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Guest Editorial

Deep Reinforcement Learning and Games

Tremendous progress of deep reinforcement learning is paving the way to artificial intelligence, computational intelligence, games and beyond.

Recently, there has been tremendous progress in artificial intelligence (AI), computational intelligence (CI) and games. In 2015, Google DeepMind published a paper "Human-level control through deep reinforcement learning" in *Nature*, showing the power of AI & CI in learning to play Atari video games directly from the screen capture. Furthermore, in *Nature* 2016, it published a cover paper "Mastering the game of Go with deep neural networks and tree search" and proposed the computer Go program, AlphaGo. In March 2016, AlphaGo beat the world's top Go player Lee Sedol by 4:1. In early 2017, the Master, a variant of AlphaGo, won 60 matches against top Go players. In late 2017, AlphaGo Zero learned only from self-play and was able to beat the original AlphaGo without any losses (*Nature* 2017). This becomes a new milestone in AI & CI history, the core of which is deep reinforcement learning (DRL). Moreover, the achievements of DRL and games are manifest. In 2017, DeepStack beat the expert in Texas Hold'em poker (*Science* 2017). DeepMind developed AlphaStar and achieved a 10:1 win rate against top players of StarCraft II in January 2019. OpenAI developed an AI to outperform the human champions in the Dota 2 game in April 2019. In these achievements in games, DRL also plays an important role.

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DRL is able to output control signals directly based on input images, and integrates the capacity for perception of deep learning (DL) and the decision making of reinforcement learning (RL). This mechanism has many similarities to human modes of thinking. However, there is much work left to do. The theoretical analysis of DRL, e.g., the convergence, stability, and optimality, is still in early days. Learning efficiency needs to be improved by proposing new algorithms or combining with other methods. DRL algorithms still need to be demonstrated in more diverse practical settings. Therefore, the aim of this special issue is to publish the most advanced research and state-of-the-art contributions in the field of DRL and its applications in games.

Needless to say, the great achievements of DRL are first obtained in the domain of games, and it is timely to report major advances in a special issue. We received a large number of submissions from many different countries. Finally, only two papers were accepted for publication in this special issue following a thorough review process.

Despite the aforementioned achievements, the best AI systems can still not beat top human players in many adversarial video games, especially for enormous state and action spaces. Barriga et al. propose a deep convolutional neural network to select abstract action choices in a limited set, to save computation time to improve low-level tactical behavior with game tree search while executing the strategic plan. Experiments show that the combined algorithm achieves higher win-rates than either of its two independent components and other state-of-the-art agents.

Deep reinforcement learning usually suffers from poor sample efficiency and slow convergence rate. Cao et al. propose an adaptive fusion-based variance reduction technique to improve sample efficiency. They also add noise to neural network weights to gain efficient exploration and ensure consistency in actions. Simulation results in robot locomotion games are presented to verify the theoretical results with competitive performance.

The above briefly introduces the accepted papers in this special issue. We thank all the authors for submitting their valuable work to this special issue. Finally, we thank IEEE CIM EiC Prof. Hisao Ishibuchi for his excellent support.