Dynamic Behavior Arbitration of Autonomous Mobile Robots Using Immune Networks

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ABSTRACT

Conventional artificial intelligence systems have been criticized for their brittleness under dynamic changing environments. Therefore, in recent years much attention has been focused on reactive planning systems(e.g. behavior-based AI, emergent computation, and so on). In this paper, we propose a new inference/consensus-making system inspired from immune system in living organisms. And we apply our proposed method to behavior arbitration of an autonomous mobile robot as a practical example. We furthermore try to evolve affinities among antibodies using genetic operators. To confirm the validity of our method, we carry out some simulations.

1. Introduction

Conventional artificial intelligent systems based on a functional decomposition, leading to a so-called "*sense-model-plan-act*" cycle have been criticized on many drawbacks over the last decade. Typical criticisms are that these systems show brittleness under environmental changes, and required much computation time for mapping obtained sensory inputs onto complex internal models before action can be taken. Therefore, in recent years much attention has been focused on reactive planning systems (e.g. behavior-based AI, new AI, emergent computation, animat approach, and so on), which have already been demonstrated robustness and flexibility against dynamically changing world [1]-[3].

On the other hand, biological information processing systems such as human beings have many interesting functions and are expected to provide various feasible ideas to engineering fields, especially robotics. Biological information system in living organisms can be mainly classified into the following four systems: (1) *brain-nervous system*, (2) *genetic system*, (3) *endocrine system*, and (4) *immune system*. Among these systems, brain-nervous and genetic systems have already been applied to engineering fields by modeling as neural networks[4] and genetic algorithms[5], and they have been widely used in various fields. Little attention, however, has been paid to application of the other systems (*i.e.* endocrine and immune systems) notwithstanding their important characteristics.

Immune system, in particular, have various interesting features such as immunological memory, immunological tolerance, pattern recognition, non-hierarchical distributed structure, and so on viewed from the engineering standpoint. In addition to the above, recent studies on immunology have clarified that the immune system does not just detect and eliminate the not-self materials called *antigen* such as virus, cancer cells and so on which come from inside/outside of the living system, rather plays important roles to maintain its own system against dynamically changing environments. Therefore, immune system would be expected to provide a new methodology suitable for dynamic problem dealing with unknown/hostile environments rather than static problem.

Based on the above facts, we have been trying to engineer methods of the immune system, and apply to robotics and so on[6]-[8]. We expect that there would be an interesting AI technique suitable for dynamically changing environment by imitating the immune system in living organisms. In this paper, we propose a new decentralized consensus-making system inspired from immune system in living organisms. To confirm the feasibility our proposed method, we apply to behavior control of an autonomous mobile robots as a practical example. Moreover, we try to evolve the proposed artificial immune system equipped with the mobile robot by adjusting affinities among antibodies through genetic process. Finally, the validity of our proposed methods are confirmed by carrying out simulations.

2. Overview of immune systems in living organisms

The basic components of the immune system are *lymphocytes* that are mainly classified into two types, namely *B-lymphocytes* and *T-lymphocytes*. B-lymphocytes are the cells produced from *bonemarrows*. Roughly 10^7 distinct types of B-lymphocytes are contained in a human body, each of which has distinct chemical structure and produces "Y" shaped *antibodies* from its surfaces (see Fig.1). The antibody specifically recognizes an *antigen* like a *key and lock relationship*. 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 regulate the production of antibodies from B-lymphocytes as outside circuits of B-lymphocyte network (idiotypic network) discussed later.

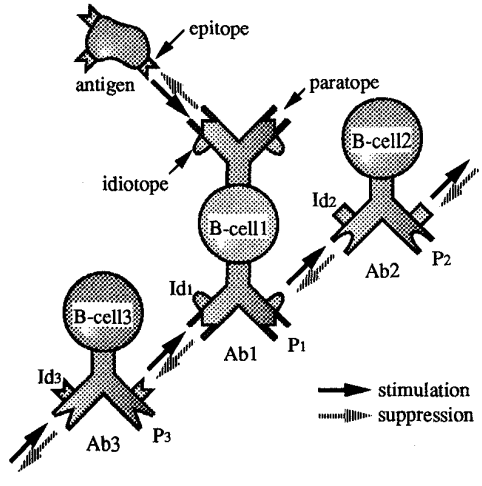


Fig.1 *Jerne's* idiotype network hypothesis.

