Emergent Construction of Behavior Arbitration Mechanism Based on the Immune System

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Abstract

We have been investigating a new behavior arbitration mechanism based on the biological immune system. The behavior arbitration mechanism and the biological immune system share certain similarities since both systems deal with various sensory inputs (antigens) through interactions among multiple competence modules (lymphocytes and/or antibodies). We have demonstrated the flexible arbitration abilities of our proposed method, however, we have not shown a solution to the problem: how do we prepare an appropriate repertoire of competence modules?

In this paper, in order to construct an appropriate immune network without human intervention, we try to incorporate an off-line metadynamics function into our previously proposed mechanism. The metadynamics function is an adaptation realized by varying the structure of the immune network. To accomplish this function, we use genetic algorithm with a devised crossover operator. Finally, we verify our method by carrying out simulations.

1. Introduction

In recent years, ***behavior-based artificial intelligence (AI) approaches*** have attracted much attention for their robustness and flexibility against a dynamically changing world. ***Brooks,*** a pioneer of the approaches, has presented ***subsumption architecture*** for behavior arbitration of autonomous robots [1,2]. He has argued that intelligence should emerge from mutual interactions among ***competence modules*** (i.e. simple behavior/action), and interactions between a robot and its environment. However, the behavior-based AI still has the following open questions: (1) how do we construct an appropriate arbitration mechanism among multiple competence modules, ***(2)*** how do we prepare appropriate competence modules.

One of the promising approaches to tackle the above mentioned problems is a biologically-inspired approach. Among biological systems, we particularly focus on the immune system, since it has various interesting features such as ***immunological memory, immunological tolerance, pattern recognition,*** and so on viewed from an engineering standpoint. Furthermore, recent studies on immunology have clarified that the immune system does not just detect and eliminate non-self substances called ***antigen*** such as virus, cancer cells and so on; rather it plays important roles to maintain its own system against dynamically changing environments through the interaction among ***lymphocytes and/or 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.

From the above facts, we particularly focused on the similarities between the behavior arbitration system and the immune system, since both systems deal with various sensory inputs (antigens) through interactions among competence modules (lymphocytes and/or antibodies). Based on this, we have proposed a new decentralized consensus-making system inspired by the biological immune system in [3,4]. We have expected that there would be an interesting AI technique suitable for dynamically changing environments by imitating the immune system in living organisms. However, the determination of the appropriate repertoire of competence modules (antibodies) still remains an open question.

In this paper, we try to incorporate an ***off-line metadynamics function*** into the previously proposed artificial immune network in order to autonomously construct appropriate immune networks. The metadynamics function would be regarded as an ***innovation mechanism,*** which is realized by varying the structure of the system. To accomplish the function, we use the genetic algorithm with a devised crossover operation. We carry out simulations and verify that the robot with our proposed method successfully selects an appropriate behavior by flexibly varying the priorities among behavior modules.

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2. Overview of the biological immune system

The basic components of the biological immune system are ***macrophages, antibodies*** and ***lymphocytes.*** *B-lymphocytes* are the cells maturing in ***bone marrow.*** Roughly 10^7 distinct types of B-lymphocytes are contained in a human body, each of which has a distinct molecular structure and produces "Y" shaped antibodies from its surfaces. The antibody recognizes specific ***antigens,*** which are the foreign substances that invade living creatures. This reaction is often likened to a ***key and keyhole relationship.*** For the sake of convenience in the following explanation, we introduce several terms from immunology. The key portion on the antigen recognized by the antibody is called an *epitope* (antigen determinant), and the keyhole portion 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"*** [5, 6, 7]. 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. As illustrated in Fig.1, 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 new parallel decentralized processing.

