Immunoid: A Robot with a Decentralized Behavior Arbitration Mechanisms Based on the Immune System

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Abstract

In recent years much attention has been focused on behavior-based artificial intelligence(AI), which has already demonstrated its robustness and flexibility against dynamically changing world. However, in this approach, the followings have not yet been resolved: how do we construct an appropriate arbitration mechanism, and how do we prepare appropriate competence modules. In this paper, to overcome these problems, we propose a new decentralized consensus-making system inspired by the biological immune system. And we apply our proposed method to behavior arbitration for an autonomous mobile robot, namely garbage collecting problem that takes into account of the concept of self-sufficiency. To verify the feasibility of our method, we carry out some simulations. In addition, we investigate two types of adaptation mechanisms, and try to evolve the proposed artificial immune network using reinforcement signals.

***Key Word**: immune network, decentralized consensus-making network, autonomous mobile robot, action arbitration, adaptation mechanism*

1 Introduction

In recent years much attention has been focused on *behavior-based AI*, which has already demonstrated its robustness and flexibility against dynamically changing world. In this approach, intelligence is expected to result from both mutual interactions among *competence modules* (*i.e.* simple behavior/action) and interaction between the robot and environment. However, there are still open questions: 1) how do we construct a mechanism that realizes appropriate arbitration among multiple competence modules, and 2) how do we prepare appropriate competence modules.

Brooks has showed a solution to the former problem with the use of *subsumption architecture* [1][2]. Although this method demonstrates highly robustness, it should be noted that this architecture arbitrates the prepared competence modules on a fixed priority basis. It would be quite natural to vary the priorities of the prepared competence modules according to the situation. *Maes* proposed an another flexible mechanism called *behavior network system* [3][4]. In this method, agents (*i.e.* competence modules) form the network using cause-effect relationship, and an agent suitable for the current situation and the given goals emerges as the result of activation propagation among agents. This method, however, is difficult to apply to a problem where it is hard to find the cause-effect relationship among agents.

On the other hand, the immune system has various interesting features such as immunological memory, immunological tolerance, pattern recognition, and so on viewed from the engineering standpoint. Recent studies on immunology have clarified that the immune system does not just detect and eliminate the non-self materials called *antigen* such as virus, cancer cells and so on, rather plays important roles to maintain its own system against dynamically changing environments through the interaction among *lymphocytes/antibodies*. Therefore, the immune system would be expected to provide a new methodology suitable for dynamic problems dealing with unknown/hostile environments rather than static problems.

Based on the above facts, we have been trying to engineer methods inspired by the biological immune system and there application to robotics [5]-[7]. We expect that there would be an interesting AI technique suitable for dynamically changing environments by imitating the immune system in living organisms. In this paper, we propose a new decentralized consensus-making system inspired by the biological immune system. We then apply our proposed method to behavior arbitration for an autonomous mobile robot, namely *garbage collecting problem* that takes into account of the concept of *self-sufficiency*. In order to verify the validity of our method, we perform some simulations. In addition, we try to evolve the proposed artificial immune network using reinforcement signals. Finally, we show an another evolutionary mechanism from the selectionist standpoint.

2 Overview of the biological immune system

The basic components of the biological immune system are *macrophages*, *antibodies* and *lymphocytes* that are mainly classified into two types, namely *B-lymphocytes* and *T-lymphocytes*. B-lymphocytes are the cells produced from *bone marrow*. Roughly 10^7 distinct types of B-lymphocytes are contained in a human body, each of which has distinct molecular structure and produces "Y" shaped antibodies from its surfaces. The antibody recognizes specific *antigens*, which are the foreign substances that invade living creature, such as virus, cancer cells and so on. This reaction is often likened to *a lock and key relationship* (see Fig.1). To cope with continuously changing environment, living systems possess enormous repertoire of antibodies in advance. On the other hand, T-lymphocytes are the cells produced from *thymus*, and they generally perform to kill infected cells and regulate the production of antibodies from B-lymphocytes as outside circuits of B-lymphocyte network (idiotypic network) discussed later.