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

Based on this fact, *N.K.Jerne*, who is an immunologist, proposed a remarkable hypothesis: *idiotypic network hypothesis*[11]-[15]. This network hypothesis is the concept that antibodies are not just isolated, namely they are communicating to each other among different species of antibodies. In other word, the immune system is constructed as a large-scaled system of lymphocytes through mutual interaction between different species of lymphocytes. This idea of *Jerne's* is schematically shown in Fig.1. The idiotope Id1 of antibody 1 (Ab1) stimulates the B-lymphocyte 2, which attaches the antibody 2 (Ab2) to its surface, through the paratope P2. Viewed from the standpoint of Ab2, the idiotope Id1 of Ab1 works simultaneously as an antigen. As a result, the B-lymphocytes 1 with Ab1 are suppressed by Ab2. On the other hand, antibody 3 (Ab3) stimulates Ab1 since the idiotope Id3 of Ab3 works as an antigen viewed from Ab1. In this way, these stimulation and suppression chains among antibodies form a large-scaled chain loop and works as a self and not-self recognizer. Again, the heart of *Jerne's* idea is that the self-nonself recognition in the immune system is carried out at system level.

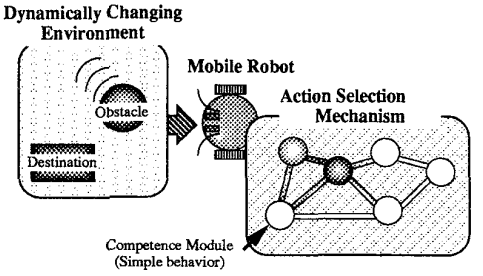
3. Action selection and Immune system

Recently, fatal limits of conventional artificial intelligence approaches based on the functional decomposition have been pointed out. Therefore, much attention has focused on the behavioral decomposition approaches. These behavior-based AI techniques demonstrate their robustness and flexibility against hostile environments, however, arbitration among competence modules (simple behavior/action) arises difficult problems. Namely, it is difficult to select a competence module suitable for the current situation and goals. To overcome this problem, several methods have been proposed. Among them, *Maes* proposed an interesting method; *behavior network system*, under which an action suitable for the current situation and the given goals emerges as the result of the interaction among competence modules[9][10].

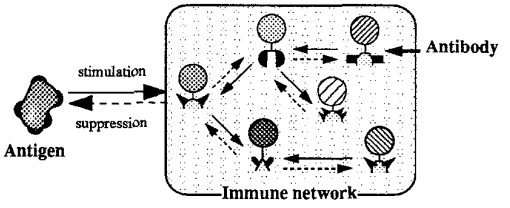
Against the above-mentioned stream of works, we approach to this problem from the immunological standpoint, namely using immune networks. Fig.2 schematically shows the autonomous mobile robots and the immune network system.

As shown in this figure, current situation, for example, distance and direction to the detected obstacle work as antigens, and competence module (simple behavior/action) and interaction between modules can be recognized as antibody (or B-lymphocyte) and stimulation/suppression between antibodies, respectively.

The basic concept of our method is that the immune system equipped with the autonomous mobile robot selects the competence module (antibody) which is most suitable for the current situation (antigen).



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



(b) Immune networks.

Fig.2: Basic concept of our proposed method.

4. Proposed consensus-making networks based on biological immune system

4.1 Problems

For convenience, we call the autonomous mobile robot with the artificial immune system "*immunobot*". To verify the ability of our proposed immune system against hostile environments quantitatively, in this study we use simulated environment for the immunobot as shown in Fig.3.

In this simulated environment, there are following three kinds of objects: 1) *predators*, 2) *obstacles* and 3) *foods*. And we assume that prespecified quantity of initial energy is given to the immunobot at the beginning of each simulation. For quantitative evaluation we use the following assumption:

(1) if the immunobot moves, it consumes energy E_m.
(2) if the immunobot is captured by a predator, it consumes energy E_p.
(3) if the immunobot collides with an obstacle, it loses energy E_o.
(4) if the immunobot picks up a food, it obtains energy E_f.
(5) Obtaining food behavior does not emerge if the energy level of the immunobot is high.(this is for preventing over-charging)

The predators attack the immunobot if they detect the immunobot within the prespecified detectable range. Therefore, to survive as long as possible, the immunobot must select a competence module (antibody) suitable for the current detected situation (antigen).

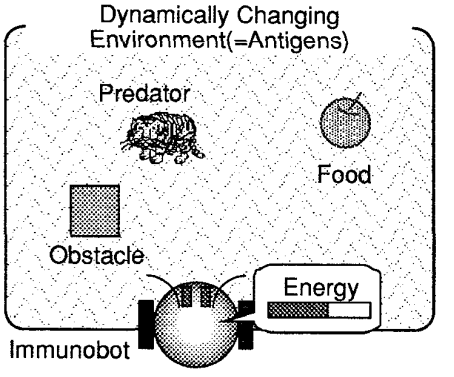


Fig.3: Simulated environment.