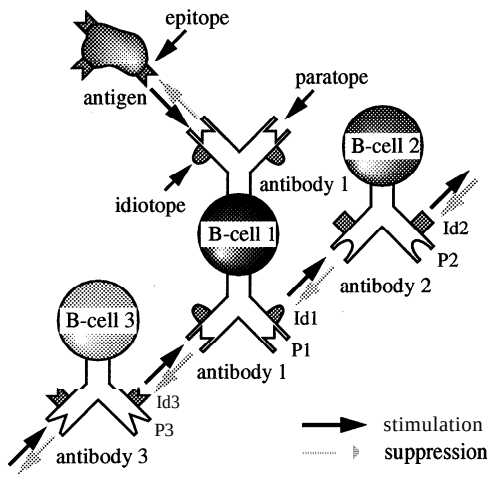


Figure 1. Jerne's idiotypic network hypothesis.

Furthermore, the structure of the network is not fixed, but varies continuously. It flexibly self-organizes according to dynamic changes of environment. This remarkable function, called ***metadynamics function*** [8, 9, 10], is mainly realized by incorporating newly-generated cells/antibodies and/or removing useless ones. Fig.2 schematically shows the metadynamics function. The new cells are generated by both gene recombination in bone marrow and mutation in the proliferation process of activated cells (the mutant is called ***quasi-species).*** Although many new cells are generated every day, most of them have no effect on the existing network and soon die away without any stimulation. Due to such enormous loss, the metadynamics function works to maintain an appropriate repertoire of cells so that the system can cope with environment al changes. The metadynamics function would be expected to provide feasible ideas to the engineering field as an emergent system.

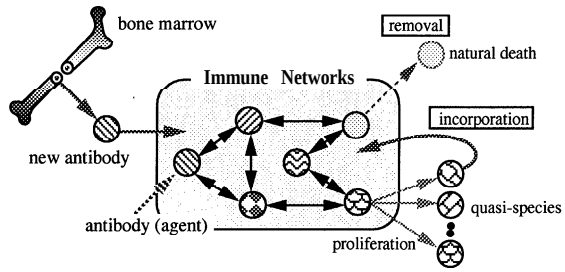


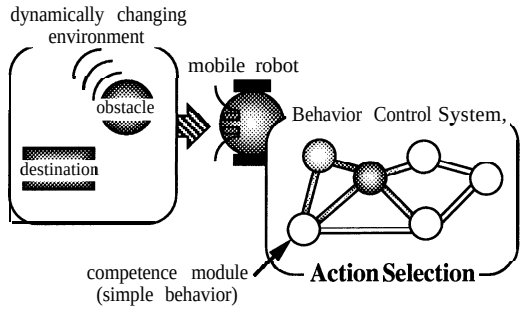
Figure 2. Metadynamics function.

3. Behavior arbitration mechanism based on the biological immune system

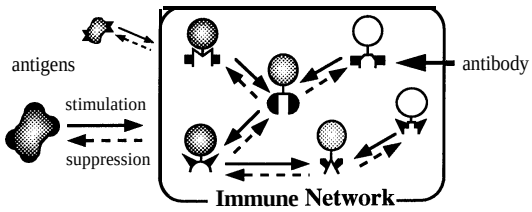
3.1 Behavior arbitration problem and the immune system

As described earlier, in the behavior-based AI, how to construct an appropriate arbitration mechanism among the prepared competence modules must be solved. We have approached this problem from an immunological standpoint, more concretely with the use of immune network architecture [3, 4]. In this section, we discuss our proposed decentralized consensus-making network based on the biological immune system. Fig.3 schematically shows the behavior arbitration system for an autonomous mobile robot and the immune network architecture. As shown in this figure, current situations detected by installed sensors work as multiple antigens (or epitope), 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 sup-

pression between antibodies. The basic concept of our method is that the immune system equipped with an autonomous mobile robot selects a competence module (antibody) suitable for the detected current situation (antigens) in a bottom-up manner. For convenience, we have dubbed the autonomous mobile robot with the immune network-based behavior selection mechanism *"immunoid"*.



(a) Behavior arbitration mechanism for an autonomous mobile robot.



(b) Immune network architecture.

Figure 3. Basic concept of our proposed method.

3.2 Description of antibody

We explain how we describe an antibody in detail. To make the immunoid select a suitable antibody against the current antigens through interacting among antibodies, we must look carefully into the description of the antibodies. To realize the above requirements, we defined the description of antibodies as follows: each antibody has one behavior/action to be executed when it is selected. And we assign a precondition to the paratope, and a disallowed condition to the idiotope, respectively.

