



# Artificial Neural Networks and Artificial Immune Systems: Similarities and Differences

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## ABSTRACT

Both the nervous system and the immune system are complex biological systems. Recognition and categorization are the major functions of both systems. The information processing principles of these natural systems inspired in developing intelligent problem-solving techniques, namely, the Artificial Neural Network (ANN) and the Artificial Immune System (AIS). Though ANNs are well established techniques and are widely used, AISs have received very little attention and there have been relatively few applications of the AIS. This paper briefly describes some of the similarities and differences of these two systems from a computational viewpoint. The paper also reports some preliminary comparative results of the artificial systems.

## 1 INTRODUCTION

Both neural networks and immunity-based systems are biologically inspired techniques that have the capability of identifying patterns of interest. They use learning, memory, and associative retrieval to solve recognition and classification tasks. But the underlying mechanisms of recognition and learning are very different. However, the immune system provides diversification instead of converging to a local or global optima. The immune system possesses self-organizing memory and it remembers its categorizations over long periods of time [11].

Artificial Neural Networks learn to associate patterns of input data with an appropriate output response by modifying their connectivity according to a defined learning algorithm. Specifically, Artificial Neural Networks are concerned with approximating input-output relationships, with many neurons linked together by connections of varying strength. The actual manner in which these connections are made determines the flow of information in the network and defines the network model. There exist many different neural network models, such as Multi-Layer Perceptrons (MLP), Hopfield Networks, Kohonen Networks, Adaptive Resonance Theory (ART), etc. each with distinct performance features [12]. They are widely

used in real-world applications in the field of signal processing, speech recognition, intelligent control, robotics, etc.

From an information-processing perspective, the immune system is a distributed system. It provides an excellent model of adaptive processes operating at the local level and of useful behavior emerging at the global level. Hoffman [13] has compared the immune system and the nervous system. He has shown many similarities between the two systems at the level of system behavior, though they differ at the respective building-block level. He postulated a symmetrical neural network model that can produce desired stimulus-response behavior similar to immune response. Other researchers have also drawn some analogies between the two systems [4].

## 2 RELEVANT BIOLOGICAL METAPHORS

The biological metaphor behind the artificial neural networks is that the brain neurons are connected via synapses where the neurons receive signals from other neurons or from an external stimulus. When a signal arrives at a synapse, it elicits the release of neurotransmitter which builds up until its concentration exceeds a certain threshold. When this happens, an action potential is elicited in the receiving cell, producing an output response [18].

The natural immune system is also a very complex system with several mechanisms of defense. There are various cell types that can attack invaders directly, and they can also secrete molecules with a variety of functions, including attacking foreign cells and signaling other immune cells to proliferate. Of these kinds of cells that participate in the immune response, lymphocytes are the most important class of immune cells. Unlike neurons, lymphocytes float freely in blood and lymph node. In particular, they patrol everywhere for foreign antigens, then gradually drift back into the lymphatic system, to begin the cycle all over again. Each lymph node contains specialized compartments where immune cells congregate, and where they can also encounter antigens. They interact with antigens at a rate dependent upon the

concentration and affinity of the antigens. There are two main types of lymphocytes, namely T cells and B cells, each having receptors on its surface to respond to a limited group of structurally related antigens.

Self-nonsel self discrimination is one of the main tasks the immune system solves, and negative selection is one of the principle mechanisms in the chain of events that results in robust self-nonsel self discrimination. This discrimination is achieved in part by T cells. T cells mature in the Thymus, where they undergo a censoring process. This process eliminates the self-reacting T cells. Specifically, the random generation of variation (in receptors) followed by selective destruction (negative selection) creates circulating T cells that react only with nonself molecules. The processes by which B cells are prevented from reacting to self molecules are not fully understood [11]. It may be that the absence of self-reactive T cells is sufficient to prevent clonal expansion of self-reactive B cells. Some T cells destroy an infected self cell (called the killer T cell) if they recognize the infection. Others are helper T cells which trigger clonal expansion (positive selection) of B cells. Affinity maturation occurs when the mutation rate of a B cell clone increases in response to a match between the clone's antibody and an antigen. Those mutant cells that bind more tightly are stimulated to divide more rapidly. Affinity maturation dynamically balances exploration versus exploitation in adaptive immunity.

