ARTIFICIAL IMMUNE SYSTEMS – MODELS, ALGORITHMS AND APPLICATIONS

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ABSTRACT

Artificial Immune Systems (AIS) are computational paradigms that belong to the computational intelligence family and are inspired by the biological immune system. During the past decade, they have attracted a lot of interest from researchers aiming to develop immune-based models and techniques to solve complex computational or engineering problems. This work presents a survey of existing AIS models and algorithms with a focus on the last five years.

Keywords: *Artificial immune systems, artificial immune networks, clonal selection, negative selection*

1.   INTRODUCTION

The primary function of a biological immune system is to protect the body from foreign molecules known as antigens. It has great pattern recognition capability that may be used to distinguish between foreign cells entering the body (non-self or antigen) and the body cells (self). Immune systems have many characteristics such as uniqueness, autonomous, recognition of foreigners, distributed detection, and noise tolerance (Castro and Zuben , 1999).
Inspired by biological immune systems, Artificial Immune Systems have emerged during the last decade. They are incited by many researchers to design and build immune-based models for a variety of application domains. Artificial immune systems can be defined as a computational paradigm that is inspired by theoretical immunology, observed immune functions, principles and mechanisms (Castro and Timmis, 2003). This report investigates the different AIS computational paradigms and introduces different AIS models and techniques developed in the literature since the work of Dasgupta et al. (2003). The studied models are mainly based on the immune network theory, clonal selection principles and negative selection mechanisms.
The rest of this report is organized as follows: Section 2 presents a theoretical background of the immune systems; Section 3 presents an overview of the existing AIS models and algorithms that are developed based on the immune system principles; Hybrid intelligent systems are presented in section 4 which highlights the integration between AIS and other soft computing techniques; Section 5 presents case studies; Section 6 highlights directions for future work and forms the conclusion of this work.

2. BIOLOGICAL BASE COMPUTATIONAL SYSTEMS: THEORETICAL BACKGROUND

2.1 The Immune System

The vertebrate immune system is composed of diverse sets of cells and molecules that work together with other systems (like neural and endocrine) for maintaining homeostatic state. The primary function of the immune system is to protect human bodies from infectious agents (such as viruses, bacteria and other parasites) commonly known as *pathogens*. Immune response is incited by the recognition of an associated molecule called *antigen*. Immune system usually works according to two mechanisms namely: Innate and Adaptive Immunity. Innate immunity is directed against general pathogens that enter the body while adaptive or acquired immunity allows launching an attack against any invader that innate system cannot remove. For more information about the immune systems, the reader can refer to (Castro and Zuben , 1999; Castro and Timmis, 2003; Timmis et al., 2004).

●   **Innate immunity:** vertebrates are born with this immunity which plays a vital role in the initiation and regulation of immune responses. Specialized cells have evolved to recognize and bind to common molecular patterns of micro-organisms. By no means does it provide complete protection, as it is primarily static in nature (Castro and Zuben , 1999).

- **Adaptive immunity** is directed towards specific invaders; either seen before or not previously encountered and gets modified by exposure to invaders. It mainly consists of lymphocytes (white blood cells, more specifically B and T type) that aid the process of recognizing and destroying specific substances, and are antigen-specific (Castro and Zuben , 1999).

o   **Clonal Selection**

Clonal selection theory was proposed by Burnet (1959). The theory is used to explain basic response of adaptive immune system to antigenic stimulus. It establishes the idea that only those cells capable of recognizing an antigen will proliferate while other cells are selected against. Clonal selection operates on both B and T cells. B cells, when their antibodies bind with an antigen, are activated and differentiated into *plasma* or memory cells. Prior to this process, clones of B cells are produced and undergo somatic hyper mutation. As a result, diversity is introduced into the B cell population. Plasma cells produce antigen-specific antibodies that are work against antigen. Memory cells remain with the host and promote a rapid secondary response (Castro and Timmis, 2003).

o   **Negative Selection**

Negative selection is a mechanism to protect body against self-reactive lymphocytes. It utilizes the immune system's ability to detect unknown antigens while not reacting to the self cells. During the generation of T-cells, receptors are made through a pseudo-random genetic rearrangement process. Then, they undergo a censoring process in the thymus, called the negative selection. In this process, T-cells that react against self-proteins are destroyed and only those that do not bind to self-proteins are allowed to leave the thymus. These matured T-cells then circulate throughout the body performing immunological functions and protecting the body against foreign antigens (Somayaji et al., 1997).

o   **Immune Networks Theory**

The immune Network theory has been introduced by Jerne (1974). The main idea was that the immune system maintains an idiotypic network of interconnected B cells for antigen recognition. These cells interconnect with each other in certain ways that lead to the stabilization of the network. Two B cells are connected if the affinities they share exceed a certain threshold, and the strength of the connection is directly proportional to the affinity they share.

3.   ARTIFICIAL IMMUNE SYSTEMS: LITERATURE REVIEW

3.1 Clonal Selection Based Algorithms

The Clonal Selection principle is the whole process of antigen recognition, cell proliferation and differentiation into memory cell (Burnet, 1959).   Several artificial immune algorithms have been developed imitating the clonal selection theory.

