Optimal Fuzzy Passing Strategy for Robot Soccer Players

Esmaeil Aatashpaz-Gargari, Babak N. Araabi and Caro Lucas

***Abstract*—This paper presents the implementation of an intelligent pass strategy for soccer robots using fuzzy logic. The proposed strategy calculates pass confidence and detects the best destination robot and best position for passing. The most important factors of a proper pass are detected and are deployed to construct the inputs of fuzzy system. The rule base of the fuzzy system is extracted by utilizing the expert knowledge. The performance of fuzzy inference system is improved by optimally determining the fuzzy membership functions using an evolutionary algorithm. In order to evaluate the designed system a visual simulation environment is prepared which enables the user to arrange players and to implement the designed strategy to detect the best destination player and send the ball.**

I. Introduction

Robot soccer game is a competition among soccer robots which has been proposed as a benchmark problem for artificial intelligence and robotic research. In this competition robots use the playground information such as position of robots and the ball and their speed to implement the game strategy. Figure 1 shows the robots soccer game.

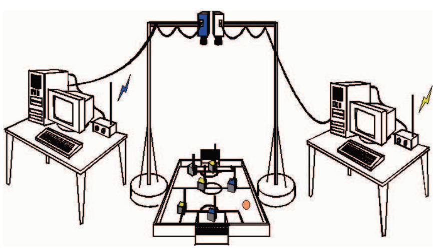

Fig. 1. Robots soccer game

Great amount of researches in the area of artificial intelligence is devoted to the soccer robots and several papers have proposed some strategies and methods for improving robots ability and teamwork in this competition. [1, 2] deal with the problem of position and shooting control for soccer robot system (SRS) using fuzzy logic. Substantial numbers of researches in the area of SRS are about obstacle avoidance and path planning of robots in the game as in [3-7] which some use fuzzy logic and evolutionary algorithms for this purpose. Also some papers like [8] have proposed some decision making strategies for soccer robots.

To succeed in a soccer robots competition, a team should have a good combination of many factors such as individual and teamwork abilities of robots and a strong game strategy. Among these factors teamwork plays an important role and it has an increasing effect on the team success. In this paper we discuss about the teamwork problem from the passing strategy point of view. The proposed strategy uses fuzzy logic to detect the destination robot and its best position for receiving the ball.

In section II, we define the characteristics of a proper pass. In section III, we study these characteristics in more details and define the inputs and output of the fuzzy system and the relevant membership function and we implement the fuzzy inference system. To improve the system performance, in section IV, a GA is employed and optimal membership functions are determined. In section X we asses the performance of the designed system using a simulation environment and eventually we draw conclusions in section XI.

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II. Defining The Characteristics Of A Proper Pass

To have a good decision making system for passing, we should define the characteristics of a proper pass. These characteristics will form the basis of our system and the precision in defining them, will cause the efficiency of the system to increase. It is obvious that a proper pass can have a great number of characteristics, but for implementing the fuzzy decision making system we just consider some of the most important ones.

A. Differences between Human and Robots in Soccer

Before defining a proper pass we should take differences between human and robots into account. In kicking the ball, robots are not as precise as human. The cause of this fault is the orientation error due to sensory error and the error in processing the image obtained from vision part. Figure 2 shows the effect of orientation error. In this figure, the distance between robot and goal assumed to be 2 meters. Wrong orientation has produced an error about 5 degrees in the robot's direction. This small error will cause the ball to hit 17.5cm $(2m * \tan(5^o) * 100)$ far from the goal center. To reduce the orientation error and for being confident of passing we should not choose a distant robot as destination and send the ball to it, nevertheless it may seem worthwhile in human soccer.

