IMMUNO THEORY APPLICATIONS IN NEURAL NETWORKS

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Keywords:Artificial Immune System,Neural Networks, Antibody(Ab), Antigen (Ag)

ABSTRACT

In this study , after a new Artificial Intelligence technique inspired from the human immune system –the Artificial Immune System (AIS) is described, it is compared with the Artificial Neural Networks (ANNs) and some immune approaches in neural networks are emphasized as application. After the artificial intelligence (AI) has come into existence, especially artificial neural networks took a great attention. ANNs have a widespread application area in engineering, physics, mathematics ,etc. Recent times some researchers begin to analyse immunology as a new field of the AI and several immuno networks has developed not only as an alternative to the neural networks but also as a complement system of neural networks to make NNs more effective.

1. INTRODUCTION

Modelling of neural system began in 1943 with McCulloch and Pitts . They modeled a single neuron as a computational unit. Since then, neural network models evolved and lots of neural network structures proposed [1]. However it was first designed for modelling the neurons in human brain in medicine sience, there exists lots of application areas of Neural Networks ranging from physics, mathemathics to engineering siences [2].

Like Neural Networks (NNs), immune system models was primarily devoloped to analyse immune system behaviour in the field of medicine. But later, its properties like pattern recognition, robustness, hybrid structures, distributed processing and self-organizing took the attention of some researchers. Immune network theory was originaly proposed by Jerne, 1974 [3]. In recent times, immunological theories has began to applied varius areas. But unlike NNs, there is no common network architecture in immunological networks. This is maybe one reason why it doesn't take attention as much as neural networks. Because human immune system works as a cognitive mechanism that recognize the patterns that can not be recognized by the nervous system, the AIS can be used as a complement of neural network architectures. Besides, although the immune system behaviour is very complex, we have more information about immune system than nervous system [4]. So, new network structures based on immunology can be proposed as an alternative to the neural networks or hybrid network structures composed of two system can be designed. In this study firstly the compatibility of neural networks with the immune networks was emphasized. Then, several applications of immunological theories to the neural networks was summarized as examples of hybrid network structures and to show the potentiality of immune networks in complementing neural network deficiencies. In the second section of the study, a brief description of immune system was made following with the comparison of AISs with ANNs in section three. In the section four after the mentioning about immunological approaches to neural networks some of them were described briefly. Consequently in section five, concluding remarks were done and it was emphasized for the researchers who will deal with this concept that if this system is used with ANN as well as with the other Artificial Intelligence techniques, there can be new expansions in the sience.

2. IMMUNE SYSTEM BEHAVIOURS

Our immune system is a defense mechanism of our bodies. It protects our body against foreign invaders by mechanisms of recognition, memory and other celluar interactions. Two type of cells named B cell and T cell (Lymphocytes) play the main role in immunity. B cell dependent response of immune system is called humoral immunity and B cells secretes Antibodies in this response to kill foreign invaders-Antigens. T cell dependent response however is against intracelluar microbes and called cell-mediated immunity. When the immune system encounters an antigen, different types of B cells secretes Antibodies. Among these Antibodies the ones that best match the Antigen prolifirate according to the hypermutation mechanism. This selection of best matching Antibodies is called positive selection. On the other hand the Antibodies can be produced that react our self cells. By a negative selection mechanism the Antibodies that recognize self-cells are killed. This is called self-tolerance. After positive selection, some Antibodies bound the Antigen causing killing of the bounded Antibody (Ab)-Antigen (Ag) structure. Besides, some other Antibodies become memory cells and remain in the immune system to respond further encounters more rapidly.

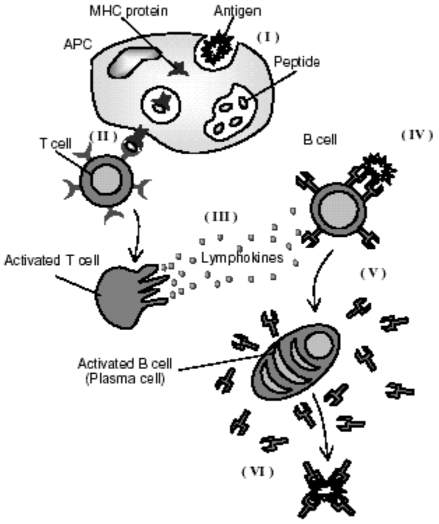

Fig.1 Immune Response to Antigen (Ag)

In the Fig.1, the basic mechanism of our bodies in the immune response is shown. For detailed information about immune system the reader is refered to [5].