Castro and Zuben (2002) proposed a clonal selection algorithm named CLONALG for learning and optimization, CLONALG generates a population of N antibodies, each specifying a random solution for the optimization process. During each iteration, some of the best existing antibodies are selected, cloned and mutated in order to construct a new candidate population. New antibodies are then evaluated and certain percentage of the best antibodies is added to the original population. Finally a percentage of worst antibodies of previous generation are replaced with new randomly create ones.

In Rouchen et al. (2003) an Immunity Clonal Strategy algorithm (ICS) which includes Immunity Monoclonal Strategy Algorithms (IMSA) and Immunity Polyclonal Strategy Algorithm (IPSA) is introduced. ICS is used to solve multi-objective optimization task. Zuo and Li (2003) proposed a Chaos Artificial Immune Algorithm (CAIF) for function optimization problem. It uses chaotic variable to perform local search and explore the solution space.

Garrett (2004) introduced an Adaptive Clonal Selection (ACS) algorithm as a modification of CLONALG. It suggests some modifications to the CLONALG based on an analysis of the operators for selecting the amount of mutation and number of clones to overcome the drawbacks of CLONALG such as the several parameters used and the binary representation. An Adaptive Immune Clonal Strategy Algorithm (AICSA) proposed for solving numerical optimization problems in Liu et al (2004). It assigns dynamically the immune memory unit and antibody population according to the Ab-Ab and Ab-Ag affinities. It also integrates the local search with the global search.

Yu and Hou (2004) presented an improved clonal selection algorithm based in CLONALG algorithm. A learning operator was introduced to enhance the learning mechanism of CLONALG and to improve the detection efficiency.

Campels et al. (2005) proposed a Real-Coded Clonal Selection Algorithm (RCSA) for electromagnetic design optimization. It suggests some modifications to the clonal selection algorithm to enable the treatment of real valued variables for optimization problems. It has some features such as the number of clones, mutation range and the fraction of the population selected each generation. In Cutello et al. (2005) an immunological algorithm is

introduced for continuous global optimization problems named OPT-IA. The main features of the proposed algorithm are the following: the cloning operator that explores the neighbourhood at each point within the search space. The inversely proportional hypermutation operator used in the algorithm where the number of mutations is inversely proportional to the fitness value. Finally, the aging operator is used to remove the oldest candidate solution from the current populations to introduce diversity and avoid local minima during the search process.

An adaptive clonal algorithm proposed in Bian and Qiu (2006) for optimal phasor measurement unit (PMU) placement. It adjusts the number of the cycle supplement population and the probabilities of hypermutation and recombination operators of the CLONALG algorithm. These modifications can enhance the optimization process and help to avoid the locally optimal traps. Cutello et al. (2006) introduced an improved version of OPT-IA called opt-IMMALG. The main modifications in this algorithm are the replacement of the binary string representation by a real-coded one and the introduction of a new inversely proportional hyper mutation operator.

Gong et al. (2007a) presented an improved clonal selection algorithm based on CLONALG with a novel mutation method, self-adaptive chaotic mutation. The main modifications are that the new algorithm adopts the logistic chaotic sequence to generate the initial antibody population, while the hypermutation adopts self-adaptive chaotic mutation. In Gong et al. (2007b) a Differential Immune Clonal Selection algorithm (DICSA) is proposed to solve the global optimization problems. It combines the clonal selection theory and differential evolution and employs three operators: a clone operator, a differential mutation crossover mutation and a standard selection operator.

A parallel clonal selection algorithm for solving the Graph Coloring Problem presented in Dabrowski and Kubale (2008). It uses an island model where every processor works on its own pool of antibodies to improve the performance. Lu and Zhichun (2008) proposed a Clonal Chaos Adjustment Algorithm (CCAA) for Multi-modal Function Optimization. In order to enhance the global convergence performance of CLONALG, it takes advantages of the ergodic and dynamic properties of chaos system, and introduces the chaotic search mechanism into the CLONALG to improve its search efficiency.

Many other clonal selection based algorithms have been introduced in the literature. Examples of these algorithms include: Jiao and Li (2005), Li et al. (2005), Jin et al. (2006), Xiu-li and Yu-qiang (2006), Halavati et al. (2007), He and Jian (2007), Hu et al. (2007), Chen (2007), Zhang et al. (2007), Li et al. (2008), Qiao et al. (2008) and Yang et al. (2008).

3.1 Negative Selection Based Algorithms

The Negative Selection is one of the mechanisms of the natural immune system that has inspired the developments of most of the existing Artificial Immune systems. In the T-cell maturation process of the immune system, if a T-cell in thymus recognizes any self cell, it is eliminated before deploying for immune functionality. Similarly, the negative selection algorithm generates detector set by eliminating any detector candidate that match elements from a group of self samples.

Negative selection based algorithms have been used in different applications areas, such as anomaly detection. Forrest (1994) proposed a negative selection algorithm. The main idea of his algorithm is to generate a set of detectors by first randomly making candidates and then discarding those that recognize training self-data, and then these detectors can later be used to detect anomaly.

