Susa 2005 Coach Description

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1. Introduction

The RoboCup coach competition mainly deals with an advice giving agent, advising a team of autonomous agents to perform better over time in front of an opponent. Recently in the 2005 Coach competitions, the structure of the competitions changed in a way to encourage team-modeling. Due to large changes made in the structure of the competitions teams need time to adapt themselves to the changes. The approaches we have used for this purpose are based on the team members' previous experience on coach competitions, and other related works in this domain.
According to the official rules, this year instead of having a coachable team playing against an opponent for the sake of better score, the team plays in front of a fixed opponent in which several playing patterns have been activated. The coach in this context is responsible for detecting the patterns and reporting them. The patterns are introduced to the coach in an offline phase, using .rcg log files. Our approach contains two phases:

1. Offline Learning
2. Online Exploration

2. Offline Learning

There are several works related to opponent modeling in RoboCup soccer simulation that make use of different approaches such as Markov modeling [1], Bayesian modeling [2], and several others.
Riley and Veloso [3] have tried to model high level adversarial behavior by classifying opponent actions belonging to one of the sets of predefined behavioral classes. Steffens [4] presented an opponent modeling framework, using this modeling technique. He assumes that some features of the opponent can be extracted and formalized using an extension of the coach language.
Based on competition conditions, we are trying to develop our previous works by using a combination of clustering and classifying methods. We are also going to implement a selection of the existing related works, and improve the approaches in our experiments.

3. Online Exploration

The result of offline Learning is saved in the pre-designed knowledge-base. During the second phase which is called online exploration, the coach agent designs a series of scenarios based on the available knowledge-base and converts them into CLang format. These scenarios are then sent to the coachable players dynamically. The rationale behind using each of these scenarios is to test one or a combination of some pre-recognized patterns. In fact they provide all of the possible conditions for the opponent team and the coach monitors the players' actions. By this means the special features of opponent players' behaviors are extracted. The patterns can be detected by applying classifying methods.

References

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