Fig.4 indicates the structure of the immunobot used in the following simulations. We equipped this immunobot with external and internal detectors. External detectors are installed in eight direction shown in Fig.4, and each can detect the existence of predators, obstacles and foods. And we assume that each detector can also detect the distance to the objects in three degrees: *near*, *mid* and *far*. On the other hand, internal sensor detects the energy level. For simplicity, we assume that the immunobot can move toward the above eight directions in the following simulations.

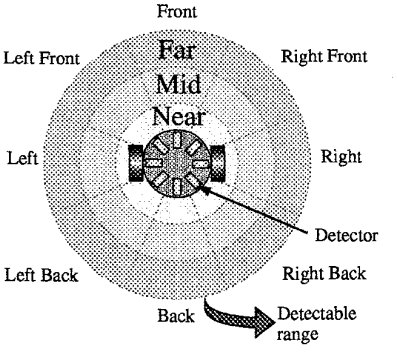


Fig.4: Structure of the immunobot.

4.2 Description of antibodies

As described earlier, in this study, the detected current situation and prepared competence module work as antigen and antibody, respectively. To make the immunobot select a suitable antibody against the current antigen, it is highly important how we describe the antibodies. Moreover, we should notice that our immunological arbitration mechanism selects an

antibody in a bottom-up manner by communicating among the antibodies. To realize the above requirements, we defined the description of antibodies as follows. As mentioned in section 2, the identity of a specific antibody is generally determined by the structure (e.g. shapes) of its paratope and idiotope. Fig.5 depicts our proposed description of antibodies

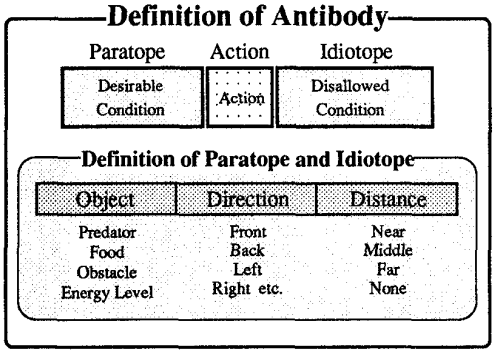


Fig.5: Description of antibodies.

As in the figure, we assign desirable and disallowed conditions to paratope and idiotope, respectively. In addition, we divide the structure of paratope and idiotope into three potions: *objects*, *direction* and *distance*.

For the ease of understanding, an example of the prepared antibody is listed in Fig.6. This antibody is activated if the immunobot detects the food in the front direction and mid range, and makes the immunobot move forward to pick it up. However, if a predator exists in front and near/mid range, or if a food exists in near range, this antibody might hesitate to be activated. Another antibodies are designed in the same way.

Note that typical inference systems (e.g. fuzzy inference) adopt a *condition-action* description framework. Against these conventional systems, our proposed system uses *condition-action-condition* fashion. This description method provides decentralized dynamic inference in a bottom-up manner.

Paratope			Action	Idiotope		
Food	Front	Mid	Move Forward	Predator	Front	Near, Mid
				Food	#	Near

Fig.6: An example of the prepared antibody.

4.3 Dynamics

For adequate selection of antibodies, we assign one state variable called *concentration* to each antibody. In this study, selection of antibodies is simply carried out in a *winner-take-all* fashion. Namely, only one antibody is allowed to activate and act its corresponding behavior to the world if its concentration surpasses the prespecified threshold. As shown in Fig.7, concentration of the antibody is influenced by the stimulation from other antibodies, the suppression from other antibodies, the stimulation from antigen, and the dissipation factor (i.e. *natural death*). The concentration of i-th antibody, which is denoted by a_i, is calculated as follows:

$$\frac{da_i}{dt} = \left\{ \sum_j m_{j,i} \cdot a_j - \sum_k m_{i,k} \cdot a_k + m_i - k_i \right\} \cdot a_i . \quad (1)$$

The first and second terms of right hand side denote the stimulation and suppression from other antibodies, respectively. The third term represents the stimulation from antigen, and the forth term the natural death.

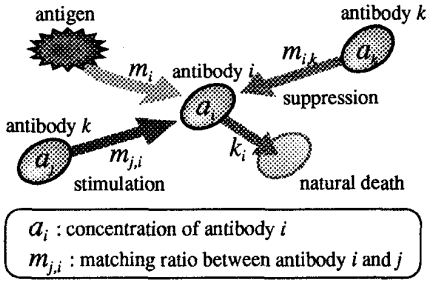


Fig.7: Dynamics.