In Ayara et al. (2002) the NSMutation algorithm is presented. It introduces somatic hyper mutation, eliminates redundancy and possesses tunable parameters. It consists of three phases: define self-data, generate candidate detector and compare the generated detector with self-data based on affinity threshold. Gonzalez and Cannady (2004) presented a self-adaptive negative selection approach for anomaly detection. It uses self-adaptive techniques for parameter tuning. The main two phases of the algorithm are: generate the initial population and the evolution of the population.

Igawa and Ohashi (2008) proposed a new negative selection algorithm named Artificial Negative Selection Classifier (ANSC) for multi-class classification. It introduces a cutting method to reduce the effect of noise. It combines the negative selection algorithm with clonal selection mechanism to solve issues that prevent negative selection algorithms from being applied to classification problems. These issues include random searching, overfitting, and incomplete information. Some other researchers proposed negative selection algorithms can be found in Zeng et al. (2007), Xia et al. (2007) and Zhengbing et al. (2008).

3.2 Artificial Immune Network Models

Based on the immune network theory proposed by Jerne (1974) which was presented in the previous section, many researchers have developed models that use ideas and concept from the immune network theory to solve problems in different application areas. The pioneer work of Ishiguro et al. (1994) and Hunt and Cooke (1996) have motivated many researchers and hence several models have been developed in the literature. Following the work

done in Dasgupta et al (2003), we will summarize some of the existing Immune network models in this section with focus on the last five years.

Timmis et al. (2000) proposed an Artificial Immune NEtwork (AINE) to perform data analysis task. It uses artificial recognition ball (ARB) to represent identical B-cells. Two B-Cells are linked together if the affinity between two ARBs is below a network affinity threshold (NAT). In Timmis and Neal (2001) a Resource Limited Artificial Immune System (RLAIS) based on AINE is developed. The main enhancements in their model are the fixed total number of B-cells presented in ARBs with centralized control where each ARB competes to allocate resources from the pool. The ARBs with no resources are removed from the network. The cloning and Mutation process and the interactions of B-Cells are done at the ARB level.

The Self-Stabilizing Artificial Immune System (SSAIS) presented in Neal (2001) based on RLAIS for continuous analysis of time-varying data. Unlike RLAIS, there is no limited number of resources and the control is decentralized to the level of ARBs. Castro and Zuben (2000) presented the aiNet model for data analysis tasks. The network of antibodies generated according to the Euclidean distance. It shares some features of AINE, but differ in that the immune network structure is not a part of the antibody cloning and selection process.

In Castro and Timmis (2002a) the Hierarchy of aiNets model based on aiNet is proposed. The main improvements to the aiNet model were the proposed stopping criterion for the network interactive process and the introduction of an automatic hierarchical method to generate a tree of aiNets capable of detecting clusters with less-uniform characteristics.

Castro and Timmis (2002b) presented the opt-aiNet model for multimodal function optimization based on the aiNet model. The main characteristics of this model are automatic determination of the population size, combination of local with global search, well defined stopping criterion and capability of locating and maintaining stable local optima solutions. Knight and Timmis (2002) proposed a Multi-layered Artificial Immune Systems (MLAIS) that is inspired by the clonal selection theory and incorporates a feedback mechanism much like the co-stimulation in the immune network theory. It incorporates the idea of a primary immune response to deal with the event of unknown data being presented to the system.

Neal (2003) proposed a modified version of SSAIS named Meta-Stable Memory Immune System for multivariate data analysis. The model uses the stimulation function and resource allocation mechanism similar to SSAIS. It differs in that the system employs the cloning process in a primary response which is mediated by the affinity threshold, but it does not consider mutation operator. In Nasraoui et al. (2003) TECNO-STREAMS model is introduced for detecting an unknown number of evolving clusters in a noisy data stream. It can model cluster with arbitrary shape since multiple B-cells can represent a single cluster.

An Artificial Immune System for E-mail Classification (AISEC) presented by Secker et al. (2003). It is capable of continuous learning for the purpose of two class classification and used for the task of electronic mail sorting. Alonso et al. (2004) proposed based on the aiNet model an approach to model an agent that plays the Iterated Prisoner's Dilemma (IDP). The agent structure consists of two immune networks: recognition AIN and a decision AIN. The main improvement to the aiNet is introduced in the mechanism the network uses to add B-cell to the memory.

Bentley and Timmis (2004) introduced the Fractal Immune Network combining the ideas of fractal proteins with immune networks. The model maps data items to fractal antigens, creates fractal recognition spaces similar to ARBs in dynamic networks and forms all network links by emission and reception of fractal cytokines. The system provides desirable clusters and data classification regardless of the data. Luh and Liu (2004) developed a Reactive Immune Network (RIN) for mobile robot learning navigation strategies within unknown environments. In their approach, a modified virtual target method is integrated to solve local minima problem. Franca et al. (2005) proposed a modified algorithm termed dopt-aiNet (opt-aiNet for dynamic environments) to deal with time-varying fitness functions as an improved version of opt-aiNet. The main improvements presented in their approach are the use of separate memory subpopulation, a line search procedure, two new mutation operator schemes, a cell line suppression mechanism, and a limited population size.

