A Complex Artificial Immune System and Its Immunity

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Summary
This paper proposes a new complex artificial immune system based on biological immune system. The complex data representation and complex expressions of weights are introduced into the traditional artificial immune system, in which binary or real value data representation was used. The proposed complex artificial immune system imitates the immune response mechanism closely and incorporates the complex partial autocorrelation coefficients of input antigen as the antigen presentation. Simulations of pattern recognition illustrate that the proposed complex artificial immune system has not only the complex memory capacity and classification ability, but also the ability of recognizing translation patterns in high accuracy, which binary artificial immune systems do not have.

Key words:
complex, artificial immune system, immune response, pattern recognition, translation recognition

1. Introduction

Over the years, biology has provided a rich source of inspiration for developing computational models and problem solving methods. The immune system, which has been recently drawn significant attention, is considered as a new biologically inspired computational intelligence approach. Based upon metaphors of the immune system, the artificial immune system has emerged. The artificial immune system is an adaptive system inspired by theoretical immunology and observed immune functions, principles and models, which are applied to many problems [1]. Since 1986 [2], a lot of works have been done on the development of artificial immune system and its applications in a variety of domains, such as machine learning [3], anomaly detection [4] [5], data mining [6], computer security [7] [8], adaptive control [9] and fault detection [10]. Moreover, as an important application of artificial immune system, pattern recognition has received a growing interest. Forrest et al. [11] proposed a binary immune system model in order to study pattern recognition and learning, which takes place at the individual and species level in the immune system. Dasgupta et at. [12] proposed a genetic algorithm to interpret chemical spectra using a binary representation. In our previous works, Tang et al. [13] proposed a binary immune network model based on biological immune response network. And a multiple-value immune network model with the advantages of fewer categories, improved memory pattern and good memory capacity [14] has been proposed. Furthermore, a novel affinity based literal interaction immune network [15] which has a better learning capacity and noise tolerance has also been proposed.

Despite the fact that the pattern recognition of artificial immune system is progressing slowly and steadily, there still remain many open issues, such as the lack of enhancement of the pattern representation and affinity measures. The definition of representation for the patterns is an important stage for performing pattern recognition with an artificial immune system. Many traditional artificial immune systems use the binary values as pattern representation, and we call them binary artificial immune system (Binary AIS) [13] [15] in this paper. Actually, it is insufficient to describe all of the pattern recognition problems only by binary values in real-life problems, such as image processing and voice recognition, which need advanced data representation. As for the transformation pattern recognition, there has been no effective algorithm of binary AIS that can recognize transformation patterns in high accuracy yet. On the other hand, as a basis for the 'Fractal', complex numbers have some useful mathematical properties and are being used widely in electronics and electromagnetism. Therefore, it can be considered as a new data representation of artificial immune system.

In this paper, a complex artificial immune system (Complex AIS) is proposed. The feature of the complex AIS is the introduction of novel complex data representation and complex expressions of weights. The key information of antigen is extracted and translated into complex number instead of the normalization of input antigen performed in binary AIS. The key feature of input antigen obtained using the key information, namely complex partial autocorrelation coefficients, has the property of being invariant to the similarity transformation of the patterns [16]. The simulations of pattern recognition illustrate that proposed complex AIS retains original features of traditional artificial immune system, such as the memory capacity and classification ability. Furthermore, a comparison with binary AIS shows that the

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complex AIS can recognize the translation of patterns correctly while the binary AIS failed to recognize.

In the next section 2, some basic concepts of nature immune systems and immune response mechanism are introduced. In the following section 3, the proposed complex artificial immune system is described in detail. In section 4, simulations on the proposed complex artificial immune system are performed. Finally, some general conclusions are provided in section 6.

2. Immune Response Mechanism

The immune system is a complex of cells, molecules and organs that represent an identification mechanism capable of perceiving and combating dysfunction from our own cells and the action of exogenous infectious microorganisms [17].In this section, the immune cells, which play an important role and the immune response mechanism will be introduced.