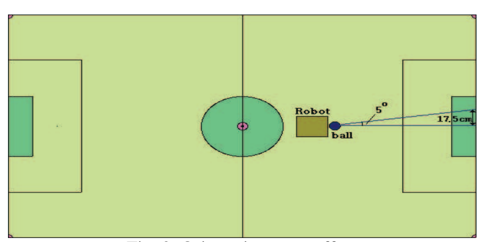

Fig. 2. Orientation error effect

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Another difference between human and robots is in ball sending speed. Human can successfully send the ball to a near player in low speed and to a far player in high speed. But because of using spring for kicking, the soccer robots usually have a constant speed or sometimes multi speed kicking system. Then another restriction in robots ability is their shooting speed. Usually the spring is stretched to maximum tension. Then sending the ball to a near robot is not reasonable too. These differences along with others which are not considered in this paper can make it difficult for us to validate our final system performance. According to humans' ability we might choose for example, player *A* and pass the ball to him but in robots point of view, it might not be the most competent destination player to receive the ball and robot may chose a player other than *A* for passing the ball. Based on these main differences along with the other ones which are not considered in this paper, we can define a proper pass for soccer robots.

B. Characteristics of a Proper Pass

The most important characteristics of a proper pass are summarized below. Definitely these are not the only characteristics of a proper pass, but these are four of the most important ones. Based on these characteristics we will define the fuzzy system inputs and output and the rule base of the system will be extracted according to them. These characteristics are

- The destination robot must be neither too near nor too far from source robot.
- The rival robots should be far from the straight line between destination and source.
- The rival robots must be far from the destination robot.
- Sending the ball should help the team to get closer to the rival goal.

III. Implementing The Fuzzy Inference System

Fuzzy systems, because of their ability to incorporate human knowledge, have successful application in various fields. We deployed the capability of fuzzy system to make a strategy for passing by soccer robots. To do this, in this section, we define inputs and output of fuzzy system and related MFs and rule base of the system.

A. Defining the Inputs and Outputs of the Fuzzy System

Having defined the most important characteristics of a proper pass, we use them to make the inputs and the output of our fuzzy inference system. For this purpose in this section, we interpret these characteristics in such a way that enable us to define linguistic variables that closely indicate them.

1) *Distance between Destination and Source Robots: T*his input can be defined as the euqlidant norm of the vector from source to destination. According to the presumed size of playground, this fuzzy variable will be limited in interval [0 18]. For this variable, we can consider three fuzzy sets Near, Medium and Far. The membership functions of this parameter in these fuzzy sets are shown in Figure 3. According to the characteristics mentioned in section II, a proper pass will have more membership in set Medium than two others.

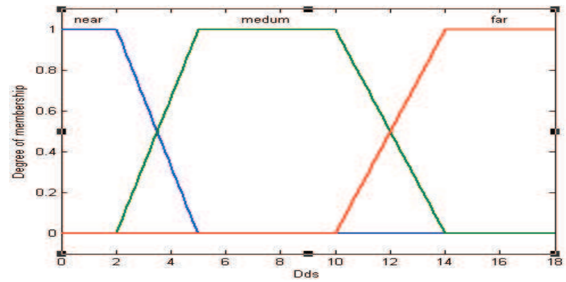

Fig. 3. Membership functions of distance between destination and source robots

2) *Distance between Rival Players and Path of ball:* If a rival player were near the straight line connecting source robot to destination, it could easily get the ball. Figure 4 depicts this situation where player number 5 is not a good one to receive the ball because players number 2 and 4 of the rival team, have blocked the path of the ball.

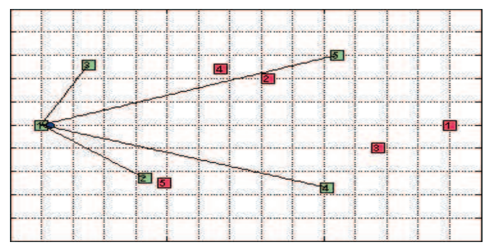

Fig. 4. Danger of rival players which are close to destination to source line

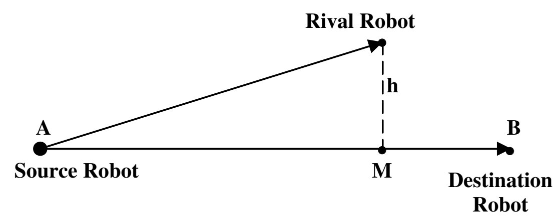

Fig. 5. Calculating the danger of rival player on the pass path

Considering Figure 5 and assuming that the maximum speed of the ball is three times the maximum speed of robots, it is obvious that if the distance between rival and point M were less than a threshold distance, the rival could posses the ball, otherwise not. This threshold distance can be obtained as follows:

$$V_p: \text{ Player Speed}$$
$$V_b: \text{ Ball Speed}$$
$$V_b = 3V_p \tag{1}$$

The time required by rival to get to the point M is

$$t_{rM} = h / V_p$$

The distance that the ball can move in this time is

$$D_b = V_b \cdot t_{rM} = V_b \cdot h / V_p$$

If this distance were less than the distance between source and point M, the rival could posses the ball, otherwise could not. Then

$$T.C.1 = \frac{AM}{D_b} = \frac{AM}{h}.\frac{V_p}{V_b} = \frac{1}{3}.\frac{AM}{h}$$

$T.C.1$ can be defined as a factor indicating the rival players ability to block the path of the ball and possess it. In crisp mode, we will have

- If ($T.C.1 > 1 \Leftrightarrow AM/h > 3$) then rival player is able to possess the ball.
- If ($T.C.1 < 1 \Leftrightarrow AM/h < 3$) then rival player is not able to possess the ball.

It is noticeable that every rival player with a $T.C.1$ greater than 1 will not certainly be able to possess the ball. because $T.C.1$ is not the only factor in getting the ball and some other factors such as quick ball path detection, and quick start, play role in the process of ball possession. Then by considering this variable as a fuzzy variable, we can model it more properly. Using AM/h instead of $T.C.1$ as a parameter showing the rival player's ability to possess the ball, we can define three fuzzy sets Low, Medium and High for this fuzzy variable. Figure 6 shows the membership functions of this variable in these sets. A proper pass will have higher degree of membership of AM/h in set Low.

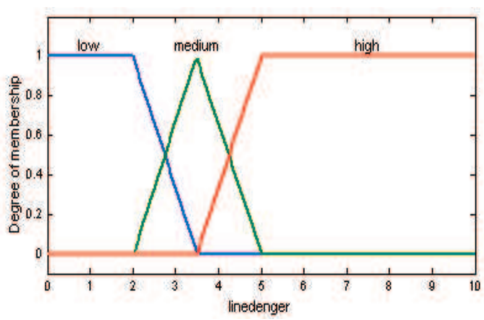

Fig. 6. Membership functions of danger of rival player which is close to pass path

3) *Distance between Rival Players and Destination Player:* A close rival player to destination robot has the ability to possess the ball. Figure 7 illustrates the situation in which a rival robot can get the ball before destination robot. In this figure, player number 5 is not a proper destination robot because rival robot number 2 is close to it.

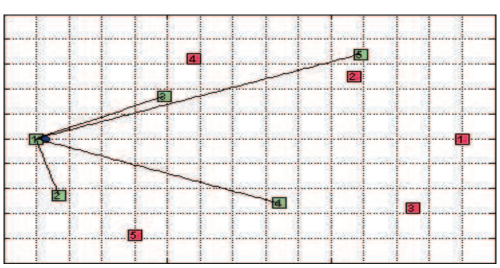

Fig. 7. Danger of rival player which is close to destination robot

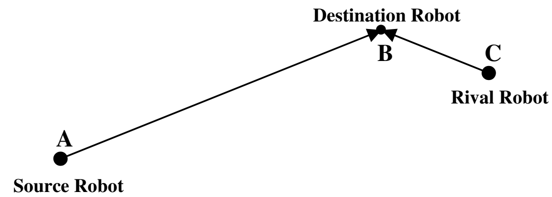

Fig. 8. Calculating the danger of rival player which is close to destination robot

For analyzing this situation in more detail, we consider Figure 8. In crisp mode, if the distance between rival and destination were less than a threshold, rival robot could possess the ball, otherwise could not. in this part we calculate this threshold distance and use it to define one of the inputs of the fuzzy system.