In Qiao and Jianping (2006) an Immune Based Network Intrusion detection System (AINIDS) is proposed. It consists of five components: a data collector, a packet head parser and feature extraction, antibody generation and antigen detection, co-stimulation and report and rule optimization components. Tian et al. (2006) proposed a modified algorithm of aiNet to solve function optimization problems. The main improvements presented in this algorithm are, 1) the searching radius is a variable parameter depending in the number of the generations in which a cell survives. 2) Reserve the cell with the largest fitness (elitist strategy). 3) The expanding rate is controlled to maintain the diversity of the network.

Graaff and Engelbrecht (2007) introduced a Local Network Neighborhood Artificial Immune System (LNNAIS) model for data clustering. Compared to the existing AIS models, LNNAIS uses the concept of artificial lymphocyte (ALC) neighborhood to determine the network links between the ALCs. There is no network affinity threshold in

this model that determines whether two ALCs should be linked to form a network. The lymphocytes neighbors are determined by their individual indexes and they interact and learn from one another to have a better local representation of patterns. Hao and Cai-Xin (2007) proposed an Artificial Immune Network Classification algorithm (AINC) for fault diagnosis of power transformer. The algorithm consists of three steps; classifying the fault samples into training antigens set and test antigens set and both sets are initialized. Secondly, uses AINC to train the antigens set to obtain memory antibodies. Finally, the Euclidean distance among the test antigens set and memory antibodies set are calculated, and fault samples are classified using the K-Nearest Neighbor (KNN) approach.

Zhang and Yi (2007) proposed a Tree Structured Artificial Immune Network (TSAIN) for data clustering and classification. In this model, a topological link is setup between two antibodies immediately after one has reproduced by another with no need to set a threshold for this connection. It consists of four phases: The clonal section, the antibody cooperation, the antibody suppression and the topology updating phases. The first two phases provide the network with self-organizing ability. The suppression and topology updating ensure the consistency of network topology with distribution of clusters.

In Lv (2007) a Chaos Immune Network (CIN) algorithm for multimodal function optimization is discussed. The main features of this algorithm are the use of chaos variable to simulate proliferation mode of immune cells to enhance searching accuracy, the stepping criteria was improved and some relevant measures have been added to avoid pre-maturation. Huang and Jiao (2007) presented an Artificial Immune Kernel Clustering Network (IKCN) for unsupervised image segmentation. It combines the artificial immune network and the support vector domain description. In this model the Image features sets will be divided into subsets by the antibodies and then each subset mapped into a hypersphere in a high dimensional feature space by a Mercer Kernel. Finally, a minimal spanning tree is used to automatically determine the final number of clusters without a predefined number of clustering. Some other proposed immune network algorithms can be found in Li et al. (2008).

4. HYBRID COMPUTATIONAL INTELLIGENT SYSTEMS

Hybrid intelligent systems development is one of the most intensively growing areas. Hybrid systems utilize various soft computing methods and techniques like artificial neural networks, fuzzy systems, artificial immune systems, evolutionary computation, and genetic algorithms. The main objective is to integrate different learning and adaptation techniques to overcome individual limitations and to achieve synergetic effects through the combination of these techniques. This has contributed effectively in the developments of a large number of new intelligent system designs in recent years.

In this context, researchers have explored combining AIS with other computational models and techniques, especially with soft-computing methods. Some of the earlier work that combined AIS ideas with genetic algorithms was developed by Hajela et al. (1997). It uses immune networks to improve the convergence of genetic algorithms for design. Dasgupta (1997) has pointed out the similarities and the differences between AIS and artificial neural networks. Nasraoui et al. (2002) proposed the Fuzzy AIS model that uses a fuzzy set to model the area of influence of each B-cell which makes it more robust to noise. Vergas et al. (2003) presented an immune learning classifier network named (CLARINET) for autonomous navigation by combining the strengths of learning classifier systems, evolutionary algorithms, and an immune network model. Xian et al. (2005) proposed a novel intrusion detection method that optimizes the objective function of unsupervised fuzzy k-means clustering based on clonal selection algorithm.

Karakasis and Stafylopatis (2006) introduced a hybrid technique for data mining tasks which combines clonal selection principles and gene expression programming. Fu et al. (2007) proposed a hybrid artificial immune network which uses the swarm learning of particle swarm optimization to speed up the convergence of artificial immune system. Gan et al. (2007) proposed a technique that combines the simple representation method of gene expression programming and the advantage of clonal selection algorithms. Danzhen et al. (2008) introduced a fuzzy artificial immune network (FaiNet) algorithm for load classification. It consists of three parts: the artificial immune network learning algorithm, the minimal spanning tree algorithm, and the classification algorithm based on fuzzy C-means algorithm.

5. CASE STUDY

Some experiments were carried out in order to test some of the existing AIS algorithms and explore their capabilities. The ClonalG and the aiNet were chosen for this case study and tested on a cancer data set. The data set consisted of 693 instances and the number of attributes was 12. The predicted output of this dataset represents the recurrence status where the value one as an output indicates the possibility of the patient getting the cancer again in the future. The results of the two experiments are discussed in the following sections.