2.1 Immune Cells

In immune system, lymphocytes are the most important cells. The two major populations of lymphocytes: B lymphocytes (B cells) and T lymphocytes (T cells). B cells mature within the bone marrow, each of the B cells expresses a unique antigen-binding receptor on its membrane after leaving bone marrow, this antigen-binding or B-cell receptor calls a membrane-bound antibody molecule. When a B cell encounters the antigen that matches its membrane-bound antibody for the first time, the binding of the antigen to the antibody causes the cell to divide rapidly and its progeny differentiate into memory B cells and effector B cells called plasma cells. Memory B cells have a longer life time, while Plasma cells produce the antibody in a form that can be secreted and have little or no membrane-bound antibody [18].

T cells also arise in the bone marrow, but they migrate to the thymus gland to mature, which is different from B cells. Helper T cell (Th) and suppressor T cell (Ts) are two sub populations of T cells. Th cells play an important role in activating and direction B cells and various other cells in the immune response. Without the ability of recognizing the antigens directly, Th cells can recognize only antigen that is bound to cell-membrane proteins called major histocompatibility complex (MHC) molecules through a unique antigen-binding molecule, namely the T-cell receptor, which is expressed on the surface of Th cells. As for the Ts cells, they are vital for the maintenance of the immune response, and can inhibit the action of immune response by secreting suppressing signals.

Besides, there are important cells called antigen-presenting cells (APCs), which also play an important role in the activation of Th cells. The antigen-presenting cells first internalize antigen, either by phagocytosis or by endocytosis, and then display a part of that antigen on their membrane bound to a MHC molecule [18], so that the Th cells can recognize the antigens by the interactions of T-cell receptor and MHC molecules.

2.2 Immune Response Mechanism

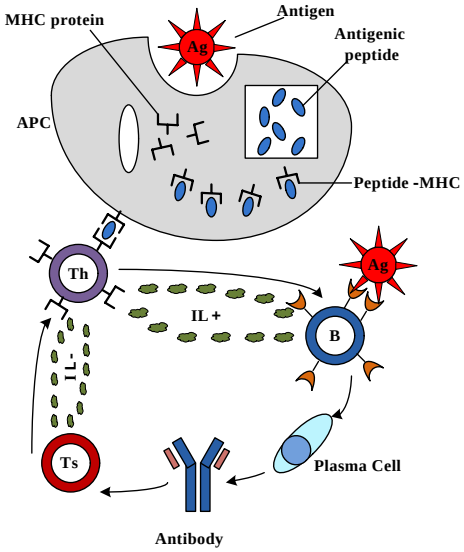

Fig. 1 Immune response process.

The immune response mechanism is shown in Fig. 1. Some antigens are recognized by B cells directly in solution, while some are ingested and digested by antigen-presenting cells, and fragmented into antigenic peptides. Pieces of these peptides are joined to MHC molecules and displayed on the surface of the APCs. The T-cell receptors expressed on the surface of Th cells recognize and interact with the peptides bound to MHC molecules, and then Th cell becomes activated. Activated Th cell divides and secretes interleukin (IL+) or other chemical signals which can stimulate B cells. Either stimulated by antigens or interleukin (IL+) secreted by Th cell, activated B cells can divide and differentiate into plasma cells and memory cells. In plasma cells, antibody molecules are synthesized greatly and secreted. After secreted antibody destroying the antigens, Ts cells are stimulated and activated, and secrete suppressing interleukin (IL-) to Th cells to modulate immune response. As for the memory cells, when they encounter the same antigens once again, they will divide into plasma cells rapidly, and generate abundant antibodies in a very short period, this is called the second response.

3. Complex Artificial Immune System

3.1 System Model

In this section, a complex artificial immune system is introduced. As shown in Fig. 2, the proposed complex artificial immune system model consists of four layers: pre-processing layer (APC layer), MHC layer, competitive layer (Th cell layer) and stimulation-inhibition layer (B cells layer). The process in each layer and the relation between them can be illustrated in general as following simple scheme:

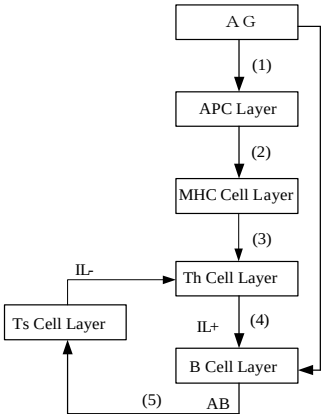

Fig. 2 Complex artificial immune system model.