4.4 Basic mechanism of the proposed consensus-making networks

Next, we explain the fundamental mechanism of our immunological consensus-making networks in detail.

For the ease of understanding, we use the situation shown in Fig.8 as an example. In this situation, four antigens listed in the same figure comes into the immunobot, and the listed five antibodies mainly participate in the consensus-making. For example, antibody 1 means that if the immunobot detects food within far range in front direction, the immunobot is permitted to move forward. However, if the immunobot recognizes other food within nearer range/ predator in front direction/ current energy level is high, this antibody would give way to other antibodies, whose paratopes represent such situations.

Suppose that the current energy level is high. In this situation, antibodies 1, 2, 3 and 5 are stimulated by the antigen. Note that each of the above antibodies increases its concentration just according to its related

antigen. However, to select an appropriate antibody, communication among the antibodies is indispensable. In the figure, the interactions between the antibodies are indicated by arrows. And the solid arrow represents stronger interaction than the shade one. Through these interactions, concentration of each antibody varies. Consequently, antibody 5 will have the highest concentration, and then permitted to be activated.

In the case of the current energy level is low, antibody 3 tends to be selected in the same way.

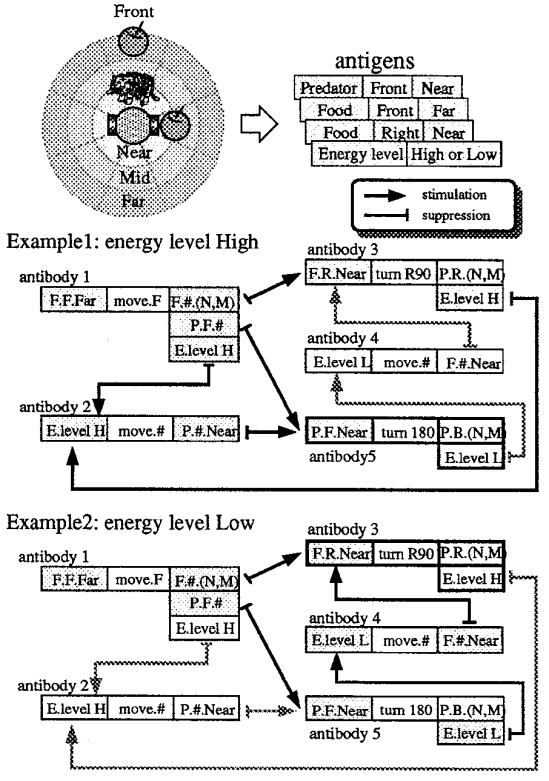


Fig.8: Examples of consensus-making networks by communicating among antibodies

5. Evolution of affinities among antibodies

As described before, idiotopes denote disallowed conditions. However, we should notice that there should be various disallowance among idiotopes. For the appropriate selection of antibodies, degree of disallowance is a significant parameter, since this parameter determines the *affinity* (i.e. strength) between antibodies (see Fig.9). In spite of this, it is very difficult to determine the magnitude of this parameter *a priori*. Therefore, in this study, we tried to adjust the affinities among antibodies using genetic algorithms. In the evolution process, we used the sum of resultant life time and remaining energy level of the immunobot as fitness function:

$$fitness = life\ time + remaining\ energy\ level. \quad (2)$$

Simulation results are depicted in Fig.10 and 11. From the figures, it is understood that the immunobot obtained more appropriate immune system through the genetic process. Simulation conditions are listed in Table 1.

Table 1: Simulation conditions.

population	20
crossover	uniform crossover
crossover rate	5-50 %
mutation rate	20 %
maximum life time	1000 steps
magnitude of affinity	0~1.0
# of antibodies	91
# of predators	5
# of obstacles	10
# of foods	10

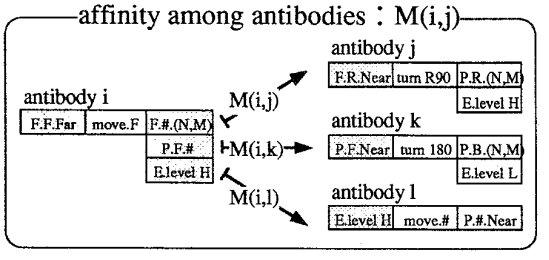


Fig.9: Affinities among antibodies.

