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Intelligent task planning and action selection of a mobile robot in a multi-agent system through a fuzzy neural network approach

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ABSTRACT

This paper proposes an intelligent task planning and action selection mechanism for a mobile robot in a robot soccer system through a fuzzy neural network approach. The proposed fuzzy neural network system is developed through the two dimensional fuzzification of the soccer field. A five layer fuzzy neural network system is trained through error back propagation learning algorithm to impart a strategy based action selection. The action selection depends on the field configuration, and the emergence of a particular field configuration results from the game dynamics. Strategy of the robot changes when the configuration of the objects in the field changes. The proposed fuzzy neural network structure is flexible to accommodate all possible filed configurations. Simulation results indicate that the proposed approach is simple and has the capability in coordinating the multi-agent system through selection of sensible actions.

1. Introduction

Robot soccer systems have been a thrust area for active research in robotics for the last several years (Kitano et al., 1998; Asada et al., 1999; Veloso et al., 1999; Huang and Liang, 2002). It makes use of several key areas such as mechanics (Pourboghrat and Karlsson, 2002), sensors (Treptow and Zell, 2004), vision (Schmitt et al., 2002), communication (Pagello et al., 1999), coordination (Kok, et al., 2005), path planning (Kim and Kim, 2003), control (Fierro and Lewis 1998), and artificial intelligence (Jolly et al., 2007). In the recent past, micro-robots and miniature robots were developed for various purposes of entertainment and education (Kim et al., 1997) and these small sized robots have all the functionalities and characteristics of the large robots. Robot soccer is a multi-agent system (MAS) consisting of autonomous mobile robots in which each robot of the team has to co-operate with others while facing competition from the opponent team. An agent may have intelligence, autonomous behaviours, and can be equipped with knowledge, motivation, reasoning, and planning capabilities. Due to inherent uncertainties and inaccuracies in the sensor data, and dynamic nature of the system, planning of a strategic action selection mechanism for the entire domain is difficult with conventional mathematical approaches. In a fuzzy inference system, fuzzy logical rules can model the qualitative aspects of human knowledge and reasoning processes without employing precise quantitative analysis. Artificial neural network (ANN) systems offer advantages of acquiring knowledge through learning (Song and Tang 2001, Jolly et al., 2007; 2008) adaptation, fault-tolerance, parallelism, and generalization. Through their hybrid form the versatility of neural networks and fuzzy logic can be combined in a neural network based fuzzy inference system and it is expected to exhibit many advantageous features. This paper utilizes a fuzzy neural network approach for modelling the action selection mechanism of an agent in the robot soccer environment.

Various techniques are introduced and improved in the recent past for the formation of a successful robot soccer team. For proper coordination, the communication among the members of a robot soccer team can be achieved (Pagello et al., 1999) through an implicit sensory feedback from the environment or through an explicit exchange of information among these robots. Coordination of non-communicative mobile robots in a MAS has been implemented using coordination graphs in the RoboCup competitions (Kok et al., 2005). Decision making of an individual agent depends on the actions of the other agents. A behaviour based cooperation and coordination of mobile robots with multiple fitness measures for various behavioural aspects has been studied in the past (Jeong and Lee,1997; Candea et al., 2001; Uchibe et al., 2002; Bonarini et al., 2003; Koyuncu and Yazici, 2005; Jolly et al., 2008). Methods for tracking the ball and the robots, coordination methods for strategic team formation, development of basic skills, and action selection (Kim et al., 1997; Huang and Liang, 2002; Weigel et al., 2002) are some key requirement for the formation of a successful team. Autonomous mobile robots can be trained to

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develop basic skills like positioning, passing, dribbling, and shooting with the help of an offline coach (Gupta et al., 2001). Probabilistic search techniques (Stroupe and Balch, 2005) are developed to determine the best action for each robot in a MAS and it uses the current team-mates positions to approximate team-mate contributions in the next step. Reinforcement learning schemes can be developed through Q-learning (Park et al., 2001) for the action selection mechanism in a MAS by dividing the robot soccer field into different regions.

Intelligence of an agent is desirable for appropriate action selection, avoiding unexpected collision with the other robots in the field, finding optimal path or intercepting the ball from the opponents (Springer et al., 1997; Kim and Kim, 2003; Abdessemed et al., 2004). Reinforcement learning schemes (Arai, et al., 1999) are desirable to acquire adaptive behaviours for avoiding surrounding obstacles in a MAS, in which the learning process is ongoing. Methods have been developed for detecting and tracking the ball in a robot soccer scenario without using the colour information (Treptow and Zell, 2004). Vision processing algorithms (Schmitt et al., 2002) and omni directional catadioptric vision systems (Limaa et al., 2001) have been developed for tracking multiple moving objects and predicts their trajectories in a MAS. Alexis (Pantola and Salvador, 2001) has presented a pose estimation algorithm using ANN, which is concerned with the determination of the position and orientation of the soccer robots from the vision data. Different schemes for the intelligent control of mobile robots are available for realizing the decisions made during the path planning stage. Adaptive control rules (Pourboghrat and Karlsson, 2002) at the dynamics level for a nonholonomic mobile robot with unknown dynamic parameters are also available. In the implementation level, emergent cooperative behaviours of the robots are realized through various control schemes (Jeong and Lee,1997; Fierro and Lewis, 1998). This paper proposes a fuzzy neural network based approach (Chao et al., 1996; Young and Wang, 2001) for the intelligent action selection mechanism of a mobile robot in a MAS.

This paper is organized as follows. The problem formulation is presented in the Section 2. The details of two-dimensional fuzzification of the soccer field and the structure of the fuzzy neural network system (FNNS) are introduced in this section. The mathematical analysis of the proposed five layer FNNS are discussed in Section 3. Method of training data generation, and simulation results are given in Section 4.

2. Problem formulation

The global objectives of an agent in a robot soccer team are to strike as many goals as possible and to defend the ball from conceding a goal. The team that can satisfy the global objectives efficiently and quickly is going to win the game. There are several conditions, which are to be fulfilled in order to satisfy the global objectives and these conditions are known as local objectives. The local objectives include defending the attack of the opponent robots, passing the ball to the team-mate, shooting the ball to the opponent goal post, avoiding the obstacles like opponent robots, goalkeeper and walls at the field boundary, acquiring control over small ball movements, and intercepting the ball from the opponent robots. If a robot in a team could pass the ball from the pass zone to its team-mate in the attack zone and the team-mate could shoot the ball to the opponent goal post avoiding the goalkeeper, then it is going to be a goal. The act of passing the ball to the team-mate and shooting the ball toward opponent goal post avoiding goalkeeper by the team-mate are the local objectives. So the problem in a robot soccer system is to find a suitable sequence of action, which will result in the fulfilment of global objective. Since robot soccer is an uncertain system, which is dynamic and competitive, the robots should be able to take a spontaneous decision out of various options that are available. The major decisions to be taken include:

- Which robot should move towards the ball.
- Through which path the robot should approach the ball.
- At what angle it has to hit the ball.
- What force it has to exert on the ball.