5.1 Experiment No. 1 : ClonalG Algorithm

In this experiment, the ClonalG algorithm was tested against the cancer dataset. Initially, the dataset was normalised to unity before being fed to the algorithm. Once the data was normalised a percentage of the samples was chosen at random and removed from the data set. This then became the sample that the detectors were trained on. The basic steps of ClonalG as presented in Castro and Zuben (2002) are as follows:

1. Initialisation: Create an initial random population of individuals (P)
2. Antigenic presentation: for each antigenic pattern, do:
   a. Affinity evaluation: present it to the population P and determine its affinity with each element in the population P;
   b. Clonal Selection and expansion: select n1 highest affinity elements of P and generate clones of these individuals proportionally to their affinity with the antigen: the higher the affinity, the higher the number of copies and vice-versa;
   c. Affinity maturation: mutate all these copies with a rate inversely proportional to their affinity with the input pattern: the higher the affinity, the smaller the mutation rate and vice-versa. Add these mutated individuals to the population P and reselect the best individual to be kept as the memory m of the antigen presented;
   d. Metadynamics: replace a number n2 of individuals with low affinity by (randomly generated) new ones;
3. Cycle: repeat Step 2 until a certain stopping criterion is met.

The above algorithm was coded in Matlab and obtained from Delahunty and Callaghan (2004), with the stopping criterion set at 500 detectors. Once the data in the data set was normalised a percentage of the self samples was chosen at random and removed from the data set. This then became the sample that the detectors were trained on. For all test runs, the accuracies were found unacceptably low and varied according to the test tolerance value. It was noticed that by increasing the threshold value, the accuracy results were improved and vice versa. All of the parameters were varied in the following way without significant effect in the results except for the test tolerance:

1. The number of detectors for the training stage was varied from $500 \rightarrow 2000$
2. The size of training samples was varied from $50 \rightarrow 500$
3. The number of final detectors for the testing phase was varied from $300 \rightarrow 700$
4. The test tolerance value was varied from $0.6 \rightarrow 1.0$

Table 1 highlights the effect of the test tolerance value change on the accuracy, sensitivity, and specificity of the algorithm.

Table 1: Test results

Test Tolerance value	Accuracy	Sensitivity	Specificity
0.6	31.4574	0.9772	0.0084
0.7	35.0649	0.9406	0.0781
0.8	40.1154	0.7945	0.2194
0.9	54.1126	0.6712	0.4810
1.0	63.4921	0.4886	0.7025

5.2 Experiment No. 2 : aiNet Algorithm

The aiNet algorithm discussed in the previous sections is a well known technique for clustering and data compression. The aiNet algorithm can be divided into two main stages. First, it performs the clonal selection principle and affinity maturation interactions similar to the clonal selection algorithm ClonalG, to produce the network of antibodies. In the second stage, the Minimal Spanning Tree (MST) is built on the antibody network, where each edge is looked at in relation to its neighbours. The inconsistent edge, whose weight is significantly larger than the average of nearby edge weights on both sides of the edge to be discarded, leading to the data partition into clusters.

In this experiment, the aiNet algorithm has been tested against the same cancer dataset used in the previous experiment then the simulation results are presented. The Matlab code is developed by Castro and Zuben (2000) which has been reported in AISWeb. The 692 samples from the cancer dataset were subdivided into two clusters. For the training purpose, the aiNet parameters were set as follows:

- The suppression threshold = 0.2
- The pruning threshold = 1.0
- Number of best matching cells to be selected (n) = 4

- Clone number multiplier (N) = 20
- Percentile amount of clones to be re-selected = 10%
- The stopping criterion is a fixed number of generations = 10.

The results show that the aiNet algorithm has successfully determined two clusters for the tested data. Figure 1 illustrates the network size per aiNet iterations. The algorithm starts from the fifth iteration to produce almost the same number of nodes. The resulting network contains an average of 442 cells, reducing the data set size to 64% of its original complexity (size). Figure 2 depicts the application of aiNet algorithm to the cancer dataset, where Figures 2(a), (b), (c) and (d) illustrate the Minimal spanning tree, clusters analysis, network dendrogram and the final network structure respectively.

