Using Fuzzy Logic to Build a Heterogeneous Multiagent System for the Robotics Soccer Problem

Marco A. C. Simões[1, 2], Helder Guimarães Aragão[2], Victor Souza[1], Simon Viegas[2], Hugo da Luz Silva[1], Jessica Meyer[1]

[1] Computer Architecture and Operating Systems Group(ACSO)
State University of Bahia (UNEB)
Rua Silveira Martins, 2555, Cabula. Salvador – BA – Brazil

[2] Intelligent Computing Research Group(GPCI)
University Center of Bahia (FIB)
Rua Xingu, nº. 179, Jardim Atalaia/STIEP. Salvador – BA – Brazil

marcosimoes@fib.br, {helderfib, okvictorok, simonpiata}@yahoo.com.br, {hugodaluz, jessy.meyer}@gmail.com

Abstract. *This paper presents the initial research results of Bahia Robotics Team. This is a new research group created to investigate the application of artificial intelligence methods in the standard problem of robotics soccer. In this work, fuzzy controllers are used to improve some abilities of the players. In the case of the attackers, the kick and the positioning ability were improved. The midfielders had their positioning and passing ability improved. The goalkeeper and the defenders had their positioning ability improved. The generated Bahia2D soccer team was tested in matches against some victorious teams from Robocup Brazil Open 2006 and from previous editions of the Robocup World Competition. The positive results achieved and the ongoing works to improve the current limitations are also presented.*

Key Words: *fuzzy logic, simulation, robotics soccer*

1. Introduction

This paper presents the first results of the research project under development by Bahia Robotics Team(BRT) consortium. BRT represents the union of the Computer Architecture and Operating Systems Group(ACSO) and the Intelligent Computing Research Group(GPCI), in order to investigate the application of artificial intelligence methods to autonomous robots, as proposed by Robocup international research initiative. At this moment, BRT is working on the development of a team for the 2D Soccer Simulation League.

Robocup World Federation organizes international robotics and artificial intelligence competitions and symposiums. The main goal of this research initiative is to investigate the use of artificial intelligence methods in autonomous multiagents systems. Robocup presents a standard problem which is investigated by researchers from many countries over the world. The standard problem is robotics soccer. The goal is to have autonomous agents controlling a robot making it able to play a soccer match with its teammates. There are many different categories divided in leagues. This paper focuses on the simulation league, especially on the 2D simulation sub-league.

This work presents studies, models and application of fuzzy controllers to intelligent soccer player agents. The goal is to develop fuzzy controllers for specialized agents in the positions: goalkeeper, center defender, wing defender, defensive midfielder, offensive midfielder and attacker. As a first work, the focus is only at kicking, passing, positioning and decision taking abilities at the controllers. At this stage, the Bahia2D team is composed by reactive agents.

This study is not worried about environment modeling details. For this reason, a base team to treat environment modeling and communication details was chosen. The UvA Base source code is used as base team. This code is also the base of UvA Trilearn 2003 [1,5], world champion team of the Robocup 2D Soccer Simulation League in 2003. This code was chosen because of its availability, quality of its world model and good abstract interface to send commands to simulator.

The next section describes the motivation to use fuzzy logic and the fuzzy controllers used to Bahia2D´s autonomous agents. Section 3 discusses the results and section 4 presents the conclusions and future works.

2. Fuzzy Controllers for Robotic Soccer Agents

The approach presented here is based on fuzzy logic controllers [4,6,9,10,11]. Fuzzy logic was chosen because of the imprecise nature of information available in robotics soccer. For example, when an attacker robot kick the ball to opponent goal, it must see if the opponent goalkeeper is on left, center or right so it can kick as farthest as possible from the goalkeeper. But there is no precise numeric definition for the linguistic terms left, center, right or far from goalkeeper. This example illustrates the imprecise nature of information that must be used in reasoning process by autonomous agents.

This section describes the first fuzzy models built from scratch by BRT. After some tests, it was decided to use the 4-3-3 offensive formation. When this formation is used, Bahia2D gets its best results. Hence, Bahia2D has one goalkeeper, two wing defenders, two central defenders, one defensive central midfielder, two offensive wing midfielders, two wing attackers, and one central attacker.