For the sake of convenience in the following explanation, we introduce several terms from immunology. The portion on the antigen recognized by the antibody is called an *epitope* (antigen determinant), and the one on the corresponding antibody that recognizes the antigen determinant is called a*paratope*. Recent studies in immunology have clarified that each type of antibody also has its specific antigen determinant called an *idiotope* (see Fig.1).

Based on this fact, *Jerne* proposed a remarkable hypothesis which he has called the "*idiotypic network hypothesis*", sometimes called "*immune network hypothesis*" [8]-[12]. This network hypothesis is the concept that antibodies/lymphocytes are not just isolated, namely they are communicating to each other among different species of antibodies/lymphocytes. This idea of *Jerne's* is schematically shown in Fig.2. As illustrated in the figure, the stimulation and suppression chains among antibodies form a large-scaled network and works as a self and not-self recognizer. Therefore, the immune system is expected to provide a new parallel distributed processing.

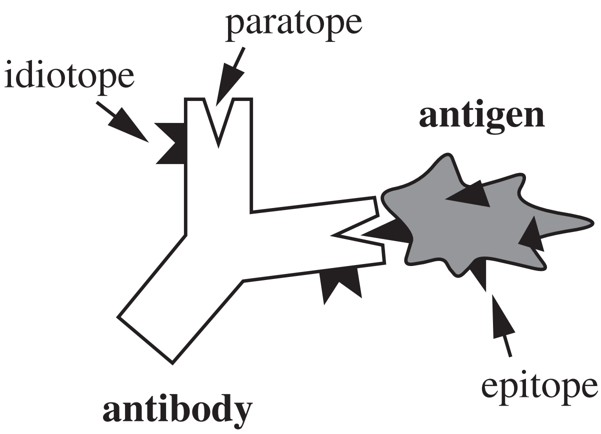


Fig.1: Structure of an antigen and an antibody.

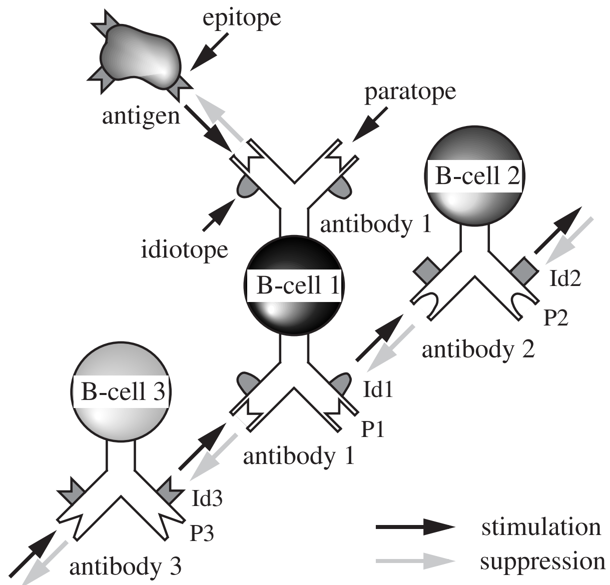
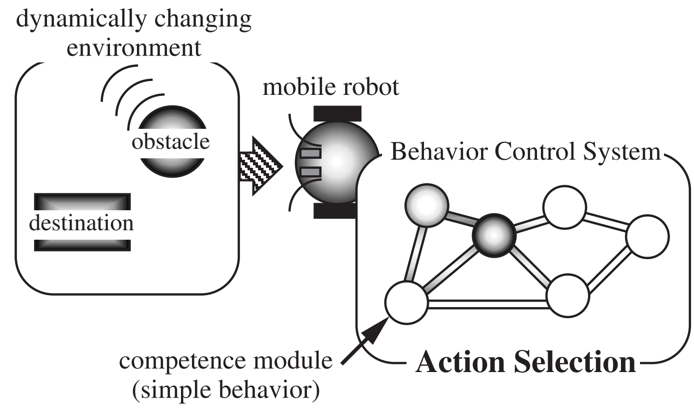


Fig.2: Jerne's idiotypic network hypothesis.