Beside the aiNet capability of reducing redundancy and describing immune network structure, including data distribution and clustering, it has some drawbacks. These include its high number of user-defined parameters and its high computational cost per iteration $O(m2)$, with relation to the number of memory antibodies (m) (Castro and Zuben, 2001).
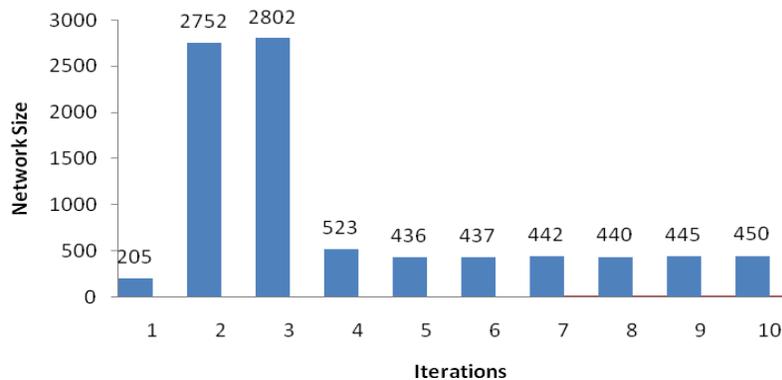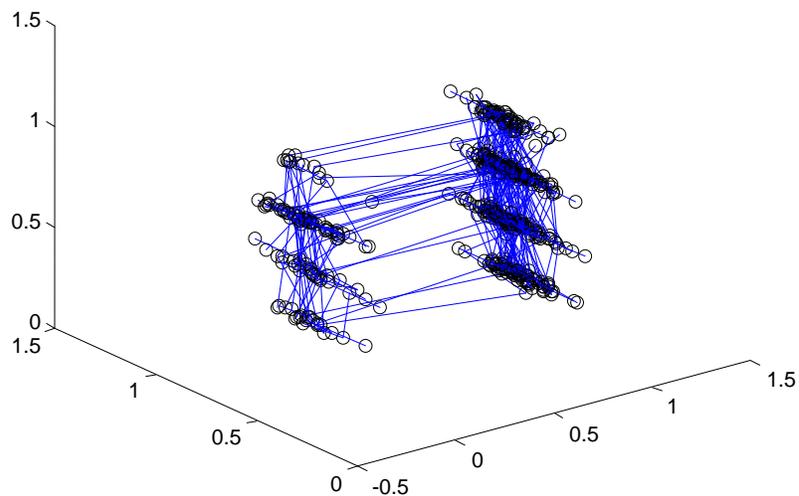

Figure 1: Network size per aiNet iterations
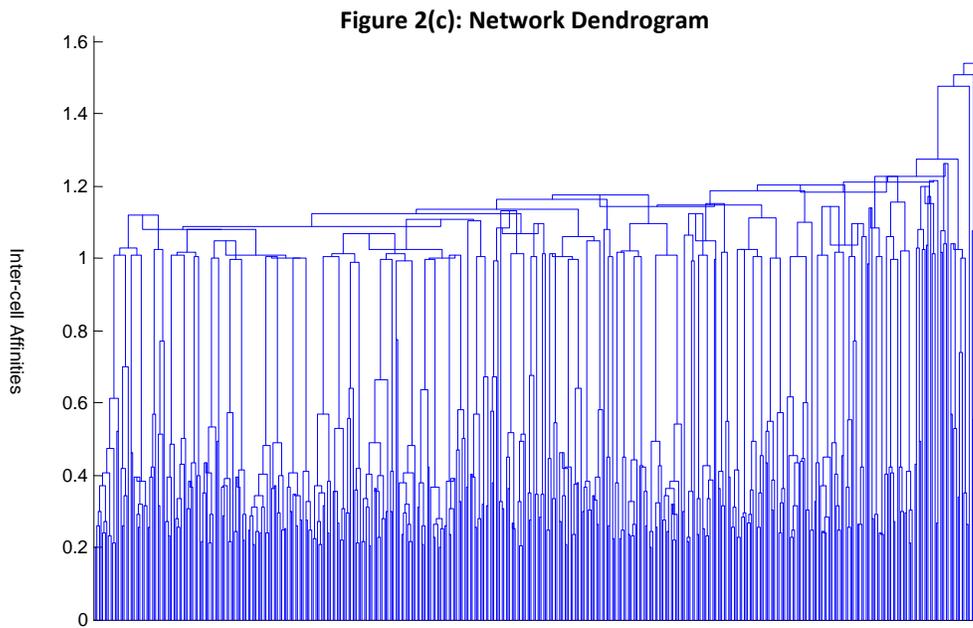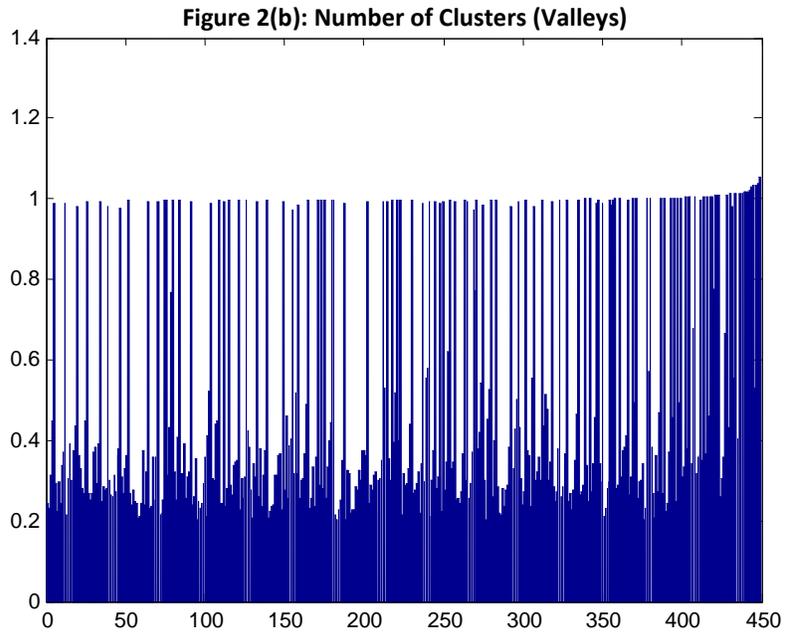

