitude UAV swarm ISAC system parameters toward the "Ten Ones" vision

System parameter	Value
Carrier frequency, $f_{\rm c}$	28 GHz
Target RCS, σ	$0.01\,\text{m}^2$
Number of elements at ISAC-TX, $M_{\rm T}$	64
Number of elements at ISAC-RX, $M_{\rm R}$	≥ 1146
Element spacing, d	5.35 mm
Bandwidth, B	≥ 150 MHz
CPI, $T_{\rm cpi}$	≥ 5.35 ms
Single element gain, G	5 dBi
Average transmit power, $P_{\rm T}$	≥ 26.6 dBm
System noise temperature, $T_{\rm s}$	300 K*
System loss, L	6 dB

*Taken from Budge and German (2020). RCS: radar cross section; ISAC: integrated sensing and communication; TX: transmitter; RX: receiver; CPI: coherent processing interval zero-forcing, and minimum mean square error beamforming. Wang Y and Qi (2025) proposed a near-field multi-user communication scheme based on a purely analog beamforming architecture. By employing only analog beamforming without requiring digital beamforming, the scheme simplified the system architecture and avoided the equivalent channel estimation process and pilot overhead required by digital beamforming.

In addition to supporting wireless communication, XL-MIMO can be used to support various sensing applications, such as sensing (Wang HZ et al., 2024), positioning (Friedlander, 2019), and tracking (Guerra et al., 2021). In Wang HZ et al. (2024), for the NUSW model, closed-form expressions for sensing SNR were derived for both XL-MIMO and XL-phased array radar modes. Compared with existing UPW models, more realistic sensing SNR scaling laws were observed. Another important metric for near-field sensing was investigated, namely, the Cramér–Rao bound (CRB). The closed-form expressions were derived based on the uniform spherical wave model for both the aforementioned radar modes, revealing that as the array size tends to infinity, the CRB for near-field XL-MIMO angle estimation tends toward a certain limit rather than decreasing unboundedly as in traditional UPW models.

In addition, benefiting from spherical wave distance sensing capability, near-field sensing can infer position rather than just direction using a single antenna array. For example, Guidi and Dardari (2021) investigated the possibility of directly locating signal sources based on wavefront curvature. For LoS signal sources, Tian et al. (2023) and Wu XH et al. (2026) presented positioning methods using XL-MIMO. Furthermore, based on accurate electromagnetic propagation models, Chen A et al. (2023) and Zhou ZW et al. (2024) proposed a general near-field positioning model that accounts for three types of observed electric fields and the generality of terminal positions. Subsequently, CRBs for the three electric field observation types were derived, and it was observed that in cases with multiple receiving antennas, estimation accuracy was improved in dimensions parallel to the receiving antenna surface. Moreover, curvature information contained in spherical wavefronts can be used to achieve signal source tracking to infer its position and movement velocity (Guerra et al., 2021).

The transition to near-field spherical wave characteristics also introduces significant challenges for channel state information (CSI) acquisition. As the channel evolves from a purely angular-domain representation to joint angle–distance characterization, channel estimation, beam training, and tracking methods face substantially increased complexity. To address this challenge, low-overhead, low-complexity CSI acquisition methods have been investigated. Cui MY and Dai (2022) introduced a polar-domain sparse representation of near-field XL-MIMO channels and proposed a compressed sensing-based estimation scheme. Extending this line of work, Chen YH and Dai (2024) considered the spatial non-stationary properties of near-field XL-MIMO channels and developed a grouped time block coding scheme that converts spatial non-stationary channels into a set of spatial stationary sub-channels, after which the compressed sensing method of Cui MY and Dai (2022) is applied for estimation. Chen KJ et al. (2024c) investigated beam training, refinement, and tracking techniques for partially connected XL-MIMO architectures. By leveraging the property that the near-field region of an extremely-large array can correspond to the far-field region of its sub-arrays, the authors proposed a unified beam training framework applicable to both near-field and far-field scenarios. Chen KJ et al. (2024d) introduced a three-stage hybrid far–near-field beam training scheme to address both the high overhead and low accuracy challenges inherent in XL-MIMO beam training.

The rapid advancement of artificial intelligence (AI) also offers new opportunities for efficient beam management. Jiang and Qi (2023) presented a deep neural network-based near-field beam training method and enhanced it with a supplementary codeword strategy, where codewords are selected based on probability vectors outputted by the network to improve beam training performance. Wang Y et al. (2025) proposed a convolutional neural network-based beam training scheme and a long short-term memory network-based beam tracking approach, significantly reducing the overhead while improving the achievable rate and beam gain.