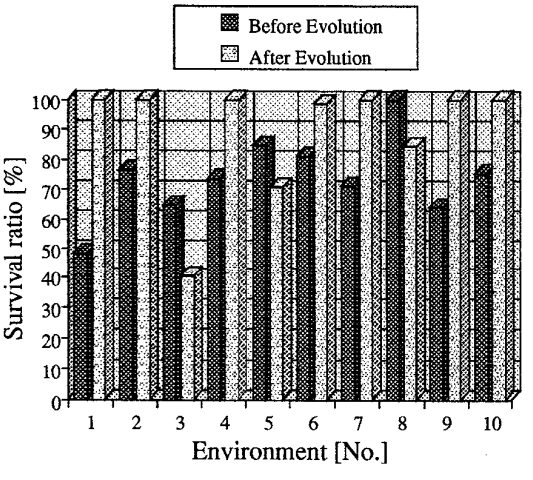


Fig.10: Simulation results (survival ratio).

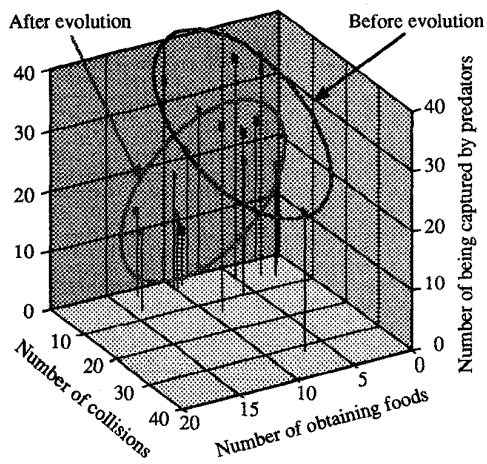


Fig.11: Quantitative comparison between before and after evolutionary processes.

6. Conclusions and Further Work

In this paper, we proposed a new decentralized inference/consensus-making system based on the biological immune system and confirmed the validity of our proposed system by applying to a behavior arbitration of autonomous mobile robots under hostile environments. And we determined pseudo-optimal values of the affinities among prepared antibodies by using genetic algorithms.

Since this study is still in a rudimentary stage of investigation, we designed antibodies *a priori* in a top-down manner. We are now investigating to construct the immune system of the immunobot in a bottom-up manner by introducing *gene recombination* and *meta-dynamics function*. Moreover, we are also trying to endow the immunobot with an on-line learning ability by introducing *T-lymphocytes* and *cytokines* from the engineering point of view.

References

[1] R.Brooks, "A Robust Layered Control System for a Mobile Robot", IEEE Journal of R&A, Vol.2, No.1, pp.14-23 (1986)

[2] R.Brooks, "Intelligence without reason", Proc. of IJCAI-91, pp.569-595 (1991)

[3] D.Cliff, et al.(eds), "From Animal to Animat3", MITPress (1994)

[4] D.E.Rumelhart, et al., "Parallel distributed processing", MITPress(1986)

[5] D.E.Goldberg, "Genetic algorithms in search, optimization and machine learning", Addison-Wesley (1989)

[6] A. Ishiguro, Y. Watanabe and Y. Uchikawa, "Fault Diagnosis of Plant Systems Using Immune Networks", in Proc. of 1994 IEEE International Conference on Multisensor Fusion and Integration for Inteligent Systems, pp. 34-42 (1994)

[7] S. Ichikawa, A. Ishiguro and Y. Uchikawa, "A Gait Acquisition of 6-Legged Walking Robot Using Immune Networks", Journal of Robotics Society of Japan, Vol. 13, No. 3, pp. 125-128 (1995) (in Japanese), also in Proc. of IROS '94, Vol. 2, pp. 1034-1041 (1994)

[8] A. Ishiguro, Y. Watanabe and Y. Uchikawa, "An Immunological Approach to Dynamic Behavior Control for Autonomous Mobile Robots", to appear in Proc. IROS '95 (1995)

[9] P.Maes, "The dynamic action selection", Proc. of IJCAI-89, pp.991-997 (1989)

[10] P.Maes, "Situated agent can have goals", Designing Autonomous Agents, pp.49-70, MIT Press (1991)

[11] N.K.Jerne, "The immune system", Scientific American, Vol.229, No.1, pp.52-60 (1973)

[12] N.K.Jerne, "The generative grammar of the immune system, EMBO Journal, Vol.4, No.4 (1985)

[13] N.K.Jerne, "Idiotypic networks and other preconceived ideas", Immunological Rev., Vol.79, pp.5-24 (1984)

[14] J.D.Farmer, N.HPackard and A.SPerelson: The immune system, adaptation, and machine learning, *Physica* 22D, pp.187-204 (1986)

[15] H.Fujita and K.Aihara, "A distributed surveillance and protection system in living organisms", *Trans. on IEE Japan*, Vol.107-C, No.11, pp.1042-1048 (1987) (in Japanese)