Depending upon the force exerted on the ball and its direction, various actions of the robot emerge. These actions are named as passing the ball, shooting the ball, dribbling the ball, and controlling the movement of the ball with the robot. In the proposed robot soccer systems, nearest robot approaches the ball and try to hit it. However in some cases, when the nearest robot makes a large angle with the ball or any obstacle is there in the path of the robot, this decision may not be effective. In these cases the other alternatives have to be checked (Jolly et al., 2007). The robot soccer field for the MiroSot small league is shown in Fig. 1, in which, robot R_2 is near the ball. However as it makes a large angle with the ball, selection of robot R_1 to move towards the ball is a better option for this configuration. The robot that is decided to approach the ball can move towards the ball in different paths (Gupta et al., 2001; Kim and Kim, 2003). So an agent has to select an optimal path, which must be shorter in length and free from obstacles. During the time of path planning, due consideration is to be given to the nonholonomic constraint imposed on the mobile robot. While approaching the ball, a robot has to select an action by deciding the force of hit and direction of hit. Angle of hit depends on a number of factors like position of ball, locations of team-mates and opponents. When the ball is near the opponent goal post, a robot tries to shoot it to the opponent's goal post. When the ball is near the vicinity of its own goal post, robot tries to block or intercept the ball from the control of the opponents. The force exerted on the ball depends on the position of the ball and game situation. Force required for passing the ball to the team-mate is different from dribbling the ball through the field. Distance between the ball and the team-mate decides the force of hit for passing the ball. For a quick movement of the ball greater force is required and it is required at the time of shooting, or sometimes during passing to prevent the interception. Generally force required to be exerted on the ball depends on the distance to which the ball is to be driven and the required velocity. Both these

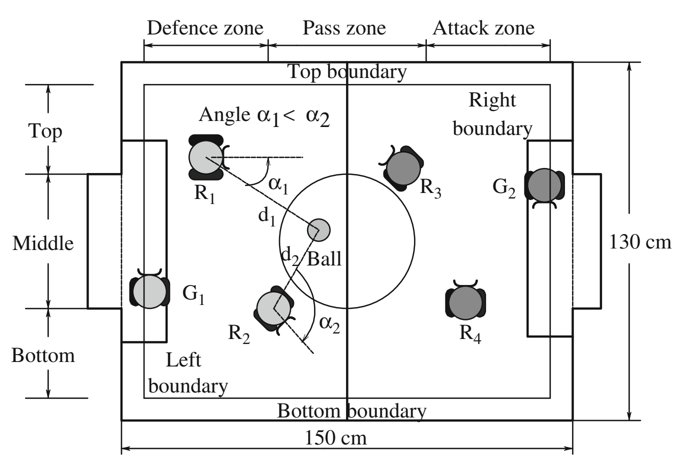

Fig. 1. MiroSot Playfield is divided into different zones.

factors depend on the ball position and the game dynamics and therefore appropriate angle and force are to be decided according to the ball position and the game dynamics. This paper proposes a strategy based intelligent action selection mechanism using FNNS, with which a robot takes sensible actions in all game situations.

Initially the playground of robot soccer system is divided into two regions, domain and boundary, so as to device different strategies for different regions. Boundary is the region near the walls of the playground. Domain is the region of the playground excluding boundary. An agent may have different strategies at the domain and the boundary. When the ball is in the boundary, the robot may not be able to hit the ball at the desired angle due to the inherent nonholonomic constraint. In such cases the robot will hit the ball towards the boundary at an appropriate angle so as to get it reflected back to the desired region of the domain. In order to implement different strategies at different areas of the domain, the domain is divided into 3 zones such as 'defence zone', 'pass zone', and 'attack zone' as shown in Fig. 1. Attack zone of the home team will be the defence zone of the opponent team. Their attack zone will be the defence zone of the home team. The pass zone is common for both the teams. The behaviour and strategy of an agent is to be changed when the zone of the ball is changed. Positions of the opponents and team-mates are also having an influence on the strategy adapted by an agent. The robot, which is approaching the ball, is exhibiting an action based on this strategy.

The robot, which is near the ball, is allowed to approach the ball and at a time only one robot from each team moves towards the ball. If the ball is in the attack zone, the robot shoots the ball towards the opponent goal post. When the ball is in the pass zone, the robot will pass the ball to its team-mate if the latter is in the attack zone. If the team-mate is away from the pass zone or attack zone it dribbles the ball towards the opponent goal post. In the defence zone, home robots tries to block or intercept the ball, then hit it away from their goal post. Simultaneously attacking robots of the opponent team tries to hit the ball for scoring a goal. The goalkeeper moves along the goal line to restrict the goals. It tries to block the movement of the ball and kick it towards the opponent's side. For further refining the rule base, in the proposed work, the domain of each zone is further divided into three sections as 'Top', 'Middle', and 'Bottom'. The number of rules for selecting an action is different for different field configurations due to the difference in their fuzzy membership values. The position and orientation of various objects at any time during the game define the configuration of the field at that time. A pose estimation algorithm (Pantola and Salvador, 2001), utilizing vision data provides the configuration of the different objects with sufficient accuracy. Using this data, distance of the various robots from the ball is determined, along with the orientation of the robot with respect to the ball. An ANN technique (Jolly et al., 2007) is used in the proposed approach for deciding which robot in the team is to approach towards the ball for a given field configuration. According to ANN, one robot from each team will be moving toward the ball. Before reaching the ball these robots are to decide the force of hit and direction of hit for the given field configuration. The path followed by the robot depends on the direction of hit and the final velocity of the robot depends on the force of hit. The configuration of the field at any time during the game can be represented by a crisp set of coordinates of various objects as

$$\Re = \{b_x, b_y, r1_x, r1_y, r2_x, r2_y, r3_x, r3_y, r4_x, r4_y, g1_x, g1_y, g2_x, g2_y\} \quad (1)$$

where $\{b_x,\ b_y\}$are the coordinates of the ball position, the home robots are represented by a set $\{r1, r2, g1\}$ and the opponent robots are represented by another set $\{r3, r4, g2\}$. In the proposed FNNS, the action of the robot R_1 on the ball can be represented as

$$A_{R_1}(F,\theta) = \Im(b_x, b_y, r2_x, r2_y, r3_x, r3_y, r4_x, r4_y, g2_x, g2_y) \quad (2)$$

In Eq. (2), F is the force exerted by the robot R_1 on the ball, and θ is the angle of hit. The Eq. (2) can be modelled through a FNNS. The arguments on the right hand side of Eq. (2) are taken from the set (1), which includes ball position, team-mate position, and opponent positions. Similar equations can be written for the other robots with the members of the set (1) influencing their action. The variables in the Eq. (2) are given as the inputs of the FNNS. FNNS can be trained for each robot depending upon its role in the game and after training they can be used for the action selection mechanism of the robots in a team. For the implementation of Eq. (2), the soccer field is fuzzified in two directions and during the fuzzification; domain of the field and its boundary has to be separated. Field is fuzzified along the length and breadth, into five levels for the generation of the rule base. The soccer field is divided into 25 regions and each of these regions are represented by a fuzzy set as shown in Fig. 2. The various fuzzy sets shown in Fig. 2 are listed in Table 1. Out of these 25 fuzzy sets, 16 of them are used to represent the boundary and 9 of them are used to represent the domain. Gaussian membership functions are used to represent the fuzzy sets.

