Large Language Model Aided Integrated Sensing and Communication for Low-Altitude Economy

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***Abstract*—The rapid expansion of the low-altitude economy (LAE) necessitates robust and intelligent integrated sensing and communication (ISAC) systems. These systems are critical for managing dense airspace, ensuring safe navigation of drones and electric vertical take-off and landing (eVTOL), and delivering seamless data services. This paper explores the transformative potential of large language models (LLMs) in advancing ISAC technologies for LAE applications. LLMs, with their profound capabilities in contextual understanding, multi-modal data fusion, and probabilistic reasoning, can be leveraged to interpret complex sensing data, optimize communication resources, and facilitate intelligent decision-making in dynamic environments. As a concrete example, we introduce an LLM-based multi-scale three-dimensional (3D) localization framework. This algorithm utilizes an LLM as a cognitive engine to integrate and analyze the acquired data streams and is capable of providing multi-scale positioning for unmanned aerial vehicles (UAVs). Moreover, we outline a number of key technical challenges as well as potential solutions associated with LLM-aided ISAC for LAE.**

***Index Terms*—AI, ISAC, LLM, Low-Altitude Economy**

I. Introduction

THE low-altitude economy (LAE) is emerging as a strategic area of technological development, driven by the rapid deployment of unmanned aerial vehicles (UAVs) and urban air mobility (UAM). Applications such as logistics delivery, emergency response, infrastructure inspection, and low-altitude tourism are expanding rapidly, with the global market expected to reach trillions of dollars in the coming decade. Enabling these applications requires a reliable and intelligent support system, with wireless communication serving as the backbone for real-time control, precise navigation, and coordinated airspace operations. To fulfill these functions, the underlying communication infrastructure must meet stringent performance requirements that support centimeter-level positioning and ultra-reliable low-latency communication (URLLC). However, in dense urban environments, conventional terrestrial cellular networks often suffer from multipath fading, signal blockage, and limited coverage. These limitations highlight the need for more robust and adaptable communication infrastructures to ensure reliable and scalable LAE deployment [1].

To address these demands, integrated sensing and communication (ISAC) has attracted considerable attention as a key enabling technology in sixth-generation (6G) wireless systems [2]. By co-designing communication and radio sensing functionalities within a unified platform, ISAC facilitates more efficient spectrum utilization and enhances environmental perception. This dual functionality is particularly suited to LAE scenarios, where UAVs and electric vertical take-off and landing (eVTOL) aircraft require both reliable connectivity and high-precision localization to ensure safety and coordination. Recent advances in high-frequency spectrum access and massive multiple-input multiple-output (MIMO) techniques have significantly improved sensing resolution and spatial awareness. However, in low-altitude environments characterized by mobility, heterogeneity, and mission variability, ISAC must fulfill multiple performance objectives such as data transmission, object detection, and trajectory tracking. Conventional optimization methods, which often rely on static modeling and handcrafted designs, exhibit limited flexibility in such dynamic conditions and are insufficient to fully exploit ISAC's potential in LAE, thus calling for intelligent methodologies [3].

The limitations of these traditional approaches have stimulated growing interest in artificial intelligence (AI) as a means of improving the adaptability and intelligence of ISAC systems [3]. AI techniques have achieved notable success in communication tasks including channel estimation, resource allocation, and interference mitigation, as well as in sensing-related tasks such as target detection, beamforming, and environmental reconstruction. Joint optimization of communication and sensing through AI has also been explored to increase ISAC efficiency. However, the majority of existing AI models are small in scale, tailored to specific tasks, and heavily reliant on supervised training with labeled data. These characteristics limit their scalability and generalization, particularly in the dynamic and heterogeneous settings of LAE-oriented ISAC.

In this context, large language models (LLMs) provide a critical advantage over conventional AI approaches for advancing ISAC intelligence [4]. Specifically, unlike conventional AI methods designed for isolated tasks, LLMs inherently support joint optimization, contextual adaptation, and intelligent coordination, which are essential for managing the multimodal, dynamic, and safety-critical demands of low-altitude ISAC operations. These attributes align well with the complex requirements of LAE scenarios, in which communication, localization, and sensing must be jointly optimized under varying environmental and mission conditions. Recent studies have demonstrated the feasibility of LLMs in applications such as beam prediction, channel modeling, and semantic