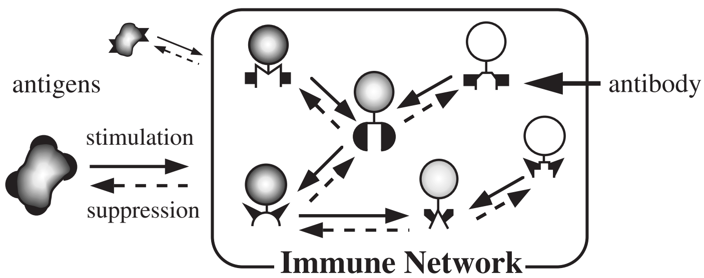
3 Proposed consensus-making network based on the biological immune system

3.1 Action selection problem and the Immune system

As described earlier, in the behavior-based AI, how to construct a mechanism that realizes appropriate arbitration among the prepared competence modules is still an open question. We approach to this problem from the immunological standpoint, more concretely with use of immune network architecture. Fig.3 schematically shows the action selection system for an autonomous mobile robot and the immune network architecture. As shown in this figure, current situations, (*e.g.* distance and direction to the obstacle, *etc.*) detected by installed sensors work as multiple antigens, and a prepared competence module (*i.e.* simple behavior) can be regarded as an antibody (or B-lymphocyte), while the interaction between modules is represented by stimulation and suppression between antibodies. The basic concept of our method is that the immune system equipped with the autonomous mobile robot selects a competence module (antibody) suitable for the detected current situation (antigens) in a bottom-up manner.



(a) An autonomous mobile robot with an action selection mechanism.



(b) Immune network architecture.
Fig.3: Basic concept of our proposed method.

3.2 Problem

For the ease of the following explanation, we firstly describe the problem used to confirm the ability of an autonomous mobile robot with our proposed immune network-based action selection mechanism (for convenience, we dub the robot "*immunoid*"). To make the immunoid really autonomous, as *Pfeifer et al.* advocated, it must not only accomplish the given task, but also be *self-sufficient*[13][14]. Inspired by their works, we adopt the following *garbage collecting problem* that takes into account of the concept of self-sufficiency. Fig.4 shows the environment. As can be seen in the figure, this environment, surrounded by walls, has a lot of garbage to be collected. And there exist a garbage can and a battery charger in a home base. The task of the immunoid is to collect the garbage, and put them into the garbage can without running out of its energy (*i.e.* battery level). Note that the immunoid consumes some energy as it moves around the environment. This can be likened to the *metabolism* in the biological system.

In this study, we assume that prespecified quantity of initial energy is given to the immunoid, and the current energy level can be detected by the simulated internal sensor installed in the immunoid. For quantitative evaluation, we also use the following assumptions:

1. The immunoid consumes energy E_m at every time step.
2. The immunoid loses additional energy E'_m when it carries garbage.
3. If the immunoid collides with obstacles (*i.e.* walls), it loses some energy E_c.

4. If the immunoid reaches the home base, it instantaneously obtains full energy.
5. If the energy level of the immunoid is high, **go_to_home_base** behavior might not emerge to avoid over-charging.

Based on the above assumptions, we calculate current energy level as:

$$E(t) = E(t\text{–}1) - E_m - E'_m - E_c \, , \qquad (1)$$

where $E(t)$ denotes the energy level at time t.

For easy understanding, we explain why this problem is suitable for the behavior arbitration problem in detail using the following situations. Assume that the immunoid is in the far distance from the home base, and its energy level is low. In this situation, if the immunoid carries the garbage, it will run out of its energy due to the term E'_m in equation (1). Therefore, the immunoid should select the **go_to_home_base** behavior to fulfill its energy. In other word, the priority of the **go_to_home_base** behavior should be higher than that of the **garbage_collecting** behavior. On the other hand, if the immunoid is in the near distance from the home base. In this situation, unlike the above situation, it would be preferable to select the **garbage_collecting** behavior. From these examples, it is understood that the immunoid should select an appropriate competence module by flexibly varying the priorities of the prepared competence modules according to the internal/external situations.