The time that the ball requires to get from source to destination is

$$t_b = \frac{d_{AB}}{V_b}$$

During this time, rival can move the maximum distance of

$$d_r = V_p.t_b = \frac{V_p}{V_b}.d_{AB}$$

If d_r were more than d_{BC} the rival could posses the ball otherwise not. Then

$$T.C.2 = \frac{d_r}{d_{BC}} = \frac{V_p}{V_b}.\frac{d_{AB}}{d_{BC}} = \frac{1}{3}.\frac{d_{AB}}{d_{BC}}$$

can be defined as a danger factor for this parameter. In crisp mode we will have

- If ($T.C.2 > 1 \Leftrightarrow d_{AB}/d_{BC} > 3$)then rival player is able to possess the ball.
- If ($T.C.2 < 1 \Leftrightarrow d_{AB}/d_{BC} < 3$)then rival player is not able to possess the ball.

For the same reasons as in part B of section III, it is better to use fuzzy sets and membership functions for the variable $T.C.2$. According to (7) and considering d_{AB}/d_{BC} instead of $T.C.2$ as a parameter indicating the rival player's ability to possess the ball, we can define three fuzzy sets Low, Medium and High for this fuzzy variable. The membership functions of this variable in these sets are shown in Figure 9. A proper pass will have higher degree of membership of AM/h in set Low.

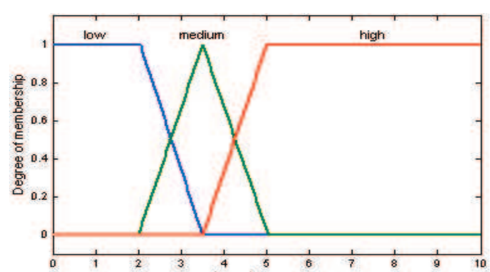

Fig. 9. Membership functions of danger of rival players which are close to destination robot

4) *Distance from Rival Goal:* A proper pass should help us to get close to the opponent's goal. Then when according to previous factors, two destination robots seem to be equal to receive the ball; the one who has less distance from rival goal will be more preferable. Figure 10 shows three region Near, Medium and Far in crisp mode. In fuzzy mode we can consider three membership functions for this parameter in the equivalent sets. Figure 11 shows these membership functions.

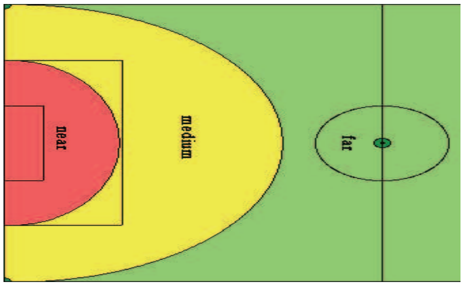

Fig. 10. Crisp partitioning of playground into 3 sets

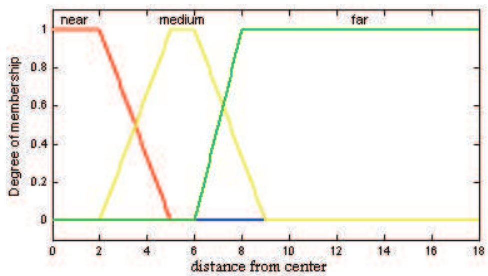

Fig. 11. Membership functions of the distance from goal parameter in the three set

5) *Pass Grade:* The fuzzy inference system has one output. This output is the value of a passing to a destination robot. We use triangular membership functions for this variable as shown in Figure 12.

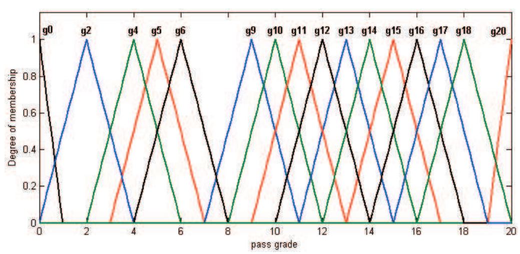

Fig. 12. Membership functions for system output

B. Rule Base Extraction

The rule base of the system is based on the characteristics that are defined for a proper pass. According to these characteristics, a destination robot that is in the situation that no rival player can block the path of the ball and possess it and is not neither too close nor too far to the source robot and is enough close to the opponent goal is the best destination and should get the most grade. Based on these characteristics, the rule base for fuzzy inference system is extracted empirically. Table I shows the rule base.

