An Engineering Immune Network Model for Pattern Recognition

Weidong SUN(Toyama University, sonkaitou@hotmail.com)Zheng TANG(Toyama University, tang@iis.toyama-u.ac.jp)Hiroki TAMURA(Toyama University, tamura@iis.toyama-u.ac.jp)Masahiro ISHII(Toyama University, ishii@iis.toyama-u.ac.jp)

Abstract: The biological immune system consists of a multitude of cells and molecules that interact in a variety of ways to detect and eliminate infectious agents. It has several useful mechanisms from the viewpoint of information processing. Our overall goal for this paper is twofold: to understand the real immune system from the information processing perspective, and to use idea generated from the immune system to construct new engineering application. As one example of the latter, we propose an engineering immune network model and apply it to pattern recognition. We test the proposed model by the simulations of alphabet patter recognition. The simulation results illustrate that the proposed model is capable of clustering similar input pattern into stable categories.

Keywords: Immune Network, Immune Response, Pattern Recognition

1 Introduction

The biological immune system is highly complicated and appears to be precisely tuned to the problem of detecting and eliminating antigens (Ag); it provides a compelling example of a massively parallel adaptive information processing system, one that we can study for the purpose of pattern recognition.

In recent year, the immune discipline has attracted biologists who are interested in modeling biological immune networks and physicists who envisage analogies between immune network models and the nonlinear dynamical systems. The theoretical development of immune networks was initiated by Jerne [1], who constructed a differential equation to describe the dynamics of a set of identical lymphocytes. After that, most efforts have been made to put the network proposal into mathematical terms [2]-[7]. Immune network concept has also been incorporated into neural networks in machines learning problems [8], in genetic algorithm [9]-[11], in learning stimulus-response behavior [12] and some other applications [13], [14]. However, in these researches the details how an immune response was concretely applied on an engineering system were not seen.

In this paper, we design and implement an engineering immune network model depending upon the immune response mechanism and apply it to pattern recognition problem. We test the proposed model by the simulations of alphabet patter recognition. The simulation results illustrate that the proposed model is capable of clustering similar input pattern into stable categories.

In the next section 2, we briefly introduce the immune system, and in the following section 3, we describe the organization of our model, further explaining immunological concepts where necessary. According to the model and its flow about information processing, we discuss the algorithm in section 4. The simulation results of testing the system out in a real environment are described in section 5. Finally, the paper is concluded with general comments concerning pattern recognition.

2 Immune System

2.1 Immune Cells

The immune system is a complex of cells that are originated in the bone marrow, molecules and organs with the primary role of limiting damage to the host organism by pathogens (called antigens, Ag), which elicit an immune response. Lymphocytes are small leukocytes that possess a major responsibility in the immune system. There are two main types of lymphocytes: B lymphocyte (or B cell), which, upon activation, differentiates into plasmocyte (or plasma cells) capable of secreting antibodies; and T lymphocyte (or T cell).

The B lymphocytes expresses, on its surface, receptors highly specific for a given antigenic determinant. The B cell receptors are a form of the antibody molecule bound to the membrane, and which will be secreted after the cell is appropriately activated. Another main functions of the B cells include the production and secretion of antibodies (Ab) as a response to exogenous proteins like bacteria, viruses and tumor cells. Each B cell is programmed to produce a specific antibody. The antibodies are specific proteins that recognize and bind to another particular protein. The production and binding of antibodies is usually a way of signaling other cells to kill, ingest or remove the bound substance.

The T lymphocytes can be subdivided into three major subclasses: T helper cells (T_H) , cytotoxic (killer) T cells and suppressor T cells (Ts). T cells mature within the thymus. Their functions include the regulation of other cells' actions and directly attacking the host-infected cells. The T helper cells, or simply T_H cells, are essential to the activation of the B cells, other T cells, macrophages and natural killer (NK) cells. They are also known as CD4 or T4 cells. The killer T cells, or cytotoxic T cells, are capable of eliminating microbial invaders, viruses or cancerous cells. Once activated and bound to their ligands, they inject noxious chemicals into the other cells, perforating their surface membrane and causing their destruction. Without their activity, immunity would certainly loose control resulting in allergic reactions and autoimmune diseases. The T cells work, primarily, by secreting substances, known as interleukin (IL), lymphokines and their relatives, the monokines produced by monocytes and macrophages. These substances constitute powerful chemical messengers. The lymphokines promote cellular growth, activation and regulation. In addition, lymphokines can also kill target cells and stimulate macrophages.

