Abstract

For a long while, the main goal of academic research in computer games was to make a suitable computer opponent for humans. To reach this goal, the first and major step was to improve the strength of the computer players. In the recent years, the computer game players have improved significantly due to the advance of search algorithms and computer technology. The computer players are now strong enough to win against average human players in classical board games such as Chess or Othello, but also in modern computer games such as Starcraft. It is perhaps time to devote more attention to other issues of computer players such as their usage for education or entertainment purposes.

The current performance of computer game players is very promising and efficient in terms of strength, but the behavior of such strong computer players is not so promising for the entertainment of players. For example, in a famous video of a computer player for Infinite Mario Bros, Mario character shows very precise movements, and no hesitation in the decisions. Such behavior looks very mechanical, in other words too strong and then not so entertaining.Furthermore, in the case of multiplayer games, since the computer player may be a partner or an opponent of the human player, such too strong or unnatural behaviors can make human players suspect that they are being cheated, and the entertainment of the game will be harmed. Hence, the production of behavior that looks natural to humans, called human-like, is essential to make computer players able to entertain humans.

Many approaches were proposed to produce human-like behavior. Schrum presented a human-like computer player based on a neural network for First-Person Shooter games. The computer player learning was supervised by human-player data recorded from past games. In 2013 Fujii et al. showed a new approach to produce human-like behavior with human-like mistakes. The biological constraints, including sensory error, perceptual and motion delay, and physical fatigue, were introduced into the path finding algorithm A* and the reinforcement learning Q-Learning. This research tried to imitate the behavior of human players by using a single behavior model, so the transition between different behaviors was not explicitly implemented, though such transition is common for human players. Then one of our goal in this research is to produce such transition between multiple behaviors.

In order to conduct a research on computer players, a suitable test-bed platform is needed. The classical platform of board games such as Chess or Go was the main target over the last 30 years. In order to play well at these board games, good reasoning and planning is required. In modern video games, other capacities such as pattern recognition, navigation and decision making in a short period are required. Furthermore, many games have imperfect information and they are played not only by one or two players but by three or even more. Thus it is a very challenging target. Recently, Sergey et al. published the platform called "Mario AI Benchmark" to evaluate computer players in a side-scrolling video game. The platform provides an API which allows developers to implement their own computer player. Some competitions were held using this platform, targeting not

only strength, but also human-likeness and entertainment. Then we also employ the same test-bed platform in this research.

In many modern video games, multiple goals are given to the players. Sometimes a player might choose to suspend the main goal of the game and challenge himself for another goal. For example in Super Mario Bros, the main goal of the game is to clear the stage within a limited time. In the beginning, the player tries to reach the goal as fast as possible. But after he finds some coins, the player might ignore the main mission and try to collect coins, which is a sub-objective of the game. He might be inspired by his greed or need of enjoyment. Or when he encounters many enemies at once, he might stop moving or collecting the coins and run away from the risk of being killed. Such behavior might be inspired by his fear. Such changes of behavior are inspired by human feelings or emotions. Hence, we believe that the production of behavior transition is important to obtain a human-like behavior.

In this study, we propose a design of human-like computer players with five emotional behaviors : "Safety", "Hurry", "Greedy", "Enjoy" and "Habit". "Safety" reflects anxiousness and fear of the player when he is on guard. "Hurry" shows speedy less careful actions, when the player is anxious about the remaining time. "Greedy" reflects the enjoyment of humans when they find rewards. "Enjoy" reflects the enjoyment and interest such as killing enemies continuously. "Habit" reflects unintended behavior such as pressing repeatedly the jump button.

And also we propose a hand-coded rule-based transition model of these behaviors.

As a preliminary experiment, we carefully investigate the human-likeness of the "Safety", "Hurry" and "Greedy" models, by comparing play videos from these models, from the A* algorithm and from human beginners. We conclude that our proposed models can successfully produce very natural behavior specific to each purpose. In the near future, automatic switching between the behaviors will be investigated with the proposed transition model. The individual performance of the behavior models and the total performance of the transition model with behavior switching will be evaluated by both of a Turing test and an entertainment test.