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A Preliminary Survey on Artificial Immune Systems (AIS): A Review on Their Techniques, Strengths and Drawbacks

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Abstract

An Artificial Immune System (AIS) is defined as computational intelligence evolved from immunology (biological immune systems) that tries to replicate the way human defensive system works. In this paper, the researchers categorize, compare, and summarize all the major techniques and algorithms of AIS. Particularly, the discussion highlights on the theoretical aspects, techniques, and algorithms of three well-established techniques of AIS, namely the negative selection algorithm, immune network algorithms, and clonal selection algorithms by focusing on their similarities and differences. In addition, this paper elaborates the differences among the techniques and algorithms in terms of the types of data, learning, concepts, elements, generation and operations, strengths and drawbacks, application areas and the evolution of AIS techniques. The techniques selected for this research was guided by beneficial previous literatures carried out by Dasgupta, de Castro, Timmis, and Luo. The findings of this study can help provide greater insights into the understanding of the three AIS techniques, which can further improve the current practice of practitioners and enrich the body of knowledge, benefiting researchers, educators, students, and others.

Keywords: Artificial Immune Systems, Artificial Immune Systems Techniques, Negative Selection Algorithms, Immune Network Algorithms, Clonal Selection Algorithms

Introduction

Artificial Immune Systems (AISs) are new immunology systems which are based on computational intelligence, that has helped developed many problem-solving techniques. In fact, some scholars assert that AIS is based on heuristic decision making that has evolved from multi-disciplinary fields, namely immunology, computer science, and engineering, which have been successfully implemented in several industrial applications such as prediction, optimization, computer science, engineering, and mathematics in the last decade of their existence. According to de Castro et al. (2002) Castro et al. (2003), AIS is specifically defined as:
“an adaptive system inspired by theoretical immunology and observed immune functions, principles, models, and mechanisms, which are implemented to problem solving.”

Technically, AIS refer to an intelligent computational tool which includes information processing, self-adapting, and self-learning system (Prashant & Mamta, 2015), that can mimic the mechanisms or processes of the human defensive system in building a shield against foreign encroachers or pathogenic infectious agents (e.g., viruses, bacteria, and other parasites), which are collectively known as pathogens or antigens.

The process of recognizing and categorizing foreign or unknown cells entering the body (non-self-cells or antigens) with the body cells (self-cells) is performed by the unique pattern-recognition capability of AIS (Al-Enezi et al., 2010). Such identification and classification is carried out by the intelligence-distributed task force that uses a network of chemical messengers for communications, working from both local and global viewpoints (Burke & Kendall, 2010). The features of AIS include learning and optimization capability, highly distributed learning and memory, robust self-organization, feature extraction, adaptation, recognition, scalability, and decentralized control mechanism (Ulutas & Konak, 2011; Prashant & Mamta, 2015).

As illustrated in Figure 1, biological immune systems are made of a multi-layered system consisting of physical barriers (e.g., the skins and respiratory systems), physiological barriers (e.g., destructive enzymes and stomach acids), and the immune systems. Essentially, AIS is formed by two major branches of the immune system, which interlinks and influences one another, namely the innate immunity and adaptive immunity that provides complete protection and aids the process of identifying and destroying antigen-specific substances respectively (de Castro & von Zuben, 1999). Furthermore, the adaptive immunity is divided into two subcategories, namely the humoral immunity and the cellular or cell-mediated immunity.

Immune systems use multilevel, overlapping defense both in parallel and sequential style and utilize dissimilar response mechanisms (differential pathways) either to neutralize the pathogenic effect or to destroy the infected cells based on the type of pathogens and the way it enters into the body (Burke & Kendall, 2010). In addition, Al-Enezi et al. (2010) and Tsankova (2009); Sidek, Mobidin, & Adam, (2018); Oboh, Chinonyelum, Edeme, (2018) state that immune systems are characterized by their unique characteristics namely uniqueness, autonomy, non-hierarchical parallel distributed detection structure, immunological tolerance, noise tolerance, micro-pattern recognition, immunological memory, self-regulation, metadynamics, diversity, and behaviors based on local interactions.
By manipulating such unique characteristics, the computational algorithms specifically targeted for classification, function optimization, pattern recognition, novelty detection, and process control can be further expanded (Khaled et al., 2011; Prashant & Mamta, 2015). To this end, a study by Hart & Timmis (2008) highlighted the practical applications of AIS in diverse domains such as computer security, invasion detection, engineering, virus detection, system control, combinatorial optimization, numerical function optimization, adaptive control systems, bio-informatics, web mining, image processing, and robotics.

From the research standpoint, studies of AIS can be classified according to three aspects, namely immune modeling, theoretical AIS, and applied AIS (Dasgupta et al., 2011). A study by Castro and Timmis (2011) indicates that the development of any biologically-inspired immune systems should focus on the appropriate development framework that incorporates a small set of fundamental elements consisting of the following:

1. A representation of system’s components.
2. A set of mechanisms to evaluate the interaction of individuals with the environment (simulated by a set of input stimuli) and with each other.
3. The procedure of adaptation that governs the dynamics of the system as for example the changeable behaviors over the time.
Affinity measures and immune algorithms play a crucial role in ensuring the findings would be significant, but the meaning and implementation of these steps are differ, depending on the problems encountered by AIS in a specific domain. In light of this backdrop, this review paper categorizes, compares, and summarizes three well-established, popular AIS techniques, encompassing their strengths, drawbacks, application areas, and the evolution of those techniques that has taken place from their early beginning till now. The paper first introduces the definition and inter-related background of AIS, and then it elaborates the methodology used throughout this paper by comparing major AIS techniques in detail in Section 2.0. Later, the paper discusses the AIS techniques and the comparison of these techniques, highlighting on their categorization, similarities and differences based on several criteria in Section 3.0. Finally, the paper summarizes the conclusion and recommendations for future research to help other researchers to carry out similar studies.