5.1.2 Sparse XL-MIMO

Conventional MIMO typically adopts half-wavelength antenna spacing for three primary reasons: first, this spacing can effectively avoid mutual coupling effects between adjacent elements; second, in rich scattering environments, a half-wavelength approximately equals a channel coherence distance, and adopting this spacing can fully obtain spatial diversity gain; third, this spacing avoids spatial aliasing or grating lobes in array beam patterns. This type of MIMO with half-wavelength spacing between adjacent elements is referred to as compact MIMO in this paper. The key concept of sparse XL-MIMO is to remove the half-wavelength antenna spacing limitation, allowing spacing between adjacent antennas to be greater than half-wavelength, enabling it to achieve a significantly higher array aperture than conventional compact MIMO without increasing the number of array elements. Under these conditions, sparse XL-MIMO offers the following advantages: higher spatial resolution, more sensing DoFs, larger near-field region, smaller mutual coupling effects, more flexible array arrangement, more economical hardware, and lower energy and signal processing overhead (Li XR et al., 2025). For 1D sparse XL-MIMO, sparse architectures can generally be classified into uniform sparse arrays (USAs) and non-USAs (NUSAs). Typical NUSA array architectures include nested arrays (NAs) (Pal and Vaidyanathan, 2010), co-prime arrays (CPAs) (Vaidyanathan and Pal, 2011), minimum redundant arrays (Maria Battaglia et al., 2025), and modular arrays (MoAs) (Jeon et al., 2021; Li XR et al., 2024). In addition, some sparse arrays are based on the optimization of antenna positions according to metrics such as main lobe beam width, sidelobe level, and null steering (Huan et al., 2023). Li XR et al. (2025) presented the array structures of 1D sparse XL-MIMO.

However, for sparse XL-MIMO, directly increasing antenna spacing beyond half-wavelength causes grating lobe problems in beam patterns. For localization or sensing, these grating lobes result in angle ambiguity problems in angle estimation, whereas for wireless communication, grating lobes may cause severe IUI (Li XR et al., 2024). On one hand, for sparse XL-MIMO wireless sensing or localization, the influence of grating lobes can be eliminated using virtual array technology

(Pal and Vaidyanathan, 2010). Specifically, this technology forms equivalent received signals of virtual arrays with $\mathcal{O}(M^2)$ elements based on the (conjugate) correlation of signals received by M elements. Element positions in the virtual array depend on the sum/difference of physical element positions, significantly extending the effective sensing aperture, thereby improving sensing accuracy, resolution, and DoFs. In addition, through antenna position optimization, the NUSA topology can be improved to effectively suppress high grating lobe problems of USAs (Chen KJ et al., 2024a).

On the other hand, despite grating lobes, Wang HZ et al. (2026) demonstrated that USA-based sparse XL-MIMO can achieve better communication performance than compact MIMO in hotspot areas with densely distributed users. This is because sparse arrays have higher spatial resolution, and the possibility of users being located at high-order grating lobes is low, enabling multi-user interference to be more effectively suppressed. Similarly, Min et al. (2024) demonstrated that NA-based sparse XL-MIMO can achieve better communication performance than compact MIMO while retaining sensing advantages. Moreover, due to the enhanced array aperture of sparse XL-MIMO systems, they exhibit better beam focusing characteristics in the main lobe for near-field communication, which enhances effective DoF in communication systems (Wang HZ et al., 2026), effectively suppresses interference (Zhou C et al., 2025), and improves communication performance. Near-field modeling introduces distance-dependent phase terms in steering vectors, enabling distance sensing in array spatial domains (Min et al., 2025b). The communication DoF denotes the number of independent parallel data streams or orthogonal signaling dimensions available for reliable transmission over a given channel.

When array dimensions expand to 2D planes, 2D sparse XL-MIMO can significantly increase sensing resolution and DoFs for the 2D angle of arrival estimation, which is particularly practical in ISAC applications. As shown in Fig. 3, typical 2D sparse XL-MIMO array architectures include the following:

Planar USA (PUSA): A PUSA features equal element spacing of $d_{\mathrm{us}} = \eta_{\mathrm{us}} d$, where $d = \frac{\lambda}{2}$ denotes the unit element spacing and $\eta_{\mathrm{us}} > 1$ denotes the array sparsity factor.

Planar MoA (PMoA): A PMoA has module spacings along the x- and y-axis of $d_{\mathrm{mo},x} = \eta_{\mathrm{mo},x} d$ and $d_{\mathrm{mo},y} = \eta_{\mathrm{mo},y} d$, respectively, where $\eta_{\mathrm{mo},x} \geq M_{\mathrm{mo},x}$ and $\eta_{\mathrm{mo},y} \geq M_{\mathrm{mo},y}$ denote the module sparsity parameters. In this configuration, $M_{\mathrm{mo},x}$ and $M_{\mathrm{mo},y}$ denote the numbers of antennas per module in each direction (Li XR et al., 2024).

L-shaped CPA: This architecture comprises two perpendicular CPAs aligned with the x- and y-axis. For the x-axis, $d_{\mathrm{f},x} = M_{\mathrm{s},x} d$ and $d_{\mathrm{s},x} = M_{\mathrm{f},x} d$ denote the spacings of the horizontal orange and blue subarrays, respectively; for the y-axis, $d_{\mathrm{f},y} = M_{\mathrm{s},y} d$ and $d_{\mathrm{s},y} = M_{\mathrm{f},y} d$ denote the spacings of the vertical subarrays (Rao et al., 2018; Zhang QT et al., 2023). In this configuration, $M_{\mathrm{f},x}$ and $M_{\mathrm{s},x}$ denote the element counts of the first and second subarrays of the 1D CPA along the x-axis, respectively, with $M_{\mathrm{f},y}$ and $M_{\mathrm{s},y}$ being similarly defined for the y-axis.