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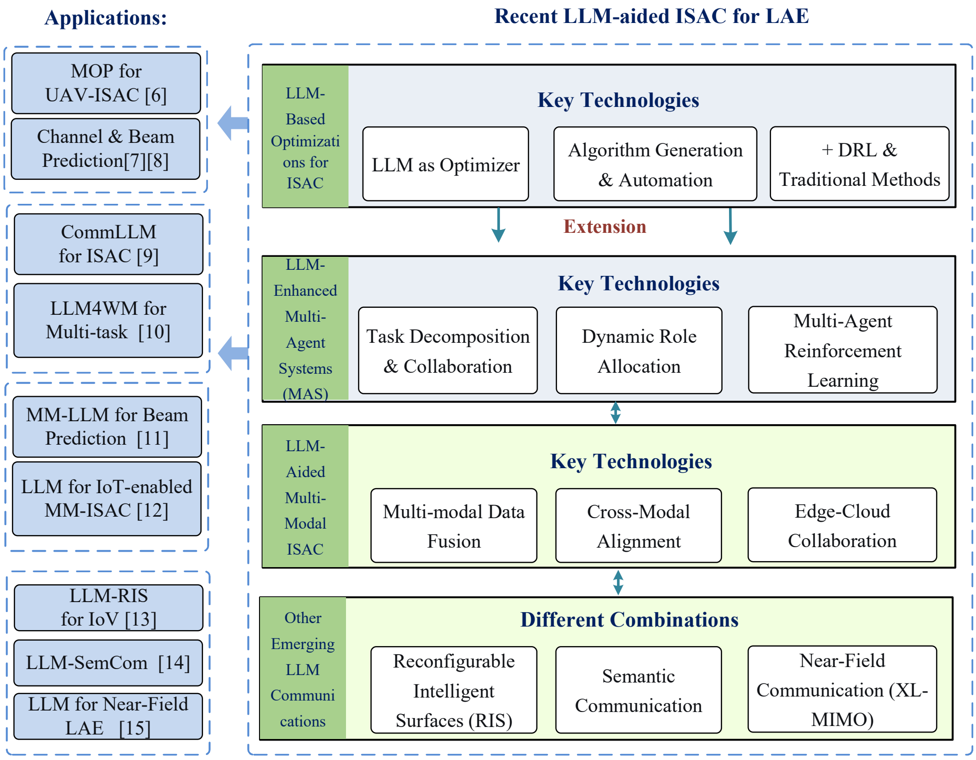

Fig. 1. Recent LLM-aided ISAC Designs for LAE.

communication, indicating their potential to unify diverse ISAC functions within a single adaptable framework. Furthermore, LLMs provide enhanced transparency and robustness in decision-making, which are critical for safety-critical aerial operations.

Looking ahead, the integration of LLMs into ISAC systems is expected to significantly enhance the capabilities of LAE infrastructure. At the physical layer, LLMs can improve modeling accuracy and signal prediction under complex propagation conditions. At the network layer, they support dynamic spectrum allocation, interference coordination, and resource orchestration across distributed UAV networks. Additionally, semantic-aware communication powered by LLMs facilitates mission-oriented information exchange and situational awareness, thereby improving collision avoidance, traffic control, and cooperative planning. The capacity of LLMs for generalization and multi-agent reasoning makes them particularly suitable for addressing the diverse and evolving challenges in low-altitude systems. These developments position LLMs not as incremental tools but as strategic enablers for next-generation ISAC in support of a resilient and intelligent LAE.

II. Recent LLM-aided ISAC Designs for LAE

A. *LLM-Based Optimizations for ISAC*

As shown in Fig. 1, the integration of LLMs with optimization techniques for ISAC systems is an emerging interdisciplinary field. It primarily focuses on leveraging LLMs' powerful reasoning and generative capabilities to enhance the modeling, solving, and optimization of complex ISAC problems. In general, LLMs can be used for the following purposes

- LLMs as optimizers: A key concept is using LLMs themselves as optimizers. For example, techniques like optimization by PROmpting (OPRO) utilize LLMs (e.g., GPT-4) to iteratively generate and evaluate solutions based on a natural language description of the problem [6].
- LLMs for algorithm generation and automation: LLMs are employed to automate the modeling and solving of optimization problems. Frameworks like operations research LLM agent (OR-LLM-Agent) can transform natural language descriptions of operations research problems into mathematical models and then into executable solving code.
- Synergy with traditional optimization algorithms: The combination of LLMs and traditional optimization algorithms is synergistic. LLMs can assist in designing and improving optimization algorithms (e.g., generating enhanced code for combinatorial optimizers), while traditional optimization algorithms can optimize LLM architectures and reduce their resource consumption through methods like model weight merging.
- Integration with other AI techniques: LLMs are often combined with other AI paradigms like deep reinforcement learning (DRL) for ISAC optimizations. For instance, DRL is used to optimize UAV trajectory, power allocation, and beamforming in ISAC systems, while LLMs can serve as intelligent coordinators and knowledge engines in such integrated systems.

In recent years, a flurry of research activities has been reported concerning the use of LLMs for solving optimization problems for ISAC-aided UAV networks. In a specific case study, in [6] the authors investigated a UAV network equipped with ISAC capabilities. In this system, multiple UAVs collaboratively perform sensing to locate ground users while simultaneously providing communication services. To balance the trade-offs between communication and sensing performance, a multi-objective optimization (MOP) problem was formulated. As detailed in [6], LLMs are employed not merely as function approximators but as black-box search operators for multi-objective optimization in UAV-ISAC networks. Unlike traditional solvers, the LLM-based approach iteratively refines solutions via natural-language prompting, effectively navigating complex trade-offs between sensing accuracy and communication.

