Title	注視点を導入した強化学習エージェントによる,視野の制約を前提とした行動獲得
Author(s)	勝又, 翼
Citation	
Issue Date	2025-03
Type	Thesis or Dissertation
Text version	author
URL	http://hdl.handle.net/10119/19790
Rights	
Description	Supervisor: 池田 心, 先端科学技術専攻, 修士 (情報科学)

Acquiring Behaviors Under Visual Field Constraints: A Reinforcement Learning Approach with Gaze Points

2310034 Katsumata Tsubasa

In recent years, artificial intelligence (AI) technology has made remarkable progress, with research advancing in various fields such as image recognition and natural language processing. Games have often been used as benchmarks for AI techniques, and research has primarily focused on improving AI strength. AI has not only surpassed professional human players in perfect-information board games such as Go and shogi but has also achieved victories in team-based real-time digital games against professional human players. These results demonstrate that one of the primary goals of game AI research–creating AI that is stronger than human players–has been achieved in many games. However, AI behaviors optimized solely for strength often deviate significantly from human-like behaviors, posing challenges when using such AI as opponents or teachers for human players. Consequently, research has been conducted to develop game AI that exhibits human-like behavior.

An approach to achieving human-like game AI involves reinforcement learning with agents that share common human constraints on movement and perception. This approach aims to develop AI behaviors that resemble human actions and do not rely on superhuman reaction speeds or highly precise inputs by training agents in environments that incorporate the recognition accuracy and response speed limitations inherent to humans. In this work, we focus on a cognitive and behavioral characteristic of humans that has received little attention so far: the tendency to act while shifting their limited field of clear vision to observe desired areas.

In this work, we aim to investigate the learning of behaviors under visual field constraints and propose an approach that equips reinforcement learning agents with dynamic gaze points. The key features of this approach are the restriction of visual information based on the distance from the gaze point and the dynamic control of that gaze point. In this framework, the reinforcement learning agent must learn in an environment where the range of accurately perceivable information is limited and where it must actively control this range. To validate this approach, we conducted experiments by introducing visual field constraints in two different game genres.

In the first environment, a Breakout game, we first confirmed that blurring the input images created a visual handicap for the reinforcement learning agent. We then conducted reinforcement learning in an environment with visual field constraints. Specifically, we used Gaussian blur (smoothing) as a blurring method and prepared three settings: no blur, weak blur where the ball remained visible, and strong blur where the ball became unrecognizable. Reinforcement learning was conducted three times for each setting, and the results showed that performance declined as the blur intensity increased. This demonstrated that the blurring process effectively functioned as a visual handicap for the agent's input.

Next, we conducted reinforcement learning in an environment where the game screen was divided into multiple areas, each with different levels of blur intensity. The game screen was divided into a 7×7 grid, where the 3×3 area centered on the gaze area remained unblurred. The weak blur was applied to the surrounding 7×7 area, while the strong blur was applied beyond that, simulating visual field constraints. The gaze area could be moved up, down, left, and right, and the agent's actions were defined as a combination of this movement and in-game actions. We created the environment so that the agent had to learn both "how to act in the game" and "where to look" simultaneously under visual field constraints and examined whether learning was feasible under these conditions. As a result of training, a comparison of the number of blocks broken in the early stages of learning showed that the agent with visual field constraints successfully broke more blocks than the agent without constraints. Despite the imposed visual limitations, these results confirmed that it is possible for an agent to learn both in-game actions and gaze movement actions at a certain level.

In the second environment, a bullet-hell shooting game, we examined how introducing visual field constraints influenced in-game behavior. By connecting the left and right edges of the screen within the game, we created an environment where agents without visual constraints could move freely without considering the screen boundaries, whereas agents with visual constraints found it difficult to see both edges simultaneously and had to act more cautiously. To implement the visual constraints, we provided the agent with two types of input: a globally blurred image covering the entire screen and a cropped 3×3 image centered on the gaze area. In contrast, the agent without visual constraints received two different inputs: a full-screen image without blur and an image centered on the agent where the opposite edges of the screen are seamlessly connected. To compare behavioral differences between these agents, we counted the number of times they crossed the screen boundaries. After training each model for 50 million steps, we found that the agent with visual constraints crossed the screen boundaries only about half as often as the agent without constraints. Additionally, heat maps representing in-game coordinates revealed differences in the behaviors of the two agents. These results confirmed that visual field constraints influenced in-game actions.

Although challenges remain, such as slower convergence in learning due to the addition of gaze selection actions and the fact that the gaze behaviors do not necessarily resemble that of humans, this work successfully implemented learning in an environment with visual field constraints and confirmed the acquisition of behaviors that take these constraints into account.