Methodology
The presentation of this paper is guided by several crucial steps starting from the selection, categorization, comparison and summarization of appropriate literature reviews, leading to a more thorough analysis. The most important keyword is "AIS", "AIS techniques", "negative selection algorithms (NSA)" , "immune network algorithms (INA)" and "clonal selection algorithms (CSA)". This excludes any hybridization of three main groups of AIS techniques. Only English literatures are considered, focusing on the theoretical aspects, techniques, and algorithms including the evolution of AIS application areas.

Information Sources
Particularly, the information retrieval is based on three digital databases namely (1) the IEEE Xplore Library; (2) the ScienceDirect database; and (3) the Web of Science (WoS) service. The selection
of these three digital databases are due to broader view of technical literature and also indexing cross-disciplinary research in sciences, social sciences, arts and humanities.

**Study Selection**
The study selection involves the searching process from multiple digital databases, followed by two iterations of screening and filtering. The main purpose of first iteration is to exclude duplication and irrelevant articles based on the titles and abstracts screening. The following iteration filtered the articles based on the thorough full text reading of the pre-screened results from the first iteration. The same eligibility criteria is used for both iterations.

**Search**
The acquisition of related information from appropriate digital database sources is done by a mix of keywords comprises of "AIS", "AIS techniques", "NSA", "INA", and "CSA" in different variations, combined by the "OR" operator. Only journals and conference articles are taken into account due to up-to-date and proper scientific works. However, other related sources from books and other type of technical reports are considered if it really matters.

**Data Selection Process**
Particularly, the discussion highlights the theoretical aspects, techniques, and algorithms of three well-established techniques of AIS, namely the NSA, INA, and CSA by focusing on their similarities and differences. The techniques selected for this research was guided by main beneficial previous literatures carried out by Dasgupta, de Castro, Timmis and Luo. Then the differences among the techniques and algorithms in terms of the types of data, learning, concepts, elements, generation and operations, strengths and drawbacks, application areas and the evolution of AIS technique are preferably filtered and summarized as in Table 1 in Section 3.0 (Results and Discussion).
The final phase is to summarize the conclusion before completing this preliminary survey paper. The findings of this study can help provide greater insights into the understanding of the three AIS techniques, which can further improve the current practice of practitioners and enrich the body of knowledge, benefiting researchers, educators, students, and others.

**Results and Discussion**
The evolution of artificial intelligence has spawned many important changes, notably in heuristic decision-making techniques, that attempt to mimic the way in which nature reacts. Some of the AIS techniques based on the nature-inspired heuristic decision making include swarm intelligence, ant colony optimization, evolutionary algorithms, genetic algorithms, and stimulated annealing. Furthermore, such techniques have been extensively adopted in supervised and unsupervised machine learning, data mining, pattern recognition, networking, anomaly and invasion detection, computer security, bio-informatics, optimization, automation and design, text and image processing, clustering and classification (Dasgupta, 2007; Prashant & Mamta, 2015). The timeline of AIS evolution begins with the immune network model, followed by NSA, immune gene libraries, associative memory, AIS, immune agent architecture, artificial germinal centers and other models followed chronologically. According to Khaled et al. (2010) and Brownlee (2007), although the models of immune systems can be theoretically limitless, AIS can be classified into four
main subfields based on the prominent immunological theories, namely NSA, INA, CSA, danger theory algorithms and dendritic cell algorithms (Dasgupta et al., 2011).

AIS Techniques
Alternatively, based on other literature, AIS can be divided into three major groups of approaches, namely NSA, INA, and CSA. In addition, there are other emerging algorithms, which are continually being developed, such as complex AIS, toll-like receptor algorithm, conserved self-pattern recognition algorithm (Prashant & Mamta, 2015), humoral immune response (Dasgupta et al., 2003), and pattern recognition receptor model (Yu & Dasgupta, 2008).

Negative Selection Algorithms (NSA)
NSA is the pioneer of AIS algorithms with a very strong temporal nature that has been widely implemented in major real-life applications, which focus on providing tolerance for self-cells. NSA was a brilliant idea proposed by Forrest to overcome problems in virus detection in the computer system and in network intrusion by applying immune-inspired techniques for pattern detection (Bradley & Tyrell, 2002). As such, NSA is also referred to as negative detection with the ability to sense foreign cells (antigens) without interrupting the self-cells. The theory of negative selection has been proposed by Timmis and Bentley (2002) indicating the body protection from self-reactive lymphocytes. In essence, the common elements of NSA are data representation, coverage estimation, affinity measures, and matching rules that are classified by different criteria as well (Ji & Dasgupta, 2007).

As proposed by Percus in 1999, NSA replicates the way in which theoretical analysis of matching and binding probabilities occur within the immune systems. For the negative selection system, the first phase is the maturation process that will hibernate for a period of time. Then, the detectors will be activated when a number of matches against incoming antigens are successfully implemented (Ma et al., 2010). Later, these activated detectors or receptors will be applied to pseudo-random genetic rearrangement process during the T-cells generation. The rationality of this random approach selection is due to its simplicity and similarity to the immune system (Bradley & Tyrell, 2002).

Then, the process continues with the censoring process that reacts in the thymus, known as negative selection. There, T-cells that respond towards self-proteins will be eliminated, and the rest will be permitted to leave the thymus (kept as detectors). If a cell fails to be matched in a certain period of time, it will age and eventually die (Ma et al., 2010). These detectors or the detector set are then implemented for the identification and detection of incoming data instance (either self or non-self) (Ji & Dasgupta, 2007). An anomaly or non-self-will materializes if the instance matches any detector. In this matter, the findings of a study by Ma et al. (2010) are illuminating, suggesting that the matching occurs for two main reasons: (a) to identify a non-self-cell as being harmful if it successfully matches against an active detector and (b) to increase the matching count by one (“1”) if it successfully matches against a yet-to-be-activated detector.

