RoboSina 2004 Team Description

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Abstract. RoboSina 2004 soccer simulation team is the result of a research project in Bu-Ali Sina University. In its first attempt, RoboSina achieved 10th place in the RoboCup 2003 world cup. Many improvements have been made on this team compared to its preceding edition, RoboSina 2003, especially in the higher-level strategies. This paper describes the main features of RoboSina 2004 as well as the improvements that have been made on this team.

1 Introduction

RoboSina 2004 is a soccer simulation team that participates for the second time in the RoboCup world cup. In its first participation, RoboSina ranked 10th among 48 teams participating the simulation league of RoboCup 2003 world cup in Italy. RoboSina is the result of a research project funded by Bu-Ali Sina University in Iran. The research group consists of four undergraduate students as well as an instructor who serves as the head of the research group. From the beginning, the group members decided not to copy codes from other RoboCup teams because most of the released source codes were not well structured and in most cases, they were not so efficient and optimized. Most of lower level parts hence have been redesigned and reprogrammed by our team members.

Having studied the low-level methods used by some previous top teams such as CMUnited, UvA Trilearn, and TsinghuAeolus [2, 3, 6], we provided several essential ideas to improve the existing low-level methods and implement them in our team. Although our higher-level strategies were very simple in the first stage of developing the team, having powerful low-level skills such as dribbling and accurate localizing made RoboSina a successful team in RoboCup 2003.

Since then, we have made several improvements in both low-level and strategy-level skills of our team. Using neural networks to achieve a more reliable scoring policy, employing reinforcement learning to obtain an enhanced blocking strategy, and utilizing Matrix Decision method to reach a more precise way for updating visual information in the world model are some of our new improvements applied to RoboSina 2004. The main features and improvements of RoboSina 2004 are addressed in the remainder of this paper.

2 Improved Localization Algorithm

One of the most important tasks for a mobile agent is to find its location in the field using visual information. Because of existence of noise in our perception information, an agent must have ability to find its location in such an environment with the least possible error. We have made a substantial effort on providing a good algorithm for localizing a player agent in the soccer simulation environment, which leads to a fast $O(n \lg n)$ time algorithm, where n is the number of flags visible in the field. We have used some *computational geometry* algorithms for intersecting convex polygons and adopt them to reach a very fast and accurate localization algorithm.

Our algorithm constructs a convex polygon corresponding to visual information obtained from each flag in the field. The algorithm then employs a *plane sweep* method in which a sweep line is moved downward over the plane and maintains the convex polygons intersecting it. Using a divide and conquer method, we developed an $O(n \lg n)$ time algorithm to compute the intersection of n convex polygons, which is a good approximation for the exact position of the player. The error of our algorithm is considerably smaller than what have already reported by many other teams. Details of our method can be found in [8].

3 Enhanced World Model

The world model of each agent is a probabilistic representation of the world state based on past perceptions. The world model is updated when the agent receives new information about the objects in the field. Unseen objects are also updated based on their last observed velocity.

In our new improvement, for each agent of the team we find a region in the field that has the most valuable data for updating the world model. To achieve this, the filed is divided into several regions by means of a gridding algorithm, and then, a very fast algorithm is used to find the 'best' region for an agent to look at.

4 Higher-Level Strategies

Our higher-level strategies were very simple in RoboSina 2003, however, we have made many improvements in the strategies in RoboSina 2004. Some of these improvements are addressed in the following subsections.

4.1 Scoring Policy

We have developed a new scoring policy for RoboSina 2004 using *neural networks* [5]. The scoring policy determines whether an agent that holds the ball attempts to shoot at the goal. It also determines the best target point in the goal, along with a probability of scoring when the ball is shot at that point. We adopted the idea of [1] to develop a new scoring policy using neural networks. We have employed a two-layered back-propagate neural network that uses tgsigmoid function in its first layer and logsigmoid in the second layer. The space before the goal is divided into 16 regions. In the training phase, the agent tries to shoot at each region more than 5000 times. According to the relative distance and relative direction of the agent to the goal and the position of the opponent goalie, the agent is either successful or unsuccessful in scoring. The network is then trained by the obtained results and the scoring regions are marked as good regions for shooting. Using this method, the percentage of successful scoring attempts of our team is raised to 75% of the shooting attempts.

4.2 Blocking Skill

Another improvement in the high-level skills is developing an enhanced blocking skill using *reinforcement learning* [4, 7]. This skill prevents an opponent to move with ball toward our goal, better to say, it enables our agents to stop a dribbler opponent. We tried to use reinforcement learning to define a *state and action space* and train our agents to select the best action in each state. In our first model, each state was defined by seven parameters, namely opponent's relative distance and direction, ball relative distance and direction, relative velocity of opponent and ball, and opponent's body direction. Such a detailed model resulted in a substantial growth of state matrix and a large amount of computation effort. To make it better, we reduced the state space by transferring the space to a vector space. Our new policy leads to a significant reduction of state space and also an easier method for state recognition. We are going to develop this idea to make it more powerful for this year competitions.

4.3 Linear Defense

Having collected soccer knowledge from some expert players and coaches, we also developed a new defensive strategy for our team. In this strategy, four defenders are organized in a linear arrange such that they can block many penetration that may be used by opponent to attack our goal. This strategy is used in real soccer to prevent attackers from moving toward goal easily. This strategy also enables a team to break an attack by putting the opponent attackers in 'offside' position.

4.4 Man-To-Man Marking

Another strategy that is implemented to be used by our team according to the status of the game is a *man-to-man marking* strategy in which each agent from the opponent team having the opportunity of scoring a goal is guarded by exactly one of our team agents such that it can not move closer to the goal, or send and receive a pass.

5 Conclusion and Future Plan

In this paper we have discussed the main features and improvements of RoboSina 2004 soccer simulation team. Our lower-levels are currently works reasonably and many improvements have been made on higher-level issues. Our future research will mainly focus on improving our higher-level strategies, using machine learning techniques and probably employing a coach to analyze the game and give advice on the best possible strategy.

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