A Soccer Robot Control Design Based on the Immune System

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Abstract

This paper proposes a control system design for soccer robots based on the immune system. The immune system is a kind of engineering model imitating the human immunity action. It has some features such as self-optimization by learning, and easiness in dynamic reconfiguration of robots themselves. Thus, the immune system can be effectively applied to robot control in dynamic environments.

The immune system is applied to construct the soccer robot control system for RoboCup. First, applying the immune system to the obstacle avoidance problem of the mobile robot, we demonstrate its validity in simulation. Next, we execute 3 to 3 soccer plays by the soccer robots in simulation. These results show that the immune system is useful for robot control.

Keywords: immune system, dynamic environments, RoboCup

1 Introduction

The problem in development of industrial robots until now is focused mainly on the improvement of accuracy and speed in robot motion, due to the use of robots in static environments such as automated factories. However, for robots which will infiltrate our daily life from now on, it is necessary to cope with dynamic environments which are continually changing around the robots. In addition, it is important to develop the capability of cooperative behavior between robot-robot and between robot-human.

In order to promote research on these problems, we have dealt with RoboCup [1] as an international robot soccer game. And we now try to design a new soccer robot control system by applying the theory of immune system (IS) which imitates the human immunity action. The IS has some features such as self-optimization by learning, and easiness in dynamic reconfiguration of robots themselves. Thus, this system can be effectively applied to robot control in dynamic environments. Kondo, et al. proposed applying the IS to action control of an autonomous mobile robot [2]. However, there are still a few examples of application of the system to continually changing environments in which robots are tasked with a job.

In this paper, we apply the IS to soccer robot control in the RoboCup small league section, and show a possibility of designing a robust robot control system which can flexibly cope with dynamic environments. First, a simulation is performed for obstacle avoidance of a small mobile robot in which the IS is installed as a controller. Furthermore, it is demonstrated to improve the capability of obstacle avoidance via a learning mechanism of the IS. Secondly, the other simulation of 3 to 3 soccer plays is performed, in which the IS is used for both of obstacle avoidance and action selection. Then, we show to improve the performance of soccer play via the learning mechanism of the IS. Finally, we give the conclusions.

2 Immune System

2.1 Summry of Immune System

The IS is a kind of engineering model imitating the human immunity action. The human being has complex immume responses via multiple mechanisms. Here, we pay attention to the immune network, i.e. network between an antigen-antibody and between antibody-antibodies which is based on the idiotypic network hypothesis proposed by Jerne [3]. We will construct the IS based on Jerne's hypothesis.

2.2 Dynamics of Immune System

The model equation which represents the behavior of the immune system is given by Kondo, et al [2]. We modify this in the following form :

$$r_i(t+1) = r_i(t) \quad + \quad \left(\frac{\sum_{j=1}^{N} T_{ij} A_j(t)}{N} + m_i - k_i \right) \cdot A_i(t) \qquad (1)$$

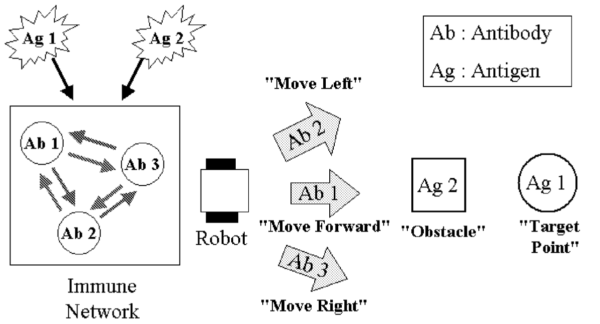

Fig. 1: Application of IS to robot control

$$A_i(t+1) = \frac{1}{1+\exp\{\beta - r_i(t+1)\}} \tag{2}$$

where A_i is the concentration number of antibody i, r_i is the parameter to determine A_i, T_{ij} is the immune network parameter which represents the relationship of stimulation and suppression between antibodies i and j, m_i is the reaction between antibody i and antigen, k_i is the number of natural death, N is the number of antibodies, and β is the threshold value. After being updated by m_i, $\sum_{j=1}^{N} T_{ij}A_j$, and k_i, the concentration number of antibody i is normalized via the sigmoid function in eq.(2).

In our robot control, the IS is used by considering that the antigen is an environmental information such as a target point and an obstacle, and the antibody is the movement direction to be selected by a robot. For example, to antibody 1 (Ab1) we give the following command, "when a target point exists in the forward direction, move forward". On the other hand, to antibody 2 (Ab2) we give the following command, "when an obstacle exists just in front, move left".

Let m_1 be 1(0) in the case that the target point exists (does not exist) in the forward direction. Similarly, let m_2 be 1(0) if the obstacle exists (does not exist) in front of the robot. On this setup, the antibodies concentration is continuously calculated by eqs.(1) and (2) from initial values $A_i(0) = 0, r_i(0) = 0$. This calculation is finished when one of antibodies concentration exceeds the fixed value decided previously. The antibody who has eventually the highest concentration determines the movement direction of the robot.