Furthermore, a fully activated detector can materializes when the matching count exceeds the pre-defined antibody activation threshold. Thus, the detection performance will be significantly affected by the sequence order of the antigens (Ma et al., 2010). That being the case, different order will lead to different set of dynamics of detector’s activation and ageing, hence resulting in different performance. Then, the matured T-cells will disseminate throughout the body to conduct immunological functions and defend the body from unknown cells (antigens) (Al-Enezi et al., 2010). Figure 3 summarizes the flow of NSA process.
According to Ji and Dasgupta (2007), the most dominant characteristics of NSA are the negative representation of information, detection mechanism by using some form of a detector, and one-class classification. The finding of a comprehensive survey of AIS conducted by Garrett (2004) indicates that NSA may not be suitable for all applications due to its distinct process compared to other algorithms. Nonetheless, the development of NSA for self-non-self differentiation in computer security and virus protection has shown remarkable results, especially in imperfect detection (Bradley & Tyrell, 2002). Likewise, NSA has also been successfully applied in a complete immune systems development for computers, namely ARTIS that has a number of advancements (Hofmeyr & Forrest, 2000; Vrettou, 2014).

**Immune Network Algorithms (INA)**

In 1974, Jerne (1974) in Al-Enezi et al. (2010) first introduced the immune network theory in which the immune system maintains an idiotypic network of interconnected B-cells for antigen recognition. The theory assumes that the interactions among immune cells cause the modulation in the behavior of the overall immune system, which leads to the generation of immune system. In modeling this idiotypic network theory, the differential equations are normally used to simulate the dynamics of lymphocytes (Tsankova, 2009).

Idiotypic network’s behavior can be considered intelligent given its ability to adapt and to display emergent properties at the local and global levels, respectively (Greensmith et al., 2010). Furthermore, by being flexible (in the selection of mechanisms), autonomous, and completely decentralized, this theory is suitable for arbitrating mobile-robot behaviors, identifying good pattern-
matching for software recommendation, and negotiating options for communication software configuration (Greensmith et al., 2010).

To understand such behaviors, an analogy involving the interactions among lymphocytes (a small leukocyte) can help explain that they are not isolated (Tsankova, 2009). For example, B lymphocytes generate Y-shaped antibodies with their distinct chemical structures, where a key and lock relationship that exists among dissimilar types of antibodies can help identify an antigen (Tsankova, 2009). These cells can stimulate and suppress one another in certain ways to form a large scale network (a parallel distributed processing architecture) that leads to the stabilization of the network. In such a network, two B-cells can connect with one another when the sharing affinities exceed a certain threshold, and the strength of the connection is directly proportional to the affinities they share. The immune network theory also involves cloning and mutating process (de Castro & von Zuben, 2000).

Essentially, there are two types of recognition, namely epitope and paratope. The former represents an antibody that can identify an antigen, and the latter represents part of the antibody that recognizes the corresponding antigen determinant (Tsankova, 2009). Paratope acts as a master key that can open up a set of locks, whereby more than one lock can open up some locks. By contrast, idiotope defines the antigenic characteristic of antibodies.

Based on Jerne’s network theory, antibodies can also possess a set of epitopes that can be identified by other antibodies. Idiotopes refer to the specific epitopes of the antibody type, and the idiootype represents the group of antibodies sharing similar idiotopes. Suppression occurs when an antibody’s idiotope is identified by other antibody’s paratopes, thus reducing their concentration. By contrast, stimulation occurs when the process is reversible, thus increasing their concentration, and the network will continually adapt itself to help maintain a stable state that reflects the global results of environment interaction (Greensmith et al., 2010). Figure 4 summaries the structure of INA and the relation between an antigen and an antibody.

A study conducted by Greensmith et al. (2010) indicate that the earliest idiotypic network-based system, namely Jisys has fully utilized the stimulation and suppression effects concept throughout a
network of antibodies. Such a network has also been hybridization with clonal expansion and somatic hypermutation within the antibody populations. From this pioneer development, new network-based systems are continually evolved, such as ANNIE/RAIN (a resource based unsupervised clustering algorithm) and aiNet. In fact, aiNet is an example of INA that is specifically designed for unsupervised clustering. The enhancement of aiNet, called opt-aiNet, is best-suited for pattern recognition and optimization, especially for multi-modal function optimization.

**Clonal Selection Algorithms (CSA)**

The clonal selection theory was proposed by Burnet in 1959, and successfully proven to be an evolutionary strategy best-suited for solving complex machine learning tasks, such as pattern recognition and multi-modal optimization (de Castro & von Zuben, 2000). This theory provides the core principles of the adaptive immune response and the main principles of modern immunology, thus highlighting a close interconnection among the clonal selection theory and other immunological theories (Brownlee, 2007). In essence, CSA primarily focuses on imitating the clonal selection principles consisting of mechanisms, clonal selection, clonal expansion, and affinity maturation via somatic hypermutation (Brownlee, 2007).

The clonal selection and affinity maturation principles demonstrate the immunoral process of initializing, reacting, and defeating the foreign invaders or pathogens. Such a process is carried out in three phases, namely the cloning, mutation and selection phases, as depicted in Figure 5.

![Clonal Selection Algorithms](https://via.placeholder.com/150)

**Figure 5: The Process of CSA**

(Siavashi *et al.*, 2011)

The clonal selection principle presents the essential features of the reactions between an immune system and an antigenic stimulus. The proposed idea is that the proliferation (division) process occurs when cells recognize the antigen, which is then classified into effector cells and memory cells (de Castro & Timmis, 2002).