TABLE I
FUZZY INFERENCE SYSTEM RULE BASE

Distance from rival goal	Distance between source and destination	Danger of rival close to source-destination line	Danger of rival close to destination	Pass grade
Near	Don't Care	High	Don't Care	g4
Near	Don't Care	Don't Care	High	g4
Near	Far	Medium	Low	g15
Near	FAR	Low	Medium	g15
Near	Near	Medium	Low	g13
Near	Near	Low	Medium	g13
Near	Medium	Low	Medium	g16
Near	Medium	Medium	Low	g16
Near	Far	Low	Low	g17
Near	Near	Low	Low	g15
Near	Medium	Low	Low	g20
Near	Far	Medium	Medium	g14
Near	Near	Medium	Medium	g13
Near	Medium	Medium	Medium	g15
Medium	Don't Care	High	Don't Care	g2
Medium	Don't Care	Don't Care	High	g2
Medium	Far	Medium	Low	g12
Medium	Far	Low	Medium	g12
Medium	Near	Medium	Low	g9
Medium	Near	Low	Medium	g9
Medium	Medium	Low	Medium	g14
Medium	Medium	Medium	Low	g14
Medium	Far	Low	Low	g14
Medium	Near	Low	Low	g13
Medium	Medium	Low	Low	g18
Medium	Far	Medium	Medium	g10
Medium	Near	Medium	Medium	g9
Medium	Medium	Medium	Medium	g12
Far	Don't Care	High	Don't Care	g0
Far	Don't Care	Don't Care	High	g0
Far	Far	Medium	Low	g9
Far	Far	Low	Medium	g9
Far	Near	Medium	Low	g6
Far	Near	Low	Medium	g6
Far	Medium	Low	Medium	g11
Far	Medium	Medium	Low	g11
Far	Far	Low	Low	g11
Far	Near	Low	Low	g10
Far	Medium	Low	Low	g15
Far	Far	Medium	Medium	g6
Far	Near	Medium	Medium	g5
Far	Medium	Medium	Medium	g9

C. System Implementation

Figure 13 shows the block diagram of fuzzy inference system used to implement the pass decision making system. The four fuzzy inputs enter the fuzzy inference system and generate the output PassGrade. Using this system the value of the passing to each of the players in the playground is calculated and the one that gets the most grade is recognized as the best destination robot and the ball is sent to it.

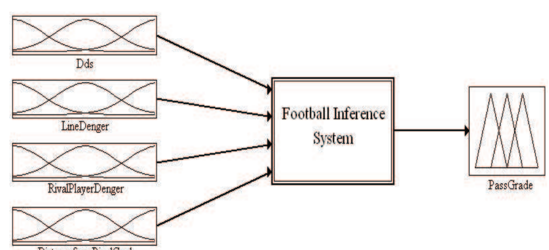

Fig. 13. Block diagram of the fuzzy inference system used for pass strategy implementation

D. Dynamic Position Analysis

A destination player might not be in a proper position to receive the ball, but it might move into another position and get the ball in a more proper situation and with a lower risk as shown in Figure 14. In this figure due to player number 5 of rival team, player number 4 can not easily get the ball. But by changing its position this player can receive the ball in a better position and with a higher accuracy.