In addition, in order to represent the appropriateness of each antibody, we introduce one state variable called ***concentration of antibody.***

3.3 Interaction between antibodies

We will now explain the interaction among antibodies, that is, the basic principle of our immunological consensus-making networks in detail. For the ease of understanding, we use the example depicted in Fig.4.

Consider the listed two antibodies that respond to the antigens C_1 and C_2, respectively. These antigens stimulate the antibodies, consequently the concentration of antibody 1 and 2 increases. If there is no interaction between antibody 1 and antibody 2, these antibodies will have the same concentrations. suppose that the idiotope of antibody 1 and the paratope of antibody 2 are the same. This means that antibody 2 is stimulated by antibody 1, and oppositely antibody 1 is suppressed by antibody 2 (indicated by the arrow). In this case, unlike the previous case, antibody 2 will have higher concentration than antibody 1. As a result, antibody 2 is more likely to be selected. This means that antibody 2 has higher priority over antibody 1 in this situation. As observed in this example, the interactions among the antibodies work as a priority adjustment mechanism.

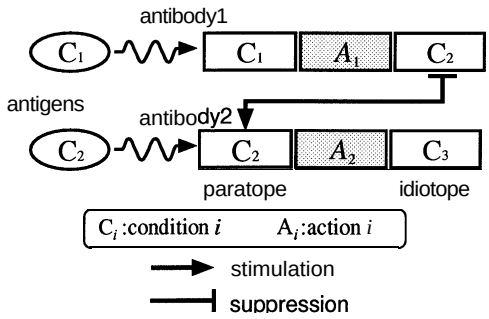


Figure 4. Interaction among antibodies.

3.4 Dynamics

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

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

$$a_i(t+1) = \frac{1}{1 + \exp(0.5 - A_i(t+1))} , \quad (2)$$

where, in equation $(1), N$ is the number of antibodies, and a and β are positive constants. m_{ji} and m_i denote affinities between antibody j and antibody i (i.e. the degree of interaction), and between the detected antigens and antibody i, respectively. The first and second terms of the right hand side denote the

stimulation and the suppression from other antibodies, respectively. The third term represents the stimulation from the antigen, and the fourth term the dissipation factor (i.e. natural *death)* [7]. Equation (2) 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 be selected and project its corresponding behavior on the world (i.e. *winner-take-all manner).*

4. Off-line innovation mechanism

In order to solve what kinds of and how many antibodies are necessary, we propose the off-line innovation mechanism inspired by the metadynamics function using the genetic algorithm with a devised crossover operator. Innovation is an adaptation realized by topological changes of the system, that is, the learning based on selection[ll, 12].

In our method, it is assumed that a chromosome represents a candidate of immune network, and each gene in the chromosome corresponds to each antibody in the immune network. The outline of the off-line innovation mechanism is as follows:

1. Initial chromosomes (population size: M) are generated by random gene combination. Note that the chromosome's length, which represents the number of antibodies, are allowed to be varied because the number of appropriate antibodies can not be predetermined.
2. Each individual, i.e. immune network-based behavior arbitration mechanism, is transplanted into the robot and evaluated.
3. M_e individuals with higher fitness are selected into the next generation (i.e. elite preservation strategy).
4. The genetic operations are performed in order to generate offsprings. Process returns to 2.

In order to determine an appropriate repertoire autonomously, we take up the *mixing pot method* [13] as a variant of crossover operator. Fig.5 schematically shows the mixing pot method. Two parents, which are picked from M_e elite, are put into different pots, in this case, pot A and pot B. Note that the number of antibodies of each parent can be different. Next all antibodies in the two pots are poured into a mixing pot. One antibody is taken out and put into pot 1 or pot 2 with equal probability $1/2$, or a 50-50 chance. The process is repeated until no antibody is in the mixing pot. Finally, pot 2 is discarded and pot 1 becomes the offspring.