The coordinates of an object are sufficient to evaluate its membership values in the fuzzy set defining the field. For any arbitrary position of the robot R_2, it will have membership in two or more fuzzy sets, and hence the effect of measurement uncertainty or noise in the measured data is reduced. A crisp set consisting of the membership values in the twenty five fuzzy sets of the field for any position of the robot R_2 can be defined as

$$MF_{r2} = \{\mu_1, \mu_2, \mu_3, \ldots, \mu_k, \ldots, \mu_{25}\} \quad (3)$$

Due to two-dimensional fuzzification, each μ_k has two components in the membership values as

$$\mu_k = \{\mu_k x, \mu_k y\} \quad (4)$$

Appropriate action of the robot R_1 on the ball for any configuration of the field can be decided by considering the non-zero members of the set (3) of the various objects in Eq. (2). Usually the value of most of the members of the set (3) of an object is zero. Position of the non-zero members in the set (3) depends on the position of the object in the field. For every change in the field position of an object, there is a corresponding change in the position of the non-zero element of its set (3). Action of a robot on the ball depends on the configuration of the field and when the configuration changes, action also changes. Therefore the required action of the robots depends on the position of the

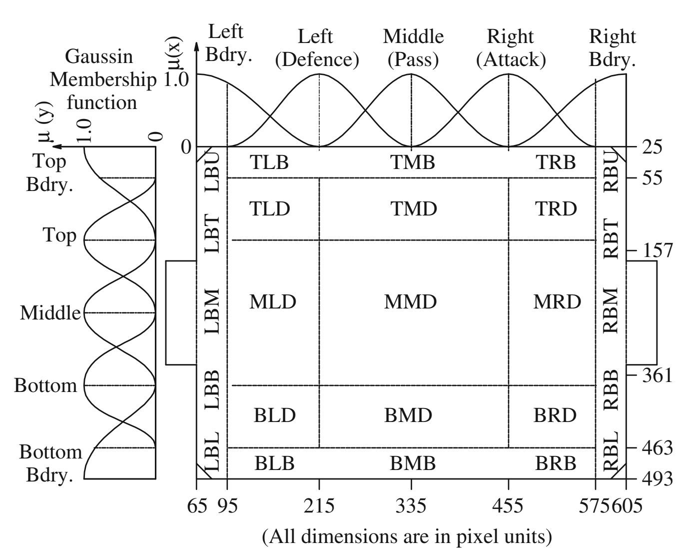

Fig. 2. Two dimensional fuzzification of the soccer field.

Table 1
Fuzzy sets defined for the fuzzification of the soccer field.

Field positions	Fuzzy sets	Field positions	Fuzzy sets	Field positions	Fuzzy sets	Field positions	Fuzzy sets	Field positions	Fuzzy sets
Left boundary up	LBU	Top left boundary	TLB	Top middle boundary	TMB	Top right boundary	TRB	Right boundary up	RBU
Left boundary top	LBT	Top left domain	TLD	Top middle domain	TMD	Top right domain	TRD	Right boundary top	RBT
Left boundary middle	LBM	Middle left domain	MLD	Middle middle domain	MMD	Middle right domain	MRD	Right boundary middle	RBM
Left boundary bottom	LBB	Bottom left domain	BLD	Bottom middle domain	BMD	Bottom right domain	BRD	Right boundary bottom	RBB
Left boundary lower	LBL	Bottom left boundary	BLB	Bottom middle boundary	BMB	Bottom right boundary	BRB	Right boundary lower	RBL

non-zero elements of the set (3) of the objects in Eq. (2). Through a FNNS the various non-zero elements of the set (3) can be combined to take an action. In the proposed work FNNS are developed for the home robots R_1 and R_2, and the effectiveness of the proposed approach is established through system simulation.

The proposed network consists of five layers; input layer, fuzzification layer, identification layer, rule layer, and defuzzification layer. Fig. 3(a) and (b) shows the part of the FNNS for robot R_1 which selects appropriate actions when the ball is in the defence zone and the opponent robots are attacking. In these figures L_i, where $i=1$ to 5 stands for the various layers of the network and the number associated with L_i represents the number of nodes in that layer. When the opponent robots drive the ball to their attack zone, home robots take a defensive strategy. For this zone ball has non-zero membership values in some of the ten fuzzy sets corresponding to the left boundary and the defence zone. In this situation robot R_1 adapt the strategy of blocking, intercepting, dribbling or kicking the ball in an appropriate direction to save the goal. The action selection mechanism of R_1 in this zone is described in the network using 132 fuzzy neurons in the fourth layer. When the ball is in the pass zone, some of the five fuzzy sets defined for the pass zone are having non-zero membership values and the nearest robot from the teams approaches the ball. Considering the robot R_1, it tries to pass the ball to robot R_2, provided R_2 is positioned ahead of R_1 in the pass zone or in the attack zone. Otherwise it kicks the ball in a direction towards the opponent goal post. The part of the FNNS showing this strategy of R_1 is represented in Fig. 3(c) through 125 fuzzy neurons in the fourth layer. The home robots must exhibit an attacking strategy when the ball is in their attack zone. When the ball is in this zone, robot R_1 (or R_2) tries to shoot the ball into the opponent goal post. At the same time the opponent robots attempt to hinder the attack. Usually opponent goalkeeper is moving along the goal line to safeguard the goal box and at the time of shoot it has to correct orientation according to the position of the ball and its direction. The shooting strategy of the robot R_1 is modelled as a part of the FNNS as shown in Fig. 3(d) using 30 fuzzy neurons in the fourth layer. Sixteen fuzzy sets are used to represent the boundary rules all around the field. If the ball is in the boundary region, it will have membership values in only one of the fuzzy sets representing the field. Correspondingly membership set of the ball defined by Eq. (3) can have only one non-zero element. Depending upon the position of the non-zero element in the set (3) of the ball, robot R_1 takes an action. Fig. 3(e) shows the part of the FNNS used for taking boundary decision using 16 neurons in the third layer. When the ball is in the boundary zone, as it is possible to take an action on the basis of the position of the ball alone, the FNNS proposed for this zone has only four layers. The structure of the fuzzy neurons used in the fourth layer of the network is shown in Fig. 4. The complete FNNS for the action selection of the robot R_1 is obtained by combining all these five parts.

3. Analysis of the layered structure of FNNS

The input output values and the nodal activities of various neurons in the different layers of the FNNS are analyzed in this section. Each of the neurons in the first layer has single input and single output. Input vector of the input layer relevant to the robot R_1 of the home team is represented as

$$\{x\}^T = \{x_i\}^T = \{b_x, b_y, r2_x, r2_y, r3_x, r3_y, r4_x, r4_y, g2_x, g2_y\} \tag{5}$$

It is assumed that x_i be the ith component of the input vector and odd values of $i$represent x-coordinates of the object in the soccer field relevant to R_1, and even value of i represent the y-coordinates of the object in the soccer field relevant to the R_1. As the neurons in the first layer are directly passed to the second layer, the outputs of this layer are given by

$$yk^1_\alpha = x^1_\alpha; \quad yk^1_\beta = x^1_\beta \tag{6}$$

where $\alpha=1, 3, 5, 7, 9$ represent x-coordinates of the object and $\beta=2, 4, 6, 8, 10$ represent the y-coordinates of the object. The symbol $k=1, 2, 3, 4, 5$ represent the object number, the objects being the ball, robot R_2, robot R_3, robot R_4, and the opponent goalkeeper G_2, respectively. Each neuron in the second layer performs fuzzification using Gaussian membership function as

$$\mathrm{net}^2_{\alpha p} = -((yk^1_\alpha - m_{xp})/\sigma_{xp})^2, \quad p = 1,2,\ldots,5 \tag{7}$$

$$\mathrm{net}^2_{\beta q} = -((yk^1_\beta - m_{yq})/\sigma_{yq})^2, \quad q = 1,2,\ldots,5 \tag{8}$$

The second layer outputs are given by

$$yk^2_{\alpha p} = \exp(\mathrm{net}^2_{\alpha p})$$
$$yk^2_{\beta q} = \exp(\mathrm{net}^2_{\beta q}) \tag{9}$$

The Gaussian function parameters m_{xp}, m_{yq}, σ_{xp}, and σ_{yq} are to be tuned through an appropriate learning algorithm. Certain restrictions are made during the construction of the FNNS and the development of the rule base, so as to simplify the network structure. These are as follows:

- The presence of an opponent robot is considered in the action of robot R_1 only when the ball is in the defence zone, so that in Eq. (9), $p=1, 2, 3$, for each object 3 and 4.
- Motion of the opponent goalkeeper is mainly along the goal line and its membership is limited to the second, third, and fourth fuzzy sets of the right boundary so that in Eq. (9), $p=1$ and $q=1, 2, 3$ for the object 5.