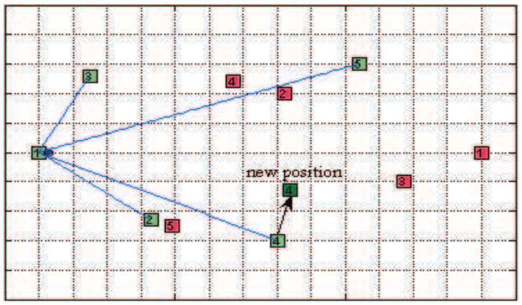

Fig. 14. Dynamic position analysis

The maximum distance that the destination player can move in the time that ball reach to it, makes a region in the playground. To find the boundary of this region we consider Figure 15.

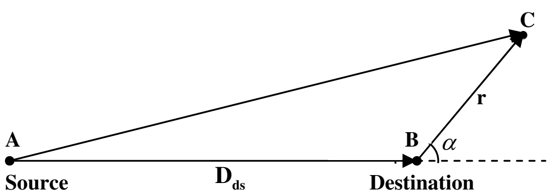

Fig. 15. Finding the boundary of moving area

The time that the ball requires to reach from point A to point C is

$$t_b = \frac{\sqrt{\left((D_{ds} + r.\cos\alpha)^2 + (r.\sin\alpha)^2\right)}}{V_b}$$

The maximum distance that destination player can move in this time is

$$r = V_p.t_b = V_p.\frac{\sqrt{\left((D_{ds} + r.\cos\alpha)^2 + (r.\sin\alpha)^2\right)}}{V_b}$$

According to the assumption (1) and by simplifying we will have

$$9r^2 = D_{ds}{}^2 + r^2 + 2rD_{ds}\cos\alpha$$

$$\Rightarrow 8r^2 - 2rD_{ds}\cos\alpha - D_{ds}{}^2 = 0$$

Solving this equation will result in

$$r = \frac{\cos\alpha + \sqrt{8 + \cos^2\alpha}}{8}.D_{ds}$$

In polar coordinates this equation represents a circle with the radius of $3/8 * D_{ds}$ and with the center located on the line crossing source and destination players with the distance of $1/8 * D_{ds}$ from destination player. The boundary of moving area is shown in Figure 16. For a dynamic analysis we assume that destination player is located in the center of this circle and before receiving ball can only move inside it. Then by searching different points in this circle we determine the best position for all destination robots and compare them to choose the best destination and its position.

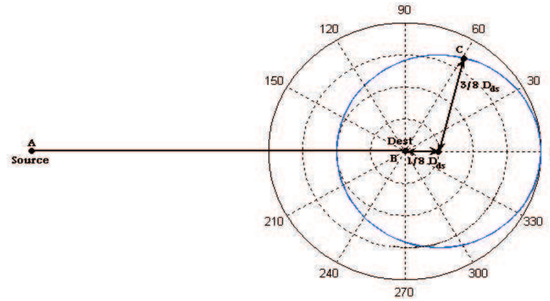

Fig. 16. Boundary of moving area

IV. Optimal Membership Functions

The performance of the designed fuzzy system was satisfying but in some rare cases it failed to detect the best destination robot to pass the ball. For solving this problem we used a GA to optimally shape the membership functions. By considering all the MFs in trapezoidal and triangular form, we put their parameters together to initiate a chromosome. The cost function of GA was the mean square of the error between the desired and actual output of the system. We arranged the robots in about 300 random positions, and determined the best destination robot and its intended (desired) grade. GA was applied to chromosomes to reach a system that its outputs for those 300 different positions be as close as possible to the desired outputs. The modified membership functions resulted from GA are shown in Figures 17 to 21.

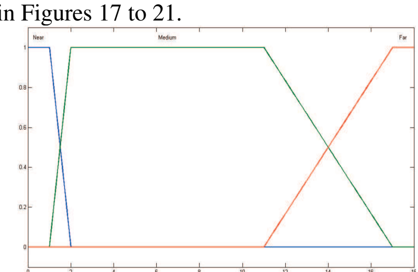

Fig. 17. Modified membership functions of distance between destination and source robots

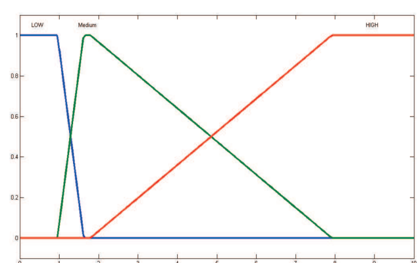

Fig. 18. Modified membership functions of danger of rival players which are close to pass path