Furthermore, in [7], a pre-trained GPT-2 model was fine-tuned for channel prediction in multi-antenna systems. Unlike conventional recurrent or convolutional networks that rely only on task-specific training data, this LLM-based approach leverages transferred structural knowledge from language modeling to capture long-range temporal dependencies in channel state sequences, leading to stronger generalization under complex channel conditions. Subsequently, the authors of [8] extended this idea to beam prediction. Here, the contextual sequence modeling capability of the LLM enables more robust inference of beamforming vectors from historical measurements, especially under the rapidly changing UE mobility patterns commonly encountered in LAE, outperforming LSTM or transformer models trained from scratch.

It is worth noting that with the deepening of research, LLM-based optimizations have the following possible applications in the ISAC-based LAE:

- UAV-enabled data collection and communication: LLM-based and DRL-based methods can optimize UAV path planning, transmitted power of IoT devices and UAVs, and resource allocation to optimize data freshness (e.g., minimize age of information) and maximize communication rates while considering sensing detection freshness. This is crucial for applications like drone communications and smart cities.
- Beamforming design: Machine learning, including potential LLM-guided strategies, is used for predictive beamforming design in ISAC systems, especially for vehicles with complex behaviors or UAV-based platforms. This enhances signal transmission efficiency and target sensing accuracy.
- Automated modeling and solving: LLM-agent frameworks can potentially automate the transformation of natural language descriptions of ISAC scenarios (e.g., multi-UAV task allocation) into precise mathematical models and subsequently into executable code, reducing reliance on expensive domain experts.

Furthermore, studies in [6]-[8] highlight that training and operating large LLMs require substantial computational resources and extensive datasets, which can pose considerable obstacles to both research and practical deployment, particularly for resource-limited edge devices in ISAC networks. Another significant challenge lies in interpreting the decision-making processes behind LLM-generated solutions or algorithms, which often remain opaque. To address this, techniques such as code evolution graphs are being actively explored to visualize and analyze the iterative development of code produced by LLMs during optimization, thereby enhancing interpretability.

In conclusion, LLMs serve not only as larger neural networks but also as flexible reasoning engines. They integrate domain knowledge, adapt through prompting or lightweight fine-tuning, and unify the sensing-communication-decision processes within a single, adaptable framework.

B. LLM-Enhanced Multi-agent Systems for ISAC

In LAE-ISAC scenarios, multi-agent systems (MAS) are essential for distributed coordination among UAVs. While conventional MAS often rely on predefined rules or reinforcement learning with limited adaptability, LLMs introduce a higher-level reasoning and contextual coordination capability that is difficult to achieve with traditional methods. Specifically, LLMs enable agents to interpret natural-language task descriptions, dynamically assign roles based on real-time context, and facilitate cross-agent knowledge transfer. The core idea is to leverage the advanced reasoning, planning, and communication capabilities of LLMs to enable multiple autonomous agents to collaborate effectively. This is a shift from traditional optimization methods to more adaptive, intelligent, and self-organizing systems. Research in this area is progressing rapidly, with frameworks being developed to optimize the structure, role allocation, and model selection for these multi-agent teams dynamically based on the task at hand.

In general, LLM-enhanced MAS for complex tasks like ISAC typically operate on several key principles:

- Task decomposition and collaboration: Complex ISAC tasks (e.g., joint resource allocation, trajectory planning, beamforming) are decomposed into smaller sub-tasks. Specialized agents, each potentially powered by an LLM optimized for a specific function, handle these sub-tasks. They collaborate through communication to achieve the global objective.
- Dynamic agent profiling and role allocation: Each agent can be assigned a specific profile or role (e.g., "spectrum allocator," "target tracker," "communication optimizer") based on its expertise. LLMs help generate and manage these roles dynamically to suit the problem.
- Learning and adaptation: These systems can be designed for continuous learning and adaptation. Agents can learn from their interactions with the environment and other agents, refining their strategies and policies over time to improve performance in dynamic ISAC environments. This can involve techniques from reinforcement learning (RL), particularly multi-agent RL (MARL) [9].

Motivated by the aforementioned compelling benefits of LLM-enhanced MAS, in [9] the authors proposed a novel multi-agent system, namely CommLLM, which is capable of solving communication-related tasks using natural language. To overcome inherent limitations of standalone LLMs,such as outdated knowledge, lack of domain-specific reasoning, and limited evaluation capabilities, the system integrates three core modules: Multi-agent data retrieval (MDR) for extracting and summarizing communication knowledge, multi-agent collaborative planning (MCP) for generating feasible solutions from multiple perspectives, and multi-agent evaluation and reflection (MER) for iterative refinement of solutions. The authors demonstrated the effectiveness of CommLLM through a case study on automated design of a semantic communication model, showing that it can produce functional and optimized code without prior explicit knowledge. This work highlights the potential of LLM-driven multi-agent systems for intelligent and adaptive 6G network optimization.

