Physical AI for Collaborative Beam Lifting

Towards Network-Aware Collaborative Construction Robotics

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Abstract

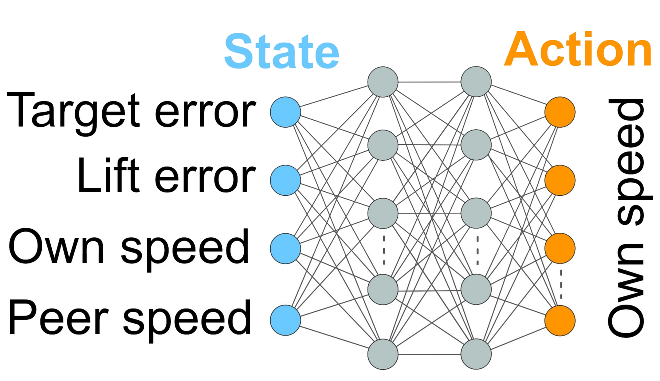
Network-constrained collaborative robotic systems enable construction automation, where multiple robots must coordinate under communication limitations. As physical interactions are difficult to model, reinforcement learning (RL) can learn control policies that satisfy task requirements. We present a prototype multi-robot solution for construction robotics, enabling decentralized coordination of mobile manipulators in a cooperative beam-lifting task. A policy is trained centrally in simulation and deployed in a decentralized manner, where each robot acts using local observations and minimal peer-state exchange. Validated on real robots, the system achieves reliable synchronized lifting, while quantitative accuracy and latency analysis is performed in simulation. Increasing latency from 16 to 337 ms raises synchronization time by 9.5×, stabilization time by 2.5×, and target error by 2.9×, while maintaining 100% task success.

Problem

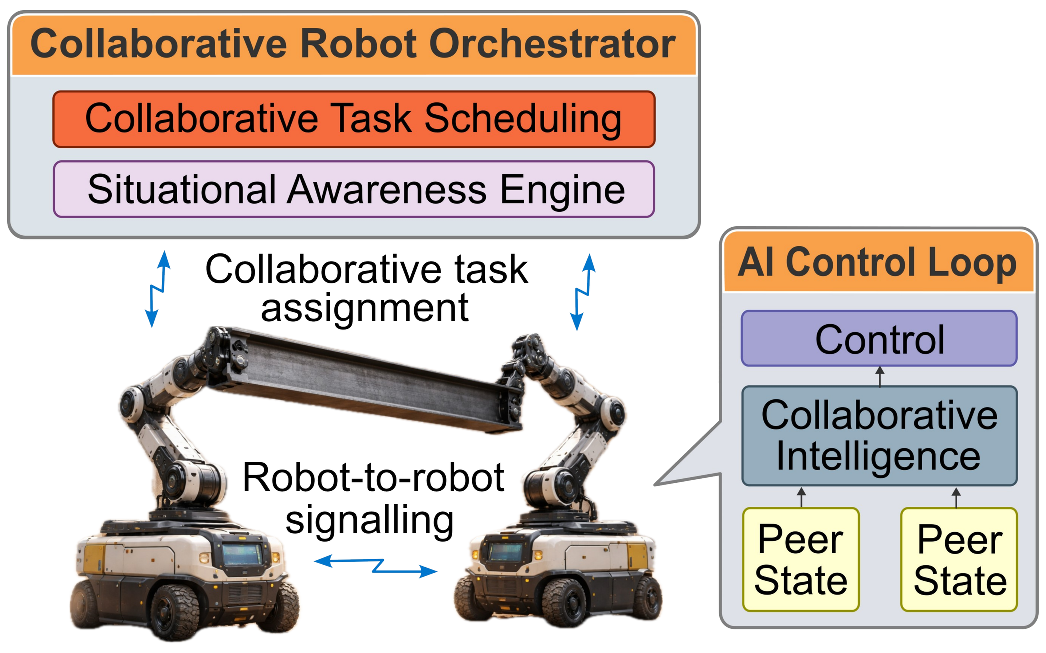
- Construction tasks require multi-robot coordination.
- Physical interaction is hard to model.
- Classic control targets single-robot tasks.
- Robot collaboration is sensitive to communication delay.

System Architecture

- **Target Architecture**: Centralized multi-robot orchestration with Situational Awareness Engine (SAE) for real-time monitoring. Communication via Private Open RAN with QoS control (delay, reliability, throughput).
- **Experimental setup**: SAE not used, ROS2-DDS over 5G.
- **AI model**: Centralized training with decentralized execution (CTDE), where each robot runs the policy locally using its own state and minimal peer-state exchanged via robot-to-robot signaling.