Unfortunately, it is quite difficult to give suitable network parameters T_{ij} because of a huge number of the combination of T_{ij}. Thus, we need an optimization method of T_{ij} by self-learning, which is discussed in the next subsection.

2.3 Learning Mechanism

An immune network can optimize its parameters by a learning method as shown below. The parameter T_{ij} is updated to improve the adaptation capability of the system by learning from a result of the action selected by the IS. In the simulation shown in Sections 3 and 4, the update rules of T_{ij} are assigned as follows:

[Update Rules]

1. In the case that the robot reaches the target point: For the selected antibody i, if its concentration exceed the fixed value, T_{ij}, which is related to other antibody j, increases based on the following:
$$T_{ij}(k+1) = 0.95 \times T_{ij}(k) + 0.05 \tag{3}$$
2. In the case that the robot collides with the obstacle: For the selected antibody i, if its concentration exceed the fixed value, T_{ij}, which is related to other antibody j, decreases based on the following:
$$T_{ij}(k+1) = 0.95 \times T_{ij}(k) - 0.05 \tag{4}$$
3. In the case that the robot cannot reach the target point in a limit time: For each i and j, T_{ij} changes based on the equation
$$T_{ij}(k+1) = 0.95 \times T_{ij}(k) + d, \tag{5}$$
where d is uniform random number on [-0.5,0.5].

3 Obstacle Avoidance Simulation

3.1 Method of Obstacle Avoidance

In this simulation, the robot can search the field divide into 16 areas (refer to the left figure of **Fig.2**), and move to one of 16 directions (refer to the right figure of Fig.2).

When the number of obstacles is only one, there exist 16 types of the obstacle detection pattern. Then, we can specify the movement direction of the robot according to each pattern in advance. Unfortunately, it becomes difficult to specify the movement direction of the robot in advance as the number of obstacles increases, because the detection pattern increases exponentially as it does. Therefore, we introduce an immune system in the next subsection to achive an easy situation where we need assign only some types of simple behavior of the robot, e.g., when an obstacle exists in the search area 6, move to direction number 15.

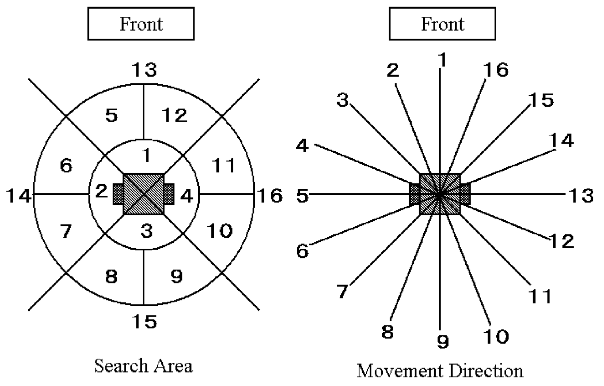

Fig. 2: Search area and movement direction

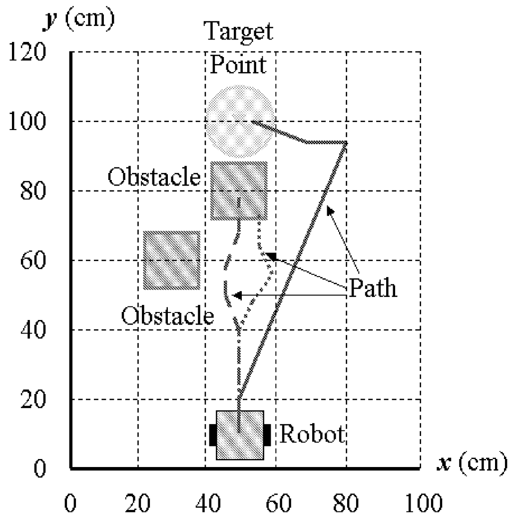

Fig. 3: Obstacle avoidance

3.2 Simulation Result

This subsection shows a result of a simulation where the robot tries to move a target point with avoidance of stationary obstacles. In this example, the target point is in front of the robot while the obstacles exist between the robot and the target point. Let antigens be the position information of the target point and the obstacles, and the antibodies be the movement directions shown in the right figure of Fig.2.

The broken line in **Fig.3** shows the path of the robot in the case that $T_{ij} = 0$ for any i and j. The robot collides an obstacle and cannot reach the target point. On the other hand, the dotted line in Fig.3 depicts the path of the robot whose parameters T_{ij} are updated once using the learning mechanism, which is shown in Section 2.3. Finally, the solid line shows the path after T_{ij} are updated 12 times until the robot reaches the target point. The iteration of the update of T_{ij} enables the robot to reach the target point with avoidance of the obstacles.

