BAHIA2D 2009: TEAM DESCRIPTION FOR BRAZILIAN ROBOCUP OPEN

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Abstract— This paper describes the history of Bahia2D team and our research in multiagent systems and artificial intelligence. Current and recent work are described and some future work is discussed. Basic abilities and coach strategies are the main topics described on this paper. The most recent work is the new abilities for the defensive system.

Keywords— Bahia2D, RoboCup, Simulation, fuzzy logic, genetic algorithms, coach

1 Introduction

The Bahia2D team has been developed by Bahia Robotics Team (BRT) research project since the second semester of 2006. BRT is coordinated by Computer Architecture and Operating Systems Group (ACSO in Portuguese) and its goal is to investigate the application of artificial intelligence methods to autonomous robots, as proposed by RoboCup international research initiative. Since 2007, BRT also started working on RoboCup's Mixed Reality sub league (MR) with BahiaMR team(Simões et al., 2008). This year, for the first time, the group also has a 3D simulation team: Bahia3D.

Within Brazil, our work has achieved some good results. At RoboCup Brazil Open 2007 we won the third place with 2D, and were the champions for MR. In 2008, our 2D team was runner-up, and achieved championship again on MR.

This TDP focuses on the Bahia2D. The present team represents an initial stage of this project, in which we have looked for acquiring experience with the environment and some renowned AI techniques. Therefore we addressed our efforts on improving the UvA trilearn ability layer(de Boer e J. R. Kok, 2002), used as our base agent, and took our first steps on developing the coach. For such activities we applied geometry, logic, fuzzy logic and neural networks approaches. The next section explores main results achieved with our soccer players agents. Section 3 refers to our work implementing the coach. In section 4 is described our current work and conclusions.

2 Abilities

Zadeh proposed Fuzzy Logic in 1965 to represent uncertain and imprecise knowledge (Zadeh, 1965). Fuzzy Sets Theory is a way to specify how much an object satisfies a vacant description. Fuzzy logic strengths come from its capacity to derive conclusions and answers based on vacant, ambiguous, incomplete and imprecise information.

In the beginning of the project, for reasons described on (Simões et al., 2007), we have decided to apply fuzzy logic(Zadeh, 1965) to improve Bahia2D performance. Primarily we focused on offensive behaviors: positioning without ball, passing quality evaluation and scoring possibility evaluation are examples of routines developed; the two latter form the basis for decision making routine when a player is in the offensive zone.

Another goal was improving defensive behavior. We thus implemented a marking routine that proved a good opportunity to apply neural networks(Kasabov, 1998). In addition, a fuzzy controller for goalie positioning, which also had ball reposition improved.

Finally, several advances were achieved from empirical observation and geometric analysis that increased several routines, such as goal kicks and crossings. This allowed us to improve global performance in a short period of time. Some of the above routines are described in next subsections.

2.1 Scoring Possibility Evaluation

This routine was implemented using a fuzzy controller that indicates scoring possibility. Its output is the variable Kick Possibility, which ranges from 0 to 10 and has the following terms: *Low* (0 to 3.75), *Average* (3.75 to 7.5) and *High* (7.5 to 10). Factors that affect the output are the distance and angle from the agent to the goal and opponents number within goal trajectory.

Some linguistic variables used for analysis are: *Close* (0.0 to 35.125), *Average* (35.125 to 50.25) and *Far* (50.25 to 67.0) to distance, *Best Angle* (-45.0 to 45.0) to the angle and *Few* (0 to 3), *Average* (3 to 6) and *Many* (6 to 11) to the amount of opponents.

2.2 Passing Possibility Evaluation

Through another fuzzy controller, we provided agents with the capability to measure success chances of

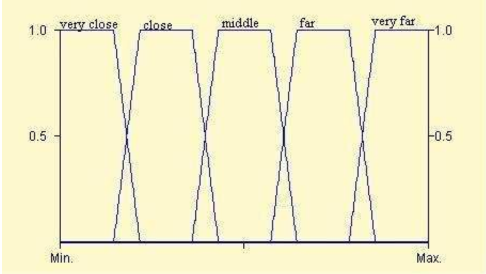

Figure 1: Domain for variable: Distance from agent to opponent goal

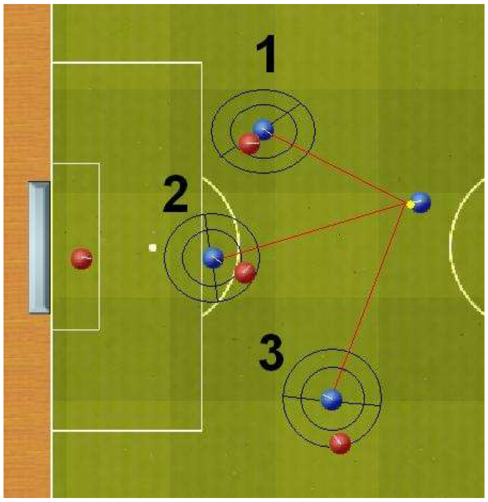

Figure 2: Analysis to see if a teammate is marked or not

passing the ball to a given agent. The controller's output is the variable Pass Possibility, which ranges from 0 to 10 and has as terms *Low* (0 to 3.75), *Average* (3.75 to 7.5) and *High* (7.5 to 10). Factors that influence such measure are distance, amount of possible interceptors and teammate's position.

