Design of an Action Select Mechanism for Soccer Robot Systems Using Artificial Immune Network

Yin-Tien Wang* and Chia-Hsing Chen

Department of Mechanical and Electro-Mechanical Engineering, Tamkang University, Tamsui, Taiwan 251, R.O.C.

Abstract

In a small-size robot soccer game, the game strategy is implemented by two major procedures, namely, Role Selection Mechanism (RSM) and Action Select Mechanism (ASM). In role-select procedure, a formation is planned for the soccer team and a role is assigned to each individual robot. In action-select procedure, each robot executes an action provided by an action selection mechanism to fulfill its role-playing. The RSM was often designed efficiently by using the geometry approach. However, the ASM developed based on geometry approach will become a very complex procedure. In this paper, a novel ASM for soccer robots is proposed by using the concepts of artificial immune network (AIN). This AIN-based ASM provides an efficient and robust algorithm for robot role select. Meanwhile, a reinforcement learning mechanism is applied in the proposed ASM to enhance the response of the adaptive immune system. Simulation and experiment are carried out in this paper to verify the proposed AIN-based ASM and the results show that the proposed algorithm provide an efficient and applicable algorithm for mobile robots to play soccer game.

Key Words: Action Select Mechanism (ASM), Artificial Immune Network (AIN), Soccer Robot, Reinforcement Learning

1. Introduction

The purpose of this research is to design a strategy planning system for multiple robots playing soccer game. The system is composed of two levels: namely, Role Selection Mechanism (RSM) and Action Select Mechanism (ASM). The RSM assigns different roles to each robot in order to work together as a team and fulfill the game strategy. When each robot is assigned a certain role, the ASM will consider what the appropriate action is for each robot to accomplish their roles. Each robot executes its own actions provided by the ASM, and a team of robots perform a formation task in the soccer game by collaboration.

In the literatures, the RSM was often developed by geometry approach based on decision tree theory [1–4]. A decision tree has several nodes arranged in a hierarchical structure as depicted in Figure 1. It is based on the instantaneous geometric situation on the soccer field, such as the absolute position of the ball and the relative position between the ball and robots, to choose the most suitable role for each of the robots. Roles of the robot can be distinguished into active robot and passive robot. Every moment in the game can only allow one robot to play as an active robot and in charge of offense and defense; while the others are passive robots to assist the active robot to carry out the mission. From Figure 1, it is easy to see that the decision tree implements the decision in a simple, apparent, multistage manner. Since each node of a decision tree uses only a simple splitting rule, the entire decision process can be implemented very fast and efficiently.

In the past, the ASM is also premeditated by using the geometry method and an action is assigned to each robot to accomplish the task based on the geometrical location of the ball or robot in the soccer field [3–4]. Tsou

*Corresponding author. E-mail: ytwang@mail.tku.edu.tw

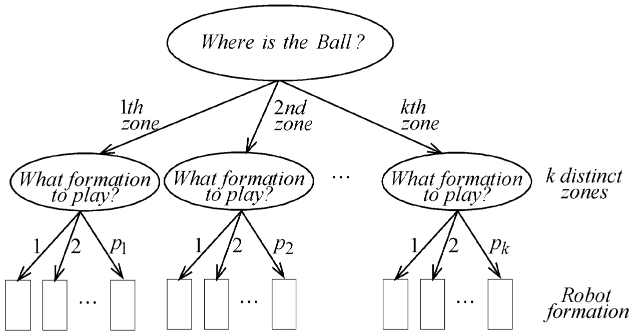

Figure 1. Decision tree.

et al. designed totally eight basic actions for soccer robot, including chase ball, dribble ball, shoot ball, sweep ball, goal keeping, blocking, active attack, and assist attack. The details of these actions are explained in Table 1. There are two major disadvantages by using the concept of geometry thinking for constructing an ASM: first, if the ball is located at the boundary of two zones, the geometry thinking method will fail to function; second, there are too many actions to be considered in order to cover all possible conditions of all geometrical divisions. In this paper, an ASM based on the artificial immune network is proposed to replace the geometry thinking method and resolve the problem of disadvantages. Meanwhile, the decision tree is still used to decide the role of each robot in this research.

In human body, the biological immune system defends the invasion of outer viruses or antigens by two successive response subsystems, including the innate immune system and the adaptive immune system. The innate immune system is a primitive non-specific recognition system which is able to "eat" the antigens and transmit the identification of antigen to adaptive immune system. The lymphocytes (B-cell) in the adaptive immune system will perform cell division and duplicate a massive number of antibodies according to the transmitted id of antigens. These antibodies are responsible to kill the invasive antigens [5]. Jerne [6] proposed the idiotypic network hypothesis which can be utilized to model the adaptive immune system [7]. The reinforcement learning mechanism in machine learning area brought in the concept of determining the priority order and meaning of antibodies [8–10] and can be utilized to enhance the biological adaptive immune system. The idiotypic network hypothesis and the reinforcement learning mechanism are two foundations of the artificial immune network.

