Soccereus 2D Simulation Team Description Paper

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Abstract. *Soccereus is a 2D soccer simulation team established by a group of undergraduate students of Sharif University of Technology. The object of this cooperation was to utilize the theoretical concepts of Artificial Intelligence in a practical field. In general soccer simulation different skills are intrinsically undeterministic. this feature makes this field a proper one for examining new Ideas. In this paper we present two new AI based approaches for enhancing the performance of shooting and dribbling actions. In practice the revised methods of shooting and dribbling result in an improvement in scoring and dribbling chances.*

[keywords] Neural Network, Artificial Intelligence, Reinforcement Learning, Dribble

1. Introduction

Robocup simulation 2D is an attempt to foster AI, robotics and other related fields through examining and integrating wide range of new strategies and techniques in a standard and interesting problem. Soccereus ,a team of five student absorbed in this area, was first created in 2011. The first attempt of the team was to develop a team on Agent2D base by H.akiyama with totally revised high level actions. Currently the team has the goal of undertaking research into areas of Machine learning and neural network with the ambition of developing a completely AI based team. The subject of this paper is to introduce techniques employed in this team specifically to propose a neural network based shoot action as well as a dribble skill that is developed by a reinforcement learning approach.

2. Overview

First in Sec.3 we express the developed method for improving the agent shooting skills and in Sec.4 we introduce a new approach for the action of dribbling.

3. Shoot

The result of a game specifically relies on the scoring ability and this makes shooting one of the most important high level skills that should be developed thoroughly. At first we implemented this action by considering motion models of ball, defense opponents and goalie in the field [5]. This approach was similar to what Riton [3] has done in extracting possible shoot points. Since all the factors that have an impact on success of scoring are unfeasible to be taken under consideration, we reached to a limit in enhancement of the method. Therefore, we decided to adapt a new approach. Since artificial neural networks (ANN) has been a popular option for data classification we employed its concepts to train the agent choosing the best parameters for a shoot.

3.1. Designing the training set

One important and basic step is designing a training set that covers all situations likely to happen. For this aim we placed the under training agent ,uniformly in a continuous environment in the penalty area. Moreover, the opponent goalie is placed randomly in active penalty area . Figure.1 shows one shot of a training episode.

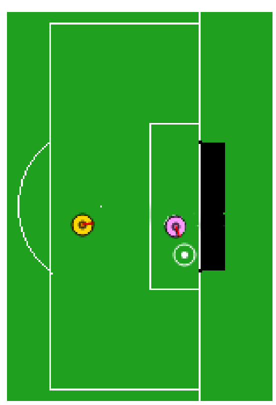

Fig. 1: A sample capture from shoot training environment

3.2. Structure of the network

In construction of our neural network input, following criteria are taken into account.

- Angle between goalie and ball path
- Angle between goalie neck and ball path
- Distance between goalie and ball
- Distance from ball to goal in ball path direction
- Ball initial velocity

The single output of the network is a Boolean determining if a goal is scored or not And based on this result sample data is classified into two classes. The network architecture is composed of an input layer with five inputs as described above, one hidden layer contaning five neurons, and an output layer of a single neuron. The activation function for all the neurons in hidden layer are linear and output layer employes the Binary Sigmoid function. It is worth to mention that for sake of accurate and fast training of such a network and because of existence of various types of dimensionalities in the input data, the step of data normalization plays an important role.

Below we compare the results of this method to results of the earlier method used in the team. The two charts in Figure.2 demonstrate the outcome of 500 rounds of shoots to the opponent goal, when kicker and opponent's goalie are randomly placed in the penalty area, as described earlier in this paper.

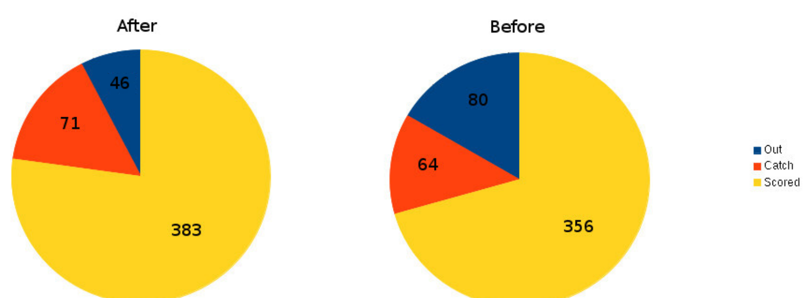

Fig. 2: Comparison of results from the old shoot algorithm with the neural networks based one.

4. Dribble

Dribbling skill is finding the appropriate angle and power for kicking the ball forward and intercepting it. But these factors should be determined based on opponent different actions and should suit different situations in the field. Although visually recognizing a dribble path for the agent is feasible like what [eskilas] has done, finding a completely machine-based solution for determining formerly mentioned factors led us to difficulty. Finally we reached the decision to train the agent in the environment and reinforcement learning(RL) was the proper choice. TD reinforcement learning is a branch of reinforcement learning which enables the agent to learn from the experience without having any knowledge about the dynamics of the environment. This feature makes this method the most suitable choice for dribble training.

4.1. Environment modeling

The agent environment modeling is composed of a set of states, actions, rewards and a policy which relate each state and action pair to the next with an immediate reward. Designing this discrete interface is the first step to take.

states of the environment are defined as an ordered pair of distance and angle from the opponent. As mentioned before, action of the agent is an ordered pair of angle and power to kick the ball. due to the fact

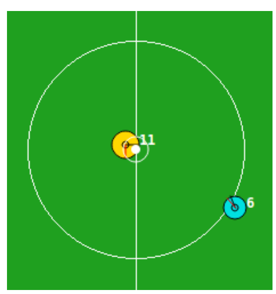

Fig. 3: A sample capture from dribble training environment.

that in TD no knowledge of the environment dynamics is supposed to be available, an action-value function is needed rather a value function. For the starting policy we set a constant value to the power and we used the angle predicted form our former dribble implementation[5]. We have employed the sarsa on-policy TD control, which updates every $Q(s_t, a_t)$ By the following relation:

$$Q(s_t, a_t) \hookleftarrow Q(s_t, a_t) + \alpha \left(r_{t+1} + \gamma Q(s_{t+1}, a_{t+1}) - Q(s_t, a_t) \right) \tag{1}$$

5. Conclusion

In this paper we proposed two new learning mechanisms for implementing dribbling and shooting skills ,in which we found room for improvement. These approaches utilized different areas of Artificial Intelligence such as reinforcement learning and neural networks. Both mechanisms showed reasonable results and in some cases, improvement to last hardwire implementation was vivid. Our study focused on dribbling skill to be improved by reinforcement learning. However, enhancement to other stochastic skills that extensively rely on complex factors of environment, such as blocking, is very likely. Moreover, our future plan is to detect the opponent formation and analyze defense holes to find the best way of penetrating in defense area. Moreover handling the noise in the environment is a consideration demanding issue.

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