The effector cells will secrete antibodies in a large numbers, whilst the memory cells, which have long life span, can perform faster and more effectively in dealing with the upcoming intrusion of similar pathogen (Castro & Timmis, 2002). These cells can operates on both B-cells and T-cells, which are rather similar but different in terms of the relation of antigens recognition and their functional
roles. Specifically, B-cells are capable of independently identifying antigen, whilst T-cells are dependent on accessory cells for their antigen recognition process. As shown in Figure 6 and Figure 7, antigens are encrusted with molecules, known as epitopes that can be recognized by receptor molecules on the surface of B-cells, namely antibodies (Ab). By contrast, to enable the recognition of antigen in T-cells, other cells called accessory cells are needed. The accessory cells will process and deliver the antigen to be recognized by T-cells. B-cells will be activated and differentiated into plasma or memory cells when their antibodies bind to an antigen. Memory cells will be produced when higher affinity cells are in contact with invading pathogen. Prior to this process, the cloning production of B-cells involves somatic hyper mutation at high rates, together with a selective force. The whole process of somatic mutation and selection is known as affinity maturation (Castro & Timmis, 2002). The result leads to the introduction of diversity to the B-cell population. Plasma cells will produce antigen- specific antibodies that work against an antigen. Memory cells remain with the host and promote a rapid secondary response (Castro & Timmis, 2003). The memory cells will also learn during this process, when the antigens have been detected from the internal of the individual organism, the recognition of B-cells will be discarded (autoimmunity). This is known as the establishment of immune toleration or self-tolerance (Khaled et al., 2010).

![Figure 6: The Recognition Process in B-cells and T-cells (Source: de Castro & Timmis, 2002)](image)

When an antibody is strongly matches against an antigen, the stimulation of corresponding B-cell occurs, leading to the cloning of more antibodies production. This fast hyper-mutation, often occurring at a rate of “one mutation per cell division” enabling a rapid response to the antigens (Burke & Kendall, 2010).

As contended by Khaled et al. (2010), CSA are formed by five main properties, namely negative selection (that contributes to the elimination of self-antigens), clonal expansion (that involves proliferation and differentiation), monospecificity (that leads to phenotypic restriction), somatic hypermutation (that detects new random genetic changes), and autoimmunity.
Generally, CSA consist of AIRS1, AIRS2, AIRS2 Parallel, CLONALG, CSCA, IMMUNOS-1, IMMUNOS-81, and IMMUNOS-99 (Khaled et al., 2010). Specifically, CLONALG is equipped with diverse properties such as maintenance of a specific memory set, selection and cloning of most stimulated antibodies, death of non-simulated antibodies, affinity maturation, and maintenance of diversity (Ulutas & Kronak, 2011).

The Strengths and Drawbacks of AIS Techniques
In this study, several well-established AIS algorithms, namely the NSA, INA, and CSA, were reviewed to highlight their mechanisms, properties, strengths and weaknesses, and the area of their applications. Additionally, relevant theories pertaining to the immune system were discussed to help explain the mechanisms by which the application of such AIS algorithms helps mimic the processes of the human defensive system to build protection from foreign invaders or pathogenic infectious agents.

Clearly, more efforts are entailed to help formulate a strong, unified framework in developing efficient and effective algorithms of the AIS. More importantly, such a framework should be conceptualized using sound mathematical or computational models of the immune system by focusing on the biological aspects of interest. In pursuing such undertakings, a focus on the danger theory, dendritic cells, and hybridization with other techniques or methods (such as soft computing or intelligent systems), and artificial tissues should be prioritized. Table 1 summarizes the properties of NSA, INA, and CSA techniques with respect to their appropriate applications.
| Criteria          | NSA                                                                 | INA                                                                  | CSA                                                                 |
|-------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|----------------------------------------------------------------------|
| **Types of Data** | • Binary data.                                                        | • Binary data.                                                        | • Binary data.                                                        |
|                   | • Real numbers.                                                      | • Real numbers.                                                      | • Real numbers.                                                      |
| **Types of Learning** | • A semi-supervised learning process, which is independent of the “normal” knowledge. | • A supervised learning process.                                   | • A supervised learning process.                                   |
| **Concept**       | • Self-non-self-differentiation.                                     | • Interconnected idiotypic network of lymphocytes and molecules and B-cells for antigen recognition. | • Cloning of two types of immunological memory as lymphocyte. • Clonal selection and affinity maturation principles that demonstrate the immunoral process of initializing, reacting, and defeating the foreign invaders or pathogens. |
| **Element**       | • Detector/receptors.                                               | • B lymphocytes.                                                     | • Epitopes.                                                          |
|                   | • Antigen.                                                          | • Y shaped antibodies.                                              | • Plasma cells.                                                     |
|                   |                                                                    |                                                                    | • Memory cells.                                                     |
| **Generation**    | • T-cells                                                           | • B-cells                                                           | • Operates both on B-cells and T-cells.                             |
| **Operation**     | • Matching and binding process/probabilities.                       | • Cloning and mutating process (based on the imitation of clonal selection principle). | • Selection, mutation, and diversity process. • Clonal selection and expansion and affinity maturation via somatic hypermutation. • Negative selection helps eliminate the self-antigens. • Clonal expansion encompasses proliferation and differentiation. • Monospecificity results in phenotypic restriction. • Somatic hypermutation identifies new random genetic changes and |
|                   | • Pseudo-random genetic rearrangement process.                     | • Rowing or pruning of edges among nodes based on affinity (similarity in the problems representation space). |                                      |
|                   | • Censoring process of the thymus called negative selection.       | • Stimulation and suppression to stabilize the network.             |                                      |
|                   | • Switching of generated T-cells in the system to accomplish the immunological job. | • Key-and-lock relations that exist among different species of |                                      |
| Characteristics |  | autoimmunity. |
|-----------------|--|---------------|
| • One-class classification.  
• Negative representation of information.  
• Detection mechanism by using some form of detector. | • Flexible selection mechanisms.  
• Autonomous and completely decentralized. | • Intelligent idiotypic network.  
• Initiation of candidate solutions, selection, clone, mutation, reselection, and population replacement.  
• Ability to reach a diverse set of local optima solutions. |

