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A Comparative Analysis of Key Technologies in Intelligent Signal Processing for 6G

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***Abstract*—The evolution of sixth-generation (6G) mobile communication systems introduces new challenges for signal processing technologies. The incorporation of emerging techniques such as ultra-massive multiple-input multiple-output (MIMO), reconfigurable intelligent surfaces (RIS), and integrated sensing and communications (ISAC) necessitates a paradigm shift in signal processing from conventional optimization methods toward intelligent approaches. This paper presents a comparative analysis of key technologies in intelligent signal processing for 6G based on a literature survey. Focusing on three core enabling technologies, the study compares traditional optimization-based methods with artificial intelligence (AI)-driven approaches in terms of their performance characteristics and application boundaries in tasks including channel estimation, beamforming, and signal detection. The findings indicate that AI-based methods offer superior performance and lower computational latency in complex scenarios, yet they continue to face challenges related to interpretability, generalization, and standardization. Model-driven deep unfolding, graph neural networks, and generative AI represent important directions for the future development of intelligent signal processing. This paper aims to provide a reference framework for theoretical research and system design in intelligent signal processing for 6G.**

***Keywords*—6G, intelligent signal processing, artificial intelligence, ultra-massive MIMO, reconfigurable intelligent surfaces, integrated sensing and communications**

I. INTRODUCTION

With the release of the IMT-2030 framework by the International Telecommunication Union (ITU), the vision for sixth-generation (6G) mobile communication systems has become increasingly clear. 6G networks are expected to support immersive applications such as holographic communication, digital twins, and extended reality, achieving orders-of-magnitude improvements in key performance indicators, including peak data rate, connection density, reliability, and positioning accuracy. To realize these goals, 6G systems will adopt a range of transformative technologies: extremely large-scale multiple-input multiple-output (MIMO) and reconfigurable intelligent surfaces (RIS) are redefining the propagation characteristics of electromagnetic waves, the terahertz band opens up ultra-wide bandwidth resources, and integrated sensing and communications (ISAC) endows networks with environmental awareness capabilities.

Academic research on signal processing for 6G has made notable progress. In extremely large-scale MIMO systems, due to either the large aperture of the antenna array or the increase in operating frequency to the terahertz band, the near-field propagation effect cannot be ignored. The spherical wavefront assumption will gradually replace the conventional planar wave model. RIS-assisted communication faces the challenge of high-dimensional, non-convex phase-shift optimization, whereas ISAC systems must resolve the inherent conflict between communication and sensing functions in waveform design. In response to these challenges, data-driven deep learning methods have shown promise, particularly for joint waveform design and real-time optimization.

This paper adopts a a comparative analysis to systematically examine the performance characteristics and the boundaries of the intelligent paradigms of conventional optimization methods and AI-driven approaches across different scenarios in three core scenarios: near-field MIMO, RIS, and ISAC. Furthermore, based on the three dimensions of performance, complexity, and interpretability, this study compares conventional methods with AI approaches in terms of their ability to handle high-dimensional non-convex problems and real-time optimization, as well as their differences in model generalization and interpretability. The paper provides a systematic classification and comparative logical framework for intelligent signal processing technologies.

II. LITERATURE REVIEW

A. *Conventional Signal Processing Methods*

Classical wireless communication signal processing is built upon well-defined mathematical models. Channel estimation typically employs least-squares (LS) and linear minimum mean-square error (LMMSE) estimators, which rely on prior knowledge of channel statistical characteristics [1]. Beamforming design is often formulated as a convex optimization or semidefinite relaxation problem, while signal detection is based on maximum likelihood or maximum a posteriori criteria. These methods have demonstrated excellent performance in 4G and 5G systems. However, in the face of new 6G scenarios, conventional methods gradually reveal three major limitations.

First, the computational complexity of conventional signal processing is excessively high. For instance, in extremely large-scale MIMO systems, channel matrix dimensions can reach thousands. RIS phase shift optimization involves tens of thousands of discrete variables, and the computational complexity of conventional iterative algorithms grows superlinearly with problem scale. Second, the issue of model mismatch sensitivity is prominent. In terahertz communications, for example, molecular absorption effects are complex and variable, making them difficult to characterize accurately with conventional statistical models. Third, environmental adaptability is insufficient. Conventional algorithms are typically designed offline for static scenarios and struggle to adapt to the highly dynamic and time-varying communication environment of 6G networks.