Two-dimensional NA: In a 2D NA, the outer orange subarray has element spacings of $d_{\mathrm{ou},x} = (M_{\mathrm{in},x} + 1)d$ along the x-axis and $d_{\mathrm{ou},y} = (M_{\mathrm{in},y} + 1)d$ along the y-axis. The inner

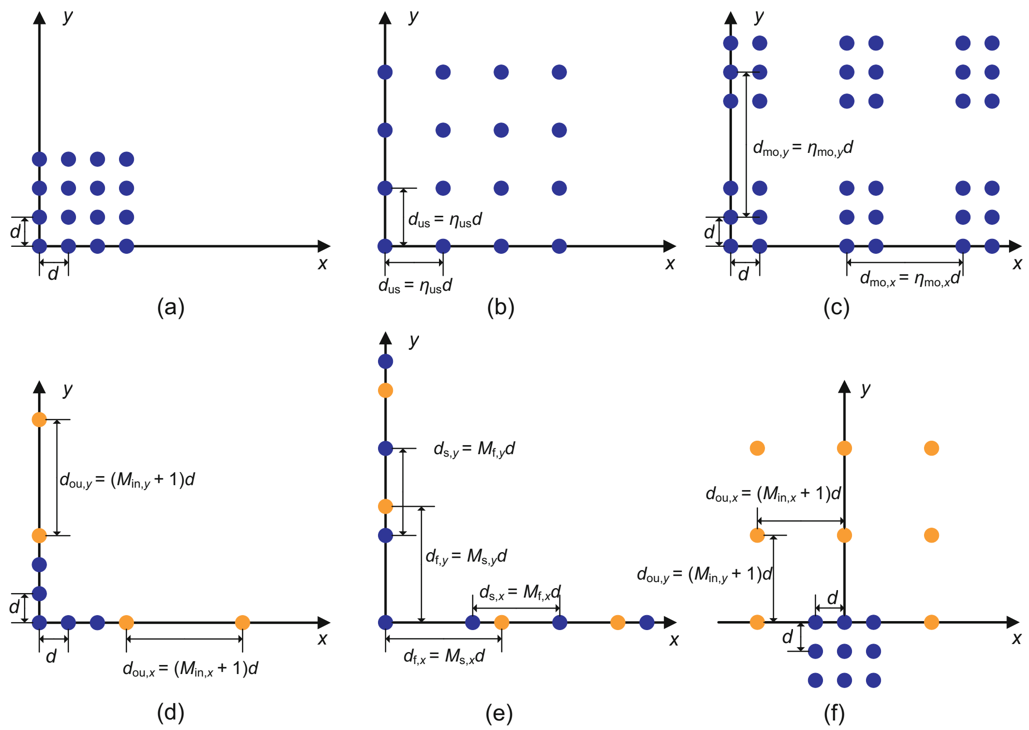

Fig. 3 Comparison of array architectures between 2D compact MIMO and sparse XL-MIMO, with the former realized using a UPA and the latter comprising PUSAs, PMoAs, PNAs, and L-shaped sparse arrays: (a) UPA; (b) PUSA; (c) PMoA; (d) L-shaped NA; (e) L-shaped CPA; (f) PNA

blue subarray maintains a unit spacing of d, where $M_{\text{in},x}$ and $M_{\text{in},y}$ denote the numbers of antennas in the inner subarray for the x- and y-direction, respectively. In particular, 2D NAs can be further divided into L-shaped NAs and planar NAs (PNAs) according to different inner and outer subarray deployment methods.

Compared with conventional uniform planar arrays (UPAs) with the same number of antennas, planar sparse arrays, such as PUSA, PMoA, and PNA, can achieve larger array apertures because their adjacent element spacing is typically greater than half a wavelength. Unlike PUSAs and PMoAs, L-shaped sparse arrays composed of two orthogonal linear arrays are designed with different sparse forms, such as L-shaped CPAs and L-shaped NAs (Niu et al., 2016). L-shaped sparse arrays not only have the advantage of independent, flexible beam control in two dimensions but also exhibit higher sensing resolution because of a larger virtual array aperture. However, L-shaped NAs only form virtual uniform linear arrays along orthogonal x- and y-axis, respectively, whereas PNAs can achieve more DoFs and virtual elements across the entire 2D plane (Pal and Vaidyanathan, 2012a, 2012b). In addition, PNAs place PUSAs and compact UPAs on opposite sides of the origin to determine an optimal structure, enabling the formation of continuous virtual elements across the entire 2D plane. Xu JR et al. (2026) compared the beam patterns of NA- and PNA-based sparse XL-MIMO with benchmark compact UPAs and proposed efficient super-resolution sensing-assisted channel estimation methods.

5.1.3 Reconfigurable antenna arrays

To meet the high-performance requirements of low-altitude UAV swarm systems, conventional arrays increase design DoFs by increasing the number of antennas; however, this leads to a rapid increase in hardware cost, power consumption, and complexity, presenting challenges in practical applications. With their characteristics of low cost, low power consumption, and high design flexibility, reconfigurable antennas can be organically combined with existing array architectures and have good application prospects in future wireless systems. Reconfigurable antennas can flexibly adjust radiation patterns, resonant frequencies, and polarization states by changing the surface current distribution, thereby adapting to dynamically changing low-altitude electromagnetic environments. Hardware implementation technologies include dynamic metasurface, parasitic element-assisted, and structurally reconfigurable antennas (Castellanos et al., 2026). Existing hybrid MIMO architectures include digital and analog beamforming. Reconfigurable antennas can introduce a third layer on existing architectures to achieve signal processing in the electromagnetic domain, thereby forming a tri-hybrid MIMO architecture, which is expected to extend the spatial processing dimensions and flexibility of the system without significantly increasing hardware complexity or power consumption (Heath et al., 2026).