(1) AG => APC layer => Output1

The antigen is considered as input of the immune system, and in APC layer, it is internalized by APCs through phagocytosis or endocytosis and fragmented if to antigenic peptide. In binary AIS [15], the antigen information is normalized in the APC layer, while in complex artificial immune system, the key information of antigen is reorganized, and complex form of this key information is outputted for further processing.

(2) Output1 => MHC cell layer => Output2

In MHC cell layer, antigenic peptide produced in APC layer joins to MHC molecules and displays on the surface of APCs. The feature extraction of information transported from APC layer is performed in this layer. As the invariant feature, the complex partial autocorrelation coefficients [19] [20] [21] are calculated and output to TH Cell layer.

(3) Output2 => Th cell layer => IL+

T-cell receptor scans the surface of APCs for specific peptide bounding MHC molecule. If the specific peptide is found, The Th cell will be activated and secrete interleukin (IL+). In Th cell layer, according to WTA (Winner-Take-all) rule, one and only one Th cell is activated and divides signals to mobilize B cells.

(4) IL+ => B cell layer => AB

B cell receives stimulation from Th cell, and divides into plasma cells. The plasma cell then synthesizes and secretes AB (antibody). In proposed complex artificial immune system, the antibody is defined as the difference between the memory feature being memorized in memory cells and the antigen feature.

(5) AB => Ts cell layer => IL-

When the antigen is excluded by the antibody, the Ts cell will be activated and secrete interleukin (IL-) to Th cells and suppress the immune response. The immune response is complete until the generation of the antibody is stopped. In this complex artificial immune system, the function of TS layer is carried out by the adjusting of weights between different layers.

3.2 System Operations

As the input of the system, the information of antigen can be expressed as a vector value mathematically as follows:

$$AG = (ag_1, ag_2, \ldots, ag_M) \tag{1}$$

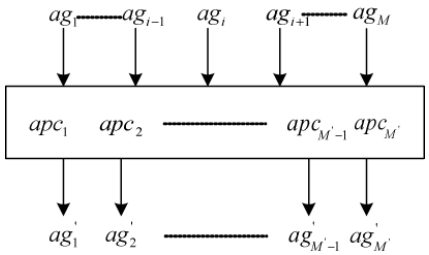

Fig. 3 APC layer process.

As shown in Fig. 3, the APC layer receives the antigen information given by:

$$apc_i = ag_i \tag{2}$$

In APC layer, the information of antigen is reorganized and only the key information is outputted. This key information is expressed as $AG' = ag'_1, ag'_2, \cdots, ag'_{M'}$. The data representation of key information is converted into complex form which is different from the binary immune systems. Each element of the key information is given by:

$$ag'_i = x_{ag'_i} + y_{ag'_i} i \tag{3}$$

where i is the imaginary number. $x_{ag_i'}$ is the real part and $y_{ag_i'}$ is the imaginary part of the complex coordinates of the key information when mapping the whole antigen to be a two dimensional coordinate space and regarding the upper left point as the origin.

Similarly, the MHC layer receives key information AG' from APC layer as (see Fig. 4):

$$MHC_i = ag_i' \tag{4}$$

In MHC layer, the feature of the input antigen is extracted based on the key information. The complex partial autocorrelation coefficients, namely $MHC' = (MHC_1', MHC_2', \cdots, MHC_m')$, which are considered as the invariant feature of the input antigen are calculated and outputted to Th cell layer.

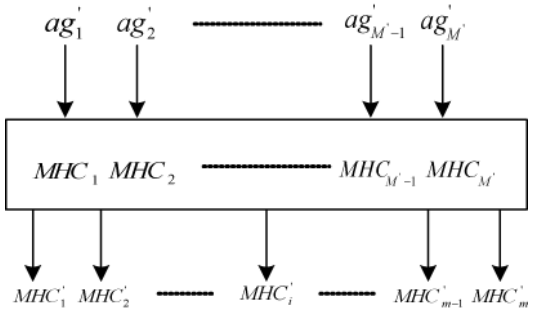

Fig. 4 MHC layer process.

In order to obtain the MHC', the complex autocorrelation coefficients are calculated with:

$$r_j = \sum_{k=0}^{M'-1} MHC_k \overline{MHC}_{(j+k) \bmod M'} \tag{5}$$

Where

MHC' is the number of the MHC cells.

$\overline{MHC}_{(j+k) \bmod M'}$ is the complex conjugate of MHC_k, which has been transposed j.