The immunological interactions are very complex even to an immunologist. But most of the interactions are well-known and the immune system covers a broad spectrum of properties that is required especially in solving complex problems. Among these properties some are: recognition, feature extraction, diversity, learning, memory, distributed detection, self regulation, threshold mechanism, co-stimulation, dynamic protection, probabilistic detection, adaptability, specifity, self tolerance and differantiation [6].

Because of the properties expressed above, the potentiality of immune system in solving complex problems was recognized and a new evolutionary branch inspired from biology has come into existence. As we say previously, there is no common architecture of the proposed network models based on immunity but to model real immune interactions, clonal selection algorithm, positive and negative selection, affinity maturation, network interactions and memory acquisition are implemented.

3. ANN & AIS COMPARISON

Our nervous system consists of neurons that are connected through synapses. The signals propagate through these connections as stimulus from neuron to neuron. The main property of nervous system is being cognitive. That is the neural system recognizes a stimulus, processes it and responds to it according to kind of stimulus and processing. Like neural system, immune system is a cognitive device, too. Furthermore, immune system recognizes foreign molecular invaders like virüs, microbe,etc. that can not be recognized by neural system. As in nervous system, immune cells produces responses to the recognized elements. Like this basic similarity, there are many similarity between immune and nervous system as well as some differences. These can be summarized as follows [7]:

In nervous system, the basic units are neurons which process the received information and transmit it through the connections. Immune system consists of Lymphocytes (B cell, T cell). The approximate number of neurons in brain is 10^{10}, whereas there are about 10^{12} Lymphocytes in our immune system. As seen, there is no so big difference between the basic units of two sysytem.

The neurons are connected via synapses. These junctions between neurons are characterized by being stimulating or depressing which give rise to different activity patterns. The interactions in the immune system occurs in physico-chemical level in cell-cell contacts. These chemical interactions can be occur in various strengths which in conjunction can be result in helping or suppressing interaction.

The main process -recognition- in nervous system is related to visual, auditory, etc. signal patterns while this process is executed at molecular level in immune system. In immune system during the recognition, the complementarity in the receptor shapes of the recognizing and recognized cells are the most important aspect .

Neural system performs its task by comparing stored patterns with the received information. On the other side, foreign antigens are distinguished from the self-cells in the immune system.

Learning occurs by changing connection strenghts in neural system. In immune system however, the number, position and the degree of interactions of Lymphocytes changes during the learning process.

When the two system is compared according to the memory concept; neural system has a memory composed of connection strenghts and this memory is associative and changeable. In immune system, some of the activated cells with antigens becomes memory cells. The memory in immune system is non-hereditary too in addition to being content adressable.

To activate neurons, the received stimulus must exceed threshold level. As like, the proliferation of the Antibody secreting B cells depends on the matching characteristics and concentration of the antigens. That is a threshold level is required to activate units in both systems.

In neural system the basic units-neurons- doesn’t changes their position in the system but in the immune system, Lymphocytes circulates in the body.

Communication in neural system between neurons occurs via synaptic connections as electrical signals. On the other hand, the cells of immune system commuicate with secreting soluble molecules in the transient cell-cell contacts.

In the nervous system, the brain controls all of the functions but there is no such central controlling organ in the immune system.

The time dependent changes in neural system occurs only in the connections strenghts. However, the concentration, position and affinities of cells varies with time in the immune system.

As seen from these similarities and differences, one system can complement other's deficiency. So, immunity based neural networks or neural based immune networks can be designed to obtain more powerful network structures. In other words hybrid architectures one gained from the other can be proposed. In the following section, the studies in this respect up to today are summarized and a few of them are introduced to give an insight about how the immunology and neural network structures can be combined.

4. IMMUNOLOGICAL APPLICATIONS IN NEURAL NETWORKS

The studies related with using immuno theories in neural networks began with the studies of Hoffmann [8] and Hoffmann *et al.* [9]. They proposed an unorthodox neural network model. Following this in 1989 and 1991, Vertosick & Kelly combined the immune network theory with parallel distrubuted processing as an alternative to neural network architectures [10, 11]. Another immune theory application in neural networks was obtained by Abbasttista *et al.*[12] in 1996. They used immunological theories to make the memory capacity and retrieval performance of a kind of discrete Hopfield network [13] better. In the year 2000, De Castro & Von Zuben [14] proposed a Boolean Competitive Neural Network, named ABNET, inspired from the immunology. In the same year, they developed an artificial immune network model-aiNet. In their paper [15] in 2001, they compared their aiNet with a neural network model (SOFM). Another area of the immunological behaviours that was used in neural networks is diversity. De Castro & Von Zuben [16] developed a SAND algorithm using ideas from immunology to diversify the initial weights of a neural network. Besides, recently Lei Wang and Michele Courant proposed a novel neural network based on immuology [17].