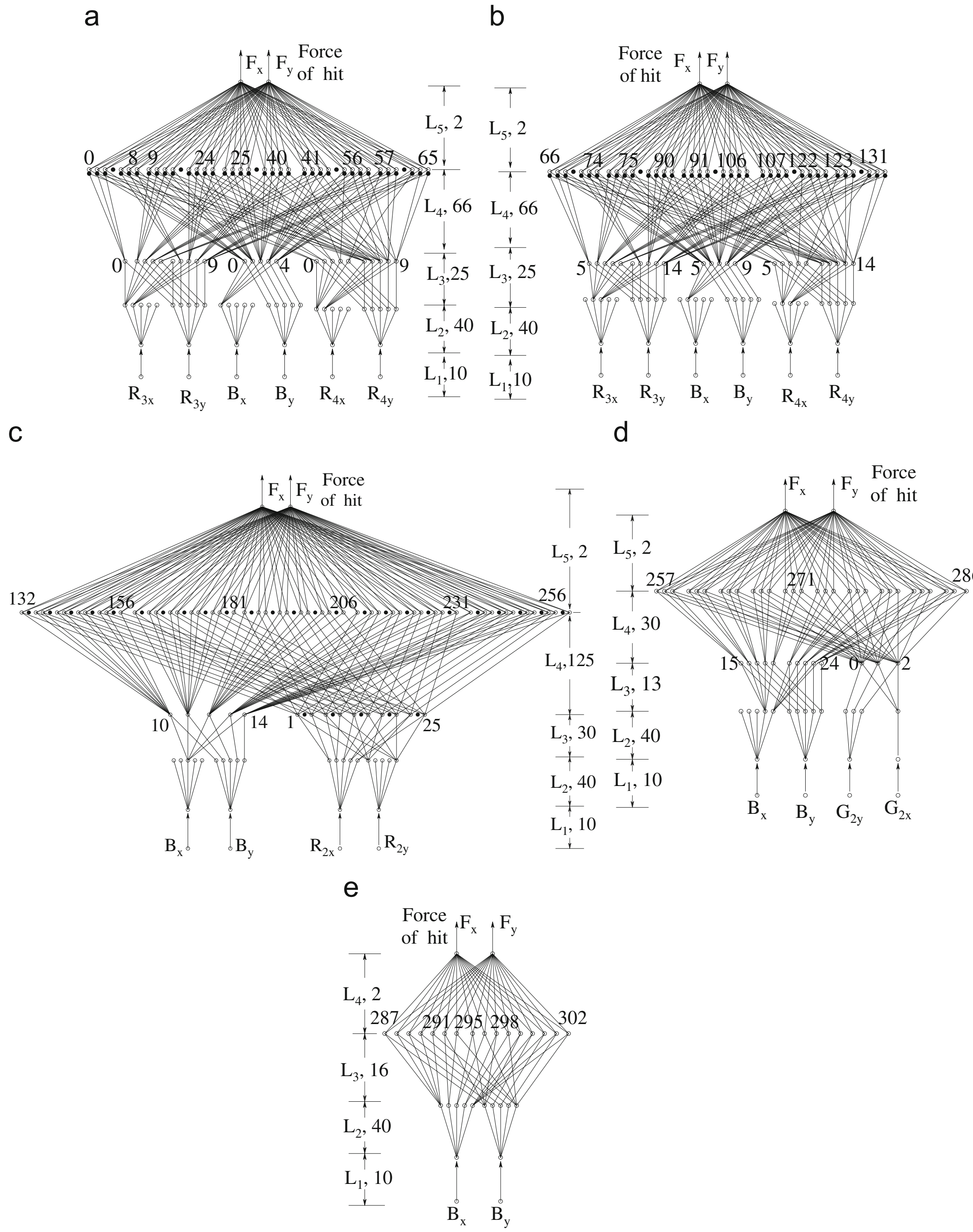

Fig. 3. (a) Part I of FNN: ball in the left boundary and robot R_1 defends. (b) Part II of FNN: ball in the defence zone and robot R_1 defend the attack. (c) Part III of FNN: ball in the Pass Zone and Robot R_1 Pass it to R_2, (d) Part IV of FNN: ball in the attack zone and nearest robot attacks. (e) Part V of FNN: Bball in the boundary zone.

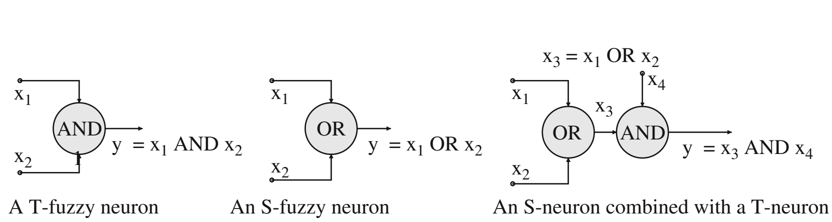

Fig. 4. Various fuzzy neurons used in the fourth layer of the FNN.

Each neuron in the third layer has two input nodes, one is from the fuzzified *x*-coordinate of the object and the other is from the fuzzified *y*-coordinate of the same object. There can be two or more output nodes. The position of an object in the field is identified through a fuzzy T-norm operation. A non-zero value of the output from the T-norm operation indicates the presence of the object in the field position represented by the fuzzy sets involved in the T-norm operation. In this application fuzzy T-norm based on algebraic product is used as it provides continuous first order derivatives as

$$\text{net}_i^3 = yk_{\alpha p}^2 yk_{\beta q}^2, \quad \text{where } i=(p-1)^*5+q \tag{10}$$

The output of the third layer are given by

$$yk_i^3 = \Im_i^3(\text{net}_i^3) = yk_{\alpha p}^2 yk_{\beta q}^2 \tag{11}$$

In the fourth layer, each neuron for the defence zone has three input nodes where as the neurons for the other zones have only two input nodes. In this zone, fuzzy operations like S-norms and T-norms and their combinations are considered for the fuzzy inferencing mechanism. Algebraic sum, which provides a continuous first order derivative compared to the logical sum or bounded sum is considered for implementing the fuzzy S-norm. However the fuzzy rules for the pass zone and the attack zone can be represented through a T-norm operation alone. Fourth layer receives the output of the third layer, the nodal activity for the various zones namely defence zone, pass zone, and attack zone are, respectively, given by

$$\text{net}D_{n_1}^4 = y1_i^3\left(y3_p^3 + y4_q^3 - y3_p^3 y4_q^3\right) \tag{12}$$