The nervous system is commonly decomposed into sensory and motor parts. An analogous separation into recognition and effector functions can be made in the immune system where effector mechanisms lead to the elimination of the antigen. In neural system, assimilation of memories appear to be achieved by alteration of the strengths of connections between neurons, rather than change within the neurons themselves. Further, the brain allows memories to be addressable by content, the frequent death of individual neurons does not drastically affect performance of the brain as a whole. Similarly, cross-reactive memory, variable cell division and programmed cell death rates allow the immune system to allocate resources (cells) dynamically as needed in a distributed environment.

One principal difference between the nervous system and the immune system is in their interaction with the external environment. Although the I/O behavior of lymphocytes *in vivo* is not known with certainty, it is most likely some simple, nonlinear function [15]. Lymphocytes can be connected to external antigens (I/O lymphocytes), or to each other via anti-idiotypic interactions [19]. According to Vertosick and Kelly [19], the clonal expansion and affinity maturation that accompany an immune response are reminiscent of Hebbian learning. In the immune system,

learning occurs through the modification of the number and affinities of the receptors. However, connections within a nervous system are deterministic, whereas the cross reaction in immune response is a stochastic process.

Though the models of neural networks and their applications have received wide attention, immune system models are of limited use. Also as compared to neurophysiology, where the Hodgkin-Huxley equations have provided a basis for modeling, there are no agreed upon generic equations describing the behavior of single immune cells [16]. However, both neural system and immune system share many common features as basic cognitive mechanisms. Table 1 summarizes the similarities and the differences between these two systems (as illustrated in [4], [9], [20]).

### 3 ARTIFICIAL IMMUNE SYSTEM MODELS

There are several models (refer [16], [17]) to study both general properties and specific immunological phenomena. The goal of these models is to deduce macroscopic principles of the system from the properties and interactions among the components of the immune system. Moreover, the natural immune system is also a source of inspiration for developing intelligent methodologies toward problem solving. A survey of the models that have been developed based on various computational aspects of the immune system and their applications to real world problems are available in [5].

#### 3.1 Immunity-Based approach for Anomaly Detection

Forrest et al. [10] developed a negative-selection algorithm for change detection based on the principles of self-nonsel self discrimination [15] by T cells. In this approach, the *self* is defined as the normal pattern of activity of a system/process or a collection that we wish to protect or monitor. A diverse set of detectors is generated in the complement space of the *self*, similar to the censoring process of mature T cells<sup>1</sup>. Then the detectors are used to monitor *Self* for changes by continually matching the detectors against the representative of *Self*. If any detector ever matches, a change (or deviation) must have occurred in *Self*. This algorithm exhibits many interesting properties in change detection. It is noted that the algorithm never reports false positive; however, depending on how the detector sets are chosen, there may be a chance of false negative.

<sup>1</sup>There are several methods [8] for generating detectors in the complement space. These methods, however, have different computational complexities, and their complexity is dependent on the choice of the matching rule and the size of the *self*.