Some linguistic variables used are *Close* (0.0 to 14.25), *Average* (14.25 to 25.5) and *Far* (25.5 to 30.0) to the distance, *Few* (0 to 3), *Average* (3 to 6) and *Many* (6 to 11) to amount of interceptors and *Before* (-30 to 0), *Equal* (0) and *After* (0 to 30) to teammate's position. When this controller informs that there is a low possibility of a successful pass, the agent carries the ball. All agents, except goalkeeper, are using this controller.

2.3 Marking

Two fuzzy controllers have been developed aiming support opponents' marking. One is responsible for deciding whether the agent should mark an opponent or find a good position and the other decides which opponent should be marked. In order to decide which kind of marking must be performed, a neural network was implemented; currently, there are two options: *Mark Ball* and *Mark Bisector*. This neural network has three levels: input, intermediate and output.

Figure 3: The number one represents MarkBall application. Number two shows MarkBisector

The input variables used are:

- Distance from agent to ball, varying up to simulated field size;
- Amount of opponents within agent's vision field;
- Amount of teammates within agent's vision field;
- Distance from agent to his own goal.

This neural network uses a linear transfer function and has fixed number of neurones for input and output levels, and changeable for the intermediate one. It was trained using an algorithm with backpropagation learning(Oliveira and Simões, 2007).

2.4 Kick to goal

To decide where to kick, the agent looks for the best balls trajectory to the goal avoiding opponents' interceptions. In order to do so, the goal is sliced into 14 zones and for each one chances of reaching the goal are analyzed. The projections of ball's trajectory and velocity are contrasted with the best set of possible opponent's decisions, from the stand point of the agent. Then, the analysis is done. If the player doesn't find a good opportunity for successfully concluding the move, i.e., scoring, the routine returns to the calling procedure, so another decision can be made.

3 Coach improvements

Among the projects developed recently, there is the routine for initial selection made by the coach. For each match the server generates a group of different heterogeneous players and the coach agent must define the most prepared types to be the team's players. The first routine developed with this purpose was based on a production system (an inference engine, rules and data bases) which classified and chose the heterogeneous types of players. The types could be classified in three groups, besides demanding a lot of modifications in the rules whether by chance they had need of changing the prioritized characteristics to the players or to add a new classification. The routine test results

Table 1: Trade-offs

	Values next to -1	**Values next to 0**	**Values next to 1**
Trade-Off 1	Lesser rate of speed loss	Standard Player	Bigger capability to turn the body
Trade-Off 2	Bigger acceleration	Standard Player	Bigger retrieval
Trade-Off 3	Bigger reaching of the ball	Standard Player	Bigger kick accuracy
Trade-Off 4	More extra stamina	Standard Player	More effort in the actions

have also not been so good. For some groups generated by the server, the number of types classified as NULL was greater than expected and, afterwards, some players started the match with types chosen randomly by the server. Thus, it was necessary to develop a different approach, which could overcame the shortcomings found in the routine.

The chosen approach was developed using Genetic Algorithm (GA) and Fuzzy Logic. In the GA, a chromosome corresponds to a possible team's lineup, is this way, each one will have 10 positions associated with players (the keeper is not considered since, for the current rules, its type cannot be different of zero or standard type). The probability to occur mutation and crossover are 1% and 30%, respectively. The crossover method used one cutting point, two individuals (chromosomes) are "cut off" in a determined point chosen randomly and their sides are crossed creating two new individuals. The selection method used is called turnstile, where the probability of an individual to be selected varies according to its performance related to the population. Each population is composed of 50 chromosomes and the stop criteria is the creation of 25 generations.

The fitness function is the sum of the individuals fitness functions for each heterogeneous type in the chromosome. The Fuzzy Logic receives, as input, parameter values of the heterogeneous type and 4 (four) values as output that describe how good are the characteristics of each player. The values of these variables are contained in the interval [-1,1]. The table 1 shows the meaning of these values for each player. The 4 (four) values are weighted indicating relevance of that characteristic for that team position, and the sum of these will be the global fitness function of that heterogeneous type for a specific player role.

Tests used 20 random seeds. For each one of them, an amazing lineup was chosen manually and compared whether the fitness function value of lineups created by the routine with GA and Fuzzy Logic could approach to the fitness function of the chosen lineup. Overall, 200 tests had been accomplished. Results show that 56% of lineups created by the routine are equal or better than the excellent lineup. Moreover, 18.5% are considered "sub-excellents" (chromosomes less than 100 points from the excellent solution) and the remaining solutions have, on average, 58.322% of excellent solution fitness.

