Strategy for Collaboration in Robot Soccer

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Abstract

Robot soccer is a challenging platform for multi-agent research, involving topics such as real-time image processing and control, robot path planning, obstacle avoidance and machine learning. The robot soccer game presents an uncertain and dynamic environment for co-operating agents [1][2]. Dynamic role switching and formation control are crucial for a successful game. The fuzzy logic based strategy described in this paper employs an arbiter which assigns a robot to shoot or pass the ball.

1. Introduction

Robot soccer games had been popular with educational institutions around the world since the inauguration of the FIRA Mirosot competition in 1996 and the RoboCup competition in 1997. These initiatives provide a good platform for multi-agent domain research, dealing with issues such as co-operation by distributed control, effective and fault tolerant communication, real-time image processing, real time robot path planning and obstacle avoidance.

In this paper, a fuzzy logic based strategy is implemented for a five-a-side robot soccer game. The fast paced nature of this domain requires real-time sensing coupled with complex strategy and game play. This has developed from just simple reactive behaviour of robots based on subsumption architectures, such as moving directly towards the ball, to arbitrarily complex reasoning procedures that take into account the various parameters of the uncertain situation and potential behaviour of competing agents.

Strategic game play involves role switching for teams with homogenous robots and formation control during offensive or defensive play [3], collision avoidance among own players when attacking the ball and obstacle avoidance of the opponents.

2. Strategy

In robot soccer systems, images of objects on the field are processed by a vision system. Analysis of this raw data will yield information such as identification of objects including ball, player, and opponents. Other information such as object identity (identity of player), opponent, position, orientation and velocity can also be computed [4].

Based on this information, each of the players carries out assigned roles including attacker, defender, sweeper and goalkeeper. The simplest role selection strategy is to have a fixed role that does not change throughout the game. However, permanent role fixing causes undesirable behaviour such as a defensive player not going for the ball even though the ball is near but outside its defence zone; or a forward player giving up its possession of ball when it incidentally enters a defence zone [5].

Role assignment used by many teams is usually computed in real time. In this context real-time is the sample rate of the system, which is normally the frame rate of the vision system (in this case 30 frames per second). Cost functions used may be the shortest distance between player and ball or may also include the player's orientation towards the ball [6][7]. Developing more complex behaviour using cost functions becomes a tedious task as it is difficult to translate domain specific expertise into an appropriate component of a cost function.

2.1. Multi-cost function role assignment

Role assignment is necessary to avoid collision of players going for the ball or no player being assign such a role to attack the ball. However, to assign a player the 'attack the ball' role simply based on its distance to the ball is not sufficient for a competitive game. In such a dynamic and competitive environment, the distance of the robot to the ball changes quickly as the ball moves and opponents come for the ball. Collisions against opponents must be avoided. Also, the main objective of the game is to score goals; and if a player is in a better position to secure a scoring chance, it must be given the opportunity. A more efficient scheme of role assignment is necessary. Parameters considered by the strategy includes the distance of the player to the ball, the orientation of the player with respect to the ball, the obstacles along the path towards the ball and the shooting angle towards the target goal.

2.2. Fuzzy Logic based role assignment

The role assignment algorithm is implemented using fuzzy logic [8]. Parameters used as inputs to the fuzzy arbiter for each robot are *distanceToBall*, *orientation*, *shootAngle* and *pathObstacle*. These fuzzy variables are defined below and illustrated in figure 1.

DistanceToBall is the distance of the robot to the ball,
Orientation is the orientation of the robot with respect to the straight line path to the ball,
ShootAngle is the angle between the path of the robot to the ball and the path of the robot to the opponent's goal mouth.
pathObstacle is the angle bounded between the vector of the robot to the ball and the vector of the robot to the obstacle.

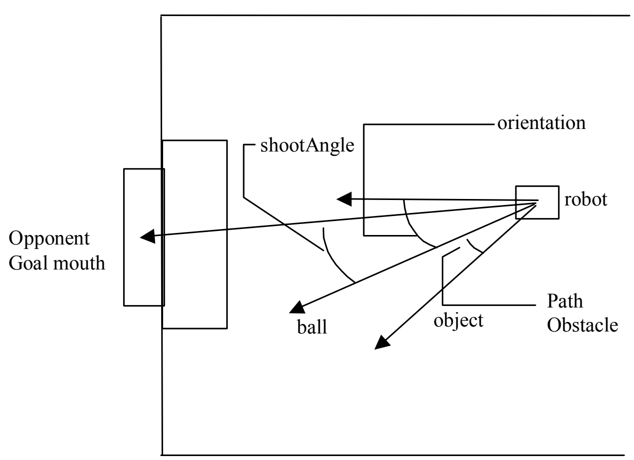

Figure 1. Illustration of fuzzy parameters

Fuzzy logic rule based reasoning is used to decide which robot should 'attack the ball'.

