Multiagent Coordination in Roombas: From a Neural Network Perspective

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***Abstract*—The abstract goes here.**

I. Introduction

II. Related Works

A. Coordinated Multiagent Reinforcement Learning

[1] Existing work typically assumes that the prob- lem in each time step is decoupled from the problems in other time steps, which might not hold in some applications. Therefore, in this paper, we make the following contributions: (i) We introduce a new model, called Markovian Dynamic DCOPs (MD-DCOPs), where the DCOP in the next time step is a function of the value assignments in the current time step; (ii) We introduce two distributed reinforcement learning algorithms, the Distributed RVI Q-learning algorithm and the Distributed R-learning algorithm, that balance exploration and exploitation to solve MD-DCOPs in an online manner; and (iii) We empirically evaluate them against an existing multi-arm bandit DCOP algorithm on dynamic DCOPs.

[2] This paper presents a model-free, scalable learning approach that synthesizes multi-agent reinforcement learning (MARL) and distributed constraint optimization (DCOP). By exploiting structured interaction in ND-POMDPs, our approach distributes the learning of the joint policy and employs DCOP techniques to coordinate distributed learning to ensure the global learning performance. Our approach can learn a globally optimal policy for ND-POMDPs with a property called groupwise observability. Experimental results show that, with communication during learning and execution, our approach significantly outperforms the nearly-optimal non-communication policies computed offline.

SBDO: A New Robust Approach to Dynamic Distributed Constraint Optimisation

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[**?**] Researchers in the field of Distributed Artificial Intelligence (DAI) have been developing efficient mechanisms to coordinate the activities of multiple autonomous agents. The need for coordination arises because agents have to share resources and expertise required to achieve their goals. Previous work in the area includes using sophisticated information exchange protocols, investigating heuristics for negotiation, and developing formal models of possibilities of conflict and cooperation among agent interests. In order to handle the changing requirements of continuous and dynamic environments, we propose learning as a means to provide additional possibilities for effective coordination. We use reinforcement learning techniques on a block pushing problem to show that agents can learn complimentary policies to follow a desired path without any knowledge about each other. We theoretically analyze and experimentally verify the effects of learning rate on system convergence, and demonstrate benefits of using learned coordination knowledge on similar problems. Reinforcement learning based coordination can be achieved in both cooperative and non-cooperative domains, and in domains with noisy communication channels and other stochastic characteristics that present a formidable c

B. Coordinated Multiagent Neuroevolution

III. Problem Formulation

A. Structure of Roomba Environment

Add description of Roomba module here...

B. Multiagent Behaviors

C. Difficulties and Challenges

IV. Implementation and Results

A. Reinforcement Learning

Add implementation details of Q-Learning and variants here...

B. Neuroevolution

Add implementation details of Neuroevolution here...

V. Results

VI. Conclusions

The conclusion goes here.

Future Works go here.

References

[1] D. T. Nguyen, W. Yeoh, H. C. Lau, S. Zilberstein, and C. Zhang, "Decentralized multi-agent reinforcement learning in average-reward dynamic dcops," in *Proceedings of the 2014 international conference on Autonomous agents and multi-agent systems*. International Foundation for Autonomous Agents and Multiagent Systems, 2014, pp. 1341–1342.

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