| Strengths |  |  |
|-----------|--|---------------|
| • Hide the self-concept.  
• Capable to differentiate between the self (body elements) and the non-self (unknown cells).  
• No prior knowledge of non-self in its training process.  
• No communication between detectors (inherently distributable).  
• Continually checks or detects the presence of any invalid operation (Bradley & Tyrell, 2002). | • Antigen recognition by maintaining an idiotypic network of interconnected B-cells – adaptive at a local level, and displays emergent properties at a global level (Greensmith et al., 2010).  
• The network continuously adapts itself to maintain a steady state that reflects the global results of environment interaction. | • The diversity initializes and protects the immune systems against antigens that neither seen before nor have some correlation with the antigens that have met before (Khaled et al., 2010).  
• Adaptive clonal selection as the parameter free version of CLONALG is best suited for static function optimization problem domains (Garrett, 2004).  
• Equipped with generalization capability (immunological cross-reaction or cross-reactive response) - more effective and rapid secondary response not only for |
| Mobile-robot behavior arbitration, identifying perfect pattern-matching for software recommendation, and negotiating options for communication software configuration. |
| --- |
| The stimulation and suppression will form a large scale network (a parallel distributed processing architecture) - leads to the stabilization of the network. |
| If the retired detector needs to be reused, it can simply reestablish with the antigen feedback mechanism (Ma et al., 2010). |
| An intrinsic of a reinforcement learning strategy that continuously improving its ability to conduct its task. |
| Effectively improved the immune response to secondary encounters - storing some high-affinity antibody producing cells from the first interaction (memory cells), simply to form a large initial improved clone for subsequent encounters (de Castro & von Zuben, 2000). |
| Learns, discovers, and detects any abnormal pattern or appearance (non-self cells) automatically (Ma et al., 2010). |
| Keeps only active detectors - reduce the capacity of detector repository within an acceptable range (Ma et al., 2010). |
| Provide symmetric protection - normal behavior detection helps to identify any malicious manipulation on detector set and the quality of the check can be traded off against the cost of performing a check. |
| The detection is adjustable between coverage (matching probability) and the number of detectors due to stabilize it. |
| If the retired detector needs to be reused, it can simply reestablish with the antigen feedback mechanism (Ma et al., 2010). |
| Itself, but also to any structurally related antigen (de Castro & von Zuben, 2000). |
| Mobile-robot behavior arbitration, identifying perfect pattern-matching for software recommendation, and negotiating options for communication software configuration. |
| The stimulation and suppression will form a large scale network (a parallel distributed processing architecture) - leads to the stabilization of the network. |
| If the retired detector needs to be reused, it can simply reestablish with the antigen feedback mechanism (Ma et al., 2010). |
| An intrinsic of a reinforcement learning strategy that continuously improving its ability to conduct its task. |
| Effectively improved the immune response to secondary encounters - storing some high-affinity antibody producing cells from the first interaction (memory cells), simply to form a large initial improved clone for subsequent encounters (de Castro & von Zuben, 2000). |
| Drawbacks                                                                 | Benefits                                                                                                                                   |
|--------------------------------------------------------------------------|-------------------------------------------------------------------------------------------------------------------------------------------|
| • Inappropriate and unsuitable for general classification method (one class based). |
| • Inappropriate for multi-class classification problems, with no mechanism to minimize the danger of over fitting and over searching. |
| • Requires conventional software or system programming to iteratively increase exemplars in order to solve classification problems in the complement space (Brownlee, 2007). |
| • The adaptation of data to the algorithm will directly reduce the algorithm’s effectiveness and disregard any important information (Ji & Dasgupta, 2007). |
| • A time-related parameters and an order-oriented (in sequence) - changing the parameters will lead to different findings (Ma et al., 2010). |
| • The conventional ways of generating detectors algorithms always lead to an exhaustive and time-consuming procedure. |
| • The achievement of optimal anomaly detection is always unguaranteed by applying these generators. |
| • Inappropriate if the space is finite and self                                                                                                                                 |
| • Apply the excitation and suppression properties of the network model supported by conventional software or system programming to iteratively refine the model. |
| • Limited applicability - large overhead of computational complexity and lack of understanding of their dynamics (Hart & Ross, 2004). |
| • Binding and stimulating of B-cells lead to a certain amount of suppression between B-cells - increases the regulatory mechanism. |
| • Labeled as strongly as absurd regarding the limited experimental evidence to support it along with its theoretical aspects. |
| • Requires an accurate estimation of the population size - smaller population can direct the algorithm towards a rapid convergence, whilst larger population requires extensive computational resources (Ulutas & Konak, 2011). |
| • Compared to other AIS systems, CLONALG has a small number of user parameters and also relatively low in complexity (Ulutas & Konak, 2011). |
| • Encounter a premature convergence problem (problems of stagnating in a local but not global optimum), and maturation processes are trapped into a local optimum (Dai et al., 2011). |
| • Insufficiently utilize system feedback information due to its random search heuristic. |
consists of only a small fraction of the available space or if space is infinite.

- Do not closely copy the natural negative selection (Ebner et al., 2002).

