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An Acquisition of Strategy in Two Player Game by Coevolutionary Agents

Jun-ichi Kushida[1], Noriyuki Taniguchi[2], Yukinobu Hoshino[3] and Katsuari Kamei[4]
[1 2] Graduate School of Science and Engineering, Ritsumeikan University
[3 4]Computer Science, Ritsumeikan University
1-1-1 Noji-higashi, Kusatsu, Shiga 525-8577, JAPAN
email: [1]kushida,[2]nori, [3]hoshino, [4]kamei @spice.cs.ritsumei.ac.jp

Abstract– The purpose of two player game is that a player beats an enemy. In order to win to various enemies, a learning of various strategies is indispensable. However, the optimal action to overcome the enemies will change when the game done over and again because the enemy's actions also change dynamically. So, it is difficult that the player aquires the optimal action and that the specific player keeps winning to various enemies.

Species who have a competition relation and affect other's existence is called a coevolution. Coevolution has recently attracred considerable interest in the community of Artificial Life and Evolutionary Computation[1].

In this paper, we apply Classifier System for agent team to two player game. A reward and a penalty are given to the used rules when the agent achieve specific action in the game and each team's rulebase are evaluated based on the ranking in the league. We show that all teams can acquire the optimal actions by coevolution

I Introduction

In two player game which played by two or more players repeatedly, it is difficult for a specific player to continue winning to various opposition. In order for the player to win many games, various strategies to overcome a opposition are required. The player select just strategies and improve it according to the situation of game and competitors. Each players always try to exceed each other. As the result, an excellent strategy was born and survives. and the level as the whole player goes up. We think that the learning of players is based on idea of coevolution.

Coevolution can discover a suitable strategy out of huge search space. Many researches on coevolution are done in the field of evolutionary computation and Artificial Life. For example, Sims' creatures (1994) and Ray's Tierra system (1991) are based on coevolutionary competing species.

In this paper, we compose coevolution model in two player game. For two player soccer game in lattice space, we adopted Classifier System that is a method for machine learning for two or more agents who have a confrontational relation. And then we evaluate each team from the viewpoint of the coevolution. We propose a learning system by coevolutionary agents in two player game and aim at acquisition of excellent strategy.

II Coevolution

A mechanism of evolution which species have a competition relation and affect other's existence is called a coevolution. The coevolution plays the essential role in evolution of an earth life. In coevolution, when themselves and a partner evolve, there is the feature that the environment where they were placed continues changing dynamically. And each species continue taking the action which he becomes advantageous to the opposition's action. In consequence, each species can obtain the action which is more excellent than competitor's action.

III System composition

Fig.1 shows the composition of a system. The league match was done by four teams. One team consists of three agents and has one rulebase. A round robin is held within teams. Whenever one turn of a league match is finished, a rank of teams in the league is determined based on the number of wins against other teams. each rule base's renewal is based on a rank of teams in the league. After renew the rule base of each team, next league match is done.

IV Evaluation of the team by coevolution

In classifier System, optimization of the whole rule base is done by optimization of the reliability of each rule. Our system links optimization of the reliability of each rule to optimization of the whole rule base.

Each team is evaluted based on the ranking in the league, and carries out evolutionary computation by GA in the rule discovery system of Classifier System. On each rulebase, parameters of GA are changed by the ranking in the league. The fixed number of rules is kept until the next generation for reliability. Furthermore, a crossover and a mutation are performed to generate new rules. As shown in Fig.2, the team

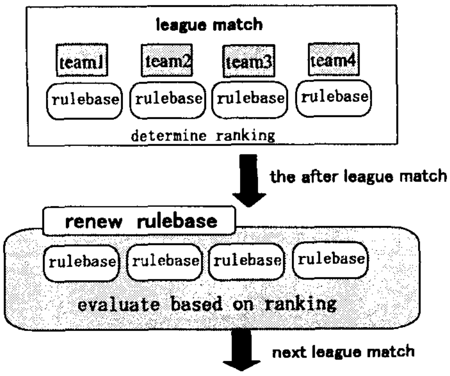

Fig. 1 System composition

placed in high rank keeps many rules and generates a few rules. In contrast, the team in low rank keeps a few rules and generates many rules. Moreover, some rules are chosen among rulebases of the top ranking team in the league, and they are added to the rulebase of the lower ranking teams. The lower ranking teams get more rules of the top ranking team. The coevolution between teams is proceeded by performing the above operation and the rulebase of each team are improved.