2.1 Controller for Kick Positioning

The main objective of this controller is to find the position in the opponent goal to kick with the best chances to score. To decide where to kick, the agent will take in consideration the opponent goalkeeper position and his own position. The output variable is *kickposition*, it has values between -7.0 and 7.0, which represents the y-coordinates of the opponent goal. The x-coordinate is the field limit, the same as the goal line, it will always be 52.5. Figure 1 represents the linguistic terms used for this variable during fuzzy reasoning process.

Input variables for this controller are *goalkeeperPosition* and *kickerPosition*. They also refers only to the y-coordinates, Figure 2 illustrates its linguistic terms. The min and max values ranges from -7,0 to 7,0 respectively.

The rule base for this controller was created using the combination of the input variables; it intends to find a position at the goal the farthest from the goalkeeper and the closest to the kicker as possible. At first, only the three attackers used this controller. Then, the offensive midfielders stated using it as well, when they are in a good position to kick to the goal.

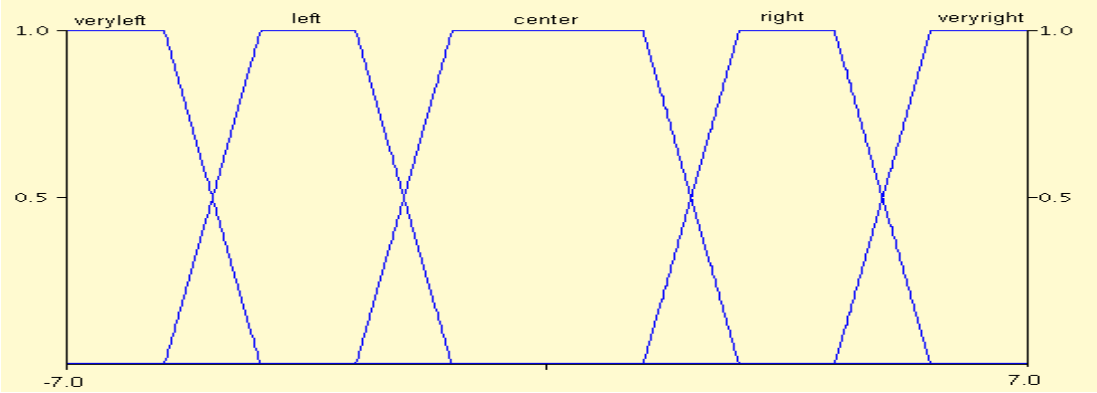

Fig. 1. Linguistic terms for goal position in the y-axis

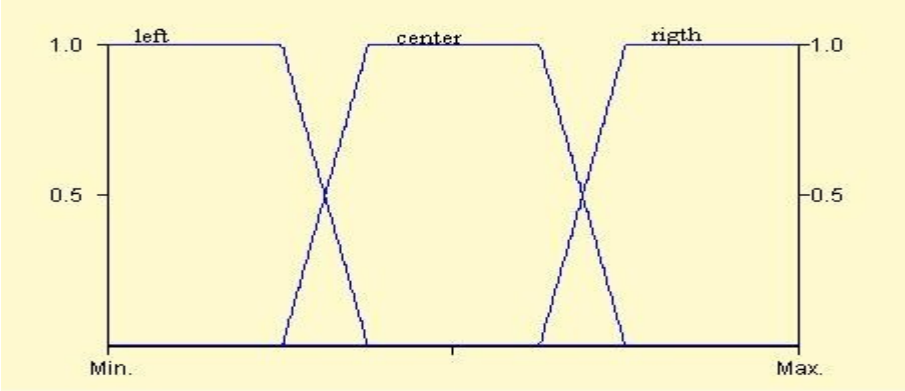

Fig. 2. Linguistic terms for position of agent in the y-axis

2.2 Controller for Attacker Positioning Without Ball

The objective of this controller is to allow the attackers, without ball, to find a position in the opponent's field, based on his own position, on the offside line and on the ball position. There was used a field division approach[1,7] where the opponent's field is divided into 9 zones.

The output variables used by the controller are the x-axis position and y-axis position, which represent the final positions that the agents should go to. Figure 3 shows the linguistic terms used for the x-axis variables. Figure 2 shows the ones for the y-axis, within the range -34 to 34.