Figure 2(a): Minimal Spanning Tree

Figure 2(b): Number of Clusters (Valleys)

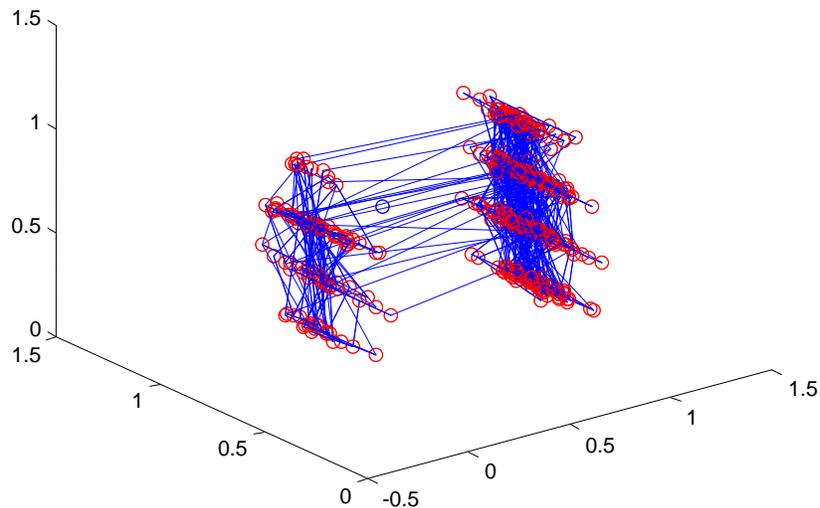

Figure 2(c): Network Dendrogram

Figure 2(d): Final Network Structure

6.   CONCLUSIONS

An overview of the Artificial Immune Systems field including a theoretical background on the main ideas and concepts of AIS and the recent advances in the literature have been presented in this survey. This has provided a motivation to continue exploring the AIS field and contribute to the development of the new AIS models and techniques.

A case study was carried out to demonstrate how the AIS approaches can be employed in dealing with real world problems and for achieving different data analysis tasks. Two experiments were conducted to test the ClonalG and aiNet algorithms respectively against a cancer dataset. In the first test, the results obtained for accuracy were unacceptably low and more improvements required for getting better outcomes. On the other hand, a correct classification was achieved in the aiNet test by detecting successfully the number and shape of the clusters for the tested dataset.

Researchers have explored the main features of the AIS mechanisms and exploited them in many application areas. Based on their aspects, some of the AIS techniques have been found to be more suitable for certain application areas compared to other AIS approaches. This survey found that negative selection models and algorithms were widely used in fault detection and computer security applications utilizing the self/non-self recognition aspect. Alternatively, the artificial immune network approaches were used in clustering, classification, data analysis and data mining applications. The clonal selection models were used mostly for optimization problems.

Although AIS models have achieved great successes in various application domains, there are still some theoretical issues that need to be further explored such as the development of unified frameworks, convergence, and scalability. The developments of the artificial immune systems would benefit not only from the inspiration of biological immune principles and mechanisms, but also hybridization with other soft computing paradigms, such as neural networks, fuzzy logic, and genetic algorithms. They could also be further studied and applied to more challenging application areas and to solve complex real world problems.

Table 2 show a chronological list of some AIS models and techniques developed in the literature since Dasgupta's et al. (2003) work. A brief description for each model or technique, the aspect of the biological immune systems modelled, the type of representation used and the application area to which AIS has been applied are included in the table.

Table 2: A Time-line of AIS works (2003-2008)

