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Investigations on Mixed Strategies Using Evaluations of Perfect Information States in the Two-Player Zero-Sum Imperfect Information Game "Geister"

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In recent years, artificial intelligence (AI) players of perfect information games such as Go and Shogi have exceeded top human players' strength. In 2015, AlphaGo was proposed, which combines Monte-Carlo tree search and deep learning techniques. AlphaGo defeated a professional Go player without handicaps for the first time and attracted public attention.

Not only great achievements have been made in perfect information games, AI for imperfect information games such as poker and mahjong has also attracted attention and made great strides. Players in imperfect information games cannot fully observe the game states, making it not trivial to search the game trees. One group of approaches is counterfactual regret minimization (CFR), which was proposed in 2008 and has achieved great results in some games. A famous example is heads-up limit hold'em poker, whose Nash equilibrium has been approximated. Another group of approaches is deep reinforcement learning, where a mahjong AI Suphx has achieved top human players' levels in 2019. Meanwhile, for other imperfect information games such as Geister, AI players' strength is still limited.

Geister is a two-player, zero-sum, deterministic, and imperfect information game. Players have blue and red pieces and can capture the opponents' pieces, similar to chess. However, a big difference from chess is that the colors are hidden to the opponents until pieces are captured, which is an interesting point of the game. It is important to guess the colors of the opponents' pieces from the past movements, or conversely to move pieces in ways that make the opponents difficult to guess.

Research on Geister AI is still under development. For example, a purple-piece-AI method won an AI competition. However, there is some regularity in the movement, and the pieces' colors are easily predicted. Specifically, most of the pieces adjacent to the opponents' pieces are red ones, and if this is known, the purple-piece-AI is easy to defeat. Therefore, it is necessary to move the pieces stochastically. Such stochastic behavior has been analyzed in 3×2 Geister with a limited move number, but the method is challenging to handle larger board sizes since the whole search tree is expanded.

This research aims to handle Geister on a larger board size (4×4) and produce stochastic behaviors. For this purpose, we do not expand the whole search tree to calculate the expected win rates. Instead, we employ a heuristic function to give evaluation values. There are many variations in how to give evaluation values. In this research, we first propose a method that evaluates

leaf nodes with non-terminal states as draws. We then propose another method that generates the win/loss database of a perfect information version of Geister and evaluates leaf nodes by the corresponding perfect information states.

To evaluate the performance of the proposed methods, we conducted battle experiments employing four types of benchmark AI players based on purple-piece-AI. First, in the games between benchmark players, it was confirmed that each player had some opponent(s) that it was difficult to win, where the win rates were under 15%. Next, the proposed methods battled against the four benchmark players. Even for the opponents most difficult to win, the win rates were 19% and 24%. Although it is hard to say that the proposed methods are overall stronger than the purple-piece-AI, we believe that stochastic moves have succeeded in reducing the risks of being exploited.