ABSTRACT

Ruiqi Wang, Purdue University, May 2026. Adaptive Human-Robot Teaming and Interaction: Embracing Heterogeneity, Operational Dynamics, and Personalized Preferences. Major Professors: Byung-Cheol Min and Baijian Yang.

Robots are increasingly expected to operate in human-centered environments, from assisting individuals in daily life to collaborating with human operators in high-stakes field operations. However, most robots still perform reliably only in controlled settings or within narrow interaction patterns. A fundamental barrier to broader deployment lies in the highly dynamic nature of humans. Humans differ in their capabilities, fluctuate in their internal states during interaction, and express diverse preferences over how robots should behave. These human-centered dynamics make fixed, one-size-fits-all robotic systems insufficient and motivate adaptive human-robot systems that can learn from and adapt to humans across users, teams, tasks, and environments.

This dissertation develops learning-based methods for adaptive human-robot systems across two levels: individual-level personalization and team-level adaptation. At the individual level, the dissertation addresses preference variability, where robots must align their behaviors with user-specific and context-dependent preferences. To this end, it develops preference-based robot learning methods across data, reward, and policy levels. At the data level, it leverages crowdsourced large language models and human-in-the-loop refinement to improve feedback efficiency and reduce the burden of collecting human preference labels. At the reward level, it develops multimodal preference modeling methods that infer preference-aligned reward structures from robot trajectory data while capturing temporal dependencies and state-action interactions. At the policy level, it proposes efficient personalization strategies that adapt robot behavior to individual preferences while preserving core task capabilities. Experiments on established robot learning benchmarks and real-world user studies in assistive robotics scenarios demonstrate improved feedback efficiency, reward alignment, task performance, and user satisfaction.

At the team level, this dissertation addresses capability heterogeneity and state uncertainty in multi-human multi-robot teams. Team-level adaptation is studied across two complementary stages. First, before execution, the dissertation develops a heterogeneityaware initial task allocation framework based on attention-enhanced hierarchical reinforcement learning, enabling robots to form effective team configurations by accounting for human capabilities, robot characteristics, and task requirements. Second, during operation, it develops a dynamic task allocation framework that reconfigures team coordination under evolving human, robot, and task states while handling imperfect, delayed, or uncertain information. Extensive experiments in large-scale environmental monitoring and field-operation-inspired scenarios demonstrate that the proposed frameworks improve allocation efficiency, scalability, and robustness compared with baseline and state-of-the-art methods.

Together, these contributions provide a unified view of adaptive human-centered robotics. By organizing human-centered dynamics into preference variability, capability heterogeneity, and state uncertainty, this dissertation shows how robots can personalize interaction at the individual level and coordinate adaptation at the team level. The resulting methods move human-robot interaction and teaming beyond fixed rules and predefined behaviors toward learning-based systems that can adapt to diverse and changing humans, supporting more natural, effective, and scalable robot deployment in domains such as assistive robotics, social navigation, disaster response, and field operations.