2.2 Immune Response

Specialized antigen presenting cells (APCs), such as macrophages, roam the body, ingesting and digesting the antigens they find and fragmenting them into antigenic peptides. Pieces of these peptides are joined to compatibility complex (MHC) molecules

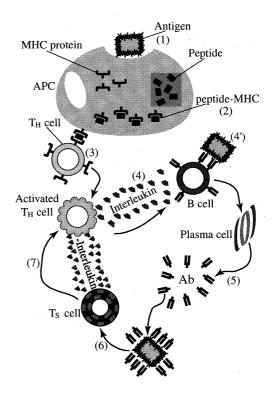


Figure 1: How Does the Immune System Protect the Living Body

and are displayed on the surface of the cell. Other white blood cells, called T cells or T lymphocytes, have receptor molecules that enable each of them to recognize a different peptide-MHC combination. T cells activated by that recognition divide and secrete lymphokines, interleukin or chemical signals, which mobilize other components of the immune system. The B lymphocytes, which also have receptor molecules of a single specificity on their surface, respond to those signals. When activated, the B cells divide and differentiate into plasma cells that secrete antibody proteins, which are soluble forms of their receptors. By binding to the antigens they find, antibodies can neutralize them or precipitate their destruction by complement enzymes or by scavenging cells. This represents the immune response process, an outline of which is shown in Fig.1[15].

3 The Engineering Immune Network Model

Fig.2 illustrates our engineering immune network model. Here, we restrict our discussion on the interaction between B cells and T cells only, although

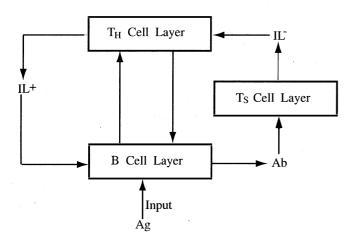


Figure 2: The Engineering Immune Network Model

various cells are participating in the immunity mechanism. The principle cells related to this action are B cells (B), T cells (T), help T cells (T_H), suppressor T cells (Ts), antigen (Ag) and antibody (Ab).

In the following simple scheme, the interactions about one cell within immune system are considered.

(1) Ag(input) \rightarrow B cell \rightarrow Output

When antigen (Ag) invades living bodies, it can be regarded as an input to the immune network and taken in by B cell, i.e., antigen insults living body and presents on the surface of skin.

First in level B1, not only the stimulation to living bodies from the speci

(2) Output \rightarrow T_H cell \rightarrow IL+

 $T_{\rm H}$ cell can recognizes the antigen information from B cell and secretes the interleukin (IL+) that activates the immune response.

(3)-IL+ \rightarrow B cell \rightarrow Antibody (Ab)

The interleukin (IL+) becomes the second signal to the B cell. Once B cell recognizes this signal, it divides into antigen synthetic cells (plasma cells), and then synthesizes and secretes the antibody finally. Here, B represents both B cell and plasma cell.

(4) Antibody \rightarrow Ts \rightarrow IL-

If the antibody excludes the antigen, we can say that the immune of living body is effective. At this time, the suppressor Ts cell will be stimulated to secrete suppressing interleukin (IL-) to suppress the immune response. The immune response is finished as long as the generation of the antibody stops. This flow depicts the process of immune response.

4 Algorithm

In this section, we discuss the algorithm of the proposed immune network model. In the proposed model (Fig.2), the antigen corresponds to input; B cell layer corresponds to attention subsystem as a feature representation field; $T_{\rm H}$ cell layer corresponds to orienting subsystem as a category representation field; Ts cell corresponds to suppressing layer and antibody (Ab) to the output. Namely, the proposed model is composed by B cell layer, $T_{\rm H}$ cell layer and Ts cell layer; connected by two connection circuits between B cell layer and $T_{\rm H}$ cell layer: w_{ij} and t_{ji} .