Moreover, in [10] a multi-task fine-tuning framework based on LLMs, namely LLM4WM, was specifically designed for wireless channel-associated tasks such as channel estimation, prediction, beam management, and environment sensing. To adapt general-purpose LLMs to the specialized domain of wireless communications, the authors introduced a mixture of experts with low-rank adaptation (MoE-LoRA) fine-tuning strategy, along with customized pre-processing and multi-task adapter modules. These components help align high-dimensional channel data with the semantic space of the LLM while enabling efficient parameter updates. The framework demonstrates strong performance across six distinct tasks, outperforming conventional deep learning models and single-task LLM fine-tuning baselines in both full-sample and few-shot settings. Overall, LLM4WM effectively harnesses the representational power of LLMs for complex wireless communication tasks, offering a scalable and unified solution for multi-task learning in 6G systems.

It is worth noting that the described capabilities of LLM-based MAS suggest several promising application areas, such as: (1) dynamic resource management: Automating and optimizing the allocation of spectral resources, power, and bandwidth between sensing and communication functions in real-time based on perceived environment and mission goals; (2) coordinated beamforming and signal processing: Managing complex multi-antenna systems for simultaneous sensing and communication, where agents collaborate to calculate optimal beamforming vectors that meet both sensing accuracy and communication rate requirements; (3) UAV swarm coordination for ISAC: Controlling swarms of UAVs performing ISAC tasks. Agents could manage individual UAV trajectory planning, collaborative sensing coverage, and communication relaying, ensuring efficient data collection and transmission while avoiding conflicts; and (4) network traffic analysis and security: Employing multiple agents to monitor network traffic (sensing function) collaboratively, detect anomalies or security threats, and automatically implement countermeasures (communication function) across the network.

In conclusion, LLM-enhanced MAS represent a promising paradigm for developing more adaptive and intelligent ISAC systems. By leveraging the strengths of LLMs in reasoning and coordination, these systems have the potential to manage the inherent complexities and trade-offs in ISAC dynamically. However, challenges related to computational efficiency, reliability, and integration need to be addressed for practical deployment. This area is likely to see significant growth, potentially leveraging techniques like automated MAS generation (e.g., MAS-GPT) and dynamic routing (e.g., MasRouter) tailored for ISAC requirements.

C. LLM-Aided Multi-Modal ISAC

The integration of LLMs with multi-modal ISAC (MM-ISAC) systems presents a highly promising and valuable direction for in-depth research. Unlike single-modal ISAC, MM-ISAC combines diverse sensing modalities (e.g., radar, LiDAR, and computer vision) with communication systems, resulting in synergistic performance improvements. By jointly leveraging multi-dimensional perceptual data and communication signals, MM-ISAC enhances spectral and energy efficiency, reduces hardware costs, and improves overall system robustness through multi-source data fusion. Furthermore, it facilitates high-precision sensing and low-latency communication, enabling advanced applications including autonomous vehicles and smart infrastructure.

MM-ISAC is evolving toward ultra-dense, heterogeneous networks with embedded intelligence. LLMs can enhance such systems by processing multi-modal data to support intelligent decision-making, such as predictive resource allocation. Furthermore, their capabilities in reasoning, planning, and coordination can be leveraged to efficiently manage and optimize multi-modal ISAC architectures.

Specifically, in [11] the authors proposed a novel framework that integrates multi-modal LLMs with ISAC systems to enhance performance in future 6G networks. The key contribution is utilizing multi-modal LLMs to process and align complex multimodal sensing data (e.g., light detection and ranging (LiDAR), radar, vision) with communication signals, enabling deeper information understanding and joint optimization. This approach improves cross-modal information fusion, generalization in dynamic environments, and supports applications like intelligent transportation and drone swarms. A case study on beam prediction demonstrates that the proposed framework outperforms traditional methods, such as the random forest, K-nearest neighbor and multi-layer perceptron methods. It is also shown that the proposed multi-modal LLMs provide remarkable proficiency in analyzing digitized sensing data from various scenarios.

More recently, in [12], the authors outlined a comprehensive system framework in which LLMs significantly enhance advanced contextual comprehension, robust object recognition, adaptive decision-making, and efficient edge-cloud collaboration for the Internet of Things (IoT). Furthermore, the study emphasized critical challenges that must be overcome to fully leverage LLM-driven MM-ISAC systems, such as the scarcity of high-quality multi-modal datasets, substantial computational demands, delicate power-latency trade-offs, and constrained edge resources. In response, several promising solutions were proposed, including synthetic data generation, effective modal compression, knowledge-guided domain adaptation, and synergistic co-design of signal processing with LLMs. The key findings of [12] underscore the considerable potential of LLMs to markedly improve sensing accuracy, communication efficiency, and intelligent automation across various IoT domains, including autonomous vehicles and smart industries.