B. Emergence and Classification of Intelligent Signal Processing

To systematically analyze the applicability of intelligent signal processing methods in 6G scenarios, a unified theoretical framework for comparison must be established. Improvements in data availability, increases in computational power, and breakthroughs in algorithmic theory have jointly driven the emergence of intelligent signal processing. Based on different learning paradigms, existing research is mainly divided into three categories: supervised learning, applicable to tasks with labeled data such as channel estimation and signal recognition; unsupervised learning, applicable to optimization problems such as precoding design; and reinforcement learning, applicable to sequential decision-making problems such as dynamic resource allocation and beam tracking.

From the perspective of the intrinsic relationship between network architecture and data structure, different neural network architectures possess varying capabilities for extracting data features. Adams and Abdelhadi compared the applicability of convolutional neural networks (CNNs), recurrent neural networks (RNNs), Transformers, and graph neural networks (GNNs) in communication problems [2]. Their study indicates that CNNs are suitable for processing the spatial structure of channel matrices with local correlations; RNNs and Transformers are suitable for temporal modeling, such as channel prediction; and GNNs can explicitly model the graph-structured relationships among multiple antennas, multiple users, and multiple RIS elements. Understanding the principles of matching between architecture and data structure is a theoretical prerequisite for designing efficient, intelligent signal-processing algorithms.

From the perspective of the relationship with models, Sankar classified intelligent methods into three categories: black-box methods (purely data-driven), white-box methods (embedding domain knowledge), and gray-box methods (model-data fusion) [3]. Among these, model-driven deep unfolding methods map each iteration of a classical iterative algorithm to a neural network layer, significantly reducing computational complexity while maintaining interpretability. Problem structure, data characteristics, and model fusion together constitute the theoretical foundation for comparing conventional methods and AI approaches across the three scenarios of near-field MIMO, RIS, and ISAC.

Existing research mostly focus on individual technical domains (e.g., beam-focusing problems in near-field communication), lacking a cross-sectional comparison of the three near-field MIMO scenarios: RIS, ISAC, and MIMO. Meanwhile, algorithmic studies tend to emphasize the design and performance validation of specific methods, lacking a systematic comparative analysis of multiple intelligent signal processing paradigms.

III. Intelligent Signal Processing Technologies in Near-Field MIMO

As one of the key enabling technologies for 6G, near-field MIMO overcomes the capacity limitations of conventional far-field communication by deploying extremely large-scale antenna arrays or operating in the terahertz band. However, the spherical wave propagation characteristics introduced by the near-field effect pose new challenges for signal processing.

A. Fundamental Characteristics of Near-Field Propagation and Signal Processing Challenge

In 6G extremely large-scale MIMO systems, as the aperture of the antenna array increases or the operating frequency rises to the terahertz band, the Rayleigh distance increases significantly, substantially expanding the near-field region to cover most practical communication scenarios. This means that the conventional far-field model based on the plane-wave assumption is no longer applicable, and the spherical-wavefront assumption provides a more accurate description of near-field propagation.

This leads to three key changes. First, beam focusing replaces beam steering: near-field beams can focus energy at specific spatial points rather than merely controlling direction. Second, distance-domain resolvability is another major change: spherical waves encode both directional and distance information, making the received signal sensitive to distance. Third, channels exhibit non-stationarity: specifically, different antenna elements exhibit distinct spatial propagation characteristics, thereby violating the stationary assumption in conventional far-field models [4].

B. Intelligent Methods for Near-Field Channel Estimation

Although conventional compressed sensing methods can exploit channel sparsity, the storage and computational overhead of constructing high-dimensional dictionaries is excessive. For near-field channel estimation, several intelligent methods have been proposed in existing research.