4.1 An Unorthodox Neural Network Model

The unorthodox neural network model that Hoffmann and Hoffmann et al. proposed considers the following counterparts of immunological elements in the developed model: the clone is represented as neuron. The rate of firing a neuron is a counterpart of the size of a clone. Besides, number of neurons forms number of clones of immune system. As like, stimulation or suppression of a neuron is equivalent of stimulation or suppression of a clone. In their model, like all other models, N-dimentional space was considered. The points in this space were represented as attractors. Learning is performed through transitions to stable steady states. These states are the ones which have higher probabilities of surviving. Fig.2 shows the learning algorihm of this model.

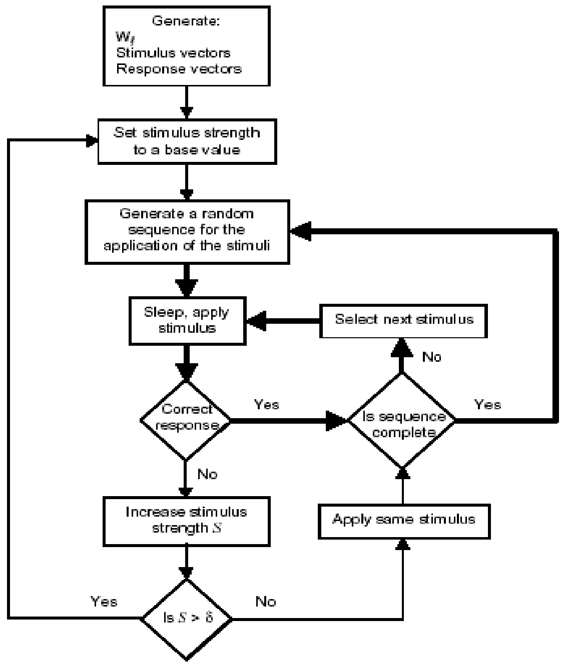

Fig.2 Learning algorihm of unorthodox neural network model

4.2 Boolean Competitive Neural Network based on Immunology (ABNET)

In this network model, Hamming shape-space was used. In this space, each point is represented by a vector of lenght l . The weight vectors of neural network was represented by Antibodies. To define the interaction between Ag and Ab, the complementarity was taken into account which will be maximum when the distance between cells is maximum. But because the complementarity determines the affinity between cells, the Hamming distance (HD) between Ab and $\overline{Ag}$ (complement of Ag) $-\|Ab-\overline{Ag}\|$ was used as a metric. This means that, when this metric is maximum that is when the HD between Ab and $\overline{Ag}$ is minimum , the affinity between Ab-Ag is minimum because the complementarity is minimum.

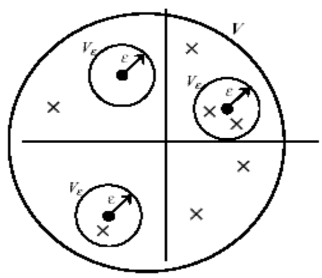

Fig.3 Hamming shape-space. • represents Ab with $\overline{Ag}$ is represented by x.

The ε parameter shown in Fig.3 is affinity thereshold. It determines the maximum HD between Ab and $\overline{Ag}$ for binding to occur between two. The circle determined by ε represents the Ab coverage which means that the number of Antigens that covered by the Ab.

4.2.1 ABNET (Antibody Network)

In this proposed network Antigens were considered as input patterns. The weights are Boolean in contrast to neural networks of which most have real valued weights. The learning algorithm of this network is shown in Fig.4

the main steps are:

- initially an Ag is presented to the network
- the Ab_k whose affinity to this Ag is max. is determined by:

$$k = \arg\max_k \|\mathbf{Ag} - \mathbf{Ab}_k\|.$$

- then the concentration level τ_j for k (j=k) is incremented and v_a=k attribution is done. Here the concentration level is the number of Antigens for that Ab and v_a is a labeling vector showing highest affinity. For example, if Ab_1 is the highest affinity Ab for Ag_2 , then v_2=1.
- weight vector w_k for the selected Ab is updated.