Building upon the aforementioned research in [11]-[12] and integrating existing studies on ISAC [2]-[4], potential applications of LLM-aided multi-modal systems may also include:

- Multi-device edge AI: Coordinating multiple ISAC devices (e.g., drones, sensors) for collaborative sensing, feature extraction, and low-latency inference at the edge.
- Robust beamforming and signal processing: Optimizing beamforming vectors and signal processing pipelines by leveraging multiple models to handle complex near-field scenarios or wideband systems.
- Autonomous system coordination: Managing UAV swarms or robotic teams for tasks like search-and-rescue, where sensing, communication, and path planning require adaptive coordination.

LLM-aided MM-ISAC represents a promising direction for developing intelligent, adaptive, and robust systems that leverage collective modal intelligence. By dynamically coordinating multiple specialized modalities, these systems can overcome limitations of single modalities and address complex sensing-communication trade-offs. However, challenges related to computational efficiency, integration, and reliability must be addressed for practical deployment.

D. Other Emerging LLM-Empowered Communications for LAE

The integration of LLMs with reconfigurable intelligent surfaces (RIS), semantic communication and near-field communication represents a transformative advancement in future communication systems. LLMs enhance these technologies through intelligent optimization, context-aware processing, and efficient resource management.

Specifically, in [13] the authors proposed an innovative framework that integrated LLMs with RIS to enhance energy efficiency and reliability in 6G Internet of Vehicles (IoV). The key contribution lies in utilizing LLMs to analyze real-time IoV data—such as channel state, vehicle mobility, and quality of service (QoS) requirements—to dynamically optimize RIS phase shifts and wireless resource allocation in complex vehicular environments. By combining RIS-assisted non-orthogonal multiple access (NOMA), the system significantly improves signal coverage and mitigates blind zones. The method also shows strong adaptability in multi-vehicle settings, outperforming conventional RIS strategies with random phase shifts and systems without RIS.

Compared to RIS, semantic communication represents another paradigm shift in 6G communications, emphasizing the transmission of meaning rather than solely syntactic elements. In [14], the authors proposed a novel semantic communication framework integrating LLMs, namely LLM-SemCom, to enhance semantic accuracy, adaptability, and personalization in 6G systems. The key contributions include: (1) a structured semantic triple representation (head, relation and tail) to reduce LLM hallucinations and ensure verifiable semantics; (2) knowledge-base-free LLM processing for dynamic adaptation across domains without static knowledge constraints; and (3) retrieval- augmented generation (RAG)-enhanced personalization to tailor outputs to user preferences while preserving semantic fidelity. Experimental results demonstrate that LLM-SemCom significantly outperforms existing methods like deep learning enabled semantic communication systems.

Moreover, [15] proposed a novel framework that integrates LLMs into near-field communications for the LAE. The authors first identified a natural synergy between LAE—which relies on UAVs—and near-field beamfocusing in extremely large-scale MIMO (XL-MIMO) systems, where spherical-wave propagation allows precise energy focusing in both angle and distance domains. To address the unique challenges of this scenario, including mixed near- and far-field user distributions and complex three-dimensional (3D) geometry with base station height and tilt, the authors introduced a new system model and defined an effective near-field region. The core contribution of [15] is an LLM-based optimization scheme built upon a fine-tuned GPT-2 model, which jointly performs user classification (near-field vs. far-field) and optimizes multi-user precoding and power allocation. The model uses specially designed adapters and loss functions to handle non-convex constraints and ensure user fairness. Simulations demonstrate that the proposed method outperforms conventional benchmarks (including CNN- and transformer-based approaches) in both classification accuracy and spectral efficiency across various system parameters, validating its robustness and generalization capability for real-world LAE applications. In the design, the fundamental challenge is bridging the domain gap between natural language and physical signal domains (e.g., CSI, beamforming vectors). This is achieved through:

- Specialized input embedding/pre-processing: High-dimensional, structured communication data (e.g., time-space-frequency CSI, channel impulse responses) are transformed into a sequence of tokens that LLMs can process. Techniques like patching (dividing data into local blocks), numerical encoding (normalization, discretization), and embedding layers map continuous physical parameters into the LLM's feature space.
- Retention of pre-trained knowledge: Often, the pre-trained LLM's core layers (e.g., attention blocks) are kept frozen or efficiently fine-tuned to preserve their general-world knowledge and reasoning abilities, which are then adapted to the communication domain.