| Application Area | | | |
|------------------|------------------|------------------|
| **Virus protection** (Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). | **Control** (Bian & Qiu, 2006; Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). |
| **Monitoring tools** (Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). | **Clustering/unsupervised clustering/classification** (Secker et al., 2003; Stibor et al., 2005; Huang & Jiao, 2008; Igawa & Ohashi, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). |
| **Binary classification** (Khaled et al., 2010; Prashant & Mamta, 2015). | **Data mining / data analysis / data visualization** (Hart & Timmis, 2008). |
| **Computer security** (Hart & Timmis, 2008). | **DNA classification** (Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). |
| **Change/anomaly detection** (Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015; Gonzalez & Cannady, 2004; Aydin et al., 2010; Gong et al., 2012). | **Solving complex machine learning tasks** (de Castro & von Zuben, 2002; Hart & Timmis, 2008). |
| **Fault / imperfect detection** (Hart & Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015). | **Pattern recognition (Dabrowski & Kubale, 2008; Khaled et al., 2010; Prashant & Mamta, 2015).** |
| **Rapid response detection system** (Hart & Timmis, 2008). | **Optimization/multi-modal optimization** (Cutello et al., 2006; Hart & Timmis, 2008; Lu & Zhichun, 2008). |
| | **Binary character recognition** (Luo et al., 2005; Luo et al., 2006; Khaled et al., 2010; Prashant & Mamta, 2015). |
| | **Numeric data classification** (Campelo et al., 2005; Khaled et al., 2010; Prashant & Mamta, 2015). |
| | **Solving complex machine learning tasks** (de Castro & von Zuben, 2002; Hart & Timmis, 2008). |
| | **A flexible alternative to genetic algorithm and evolutionary algorithm** (Hart & Timmis, 2008). |
| | **A strong method to deal with complex...** |
| Evolution of AIS Techniques | • NSA (Forrest et al., 1994).  
|                           | • NS Mutation Algorithm (somatic hyper mutation).  
|                           | • A self-adaptive negative selection technique for anomaly detection - self-adaptive techniques for constraint tuning (Gonzalez & Cannady, 2004).  
|                           | • Self detector classification method (Stibor et al., 2005).  
|                           | • Two Evolutionary Negative Selection Algorithms (ENSA) implementing binary representation (Luo et al., 2005).  
|                           | • Novel negative selection algorithm called r[]-NSA with binary representation (Luo et al., 2006).  
|                           | • Fast negative selection algorithm (multi- |  
|                           | • Immune network theory (Jerne, 1974).  
|                           | • Self-Stabilizing Artificial Immune System (SSAIS) for determining time-varying data using Resource Limited AIS(RLAIS) (Gong et al., 2012).  
|                           | • AIS for E-mail Classification (AISEC) (Secker et al., 2003).  
|                           | • Multimodal function optimization – used improved chaos immune network (Jia, 2007).  
|                           | • Immune Kernel Clustering Network (IKCN) – adaptation of immune network and the support vector machine (Huang & Jiao, 2008).  
|                           | • CLONALG(for machine learning and pattern recognition) (de Castro & von Zuben, 2002).  
|                           | • Adaptive CSA (Garrett, 2004).  
|                           | • Adaptive Immune Clonal Strategy Algorithm (AICSA) - combines the global and local search (Ruochen et al., 2003).  
|                           | • Adaptation of learning operator in the CSA - increase the learning and detection efficiency (Yu & Hou, 2004).  
|                           | • A Real-Coded CSA (RCSA) for numerical electromagnetic problems (Campelo et al., 2005).  
|                           | • An adaptive CSA for optimal phasor measurement unit (PMU) placement (Bian & Qiu, 2006).  
|                           | Combinatorial optimization problems, as it has the capability to enlarge the solution space (Hart & Timmis, 2008; Ruochen et al., 2003; Peng & Lu, 2015).  

& Timmis, 2008; Khaled et al., 2010; Prashant & Mamta, 2015).  
Khaled et al., 2010; Prashant & Mamta, 2015).  
- Optimization (multi-modal function optimization) (Jia, 2007; Hart & Timmis, 2008).  
- Mobile-robot behavior arbitration (Hart & Timmis, 2008).  
- Identification of good matches for recommendation software (Khaled et al., 2010; Prashant & Mamta, 2015).  
- Negotiation options for configuring communication software (Hart & Timmis, 2008).
pattern matching algorithm) in an input string by only one scan operation (Luo et al., 2006).

- New selection algorithm based on NSA and decision theory (Caldas et al., 2007).
- Artificial Negative Selection Classifier (to overcome over fitting and over searching) - allows multiclass classification (Igawa & Ohashi, 2008).
- Chaotic-based hybrid negative selection algorithm (anomaly detection problem) (Aydin et al., 2010).
- Efficient negative selection for anomaly detection (Gong et al., 2012).

- OPT-IA which solves global numerical optimization problem - ioning, hyper mutation and aging (Cutello et al., 2005).
- Trend Evaluation Algorithm to evaluate price time series data (Wilson et al., 2006).
- opt-IMMALG (optimization immune algorithm) (Cutello et al., 2006).
- An improved CSA based on CLONALG with a novel mutation method, self-adaptive chaotic mutation (Gong et al., 2007).
- A Differential Immune CSA (DICSA) 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 (Gong et al., 2007).
- Parallel CSA for Graph Colouring Problem (Dabrowski & Kubale, 2008).
- A Clonal Chaos Adjustment Algorithm (CCAA) - designed for Multi-modal Function Optimization (Lu & Zichun, 2008).
- Elitist Immune Programming (EIP) -concept of elitism (Ciccazzo et al., 2008).
- CSA using agent-based approach (Purbasari et al., 2013).
- Bi-direction quantum crossover (Dai et al., 2014).
- New hybrid learning CSA (HLCSA), a combination of two learning approaches:
| | | Baldwinian learning and orthogonal learning (Peng & Lu, 2015). |
Conclusion
In this study, a preliminary survey of the previous literature was carried out by the researchers to identify the current AIS techniques that have been widely adopted in many studies in this particular domain. Notably, three dominant AIS techniques and algorithms such as the NSA, INA, and CSA were analyzed to reveal their similarities and differences in their theoretical principles, mechanisms, and properties, culminating in the highlight of their unique strengths and weaknesses. Thus, a reliable framework or a sound methodology is entailed to help guide the development of precise models of immune systems by which the unique properties of such techniques and algorithms can be tapped harmoniously. In view of the emerging knowledge of immune systems and new development in artificial intelligence, more efforts are required to further improve existing AIS techniques such that their applications will bring more benefits to all the stakeholders.