Before starting the network training process, it is necessary to initialize all weight vectors w_{ij} and t_{ji} . For all *i* and *j*,the weight vectors from B cell layer to T_H cell layer can be given as

$$w_{ij} < \frac{L}{L - 1 + N} \tag{1}$$

where

-13-

L = constant > 1 (typically, L = 2)

N = the number of B cell in B cell layer

M = the number of T cell in T_H cell layer

This value is critical; if it is too large the network can allocate all B cells to a single input vector.

On the other hand, for all i and j, the weight vectors from $T_{\rm H}$ cell layer to B cell layer are all initialized to 1, so

$$t_{ji} = 1 \tag{2}$$

The value is also critical; if it is too small there will be no matches at the B cell layer and no training.

When antigen (Ag) as input reached at B cell layer, it is transformed into a activation pattern across the cells of B cell layer. In B cell layer each cell whose activity is sufficiently large generates excitatory signals along pathways to target cells at the next processing stage: T_H cell layer. Because initially there is no output from B cell, any component of Ag that is one provides the second input, thereby causing its associated B cell to fire and output a one. Thus, at this time, the output vector of B cell layer, we let it be C, will be identical to Ag. Fig.3 illustrates the output from B cell to T cell.

When a signal from a cell in B cell layer is carried along a pathway to $T_{\rm H}$ cell layer, the signal is multiplied, or gated, by the pathway trace, w_{ij} . The gated signal, we let it be U, reaches the target node: T cells. Namely, for all *i* and *j*:

$$u_j = C \ w_{ij} = Ag_i \ w_{ij} \tag{3}$$

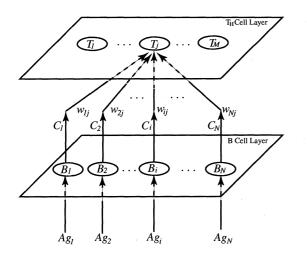


Figure 3: Weight Connection from B Cell to T Cell

In the following process T_H cell will choose the cell, which receives the largest input by competition interaction. That is to say, the j^* th T_H cell that received the largest stimulus can be chosen and it can secrete interleukin(IL+)at this time. The value of the j^* th T_H cell is computed as:

$$u_{j^*} = max\{u_j \quad j = 1, 2, \dots M\}$$
 (4)

The interleukin(IL+) is then weighted and send back to B cells once again by the pathway of t_{ji} (see Fig.4). We call it memory pattern. Thus, the new output vector C of B cell layer become

$$c_j = t_{j^*i} A g_i \tag{5}$$

If a vector X is represented to ||X||, then

$$||Ag|| = \sum_{i=1}^{N} Ag_i \tag{6}$$

$$||C|| = ||T Ag|| = \sum_{i=1}^{N} t_{j^{*i}} Ag_i$$
 (7)

Once B cell recognizes this signal, it divides into antigen synthetic cells (plasma cells), and then synthesizes and secretes the antibody finally. Here, antibody is regarded as the similarity between the input vector and memory vector and we compute the similarity as follow.

$$Ab = \frac{||C||}{||Ag||} \tag{8}$$

The input pattern mismatch occurs if the following inequality is true

$$Ab < \rho \tag{9}$$

where, ρ , which is called vigilance parameter, is set in the range of 0 to1,depending upon the degree of mismatch that is to be accepted between the memory pattern and the input vector.

If the two patterns differ by more than the vigilance parameter, a reset signal is sent to disable the firing unit in the T_H cell layer. The effect of the reset is to force the output of the T_H cell layer back to zero, disabling it for the duration of the current classification in order to search for a better match. Namely, in this case inhibitory interleukin (IL-) is secreted from the Ts cells. The inhibitory interleukin(IL-) tends to suppress the T_H cells that secrete the excitatory interleukin. Thus, a new competition in T_H cell layer occurs. The same process will be repeated until the similarity is decreased below the vigilance parameter.

If the similarity is below the vigilance level, the memory pattern must be searched, seeking one that matches the input vector more closely, or failing that, terminating on an uncommitted cell that will then be trained. That is to say, the winner is accepted and it represents the category of this kind of antigen. i.e., the recognition for this kind of antigen of immune network is successful. And then the network enters a training cycle that modifies the weights both w_{ij} and t_{ji} .