According to Eqs. 5, the values of complex autocorrelation coefficients $r_0, r_1, \cdots, r_m$ can be obtained.

Still, a matrix namely A is defined to express the complex autoregressive coefficient $a_1, a_2, \cdots a_m$, thus, the element in MHC layer MHC_i can be expressed by linear combination of preceding m elements as:

$$MHC_i = \sum_{k=1}^{m} a_k MHC_{i-k} \tag{6}$$

The complex partial autocorrelation coefficient MHC' can be computed in this way:

When j = 1,

$$MHC_1' = A_{11} = \frac{r_1}{r_0} \tag{7}$$

And when $j \geq 2$,

$$MHC_j' = A_{jj} = \frac{r_j - \sum_{k=1}^{j-1} r_{j-k} A_{(j-1)k}}{r_0 - \sum_{k=1}^{j-1} r_k \overline{A}_{(j-1)k}} \tag{8}$$

$$A_{jk} = A_{(j-1)k} - MHC_j' \overline{A}_{(j-1)(j-k)} \quad , k < j \tag{9}$$

Where $\overline{A}$ is the conjugate of matrix A.

Using Eqs. 6-9, we can obtain MHC', each element of which has complex expression given by

$$MHC_i' = x_i + y_i i \tag{10}$$

Where x_i is the real part and y_i is the imaginary part of MHC_i'.

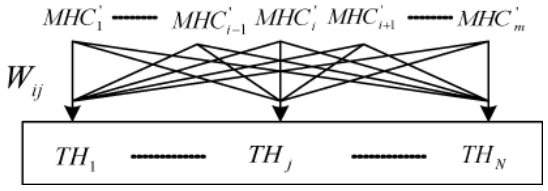

Fig. 5 Th cells' responses to MHC layer.

The Th cells represent the antigen category, with the key properties of contrast enhancement of filtered antigen information, and reset, or enduring inhibition, of active Th cell layer cells [22]. As shown in Fig. 5, Th cell layer received information from MHC layer through different weight channels. The weight W indicating the different stimulus to Th cells from each MHC cell is defined as:

$$w_{ij} = a_{ij} + b_{ij} i \tag{11}$$

Where a_{ij} is the real part and b_{ij} is the imaginary part. Thus, the state of each Th cell is given by:

$$TH_j = (MHC_i^{'}, w_{ij}) = \sum_{i=1}^{m} (x_i * aij + y_i * bij) \quad (j = 1,2,\cdots,N) \tag{12}$$

As a competition cooperation layer, it is important to decide the winner Th cell according to WTA rule. The winner Th cell which receives the maximally stimulus is activated while the other Th cells are inhibited namely:

$$TH_{j\max} = \max\{TH_j\} \quad (j = 1,2,\cdots,N) \tag{13}$$

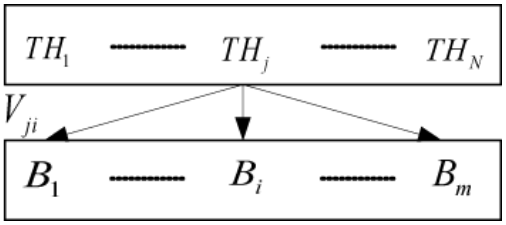

Fig. 6 B cells' responses to Th cell layer.

The Th cell with value $TH_{j\max}$ is then activated. As shown in Fig. 6, the activated Th cell stimulates B cells through different weight channels V namely:

$$v_{ji} = a_{ji}^{'} + b_{ji}^{'} i \tag{14}$$

Thus, the memory feature in B cell layer is defined as:

$$B_{ji} = kv_{ji} \tag{15}$$

Where k (0<k<1) is a feedback parameter from Th cell layer.

As introduced above, the antibody AB is defined as the difference between the antigen feature and memory feature. In order to obtain the antibody, an affinity evaluation parameter E, which expresses the similarity between the antigen feature and the memory feature, is defined in advance given by:

$$\begin{aligned} E(j) &= (MHC_i^{'}, B_{ji}) \\ &= k\sum_{i=1}^{m} (x_i * a_{ji}^{'} + y_i * b_{ji}^{'}) \end{aligned} \tag{16}$$

Thus, the antibody AB can be expressed as follows:

$$AB_t(j_{\max}) = \frac{\left\| E_t(j_{\max}) - E_{t-1}(j_{\max}) \right\|}{\left\| \sum_{i=1}^{N} E_{t-1}(i) \right\|} \tag{17}$$

where t is the system operation period.
Furthermore, a system tolerance ρ is defined to measure whether the antibody matches antigen. If the antibody is more than the system tolerance namely,

$$AB_t(j_{\max}) > \rho \quad (0 < \rho < 1) \tag{18}$$

A reset signal is sent back to Th cell layer, and force the output of Th cell layer back to zero. While another search for better match is performed, and a new competition is carried out in Th cell layer.