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References
Al-Enezi, J. R., Abbod, M. F., & Alsharhan, S. (2010). Artificial immune systems - Models, algorithms and applications. IRRAS, 3(2), 118-131.
Aydin, I., Karakose, M., & Akin, E. (2010). Chaotic based hybrid negative selection algorithm and its applications in fault and anomaly detection. Expert Systems with Applications, 37(7), 5285–5294.
Bian, X., & Qiu, J. (2006). Adaptive clonal algorithm and its application for optimal PMU placement. Paper presented at the Proceedings of International Conference of IEEE on Communications, Circuits and Systems.
Bradley, D. W., & Tyrell, A. M. (2002). Immunotronics - Novel finite-state-machine architectures with build-in self-test using self-nonself differentiation. Paper presented at the IEEE Transactions on Evolutionary Computation.
Brownlee, J. (2007). Clonal Selection Algorithms. Retrieved from CIS Technial Report. (070209A).
Burke, E. K., & Kendall, G. (2010). Search Methodologies: Introductory Tutorials in Optimization and Decision Support Techniques. New York, NY: Springer US.
Caldas, B., Pita, M., & Buarque, F. (2007). How to obtain appropriate executive decisions using artificial immunologic systems. Paper presented at the 6th International Conference on Artificial Immune Systems (ICARIS 2007).
Campelo, F., Guimaraes, F., Igarashi, H., & Ramirez, J. (2005). A clonal selection algorithm for optimization in electromagnetics, IEEE Transactions on Magnetics, 41(5), 1736 – 1739
Ciccazzo, A., Conca, P., Nicosia, G., & Stracquadanio, G. (2008). An advanced clonal selection algorithm with ad-hoc network-based hypermutation operators for synthesis of topology and sizing of analog electrical circuits. Paper presented at the 7th International Conference on Artificial Immune Systems.
Cutello, V., Narzisi, G., Nicosia, G., & Pavone, M. (2005). An immunological algorithm for global numerical optimization. Paper presented at the Artificial Evolution: 7th International Conference, Evolution Artificielle.
Cutello, V., Nicosia, G., & Pavone, M. (2006). Real coded clonal selection algorithm for unconstrained global optimization using a hybrid inversely proportional hyper mutation operator. Paper presented at the 21st Annual ACM Symposium on Applied Computing.

Dabrowski, J., & Kubale, M. (2008). Computer experiments with a parallel clonal selection algorithm for the graph coloring problem. Paper presented at the IEEE International Symposium on Parallel and Distributed Processing.

Dai, H., Yang, Y., & Li, C. (2011). Dynamic quantum crossover based clonal selection algorithm for solving travelling salesman problem. Advances in Information Sciences and Service Sciences (AISS), 3 (11), 1.

Dai, H., Yang, Y., Li, H., & Li, C. (2014). Bi-direction quantum crossover-based clonal selection algorithm and its applications. Elsevier’s Expert Systems with Applications, 41(16), 7248–7258.

Dasgupta, D., Yu, S., & Majumdar, N. S. (2003). MILA - Multilevel immune learning algorithm. Paper presented at the Genetic and Evolutionary Computation Conference (GECCO 2003).

Dasgupta, D. (2007). Advances in artificial immune systems. Paper presented at the IEEE Computational Intelligence Magazine.

Dasgupta, D., Yu, S., & Nino, F. (2011). Recent advances in artificial immune systems: Models and applications. Applied Soft Computing, 11: 1574–1587.

De Castro, L. N., & von Zuben, F. J. (1999). Artificial Immune Systems: Part I – Basic Theory and Applications. Retrieved from Technical Report 210. (TR- DCA 01/99).

De Castro, L. N., & Zuben, V. F. J. (2000). Artificial Immune Systems: Part II – A Survey of Applications. Retrieved from Technical Report. (DCA-RT 02/00).

De Castro, L. N., & Zuben, V. F. J. (2002). Learning and optimization using the clonal selection principle. IEEE Transaction Evolutionary Computation, 6(3), 239-251.

De Castro, L. N., & Timmis, J. (2002). An artificial immune network for multimodal function optimization. Paper presented at the Proceedings of IEEE Congress on Evolutionary Computation (CEC’02).

De Castro, L. N., & Timmis, J. (2003). Artificial immune systems as a novel soft computing paradigm. Soft Computing Journal, 7(7), 526-544.

Ebner, M., Breunig, H. G., & Albert, J. (Eds.). (2002). On the use of negative selection in an artificial immune system (MPP): Proceedings of the International Conference Genetic and Evolutionary Computation (GECCO 2002), The Roosevelt Hotel, 2002. New York, NY: Morgan Kaufmann Publishers.

Forrest, S., Perelson, A. S., Allen, L., & Cherukuri, R. (1994). Self-nonself discrimination in a computer. Paper presented at the Proceedings of IEEE Symposium on Research in Security and Privacy.

Garrett, S. M. (2004). Parameter-free, adaptive clonal selection. Paper presented at the Proceedings of Congress on Evolutionary Computing (CEC 2004).

Gong, M., Jiao, L., Zhang, L., & Ma, W. (2007). Improved real valued clonal selection algorithm based on novel mutation method. Paper presented at the Proceedings of International Symposium on Intelligent Signal Processing and Communication Systems.

Gong, M., Zhang, L., Jiao, L., & Ma, W. (2007). Differential immune clonal selection algorithm. Paper presented at the Proceedings of International Symposium on Intelligent Signal Processing and Communication Systems.
Gong, M., Zhang, J., Ma, J., & Jiao, L. (2012). An efficient negative selection algorithm with further training for anomaly detection. *Knowledge-Based Systems*, 30, 185–191.

Gonzalez, L., and Cannady, J. (2004), June 19-23. A self-adaptive negative selection approach for anomaly detection. Paper presented at the Congress on Evolutionary Computation.

Greensmith, J., Whitbrook, A., & Aickelin, U. (2010). *Handbook of Metaheuristics (2nd edition)*. M. Gendreau, and J. Y. Potvin (Ed.). New York, NY: Springer.

Hart, E., & Ross, P. (2004). Studies on the implications of shape-space models for idiothetic networks. Paper presented at the Proceedings of the 3rd International Conference on Artificial Immune Systems (ICARIS 2004).