Huang *et al.* employed a low-rank sparse tensor recovery method, modeling the cascaded channel of an RIS-assisted millimeter-wave OFDM system as a low-rank sparse tensor in the angle-delay domain. Their results show that this method outperforms the conventional alternating least squares algorithm in terms of normalized mean square error [5]. Hussein *et al.* proposed a CNN-based channel estimation method, demonstrating that deep learning can be effectively applied to both cascaded and separated channel estimation in RIS-MIMO systems. Their study confirms its superiority over conventional methods in terms of estimation accuracy and reliability [6]. For near-field channel estimation, Gao *et al.* designed a deep unfolding-based approximate message passing method, mapping each iteration of the approximate message passing-sparse Bayesian learning algorithm to a layer of a deep neural network. By learning optimal update rules, this method improves estimation performance while preserving channel sparsity. Experimental results show that this algorithm outperforms conventional compressed sensing methods across performance, complexity, and robustness [7].

C. Intelligent Design of Near-Field Beam forming

Near-field beam forming requires joint control of energy distribution in both angular and distance dimensions. Conventional methods typically rely on a preset codebook for beam search; however, as the array scale increases significantly, the codebook size grows dramatically,

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resulting in a substantial decrease in search efficiency.

For the near-field beamforming problem, Elhattab and colleagues proposed an AI-based beam prediction technique that uses environmental information (user location, historical beams) to predict the optimal beam index directly. This approach can replace conventional exhaustive beam scanning schemes and reduce beam training overhead by more than 70% [8]. Liu and colleagues attempted to directly generate beamforming vectors using neural networks, jointly optimizing metrics such as communication rate or energy efficiency through end-to-end training. Their results confirm that this method achieves more stable link quality in dynamic scenarios compared to conventional codebook-based schemes [9].

Table 1. Comparison Between Conventional Methods and AI-Based Approaches in Near-Field MIMO

Comparative Dimensions	**Conventional Optimization Methods**	**AI-based Methods**
Representative Techniques	Compressed sensing, iterative thresholding algorithms, codebook scanning	Deep unfolding, CNN-based denoising, neural beam forming
Computational Complexity	High (grows superlinearly with the number of antennas)	Low (fixed complexity for forward inference)
Performance-Advantage Scenarios	High SNR, precisely known channel models	Low SNR, limited pilots, model mismatch
Environmental Adaptability	Requires re-modeling to adapt to new scenarios	Retrainable to accommodate environmental changes
Interpretability	Strong (mathematically transparent)	Weak (black-box nature)
Real-Time Capability	Poor (time-consuming iterative convergence)	Excellent (millisecond-level inference)

As shown in Table 1, a complementary relationship exists between the two types of methods: conventional methods perform stably in scenarios with accurate models and low real-time requirements, whereas AI-based methods offer advantages in scenarios with low signal-to-noise ratio (SNR), limited pilots, or dynamic environments. Therefore, in practical applications, trade-offs must be made among performance, speed, and interpretability according to specific requirements.

IV. SIGNAL PROCESSING TECHNOLOGIES FOR RIS-ASSISTED COMMUNICATIONS

A. *RIS Working Principle and Model*

Unlike near-field MIMO, reconfigurable intelligent surfaces (RIS) reconstruct the propagation environment through passive reflecting elements rather than by expanding the scale of antenna arrays. Since RIS elements are passive and cannot actively transmit or receive signals, channel estimation must be performed indirectly via cascaded channels at the base station. Meanwhile, the discrete phase constraints imposed by a large number of reflecting elements render the optimization problem highly nonconvex. These characteristics exacerbate the computational bottlenecks of conventional methods, making intelligent signal processing an important research direction for RIS-assisted communications.

B. *Intelligent Methods for Cascaded Channel Estimation*

For the RIS cascaded channel estimation problem, conventional methods fall into two main categories. One category is compressed sensing methods, which exploit the sparsity of channels in the angular domain. However, these methods require a high-resolution sensing matrix. The other category is tensor decomposition-based methods, which leverage the low-rank property of channel matrices for parameter estimation but suffer from excessive computational complexity.

Existing intelligent channel estimation methods can be divided into three categories. The first category is based on deep neural networks that directly map received pilots to cascaded channel parameters in an end-to-end manner, thereby avoiding explicit modeling. The second category is based on graph neural networks, which exploit the grouping structure of RIS elements and channel sparsity to reduce computational complexity while maintaining scalability. The third category is based on meta-learning, which pre-trains models on multiple scenarios to enable rapid adaptation to new environments.

