**EE422/CS421Introduction to Robotics**

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# Week 1 Report: Introduction to Multi-Robot Collaboration Using Deep Learning

## 1. Introduction

The concept of multi-robot collaboration involves the simultaneous operation of multiple robots working together towards a shared objective. These systems aim to increase efficiency, scalability, and robustness in various real-world tasks ranging from logistics to disaster recovery. With the integration of deep learning, robots gain the ability to perceive, learn, adapt, and coordinate autonomously in dynamic environments.

## 2. What Are Multi-Robot Systems (MRS)?

A multi-robot system (MRS) is a group of robots that operate collaboratively. Each robot in the system can be responsible for sensing the environment, making decisions, and executing tasks either independently or in coordination with others.

Key functions include:  
- Perception: Environmental sensing using cameras, LiDAR, etc.  
- Decision-making: Local or shared task planning.  
- Task allocation: Who does what, and when.  
- Coordination: Ensuring robots work together efficiently.

## 3. Centralized vs. Distributed Architectures

Centralized Systems:  
- All decisions are made by a central controller.  
- Advantages: Simpler planning, global awareness, easier debugging.  
- Disadvantages: Single point of failure, poor scalability, high communication load.

Distributed Systems:  
- Each robot makes its own decisions and collaborates with others.  
- Advantages: High fault tolerance, scalability, flexibility.  
- Disadvantages: Complex coordination, potential for conflicting actions.

## 4. Role of Deep Learning in Multi-Robot Systems

Deep Learning empowers robots with:  
- Advanced perception via Convolutional Neural Networks (CNNs).  
- Communication modeling using attention-based networks (e.g., CommNet).  
- Reinforcement learning to learn optimal policies over time (e.g., MARL).  
- High-level task reasoning through large language models (LLMs) for natural task decomposition and coordination (e.g., COHERENT framework).

## 5. Reinforcement Learning Process in Multi-Robot Systems

Reinforcement Learning (RL) is a powerful framework that enables robots to learn optimal behaviors through interaction with their environment. In multi-robot settings, each robot (or agent) interacts with the environment to maximize long-term cumulative reward through trial-and-error learning.

Key Elements of the RL Process:  
- Agent: The decision-maker (robot).  
- Environment: The world the agent interacts with.  
- State: The current situation observed by the agent.  
- Action: The decision taken by the agent at a given state.  
- Reward: Feedback received from the environment indicating success or failure.  
- Policy: The strategy mapping states to actions.

Learning Loop:  
1. The agent observes the current state.  
2. It selects an action based on its policy.  
3. The environment provides a reward and a new state.  
4. The agent updates its policy based on the reward.  
5. This loop repeats until the policy converges.

In multi-robot systems, RL can be applied in two main forms:  
- Independent Learning: Each robot learns its own policy.  
- Multi-Agent RL (MARL): Robots coordinate or compete, learning in a shared environment.

Common Algorithms:  
- Q-Learning: Tabular method for small discrete spaces.  
- Deep Q-Network (DQN): Uses neural networks to generalize over large spaces.  
- Policy Gradient Methods (e.g., PPO, A3C): Learn policies directly.  
- Multi-Agent Algorithms (e.g., MADDPG, QMIX): Tailored for coordination in multi-robot settings.

Benefits:  
- Adaptability to dynamic environments.  
- Capable of handling complex decision-making.

Challenges:  
- High sample complexity.  
- Sensitive to reward design.  
- Coordination difficulties in multi-agent cases.

## 6. Key Literature and Open-Source Projects Reviewed

[7] Testa et al. (2023): A tutorial on distributed optimization in robotics, covering consensus, task allocation, and available simulation toolboxes.

[8] Wu & Suh (2024): A comprehensive survey on learning-based methods for robot collaboration, highlighting imitation learning, reinforcement learning, and multi-agent coordination.

[9] COHERENT Project (2024): A novel LLM-powered collaboration framework for heterogeneous robots, enabling long-horizon and complex task execution through a plan-execute-feedback loop.

Open-Source Tools Reviewed:  
- REMROC (Bosch): https://github.com/boschresearch/remroc  
- MultiRoboLearn: https://github.com/JunfengChen-robotics/MultiRoboLearn  
- ROS 2 multi-robot programming book: https://osrf.github.io/ros2multirobotbook/

## 7. Summary and Next Steps

In this first week, the groundwork for understanding multi-robot collaboration and its deep learning integration has been laid. The following was achieved:  
- Clarified definitions of MRS, centralized and distributed systems.  
- Reviewed core academic literature and real-world examples.  
- Identified relevant open-source tools and frameworks.

Next Week Goals:  
- Dive deeper into Multi-Agent Reinforcement Learning (MARL).  
- Begin testing basic multi-robot collaboration in ROS 2 or Gazebo.  
- Develop a simple scenario (e.g., warehouse robots) with basic task allocation.