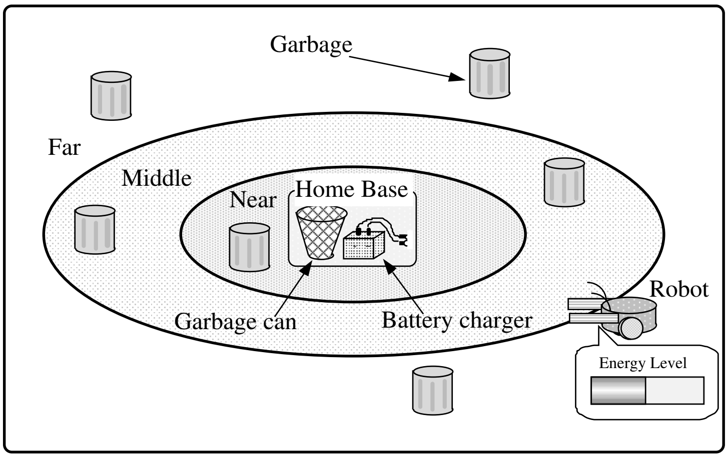


Fig.4: Environment.

3.3 Definition of the antigens and antibodies

As described earlier, the detected current internal/external situation and the prepared simple behavior work as an antigen and an antibody, respectively. In this study, each antigen informs the existence of garbage (direction), obstacle (direction) and home base (direction and distance), and also current internal energy level. For simplicity, we categorize direction and distance of the detected objects and the detected internal energy level as:

- direction → *front, right, left, back*
- distance → *far, middle, near*
- energy level → *high, low.*

Next, we explain how we describe an antibody in detail. To make the immunoid select a suitable antibody against the current antigen, we must look carefully into the definition of the antibodies. Moreover, we should notice that our immunological arbitration mechanism selects an antibody in a bottom-up manner through interacting among antibodies. To realize the above requirements, we defined the description of antibodies as follows. As mentioned in the previous section, the identity of each antibody is generally determined by the structure (*e.g.* molecular shape) of its paratope and idiotope. Fig.5 depicts our proposed definition of antibodies. As depicted in the figure, we assign a pair of desirable condition and action to the paratope, and the ID-number of the disallowed antibodies and their degree of disallowance to the idiotope, respectively. The structure of the desirable condition is the same as the antigen described above. And we prepare seven kinds of actions for the immunoid: *move forward, turn right, turn left, turn back, explore, catch garbage, search for home.*

In addition, for the appropriate selection of antibodies, we assign one state variable called *concentration* to each antibody.

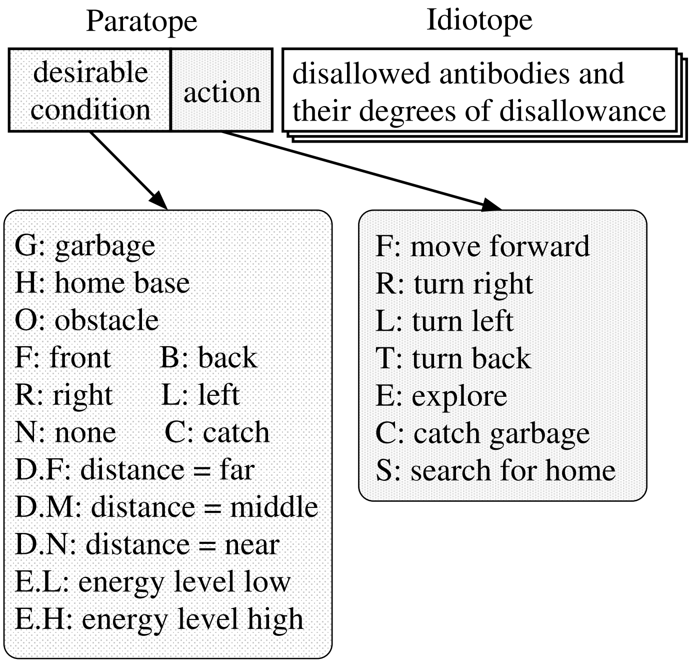


Fig.5: Definition of antibody.