Chen KJ et al. (2025a) introduced a dual-band reconfigurable antenna array (DBRAA) architecture operating at millimeter-wave and sub-6 GHz bands. As shown in Fig. 4, in a DBRAA, millimeter-wave antennas are arranged in a UPA with half-wavelength spacing, featuring N_{row} rows and N_{col} columns. Each sub-6 GHz antenna comprises a combination of 2×2 millimeter-wave antennas. Positive-intrinsic-negative diodes are used to connect millimeter-wave antennas, and the position of the combined sub-6 GHz antennas can be adjusted by controlling their on/off states. This architecture achieves dual-frequency functionality with the same array and avoids hardware overhead, while flexibly configuring the positions of sub-6 GHz antennas and the connections among millimeter-wave antennas and RF chains, thereby adapting to dynamic channel environments.

Another approach presented by Chen KJ et al. (2025b) employs a reconfigurable pixel antenna (RPA) to obtain an electronic MA array (REMAA). As shown in Fig. 5, an RPA consists of multiple pixel elements connected by RF components. By controlling the connection states of these RF components, the antenna radiation pattern can be changed, achieving the same effect as physically changing the radiation point position, thereby developing an RPA-based electronic MA (REMA). By arranging multiple REMAs and connecting them directly to RF chains, a partially connected REMAA architecture can be constructed, where each RF chain can select only one radiation point from its corresponding candidate radiation point set for transmission. By expanding one REMA and connecting it to RF chains through a switch network, a fully connected REMAA architecture can be constructed, where each RF chain can connect to all candidate radiation points. Compared with mechanical MAs, the REMAA architecture has the capability of fast and precise adjustment and can better

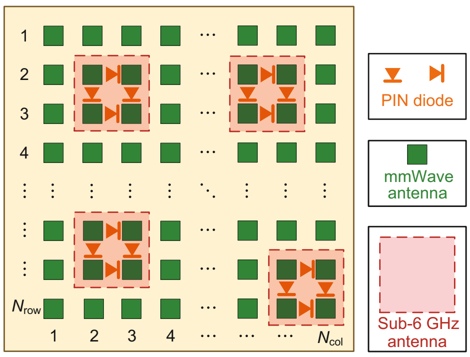

Fig. 4 Illustration of the dual-band reconfigurable antenna array (DBRAA). Reprinted from Chen KJ et al. (2025a), Copyright 2025, with permission from IEEE

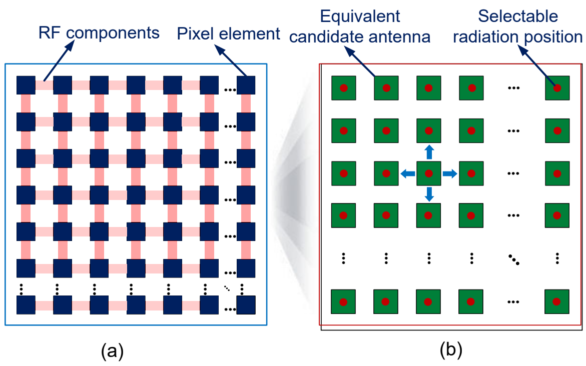

Fig. 5 Illustration of the reconfigurable pixel antenna (RPA) (a) and RPA-based electronic movable antenna (REMA) (b). Reprinted from Chen KJ et al. (2025b), Copyright 2025, with permission from IEEE

adapt to dynamic channel environments.

Further extending this concept, Li YC et al. (2026) proposed a tri-hybrid beamforming architecture based on radiation center reconfigurable antenna arrays (RAAs), where the digital, analog, and electromagnetic beamformers are jointly optimized. In this framework, electromagnetic beamforming is formulated as a radiation center selection problem. The tri-hybrid beamforming architecture integrates reconfigurable antenna technology into the conventional hybrid beamforming architecture, providing a low-cost, low-power, and highly scalable means to increase the number of DoFs of the system. The hardware implementation and reconfiguration strategies of RAAs and the interconnection among the three layers of the tri-hybrid beamforming architecture can be tailored to specific requirements. For communication, this architecture is expected to fully exploit diversity and multiplexing gains, enhancing reliability and spectral efficiency. For sensing, it enables multidimensional observation of the same target, potentially improving detection and estimation performance.

Several other state-of-the-art antenna array concepts have also emerged as frontiers to improve the performance of UAV ISAC. Specifically, MA and fluid antenna systems (FASs) enable dynamic adjustment of antenna positions to exploit spatial channel variations, thereby significantly improving communication rates and sensing accuracy in UAV-enabled ISAC systems (Liu WC et al., 2025; Wang PL et al., 2025). Reconfigurable holographic surfaces (RHSs) provide a lightweight and energy-efficient solution for UAV platforms by enabling holographic beamforming through numerous metamaterial elements (Zhang SW and Ding, 2025). Furthermore, Yao et al. (2026) demonstrated the benefits of combining an RHS-equipped UAV with a RIS to enhance link reliability. Rotatable antennas leverage the mechanical steering of directional patch antennas to provide additional spatial DoFs, effectively mitigating direct-path interference and improving sensing performance in both monostatic and bistatic UAV-aided ISAC architectures (Zheng et al., 2025).