Based on [15], further potential applications of LLMs for near-field LAE include: (1) near-field channel modeling and prediction: LLMs could model the complex spatial characteristics of near-field channels (especially for LAE), capturing user position, array geometry, and frequency dependencies more effectively than traditional models, potentially predicting channel variations with high accuracy. (2) resource allocation and optimization: LLMs could intelligently allocate resources like power and bandwidth in near-field LAE networks, considering the unique interference patterns and multi-user dependencies in this regime. (3) system state estimation and calibration: LLMs might assist in estimating user positions or calibrating large arrays in the near-field based on received signals, leveraging their sequence analysis capabilities. At the same time, as shown in Fig. 2(d), when a sequence of continuously sampled observations along a trajectory is input, the localization results for each point exhibit spatially coherent motion trends, indicating that the framework can already capture the dynamic features of trajectories.

Using LLMs to empower RIS, semantic communication and near-field communication for LAE is a forward-looking research concept with significant potential but also considerable challenges. Current research demonstrates the viability of LLMs for physical layer tasks like channel prediction, providing a foundation. For example, as shown in [15], success in near-field LAE will likely depend on innovative architectures for handling spatial electromagnetic data, efficient tuning strategies, and robust integration schemes combining data-driven LLM strengths with model-based communication theory. As 6G research progresses towards native AI integration, investigating LLMs for managing the complexities of advanced systems like near-field LAE is a promising and potentially transformative direction. However, addressing the challenges of complexity, reliability, and integration will be crucial for practical deployment.

III. An LLM-based Multi-Scale 3D Localization for LAE

As operational demands in complex 3D airspace continue to grow, high-precision positioning has become a critical foundation to ensure flight safety, communication reliability, and task efficiency.

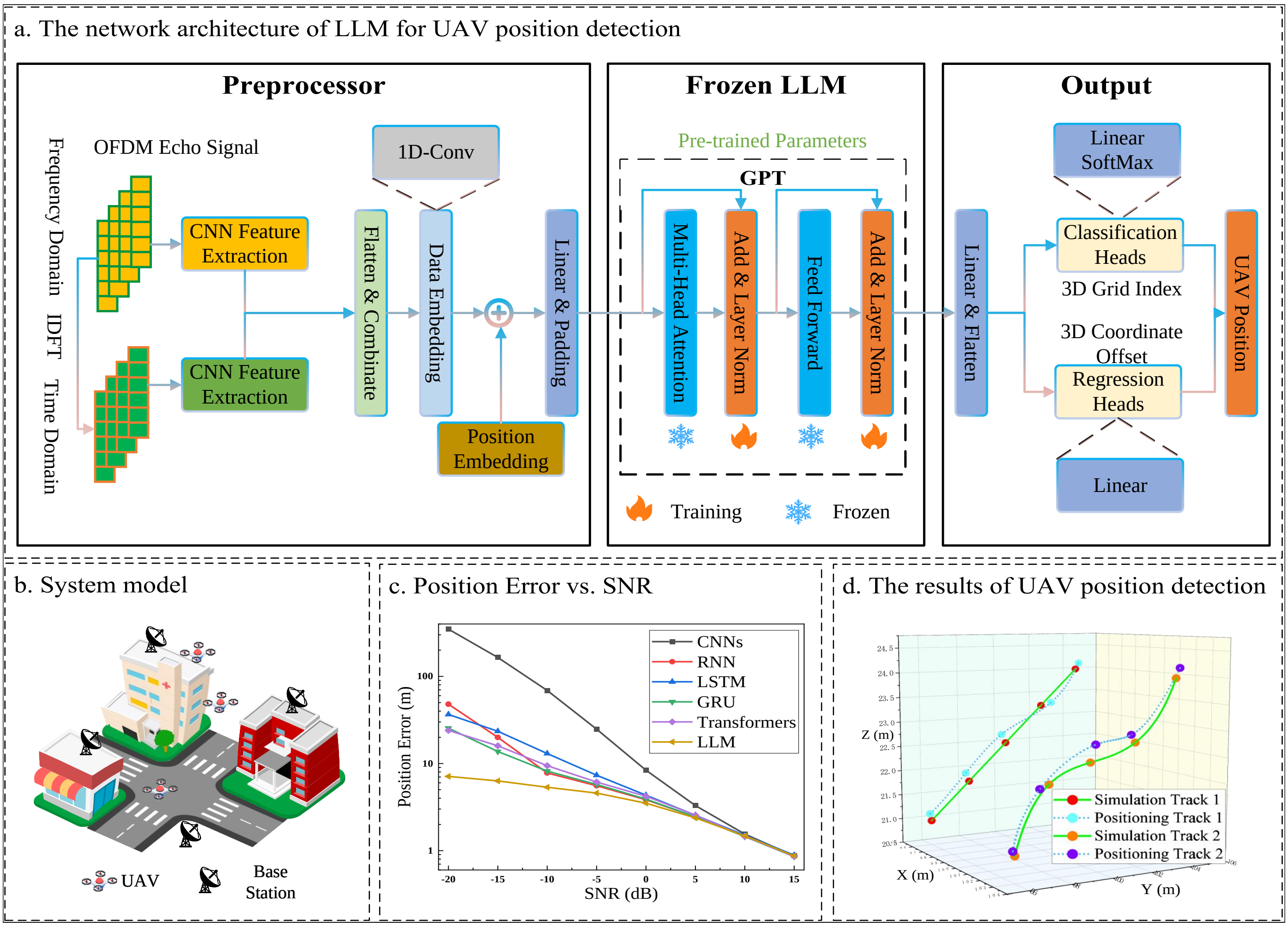

Fig. 2. An example of 3D UAV localization based on LLM.