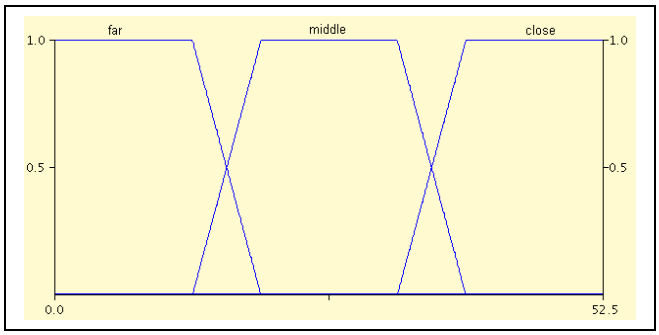

Fig. 3. Fuzzy sets for the x-axis variables

The input variables are the player position, the ball position and the offside position on the x-axis.

The rules for this controller were created in a way that the agent could only move to adjacent quadrants. The movement occurs in shorts distances, because in each cycle the

perceptions can change and so the direction that the agent should move. For example, an agents positioned at the 8th quadrant can only move to the 4, 5, 6, 7, 8 or 9th quadrant, because he can't make to the 1, 2 nor 3rd quadrant within the next cycle. This was defined by creating rules that have the same values for inputs, but different outputs and weights. The rules that make the agent stay at his quadrant, when the ball is at another, have lower weights, making him always move into the ball direction.

2.3 Controller for Offensive Wing Midfielders Decision Taking

The objective of the Fuzzy controller for the offensive wing midfielders is to decide what he should do when in ball possession. The attacker should make a decision analyzing his global position, the distance to the closest opponent, the distance from the closest teammate to the opponent goal, the number of opponents near the closest teammate, and his distance to this teammate. The output variable is a value, and depending on its range, a decision to kick, dribble, pass, pass through or conduct is made. The domain of the output variable varies between 0 and 5, and each range represents a decision.

Figure 4 represents the linguistic terms used for the variable of the number of opponents. Figure 5 represents the linguistic terms used for the variables distance from agent to closest opponent, distance from agent to the goal, distance from the closest teammate to the goal and distance from agent to closest teammate. Figure 6 illustrates the domain of the output variable that represents the offensive wing midfielders' decision taking.

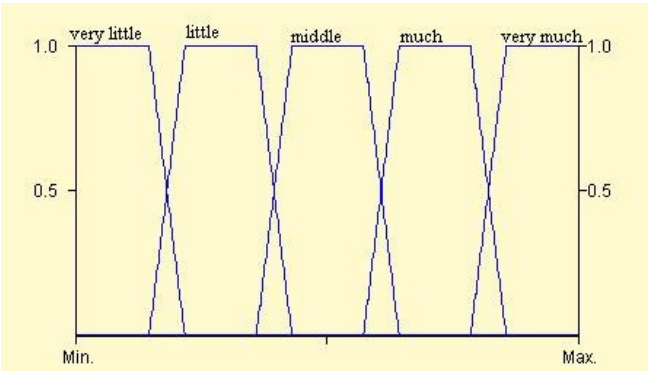

Fig. 4. Domain for number of opponents near teammate agent variable

The rules for the controller were created from the combination of the input variables, always aiming to decrease the possibility of losing the ball and to increase the chances of scoring.

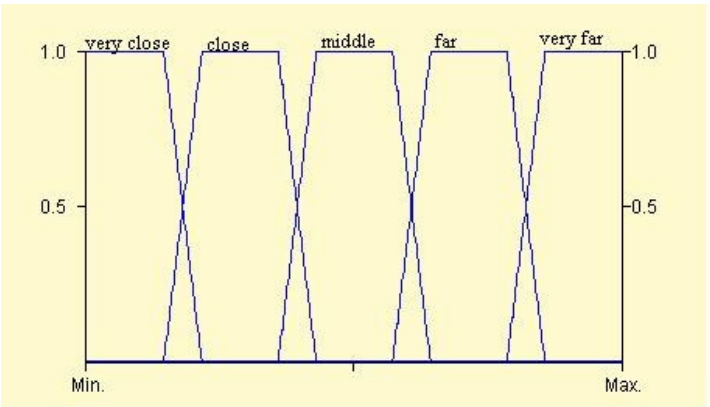

Fig. 5. Domain for variables: distance from agent to opponent, distance from agent to opponent goal, distance from closest teammate to opponent goal, and distance from agent to closest teammate.

2.4 Controller for Defensive Center Midfielder Positioning

The defensive midfielder has a fuzzy controller, whose objective is to settle strategically the player in his actuation area, taking the ball and his own position in consideration. There were defined two rule bases: one for the x-axis and another for the y-axis.