Table 3 comprehensively compares the aforementioned array architectures in terms of their communication and sensing DoFs, implementation complexity, and suitability for low-altitude UAV swarm ISAC systems. RAAs, MA, and FAS also have sensing DoFs of $\mathcal{O}(M^2)$ because they can form the same array architectures as sparse XL-MIMO by reconfiguration, mechanical movement, or fluid flow. However, the latter two adjustment methods introduce moderate hardware complexity.

5.2 Sparse time–frequency resource selection

As discussed in Section 4, ISAC systems for low-altitude UAV swarms require at least a bandwidth of 150 MHz. However, in uplink multi-user ISAC systems, only a fractional bandwidth can be allocated to each user (Xiao et al., 2025). Thus, the delay and Doppler resolution are severely limited by the bandwidth and time duration of the received signals, respectively. Consequently, achieving high-performance delay and Doppler sensing with limited bandwidths and signal CPI becomes an important consideration. In Section 5.1.2, we discussed implementing sparse sampling in the spatial domain using sparse arrays, thereby increasing the effective sensing aperture using virtual array technology and improving sensing resolution and accuracy. In this subsection, we discuss sparse resource allocation in the delay and Doppler domains to achieve high-resolution estimation of the target delay and Doppler.

Because range and Doppler estimation signal processing procedures have similarities, this subsection focuses on range estimation and assumes that all targets are stationary (Dai et al., 2026). For delay-domain range estimation, the ambiguity function is $G_\eta(\varDelta_k) = \frac{1}{N_{\mathrm{sp}}^2}\left|\frac{\sin(2\pi N\Delta f \varDelta_k/c)}{\sin(2\pi\eta\Delta f \varDelta_k/c)}\right|^2$, where $\varDelta_k = R - R_k \in [-d_{\mathrm{unamb}}, d_{\mathrm{unamb}}]$ denotes the difference between observed distance R and target distance R_k, $d_{\mathrm{unamb}} = \frac{c}{2\Delta f}$ denotes the OFDM radar maximum unambiguous detection range corresponding to subcarrier spacing Δf, η represents the frequency-domain downsampling interval for subcarrier sparse resource allocation, N represents the total number of consecutive subcarriers, and $N_{\mathrm{sp}} = \lfloor \frac{N}{\eta} \rfloor$ denotes the number of samples after downsampling. Because range resolution is typically defined as half the main lobe width, $\mathrm{BW} = \frac{c}{N\Delta f}$, the range resolution based on sparse subcarrier data can be defined as $\varDelta_{\mathrm{r}}^{\mathrm{res}} = \frac{\mathrm{BW}}{2} = \frac{c}{2B}$, where $B = N\Delta f$ denotes the total system bandwidth. As shown in Fig. 6, the grating lobe positions of the periodogram are $\varDelta = \frac{nc}{2\eta\Delta f}$ $(n = \pm1, \pm2, \cdots, \pm\eta)$, and the periodic characteristics of grating lobes lead to range ambiguity. Consequently, the maximum unambiguous sensing range that can be achieved by frequency-domain downsampling equals the grating lobe spacing $d_{\mathrm{unamb}}^{\mathrm{sp}} = \frac{c}{2\eta\Delta f}$. Downsampling can achieve the same range resolution as using full-bandwidth subcarrier data; however, its maximum unambiguous range decreases as η increases.

Xiao et al. (2025) proposed a two-stage delay estimation method for uplink ISAC systems. This approach achieves full-bandwidth delay resolution and an unambiguous detection range using only partial bandwidth. The method comprises

Table 3 Comparison of different array architectures with M active array elements

Array architecture	Communication DoFs	Sensing DoFs	Complexity	Suitability for UAV swarms
MIMO	Low	$M-1^*$	Low	Low
XL-MIMO	High	$M-1^{**}$	High	Moderate
Sparse XL-MIMO	High	$\mathcal{O}(M^2)$	Low	High
RAAs	High	$\mathcal{O}(M^2)$	Low	High
MA/FAS	High	$\mathcal{O}(M^2)$	Moderate	Moderate
RHS	High	$M-1$	Moderate	Moderate
Rotatable antenna	High	$M-1$	Moderate	Moderate

$^*M \le 64$; $^{**}M \ge 256$

coarse and high-resolution estimation stages. In the first stage, the user equipment sends uplink signals over a set of centralized subcarriers to obtain a coarse delay estimate within the fully unambiguous range of the system. Subsequently, an optimal downsampling factor is determined, and distributed subcarriers are used to refine the delay estimate. This two-stage strategy improves estimation accuracy using higher delay resolution while avoiding ambiguity. Numerical results confirm that the proposed method delivers improved sensing performance compared with conventional centralized subcarrier allocation schemes.