Rules are of linguistic form such as

if *distanceToBall* is ***near*** or *orientation* is ***front*** or *shootAngle* is ***perfect*** or *pathObstacle* is ***none*** then *roleAssigned* is ***high***;
or
if *distanceToBall* is ***far*** or *orientation* is ***front*** or *shootAngle* is ***good*** or *pathObstacle* is ***block***, then *roleAssigned* is ***low***;

where *roleAssigned* is the output fuzzy membership of every robot considered according to the rule based reasoning. Finally, the robot with the highest *roleAssigned* membership is assigned to attack the ball.

2.3. Fuzzification

Unlike the usual fuzzification techniques of using several triangular or trapezium fuzzy membership functions over the ranges of its input [9] [10], a single function is used.

To fuzzify the distance variable, the ratio of the minimum *distanceToBall* to the *distanceToBall* value is used, see equation 1. That is, the nearest robot to the ball will have a membership of value 1.0 for this variable.

$$\mu_{\text{distanceToBall}} = \frac{\text{distanceToBall}_{\text{min}}}{\text{distanceToBall}} \qquad (1)$$

Equation 2 and 3 describe the membership function for the *Orientation* and *ShootAngle* variable. A single cosine function is used. The robot that is directly facing the ball will have an orientation angle of 0 degrees, and a membership value of 1.0 for *Orientation.* Similarly, the robot that is facing the ball and the opponent's goal mouth will have membership value of 1.0 for *ShootAngle*.

$$\mu_{\text{Orientation}} = \cos(\text{Orientation}) \quad \text{for } -90 <= Orientation <= 90$$
$$\mu_{\text{Orientation}} = 0.0 \quad \text{otherwise.} \qquad (2)$$

$$\mu_{\text{ShootAngle}} = \cos(\text{ShootAngle}) \quad \text{for } -90 <= ShootAngle <= 90$$
$$\mu_{\text{ShootAngle}} = 0.0 \quad \text{otherwise.} \qquad (3)$$

For the *pathObstacle* variable, a single sine function is used, see equation 4. If there is an object which is in the path of the robot to ball, the *pathObstacle* will be 0 degrees and has a membership value of 0.0 as its path is completely blocked.

$$\mu_{\text{pathObstacle}} = \sin(\text{pathObstacle})$$
$$\text{for } -90 <= pathObstacle <= 90$$
$$\mu_{\text{pathObstacle}} = 0.0 \text{ otherwise.} \quad (4)$$

2.4. Defuzzification

The 'or' operation used is the algebraic sum operation. All the fuzzy memberships are added together and the resultant is the membership value of the *roleAssigned*. The robot with the highest membership value is assigned the highest priority order among the robots to the role of "attack the ball".

2.5. Formation

The collaboration between players is achieved through the introduction of a formation for the team. This formation decomposes the task space defining a set of roles. The formation is generally a triangle. The player assigned the role to attack the ball is the attacker. Two players will be positioned on its left and right side. The left player plays the role of the left sweeper and the right player the role of right sweeper. The positions are determined according to the location of the ball in the zones as shown in figure 2. These positions are usually at a distance of 40 to 70cm behind and to the left and right of the attacker.

The decision to position a particular robot as left or right sweeper is similar to the fuzzy arbiter structure described in section 2.2. However, the *shootAngle* is not used as a parameter. The use of this fuzzy arbiter ensures that the robot in the best position, in terms of distance, orientation and obstacle along the path, will be selected to move to this position.

Figure 3 and 4 illustrate the formation of the offensive players for two different ball positions. The remaining players on the team take up defensive roles, such as goal keeper and full back.