Reference	Model or technique description	Aspects of the BIS modelled	Type of representation used	Applications
(Neal, 2003)	Meta-stable memory immune system for multivariate data analysis.	Immune Networks	Real-valued	Data analysis
(Rouchen et al., 2003)	An Immunity Clonal Strategy Algorithm (ICS) to solve multi-objective optimization task.	Clonal Selection	Real-valued vectors	Optimization
(Zuo and Li, 2003)	A Chaos Artificial Immune Algorithm (CAIF) by integrating of chaotic search and CLONALG	Clonal Selection	Real-valued vectors	Optimization
(Nasraoui et al., 2003)	Techno – streams model for detecting an unknown number of evolving clusters in a noisy data stream	Immune Networks	Real-valued	Clustering
(Secker et al., 2003)	An artificial immune system for E-mail classification (AISEC)	Immune Networks	Two-part words vector	Classification
(Garrett, 2004)	An Adaptive Clonal Selection (ACS) algorithm that suggests some modifications to the CLONALG	Clonal Selection	Real-valued vectors	Optimization
(Gonzalez and Canady, 2004)	A self adaptive negative selection algorithm for anomaly detection.	Negative Selection	Binary strings, real-valued	Anomaly Detection
(Yu and Hou, 2004)	An improved Clonal selection algorithm based in CLONALG	Clonal selection Ag-Ab binding	Binary Strings	Machine Learning
(Liu et al., 2004)	An Adaptive Immune Clonal Strategy Algorithm (AICSA)	Ag-Ab binding Clonal Selection	Real-valued vectors	Numerical Optimization problems
(Bentley and Timmis, 2004)	A Fractal immune networks model combining the ideas of fractal proteins with immune networks.	Immune Networks	Real-valued	Classification, Clustering
(Luh and Lin, 2004)	A Reactive Immune Network (RIN) for mobile robot learning navigation strategies within unknown environments	Immune Networks	Real-valued	Robots
(Campels et al., 2005)	A Real-coded Clonal selection Algorithm (RCSA) that enable the treatment of real valued variables for optimization problems.	Clonal Selection	Real-valued vectors	Electromagnetic design optimization
(Franca et al., 2005)	A modified algorithm named dopt-aiNet as an improved version of opt-aiNet to deal with time – varying fitness functions	Immune Networks	Real-valued vector	Optimization
(Xian et al., 2005)	A novel unsupervised Fuzzy K-Means (FKM) clustering anomaly detection algorithm based on clonal selection algorithm.	Clonal Selection	Numeric characteristic variables	Computer Security
(Cutello et al., 2005)	Immunological algorithm for continuous global optimization problems name OPI-IA	Clonal Selection	Binary String	Optimization
(Cutello et al., 2006)	An improved version of OPT-IA called Opt – IMMALG	Clonal Selection	Real-code	Optimization
(Qiao and Jianping, 2006)	An Immune based Network Intrusion Detection System (AINIDS)	Immune Networks	Rules	Computer Security

Reference	Model or technique description	Aspects of the BIS modelled	Type of representation used	Applications
(Bian and Qiu, 2006)	An adaptive Clonal algorithm that suggests some modifications to the CLONALG	Clonal selection, receptor editing	Binary strings	Optimization
(Karakasis et al., 2006)	A hybrid model which combines clonal selection principles and gene expression programming	Clonal selection	Symbol Strings	Data Mining
(Tian et al., 2006)	A modified algorithm of aiNet to solve function optimization problems	Immune Networks	Real-valued vector	Optimization
(Hao and Cai-Xin, 2007)	Artificial immune network classification algorithm (AINC) for fault diagnosis of power transformer.	Immune Networks	Real-valued	Classification
(Zhang and Yi, 2007)	A Tree structured artificial immune network (TSAIN) model for data clustering and classification.	Immune Networks, Clonal Section	Real-valued	Classification, Clustering
(Fu et al., 2007)	A hybrid artificial immune network that uses the swarm learning	Immune Networks	Real-valued	Optimization
(Lv, 2007)	A chaos immune network algorithm combines chaos idea with immune network to improve its ability of searching peaks.	Immune Networks,	Real-valued	Optimization
(Zeng et al., 2007)	A feedback negative selection algorithm (FNSA) for anomaly detection.	Negative Selection	Real-valued	Anomaly Detection
(Huang and Jiao, 2007)	An Artificial Immune kernel clustering network (IKCN) for unsupervised image segmentation.	Immune Networks	Real-valued, Image features sets	Clustering
(Gan et al., 2007)	A technique that combines gene expression programming with clonal selection algorithm for system modelling & knowledge discovery.	Clonal selection	Symbol Strings, Binary String	System Modelling
(Graaff and Engelbrecht, 2007)	A local network neighbourhood artificial immune system (LNNAIS) model for data clustering	Immune Networks	Real-valued	Clustering
(Gong et al., 2007a)	An improved clonal selection algorithm based on CLONALG with a novel mutation method, self adaptive chaotic mutation.	Clonal Selection	Real-valued	Optimization
(Gong et al., 2007b)	A differential immune Clonal selection algorithm (DICSA) combining the mechanism of Clonal selection & differential evolution	Clonal selection	Real-valued	Optimization
(Zhengbing et al., 2008)	A novel anomaly detection algorithm based on real-valued negative selection system	Negative Selection	Real-valued vectors	Anomaly Detection
(Dabrowski and Kubale, 2008)	A parallel Clonal selection algorithm for solving the Graph colouring problem	Clonal selection	Real-valued	Optimization

Reference	Model or technique description	Aspects of the BIS modelled	Type of representation used	Applications
(Danzhen et al., 2008)	A Fuzzy artificial immune network (FaiNet) algorithm for lead classification that includes three parts, AIN learning algorithm, MST algorithm and fuzzy C-means algorithm.	Immune Networks	Real-valued vectors	Classification
(Lu and Zhichun, 2008)	A clonal chaos Adjustment Algorithm (CCAA) that improves the search efficiency of CLONALG	Clonal Selection, Immune Networks	Real-valued	Multi-modal function optimization
(Igawa and Ohashi, 2008)	Artificial Negative selection Classifier (ANSC) that combines the negative selection algorithm with clonal selection mechanism.	Negative selection, clonal selection	Real-valued	Multi-class Classification

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