3.4 Interaction between antibodies

Next, we explain the interaction among antibodies ,that is, the basic principle of our immunological consensus-making networks in detail. For the ease of understanding, we assume that the immunoid is placed in the situation shown in Fig.6 as an example. In this situation, three antigens listed in the figure possibly invade into the immunoid's interior. Suppose that the listed four antibodies are prepared in advance that respond to these antigens. For example, antibody 1 means that if the immunoid detects the home base in the right direction, this antibody can be activated and would cause **turn_right** action. However, if the current energy level is high, this antibody would give way to other antibodies represented by its idiotope (in this case, antibody 4) to prevent over-charging.

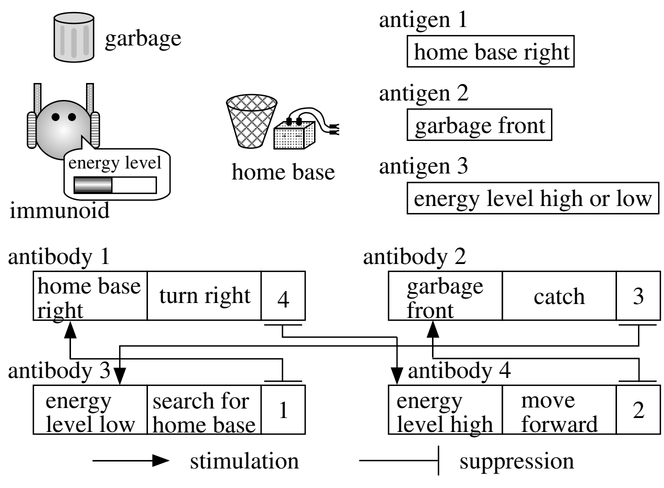


Fig.6: An example of consensus-making network by interacting among antibodies.

Now assume that the immunoid has enough energy, in this case antibodies 1, 2 and 4 are stimulated by the antigens. As a result, the concentration of these antibodies increases. However, there are interactions indicated by arrows among the antibodies through their paratopes and idiotopes. Consequently, the concentration of each antibody varies. Finally, antibody 2 will have the highest concentration, and then permitted to be activated.

In the case where the immunoid has not enough energy, antibody 1 tends to be selected in the same way. As observed in this example, the interactions among the antibodies work as a priority adjustment mechanism.

3.5 Dynamics

The concentration of i-th antibody, which is denoted by a_i, is calculated as follows:

$$\frac{dA_i(t)}{dt} = \left(\sum_{j=1}^{N} m_{ji} \cdot a_j(t) - \sum_{k=1}^{N} m_{ik} \cdot a_k(t) + m_i - k_i \right) \cdot a_i(t) \qquad (2)$$

$$a_i(t+1) = \frac{1}{1 + \exp\left(0.5 - A_i(t)\right)}\ , \qquad (3)$$

where, in equation (2), N is the number of antibodies. m_{ji} and m_i denote affinities between antibody j and antibody i (i.e. the degree of disallowance), and antibody i and the detected antigen, respectively. The first and second terms of the right hand side denote the stimulation and suppression from other antibodies, respectively. The third term represents the stimulation from the antigen, and the forth term the dissipation factor (i.e. *natural death*) [9]. Equation (3) is a squashing function to ensure the stability of the concentration. In this study, selection of antibodies is simply carried out on a *roulette-wheel manner* basis according to the magnitude of concentrations of the antibodies. Note that only one antibody is allowed to activate and act its corresponding behavior to the world.