Outputs of the fourth layer neurons are calculated using a zone indicator 'Z' so that Z is D for defence zone, Z is P for pass zone, and Z is A for attack zone. Thus the output of the fourth layer is

$$yZ_{n_1}^4 = \Im_{n_1}^4(\text{net}Z_{n_1}^4)$$

$$yD_{n_1}^4 = y1_i^3(y3_p^3 + y4_q^3 - y3_p^3 y4_q^3) \tag{13}$$

$$yP_{n_2}^4 = y1_i^3 y2_j^3 \tag{14}$$

$$yA_{n_i}^4 = y1_i^3 y5_r^3 \tag{15}$$

Fifth layer is the defuzzification layer and in this Layer crisp actions are computed using centre of area defuzzification method (Chao et al., 1996; Tsoukalas and Uhrig, 1997). Each of the 303 neurons in the fourth layer is connected to two output neurons in the fifth layer. Combining the neurons in the different zones of the soccer field, input to the fifth layer can be represented as

$$\upsilon_f^5 = \text{net}_f^5 / \textstyle\sum_{K=1}^{303} x_K^5 = \sum_{K=1}^{303} w_{fK}^5 yZ_K^4 / \sum_{K=1}^{303} yZ_K^4; \quad f=1,2 \tag{16}$$

Final output of the network is obtained after the activation in the neurons of the output layer as

$$y_f^5 = \phi(\upsilon_f^5) = \upsilon_f^5; \quad f=1,2 \tag{17}$$

where f is the number of neurons in the output layer of the FNNS. Using a rule base, developed on the basis of the knowledge acquired from the experts, the desired action of a robot on the ball for a given field configuration can be decided. Eq. (17) predicts the action of the network for the same configuration of the field by assigning suitable initial values to the parameters of the FNNS. Adjusting the network parameters through the error back propagation learning (Chao et al., 1996; Haykin, 1999) algorithm, the difference between the actions inferred from the rule base and the action predicted can be minimized. Network parameters include, synaptic weights at the output layer of the network and the Gaussian function parameters used in the second layer for fuzzification. In the error back propagation learning algorithm, error at the output layer is propagated back and the local gradient of the error is calculated for each layer. For a desired output d_f^5 the error at the output node during the nth step of the gradient decent learning is given by

$$e_f^5(n) = d_f^5 - \upsilon_f^5(n) \tag{18}$$

The error function that is used as an objective function for the optimization of the network parameters is given by

$$E(n) = \frac{1}{2}\sum_{f=1}^{2}(e_f^5(n))^2 \tag{19}$$

Using the error gradient of this objective function obtained in the nth step of the learning cycle, local gradient at the output layer can be evaluated. The local gradient at the fth neuron in the output layer is given by

$$\delta_f^5 = -\frac{\partial E(n)}{\partial \text{net}_f^5(n)} = -e_f^5(n) / \sum_{K=1}^{303} yZ_K^4(n) \tag{20}$$

where yZ_K^4 is the output from the fth neuron in the preceding layer for the zone 'Z'. The local gradient of the neurons in the fourth layer can also be calculated as

$$\delta_K^4 = \sum_{f=1}^{2} e_f^5(n)\left(\partial e_f^5(n)/\partial \upsilon_f^5(n)\right)\left(\partial \upsilon_f^5(n)/\partial yZ_K^4(n)\right) \tag{21}$$

Using Eqs. (16) and (18)

$$\frac{\partial e_f^5(n)}{\partial \upsilon_f^5(n)} = 1, \quad \frac{\partial \upsilon_f^5(n)}{\partial yZ_K^4(n)} = (w_{fK}^5(n) - \upsilon_f^5(n)) / \sum_{K=1}^{303} yZ_K^4(n)$$

Using this equation in (21) the local gradient of the neurons in the fourth layer can be obtained as

$$\delta_K^4(n) = \sum_{f=1}^{2} \delta_f^5(n)(w_{fK}^5(n) - y_f^5(n)) \tag{22}$$

Neurons in the third layer belong to various objects in Eq. (5). In the proposed structure of FNNS, there are twenty five neurons for the identification of the ball, twenty five neurons for the identification of the robot R_2, fifteen neurons for the identification of the robot R_3, fifteen neurons for the identification of the robot R_4, and three neurons for the identification of the opponent goalkeeper. Local gradient for a neuron i of an object k in the third layer can be written as

$$\delta k_i^3(n) = -\frac{\partial E(n)}{\partial \text{net}k_i^3(n)},$$

$i=1,2,3,\ldots$ is the number of neurons of the object k (23)

$$\delta k_i^3(n) = -\frac{\partial E(n)}{\partial yk_i^3}\frac{\partial yk_i^3(n)}{\partial \text{net}k_i^3(n)} \tag{24}$$

$$\delta k_i^3(n) = \left(\sum_{K=1}^{303} \delta_K^4(n)\frac{\partial yZ_K^4(n)}{\partial yk_i^3(n)}\right) \tag{25}$$

The derivative on the right hand side of Eq. (25) is evaluated by considering Eqs. (13)–(15) and also from the fact that δk_i^3 depends on $\delta_K^4(n)$ to which kth object has a link. For other $\delta_K^4(n)$ the corresponding derivatives will be zero. Object 1 is the ball and it is linked to all neurons in the fourth layer. Object 2 is the teammate of the robot R_1, and it is linked to all the 125 neurons in the pass zone (K=133–257). Object 3 and Object 4 represent the opponent robot, and it is linked to all the neurons in the defence zone (K=1–132). Object 5 is the opponent goalkeeper and it is linked to all the neurons in the attack zone (K=258–287). For the neurons in the second layer, local gradients are evaluated separately for the x-neurons and the y-neurons as

$$\delta_{\alpha p}^2 = -\frac{\partial E(n)}{\partial \text{net}_{\alpha p}^2(n)} \tag{26}$$

where the index $\alpha=1, 3, 5, 7, 9$ represents the x-coordinates of the various objects and $p=1, 2, 3, 4, 5$ are the neurons representing different levels of fuzzification.

$$\delta^2_{\alpha p} = -\frac{\partial E(n)}{\partial y^2_{\alpha p}} \frac{\partial y^2_{\alpha p}(n)}{\partial \mathrm{net}^2_{\alpha p}(n)} \tag{27}$$

$$\delta^2_{\alpha p} = \sum \delta k^3_i(n) y k^3_i(n) \tag{28}$$

Local gradient for a y-neuron in the second layer can be obtained in the same manner as

$$\delta^2_{\beta q} = \sum \delta k^3_i(n) y k^3_i(n) \tag{29}$$

where the index $\beta=2, 4, 6, 8, 10$ represents the y-coordinates of the various objects and $q=1, 2, 3, 4, 5$ are the neurons representing different levels of fuzzification. In these equations $k=1, 2, 3, 4, 5$ stands for the object number. Network parameters are optimized through the minimization of the error function given in Eq. (19). Gradient of the error function is evaluated with respect to the various network parameters. Local gradients determined in the previous steps are used for evaluating the gradient of the error function. Synaptic weights in the fifth layer can be modified iteratively using Eq. (20) as

$$w^5_{fK}(n+1) = w^5_{fK}(n) + \eta \delta^5_f y Z^5_f(n) + \mu \Delta w^5_{fK}(n) \tag{30}$$

where the learning rate η and the momentum coefficient μ can be suitably selected between 0 and 1. Similarly the adaptive rule for the Gaussian function parameters in the second layer can be written using the local gradient calculated in Eqs. (28) and (29) as

$$\sigma_{xp}(n+1) = \sigma_{xp}(n) + \eta \delta^2_{\alpha p}(2(x_\alpha - m_{xp})^2/\sigma_{xp}{}^3) + \mu \Delta \sigma_{xp}(n) \tag{31}$$

$$\sigma_{yq}(n+1) = \sigma_{yq}(n) + \eta \delta^2_{\beta q}(2(x_\beta - m_{yq})^2/\sigma_{yq}{}^3) + \mu \Delta \sigma_{yq}(n) \tag{32}$$

$$m_{xp}(n+1) = m_{xp}(n) + \eta \delta^2_{\alpha p}(2(x_\alpha - m_{xp})/\sigma_{xp}{}^2) + \mu \Delta m_{xp}(n) \tag{33}$$

$$m_{yq}(n+1) = m_{yq}(n) + \eta \delta^2_{\beta q}(2(x_\beta - m_{yq})/\sigma_{yq}{}^2) + \mu \Delta m_{yq}(n) \tag{34}$$