However, the low-altitude environment introduces multipath propagation, strong interference, and rapid channel variations, which pose significant challenges for conventional techniques. To address these issues, this work leverages single-shot orthogonal frequency-division multiplexing (OFDM) signals and LLMs to achieve efficient and accurate UAV positioning[1].

As illustrated in Fig. 2, UAVs are distributed within a cell-sized 3D space, where multiple base stations transmit OFDM signals. These signals are reflected by UAVs and received back through a fading channel. At the receiver, the cyclic prefix (CP) is removed, followed by a discrete Fourier transform (DFT) to obtain frequency-domain representations. An inverse DFT (IDFT) is then performed to reconstruct time-domain signals, preserving both temporal and spectral features and effectively enhancing robustness against channel variations.

Then, as shown in Fig. 2(a), the specific LLM used in this study is built upon the encoder structure of the GPT-2 model. It consists of a 12-layer Transformer with a hidden dimension of 768 and employs a 12-head self-attention mechanism. The model contains approximately 83 million parameters in total, among which only about 2.56 million are fine-tuned to adapt it to the sensing task. As shown in Fig. 2(a), in our design, the preprocessing process of LLM mainly includes two core stages: feature extraction and embedding fusion. First, frequency-domain and time-domain signals undergo initial feature extraction through a three-layer convolutional network with identical structures. The extracted features are then expanded and merged, followed by further fusion via a 1D convolutional layer to form the data embedding. Simultaneously, the 3D coordinates of each base station are mapped to the corresponding dimensions of a high-dimensional vector using sine-cosine functions of varying frequencies to create a cosine positional encoding, generating the positional embedding. Finally, the data embedding and positional embedding are added together, achieving the fusion of signal features and spatial information to provide a joint input representation for the subsequent model. Benefiting from the large parameter scale and cross-domain representation capability of the LLM, the model can automatically capture complex nonlinear channel features and maintain high feature extraction capability even with limited or noisy data. A parameter-efficient fine-tuning strategy is adopted, freezing most parameters while updating only critical components such as layer normalization and positional embeddings, which significantly reduces training and inference overhead while fully exploiting the expressive power of the large model.

To achieve precise 3D positioning, the framework employs three classification heads and three regression heads in parallel. The classification heads predict UAV grid indices in 3D space, rapidly narrowing the search region, while the regression heads refine coordinate offsets within each grid cell, achieving sub-grid accuracy. A key strength of this design is its adaptability

[1]Although this example specifically investigates high-precision localization as a core sensing task, we employ the general term ‘ISAC’ to maintain alignment with standard field nomenclature and to encompass the wider range of potential sensing functionalities.

to different spatial resolutions: fine grids (e.g., 0.1 m) enable centimeter-level precision at higher computational cost, whereas coarser grids (e.g., 0.5 m or 1 m) reduce complexity while maintaining adequate accuracy for latency-sensitive or resource-constrained scenarios.

Simulation results with a 0.1 m spatial resolution validate the effectiveness of the proposed approach. As shown in Fig. 2(c), under high SNR conditions, all models—including long short-term memory (LSTM), Transformers, convolutional networks (CNNs), gate recurrent units (GRU), and recurrent neural network (RNN)—perform similarly. But due to the round-trip path loss experienced by sensing signals, the effective SNR of the sensing link is typically much lower than that of the communication link, making positioning capability under low-SNR conditions particularly worthy of consideration. Obviously, in low-SNR scenarios, the LLM-based framework demonstrates superior robustness. Notably, the LSTM model exhibits the largest positioning error, while the proposed approach consistently achieves the highest accuracy, highlighting the advantage of large models in noise resilience, deep feature extraction, and generalization. At the same time, as shown in Fig. 2(d), when a sequence of continuously sampled observations along a trajectory is input, the localization results for each point exhibit spatially coherent motion trends, indicating that the framework can already capture the dynamic features of trajectories.

Although this work focuses on UAV localization, the proposed framework shows strong potential for broader ISAC applications. Leveraging grid-based classification, fine-grained regression, and the transfer capability of large language models, it can be extended to vehicle positioning in intelligent transportation systems, indoor localization in smart factories, and joint radar-communication tasks. This demonstrates that combining single-shot OFDM signaling with large language models provides a robust, accurate, and scalable solution for diverse wireless localization scenarios.