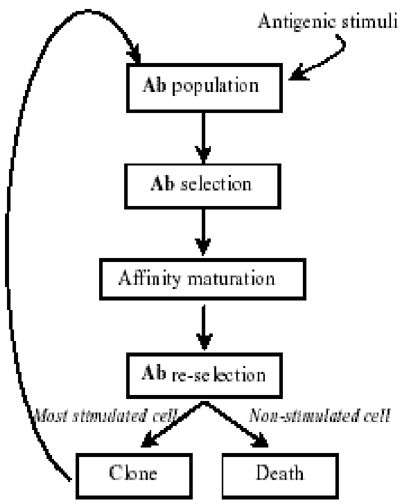

Fig.4 ABNET learning algorithm

These processes occurs in network growing, network pruning and weights updating phases. For detailed information about these phases and some examples of application results together with comparisons , the reference [14] can be read.

4.3 aiNet & SOFM

De Castro and Von Zuben proposed a new network structure based on immunology for data analysis in 2000 [18]. In their paper [15], they detailed the learning algorithm of aiNet and compared it with SOFM as a neural network model. It can be said that, the learning algorithm of their proposed network is much like an evolutionary algorithm. In structure however, it resembles to neural networks. The basic unit in the aiNet is shown in Fig.5.

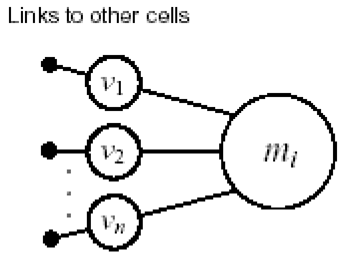

Fig.5 Basic unit of aiNet

In this figure, m_i represents the internal image of the Ag and v_1,v_2,....v_n are teh connection strenghts with other units (cells). A few difference from a neuron model can be stressed here. First, two-way information flow is performed in the aiNet basic unit unlike the artificial neuron model. That is, each basic unit recognizes the other units as well as being reognized by them. The connection strenghts between them represents the affinities. Besides, although the neuron process the information that received, the aiNet basic unit only represent an internal image of the input pattern (Ag). The learning algorithm of aiNet is summarized as follws:

(1) for each input pattern Ag_j(j=1,2,.....M):
   (1.1) with clonal selection algotihm (CLONALG), select the best matching individuals in the Ab repertuary to given Ag_j and obtain a clone set by a hypermutation and affinity maturation mechanisms.
   (1.2) determine the affinity between the elements of clone set.
   (1.3) eliminate the elements whose affinities are higher than a threshold (defined as a-priori).
   (1.4) conctanate the clone set (memory set) with the present Ab repertuary.
(2) determine the similarity between the units of Ab repertuary and eliminate those whose similarities are higher than a threshold.
(3) evaluate stopping criterion and go to step 1 is it doesn't reached.

Here, the process in steps 1.2, 1.3 and 2 represents the self-tolerance property of immune system. After learning, two matrixes are obtained as outputs-one containing the coordinates of memory Antibodies (m_i). The other matrix contains the similarities between these Antibodies.

De Castro and Von Zuben compared aiNet with SOFM both emprically and theorically in [15].They concluded their paper by stressing that both network structures have advantages with deficiencies and they can be combined in a manner that one can be gained from the other.

4.4 SAND

It is known that the choose of initial weight vectors in supervised learning of multilayer feedforward neural networks is very important. There are some methods to generate the initial weights like BOERS[19], WIDROW [20], KIM [21], OLS[22] and INIT [23]. De Castro and

Von Zuben used the property of diversity in immune system to develop a new strategy for generating initial weight vectors [16],[3]. Their strategy, named Simulated Annealing Aproach to Diversity (SAND), aims generating the most diverse population of Ab repertuary. Each Ab represents the the weight vector of a neuron.

They compared SAND with other methods on several benchmark problems. From the comparison, it must be emphasized that the proposed method doesn't considers the training data to generate initial weights unlike the other methods.

CONCLUDING REMARKS

Artificial Immune System constitutes a new evolving branch of the AI. The characteristics like cognition, self-tolerance, size-control, memory,etc. allows it to be used in complex problems where classical engineering techniques can not be applied. Because there are many similarities between immune and neural systems, AISs and ANNs can be used in a manner that complement each other as weel as immune theories can be used in Neural Networks to increase their performance. In this study after the similarities and differences between AISs and ANNs were presented, the studies done up to today in this area were summarized with brief descriptions of some of them. When looked from the perspective of these studies, a new area of Artificial Intelligence is waiting for us. It is possible to combine ANN and immunological behaviours in such a scheme that more complex problems can be solved more effectively.

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