Training is the process in which a set of input vectors are presented sequentially to the antigen input of the network, and the network weights are so adjusted that similar vectors activate the same T_H cell. If the same antigens invade once again, the immune response can be activated by the network recognition rapidly; a large quantity of antibodies is generated in a very short period (the secondary immune response). For all *i* and *j*, the adjusting

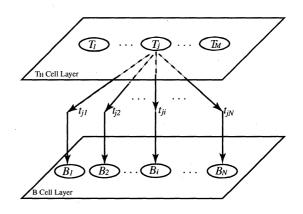


Figure 4: Weight Connection From T Cell To B Cell

-14-

		$\begin{array}{c} \bigcirc \bigcirc$
OOOOOO OOOOOO OOOOOOO OOOOOO		
		$\begin{array}{c} \bullet \bullet \circ \circ \circ \circ \circ \bullet \bullet \bullet \circ \circ \circ \circ \bullet \bullet \bullet \circ \circ$

Figure 5: Recognition Patterns From Letters A To Z

weight equations can be given

where, l > 1 is constant.

5 Simulation

Several simulations on binary immune network have been selected to illustrate the immunity of our immune network model.

In our trials, we resume the number of B cell is N = 64, T_H cell is M = 26; and select the alphabet letters that are shown in Fig.5 as the input vector Ag. Letters are shown as patterns of small circles on an 8-by-8 grid. Each filled circle represents a component of the Ag vector with a value of one; all open circles are components with values of zero. First, we let the network vigilance $\rho = 0.5$, and observe how this network performs on the pattern recognition problem.

In Fig.6, letters on the left represent input pattern; letters on the right represent the memory patterns, each is the set of the value of the components of a vector T_j .

Initially, the letter A is inputted to newly initialized system. Because there is no memory pattern that matches it within the vigilance limit, the search phase fails; a new cell is assigned in the $T_{\rm H}$ cell layer and its category number is given as 25 by the network. In the meantime the weights T_j are set to equal the corresponding components of the input vector, with w_j becoming a scaled version.

Then, the letter B is presented and then first searches A's category 25. This also fails in the search phase and another new neuron is assigned in the category number 17. This is repeated for the letter C. When letter D is presented, it searches the memory category 25,17 and 19; having nothing in common with those patters A, B and C, it then goes directly to an uncommitted neuron and establishes category 1.

In this case, the learning for the input patterns A, B, C and D is successful. The network is trained by adjusting top-down and bottom-up weights so that when the learned patterns are again presented they can directly accesses their original categories easily.

Figure 6: The Recognition Process of Letter A, B, C And D

Fig.7 shows another classification process for pattern Z. Before inputting pattern Z, the network has learned the letters from A to Y successfully and assigned their category respectively. In this case $(\rho = 0.5)$, category 6 has involved letter G, Q, S and T, the memory pattern is shown in Fig.7 (a). In the same way, category 4 has involved letter H, M and P, the multiplied pattern is shown in Fig.7 (b); category 3 has involved letter U and V; the multi-

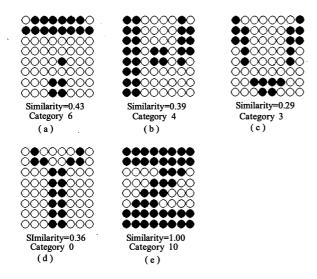


Figure 7: The Classification Process of Letter Z with Network Vigilance 0.50.

plied pattern is shown in Fig.7 (c); category 0 has involved letter I, J and Y, the multiplied pattern is shown in Fig.7 (d).

The first step shows the response of the memory pattern (a) to the input pattern Z (Fig.7 (a)). When letter Z as input pattern is represented, it is matched with the memory pattern in category 6 and the similarity between them is computed to be 0.43. The similarity (0.43) is less than the network vigilance (0.50); it suggests the letter Z is not belong to this category 6. Therefore, category 6 is suppressed. And then, the searching will go on.

The second step shows the response of the memory pattern (b) to the input pattern Z (Fig.7 (b)). In the same way as the first row the matching, comparison and similarity computation between letter Z and the memory pattern are implemented. The computed similarity is equal to 0.39; it is less than the vigilance 0.5, too. Of course it is suppressed too and leaves from category 4 for next search.

The third step shows the response of the memory pattern (c) to the input pattern Z (Fig.7 (c)).