Similarly, Dai et al. (2024) introduced another low-complexity scheme for range estimation. The scheme employs uniform downsampling in the subcarrier domain to reduce computational load and establishes explicit mathematical relationships among range resolution, maximum unambiguous range, and downsampling interval. The method first constructs a low-dimensional data matrix to reduce complexity and then uses centralized subcarrier data to resolve range ambiguity. This two-stage process enables high-resolution range estimation with a constant unambiguous range at a significantly reduced computational cost. Comparisons with the conventional MUSIC algorithm demonstrate that the proposed scheme achieves substantial complexity savings with only marginal performance degradation. Note that the framework can also be extended to super-resolution Doppler estimation.

Moreover, in practical ISAC systems, communication scatterers may be detected as radar targets, and environmental radar targets typically act as communication scatterers. This creates a joint sparsity structure between communication and sensing channels, allowing the delay and Doppler parameters of sensing targets to be estimated jointly with the communication channel parameters. By leveraging this insight, Chen KJ and Qi (2024) developed a joint sparse Bayesian learning algorithm for simultaneous estimation of communication channels and sensing parameters. This joint approach outperforms schemes that estimate communication and sensing parameters independently.

The sparse time–frequency resource allocation and sparse array architectures presented in Section 5.1.2 can be combined into a unified signal processing framework, because sensing in the angle, delay, and Doppler domains has similar array steering structures (Dai et al., 2026). Specifically, Zhang WJ et al. (2026) established the Cramér–Rao lower bound (CRLB) for single-target parameter estimation under non-uniform sparse resource allocation and proposed an autocorrelation-based virtual sensing method for multitarget scenarios. The method generates a virtual signal with significantly larger bandwidth to achieve enhanced peak-to-sidelobe ratios (PSLRs) and near-full-bandwidth estimation accuracy. Moreover, Li PS et al. (2025) developed adaptive sparse time–frequency resource allocation strategies that jointly optimize the selection and power of sensing-dedicated resource elements to directly control ambiguity function properties. The strategies achieved either maximized weighted delay–Doppler resolution or minimized delay–Doppler PSLR, thereby demonstrating sensing performance nearly identical to radar-only benchmarks under communication quality of services constraints.

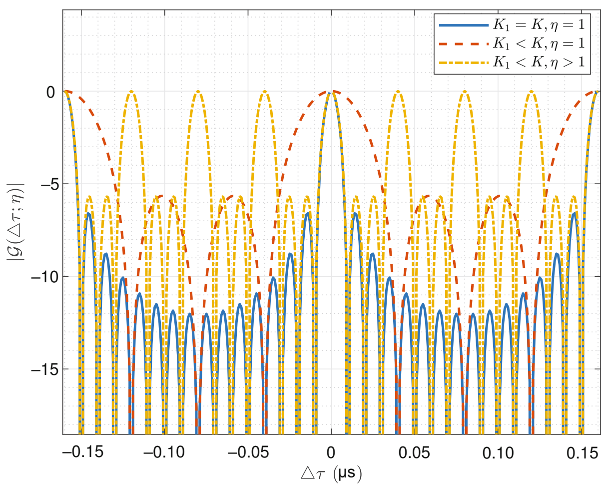

Fig. 6 Delay resolution and unambiguous range versus the number of allocated subcarriers K_1 and η

5.3 CKM-assisted complex low-altitude ISAC

As discussed in Section 3, low-altitude UAV swarm ISAC systems face severe challenges stemming from complex low-altitude environments, including signal blockages, multipath propagation, strong clutter, and frequent NLoS conditions. These factors significantly degrade communication reliability and sensing accuracy, particularly for small and slow UAVs with weak radar echoes. Consequently, even advanced arrays and algorithms may suffer from performance degradation, primarily because of the lack of prior environmental knowledge and the high overhead of real-time channel estimation. This motivates the introduction of CKM as a complementary paradigm.

CKMs, which are based on big data and AI technology, serve as databases indexed primarily by mobile node (virtual) positions. CKMs can directly reflect channel characteristics at specific locations, and these characteristics are independent of transceiver activity states (Zeng Y and Xu, 2021). By integrating massive historical data from terminals within a region, CKMs achieve prior acquisition of wireless channel environment information based on the position or virtual position, avoiding repeated real-time environment sensing and channel acquisition. This significantly enhances the system's cognitive ability of the local wireless environment, supporting the paradigm shift from conventional environment-unknown communication and sensing to future environment-aware communication and sensing.

By containing location-specific channel information, CKMs can significantly enhance wireless positioning and sensing performance in complex low-altitude environments, offering forward-looking potential for low-altitude UAV swarm operations. For instance, Zeng Y et al. (2021) leveraged a 3D spatial CKM to enable cellular-connected UAVs to optimize flight trajectories and avoid the coverage gaps of cellular BSs. This task would be challenging to accomplish using conventional training-based channel estimation. CKMs also enrich conventional positioning methods. In geometric positioning, which estimates target locations from geometric parameters relative to anchor nodes, CKMs can simplify anchor selection by providing prior environmental knowledge. Long et al.

