Team HillStone2016 in the 2DSimulation League Team Description Paper

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Abstract. Team HillStone has taken part in 2D simulation league of RoboCup Japan Open Competition from 2009 in Osaka. We adopted a defensive strategy of allocating player to a ball position, and use a ILP algorithm for an effective tactics searching. We discuss a possibility of the strategy and evaluation in our simulation.

1 Team History

Team HillStone is consisted of joint effort by two Japanese research groups:

Tamagawa University (TU): a group from the faculty of engineering at TU has joined RoboCup Japan Competitions since 2009. They got the best result (third rank) at RoboCup Japan Competition 2014 in Fukuoka. Members from TU are interested in a compliant human-machine interaction architecture based on human intention estimation by robots. This research is motivated by a desire to minimize the need for classical direct human machine interface and communication. The student members are all undergraduate, and receive professional guidance by Prof. Omori of TU.

Tokyo University of Technology (TUT): a group from the faculty of computer science, at TUT has joined RoboCup Japan Competition since 2014 in Fukuoka. A reason of their joining to RoboCup Competition was that a leading member, Dr. Watanabe, has moved to TUT from TU as an associate professor, and he broaden his experience there. Members from TUT are developing a software tool for an analysis of team strategy.

2 Team System Development

2.1 Development result in Tamagawa University



Fig. 1 System configuration diagram of soccer simulator

Figure 1 shows a system configuration of soccer simulator. TU students were not familiar to the simulator and its programming, we began understanding of the system. Currently, we are implementing a defensive formation and developing a one-two pass behavior. We are using the fedit version 2-0.0.0 for the defensive formation development, and are creating an allocation of players for the fedit2. A sample of created allocation is shown in Figure.2.



Fig.2 A sample of created player's allocation in fedit2.

Our strategy of defensive formation is to locate a player at a ball position where an opponent player must be there. By doing so, at least one player can press and defense to the opponent to prevent making effective pass or shoot.

But, the drawback also exists. Large stamina consumption occurs because the defense player has to run quickly toward the ball position when an opponent team player come into his defense zone. The other is a higher risk of foul because the running action is almost same as a tackling action. To avoid these drawbacks, as a future challenge, we should create a chain of cooperative actions program for the defenders until we join RoboCup World Championship. The program works as follows. In a case of opponent player carrying a ball into a defense zone, we plan our defenders come and enclose the ball holder from multiple direction to block all effective pass course.

2.2 Development result in Tokyo University of Technology

TUT student of our team member is developing effective attacking patterns for each of an opponent team by using an inductive logic programming (ILP). ILP is one of a machine learning method. Using the learning method, we expect obtaining an effective attacking pattern for a specific team from a set of 2D soccer simulation log data. So this method facilitates our attacking tactics more suitable for the team. ILP though not widely used the soccer tactics search, an evaluation of the learning result will give us new insights on an applicability of machine learning to the 2D simulation and an idea of new learning strategy.

In our intuition, it is not easy to find general rules that are suitable for a final shooting approach. For the problem, we developed a new algorithm that makes use of one more abstracted positional relationship between a ball holder and an opponent player [2015]. In an example in Figure 3, a learning result says "good action includes a long pass that send a ball from a center circle to a side player near the goal".



Fig.3. Examples of action chain extracted by a predicate logic

To evaluate effectiveness of the learning method, we executed 20 times of game simulation between our program and former HillStone program. The action chain hypothesis has successfully extracted from the log data. Other hypotheses extracted from the data were ones like "a good action includes a pass to ally when an opponent player is near" and "a good action contains a pass when the player is surrounded by the opponent players". We expect the extracted hypotheses reflect actual characteristics of the opponent team. Their evaluation is also our mission in RoboCup World Champoinship 2016.

3 References

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