In this paper, it is proposed to construct an Action Select Mechanism for soccer robots based on the concepts of AIN. The main contribution of the research is to reduce the complexity of designing the robot actions by using the AIN-based ASM. After applying AIN to the ASM, only three actions are necessary for the robot soccer game, including ball chasing, opponent blocking, and space chasing. A robot chooses one of the actions to carry out the role appointed to it from the RSM depending on which antibody with the highest concentration is triggered. Table 2 depicts the functions of these actions and the situation it is used for. The reinforcement learning mechanism is utilized to determine the priority order of antibodies at the initial stage of soccer games, and then the game strategy is carried out according to the priority order. Therefore, a tactic-based decision system, as shown in Figure 2, is formed for a soccer robot team.

2. Robot Behavior-Based Controller

A behavior-based controller is designed for the robots to accomplish the soccer game by using an AIN-based action select mechanism. This section describes the procedure of building an AIN model, which includ-

Table 1. Actions of geometry thinking ASM

Chase ball	When robot is far away from ball, this action is given to go after the ball.
Dribble ball	If robot is closed to the ball, this action is called to take control of the ball.
Shoot ball	If robot is closed to the ball and goal, this action is used to shoot the ball.
Sweep ball	While the ball is in the corner or boundary, the robot uses this action to sweep the ball out.
Goal keeping	Robot plays as a goal keeper gets this action to prevent losing point.
Blocking	If an opponent and the ball are close to our goal, the closest robot goes between the opponent and ball trying to block the way.
Active attack	If ball is near the opponent's goal, the closest robot will play as an attacker.
Assist attack	Robot closest to the attacker gets ready to attack in case the attacker misses.

Table 2. Actions of AIN-based ASM

Ball Chasing	When the concentration of ball is the highest, this action is selected by robot, and it will chase toward the ball.
Opponent Blocking	Robot moves to a point between opponent and ball to prevent opponent takes control of the ball. This action is taken when the concentration of opponent is the highest.
Space Chasing	This action is only used when the concentration of ball is the highest, and under the following condition: a) opponent is within 5 inches from robot, b) opponent and ball are in the same quadrant, c) opponent is between robot and ball.

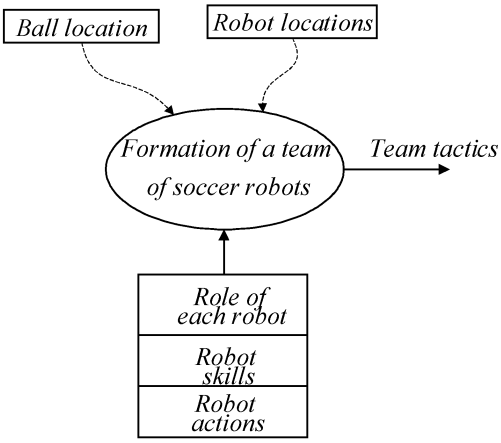

Figure 2. Tactic-based decision system.

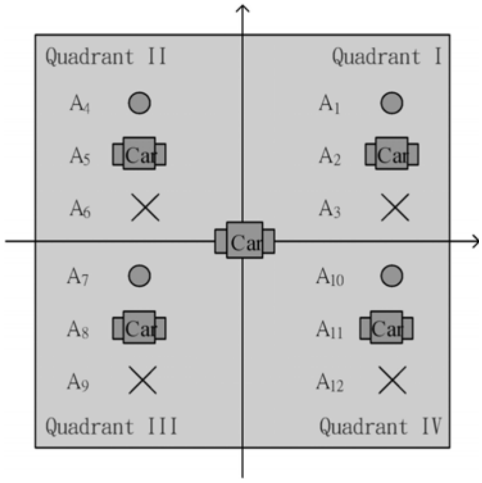

Figure 3. Scheme of antibodies for a robot.

ing the function of environment detection, and the definition of terminology.

In regard to the function of environmental detection, immune system generates a series of chemical reaction in order to defend invasion of outer viruses. The AIN model focuses on the successive processes of antigen recognition and antibody reaction: the receptors of B-cell recognize an antigen and perform cell division, and then specialize into plasma cell to produce antibody. Each kind of antibody is with one aim to recognize certain antigen and destroy it. In this research, we model the sensing and reaction of a soccer robot by using the AIN model. A robot is located at the origin of a coordinate, and then the soccer field is divided into four quadrants, as shown in Figure 3. Each quadrant has three antibodies, including the ball, one opponent robot, and a space. Space means there is neither ball nor opponent robot in the quadrant. As shown in Figure 3, there are total of 12 antibodies for each robot. The AIN investigates each quadrant around the robot, and then stimulates antibodies according to the circumstance.