The x-axis tactics is to move the player in the direction of the ball, its intensity depends on the ball and player global positions, that is, depending on the position of each object, the player will tend to get more, or less, close to the ball.

For the y-axis the movement occurs in a similar way as for the x-axis, but also taking the y-coordinate in consideration. Furthermore, the x-coordinate of the ball is added to the rule base and has an expressive weight over the final positioning decision. The farther the ball is from his field, the more the midfielder will tend to stay at the center, avoiding, then, unnecessary moves.

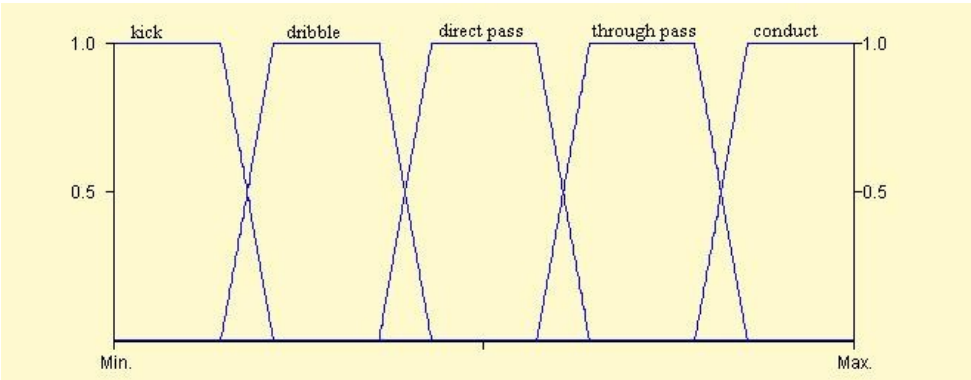

Fig. 6. Domain for offensive midfielders' controller output variable.

The domain for the y-axis was defined between -40 and 0. However, when this model was implemented the agent's behavior was not the one desired, because the defensive midfielder has been positioned between the two center defenders. To correct this bad positioning, there was made an empirical adjustment of 15 meters to the right, modifying the domain within the range -30 to 15.

2.5 Controller for Wing Defenders Positioning

The objective of this controller is to allow the wing defenders without ball to move along the defensive field laterals. The controller makes the wing defender always attracted to the ball. This way, when the ball goes to the opponent's field, the wing defender goes after it until almost half of the opponent's field. This behavior makes the wing defenders defend or attack, depending on the ball position.

The output variables used by the controller are the x-axis position and y-axis position, which represent the final position that the agents should go to. The x-axis variables have the following linguistic terms: near (-45 to -15), middling (-15 to 15) and far (15 to 45).

2.6 Controller for Central Defenders Positioning

The objective of this controller is to allow the central defenders without ball to position themselves searching for the ball and staying at center of the defensive field. For this controller the y-axis was divided into two zones, *LeftCenter* and *RightCenter*, making him stay at the defensive center, leaving the laterals for the wing defenders.

The output variables used by the controller are the x-axis position and y-axis position, which represent the final position that the agents should go to. The x-axis variables have

the following linguistic terms: near (-45 to -28.125), middling (-28.125 to -11.25) and far (-11.25 to 0). The y-axis variables have the following linguistic terms: Left (-34.0 to -19.428), *LeftCenter* (-19.428 to -4.85), Center (-4.85 to 9.71), *RightCenter* (9.71 to 24.28) and Right (24.28 to 34).

2.7 Controller for Goalkeeper Positioning

The goalkeeper moves to a certain position of the goal, as he notices that a player from another team is in a kickable distance from the goal. Depending on which direction comes the player and on his own position, the goalkeeper reacts according to a rule base defined with the XFuzzy, moving to a pre-established range of coordinates. In case the attacker is too close from the goal, he assumes a different pattern, more appropriated for the situation.

The *PosGoalie* and the *PosPlayer* are the input variables for the rule base *Catch*. According to these variables, the rule base provides an output variable called *PosCatch*, which is exactly the position that the goalkeeper should take to catch the ball.

After some tests, this model was considered incomplete, because it defines only the goalkeeper position into the y-axis. It lets the goalkeeper too ahead of the goal in situations when the ball comes from the lateral or fouls.