3.6 Results

To verify the feasibility of our proposed method, we carried out some simulations. In this study, we prepared 22 antibodies of which paratope and idiotope are described *a priori* (Fig.7). As a rudimentary stage of investigation, we determined the degree of disallowance of each antibody heuristically. In the figure, note that the degrees are omitted in each idiotope for lack of space.

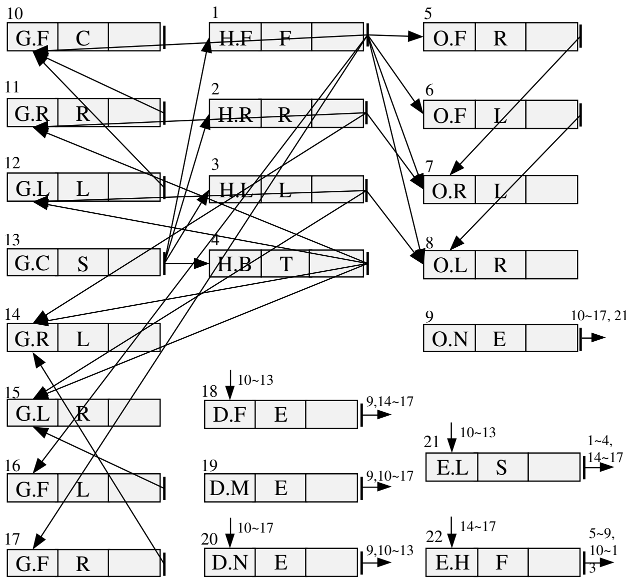
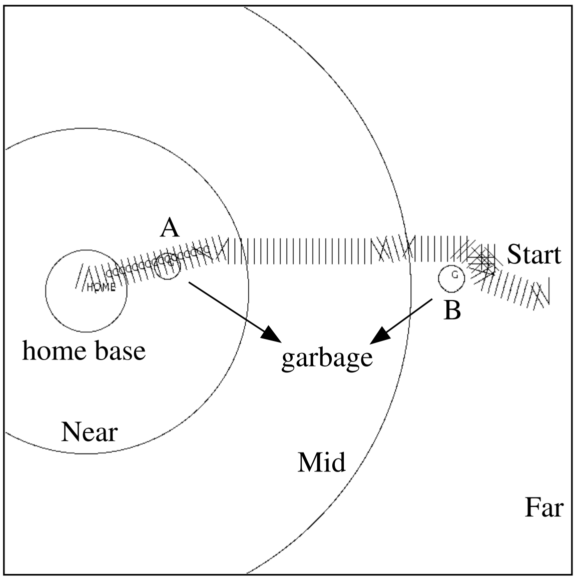


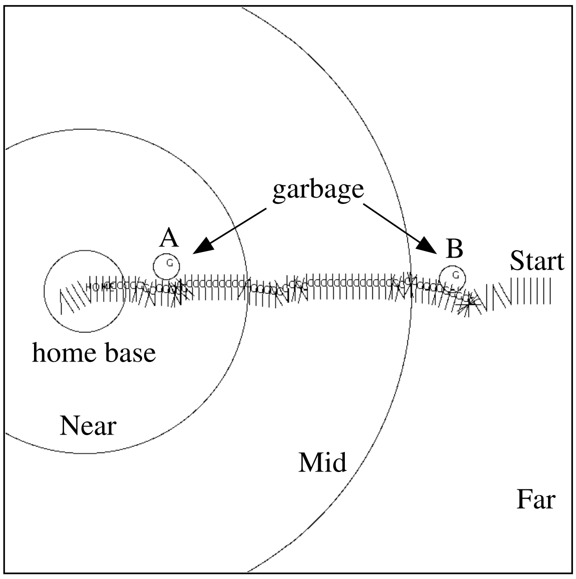
Fig.7: Prepared immune network.

At the beginning of the experiments, we equipped the immunoid with the maximum energy level (*i.e.* 1000). Typical results obtained in the simulations are as follows: while the energy level is enough, the immunoid tries to collect garbage and carry to the home base. As the remaining energy runs out, the immunoid tends to select an antibodies concerned with **go_to_home_base** and/or **search_for_home_base** behaviors. After successful reaching the home base, the immunoid starts to explore again. Such a regular behavior could be frequently observed in the simulations.