Epitope is an antigenic determinant of outer viruses and acts as the connecting part with antibody. The corresponding combining site on antibody is called a paratope [5]. In this research, the information of the ball, opponent robots, or other substance in a quadrant is utilized as an epitopes. A robot accepts at least one epitope from each quadrant around it at the same time, such as no object or a few numbers of epitopes. For example, there are two objects, namely, the ball and opponent robot. In motion control, after the robot moves a step, the AIN investigates all quadrants for the ball or opponent robots, and then determines antigens according to the detected information. Antibodies will be stimulated if there are ball or opponent robots, or neither the ball nor opponent robot in a quadrant area. When an antibody has been simulated, it means that the paratope and the epitope are combined together. We define an affinity to represent the relationship between the paratope and the epitope. The following equation is used to define the affinity m_i of the artificial immune network [7]:

$$m_i(k+1) = \begin{cases} 1 & \text{if the paratope of antibody } i \text{ is combined with an epitope} \\ 0 & \text{otherwise} \end{cases}$$

where k is the time step. A robot collects multiple epitopes from the surrounding quadrants, and there are not only one corresponding paratopes. Therefore, the decision of the number of triggered antibodies depends on how many epitopes collected by a robot.

According to idiotypic network hypothesis [6], antibodies can bind not only with antigens, but also with other antibodies through their idiotopes and paratopes. These antibodies form an artificial immune network by the suppression and stimulation effects among them. The stimulation and suppression of antibody i triggered by antibody j is represented by the affinity m_{ij} and defined as the follows,

$$m_{ij}(k+1) = \begin{cases} \dfrac{1}{1+\exp(0.5-m_{ij}(k))} & \text{if antibody } i \text{ is triggered} \\ m_{ij}(k) & \text{otherwise} \end{cases}$$

In AIN, the immune response, the reaction of an antibody to antigens, is modeled by the definition of concentration. If there are N antibodies, the concentration x_i of antibody i is expressed as the following first-order differential equation [7],

$$\frac{dx_i(k+1)}{dt} = \left(\sum_{j=1}^{N} m_{ij} X_j(k) - \sum_{l=1}^{N} m_{li} X_l(k) + m_i - k_i \right) X_i(k) \tag{1}$$

$$X_i(k+1) = \frac{1}{1+\exp(0.5-x_i(k+1))}$$

By the method of stimulation and suppression among antibodies, the antibody has the largest value of concentration is triggered. Similarly in this research, the robots decide the next action according to the antibody having highest concentration. If there is more than one antibody containing the highest concentration, the following priority orders can be applied to the immune response antibody,

Ball > Space > Opponent robot;
Quadrant I > Quadrant II > Quadrant III > Quadrant IV.

The flow chart of an AIN behavior-based controller system in soccer robot game is shown in Figure 4, containing three portions: antigenic detection, artificial immune network, and reinforcement learning mechanism. The portion of antigenic detection is composed of environment detection and antigen determination. The main purpose of this section is for the robots to investigate the field, which is divided into four quadrants, and then marshal the information to detect the antigens. In the por-