3. Partial Results

The chosen method to validate the fuzzy controllers described on section 3 was the execution of simulated matches between Bahia2D and the following teams: UvA Trilearn Base, UvA Trilearn 2003, MecaTeam[2], Brainstormers[8] and Dainamite[3]. The controllers were added little by little. This way, it was possible to study each controller effect to the players' performance and team performance.

Initially, only the kick controller and attackers positioning controller were added. With this configuration, there were simulated ten matches against each opponent, totaling fifty matches. Bahia2D has won ten matches and has lost forty. In all the matches, Bahia 2D has scored twenty eight goals (0.56 goal per match) and it has suffered 461 goals (9.22 goals per match). During the matches against UvA Base, Bahia2D attackers had their best performance, increasing their number of kicks to goal, number of goals scored and number of victories. Matches against MecaTeam have been quite poised with 0.9 goal scored per match and four victories.

Table 1. Goals per 100 Kicks statistics in the first fifty matches

	Bahia2D	UvA Base	Mecateam	UvA 2003	Dainamite	Brainstormers
Goals/ 100 Kicks	6,52	6,03	5,45	65,57	60,30	48,94

The other opponents are more complete and experienced teams and defeats were expected because only the three attackers agents were implemented, at this stage. However, three goals have been scored against Dainamite.

Table 1 presents a statistic of goals per 100 kicks during these fifty matches. It is clear the evolution of Bahia2D when compared to its base team (UvA Base). It is also noticeable a little superiority when compared to Mecateam. UvA 2003, Dainamite and Brainstormers are in a much higher level of performance. Figure 7 illustrates an example of a goal scored by Bahia2D in a match against Dainamite. The attackers are the players number 9, 10 and 11 that are marked.

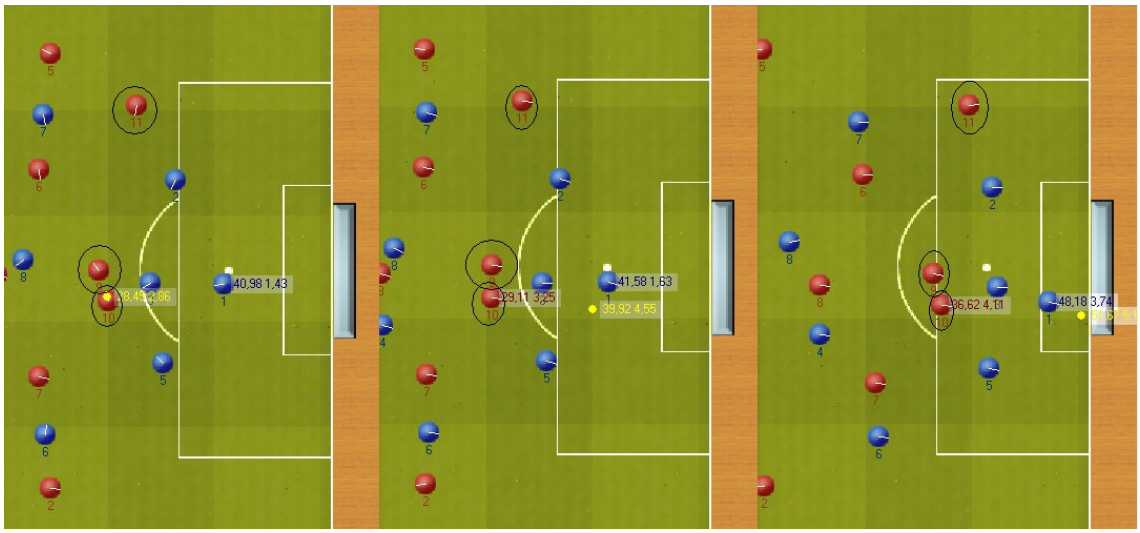

Fig. 7. A goal scored by Bahia2D against Dainamite

As a first evaluation of the kick controller, the results were considered positive in matches against UvA Base and MecaTeam. But there is strong evidence that is necessary to develop a more sophisticated strategy using passes, for example, to win matches against higher level teams as UvA 2003, Dainamite and Brainstormers.

The evaluation of the attackers positioning controller is more difficult. However, during the matches it is easy to notice that all offsides occurrences are in situations where the opponent defenders move forward a little time before the pass to Bahia2D attacker. In UvA Base implementation is common to see attackers staying in offside position during a long time.