If the antibody is equal to or less than the system tolerance namely,

$$AB_t(j_{\max}) \le \rho \quad (0 < \rho < 1) \tag{19}$$

It means that, the antigen and antibody are matched, and the winner $TH_{j\max}$ cell is represents the category of this kind of antigen. Then the system updates weight w_{ij} and v_{ji} given by:

$$w_{ij_{\max}} = MHC^{'} w_{ij_{\max}} = x_i * a_{ij_{\max}} + y_i * b_{ij_{\max}} i \tag{20}$$

$$v_{j_{\max} i} = k(B_i v_{j_{\max} i}) = k(a_i^{'} * a_{j_{\max} i}^{'} + b_i^{'} * b_{j_{\max} i}^{'} i) \tag{21}$$

with k (0<k<1) and, for all $j \neq j_{\max}$

4. Simulations

The simulations of pattern recognition with the proposed complex AIS are performed in this section. First the capabilities of learning and immune memory will be illustrated. Following by this, the classification of transformation patterns is described to illustrate that the proposed complex AIS has the abilities of discrimination of self from non-self, which is considered as one of the essential features of immune response. Finally, the transformation of pattern recognition processes on both binary AIS and complex AIS are compared to show that the proposed complex AIS can recognize the transformation of patterns in high accuracy while the binary AIS failed to recognize.

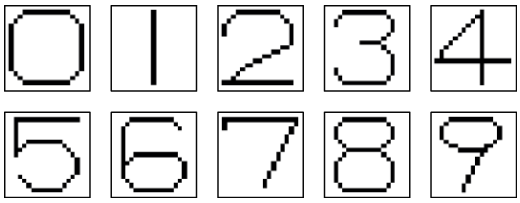

Fig. 7 Standard patterns.

Similar to the primary and secondary response in nature immune system, the learning process is regarded as the primary response and recognition process is regarded as the second response respectively. In learning process, the standard input patterns (See Fig. 7) are inputted into the system repeatedly, through being trained repeatedly, the weights between different layers are adjusted according to different input patterns. In the recognition process, the input pattern can be recognized rapidly.

The standard patterns are the same as that used in our previous works [15], and each of them is composed of 19 X 19 pixels. The black pixels are expressed by the value of "0", while the white pixels are expressed by the value of "1". The following procedure describes the processes of proposed complex AIS while learning:

Step 1. Initialize the real part and imaginary part of weights w_{ij} and v_{ji} with the number between 0 and 1 randomly.

Step 2. In APC layer, seek the boundary points of input pattern, which have the value of "1". Calculate the complex coordinates of boundary points in a two dimensional coordinate space, the origin of which is set to be upper left point. The input of this layer AG's number M is calculated to be 361, and the cells number of this layer $M^{'}$ depends on the number of boundary points.

Step 3. In MHC layer, of which the number of cells is the same as that in APC layer, using Eqs. 5 - 9, calculate the value of $MHC^{'}$. In addition, the number of $MHC^{'}$ m is set to be 50.

Step 4. In Th cell layer, using Eqs. 12 and Eqs. 13 to find out the winner Th cell with the value of $TH_{j\max}$. Each Th cell represents a category of pattern, so the number of cells in this layer N is set to be 10.

Step 5. Compute the antibody AB using Eqs. 16 and Eqs. 17, and decide whether to reset or not by Eqs. 18 and Eqs. 19. If reset, go to step 4 and perform again until reset does not occur. Otherwise, go to next step.

Step 6. Update the weights using Eqs. 20 and Eqs. 21.

Step 7. Go to step 2 for next input pattern.