The fourth step shows the response of the memory pattern (d) to the input pattern Z (Fig.7 (d)). Among them letter Z is not belong to category 3 and 0 since their similarity is below the vigilance. After the letter Z had searched the similar category in the network, mismatched with all the memory patterns within the vigilance limit, it directly accesses the empty category 10 with similarity 1.0. Fig.7 (e) shows the adjusted memory pattern of letter Z.

In order to illustrate how our immune network

codifies a more complex series of patterns, we show in Fig.8 the trials of a simulation using alphabet letters.

In Fig.8a, the vigilance parameter is $\rho = 0.5$. In Fig.8b, the vigilance parameter is $\rho = 0.9$. Three properties are notable in these simulations.

First, choosing a different vigilance parameter can determine different coding histories, such that higher vigilance induces coding into finer categories.

Second, the network modifies its search order on each trial to reflect the cumulative effects of prior learning, and bypasses the orienting subsystem to directly access categories after learning has taken place.

Third, the weights tend to be more abstract because they must approximately match a larger number of input pattern exemplars.

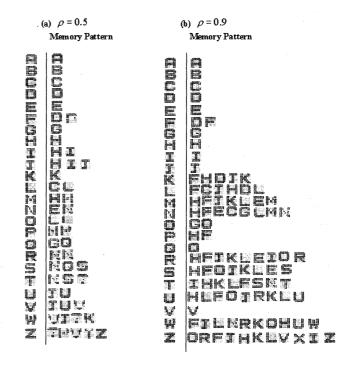


Figure 8: The Comparison of Classification With Differential Vigilance.

6 Conclusions

According to the immune response, an engineering immune network model that performs a pattern recognition task was presented. Simulations performed the efficiency of the proposed model in binary pattern (antigen) recognition and shown that the proposed model had the following features: competitive learning, automatic generation of the category and binary representation of the connection weights; and it is able to cluster similar input patterns into stable categories.

References

- N.K. Jerne, "Towards a network theory of the immune system," Ann. Immunol, vol.125c, pp.373-389, 1974.
- [2] A.S. Perelson, ed., "Theoretical Immunology, part I and II," Addison-Wesley, Redwood City, CA, 1988.
- [3] H. Atlan and I.R. Cohen, eds., "Theories of Immune Networks," Springer-Verlag, Berlin, 1989.
- [4] N.K. Jerne, "The Immune System: A Web of V-Domains," The Harvey Lectures, series 70, 93-110, Academic Press, 1976.
- [5] A.S. Perelson, "Immune Network Theory," Immunology Review, No.10, pp.5-36, 1989.
- [6] T.Ikegami, "Dynamical behavior of the immune network," Progress of Theoretical Physics, No.81, pp.309-320, 1989.
- [7] J.D. Farmer, N.H.Packard, and A.S. Perelson, "The immune system, adaptation, and machine learning," Physical, NO.D22, pp.187-204, 1986.
- [8] J.Faro asn S.Velasco, "Studies on a recent class of network models of the immune system," J.Theor. Biol., NO.164, pp.271-290, 1993.
- [9] J.D. Farmer, "A rosetta stone for connectionism." Physic, No. D42, pp.153-187, 1990.
- [10] H. Bersini and F. L. Varela, "The immune recruitment mechanism: A selective evolutionary strategy," Proc. ICGA-91, pp.520-526, 1991.
- [11] R.Hightower, S, Forrest, and A.S. Perelson, "The evolution of secondary organization in immune gene libraries." Proc. Second European Conference on Artificial Life, 1993.
- [12] G.W. Hoffmann, "A neural network based on the analogy with immune system," J. Theor, Bilo., No.122, pp.33-67,1986.

- [13] J.O. Kephart, "A biologically inspired immune system for computers," in Artificial Life, ed. C.G., Langton, Addison-Wesley, Redwood City, CA,1994.
- [14] S.Forrest, B.Jovornik, R.E. Smith, and A.S. Perelson, "Using genetic algorithms to explore pattern recognition in the immune system." Evolutionary computation, NO.1, pp.191-211,1993.
- [15] L. N. Castro, and F. J. V. Zuben, "Artificial Immune Systems: Part I -Basic Theory and Applications," Technical Report, TR-DCA, 01/99, 95p., 1999, URL: http://www.dca.fee.unicamp.br/-lnunes