C. *Intelligent Algorithms for RIS Phase Shift Optimization*

The RIS phase-shift optimization problem is typically constrained to discrete phases, to maximize the system sum rate or minimize transmission power. Conventional algorithms such as semidefinite relaxation and manifold optimization can achieve near-optimal solutions. However, their computational complexity grows rapidly with the number of RIS elements, making real-time deployment difficult.

Current intelligent optimization methods are mainly based on deep reinforcement learning (DRL) and supervised learning. DRL-based RIS control models both the base station and the RIS as agents, using the user communication rate as the reward signal to learn an optimal phase-shift configuration policy through continuous interaction with the environment. This approach can adapt to dynamic channels and support online updates, but its sample efficiency is low. Supervised learning methods first generate labeled data using conventional optimization methods, then train neural networks to predict optimal phase shifts directly. These methods offer fast inference speed, but performance heavily depends on the quality of the labeled data.

A comparison of different RIS optimization methods is shown in Table 2. In summary, convex optimization and manifold optimization are theoretically rigorous but computationally intensive, making them suitable for small-scale or offline scenarios. Intelligent methods such as DRL, supervised learning, and graph neural networks offer advantages in inference speed and environmental adaptability. However, each has limitations in terms of sample efficiency, label quality, and graph structure design. In practice, the choice of method should be based on factors such as RIS scale, environmental dynamics, and available computational resources [10].

Table 2. Comparison of Different RIS Optimization Methods

Method Category	Advantages	Disadvantages	Applicable Scenarios
Convex Optimization (SDR, SDP)	Theoretical optimality guarantees	Excessive computational complexity	Small-scale RIS, offline design
Manifold Optimization	Good convergence properties	Requires continuous relaxation of discrete constraints	Medium-scale RIS
Deep Reinforcement Learning	Adapts to dynamic environments, online learning	Low sample efficiency, unstable training	Dynamic scenarios, time-varying channels
Supervised Learning	Fast inference speed	Depends on quality of labeled data	Static scenarios, known channel distributions
Graph Neural Networks	Good scalability, structure-aware	Requires graph structure design	Large-scale RIS, distributed deployment

V. INTELLIGENT SIGNAL PROCESSING TECHNOLOGIES FOR INTEGRATED SENSING AND COMMUNICATIONS

A. *Basic Principles of ISAC and Performance Trade-offs*

ISAC focuses on the fusion of communication and sensing functionalities rather than on merely antenna arrays or environmental control technologies. ISAC aims to simultaneously achieve communication, data transmission, and environmental target sensing on the same hardware platform and spectrum resources. The core challenges faced by its signal processing include the following. Communication pursues high data rates and emphasizes beam alignment with user directions, whereas sensing requires beam coverage of target areas and echo processing. There are inherent conflicts between the two regarding waveform design, power allocation, and beam direction. Conventional ISAC design mostly employs optimization-based methods, formulating sensing metrics (e.g., the Cramér–Rao lower bound and the signal-to-interference-plus-noise ratio) as constraints or objectives, and solving multi-objective optimization problems [11]. However, as the number of targets increases and scenarios become more complex, the optimization problems become highly non-convex and dynamic, making real-time solutions difficult for conventional methods.

B. *Intelligent Methods for Sensing-Assisted Communications*

Sensing information can significantly enhance communication performance. By sensing user locations and environmental maps, channel variations can be predicted and beams adjusted in advance. Deep learning-based sensing-assisted communication frameworks have been validated with CNNs combined with radar echoes: environmental features are extracted and fed into beam prediction networks. Transformers are used to capture temporal dependencies between user movement trajectories and channel evolution. In addition, graph neural networks model interactions among multiple targets [12].

C. *Intelligent Methods for Communication-Assisted Sensing*

Communication signals can also be used to improve sensing performance. Multi-base-station cooperative sensing (distributed ISAC) can leverage information from multiple perspectives to improve localization accuracy, but faces challenges in high-dimensional data fusion and fronthaul overhead. A federated learning-based distributed sensing framework allows multiple base stations to share models rather than raw data, achieving cooperation while preserving privacy.