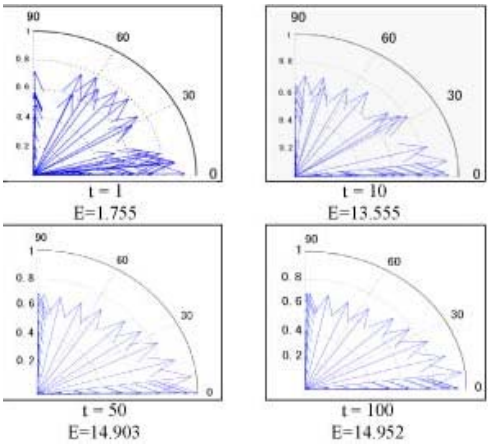

Fig. 8 The memory pattern of number "5" in B cell layer.

In addition, the system tolerance ρ is set to be 0.05 and the number of cells in B cell layer m is set to be 50. The memory patterns and weights in the system are updated along with learning process. As an example, the memory pattern of number "5" in B cell layer according to the different learning period is shown in Fig. 8. The pattern is shown in a compass plot, in which the values of the pattern are displayed by the arrows. The upper left of the figure shows the memory pattern (t=1) after training for the first time with affinity of E=1.755. Because the weights are initialized by step 1, it is quite similar to the random initialized pattern, and obviously the affinity is low, the memory pattern and the system weights need more learning. The upper right of the figure shows the memory pattern when t=10, it is clearly different from the pattern when t=1 and the affinity is E=13.555. The lower left and lower right of the figure show the memory pattern in learning period t=50, t=100 respectively. From the value of affinity E=14.903 and E=14.952, the learning is tend to be stable and according to Eqs. 17, AB = 0.001 can be obtained. It means that the learning is complete successfully.

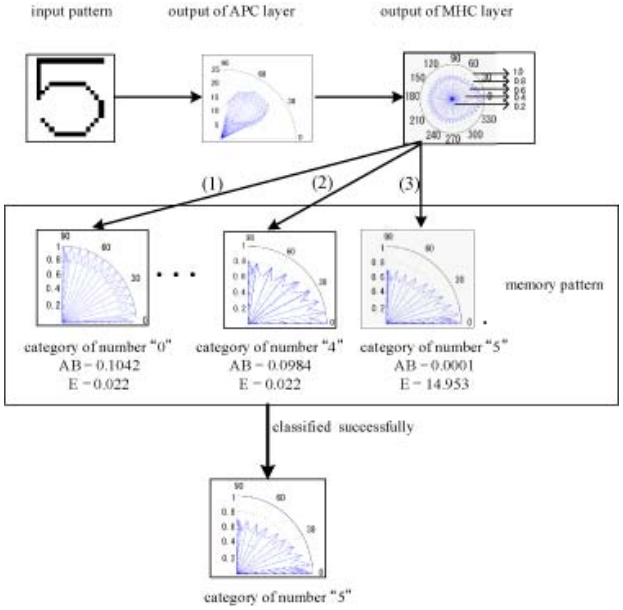

Fig. 9 Classification of standard pattern of number "5".

The classification simulation of the proposed complex AIS is shown in Fig. 9. In the first row, the standard pattern of number "5" is inputted into the system. According to Step 2, the boundary points are sought, the number of the boundary points is computed to be 39. The complex coordinates of these points are calculated and shown in the middle. In the MHC layer, the output of APC layer is received and the complex partial autocorrelation coefficients are calculated. The output is shown on the right of the first row. The second row depicts the memory pattern saved in B cell layer. (1) shows the response of memory pattern "0" to the input standard pattern of number "5", by Step 5, AB is computed to be 0.1042, which is larger than the system tolerance 0.05. So it is suggested that the input pattern does not belong to the category of number "0". Thus, this category is suppressed. (2) shows the response of memory pattern "1" to the standard pattern of number "5".Similarly, AB is computed to be 0.0984, which is also larger than the system tolerance. Therefore, the category of number "1" is also suppressed. Then (3) shows the response of memory pattern "5" to the input pattern, and AB is computed to be 0.0001, which is smaller than the system tolerance. Thus, the input standard pattern of number "5" is classified into category of number "5". In the third row, the matched memory pattern is depicted and classification is complete.