In order to evaluate the ability of our proposed arbitration mechanism, we furthermore carried out simple simulations by varying the initial energy level. Fig.8(a) and (b) are the resultant trajectories of the immunoid in the case where the initial energy level is set to 1000 (maximum) and 300, respectively. In case 1, due to the enough energy level, the immunoid collects the garbage *B* and successfully reach the home base. On the other hand, in case 2, due to the critical energy level the immunoid ignores the garbage *B* and then collects the garbage *A*. From these figures, it is understood that the immunoid selects an antibodies suitable for the current situations by flexibly changing the priorities of the antibodies.



(a) Case 1 (initial energy level = 1000).



(b) Case 2 (initial energy level = 300).
Fig.8: Resultant trajectories.

To make our proposed method convincing, demonstration in real environments is highly necessary. We are currently transplanting our proposed method to a real experimental mobile robot. Fig.9 illustrates the real experimental robot (Khepera™) used to confirm the validity of our method.

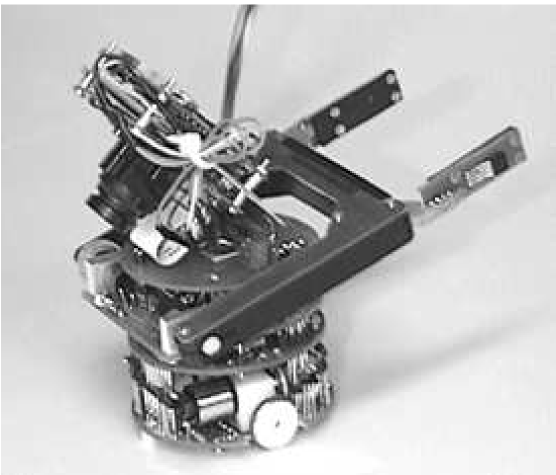


Fig.9: Real experimental robot (Khepera™).

4 Adaptation mechanisms

For more usefulness, as some researchers have been pointed out, the introduction of some adaptation mechanisms is highly indispensable. Adaptation mechanism is usually classified into two types: *adjustment* and *innovation*[15][16]. In the followings, we propose an adjustment mechanism suitable for the proposed system, and show a possible/promising innovation mechanism.

4.1 Adjustment mechanism

For an appropriate consensus-making, it is necessary to appropriately determine the disallowed antibody and its degree of disallowance m_{ij}, *i.e.* priorities among antibodies. To realize this aim, we propose an on-line adaptation mechanism using the advantages of the prementioned description of antibodies. Additionally, it is desired that this mechanism can even work under the situation where the idiotopes of the prepared antibodies are initially *tabula rasa* (blank) through the obtained reinforcement signals.

For the ease of the following explanation, we assume that antigen 1 and 2 invade into the immunoid's interior (see Fig.10). In this example, antibody 1 (Ab_1) and 2 (Ab_2) are simultaneously stimulated by each antigen. Consequently, the concentration of each antibody increases. However, since the priority between Ab_1 and Ab_2 is unknown (because idiotopes are initially *tabula rasa*, there are no stimulation/suppression chain), in this case, either of them can be selected randomly.

Now, assuming that the immunoid randomly selects Ab_2 and then receives a positive reinforcement signals as a reward. To make the immunoid tend to select Ab_2 under the same or similar antigens(situation), we record the ID-number of Ab_2 (*i.e.* 2) in the idiotope of Ab_1 and increase a degree of disallowance m_{12}. In this study, we simply modify the degree of disallowance as:

$$m_{12} = \frac{T_p^{Ab_1} + T_r^{Ab_2}}{T_{Ab_2}^{Ab_1}} \tag{4}$$

$$m_{21} = \frac{T_r^{Ab_1} + T_p^{Ab_2}}{T_{Ab_2}^{Ab_1}}, \tag{5}$$

where $T_p^{Ab_1}$ and $T_r^{Ab_2}$ represents the number of times of receiving penalty and reward signal when Ab_1 is selected. $T_{Ab_2}^{Ab_1}$ denotes the number of times when both Ab_1 and Ab_2 are reacting to their specific antigens.