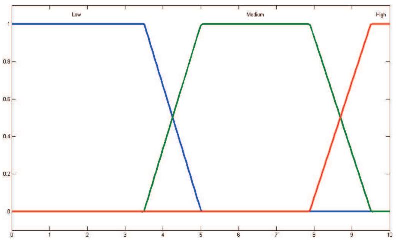

Fig. 19. Membership functions of the distance from goal parameter in the three set

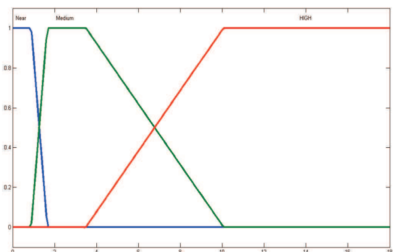

Fig. 20. Membership functions of the distance from goal parameter

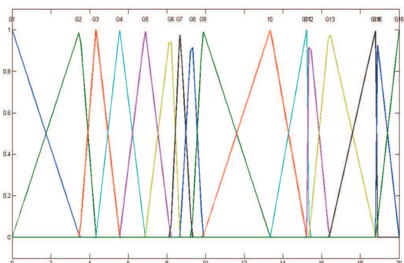

Fig. 21. Modified membership functions of systems output

V. Simulation

To test the system a simulation environment is prepared. Figure 22 shows a screenshot of this environment. Using this simulator we can easily test the system involving changing the position of each player and seeing the result of fuzzy system and identifying the best player who can get the ball. As shown in Figure 16 fuzzy inference system has detected the player number 4 as the best and the most confident player who can receive the ball. This player has scored 16.057 out of 20. According to the results from modified fuzzy inference system, meanwhile receiving the ball, this player should move to the position (11.8, 3.76)

VI. Conclusion And Discussion

In this paper we proposed the implementation of intelligent pass strategy for soccer robots using fuzzy logic. Having defined the most important features of a proper pass, we determined inputs and output of the fuzzy inference system. The related membership functions were obtained in two ways. First, these MFs were obtained empirically. In this case the designed system performed well, but in some rare cases it failed to detect the most competent destination robot. In next step we employed a GA to determine MFs so that mean square error between the desired and actual output of fuzzy system is minimized. Applying GA reduced the MSE of the system and changed it from 0.57 to 0.23. It was clear that shaping the MFs by GA improved the performance of the system but GA was not as successful as we supposed to be and it couldn't decrease the MSE to about zero. Analyzing the problem in more details concluded that the inputs of the system were not sufficient and this complicated system can not be properly modeled by only 4 main inputs. It is suggested that for increasing the system performance the number of inputs increase and some other features such as speed and orientation of players, result dependent game strategy and position dependent rule confidence be considered in design of the fuzzy inference system. We determined the rule base of fuzzy system empirically but as another improvement in system performance, the rule base can be obtained optimally by using an evolutionary algorithm as we did for MFs.

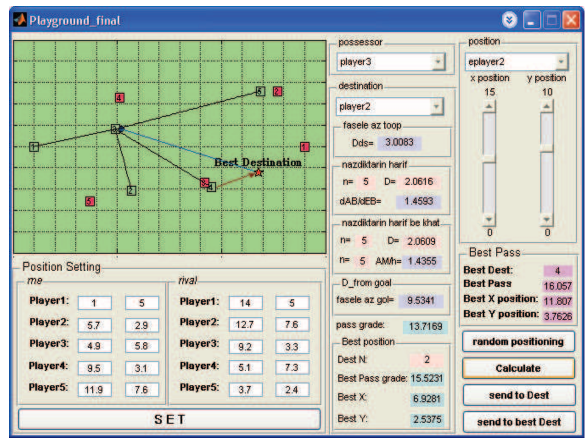

Fig. 22. The simulation environment prepared to test the system.

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