Abstract. TsinghuAeolus, a RoboCup simulation team, is developed by the Tsinghua RoboCup Research Group. who interests cover both education and research. After five years research and development, TsinghuAeolus is making yet more improvement in the year 2005. In this paper we discuss recent advancements of our team, including a new opponent-modeling mechanism that has improved the adaptability for autonomous agents.

1 Introduction

TsinghuAeolus2005 is developed on the basis of our team in Lisbon. The overall design features reactive agent architecture with a decision-making mechanism and an advice-taking mechanism. Recently we have new progress in improving the opponent-modeling mechanism, and we shall be able to demonstrate its effects in TsinghuAeolus2005.

In the next section, we explain more about the opponent-modeling mechanism, and in section 3 we conclude with problems and our plan for future work.

2 Opponent-modeling Mechanism

Adaptability has always been a desirable property for autonomous agents. We have introduced online learning and external advice taking in our agent, but the performance is not good enough. So we recently focus our research on opponent-modeling, which could be a key solution for the adaptability.

What we've already done last year is modeling for individual opponent position. By figuring out the statistical relationship between opponent movement and ball position, we shall have greater accuracy in the forecasting of opponent positions that would make our world model more exactly. Based on this, we'll continue our research on the opponent formation, which is, how their agents pass ball to each other,
how their agents act during a specifically period, and so on. Such studies enable us to find the loophole of the opponent so as to adjust our parameters accordingly.

Opponent modeling for specifically scenes are also useful and worth for research. We choose some frequent scenes, in order to get enough statistics in one game, use Clang to describe them, so they could be easily recognized. Then, by analysing these data, we come to the probabilities of the opponent's various behaviors so that the agent will react more pertinent when matched to the scenes.

3 Conclusion

In this paper we mainly discuss how to achieve adjustable autonomy in TsinghuAeolus through opponent-modeling. While our approach has been proved effective in practice, there is still much room for improvement, because we can’t make an accurate model, so the agents can not always make use of it. We plan to acquire new models from new perspectives in future.

References

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