After the attackers' evaluation, the other controllers were added to the team. With this new configuration there were simulated six matches against six different teams: YowAI2005[12], MecaTeam, Dainamite, Brainstormers, RoboSina[13], and UvA 2003. There were also simulated other six matches of UvA Base against these teams. The objective is to compare Bahia2D performance with its base team when playing against the same opponents.

In this new round of tests, the first measurement was the amount of wrong passes on each position. In table 2, it is possible to verify that only Bahia2D's wing defenders and offensive midfielders had a best passing performance than UvA Base's correspondent players. Offensive midfielders are the unique player type in Bahia2D that use a fuzzy controller that try to increase passing quality. These players only try to pass the ball to a teammate when its perception indicates that that is a well positioned teammate to receive the ball. These results indicate that the pass quality of offensive midfielder (and other players in future implementations) can be increased using fuzzy controllers.

Bahia2D goalkeeper never passes the ball to the wing defenders. He only passes to the central defenders or the defensive midfielder, depending on their position. For that reason, the wing defenders of UvA Base have more ball possession than Bahia2D's wing defenders. This fact should explain the apparent best result for Bahia2D in this statistic for this specific position. For all others player types where no passing improvement were implemented, UvA Base had a best pass performance.

Table 2. **Number of Wrong Passes for each player type in Bahia2D and UvA Base teams during the six matches each team played against the six opponents used in tests.**

Position/Wrong Passes	Bahia2D	UvA Base
Wing Defenders	33	66
Central Defenders	82	46
Defensive Midfielder	53	38
Offensive Midfielders	47	63
Attackers	165	140

The next result measured was the amount of kicks to opponent goal that each team executed during the six matches. Bahia2D tried 36 kicks and UvA Base performed 98 kicks. From this result and the pass quality metrics in table 2, it is possible to conclude that with Bahia2D the low quality of pass present in many players is responsible for the difficulty to get the ball from defensive to offensive pitch. It is possible that, enhancing pass quality of other player types, Bahia2D´s players get more kick opportunities.

The last result presented in this paper is the evaluation of the goalkeeper performance. For this purpose, two measurements were performed. The first measure is the percentage of correct passes in ball repositions executed by each goalkeeper. Bahia2D goalkeeper had 75% of correct passes against 53% of UvA Base goalkeeper. Although 25% of errors in ball reposition is an undesirable statistic, it is evident the improvement of this Bahia2D goalkeeper reposition when compared with UvA Base. This enhancement was implemented thru a hand-coded routine that chooses a player between central defenders and defensive midfielder to pass the ball. The routine chooses the player that is best positioned with fewer opponents close to it. There is also evidence that using a more intelligent method is possible to increase this statistic.

The second measure is the percentage of successful defenses executed by the goalkeeper when the opponents kick to goal. Bahia2D had 41.3% of successful defenses against 42.5% of UvA Base. Although, these numbers indicates an equal performance of both goalkeepers, it is important to notice that opponents executed 184 kicks against Bahia2D goalkeeper, while the same opponents performed only 113 kicks against UvA Base goalkeeper.

These results confirmed the first impression that the goalkeeper fuzzy controller is incomplete. It lacks a better positioning in the x-axis and a better ball reposition strategy.

4. Conclusions and Future Work

This paper presented the first results of fuzzy controllers developed to build a reactive level of Bahia2D team's agents. The tests performed and described in section 4 demonstrated that is possible to enhance some abilities using fuzzy controllers.

It should be noticed that pass quality of offensive midfielders, positioning of attackers and kicking quality were enhanced when compared to base team. It is clear that these abilities may be enhanced with future work in these controllers and new controllers.

Another important conclusion is that the pass quality is a fundamental ability to overall team performance. The greater difficulty of Bahia2D's players is to take the ball to its offensive field, because the defensive players don't have a good pass quality.

As future work, BRT will study new enhancements in pass quality as priority job. To achieve this goal, enhancements to current fuzzy controllers and use of other methods

such as, neural networks, reinforcement learning and evolutionary computing will be considered.

Another important future work is to complete the goalkeeper fuzzy controller for best positioning and build a ball reposition intelligent strategy. Bahia2D team also lacks a communication level in its agents that would make the players able to communicate each other. This work will turn Bahia2D's agents in a complete multiagent system. Learning strategies should also be used to permit adaptation when faced to unexpected situations during the matches. A strategy to deal with fouls is also a desired future work.

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