We should notice that this procedure works to raise the relative priority of Ab_2 over Ab_1. In the case where the immunoid receives a negative reinforcement signal, we record the ID-number of Ab_1 (*i.e.* 1) in the idiotope of Ab_2 and modify m_{21} in the same way. This works to decrease the relative priority of Ab_2 over Ab_1. In simulations, it is observed that this adjustment mechanism works to improve the performance of the immunoid (*e.g.* ability of self-sufficiency) gradually as iterated. We are currently implementing this mechanism into the real experimental system.

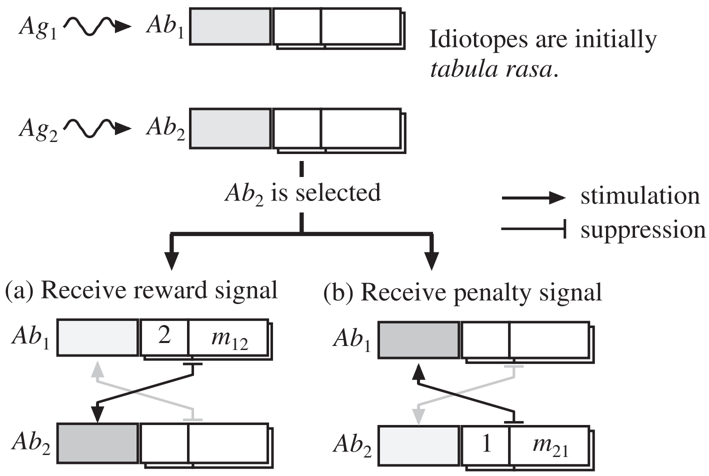


Fig.10: Learning process.

4.2 Innovation mechanism

In the above adjustment mechanism, we should notice that we must still describe the paratope of each antibody in a top-down manner. One obvious and promising candidate to avoid such difficulties is to combine an innovation mechanism with the proposed adjustment mechanism. In the biological immune system, the *metadynamics function* can be instantiated as a innovation mechanism [17]-[19]. The metadynamics function works to maintain appropriate repertoire of antibodies by incorporating new types (these are generally generated as *quasi-species* through the proliferation process of the activated antibodies) and removing useless ones. Fig.11 schematically shows the concept of the metadynamics function. Incorporating this mechanism is currently under investigation.

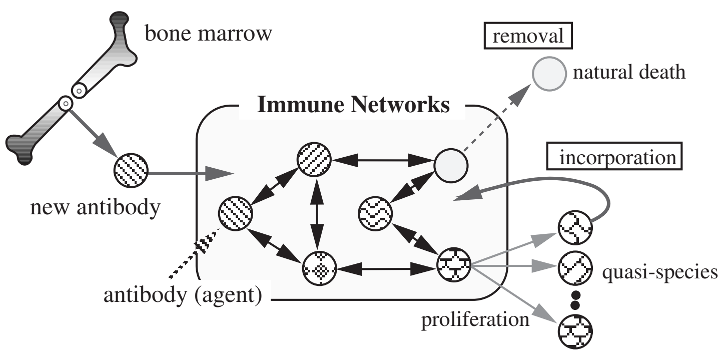


Fig.11: Metadynamics function.

5 Conclusions and Further work

In this paper, we proposed a new decentralized consensus-making mechanism based on the biological immune system and confirmed the validity of our proposed system by applying to an behavior arbitration for an autonomous mobile robot. And we showed an adaptation mechanism for an appropriate arbitration using reinforcement signals.

Since this study is still in a rudimentary stage of investigation, we designed antibodies a priori in a top-down manner. For more usefulness, we must clarify how to combine the proposed adjustment and innovation mechanisms. This is currently undertaking.

Acknowledgments

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