Abstract

For many years, games are the test bed of Artificial Intelligence. In the past, board games are the default one. Chess, Checkers, Othello, Go, etc., have been focused by researchers for decades. Now, in most, or perhaps eventually all, of theses games, the performance of computer programs has surpassed human champions. As a result, researchers have been shifting their focus to other areas such as video games.

Fighting games is a common type of videos games. In fighting games, there usually have two players fight each other in an arena. Currently, AI for fighting games is usually rule-based, which means theirs actions is predefined by their programmers. Strong tree search approaches in board games such as Minimax or Monte-Carlo Tree Search have not been always successful when applied to fighting games as well as video games in general. The reason is the limitation of time. In fighting games, it is often desirable to simulate a real-time environment. Usually, the time is divided in to small time windows. In each time window, the game will update its current state and players may input an action. For a computer program, it often means that it must decide its action in a very short time. The challenge is that conventional search algorithms usually take longer to find a good action. Hence, most of fighting game's programs are rule-based.

In this thesis, we presents our player in Fighting ICE, a fighting game framework from ICE Lab. The game has competition for computer programs which held annually in CIG since 2013. Our player use a combination of Monte-Carlo Tree Search and Reinforcement Learning. Monte-Carlo Tree Search is chosen because of its generality. However, in many cases, it fails to find a good action because of the time limit. Reinforcement Learning is chosen to improve the performance of Monte-Carlo Tree Search. We use it to predicting promising moves. Those moves are then presented to Monte-Carlo Tree Search and it will focus on those moves to decide the best one. The search result is given back to Reinforcement Learning so it could learn better prediction next time.

Our player shown good performance against top 4 of last year top competitors, all of them are ruled-based approaches. In our 120-round test, our player have better records than all of them. However, weaknesses particularly in state representation held back our player performance, making it weaker to certain conditions. Nonetheless, the potential of our approach have been confirmed.