Title	人間プレイヤを活躍させる協力型ゲームの味方AI
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Abstract

In recent years, artificial intelligence (AI) techniques have made significant progress and have been widely used in various applications. In some applications, AI agents are employed to replace human resources where an example is self-driving cars. Digital games are also a field with significant progress in AI. In digital games, to create good AI players as humans' alternatives, it is required to make the AI players as strong as humans. In this sense, creating strong AI players has been a research topic where plenty of achievements were obtained.

Among digital games, AI players as teammates are employed in cooperative multiplayer games when human players cannot form a team. Therefore, cooperation between the teammate AI and the human players is important in this game genre. There are various behaviors required for cooperation, including cooperative behaviors in order to achieve the main goal of the game, cooperative behaviors that fit other players' senses of values, and human-like behaviors.

However, for beginners and intermediate players, it is not always the most desirable to have AI players that "successfully achieve the main goal of the game in an environment with human players". More specifically, even if the players can win as a team, human players may not feel interested because they cannot "play active roles". This paper aims to create teammate AI that supports human players to let them play active roles even with sacrifice to achieve the main goal. For this purpose, we believe that human players' intentions, such as "wanting to attack" or "wanting to survive", should be respected and that cooperative actions should be made to support human players' intentions.

In this study, we employ DungeonEscape, a game where three players try to escape from a dungeon by defeating a dragon. We extend the game so that the above-mentioned intentions or emphasized behaviors are easier to occur and be recognized. Then, we (1) consider typical intentions that may occur in this extended game and create an intention agent that acts according to each of the intentions, (2) create a support AI for each of the intention agents to support the agent's intention, (3) create a predictor that predicts intentions from the actions of intention agents, and (4) use the predictor to predict human players' intentions and provide the support AI corresponding to the predicted intentions as teammates.

For (1), we first considered that attack-oriented, survival-oriented, efficiency-oriented, and peer-oriented are representative intentions. In more detail, we defined attack-oriented players as those who tend to take the initiative in attacking enemies, survival-oriented players as those who tend to give priority to being alive, and efficiency-oriented players as those who try to clear the game as quickly as possible. The specific goal of this research is to support these players. We then created AI agents with these intentions so that we could create support AI for

(2) and train intention predictors for (3). Ideally, it was better to use human players' data to train the intention predictors since we want to support human players. However, since it was difficult to collect data from human players due to cost, we created the intention agents using reinforcement learning with rewards corresponding to the intentions.

Next, we conducted experiments and confirmed that the three created intention agents indeed acted in response to the corresponding intentions. Compared to the attack rate of 0.33 for the default agent with no intentions, the attack rate for the attack-oriented agent increased to 0.41. For the survival-oriented agent, we also used the attack rate as the evaluation. The reason was that players in DungeonEscape die if they attack the dragon. In other words, the players are likely to survive if they do not attack the dragon. Thus, the attack rate reflects the survival intention to some extent. The attack rate for the survival-oriented agent decreased to 0.01, which was much lower than the default agent's 0.33. For the efficiency-oriented agent, the clear time of the game decreased by about 12%.

For (2), we trained intention-supporting AI, whose goal is to support the actions of intention agents. During training, two instances of the intention-supporting AI were paired with an intention agent. We fixed the intention agent and used reinforcement learning to train the intention-supporting AI. We designed the rewards for reinforcement learning in a way that the AI receives high rewards when the intention agents find them in favorable situations. For example, attack-supporting AI receives high rewards when attack-oriented agents attack the dragon. By doing so, the intention-supporting AI learns behaviors that assist the intention agents in achieving their goals. Taking the same example of the attack-supporting AI, moving away from the dragon and giving up to attack are desired behaviors.

In our evaluation experiments, we demonstrated the effectiveness of the intention-supporting AI by comparing two cases: an intention agent paired with the default agents and the same intention agent paired with the corresponding intention-supporting AI. The attack-oriented agent paired with the attack-supporting AI had an attack rate of 0.89, which was higher than 0.41 when paired with the default agents. The survival-oriented agent paired with the survival-supporting AI had an attack rate of 0.005, which was lower than 0.012 when paired with the default agents. As for efficiency-oriented agents, we consider that efficiency-oriented agents themselves serve as the efficiency-supporting AI. When the efficiency-oriented agents were paired together, the clear time of the game was reduced by nearly 10%.

For (3), we trained a binary classifier to predict whether the intention is attack-oriented or survival-oriented. We used game logs collected from intention agents as the training data. In more detail, the inputs to the classifier contained the coordinates of the player's position, the coordinates of the dragon's position, and the distance between the player and the dragon. The accuracy of the classifier was 0.905, even with a simple neural network.

For (4), by combining the intention classifier and the intention-supporting AI, we created an integrated intention-supporting AI that provides the intention-supporting AI corresponding to the predicted intention as teammates. Evaluation experiments on the integrated AI showed that the AI was generally able to correctly support the player's intentions, with an attack rate of 0.77 for the attack-oriented agent and an attack rate of 0.01 for the survival-orientated agent. Furthermore, we verified the robustness of the integrated AI by including fluctuations and delays in the evaluation, taking into account that our final goal is to support human players. The results showed that it was difficult for the integrated AI to let human players play active roles. However, the results also showed that as long as the players had some clear intentions, such as attack-oriented and survival-oriented, the integrated AI was able to provide the corresponding support.