4 3 to 3 Soccer Play Simulation

4.1 Soccer Robot Control

Next, we perform a simulation of a soccer game, which continues until one of three player robots shoot a ball to an opponent goal, which is defended by three opponent robots. In this simulation, the antigens are given from the position information of the player robots, the opponent robots and the ball. The antibodies are assigned as robot actions such as a dribble, a pass and a shoot. Each player robot distinguishes 9 types of the field situation from 2 information, that is the ball position and the ball owner. Each robot receives a command according to the situation, e.g., if there exists the ball near the opponent goal and one of player robots has the ball, then this robot receives the command "move to the opponent goal", another does "move to near the opponent goal", and the other does "move to center".

We perform simulations in 10 cases, where one of opponent robots is a goalkeeper the others chase the ball without obstacle avoidance action. The movement velocities of the opponent robots and the player robots are equal.

4.2 Extended Learning Rules

In the simulation of the soccer game, the following are attached to the update rules of T_{ij}.

[Additional rules]

1. If the player robots never score in a limit time, these parameters are updated so that the antibody selected then becomes more difficult to be selected.

2. When the player robots change the role, the following update is performed for each robot according to the action evaluation which is introduced below. If the value of the evaluation is positive, T_{ij} is updated for the antibody selected then to become easier to be selected. If the value is negative, T_{ij} is updated for it to become more difficult to be selected.

[Action Evaluation]

Let $EL_i(t)$ be the distance between the ball and the opponent robot i at the time t:

$$EL_i(t) = \sqrt{(bx(t) - ex_i(t))^2 + (by(t) - ey_i(t))^2}, \tag{6}$$

where $(bx(t), by(t))$ and $(ex_i(t), ey_i(t))$ represent the ball position and the position of the opponent robot i, respectively, and t is the time just after the change of the robots' roles. Similarly, let $GL(t)$ be the distance between the ball and the opponent goal at t:

$$GL(t) = \sqrt{(bx(t) - gx)^2 + (by(t) - gy)^2}. \tag{7}$$

The following is the action evaluation which the additional rule 2. uses.

> The action evaluation is set positive if $P(t) > P(t-1)$, and is negative if $P(t) < P(t-1)$. The parameter T_{ij} is not updated if $P(t) = P(t-1)$.

$$P(t-1) = \sum_{i=1}^{E} \frac{1}{EL_i(t-1)} - \frac{1}{0.5 \times GL(t-1)}, \tag{8}$$

$$P(t) = \sum_{i=1}^{E} \frac{1}{EL_i(t)} - \frac{1}{0.5 \times GL(t)}. \tag{9}$$

4.3 Simulation Results

Fig.4 shows the simulation result with the non-updated T_{ij}. Each player robot cannot pass and dribble well, and an opponent robot take the ball from one in a moment. On the other hand, after the update of T_{ij} using that learning mechanism, the player robots can get a score with suitable actions as shown in **Fig.5**. The player robots can score 7 goals in 10 simulations after learning, while they cannot before learning. This simulation result illustrates clearly the improvement of the ability of the player robots by learning.

5 Conclusions

In this paper, we have constructed the multi-robot control system for RoboCup. This system can flexibly deal with dynamic environments by using the IS. The simulation results show the effectiveness of the IS for robot control.

There remain some problems in developing more efficient learning mechanisms and implementing this IS with real robots.

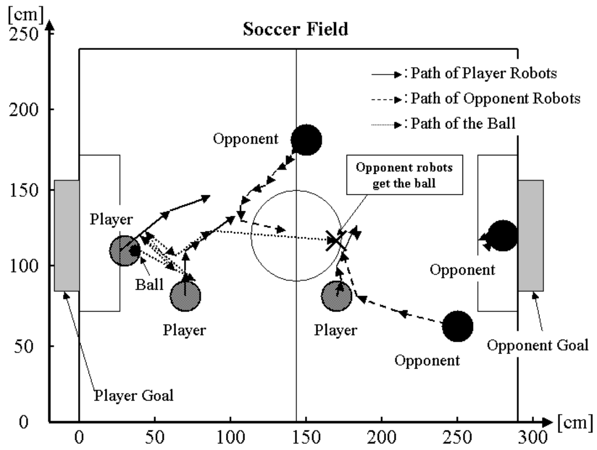

Fig. 4: Simulation result of soccer play before learning

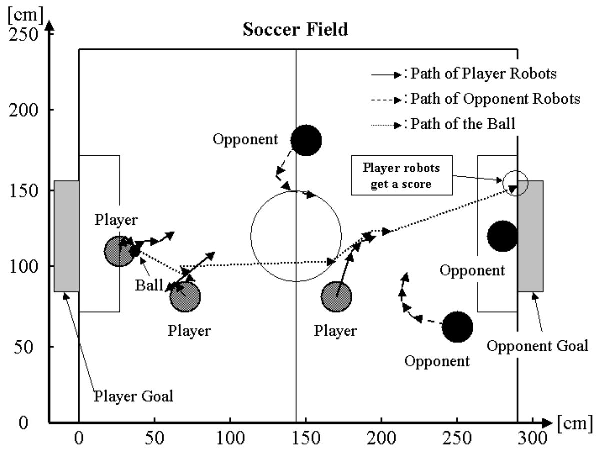

Fig. 5: Simulation result of soccer play after learning

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