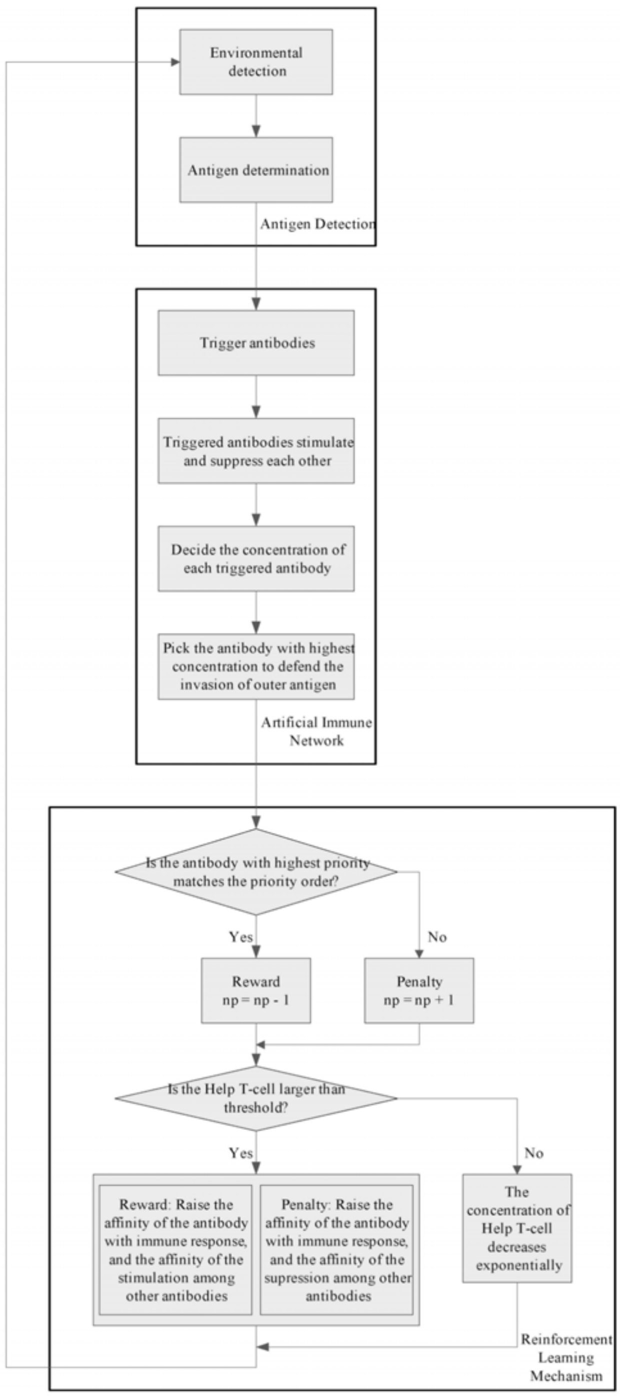

Figure 4. Flow chart of immune behavior controller system.

tion of artificial immune network, there are antibody triggering, stimulation and suppression among antibodies, and the calculation of antibody concentration. Based on the environmental information obtained from antigenic detection, the robots determine which antibodies to activate. These antibodies influence their own concentration and change the affinity because of stimulation and suppression among themselves. Finally, the robots choose the antibody with the highest concentration to defense the antigens from outside, and also select an action.

3. Reinforcement Learning Mechanism

In the third portion of the flow chart in Figure 4, the reinforcement learning mechanism compares whether the antibody with the highest concentration is conformed to the priority order. If the antibody matches the priority order, a reward is offered; otherwise a penalty is given. The reward and penalty will affect the concentration of Help T-cell. If the concentration of Help T-cell reaches a threshold, the Help T-cell will take action and influence the affinity of the triggered antibody, and then help the antibody to learn and memorize the history of robot action. The reinforcement learning mechanism which has a system of reward and penalty is utilized to enhance the speed of producing antibodies by affecting the calculation of the affinity. In every time step, the conditions of the environment are transformed into the invasive antigens by the sensor, and then several antibodies fitted in the environmental conditions are triggered. The antibody with the highest concentration is selected to be the subject of the immune response. If this response conforms to the expected response, a reward signal is offered; otherwise a penalty signal is given. The reward signal acts on the stimulation of the triggered antibody's concentration. On the other hand, the penalty signal increases the concentration of Help T-cell, which enhances the suppression of the triggered antibody's concentration. By doing so the chance to trigger the other antibodies is raised, and the learning ability of the artificial immune system is improved. The definition of the concentration of Help T-cell is expressed as

$$\mathrm{T_h}(k+1) = \frac{1}{1+\exp(-\eta \cdot \mathrm{np})} \tag{2}$$

where η is the growing factor; np is the number of times the penalty is offered. When the concentration of $\mathrm{T_h}$ is higher than a threshold concentration, δ, the learning rate γ is greater than zero; otherwise it is set to be zero,

$$\begin{aligned} &\text{If } (\mathrm{T_h} > \delta) \quad \text{Then } (\gamma > 0) \\ &\qquad\qquad\qquad\quad \text{Else } (\gamma = 0) \end{aligned}$$

The antibody, which gets a reward, will change its affinity. The stimulative affinity of antibody *i* stimulated by antibody *j* is defined as

$$m_{ij}(k+1) = \frac{1}{1+\exp(0.5-(1+\gamma)m_{ij}(k))} \tag{3}$$

The learning mechanism of the artificial immune network in this research has two phases: the immune response mode and immune tolerant mode. At immune response mode, the B-cells and Help T-cells grow exponentially. In the early stage of immune response, the antibody can not recognize any antigen; therefore, the function of the Help T-cell is designed to assist the capability of recognition for the antibody. Antibody is trained to memorize antigen at this phase. In the soccer robot case, the robot continuously learns different behavior mode in order to handle an unfamiliar environment. When np is zero, the Help T-cell constrains the growth of the B-cell and the immune tolerant mode will start to function. In the immune tolerant mode, the antibody can recognize an antigen, and the robot has steady mode and ability to handle all kinds of environmental conditions it confronts. The calculation of the concentration of Help T-cell in Equation (2) will be changed to

$$\mathrm{T_h}(k+1) = \mathrm{T_h}^{\eta}(k) - \lambda \tag{4}$$

where λ represents the decay factor. In the immune tolerant mode, the Help T-cell does not grow exponentially. When the concentration of $\mathrm{T_h}$ no longer affects the affinity of antibody, it means that the antibody can fully recognize all kinds of antigen, and the learning of the immune system is completed. If any unexpected circumstance happens, it means that the antigen is not yet been recognized by the system. Therefore, the learning mechanism will go back to the immune response mode and learn again. Figure 5 depicts the concentration of a