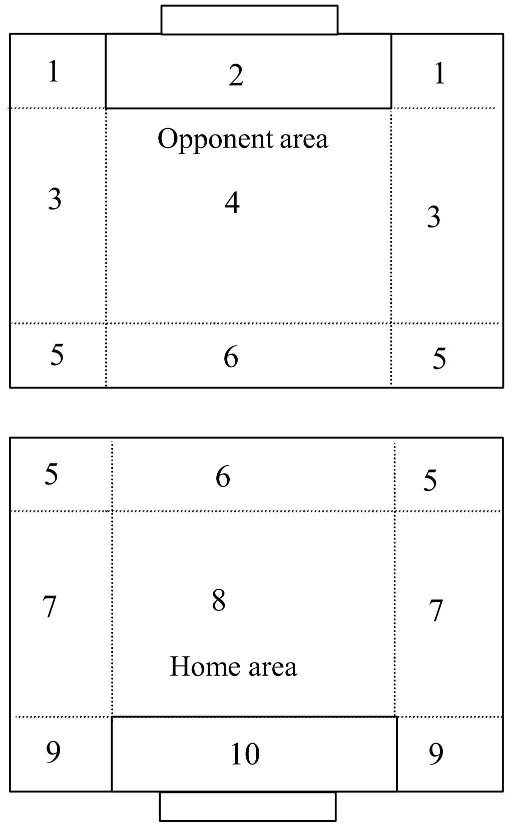

Figure 2. Field zone formation

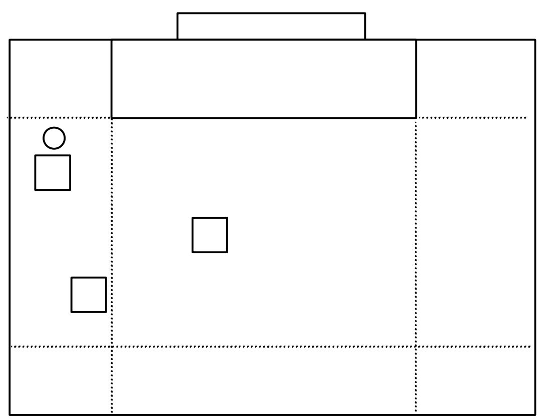

Figure 3. Formation with ball in zone 3

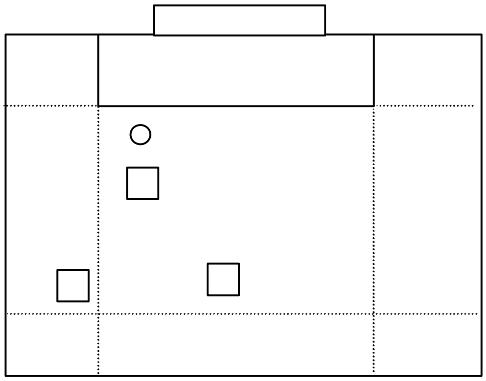

Figure 4. Formation with ball in zone 4

3. Results

This section examines the performance of the fuzzy role selection system. The role selector can unambiguously select between different robots based on the fuzzy rule base that has been specified.

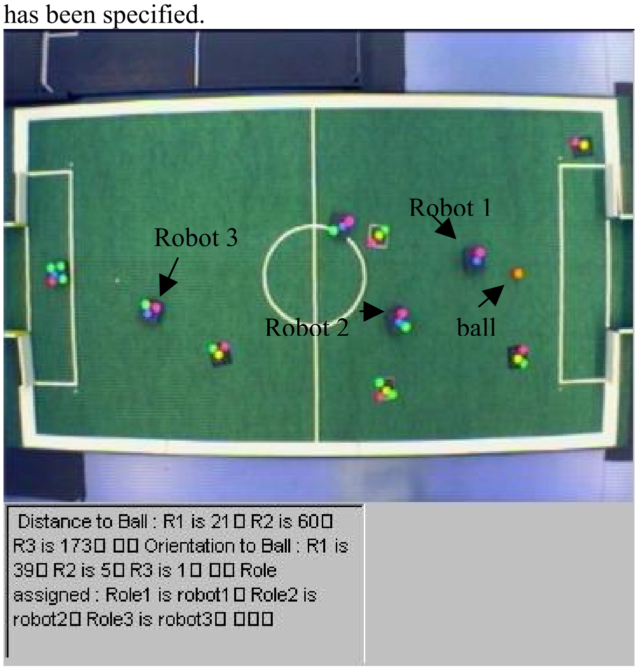

Figure 5. Robot 1 with good position

Figure 5 shows the result of role assignment for two robots positioned at different distances and orientation from the ball. Robot 1 is nearer the ball, however, it has an orientation that is facing slightly away from the ball. Robot 2 is at a better angle, however, its distance from the ball is much further, as such, the fuzzy arbiter assigns Robot 1 to go for the ball.

