Abstract

Wireless Sensor Networks (WSNs) serve as the backbone for a myriad of Cyber-Physical Systems (CPS), ranging from environmental monitoring to autonomous robotics. In these applications, accurate node localization is indispensable for interpreting sensed data and enabling geometric routing. However, achieving robust and scalable sensor network localization in distributed settings remains a formidable challenge due to the intrinsic nonconvexity of distance-based constraints, the ubiquity of measurement noise, and the complexities of irregular network topologies. This dissertation systematically addresses these challenges by developing a progressive framework that evolves from rigorous geometric modeling to data-driven collaborative learning.

The first part of this dissertation establishes a theoretical foundation based on algebraic graph theory and barycentric coordinates. Addressing the fundamental issue of nonconvexity, a linearization framework based on barycentric coordinates is proposed to transform nonlinear distance constraints into a global sparse linear system. Leveraging this algebraic structure, the dissertation derives necessary and sufficient conditions for unique node localizability in general d-dimensional spaces. These theoretical findings are operationalized into two key algorithmic contributions: a distributed verification mechanism that explicitly identifies localizable nodes, and a finite-time distributed localization algorithm guaranteeing exact position recovery.

To extend this approach to realistic noisy settings, a robust two-stage framework is developed, synergizing deterministic geometry with statistical optimality. By using the aforementioned linearized solution as a bounded initialization, this approach generates globally valid starting points independent of prior knowledge, effectively bypassing the local minima issues inherent in nonconvex optimization. Subsequently, a distributed refinement mechanism is introduced to iteratively maximize the likelihood function. A critical theoretical innovation lies in bridging cooperative game

theory with statistical signal processing: the refinement process is modeled as an exact potential game, where the Nash Equilibrium (NE) is rigorously proven to coincide with the global Maximum Likelihood Estimation (MLE) solution. This design effectively resolves the tension between global stability and local accuracy, ensuring consistent robustness against Gaussian noise.

Overcoming the scalability and sensitivity limitations of model-based methods in sparse topologies, the second part of the dissertation transitions toward a data-driven learning paradigm. A specialized Graph Neural Network (GNN) architecture is proposed to explicitly incorporate distance measurements and uncertainty into edge-conditioned message passing and global attention mechanisms. Unlike conventional approaches treating measurements as abstract weights, this design preserves geometric semantics throughout the representation learning process. Theoretical analysis establishes stability guarantees, while empirical results demonstrate significant improvements in scalability and generalization across irregular networks where traditional algebraic methods fail.

Finally, the dissertation reformulates sensor network localization as a collaborative sequential decision-making problem. Leveraging Multi-Agent Reinforcement Learning (MARL), sensors function as intelligent agents that actively refine their position estimates via iterative updates based on local observations. This paradigm shift achieves superior accuracy and robustness in noise-heavy environments, enabling agents to autonomously resolve ambiguities and correct errors that purely feedforward regression models cannot handle.

Collectively, this dissertation bridges the gap between classical estimation theory and modern artificial intelligence, offering a comprehensive suite of algorithms that make distributed localization more solvable, robust, generalized, and intelligent.