(2022) introduced a CKM-based environment-aware anchor selection scheme, using the Bayesian CRLB as a positioning accuracy metric. This approach outperforms conventional selection strategies based on the minimum distance or simply activating all anchors. In addition, Zeng SQ et al. (2023) proposed a CKM-assisted LoS identification and beamforming method using ISAC echoes. When an LoS link is confirmed, extended Kalman filtering is applied for UAV tracking; otherwise, the UAV switches to an alternative BS to maintain connectivity, thereby improving both tracking and communication performance. For fingerprint-based positioning, CKMs extend beyond conventional site-survey fingerprints by incorporating heterogeneous and diverse channel information, which increases the fingerprint database and enhances positioning resolution. Moreover, CSI extracted from CKMs is more stable and device-independent than conventional received signal strength measurements, making CKM-aided positioning more robust to environmental dynamics and varying device types (Zeng Y et al., 2024).

Moving forward, the deep integration of UAV swarms with ISAC will create further opportunities for CKMs. CKMs can help avoid redundant sensing, suppress clutter, and assist in anchor selection and resource allocation. Early work in this direction includes the use of a clutter angle map, which is a specialized form of CKM, to pre-acquire clutter angle information at target locations and subsequently remove corresponding sensing signal components, thereby improving estimation accuracy for slow and small targets (Xu ZH et al., 2024). Another study (Zhang CY et al., 2025) proposed a CKM system built on the ISAC infrastructure, illustrating a mutually beneficial relationship: during the map construction phase, ISAC BSs collect channel feedback, such as beam indices and channel gains; in the application phase, the BSs retrieve the optimal beam index associated with a user's position from the database, enabling training-free millimeter-wave beam alignment. Most existing studies assume the presence of LoS links; however, low-altitude urban environments typically suffer from signal blockage and NLoS propagation. Relying solely on LoS links limits the joint application of CKMs and ISAC. Therefore, research under NLoS conditions is critical. In Wu D et al. (2025), environment-aware NLoS ISAC was achieved using a channel angle–delay map, a type of CKM that derives angle–delay priors for sensing channels by leveraging the relationship between communication and sensing angle–delay distributions. This approach enables sensing-based localization in NLoS settings and exhibits significantly higher accuracy than geometric triangulation and other wireless environment sensing techniques.

6 ISAC based on low-altitude UAV swarms

By leveraging the aforementioned technologies, ISAC systems based on UAV swarms become more realistic. Different from the aforementioned ISAC for low-altitude UAV swarms, the content discussed in this section does not view UAV swarms as communication users and sensing targets, but rather treats them as aerial BSs or anchor points to optimize system communication and sensing performance.

UAV swarms offer considerable advantages because of their collective payload capacity, expanded communication and sensing coverage, and resilience against anomalies, making them an extensively studied platform for communication and sensing applications. For instance, a two-level hierarchical UAV swarm architecture has been developed to address 3D irregular terrain coverage problems, along with a coverage trajectory algorithm based on a star communication topology. This approach achieves full regional coverage with minimal redundancy (Mou et al., 2021). In another study, a robust waveform recognition algorithm was proposed for UAV swarm communications in multipath channels. The algorithm maintains high recognition accuracy even under challenging conditions such as alpha-pulse interference, multipath fading, and frequency offset (Zhai et al., 2022). Further research addresses channel estimation and self-positioning for UAV swarms with dynamically unknown inter-UAV distances, introducing a method that reduces the training overhead for channel estimation and a low-complexity self-positioning algorithm that avoids exhaustive search (Fan et al., 2019).

Notably, the integration of UAV swarms with MA technology has resulted in a two-level MA system for low-altitude operations (Lu et al., 2025). In this system, each UAV is equipped with a local MA array, and the swarm can cooperatively combine these arrays into a larger distributed MA system. The authors formulated an optimization problem to maximize the minimum achievable rate of ground users through the joint optimization of 3D UAV deployment, onboard array configurations, and receive beamforming while considering sparse array arrangements. Numerical results demonstrate the superior performance of this two-level design.

Integration of UAV swarms with ISAC has also emerged as a research focus. For example, Zhu et al. (2025) proposed a reinforcement learning (RL)-based resource allocation framework to provide sensing prior information for UAV ISAC. Another study introduced a multi-agent RL framework applicable to ISAC, formulating UAV swarm positioning and trajectory optimization as a partially observable Markov decision process. This approach enhances overall sensing performance and environmental adaptability at the cost of increased complexity (Atsu et al., 2024). To address the need for precise localization and sensing of densely distributed UAV swarms, a recent study explored an integrated super-resolution sensing and symbiotic communication system deploying 3D sparse XL-MIMO with low-altitude UAV swarms (Xu JR et al., 2026). The authors proposed a super-resolution sensing-assisted channel estimation method and verified its superiority in both sensing and communication performance compared with conventional compact MIMO arrays.

7 Future research directions and development trends

Building upon the future vision, technologies, and paradigms discussed in the preceding sections, we now provide several open problems and promising opportunities that warrant further investigation to fully realize the potential of low-altitude UAV swarm ISAC systems.

1. Low-altitude UAV swarm 3D ISAC. Low-altitude UAV swarms extend existing 2D wireless networks for ground users and targets to the 3D space simultaneously accommodating

ground and low-altitude users and targets. This extension is significant given that low-altitude-oriented 3D ISAC has more practical significance for achieving low-altitude UAV swarm sensing and communication. This study discusses some novel array structures for low-altitude UAV swarm ISAC. However, existing studies are mostly based on the 2D space. For the low-altitude 3D space, the characteristics of these array structures may change and require further clarification and analysis.

