MACHINE LEARNING-BASED BEAMFORMING FOR INTEGRATED SENSING AND COMMUNICATION

Integrated Sensing and Communication (ISAC) is poised to be a transformative technology in future wireless networks, particularly at millimeter-wave (mmWave) and terahertz (THz) frequencies. By seamlessly integrating radar sensing with communication systems, ISAC enhances spectrum efficiency while minimizing hardware costs, size, weight, and computational demands. These advancements open new opportunities across various domains, including automotive technology, the Internet of Things (IoT), Extended Reality (XR), and robotics.

Recognizing its significance, the NextG Alliance's 6G Roadmap highlights ISAC as a key technology for 6G. Similarly, the European Telecommunications Standards Institute (ETSI) has established an Industry Specification Group (ISG) dedicated to ISAC. This group aims to develop a roadmap, prioritize sensing types, and define ISAC use cases for potential inclusion in future 6G releases under the 3rd Generation Partnership Project (3GPP). Additionally, the World Economic Forum has identified ISAC as one of the top 10 emerging technologies.

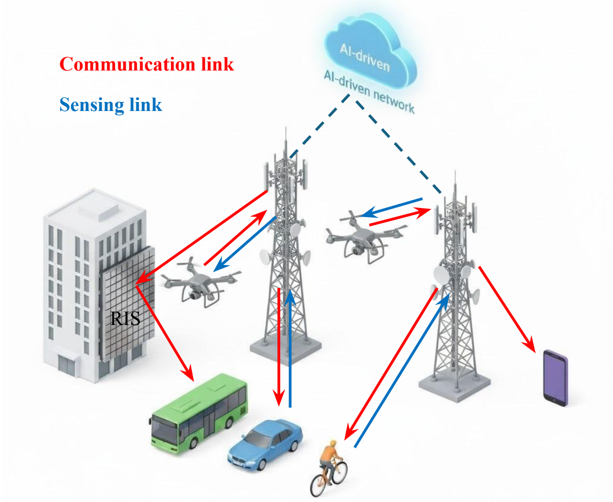

Figure 1: Illustration of key elements in an ISAC network, where a reconfigurable intelligent surface (RIS) assists the system in improving outage performance. The AI-driven network enables intelligent, coordinated, and proactive decision-making.

Beamforming Challenge

A defining feature of future ISAC systems is the deployment of large antenna arrays at transmitters and/or receivers. To fully exploit the benefits of these multi-antenna systems, efficient beamforming vector design is crucial. However, the beam design criteria for communication and sensing differ significantly. For communication, beamforming typically aims to direct signal power toward the receiver for maximum data transmission efficiency. In contrast, radar sensing often benefits from wider beam patterns to gather comprehensive environmental information from multiple scatterers. As a result, designing unified ISAC beam patterns requires balancing these competing objectives. Moreover, configuring massive MIMO links with minimal overhead remains a significant challenge, particularly in hardware-constrained systems, such as analog and hybrid beamforming architectures. Addressing these constraints is critical for the practical deployment of ISAC systems.

Machine Learning-based Beamforming

Machine learning (ML) has demonstrated exceptional capabilities in extracting spatial and temporal patterns, approximating complex models, and solving challenging optimization problems. In recent years, ML has been successfully applied to various aspects of wireless communications and sensing. For example, deep learning models have been used to optimize modulation and coding schemes, develop site-specific beam codebooks for mmWave systems, and enhance wireless resource allocation in complex network environments. Given these successes, it is natural to explore how ML can address key challenges in ISAC systems.

Therefore, in this research, we aim to use machine learning to optimize the ISAC beamforming design.

Case Study

As illustrated in Fig. 2, we use a system setup where a dual-functional radar communication (DFRC) base station (BS) serves a single antenna communication user (CU) while simultaneously sensing a single target. The base station (BS) is equipped with M transmit antennas and N receive antennas. Within this ISAC framework, we evaluate its joint sensing and communication (S&C) performance using two key metrics: the communication rate and the sensing rate. The communication rate measures the maximum achievable data throughput between the BS and users, reflecting the efficiency of information transmission over the wireless channel. The sensing rate, on the other hand, quantifies the system's capability to extract environment-related information, such as target detection, localization, or parameter estimation, within a given bandwidth and time duration. Together, these metrics provide a unified view of how effectively the ISAC system supports both data communication and environmental sensing simultaneously. Both rates depend on the beamforming vector w, making it challenging to optimize them simultaneously.

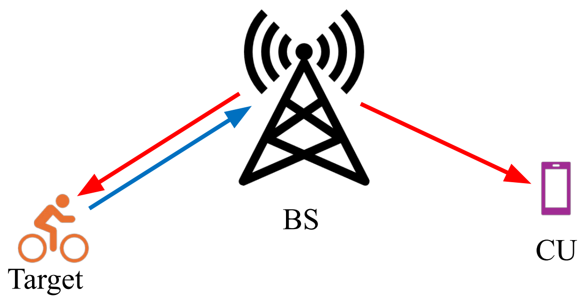

Figure 2: ISAC system setup

To this end, we propose a deep neural network (DNN) model. The model takes the communication channel and sensing channel as inputs and predicts the beamforming vector. It is trained using backpropagation to optimize the beamforming vector, achieving a balance between the communication rate and the sensing rate.

The DNN model consists of fully connected layers with ReLU activation, and we use the Adam optimizer for training. After testing, we fine-tune the hyperparameters to ensure model convergence, leading to a stable training process.

To train the model, we generate random channel data and adopt an unsupervised learning approach, where the model continuously refines the beamforming vector w without prior knowledge of the optimal solution. To evaluate its effectiveness, we compare the model's performance with the analytical solution.

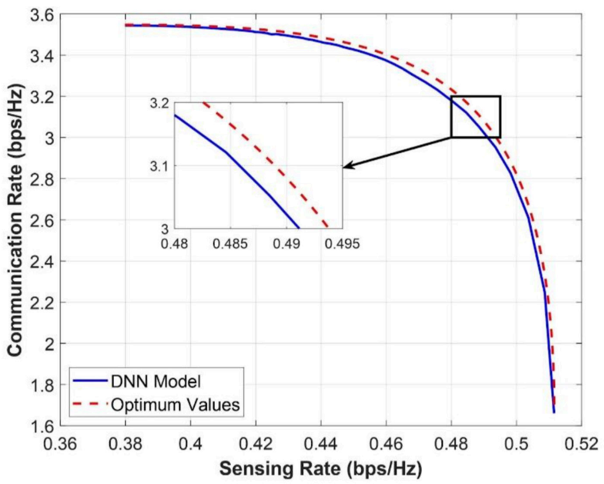

Figure 3: Pareto boundary comparison.

We experiment with the results of the DNN model and observe how maximizing one rate affects the reduction of the other rate. Rate tuples on this boundary can be obtained using the rate profile-based method. The Pareto boundary obtained using the DNN model is closely aligned with the results derived from the analytical optimum values obtained from [1]. These results show that the unsupervised learning approach can be extended to solve complex optimization problems without knowing the optimum solution. It can be extended to beamforming, leading to higher performance in telecommunication systems.

Conclusion

This investigates the role of beamforming in ISAC and proposes a deep learning-based approach to optimize beamforming vectors, balancing both communication and sensing performance. The DNN model effectively learns an adaptive strategy that balances CR and SR using unsupervised learning methods. The experimental results confirm that the model closely approximates the Pareto optimal boundary and demonstrates robustness under different channel conditions. The findings highlight the potential of deep learning in real-time beamforming optimization for ISAC systems and demonstrate that deep learning models can closely approximate analytical solutions.

References

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