In the simple mixing pot method, individuals, such ad antibodies, with the same features are assumed not to be poured into the same pot. This means that if the parents are the same, then the offspring will be exactly the same as the parents. On the other hand, in the devised mixing pot method, antibodies with the same features can coexist in pot 2. Notice that this can not be allowed in pot 1. Due to this, the offspring created by this genetic operator tend to consist of smaller repertoire compared to parents.

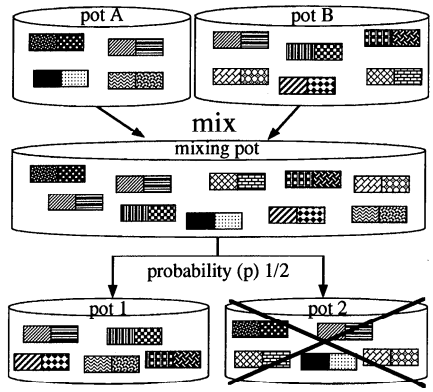


Figure 5. Mixing pot method.

5. Simulation

5.1 Problem

To confirm the feasibility of our proposed innovation mechanism, we carry out some simulations. The simulated environment contains a charging station (CS), a recycle station (RS) and garbage stations (GS). We assume that the immunoid has an initial internal energy at the beginning of simulations and consumes some energy E_m with every step. This can be similar to the *metabolism* in the biological system. The immunoid can recharge its energy in the CS when it has low energy. However, if the battery level in the CS is 0, the immunoid can not refill its energy. To increase the battery level in the CS, the immunoid must carry the garbage from the GS to the RS, and then transform the garbage into some energy in the CS.

In the simulation, the immunoid can detect its current internal energy level I, battery level B in the CS, and the amount of collected garbage G. For simplicity, I, B and G are categorized into two states (high or low). And it is capable of four kinds of behaviors: go *to GS and collect garbage, go to CS, go to RS and none.* The behaviors are predefined in the form of an if-then rule because we focus on behavior arbitration. The detailed descriptions of epitope, paratope, idiotope and behavior are shown in Fig.6.

The aim of the immunoid is to survive as long as possible, that is, not to run out of its energy. To realize the aim, the immunoid should select an appropriate behavior by flexibly varying the priorities among behavior modules. In other words, the robot with a fixed-priority-based arbitration mechanism like the subsumption architecture can not cope with this problem.

In the innovation mechanism, population M, M_e and mutation rate is set to 30, 6 and 0.1, respectively. Additionally, fitness for each immune network is defined by the sum of resultant lifetime in 6 different initial conditions. Each initial condition has different initial values of I (is 50 or 100), B (is 0 or 50 or 100) and G (is 0 or 50 or 100). Since it is assumed that maximum lifetime in each initial condition is 500, maximum fitness is 3000 (6 x 500).

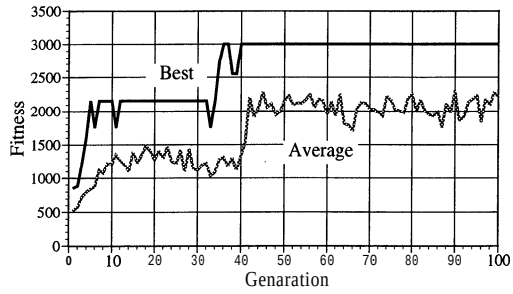
epitope, paratope, idiotope		Action
Internal energy level	: High (I.H)	Go to garbage station (Gs)
	: Low (I.L)	Go to charging station (Cs)
Collected garbage	: Much (G.M)	Go to recycle station (Rs)
	: Little (G.L)	None (N)
Battery level	: High (B.H)	
	: Low (B.L)	

Figure 6. Description of epitope, paratope, idiotope and action.

