論 文 の 要 旨

題 目　Studies on Learning-Based Methods for Controllers of Multi-Agent Systems
(マルチエージェントシステムのコントローラの学習型手法に関する研究)

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This thesis focuses on developing collective behaviors for Multi-Agent Systems (MASs). An MAS is a system composed of multiple autonomous agents interacting with each other and the environment without relying on a centralized control structure. Although agents in MASs can have pre-designed behaviors, complex environments often make it difficult or even impossible to develop appropriate agent behaviors in advance. Learning-based methods offer an alternative approach, allowing agents to learn new behaviors online to improve the performance of the entire MAS steadily. The two main learning-based methods used in MAS are Evolutionary Robotics (ER) and Deep Reinforcement Learning (DRL). This thesis presents contributions to the field of MASs from the following two aspects.

Firstly, this thesis discusses how the evolutionary robotics approach can be applied to develop controllers with image inputs. The ability of agents to perceive and interpret their environment is crucial for effective interaction. Among various sensory inputs, camera inputs play a pivotal role, providing rich visual information that can be critical for object recognition and coordination among agents. However, evolutionary algorithms have limitations when used with high-dimensional inputs. Therefore, a deep neuroevolution method is proposed to generate collective behaviors. The results of computer simulations show that the proposed method outperforms Deep Q-Learning, a typical DRL approach, and demonstrates higher flexibility, scalability, and fault tolerance.

Secondly, this thesis investigates how the DRL approach can be applied to generating collective behaviors for MASs. Although DRL has achieved many successes in static environment tasks, it suffers from the sparse reward problem, where it is difficult for the agent to obtain rewards during exploration, resulting in slow learning speeds and poor performance. An intuitive solution is reward shaping, where denser rewards are designed for various agent behaviors. However, in some complex scenarios, it is practically infeasible to design rewards for specific behaviors of agents due to the vast state and action space. An alternative solution is Hierarchical Reinforcement Learning (HRL), where the original task is decomposed into multiple sub-tasks. Sub-controllers are first trained to complete corresponding sub-tasks. The high-level controller is then trained to activate different trained sub-controllers to accomplish the original task. However, when the training environment changes, it is hard to guarantee that pre-trained sub-controllers can still stably complete the corresponding sub-tasks. This thesis proposes novel methods integrating DRL with Imitation Learning (IL) and HRL to overcome the sparse reward problem. The collective behaviors are evaluated in a beach volleyball game and a key-to-door transport task. The results show that the proposed methods overcome the sparse reward problem and outperform conventional DRL and HRL methods.