IV. Further Issues For LLM-aided ISAC Designs

The integration of LLMs into ISAC for LAE shows promising potential, but the field is still in its early stages. Current research mainly focuses on proof-of-concept work, leaving key theoretical and practical challenges unresolved. These include model specialization for multi-modal, mission-specific tasks, ensuring low-latency inference under resource constraints, and developing trustworthy frameworks for safety-critical operations. This section outlines key areas that require further exploration to enable the practical deployment of LLM-aided ISAC in low-altitude environments, as illustrated in Fig. 3.

A. Multimodal and Few-Shot Adaptation for ISAC UAVs

UAV localization in low-altitude environments involves multi-source sensor data, including OFDM echoes, visual imagery, and LiDAR signals, making multimodal fusion highly complex. At the same time, high-quality labeled data are scarce, and conventional LLMs are prone to over-fitting in few-shot scenarios.

Future research efforts should concentrate on developing LLM architectures that are capable of multi-modal feature fusion and few-shot adaptation, thereby improving generalization and positioning accuracy. Key technical strategies may include modality-specific embeddings, cross-modal attention mechanisms, and meta-learning approaches. Such architectures would allow ISAC-LLMs to efficiently learn from limited heterogeneous data and support multitask UAV localization in low-altitude operations. Concurrently, it is essential to design adaptive resource allocation schemes that dynamically balance communication and sensing requirements in real time.

B. Real-Time Inference and Dynamic Update for LAE

Real-time adaptability is a critical requirement for ISAC in the LAE, where UAVs and eVTOLs must perform precise localization and rapid decision-making amidst constantly changing environmental conditions. However, existing LLMs exhibit significant inference delays and computational overhead, which hinder their ability to meet the ultra-reliable low-latency communication (URLLC) demands of the LAE. This issue is particularly pronounced in ISAC, where the integration of communication, sensing, and control functions must occur under highly dynamic conditions such as rapid mobility, multipath interference, and variable mission scenarios.

Future research should therefore prioritize the development of real-time inference mechanisms that enable LLMs to process data and adapt swiftly to evolving operational conditions. The adoption of edge computing and distributed processing frameworks can facilitate the offloading of inference tasks to geographically distributed nodes, thereby reducing response times and alleviating computational bottlenecks. Additionally, the incorporation of incremental learning techniques and task-specific adaptation mechanisms will be crucial for ensuring that LLMs maintain high accuracy and low latency across a broad range of operational contexts.

C. Trustworthy and Explainable ISAC-LLM for Safety-Critical Operations

Safety-critical tasks in low-altitude environments demand highly reliable localization, communication, and sensing. The "black-box" nature of LLMs may lead to mislocalization, erroneous target detection, or communication failures, posing significant operational risks.

Future research should emphasize trustworthiness and explainability, leveraging causal reasoning, interpretable machine learning, and reinforcement learning from human feedback to enhance transparency and human oversight [16]. Robust validation frameworks are essential to ensure that ISAC-LLM outputs comply with the high safety requirements of low-altitude operations, supporting critical missions such as emergency response, logistics, and air traffic management.

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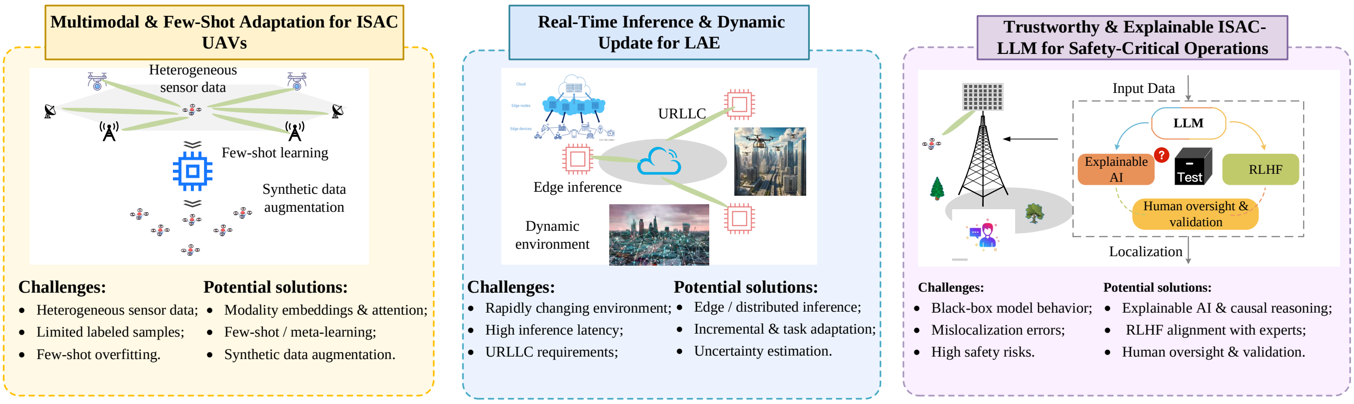

Fig. 3. Some open issues for future LLM-aided ISAC for Low-Altitude Economy.

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