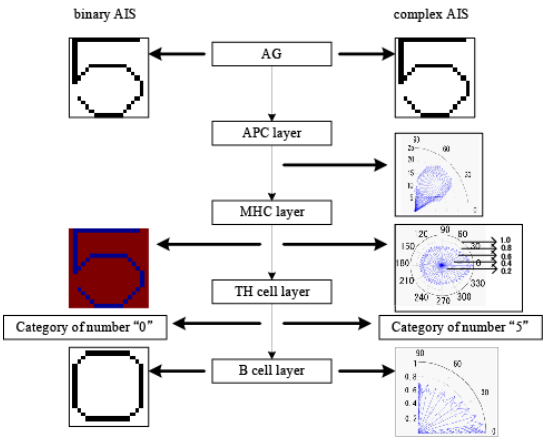

Fig. 10 Comparison of binary AIS and complex AIS with scale pattern of number "5".

A comparison of transformation pattern recognition on both binary AIS and complex AIS is performed and the process is shown in Fig. 10. The scale pattern of number "5" is considered as the input of both binary AIS and complex AIS. In binary AIS, the APC layer and MHC layer are considered as a whole layer, namely APC layer, in which the normalization of input pattern is done. This normalization is achieved by dividing each element of the input pattern by input pattern's length and the length is found by taking the square root of the sum of the square of all vector's components [15]. The output of APC layer in binary AIS is composed of the red points with the value of 0 and the blue points with the value of 0.13. In complex AIS, the function of APC layer and MHC layer are separated. Different from the binary AIS, the input pattern does not need to be initialized. Instead of this, complex coordinates of the boundary points of input pattern are calculated in APC layer, and in MHC layer, the complex partial autocorrelation coefficients of the input pattern are computed using the output of APC layer (See the corresponding output of these two layers). The output of MHC layer, namely the key feature of input pattern, has the property of being invariant to the similarity transformation of the patterns. In Th cell layer of both binary AIS and complex AIS, the WTA rule is used to determine the winner Th cell. Because of the scale input pattern, which is quite different from the standard pattern, the winner Th cell represents the category of number "0" in binary AIS, while in complex AIS; the winner Th cell represents the category of number "5". The corresponding memory patterns in B cell layer are shown in the last row of the figure. According to the system process respectively, it is obvious that the complex AIS can recognize the scale input pattern correctly while the binary AIS cannot.

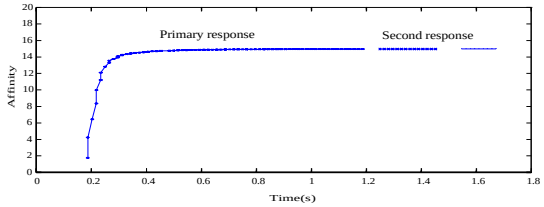

Fig. 11 Primary response and secondary response of number "5".

The primary and secondary response is the important feature of an artificial immune system. The simulation is performed to illustrate the primary and secondary response of proposed complex AIS. As shown in Fig. 11, the horizontal axis is system runtime and vertical axis is the affinity calculated by Eqs. 16 with the parameter of $j_{\max}$. System takes 0.19s (0s - 0.19s) to perform the preprocess (reading input files and initializing weights). In primary response, system takes about 1s (0.19s - 1.2s) to update memory patterns and weights between different layers. It is too short for the system to recognize the input pattern only once, so we measure the time of 100 times recognition in the figure. When the pattern of number "5" is inputted again after primary response is complete, it can be recognized rapidly, and about 0.2s (1.25s - 1.45s) is taken to recognize input pattern in high accuracy for 100 times. An even shorter time (1.55s - 1.67s) is spent to recognize translation pattern correctly for 100 times. The time between 1.2s - 1.25s and 1.45s - 1.55s is taken to read input patterns.

4. Conclusions

In this paper, a new complex artificial immune system is proposed based on an immune mechanism, in which the binary representation is extended to complex representation. The proposed complex AIS shows that the complex representation can be incorporated into artificial immune system naturally. The pattern and weights between different layers are manipulated and memorized as complex styles. Besides, the functional improvement of APC layer and MHC cell layer is also a novel characteristic of proposed complex AIS.

The simulations of pattern recognition shows that proposed complex AIS not only retains immunity of traditional artificial immune system, but also has the advantages of improved complex memory capacity, ability of transformation pattern classification and applicable complex affinity measure. Moreover, a comparison with binary AIS has been carried out and shows that the complex AIS has the ability of recognizing the translation of patterns correctly that the binary AIS does not have.

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