Hart, E., & Timmis, J. (2008). Application areas of AIS: The past, the present and the future. *Applied Soft Computing*, 8(1), 191-201.

Hofmeyr, S. A., & Forrest, S. (2000). Architecture for an artificial immune system. *Evolutionary Computing*, 8(4), 443–473.

Huang, W., & Jiao, L. (2008). Artificial immune kernel clustering network for unsupervised image segmentation. *Progress in Natural Science*, 18(4), 455–461.

Igawa, K., & Ohashi, H. (2008). A negative selection algorithm for classification and reduction of the noise effect. *Application Soft Computation*, 431-438.

Jerne, N. K. (1974). Towards a network theory of the immune system. *Annals of Immunology 125C*, 373-389.

Ji, Z., & Dasgupta, D. (2007). Revisiting negative selection algorithms. *Evolutionary Computation*, 15(2), 223-251.

Jia, L. V. (2007). Study on chaos immune network algorithm for multimodal function optimization. Paper presented at the *Fourth International Conference on Fuzzy Systems and Knowledge Discovery*.

Khaled, A. A. S., Hatim, M. A. K., & Nabil, A. I. (2010). Artificial immune clonal selection classification algorithms for classifying malware and benign processing using API call sequences. *International Journal of Computer Science and Network Security (IJCNSNS)*, 10 (4), 31-39.

Lu, H., & Zhichun, M. (2008). A clonal chaos adjustment algorithm for multi-modal function optimization. Paper presented at the *Proceedings of the 27th Chinese Control Conference*.

Luo, W., Wang, J., & Wang, X. (2005). Evolutionary negative selection algorithms for anomaly detection. In *8th Joint Conference on Information Science (ICIS 2005)*. Paper presented at the Marriott Center, Salt Lake City, Utah, 21-26 July (pp. 440-445). Red Hook. NJ: Curran Associates, Inc.

Luo, W., Wang, X., Tan, Y., & Wang, X. (2006). A novel negative selection algorithm with an array of partial matching lengths for each detector. Paper presented at the *9th International Conference on Parallel Problem Solving from Nature*.

Luo, W., Wang, X., & Wang, X. (2007). A novel fast negative selection algorithm enhanced by state graphs. Paper presented at the *6th International Conference on Artificial Immune Systems (ICARIS 2007)*.

Ma, W., Tran, D., & Sharma, D. (2010). Negative selection as a means of discovering unknown temporal patterns. *World Academy of Science, Engineering and Technology*, 65, 1033-1039.

Neal, M. (2003). Meta-stable memory in an artificial immune network. Paper presented at the *Proceedings of the 2nd International Conference on Artificial Immune Systems*.
Peng, Y., & Lu, B. L. (2015). Hybrid learning clonal selection algorithm. *Information Sciences*, 296(1), 128-146.

Prashant, K. M., & Mamta, B. (2015). Artificial immune system: State of the art approach. *International Journal of Computer Applications* (0975 – 8887), 120(20), 25-32.

Purbasari, A., Iping, S. S., Santoso, O. S., & Mandala, R. (2013). Designing artificial immune system based on clonal selection: Using agent-based modeling approach. Paper presented at the 7th Asia Modelling Symposium (AMS).

Ruochen, L., Haifeng, D., & Licheng, J. (2003). Immunity clonal strategies. Paper presented at the *Proceedings of Fifth International Conference on Computational Intelligence and Multimedia Applications*.

Secker, A., Freitas, A., & Timmis, J. (2003). AISEC: An artificial immune system for e-mail classification. Paper presented at the *Proceedings of the Congress on Evolutionary Computation of IEEE*.

Siavashi, E., Pahlavanhoseini, A., Pejmanfar, R., & Khanjanzadeh, A. (2011). Using clonal selection algorithm to optimize the induction motor performance. *Canadian Journal on Electrical and Electronics Engineering*, 2(9), 433-437.

Stibor, T., Mohr, P., Timmis, J., & Eckert, C. (2005). Is negative selection appropriate for anomaly detection? Paper presented at the 2005 *Conference on Genetic and Evolutionary Computation (GECCO 2005)*.

Timmis J., & Bentley, P.J. (Eds.). (2002). *Negative selection: How to generate detectors: 1st International Conference on Artificial Immune Systems*, University of Kent, 2002. Kent: Canterbury Printing Unit.

Tsankova, D. D. (2009). Emotional intervention on an action selection mechanism based on artificial immune networks for navigation of autonomous agents. *International Society for Adaptive Behavior*, 17(2), 135-152.

Ulutas, B. H., & Konak, S. K. (Eds.). (2011). *A Review of Clonal Selection Algorithm and Its Applications*. New York, NY: Springer.

Wilson, W. O., Birkin, P., & Ackelin, U. (2006). Price trackers inspired by immune memory. Paper presented at the 5th *International Conference on Artificial Immune Systems (ICARIS 2006)*.

Yu, Y., & Hou, C. Z. (2004). A clonal selection algorithm by using learning operator. Paper presented at the *Proceedings of the Third IEEE International Conference on Machine Learning and Cybernetics*.

Yu, S., & Dasgupta, D. (2008). Conserved self-pattern recognition algorithm. Paper presented at the 7th *International Conference on Artificial Immune Systems*.

Sidek, S. F. M. Y. A. N. M., Mobidin, H. Z., & Adam, S. N. A. (2018). Big Data towards Decision Making Culture in Organization. International Journal of Academic Research in Progressive Education and Development, 7(3), 103–115.

Vrettou, A. (2014). The “Very Successful L2 Learner” In The Sixth Grade Of The Greek Elementary School As Portrayed Through A Qualitative Study. *Multilingual Academic Journal Of Education And Social Sciences*, 2(2), 1–14.

Oboh, J. O., Chinonyelum, O. J., Edeme, R. K. (2018). Tax Revenue and Economic Growth in Selected ECOWAS Countries, Evidence from Sure Model, International Journal of Academic Research in Accounting, Finance and Management Sciences 8 (3): 310-324.