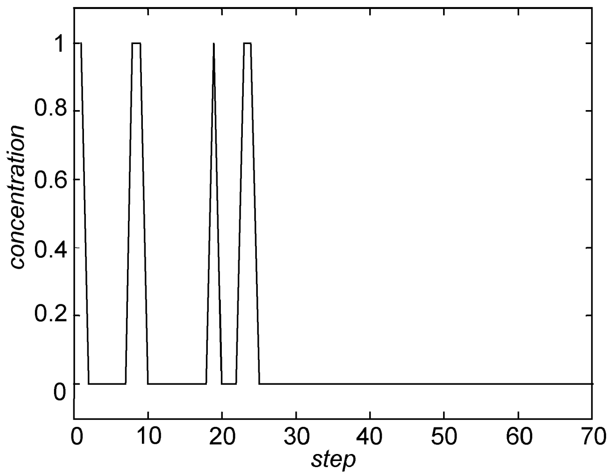

Figure 5. The concentration of T-cell.

T-cell during a simulation process, while the affected concentration of an antibody is plotted in Figure 6. From the figures, we can see that the concentration of the antibody is stimulated or suppressed exponentially by the concentration of the T-cell. When the concentration of the antibody is in saturation, the concentration of T-cell will decay to zero value according to Equation (4).

4. Simulation Results

In this section, an example of 3 versus 3 robot soccer game is demonstrated by using the FIRA simulator [11]. In the example, the decision tree is used to decide the role of each robot, and the artificial immune behavior controller is employed to determine what action each robot should take. The roles of the robots are defined as striker, fullback, and goalkeeper. The characters of striker and fullback are differentiated as active and passive respectively according to the relative position of robots to the ball. For the active robot, its main purpose is to chase and shoot the ball. If there is no opponent robot trying to take over the ball or block the way, this action will be rewarded and the robot will keep chasing the ball. For the passive robot, the objective of the robot action is to assist the attack.

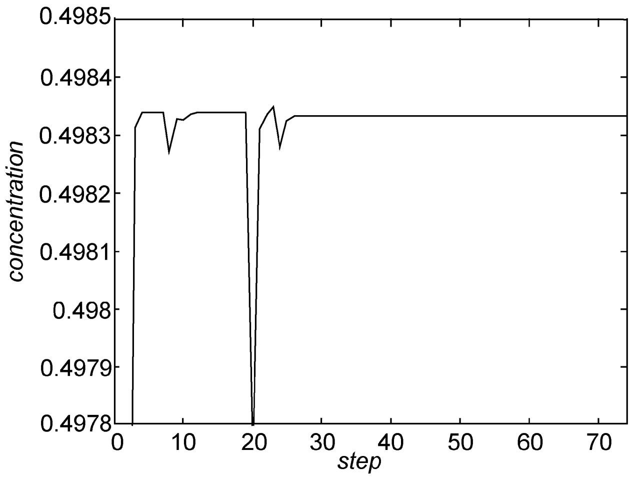

Figure 6. The concentration of an antibody.

The command generating algorithm proposed by Bowling and Veloso [12] is utilized to create a point-to-point motion planner for the robots. The velocity of a soccer robot can be presented as

$$\begin{bmatrix} \dot{x}(k) \\ \dot{y}(k) \\ \dot{\theta}(k) \end{bmatrix} = \begin{bmatrix} \cos\alpha & 0 \\ \sin\alpha & 0 \\ 0 & 1 \end{bmatrix} \begin{bmatrix} v(k) \\ \omega(k) \end{bmatrix}$$

where $v(k)$ and $\omega(k)$ are the linear and angular velocities of the robot; α is the angle between the robot heading direction and the line to the target point. This angle α, as shown in Figure 7, can be obtained by

$$\alpha = \alpha_1 - \alpha_2 \tag{5}$$

α_1 is the angle between the line to the target point and the line of horizontal coordinate; α_2 is the angle of between the robot heading direction and the line of horizontal coordinate. In order to reach the target point, the velocity calculation for the left and right wheels of the robot is expressed as

$$v_l = v(s - r)$$

$$v_r = v(s + r)$$

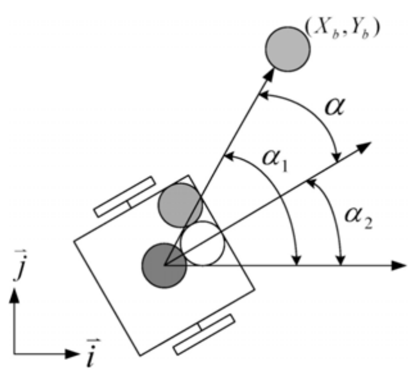

Figure 7. Diagram of the angle α.