2. Low-altitude UAV swarm near-field ISAC. As existing wireless system frequency bands continue to increase from sub-6 GHz to millimeter-wave to terahertz and the array scale continues to expand from MIMO to massive MIMO to XL-MIMO, near-field effects become increasingly obvious and must be modeled in electromagnetic wave propagation. This has a significant effect on both communication signal processing and sensing algorithms. Two key open research questions remain: first, how to address problems introduced by near-field effects, such as the effect of distance-dependent phase terms after second-order approximation in steering vectors on communication and sensing signal processing; second, how to use near-field effects, such as solving NLoS communication problems through Bessel or Airy beams. The use of near-field effects to achieve additional distance sensing capabilities to improve communication and sensing performance also needs to be explored.

3. CKM-based low-altitude UAV swarm ISAC. Currently, CKM research is very active. Using this database, much environment-related prior information can be obtained to improve the efficient environment sensing ability of UAV swarms. However, the potential of CKMs has not been fully exploited. Channel-related prior information stored in CKM databases includes not only channel strength information but also path information (such as the number of paths, number of path hops, and path delay) and angle information (such as angles of departure and arrival). There are more possible LoS scenarios in the low-altitude space. Combined with the high flexibility of UAV swarms, optimizing UAV swarm positions and trajectories using rich prior information will provide more significant gains for communication and sensing. Therefore, more CKM information needs to be used to assist low-altitude UAV swarm 3D ISAC.

4. Low-altitude UAV swarm ISAC super-resolution low-complexity algorithms. With the development of the low-altitude economy and the explosive growth of low-altitude UAVs, high-density, large-quantity target communication and sensing scenarios are becoming increasingly common, placing higher demands on the anti-interference capability of communication systems and the resolution and DoFs of sensing systems. Taking sensing as an example, to achieve high-resolution and large DoFs, a direct method involves increasing the number of antennas in the array and expanding the array aperture. However, this approach directly causes an extremely high software and hardware overhead and a rapid increase in sensing algorithm complexity, making its practical application difficult. This paper preliminarily discusses some sparse structure forms, such as sparse antennas in the array spatial domain and sparse resources in time–frequency domains, to achieve high sensing resolution with fewer antennas or time–frequency resources through the virtual domain, hybrid domain, and two-stage signal processing at lower complexity. However, existing research has not conducted a deeper exploration of sensing algorithms. For future ultra-dense communication and sensing, super-resolution low-complexity sensing algorithms are required.

5. AI-based low-altitude UAV swarm ISAC. First, AI can assist in complex electromagnetic environment modeling and dynamic prediction. Using models such as deep learning and graph neural networks, spatial–temporal features can be extracted in real time from historical channel data, CKM databases, and UAV trajectory and altitude information, achieving rapid prediction of low-altitude channels, obstacle distribution, and target dynamics, thereby enhancing communication link stability and sensing accuracy. Second, AI can be used for intelligent beam management and resource scheduling of UAV swarms, autonomously planning array formation methods, power allocation, spectrum resources, and UAV formation via RL, multi-agent learning, and other methods to maximize joint performance metrics of communication and sensing. Furthermore, AI is expected to be deeply embedded in ISAC signal processing workflows, such as AI-enhanced near-field signal processing, super-resolution parameter estimation, and generative model-based channel completion and denoising technologies, overcoming the performance bottlenecks of conventional algorithms in complex multipath, high-interference environments, thereby achieving low-complexity, high-precision communication and sensing. Finally, AI can be used to improve the autonomous decision-making abilities of UAV swarms, enabling them to adaptively adjust positions, altitudes, and coordination methods in dynamic low-altitude environments, solving problems such as occlusion changes, strong target mobility, and coordination difficulties with large swarm scales.

8 Conclusions

Low-altitude UAV swarm ISAC is a critical cornerstone for supporting the rapid development of low-altitude economy and enabling 6G low-altitude intelligent networking. This paper systematically reviews current research and analyzes core challenges such as low–slow–small characteristics and large-quantity, high-density UAVs operating in complex environments. Furthermore, we propose visionary "Ten Ones" performance metrics for future low-altitude UAV swarm ISAC scenarios and explore key enabling technologies, including novel array architectures, sparse time–frequency resource allocation, and CKMs, to achieve high-performance communication and sensing. The potential of using low-altitude UAV swarms as aerial ISAC platforms is also investigated. Finally, five future research directions are outlined, focusing on low-altitude 3D space utilization, near-field modeling, CKMs, super-resolution low-complexity algorithms, and AI-driven solutions. As these technologies advance, low-altitude UAV swarm ISAC will play an increasingly significant role in airspace development, smart transportation, emergency rescue, and national defense, fostering the deep integration and high-quality growth of the low-altitude economy and 6G wireless networks.

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Author contributions

Hongqi MIN and Yong ZENG outlined the paper. Dingbang YANG and Chenhao QI conducted the literature review, drew the figures, and drafted the paper. Hongqi MIN, Dingbang YANG, Chenhao QI, and Yong ZENG revised and finalized the paper.

Conflict of interest

All the authors declare that they have no conflict of interest.

Declaration on the use of generative AI tools

During the preparation of this work, the authors used ChatGPT to improve language. After using this tool, the authors reviewed and edited the content as needed and take full responsibility for the content of the published article.

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