Features	Neural System	Immune System
Similarities:		
Basic Unit	Neurons are basic processing units in the brain. Each neuron has three parts: <i>soma</i> - the cell body, <i>dendrites</i> for carrying in information, and <i>axon</i> for carrying out information from the neuron.	Lymphocytes (B cell, T cell etc.) are an important class of immune cells. Each lymphocyte has about 100,000 receptors on its cellular membrane that enable it to recognize one specific antigen.
No. of Units	There are approximately $10^{10}$ neurons in the brain.	Humans have lymphocytes of the order of $10^{12}$ .
Interaction	The synaptic junctions between neurons can be excitatory (stimulating) or inhibitory (depressing) which give rise to many different activity patterns.	The inter-lymphocyte interactions via cell-cell contact, or via chemical mediators have varying strengths which can be helping or suppressing.
Recognition	Recognize visual, auditory and other signal patterns.	Recognition occurs at the molecular level and is based on the complementarity in shape between the receptor and patterns stored in the epitope of the antigen.
Task perform	Distinguish between the stored patterns and conscious imagination.	Distinguish between foreign antigens and the cells or tissues of the host.
Learning	A combination of global/local learning rule occurs, where the global mechanism performs certain tasks and then uses the local mechanism for training/learning (to tune the strength of synaptic links).	Changes in lymphocyte concentration are the mechanism for learning and takes place during the primary response according to the mutual recognition and inter-cellular binding.
Memory	Patterns of synaptic strengths constitute a memory which is auto-associative and non hereditary.	When lymphocytes are activated, a few of each kind become special memory cells which are content-addressable, but not hereditary.
Threshold	There is a threshold of connection strength for firing of neurons. The average strength is proportional to the weight of each connection.	Immune response and the proliferation of the immune cells takes place above a certain matching threshold. The matching depends on the strength of the chemical reaction.
Robustness	Very flexible and damage-tolerant.	Scalable and self-tolerant, but not well understood.
Differences:		
Location	Position of the neurons are fixed.	Lymphocytes are positioned throughout the body.
Communications	Takes place through the linkage hardware e.g. axons, dendrites as electrical signals.	Transient cell-cell contacts and/or via secretion of soluble molecules.
State	Activation level of the neural system.	Free antibody/antigen concentration.
Control	Brain controls the functioning of the nervous system.	No such central organ controls the functions of the immune system.

Table 1: The table shows the similarities and differences of the *Neural System* and the *Immune System*.

Dasgupta and Forrest [6], [7] experimented with several data sets to investigate the performance of the negative selection algorithm for detecting anomaly in the data series. In these experiments, the notion of self is considered as the normal behavior patterns of the monitored system. So, any deviation that exceeds an allowable variation in the observed data, is considered as an anomaly in the behavior pattern. In particular, the anomaly detection problem is reduced to the problem of detecting whether or not an observed data pattern has changed (actually matched using negative selection), where a change (or match) implies a shift in the normal behavior patterns. Overall, the approach can be summarized as follows:

1. Collect time series (sensor) data that sufficiently exhibit the normal behavior of a system (these may be raw data at each time step, or average values over a longer time interval).
2. Examine the data series to determine the range of variation in data patterns and choose the encoding parameter according to the desired precision.
3. Encode each value in binary (string) form within the observed data range.
4. Select a suitable window size that can capture regularities (of interest) in data patterns.
5. Slide the window along the time series (in non-overlapping steps) and store the encoded string for each window as *self*, from which detectors will be generated.
6. Generate a set of detectors that do not match<sup>2</sup> any of the self strings.
7. Once a unique set of detectors is generated from the normal database of patterns, it can probabilistically detect any change (or abnormality) in patterns of unseen time series data.
8. When monitoring the system, we use the preprocessing parameters in step 3 to encode new data patterns. If a detector is ever activated (matched with current pattern), a change in behavior pattern is known to have occurred and an alarm signal is generated regarding the abnormality. We use the same matching rule (for monitoring the system) as was used in generating detectors.

This approach relies on sufficient enough sample of normal data series that can capture the semantics of the data patterns and can represent the system behavior. These data are used as self to generate a diverse set of detectors that probabilistically

<sup>2</sup>A partial matching rule is used, in which two strings match if and only if they are identical at some predefined number ( $r$ ) of contiguous positions.