The parameters s and r are related to the angle α with the following equations,

$$s = \cos^2\alpha \cdot \mathrm{sgn}(\cos\alpha)$$

$$r = \sin^2\alpha \cdot \mathrm{sgn}(\sin\alpha)$$

The reason to take square of cosα and sinα is to keep the value of ($s \pm r$) in the range of [0,1]. The velocities of left and right wheels obtained by this approach are signed; therefore, the robot can move either forward or backward direction to approach the target. In this case, it doesn't have to consider the relative direction, and let the robot's movement becomes more smooth and fast. Bowling and Veloso [12] also designed a calculation method of robot heading angle, so that the robot can keep at desired angle when it moves to the target. This new target angle of the robot is

$$\alpha_1^* = \alpha_1 + \min(\theta, \tan^{-1}(\frac{c}{d})) \tag{6}$$

where θ is the angle defined as shown in Figure 8; d is the distance between the robot and its target; c is the clearance parameter. Substitute the new target direction angle α_1^* for α_1 in Equation (5), and then calculate the velocities of the right and left wheels. Therefore, the robot can move to the target and keep in the direction, α_2^*.

Figure 9 depicts the simulation results of an example by using the FIRA simulator. At the beginning of the game, the opponent robots are located on the right half of the field, and our robots are located on the left-half field. During the soccer game, the decision tree assigns various roles to our robots, including the goalkeeper, fullback, and striker. After the roles are assigned to the robots, the AIN-based ASM select an action for each robot. From the figures it can see that the striker adopts the action of ball chasing and shooting, and the fullback moves to defend our goal. When the striker reaches the opponent's goal with the ball, Figure 10(c), the fullback heads forward and assists the attack, as shown in Figure 10(b), and the goalkeeper still remain the action of defending our goal, as shown in Figure 10(a).

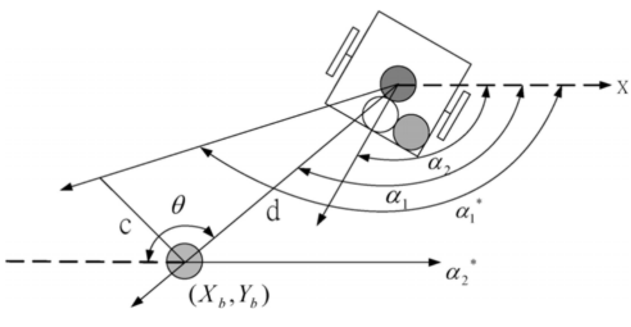

Figure 8. New angles α_1* and α_2*.

5. Experimental Results

The proposed AIN-based ASM is applied to the small-size robot soccer game, in which the global coordinates of the soccer robots are obtained by using an appropriate image process method. Knowing the geometric locations of the ball and robots on the soccer field, the experimental test is carried out by three major steps. First, according to the situation in the soccer field, a team formation is chosen for the soccer team and a role is selected for each individual robot by using decision-tree RSM. Second, each robot executes an action provided by the AIN-based ASM to fulfill its role-playing. Finally, the robot action is performed by using a point-to- point motion controller.

In this example, initially the ball is located between two robots of our team. The robot near our goal (the upper one) is the fullback robot, while the other robot is the vanguard robot. Initially, the RSM by decision tree assigns the fullback robot as a striker, and the vanguard robot as an assistant striker. In Figures 11(a–c), the fullback robot pushes the ball to the enemy goal at the beginning. When the ball was pushed to the front of two robots, the RSM will switch the roles of the two robots. In this case, the vanguard robot will become the striker and the fullback robot becomes an assistant striker. The vanguard robot pushes the ball to the enemy goal, and the fullback robot will go back to our goal, as shown in Figures 11(d–f).

6.Conclusion

In this paper, an action select mechanism based on the concepts of artificial immune network is proposed for a tactic-based decision system for robots playing soccer game. The decision tree method is applied to the upper level of the strategy planning system, which can choose a