4. Training data generation

The input to the FNNS consists of the coordinates of the various objects represented in Eq. (5). The desired output of the FNNS is the best possible action of the robots for that field configuration. For the simulation of the proposed FNNS, the soccer field is defined in terms of the pixel values. The size of the field and the various zones are initialized with the pixel values according to the MiroSot small league game as shown in Fig. 2. Using a random number generation algorithm, coordinates of the various objects are generated zone by zone. A set of 1000 field configurations is a reasonable representation of the game situation. The desired action of the robot R_1 on the ball corresponding to each configuration of the field is determined using the rule base. A particular configuration of the field taken from the training set is shown in Fig. 5(a). For this configuration, a crisp set of membership values can be determined for each object as given in Eq. (3). The action of the robot depends on the non-zero members of these sets. Combining the non-zero membership values of the relevant objects, zone by zone, a rule base can be developed. Since each object is fuzzified into five levels along the length and breadth, the number of rules involved seems to be large. However all these rules are not required in deciding an action because strategies of the robot depend on its zone. The rules are written for zones, so that the number of active rules for a field configuration is limited. For the configuration in Fig. 5(a), ball is in the defence zone, having membership in four fuzzy sets such as (Defence, Top), (Defence, Middle), (Left Bdry, Top), and (Left Bdry, Middle). Opponent robot R_4 is in the pass zone with membership in four fuzzy sets (Pass, Middle), (Pass, Bottom), (Defence, Middle), (Defence, Bottom), and robot R_3 is located in the attack zone. For defining rules for the action selection of the robot R_1 to defend the ball, only the opponent robots having a membership in the defence zone or pass zone are to be considered. This is because the zone of the ball is not overlapping with any other zone other than the pass zone. Therefore, without considering an opponent robot R_3 standing in the attack zone or opponent goalkeeper G_2 reasonable actions can be taken. Thus the number of rules involved for selecting an action is reduced to a great extent. In this particular case only 16 rules (4×4) are contributing towards the calculation of the crisp action for R_1. Crisp action is calculated using the centroid defuzzification method as

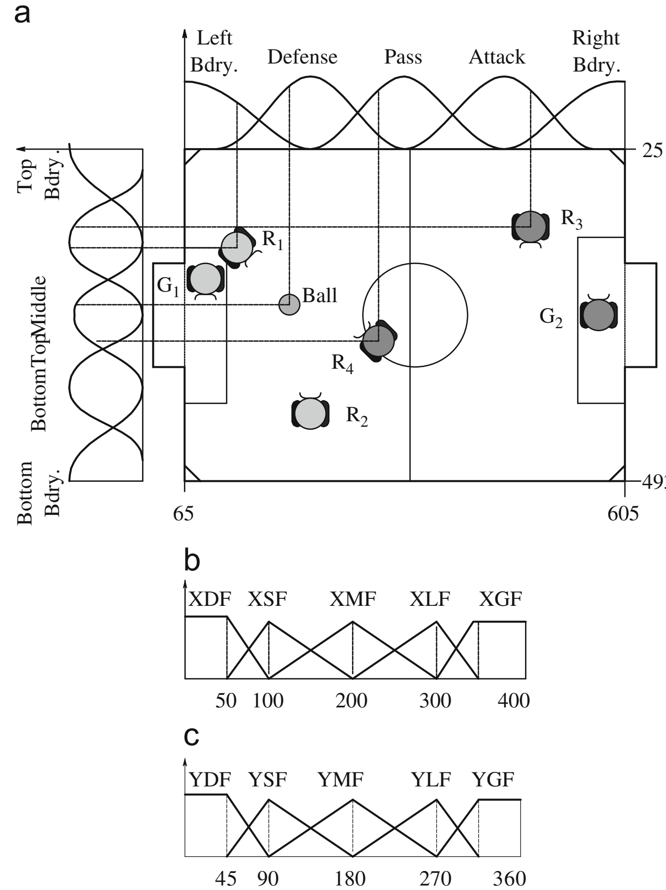

Fig. 5. (a) Fuzzified robot soccer field for rule generation, (b) fuzzification of the force of hit along field length, and (c) fuzzification of the force of hit along field width.

$$\text{Crisp Action} = \left(\sum_i^n (\text{Rule strength})_i (\text{Fuzzy action}) / \sum_i^n (\text{Rule strength})_i \right) \tag{35}$$

In Eq. (35), rule strength is the membership value of the rule, and n is the number of rules involved. After developing a rule base, best possible action can be found through fuzzy inferencing. During the time of fuzzy inferencing each rule is fired with certain strength. This firing strength will be the membership value of the objects involved in the rules. Knowledge of an expert is essential for specifying the force of hit and direction of hit for various game situations in developing a rule base. Force exerted on the ball corresponding to each action of the robot has to be properly scaled and fuzzified before making a rule base. Forces along the length of the field are fuzzified into five levels as shown in Fig. 5(b) and they are represented through linguistic variables such as 'Dribbling Force (XDF)', 'Small Force (XSF)', 'Medium Force (XMF)', 'Large Force (XLF)', and 'Great Force (XGF)'. Similar fuzzy sets are defined to fuzzify the forces along the breadth of the field as shown in Fig. 5(c).

5. Results and discussion

The effectiveness of the proposed FNNS architecture for the intelligent task planning and action selection of a mobile robot in a multi-agent system is established through simulation. FNNS algorithm is implemented in a visual C++ environment, and it consists of three stages. In the first stage a separate algorithm is developed for generating the training data using a fuzzy inferencing system described in the previous section. It is verified that the training set contains representatives from every part of the field. If the generated training data is not representing every part of the field, then synaptic weights of the corresponding neurons in the fifth layer of the network are not improved through learning. This is because fuzzy sets representing those regions are always having zero membership values, and hence neurons representing that region of the field are not fired. Every possible configurations of the field will be modelled with a combination of one or more fuzzy neurons of the proposed FNNS. Desired output for the network obtained with the rule base representing the actual action of the robot is logically verified.

In the second stage of the simulation, learning algorithms are developed for the FNNS through error back propagation techniques using the Eqs. (30)–(34). All synaptic weights in the fifth layer are initialized to zero. The centres of the Gaussian functions are initialized to corresponding pixel values shown in Fig. 2 and considering the spread of the membership functions as 3σ the variances of the Gaussian functions can be initialized. All the objects are initialized with the same centre and variance. Learning curve of the trained FNNS is shown in Fig. 6 indicate that learning process is fast and the value of the error function decreased to an acceptable level. During the learning, parameters of the Gaussian function for each object is changed separately, as each object is considered to have its own perspective about the field. Convergence of the most of the Gaussian function parameters during the learning phase is too close to their initial values.