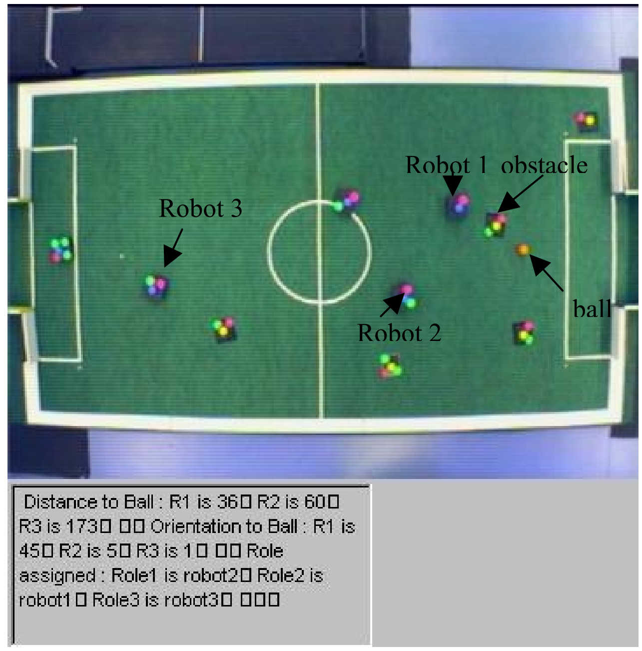

Figure 6. Robot 2 unobstructed and with good position

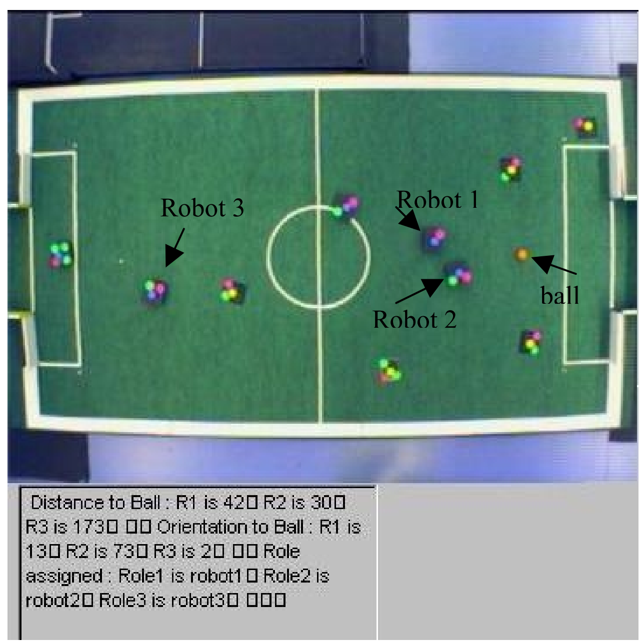

Figure 7. Robot 1 has a good orientation to the ball

Figure 6 shows that obstacles along the path of the robot have a significant effect on the role assignment. Robot 1 is nearer, has a better orientation towards the ball and a better shoot angle towards the opponent's goal. However, due to the obstacle along the path, it will not have a good shot at goal; therefore Robot 2 is assigned to attack the ball.

Figure 7 shows that orientation is considered an equally important a parameter. Robot 2 is nearer the ball, has no obstacle along the path, the shoot angle is good if it makes a quick turn and then goes for the ball. However, its orientation towards the ball is bad, thus a shot at goal is not likely to create a scoring chance. Robot 1 is assigned to attack the ball.

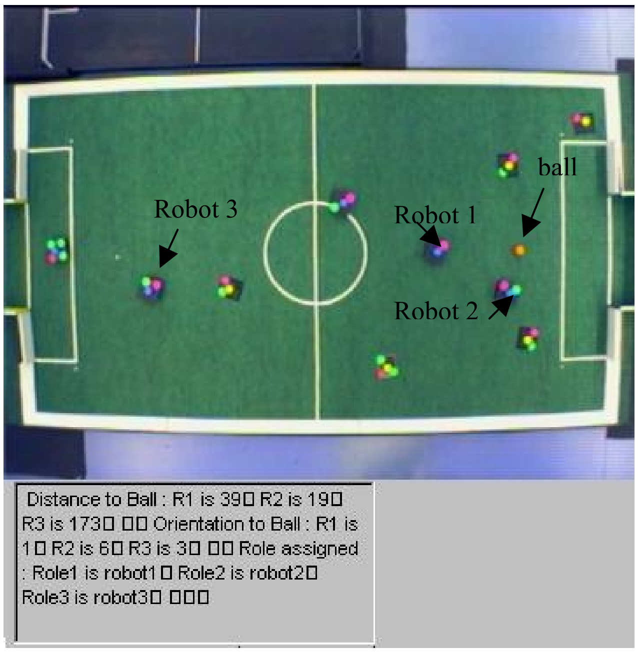

Figure 8. Robot 1 has a good shoot angle

Figure 8 shows that the shoot angle is a significant parameter. Robot 2 is nearer the ball, has a better orientation towards the ball with no obstacle in between; however its shoot angle is not good at all. If it will attempt a shot, chances are it will end up in the corner of the field. Robot 1 is assigned to attack the ball.

4. Conclusion

In the development of robot soccer where players are homogenous, role switching becomes a necessity to formulate an efficient strategy to achieve the goal of a successful game. Using a fuzzy rule based approach allows the strategy for role selection to be naturally developed using domain expertise rather than the alternative of trying to find a suitable cost function that would provide the same performance.

The development work on collaboration of multi-agents based on role assignment and formation will continue. Other parameters that will be considered in future development include ball passing rather than just goal scoring, intelligent shooting at goal for a more integrated system as well as intelligent defensive strategies.

5. References

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