The new purpose of this project is to increase the number of excellent solutions created by the routine. At a first glance, we will analyze other projects that use Genetic Algorithm in similar problems to the coach's choice to find out crossover techniques and selection methods that can improve the process. With a profound heterogeneous study, it was discovered that the process performed by the current routine reach two seconds (maximum) and the available time for the server is approximately 30 seconds. Thereby, it is also being cogitated to increase the number of chromosomes and/or created populations thus, to comprehend a largest universe of possible solutions to be evaluated (das Virgens Silva, 2009).

4 Work in progress and Conclusion

As time passed, some issues on team that were already improved begun to demand more robust and efficient approaches. Goalkeeper's positioning and defenders' behavior are two examples of such problem.

An analysis of goalkeeper's behavior led us to conclude that it's positioning allowed for a high amount of goals in the corner and goals from crossed balls. The former happened because the keeper was calculating it's position to the opponent's kick based on a line between the middle of its own goal and the ball, hence opponent attacks from field sides enlarged its distance to the poles. The latter was being caused by keeper advancements, staying positioned too far from goal and turnng easier for opponents who receive crossed balls to score.

To address the problem of suffering goals in the corners, it was proposed that the shaft that connects the ball to the goal on which the goalkeeper positions himself, is not calculated based on the center of the goal, but moves to the sides of the ball in proportion. Thus, when the opponent attacks by the sides, the goalkeeper closes more evenly the two corners, suffering far less goals.

In order to address the problem of taking goals from crossed balls in the area, the boundaries of the goalkeeper position were modified: we brought it near to the goal and changed the area where it operates. What was once an area of rectangular shape, now has the form of a trapezoid, as shown in the Figure 4. Thus, the goalkeeper is not going too far unnecessarily and the opponent's kicks becomes more difficult. We achieved a reduction in the number of goals conceded, by changing this.

These improvements caused significant changes in tests against PetSoccer team, 2008 Brazilian champion. In 200 tests, in which 100 with an older goalkeeper, and 100 with the current, there were a reduction of 1.73 goals per game and the passing of 13% to 32.5% of wins.

Concerning to the defenders, despite of the en-

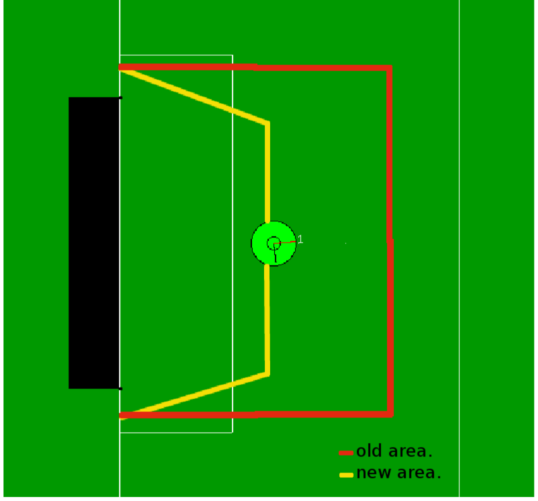

Figure 4: Goalkeeper's new positioning

hancements described on 2, they still present big issues, specially against stronger opponents. So, we re-evaluated the solution in use, studying its proposal and associated source. Defenders' behavior was observed through several matches and a list of problems was generated, each problem being associated to a flaw in the existing proposal. They were then classified relating to when they occur, as follows:

- Positioning;
    - Gathering data;
    - Behavior;
- Ball interception;
- Transversal;

Positioning issues represent problems in players' decision making that lead to inefficient defense. *Gathering data* subdivision names problems caused by lack of best information to decision making, e.g. when a defensive player does not mark its opponent for not noticing its presence; *behavior* means problems arised from flaws in the proposal itself, e.g. two or more defenders making the same decision. *Ball interception* problems are flaws in the ball taking. Not using **tackle** command, for instance, is a serious fault to ball interception. *Transversal* issues are related to player's global behavior and usually relate to basic abilities, such as slow players velocities while running.

Working from that classification, problems were mapped into requisites. These were rated by priority and associated technical difficulty. Those factors allowed us to decide about which requisites would be implemented first. We started then solving issues on gathering data, implementing and algorithm to control the player's neck. Generally speaking, decision making is done in two distinct moments: first a list of important objects is filled with players relevant to a given situation. This list is update on each new circle. After that, list objects are scheduled so to determine which one must be observed in the current cycle. The algorithm goal is to maximize players confidence on information about each relevant player to the actual moment in the game. This implementation is being tested now.

After Brazil Open, we intend to work in two fronts. One will implement another level over our current reactive level, being responsible to perform planning during matches. The other will work improving basic abilities level. The planner level will make decisions based on the interface provided by the lower level that contains the basic abilities.

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