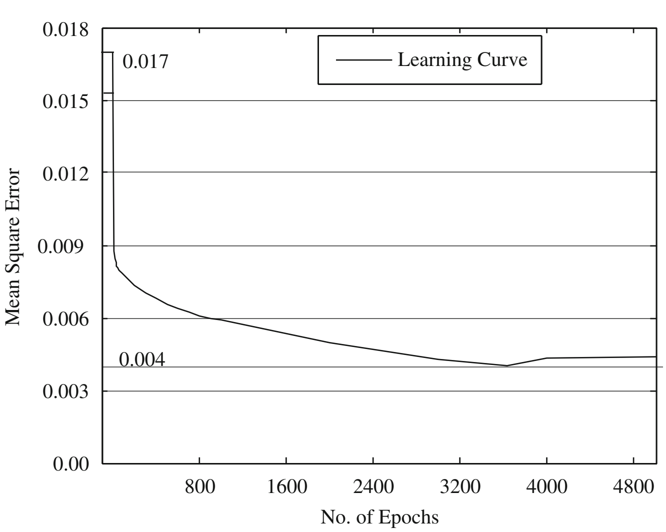

Fig. 6. Learning curve of the FNNS.

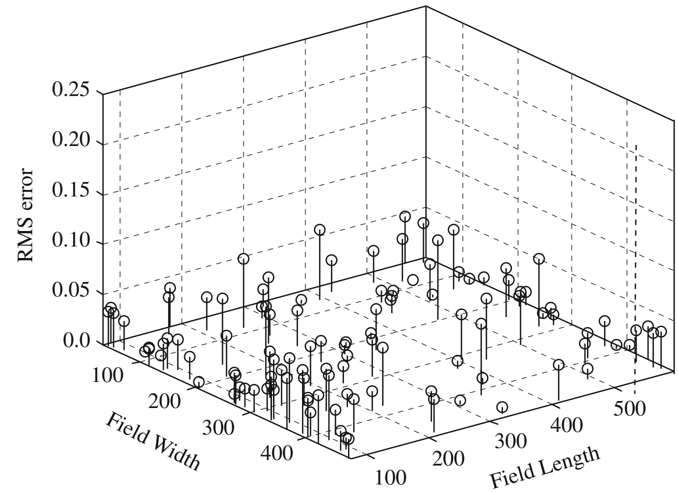

Fig. 7. RMS errror for a few training samples.

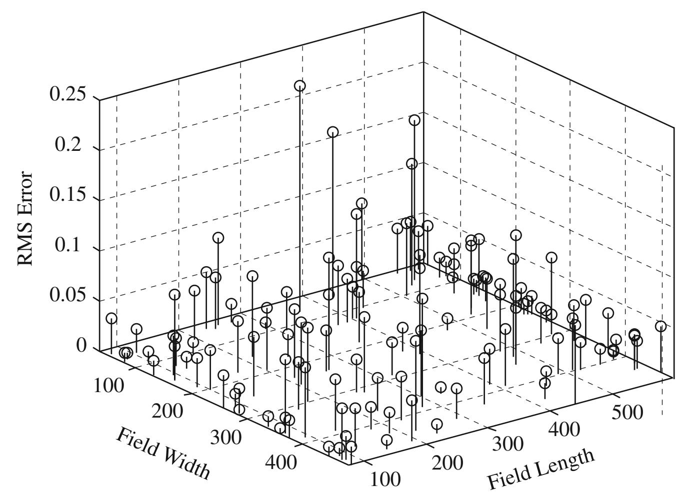

Fig. 8. RMS error for few test samples.

In the third stage, the trained network is tested with a set of 1000 field configurations to assess the capability of the network in taking intelligent actions. It is observed that the capability of the FNNS for taking diversified actions depending upon the various game situations is significant and practically spontaneous. Fig. 7 shows the RMS value of the error left with the random sample of the training data and Fig. 8 shows the RMS value of the error left with the random sample of the test data. These figures indicate the good generalization characteristics of the trained FNNS in most of the cases. During generalization, nearly 10% of the case systems show an error higher than that obtained during the training period. The configuration for which, action taken by the FNNS deviates much from the expected actions are studied. It is found that even though the magnitude of RMS error deviates from the expected value, the selected actions are logical and strategic for that situation. Figs. 9 and 10 show the direction of action taken by FNNS for robot R_1 with the training set and with the test set. From these direction plots it can be seen that the effort of the robot R_1 is to bring the ball always to the opponent

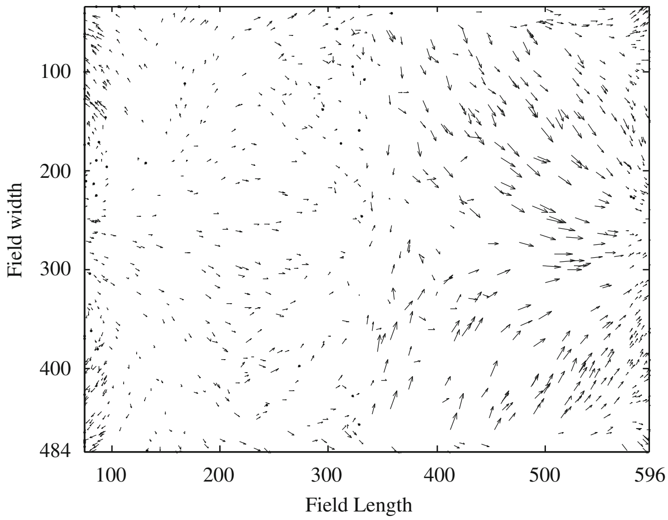

Fig. 9. Angle of hit by R_1 for 1000 training data.

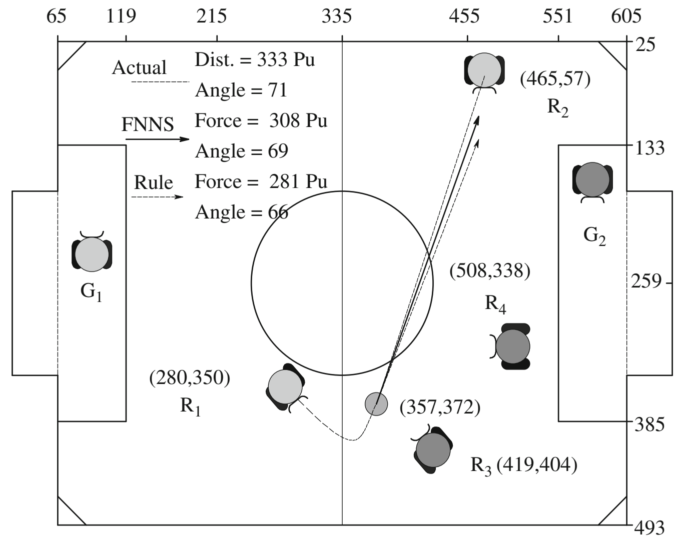

Fig. 12. Robot R_1 passes ball to team-mate R_2.

