Title	ローグライクゲームにおける長期的戦略の学習
Author(s)	高橋，一幸
Citation	
Issue Date	2019-03
Type	Thesis or Dissertation
Text version	author
URL	http://hdl.handle.net/10119/15935
Rights	
Description	Supervisor: 池田 心，先端科学技術研究科，修士（情報科学）

The Development of Rogue-like Games Computer Player with Long-term Strategy

1610110 Kazuyuki Takahashi

In recent years, the performance of computer game player is improved significantly due to the performance of hardware and the advancement of computation technique. DeepBlue(IBM) computer chess won against Kasparov who was world champion in 1997. AlphaGo of DeepMind won against the champion of the game of Go Ke Jie in 2017. DeepMind also presents Deep Q-Network(DQN) computer player of the arcade game Atari(which contain various type of games) in 2016 which is able to clear 49 games. And 29 games among that, the player is able to break a human professional record. Thus, it is shown that the performance of AI in term of strength already surpass human professional level not only in classic board game but also the Arcade game.

Almost all games can be the target of research, but in some genres of games, it is often difficult to develop/reproduce the game environment for research, or there often are too much/complex rules in a game. So, for academic research, "open source academic platform" have been frequently developed and employed. Such as MetaStone, FightingICE, or Mario AI Benchmark which is very similar to original games, TORCS, digital curling, or aiwolf which simplify original game rules.

"Roguelike" is one of the popular game genres which also known in Japan as "Mystery dungeon series". In the "Roguelike games", the player needs to concern long term resource management, short-term fighting strategy, the dilemma of exploring/harvest, and dense/sparse behavior selection. Each task is very challenging and necessary for AI development. Such task is also appearing in the other complex game such as StarCraft, however the more complex of a game is, the more difficult it is to analyze and develop. Thus, the development of roguelike research platform with moderate complexity is beneficial for research subjects.

In this research, we developed an academic research platform and proposed/created game AI for the rogue-like game. In order to develop a platform for research, we enumerated and organized the element features and extracted the basic essential elements in common for many titles. The rules of the game are formulated based on "Berlin Interpretation" which is a published definition of a rogue-like game.

By using the platform, we firstly tried rule-based player with the decision tree of if-then as the baseline of the other method. This decision tree represented the thinking while playing out in priority order, which is not a smart

AI. Thus, the winning (game clear) percentage was about only 70.8%. We confirmed the behavior and found that the player was unable to escape to the aisle when surrounded by multiple enemies.

In order to improve the tactical aspect of the rule base player, the Monte Carlo method (depth limited Monte Carlo method, DLMC) is introduced to improve short-term decision-making. In DLMC simulation, since it is terminated at a fixed depth, very small calculation cost for the simulation operation can be expected. However, unlike the primitive Monte Carlo method, a state evaluation function of the leaf node is needed. Here, we prepared and adjusted the value function manually. As a result, a winning percentage of 82.3% was obtained. Improvements such as "escape into the aisle and make a one-on-one situation" can be confirmed in AI behavior, however, wasteful use of items at unnecessary scenes was also seen.

Finally, we attempted to improve the state evaluation function of DLMC, which had been created and adjusted manually, by one of the supervised learning methods i.e. averaged perceptron. There are options other than data number, learning parameters, etc. for of training data preparation, or training process. For example, when "data collection is performed", "how to express the state", "How to handle rare data that is difficult to collect in normal play" etc. It is difficult to cover overall. Therefore, in this research, we narrowed down and compared just some of them. In this research, the collecting data was done at "only when descending stairs" And "every battle is over". We found no significant difference between them. Thus subsequent data collection was taken at the end of a battle, due to the natural nature of the timing and a large number of data that can be collected. Next, we also compared "feature representation quantities between linear representation and one hot table" and "incensement of rare data". As a result, we obtained the same performance as DLMC using state evaluation function created by hand.