D. *Intelligent Methods for End-to-End Integrated Design*

Both sensing-assisted communication and communication-assisted sensing represent unidirectional empowerment, whereas end-to-end integrated design pursues joint optimization of communication and sensing. Wang *et al.* addressed the difficulty of achieving global joint optimization in RIS-assisted ISAC systems due to decoupling constraints in conventional alternating optimization, proposing a unified optimization framework based on end-to-end deep learning. This framework simultaneously optimizes base-station beamforming, RIS phase configuration, and receiver-side signal processing using deep neural networks, achieving better bit-error-rate and radar signal-to-noise-ratio performance than conventional methods [13]. Mateos-Ramos *et al.* addressed model mismatch in conventional ISAC signal processing algorithms caused by hardware impairments, proposing a differentiable orthogonal matching pursuit algorithm to learn the parameters of transceiver hardware impairments. Their approach achieved higher detection probability, better localization accuracy, and lower symbol error rate [14]. Furthermore, Jiang *et al.* addressed the excessive computational complexity of joint design of symbol-level precoding waveforms and RIS passive beamforming in RIS-ISAC systems, unfolding the iterative process of the alternating direction method of multipliers (ADMM) into a neural network, achieving performance comparable to conventional optimization methods but with substantially reduced computational complexity [15].

Table 3. Comparison of ISAC Waveform Design Methods

Waveform Design Method	Communication Performance	Sensing Performance	Implementation Complexity	Intelligent Empowerment Approach
Communication-Prioritized	Excellent	Good	Low	AI-enhanced sensing information extraction
Sensing-Prioritized	Good	Excellent	Medium	AI-enabled data embedding into modulation
Joint Optimization Design	Excellent	Excellent	High	AI-generated end-to-end waveforms

VI. Discussion

This paper has systematically reviewed three major scenarios: near-field MIMO, RIS-assisted communications, and integrated sensing and communications. Near-field MIMO originates from the joint range-angle resolution brought by spherical waves, RIS from the double-hop attenuation of cascaded channels and discrete phase constraints, and ISAC from the inherent conflict between communication and sensing objectives. These differences determine the forms of AI adaptation in each scenario. In near-field MIMO, AI primarily reduces the overhead of codebook search and channel estimation. In RIS, AI replaces high-dimensional non-convex optimization and supports online learning. In ISAC, AI enables end-to-end joint waveform optimization. The greater the model complexity and environmental dynamics, the larger the relative benefit of AI-based methods. Deep unfolding methods excel in scenarios that require interpretability (e.g., RIS phase-shift optimization, ISAC waveform design). In contrast, reinforcement learning, despite its potential for dynamic decision-making tasks, still faces sample efficiency as a major bottleneck.

Nevertheless, current challenges remain, including the lack of design principles for balancing interpretability and performance, as well as the absence of unified evaluation standards. Future breakthroughs are needed in directions such as explainable AI, digital twin-assisted training, integration of electromagnetic information theory, and novel computing paradigms.

VII. Conclusion

This paper systematically reviews and compares intelligent signal processing technologies across three core 6G scenarios: near-field MIMO, RIS-assisted communications, and integrated sensing and communications. The study compares the complementary relationships between conventional optimization methods and AI-driven approaches in terms of performance, complexity, and interpretability. It is shown that AI-based methods offer significant advantages under complex conditions such as low SNR, limited pilots, and dynamic environments. Model-driven deep unfolding, graph neural networks, and deep reinforcement learning are emerging as important directions for balancing performance and interpretability. Although challenges remain in generalization, standardization, and hardware implementation, intelligent signal processing has evolved from an auxiliary tool into a core paradigm for 6G physical-layer design.

This paper has certain limitations. It relies on secondary data and existing literature and lacks sufficient simulation validation. It only examines results reported in the literature under specific simulation conditions and lacks a unified cross-scenario evaluation benchmark. Furthermore, challenges such as the generalization capability of AI methods, hardware compatibility for real-time deployment, and standardized interface design have not been explored. Future research can construct a unified cross-scenario simulation platform and conduct further validation for joint RIS-ISAC systems.

Conflict of Interest

The author declares no conflict of interest.

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