4-layer MLP of the RL-based AI model: 4-node input state, two 32-node hidden layers, and a 9-node action output.



System architecture with Collaborative Robot Orchestrator and AI Control Loop at the the Robot Orchestrator.

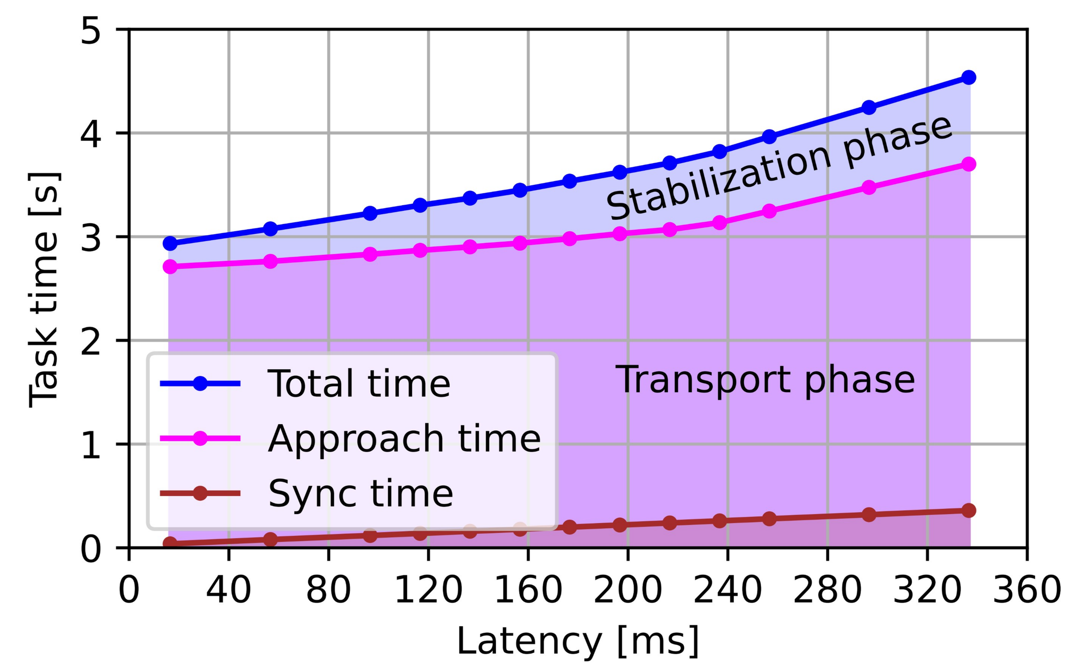
Real-World Experiment

- **Venue**: Testing was conducted in controlled environmental conditions at Fraunhofer IPK facility (Berlin) in Feb-Mar 2026.
- **Robots**: Two robots equipped with MIR100 mobile base, UR5 manipulator, a Weiss parallel gripper, and RGB-D camera.
- **Software**: ROS2-based Collaborative Robot Orchestrator (CRO) deployed on an edge server, and ROS2-based Robot Supervisor running on each robot with a 20 ms UR5 arm control period receiving peer robot state.
- **Network**: ROS2-DDS with wireless communication.
- **Task**: NN-based cooperative beam lifting to a CRO-assigned height.
- **Evaluation**: An RL-trained AI model, developed in the proprietary ENKI AI simulator using 1.5 million observations, successfully executed the collaborative beam lifting task in Gazebo and on real robots at the Fraunhofer IPK lab. Subsequently, the model was evaluated under varying robot-to-robot latency in the proprietary simulator, monitoring task success rate, target and lift error, and task execution time decomposed into sync, transport, and stabilization phases.

Beam lifting at the Fraunhofer IPK laboratory in Berlin.

Results

- **Success rate**: 100% across all latency levels maintaining the target within 2 mm accuracy for 10 consecutive steps.
- **Accuracy**: Increasing latency from 16 to 337 ms raises target error by 2.9×, with magnitude dependent on NN training.
- **Task execution time**: Latency increase from 16 to 337 ms raises synchronization time by 9.5×, stabilization time by 2.5×, and target error by 2.9×, while maintaining 100% task success. With arm speed of 0.1 m/s, the minimum transport time is 2.62 s, indicating near-optimal decentralized execution.



KEY INSIGHTS

- **AI Model (CTDE)**: Peer-to-peer observation sharing enables coordinated scalable multi-robot behavior in real-world tasks.
- **Training**: Careful reward shaping is critical to balance success rate, accuracy, and task execution time, ensuring stable behavior.
- **Accuracy**: Learned policies maintain the required 2 mm accuracy across latency levels, but performance degrades under out-of-distribution timing, with final error also depending on NN training.

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