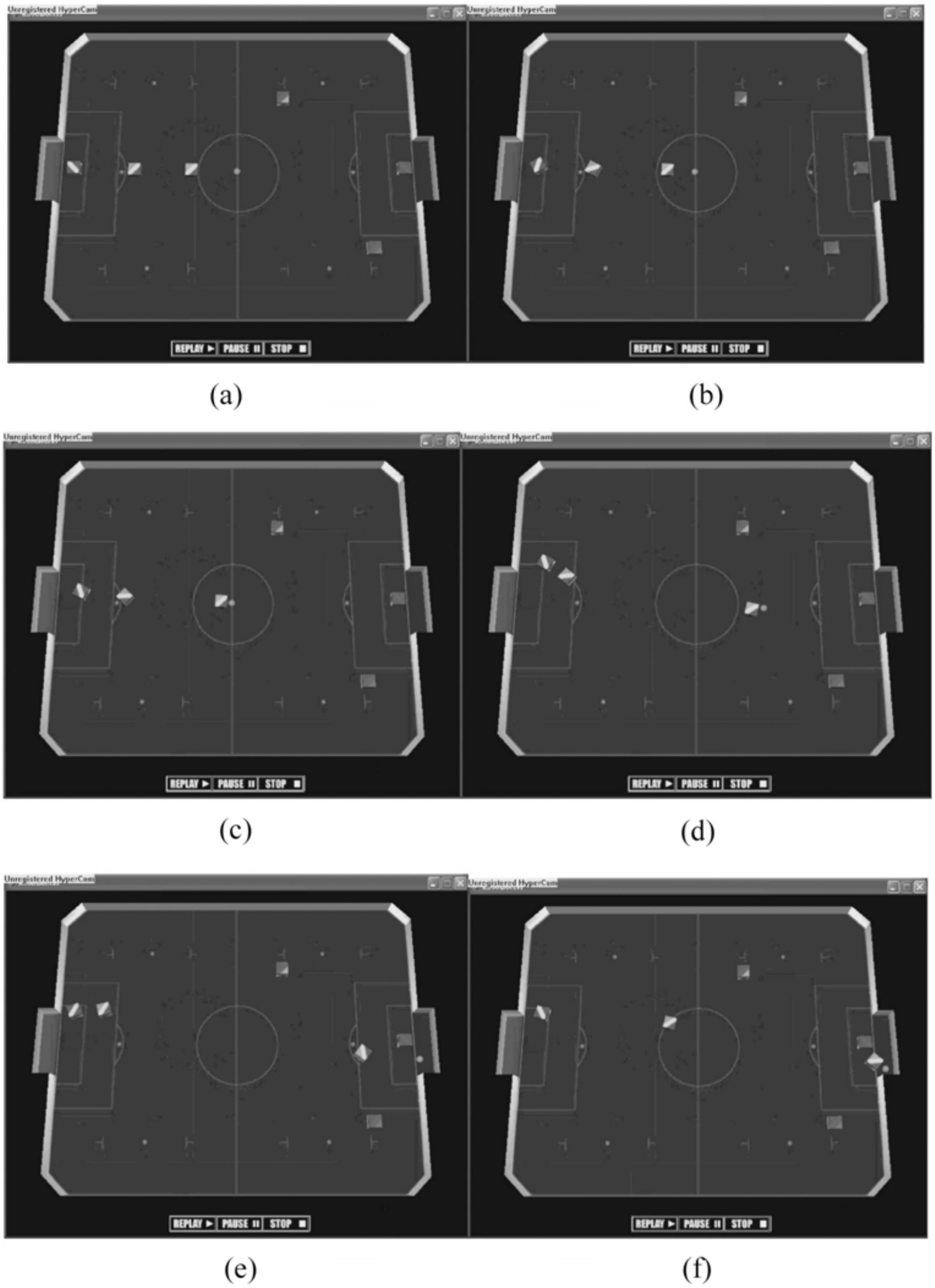

Figure 9. Simulation of AIN-based ASM in 3 versus 3 robot soccer game.

team formation and assign an applicable role to a robot according to the location of the robot in the soccer field. After the role is selected, the lower level of the strategy planning system, the action select mechanism, starts to work. Using the concept of immunology, the action select mechanism consists of the antigen detection, artificial immun network, and reinforcement learning mechanism. The concentrations of antibodies on the soccer fields, such as the ball, opponent robots, and space, are analyzed, and the antibody with the highest concentration is triggered, such that each of our robots can be appointed to a certain action. The reinforcement learning mechanism assures that each robot performs the right action by offering a reward, otherwise a penalty is given. This helps the antibodies to learn and memorize the actions of the robots. In the application of multi-robot soc-

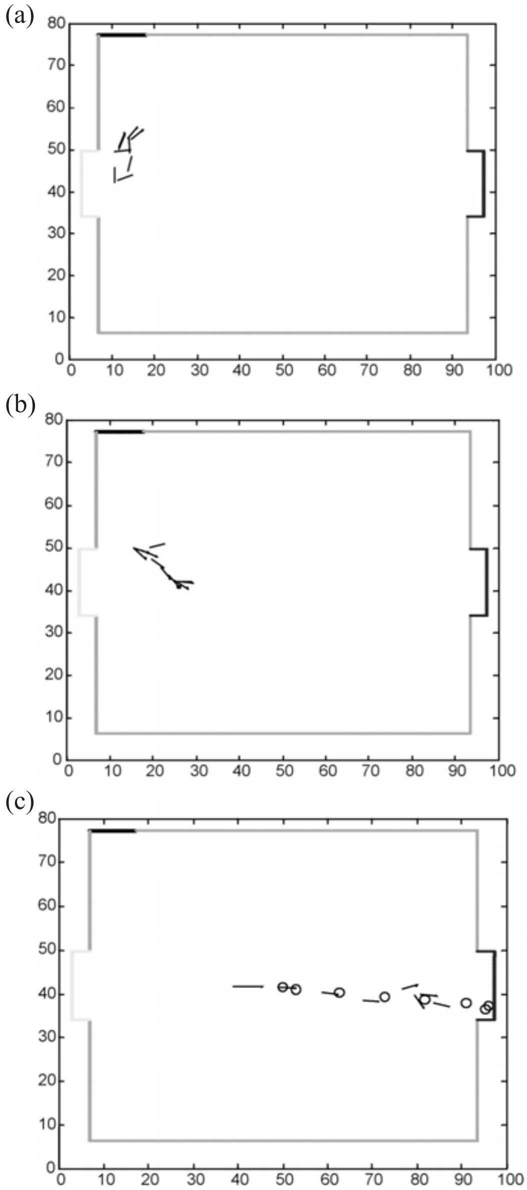

Figure 10. Positions of the soccer robots.