detect changes without requiring prior knowledge of anomaly (or faulty) patterns. This method has been successfully applied to a number of test cases. In this paper, we report a set of experiments using a data series (figure 1), where signals of varying amplitude are observed under normal behavior. The data patterns, however, show regularities over a period of time. Detecting unknown changes (noise) in this signal pattern is a very difficult task, although monitoring such changes is essential in some applications. However, most existing threshold-based methods fail to detect small changes because of varying boundary conditions. The details of the experiments along with the effect of parameter settings is reported elsewhere [6]. Figure 2 shows a typical result demonstrating that the algorithm can easily detect noisy signals by monitoring with a small set of detectors. In particular, a set of 20 detectors were generated from initial data (data during 0 to 50 time steps are assumed as the normal pattern of signals). The detector set was then used to monitor future signal patterns (test signals), and it could detect changes during the time period 75 and 85. This suggests that the detection of gradual change can be monitored with a suitable detector set.

Further experiments were performed for comparing the results with a neural network (in particular, ART1 [2], [3]) using the same data set. An ART [1] is a self-organizing competitive learning ANN which can develop stable recognition codes in response to arbitrary sequences of input patterns. Figure 3 shows the preliminary result which indicates the formation of templates and subsequent updating (recoding) of existing templates during the unsupervised learning phase. The graph leveled off well within 40 time steps which exhibits that the network settles into a steady resonance state. However, during the time period between 75 and 85 there are generation of new templates and recoding of existing templates which indicate the novelty in signal patterns. The results qualitatively agree in both cases (ANN and AIS), though a careful quantitative comparison of two approaches is an important area of further research.

Based on the initial experiments, Dasgupta and Forrest [7] observed the following similarities and differences between the negative selection algorithm [10] and the ART network in their experiments on anomaly detection [6] in time series data.

- An ART network detects novel patterns deterministically, whereas in the immunological approach detection is probabilistic (particularly, the generation of detectors).
- The ART network tries to recognize/classify an input pattern in the space defined by the training

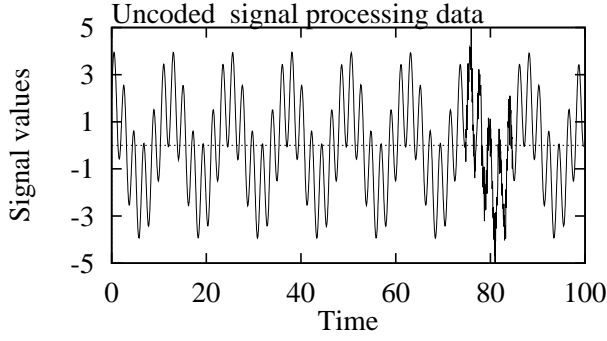


Fig. 1. An example of signal processing data series. Here the signals are noisy during the time period 75 and 85.

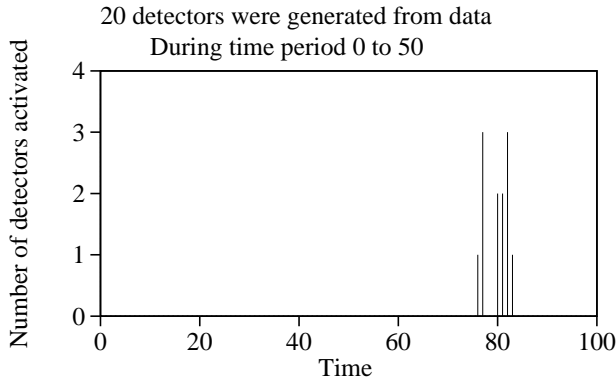


Fig. 2. The vertical lines indicate the activation of detectors indicating the changes in signal pattern. The detectors are only activated during the time period when signals get distorted as in figure 1.

