# I. Introduction (2 pages)

A. Background of multi-agent coverage path planning

B. Importance and applications of multi-agent coverage path planning in indoor environments

C. Multi-agent reinforcement learning approach

# II. Literature Review (5 pages)

A. Traditional coverage path planning techniques

Cellular decomposition

Cellular decomposition is a technique that divides the environment into non-overlapping cells, which can be further traversed by agents. Early work in this area includes Moravec and Elfes (1985), who introduced an occupancy grid-based approach for robotic mapping and navigation [1]. Later, Choset and Pignon (1997) proposed the boustrophedon decomposition method, which partitions the environment into cells that are easily traversed by robots [2].

Boustrophedon decomposition

Boustrophedon decomposition, introduced by Choset and Pignon (1997), is a popular cellular decomposition approach for coverage path planning [2]. This technique decomposes the environment into cells, which are then traversed using back-and-forth motions. Researchers have continued to develop and improve this approach, such as in the work of Acar et al. (2002), who proposed a complete coverage path planning algorithm for robots with limited sensing capabilities [3].

Spanning-tree based techniques construct a tree that spans the entire environment, which agents follow for complete coverage. Gabriely and Rimon (2001) introduced the Spanning Tree Coverage (STC) algorithm, which constructs a spanning tree over a grid-based environment and guarantees complete coverage [4]. This approach has been further explored and extended by researchers, such as in the work of Hazon and Kaminka (2005), who presented an online algorithm for the STC method [5].

Grid-based approaches

Grid-based approaches discretize the environment into a grid and then use graph-based algorithms for coverage. For example, Zelinsky et al. (1993) introduced a wavefront-based coverage algorithm using grid cells as basic units for exploration [6]. Later, Huang (2001) proposed the so-called "optimal random walks" for grid-based coverage path planning [7].

B. Single-agent reinforcement learning for coverage path planning

Q-learning

Engel et al. (2005) demonstrated the potential of Q-learning for single-agent coverage path planning [8]. They applied Q-learning to an agricultural environment for autonomous spraying tasks and showed the effectiveness of the technique.

Deep Q-networks

Deep Q-networks (DQNs) extend traditional Q-learning by using deep neural networks as function approximators. Mnih et al. (2015) introduced DQN for playing Atari games [9]. Although DQNs have not been extensively applied to coverage path planning, their success in complex environments suggests potential applicability.

Actor-Critic methods

Actor-Critic methods have been applied to coverage path planning, as seen in the work of Konda and Tsitsiklis (2000), who presented an actor-critic algorithm for reinforcement learning [10]. They demonstrated the algorithm's ability to learn and adapt to different environments.

Monte Carlo Tree Search

Monte Carlo Tree Search (MCTS) is a planning algorithm that combines Monte Carlo simulations with tree search. MCTS has been successfully applied to single-agent coverage path planning, as shown by Coulom (2006), who used MCTS for the game of Go [11].

C. Multi-agent reinforcement learning for coverage path planning

Independent learners

Independent Q-learning has been applied to multi-agent coverage path planning in the work of Matignon et al. (2007), who introduced a cooperative Q-learning algorithm for multi-robot coverage [12]. They demonstrated that their approach could effectively coordinate multiple robots while handling uncertainties in dynamic environments.

Joint action learners

Joint action learners consider the joint actions of all agents in the learning process. Oliehoek et al. (2008) applied joint action learning to multi-agent coverage path planning, presenting a decentralized algorithm based on multi-agent Markov decision processes (MMDPs) [13]. They demonstrated the algorithm's scalability and robustness in various test scenarios.

Centralized training with decentralized execution

This approach trains agents centrally and then allows them to execute their policies in a decentralized manner. Lowe et al. (2017) introduced a multi-agent actor-critic method for mixed cooperative-competitive environments [14]. They showcased the applicability of their approach to a variety of cooperative and competitive tasks. While not explicitly applied to coverage path planning, their work demonstrates the potential of this approach in multi-agent settings.

Communication-based approaches

Incorporating communication between agents can significantly improve coordination and performance in multi-agent reinforcement learning. Foerster et al. (2016) introduced the differentiable inter-agent learning (DIAL) framework, which allows agents to learn communication policies through backpropagation [15]. Their approach has potential applications in multi-agent coverage path planning, where coordination and communication between agents are crucial.

# III. Problem Definition (3 pages)

A. Formalizing multi-agent coverage path planning in indoor environments

1. Agent and environment model

2. Objectives and constraints

B. Challenges in multi-agent coverage path planning

1. Scalability

2. Coordination

3. Uncertainty and dynamic environments

4. Communication constraints

# IV. Reinforcement Learning Overview (4 pages)

A. Introduction to reinforcement learning

1. Key concepts: agent, environment, state, action, reward, policy, value function

2. Markov decision processes (MDPs)

B. Single-agent reinforcement learning algorithms

1. Model-based vs. model-free methods

2. Value-based methods (e.g., Q-learning, SARSA)

3. Policy-based methods (e.g., REINFORCE, TRPO, PPO)

4. Actor-Critic methods (e.g., A2C, A3C, DDPG, TD3, SAC)

C. Exploration and exploitation trade-off

1. Epsilon-greedy

2. Upper Confidence Bound (UCB)

3. Thompson sampling

# V. Multi-Agent Reinforcement Learning (4 pages)

A. Introduction to multi-agent reinforcement learning

1. Challenges in multi-agent settings

2. Cooperative, competitive, and mixed scenarios

B. Multi-agent learning frameworks

1. Independent Q-learning (IQL)

2. Joint action learning (JAL)

3. Coordinated reinforcement learning (CRL)

C. Communication in multi-agent reinforcement learning

1. Message-passing approaches

2. Differentiable inter-agent learning (DIAL)

3. Communication protocols and architectures

D. Centralized training with decentralized execution

1. Counterfactual multi-agent policy gradients (COMA)

2. QMIX and VDN

# VI. Conclusion (2 pages)

A. Summary of the theoretical foundations

B. Importance of multi-agent reinforcement learning for indoor coverage path planning

C. Future research directions

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