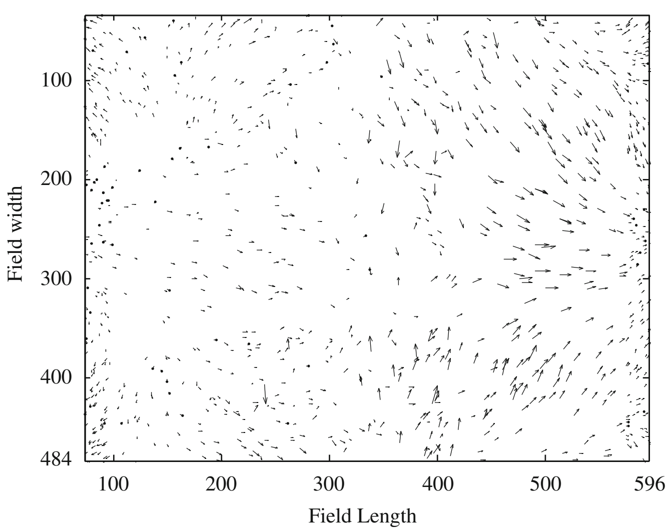

Fig. 10. Angle of hit by R_1 for 1000 test data.

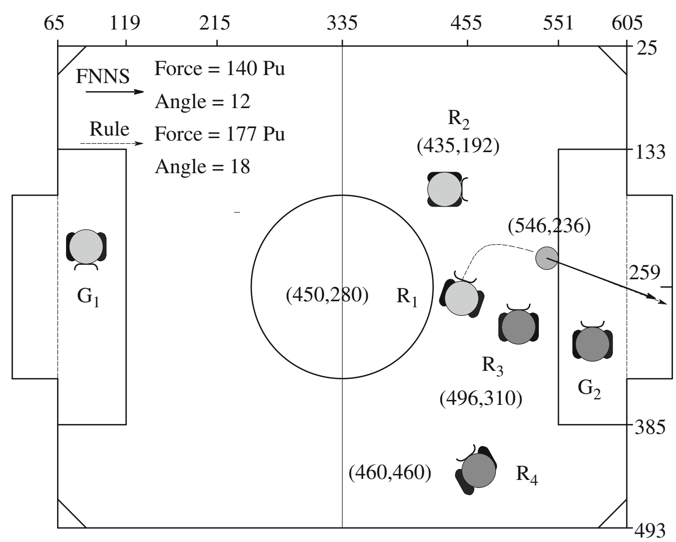

Fig. 13. Shooting action of robot R_2.

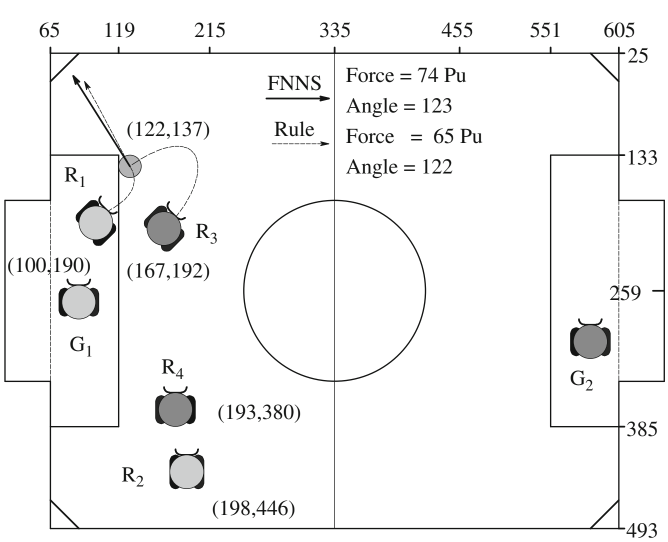

Fig. 11. Robot R_1 defends the attack of Robot R_3.

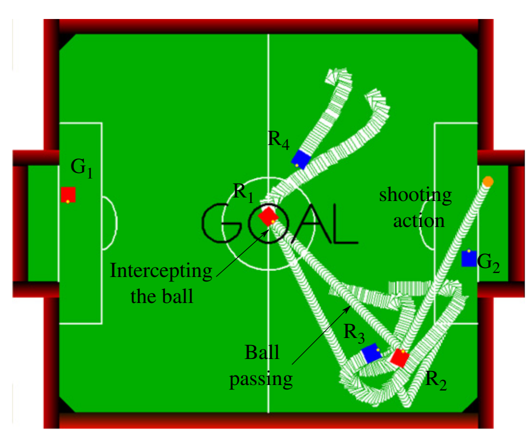

Fig. 14. Robot soccer simulation exhibits ball passing and shooting behaviour.

goal box, at the same time the robot hits the ball away from its own goal box.

The direction of action taken by the robot R_1 is always aimed to the opponent goal box as per the strategy adopted in the

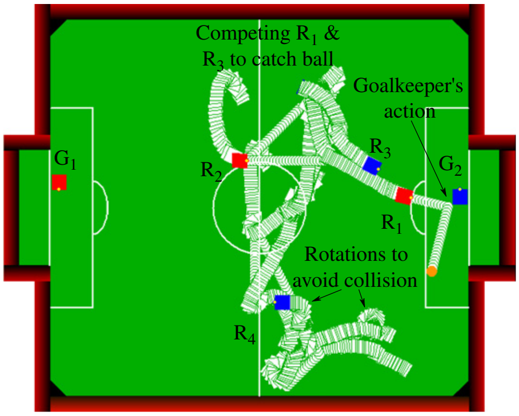

Fig. 15. The robot soccer simulation goalkeepers blocking behaviour.

development of the FNNS. Using FNNS, a Robot can exhibit appropriate actions in the defence zone, pass zone, attack zone, and in the boundary of the field. This point is further illustrated in Figs. 11–13 using a few sample configurations from the test data set. It is seen that, as shown in Fig. 12, action of the FNNS is according to the action predicted by the rule base. For a given strategy the proposed FNNS is useful for the action selection of both the robot R_1 and R_2. The investigations revealed that the proposed FNNS is successful in selecting a sensible action for any possible field configuration. As the strategy of the opponent robots is different from that of the home robots, and their FNNS is to be trained separately.

The effectiveness of the FNN based technique is further illustrated through the robot soccer simulation shown in Figs. 14 and 15. In this simulation, top view of the soccer robot system, which is equivalent to the image captured by the vision camera, is generated. Playground, robots, and the ball are generated are same as the FIRA's MiroSot small league specifications (www.fira.net) using thread functions. The various algorithms implemented and tested through this simulation include the high level decision making through ANNs (Jolly et al., 2007); intelligent action selection mechanism based on FNNS and a Bezier curve based path planning techniques. In the simulation home team with robots R_1, R_2, G_1 is coloured RED while the opponent team with robots R_3, R_4, G_2 is coloured BLUE. According to this action selection mechanism, the action of an agent depends on the field configurations. This simulation exhibit various coordinated behaviours such as ball passing, blocking, goal shooting, obstacle avoidance, and interception. These simulations show that coordination, corporation and intelligent decision making can be possible with FNN based action selection mechanism.

6. Conclusion

A fuzzy-neural network based intelligent task planning and action selection mechanism has been proposed in this paper, for a mobile robot in a robot soccer system. The proposed fuzzy neural network system has been trained using error back propagation learning algorithm. A two dimensional fuzzification of the robot soccer field has been attempted in this work for the construction of the proposed fuzzy neural network system. The strategy based action selection depends on the field configuration, and emergence of a particular field configuration in turn depends on the game dynamics. A robot changes its strategy when the configuration of the objects in field changes. The development of an FNNS based approach for the determination of the goalkeeping strategy of the home goalkeeper for different shooting positions and ball directions are under progress. The proposed architecture fuzzy neural network system has been found flexible to accommodate all possible filed configurations.

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