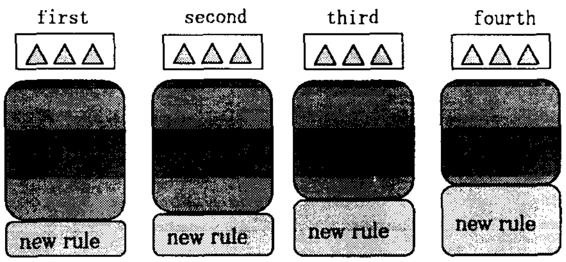

Fig. 2 Renew of rulebase

V Game simulation

A Game environment

An experiment environment is a soccer type game. Fig.3 shows the starting environment of the game, and the play always restarts in this starting environment after a goal. The field is the lattice space of 9×12. The purpose of both agents is to keep a ball and to take it to enemy's goal. The game is finished when both agents have moved in a preset steps M. When the agent carry a ball to the enemy's goal, it considers as one score. The team getting more points wins the game.

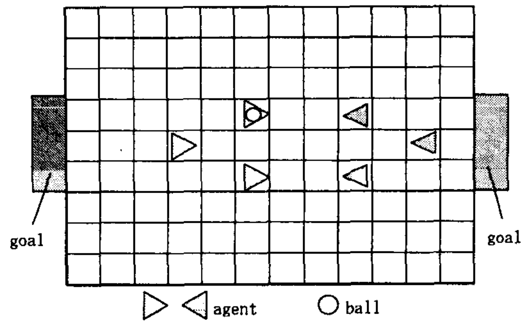

Fig. 3 Experiment environment

B Agent's action

The agent's actions are the move, the dribble and the tackle. As shown in Fig.4, the move and the dribble are movable in the circumference eight directions as one step. The tackle is done when both of agents move to same position. As shown in Fig.5, if the defensive agent succeeds in his tackle, he takes the ball and moves to the target position. The dribble can move to the target coordinates, with keeping a ball. In the kick, a agent can move ball to 1 coordinates detached as shown in Fig.5. A reword and a penalty are given to the each agent's used rule at the time of the goal and a tackle success by profit sharing.

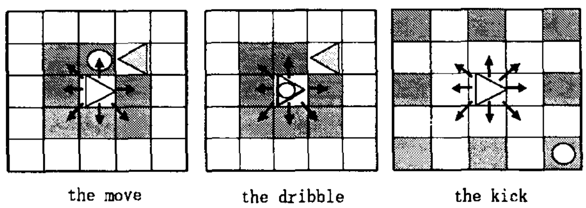

Fig. 4 Move direction

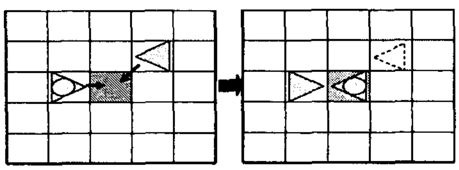

Fig. 5 The tackle

C Sensory input

The position of agent in the field and the view information are received from environment as a sensory input. As shown in Fig.6, the position of agent is divided into three area and inputted. The view of agent is expressed in the lattice space of 5×5. The position of ball, enemies and allies in a field of view can be recognized.

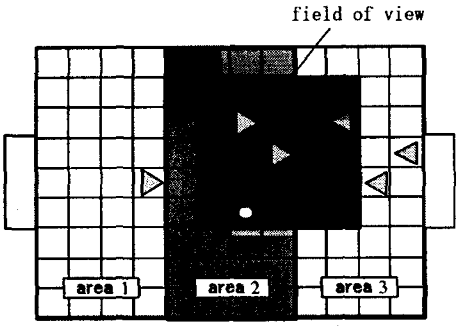

Fig. 6 Agent's area and view

D Rule composition

A rule is a production rule(if-then rule). The condition portion is expressed by the agent area in the field and the ally area, the ball area and the enemy area in the lattice space of 5×5 as shown in Fig.7. The rules fitting in sensory inputs are searched among the rule base, and each agent's action is done. As shown in Fig.7, if the agent area and the position of enemies, a ball, and allies in the view of agent are contained rule's each area, the rule fired. The case where two or more rules fired, it determines by performing roulette selection by reliability. In the action part, some action and directions are described. As shown in Fig.8, the length of an action part changes by the rule. Thereby, each agent determines action of two or more steps by select rule.

