# 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

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

Agent and environment model

In the context of multi-agent coverage path planning, the environment is typically represented as a discretized grid or a graph, where each cell or node corresponds to a location in the indoor environment [1]. Obstacles, such as walls or furniture, are represented as blocked or inaccessible cells or nodes. Each agent in the system is a mobile robot equipped with sensing and actuation capabilities, allowing it to perceive and navigate the environment. The agent's state may include its current position, orientation, and other relevant information, such as the local map or the status of neighboring agents.

Agents are assumed to be homogeneous in terms of their capabilities, and their actions may include moving to neighboring cells or nodes, rotating, or communicating with other agents. The transition model, which describes how an agent's state changes based on its actions, can be deterministic or stochastic, depending on the nature of the environment and the robots' dynamics [2].

Objectives and constraints

The primary objective in multi-agent coverage path planning is to minimize a cost function, such as the total time or distance traveled, while ensuring complete coverage of the environment [3]. This objective can be formalized as a multi-objective optimization problem, taking into account various constraints, such as the agents' limited sensing and actuation capabilities, communication limitations, and collision avoidance requirements [4].

In addition to the primary objective, secondary objectives may also be considered, such as minimizing energy consumption or balancing the workload among agents. These secondary objectives can be integrated into the cost function, either as weighted components or through the use of multi-objective optimization techniques [5].

B. Challenges in multi-agent coverage path planning

Scalability

As the number of agents and the size of the environment increase, the complexity of the multi-agent coverage path planning problem grows, making it challenging to develop algorithms that can efficiently handle large-scale scenarios [6]. Scalability issues can arise due to the combinatorial explosion of possible agent actions and states, as well as the increased communication overhead among agents. Developing scalable algorithms that can handle a large number of agents and complex environments is a crucial aspect of multi-agent coverage path planning research.

Coordination

Coordinating the actions of multiple agents is a central challenge in multi-agent coverage path planning. Agents must learn to collaborate and avoid conflicts, such as collisions or redundant coverage, while working together to achieve complete and efficient coverage of the environment [7]. Coordination can be achieved through various approaches, including centralized decision-making, distributed decision-making, or a hybrid of both. However, designing effective coordination strategies that balance optimality, computational complexity, and robustness remains an ongoing research problem.

Uncertainty and dynamic environments

Indoor environments can be subject to uncertainties and dynamic changes, such as moving obstacles, variations in lighting conditions, or sensor noise. These factors can affect the performance of multi-agent coverage path planning algorithms, making it challenging to develop robust and adaptive strategies [8]. Addressing uncertainties and dynamic changes in the environment requires the development of algorithms that can effectively handle incomplete or noisy information and adapt their behavior in real-time based on new observations.

Communication constraints

In multi-agent coverage path planning, communication among agents plays a crucial role in facilitating coordination and information sharing. However, communication in indoor environments can be subject to constraints, such as limited bandwidth, latency, or intermittent connectivity [9]. These constraints can impact the performance of multi-agent coverage path planning algorithms, making it challenging to maintain effective coordination and information sharing among agents. Developing algorithms that can handle communication constraints and adapt their behavior based on the available communication resources is an essential aspect of multi-agent coverage path planning research.

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# IV. Reinforcement Learning Overview

**A. Introduction to reinforcement learning**

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

Reinforcement learning (RL) is a branch of machine learning that focuses on training agents to make decisions based on their interactions with the environment [1]. The key components of an RL problem include an agent, a state space, an action space, a reward function, and a policy. The agent learns an optimal policy, a mapping from states to actions, by exploring the environment and receiving feedback in the form of rewards or penalties.

Markov decision processes (MDPs)

A fundamental concept in RL is the Markov decision process (MDP), which is a mathematical framework used to model decision-making problems in stochastic environments [2]. An MDP is defined by a tuple (S, A, P, R, γ), where S is the state space, A is the action space, P is the transition model, R is the reward function, and γ is the discount factor. The objective in an MDP is to find an optimal policy that maximizes the expected cumulative discounted reward.

**B. Single-agent reinforcement learning algorithms**

Model-based vs. model-free methods

Reinforcement learning methods can be broadly categorized into model-based and model-free approaches. Model-based methods rely on an explicit model of the environment's dynamics, such as the transition model and the reward function, to plan actions and update the agent's knowledge [3]. In contrast, model-free methods do not require explicit knowledge of the environment's dynamics and instead learn directly from the agent's interactions with the environment [4].

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

Value-based methods learn an optimal value function, which is then used to derive an optimal policy. Q-learning is a widely used model-free, value-based method that estimates the action-value function Q(s, a) [5]. SARSA is another value-based method similar to Q-learning, with the main difference being that SARSA is an on-policy method, while Q-learning is off-policy [6].

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

Policy-based methods directly learn the optimal policy without estimating a value function. REINFORCE is a classic policy-based method that uses the policy gradient to update the policy parameters [7]. More advanced policy-based methods, such as Trust Region Policy Optimization (TRPO) and Proximal Policy Optimization (PPO), have been proposed to improve the stability and efficiency of policy gradient methods [8, 9].

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

Actor-Critic methods combine aspects of both value-based and policy-based methods, using a value function (critic) to estimate the action-value function Q(s, a) and a separate policy function (actor) to choose actions. Asynchronous Advantage Actor-Critic (A2C) and its parallelized version, A3C, are popular actor-critic methods [10]. Other advanced actor-critic methods include Deep Deterministic Policy Gradient (DDPG) for continuous action spaces, Twin Delayed DDPG (TD3), and Soft Actor-Critic (SAC) [11, 12, 13].

**C. Exploration and exploitation trade-off**

Epsilon-greedy

Epsilon-greedy is a simple exploration strategy in which the agent chooses a random action with probability ε and the action with the highest estimated value with probability 1-ε [14].

Upper Confidence Bound (UCB)

UCB is a more sophisticated exploration strategy that balances exploration and exploitation by taking into account both the estimated value of an action and its uncertainty [15]. The agent selects actions based on upper confidence bounds, which provide an optimistic estimate of the action's potential value.

Thompson sampling

Thompson sampling is another exploration strategy that addresses the exploration-exploitation trade-off by maintaining a Bayesian posterior distribution over the action-value function and sampling actions according to their probability of being optimal [16]. This approach allows the agent to adaptively balance exploration and exploitation based on the uncertainty in its estimates.

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# 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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