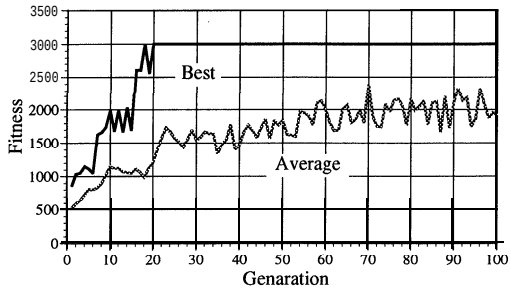
5.2 Results

The transitions of the fitness with the simple and the devised mixing pot method are represented in Fig.7 (a) and (b). From these figures, maximum fitness appears at the 35th generation in the simple method and at the 18th generation in the devised method. Fig.8 (a) and (b) are the transitions of the number of antibodies under the same condition of Fig.7 (a) and (b), respectively. Interestingly, in the devised mixing pot method, the number of antibodies in immune networks gradually decreases, and finally settles to a smaller value than in the simple method. In summary, our devised method finds the appropriate immune network not only faster but also with a smaller number of antibodies than the simple method.

Fig.9 illustrates an obtained immune network with best fitness in 100 generation using the devised mixing pot method. The trajectory of the immunoid by the immune network in a given initial condition appears in Fig.10. The initial condition is that the immunoid equipped with maximum energy level has no garbage, and there is no battery in the CS. As shown in the figure, first, the immunoid goes to the GS in order to collect the garbage, and goes to RS to translate it into



(a) Simple mixing pot method.



(b) Devised mixing pot method.

Figure 7. Transitions of the fitness.

battery energy in the CS. As a result, since the immunoid almost runs out of its internal energy and the CS has enough energy, it goes to the CS to fulfill its energy. In this way, the immunoid can move around the environment without running out of its internal energy. Surprisingly, such a flexible behavior arbitration is realized by the small number of behavior primitives. Therefore, we can understand that the devised mixing pot operator works well to select appropriate repertoire.

6. Conclusions and further work

In this paper, we proposed an off-line metadynamics mechanism for our immune network-based behavior arbitration by the genetic algorithm with the devised crossover operation. And we applied it to the behavior arbitration for an autonomous mobile robot in a simulated environment and validated our proposed method.

However, in the biological immune system, the structure of the network varies continuously. In further work, we must consider an *on-line* innovation mechanism inspired by the biological immune system.

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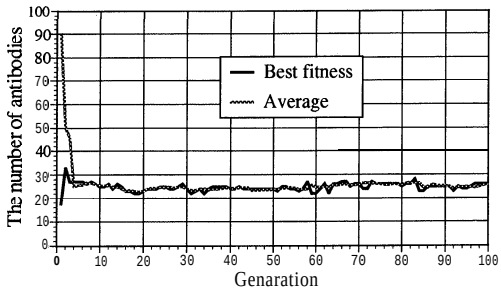
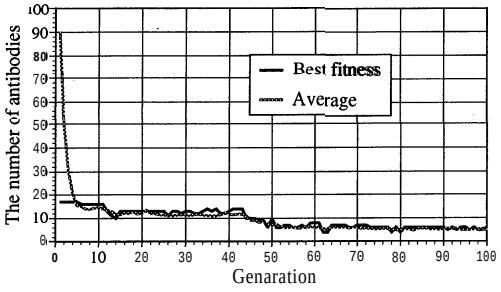


(a) **Simple mixing pot method.**



(b) Devised mixing pot method.

Figure 8. Transitions of the number of antibodies.

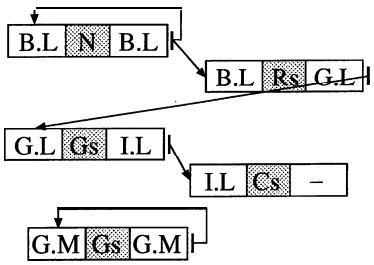


Figure 9. Obtained immune network.

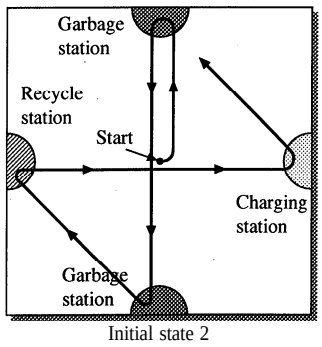


Figure 10. Trajectory of immunoid.

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