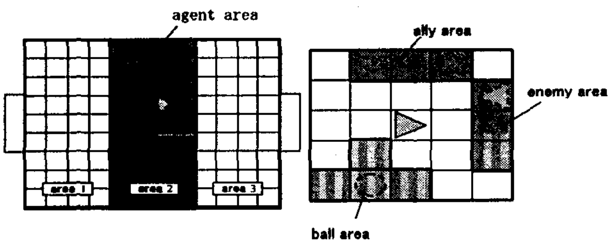

Fig. 7 The condition portion

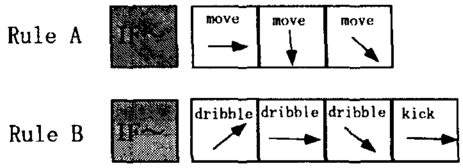

Fig. 8 The action portion

VI Results and Considerations

One game was finished in M = 50 steps. The game was done five times, then the team having more wins than losses is the winner of the match. The league match performed 10000 times by the four teams. The initial rules of teams 1 through 4 are generated at random.

As the simulation results, the rate of win of team 1 show in Fig.9. The rate of win is always increase and decrease repeatedly, and other teams's rate of win changed similarly. Next, examples of scoring and tackling are shown in Fig.10, 11 and 12. Fig.10 is the most appeared scoring pattern, the agent who keep the ball first dribbles to the enemy's goal. Fig.11 is a tackling pattern, agent who placed back of field stay around the own goal and tackled to the enemy who has approached. As shown in Fig.12, agent tackles near the center of the field and dribble to enemy's goal. In each team, these strategies were appeared and it was repeated periodically.

From the above results, each team acquired the effective rules with the rulebase by learning to correspond to the others, and each team's strength wasn't stabilized through the league. This is considered that learning of each team progressed according to scenario of coevolution.

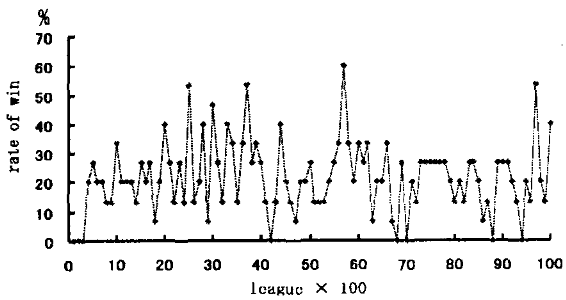

Fig. 9 The rate of win of team 1

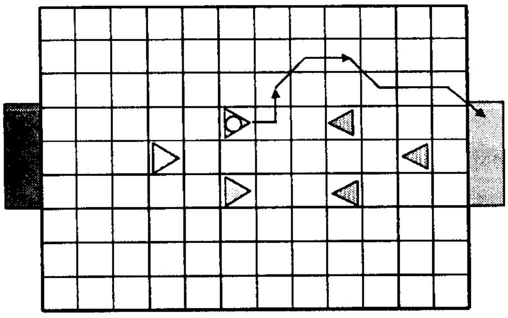

Fig. 10 The most appeared scoring pattern

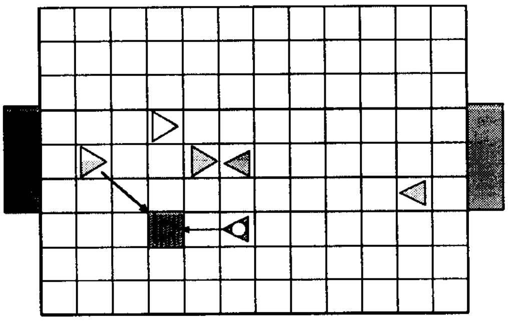

Fig. 11 The tackling pattern

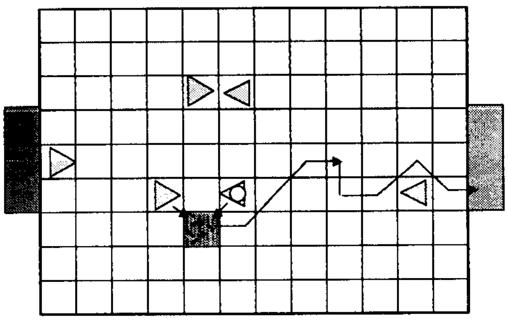

Fig. 12 The scoring pattern

VII Conclusions

In this paper, we propose a learning system by coevolutionary agents in two player game and experimented on the learning of agents in a group who repeats fighting each other with change of generations in the always changing environment. Every team could acquire the optimal action by coevolution and transition of strategies was able to be checked.

In the future, we aim at acquisition of more complex strategies and intend to propose the learning system which has improved an issue of coevolution such as stagnation of evolution and convergence to local minimum.

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