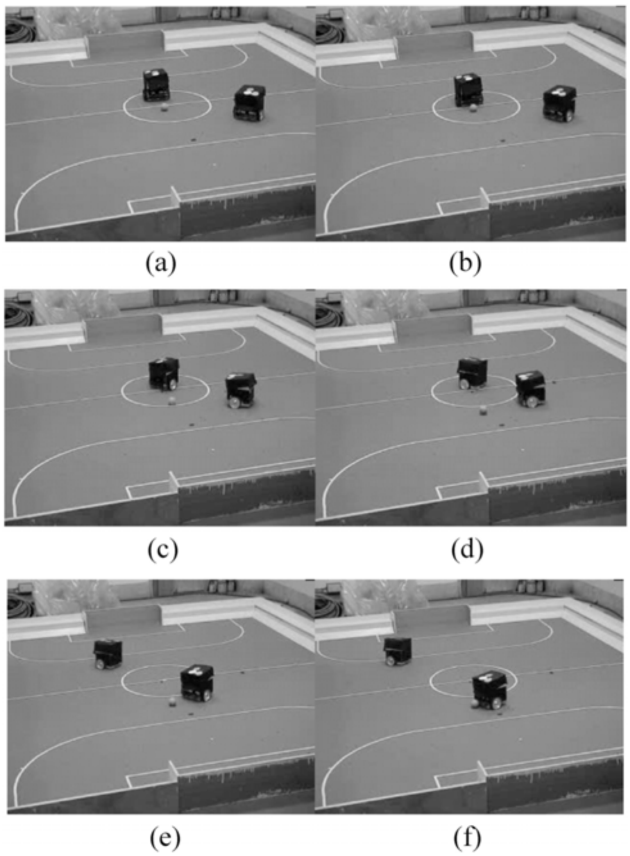

Figure 11. Experimental results.

cer game, this research has finished 1-on-1, 2-on-2, and 3-on-3 soccer games, simulated the AIN-based ASM by using the FIRA simulator, and tested the algorithm on a real soccer field. The results show that the AIN-based controller can carry out desirable performances.

Acknowledgment

This work was supported by the National Science Council in Taiwan to Y.T. Wang under grant no. NSC 95-2221-E-032-055-MY2.

References

[1] Sethi, I. K., "Entropy Nets: From Decision Trees to Neural Networks," *P. IEEE,* pp.1605−1613 (1990).

[2] Liang, C.-C., "Development of A Multiple-Soccer-Robot System," Ph.D. Dissertation, Department of Mechanical Engineering, National Taiwan University, Taiwan (2000).

[3] Liu, C.-H., "Tactic Design and Formation Control for 5-on-5 Soccer Robot Systems," (in Chinese) Master Thesis, Department of Mechanical and Electrical Engineering, Tamkang University, Taiwan (2003).

[4] Tsou, T.-Y., Liu, C.-H. and Wang, Y.-T., "Team Formation Control for Soccer Robot Systems," *Proc. IEEE International Conference on Networking, Sensing, and Control* (2004).

[5] Roitt, I., Brostoff, J. and Male, D., *Immunology,* Mosby International Ltd (1998).

[6] Jerne, N. K., "The Immune System," *Sci. Am.,* Vol. 229, pp. 52–60 (1973).

[7] Farmer, J. D., Packard, N. H. and Perelson, A. S., "The Immune System, Adaptation, and Machine Learning," *Physica D,* Vol. 22, pp. 187–204 (1986).

[8] Sanchis, A., Isasi, P., Molina, J. M. and Segovia, J., "Applying Classifier Systems to Learn the Reactions in Mobile Robots," *Int. J. Syst. Sci.,* Vol. 32, pp. 237–258 (2001).

[9] de Castro, L. N. and Von Zuben, F. J., "Learning and Optimization Using the Clonal Selection Principle," *IEEE T. Evolut. Comput.,* Vol. 6, pp. 239–251 (2002).

[10] Luh, G.-C. and Cheng, W.-C., "Behavior-Based Intelligent Mobile Robot using An Immunized Reinforcement Adaptive Learning Mechanism," *Adv. Eng. Inform.,* Vol. 16, pp. 85–98 (2002).

[11] FIRA, http://www.fira.net.

[12] Bowling, M. and Veloso, M., "Motion Control in Dynamic Multi-Robot Environments," *Proc. IEEE International Symposium on Computational Intelligence in Robotics and Automation,* pp. 168–273 (1999).

Manuscript Received: Jun. 30, 2007
Accepted: Jul. 17, 2008