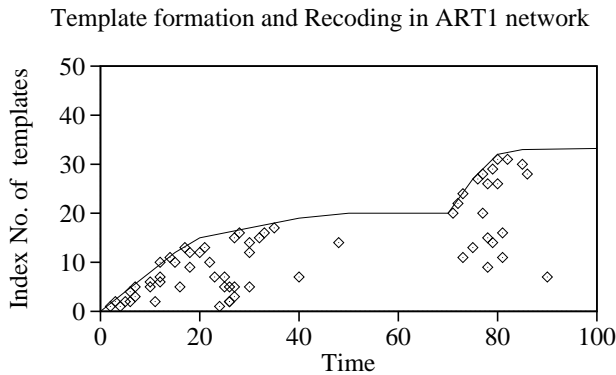


Fig. 3. The generation of new and recoding of existing templates (after the training phase) indicate novelty in signal patterns.

data set (actual encoded space of data or signals), but on the contrary the anomaly detection algorithm based on the negative selection, recognizes patterns in the complement space as novel.

- ART network's (binary version, ART1) pattern recognition mechanism deals with Hamming space, but the current implementation of the negative selection approach uses an  $r$ -contiguous space matching rule.
- ART's vigilance threshold ( $\rho$ ) provides a degree of sensitivity in discriminating input patterns, and forming clusters (or classes). A  $\rho$  value near zero gives a network with low discrimination, and a value near one gives a network with high discrimination (forming many clusters). An optimal vigilance value creates a reasonable number of clusters with minimum error. A similar effect is also noticed while choosing a matching threshold,  $r$ , in the negative selection algorithm.
- In an ART network, a cluster (or class) is represented in its neural memory as a template. A template is an abstraction of the patterns in a cluster which are formed and modified during the learning (training) process. So the number of templates increases (for a fixed parameter setting) according to the diversity in input patterns. In the negative selection algorithm, the effect of such diversity in data is opposite; also there is an indication that for an independent self (a training data set), the size of a detector set remains almost unchanged for a fixed probability of success (or failure) [10].
- An ART network learns the semantics of the time series on-line, and in principle, the rate of template formation reduces to zero when the learning is complete; but the negative selection algorithm detector generation is off-line, and largely depends on the normal time series (training) data and other parameters of the algorithm. However, it may be possible to produce detectors on-line using a different algorithm for generating detectors.
- During testing (or monitoring) new data patterns in an ART network, the existence of novel patterns is determined by examining the frequency and the degree of template formation and recoding. Activation of any detector (or a threshold number) determines the change in the behavior pattern of data in the implementation of the negative selection algorithm.
- Recognizing an input pattern is a global decision over the ART network (while determining

the class memberships of object represented by the input patterns), whereas the recognition of a novel pattern by detectors in the negative selection algorithm is a decentralized local decision, which appears to be an important advantage over the ART methodology. This property results in generating a quick response to any changes, and may be very useful in monitoring safety-critical systems.

#### 4 SUMMARY

Like the nervous system, the immune system can learn new information, recall previously learned information and perform pattern recognition tasks in a highly decentralized fashion. In particular, it learns to recognize relevant patterns, remember patterns that have been seen previously, and use combinatorics to construct pattern detectors efficiently. Also, the overall behavior of the immune system is an emergent property of many local interactions. It has been suggested [17] that the immune system functions as a kind of “second brain” because it can store memories of past experiences in strengths of the interactions of its constituent cells, and it can generate responses to new and novel patterns (new antigens). Furthermore, the immune response develops in time and the description of its time evolution is an interesting problem in dynamical systems [16]. Similar to the artificial neural network, the artificial immune system is also trained to learn the dynamics and the statistical properties of the monitored system. Like ANN algorithms, it is necessary to tune control parameters of AISs to get the best performance. The associative memory characteristics of the Hopfield network [12] are also present in the immunological models [14].

Many biologists believe that the immune system is in principle more complex than the brain-nervous system. Different theories have been suggested based on experimental evidences. Some of these theories are contradictory regarding the way cellular interactions occur in the immunological response. Because of the lack of understanding, there is still no unified model or view that accounts for all known immunological phenomena. Also there remains open questions whether the immune system operates at steady state, oscillates or chaotic. However, the remarkable pattern recognition abilities of animal immune systems suggest that immune-system based algorithms are well worth exploring. Future research should investigate various computational properties of the immune system, improvements to the existing AIS models, and exploring new application areas for the AIS.

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