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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.

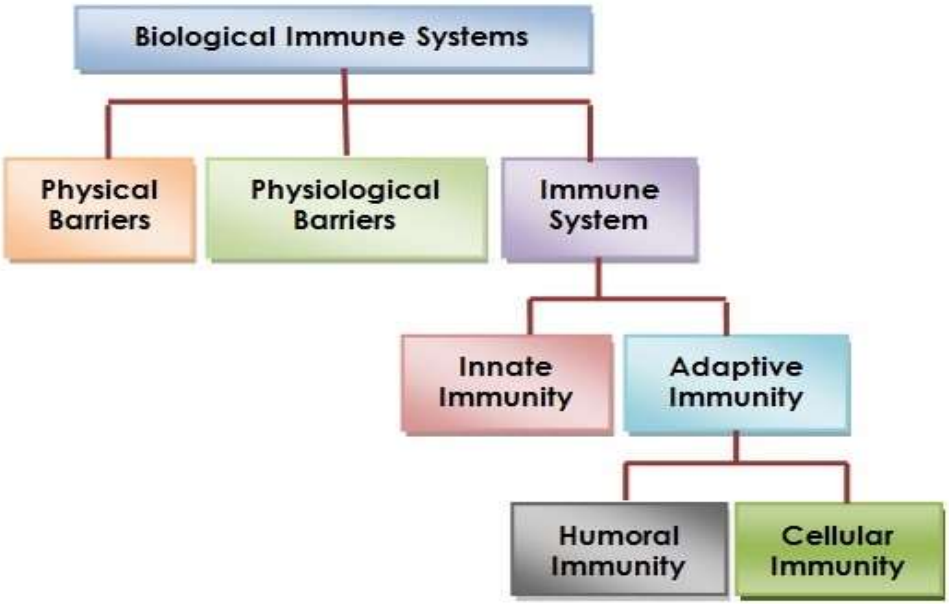


Figure 1: Summarization of Biological Immune Systems' Structures (Source: de Castro & von Zuben, 1999)

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 *at 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.

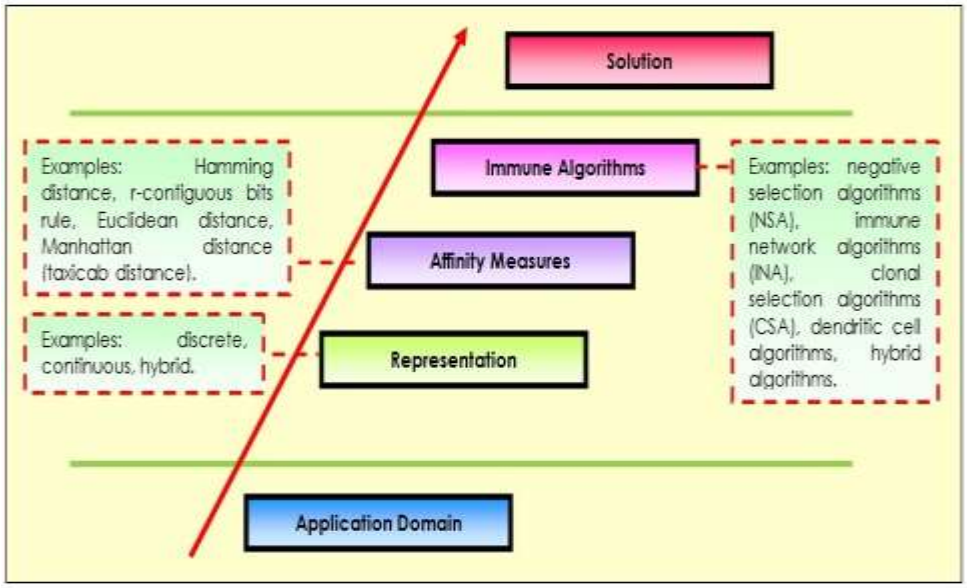


Figure 2: Layered Framework of AIS Development for Problem Solving (Source: Dasgupta., 2007)

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 lympocytes. 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.

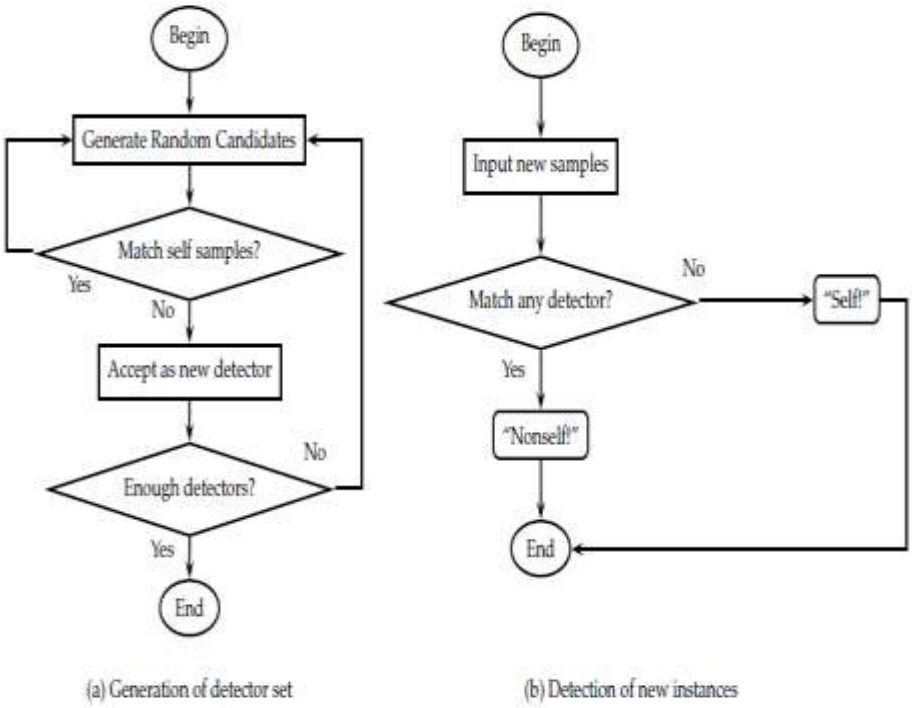


Figure 3: Outline of a Typical NSA Process
(Source: Ji & Dasgupta, 2007)

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) indicate 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 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 idiotype 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.

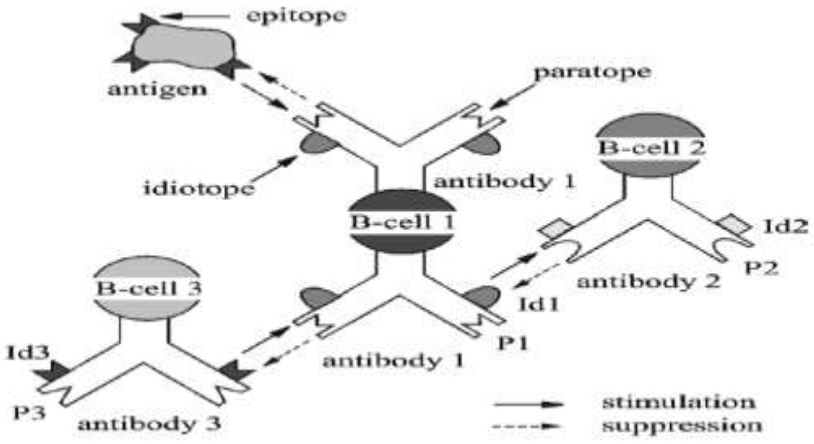


Figure 4: Structure of INA
(Source: Tsankova, 2009)

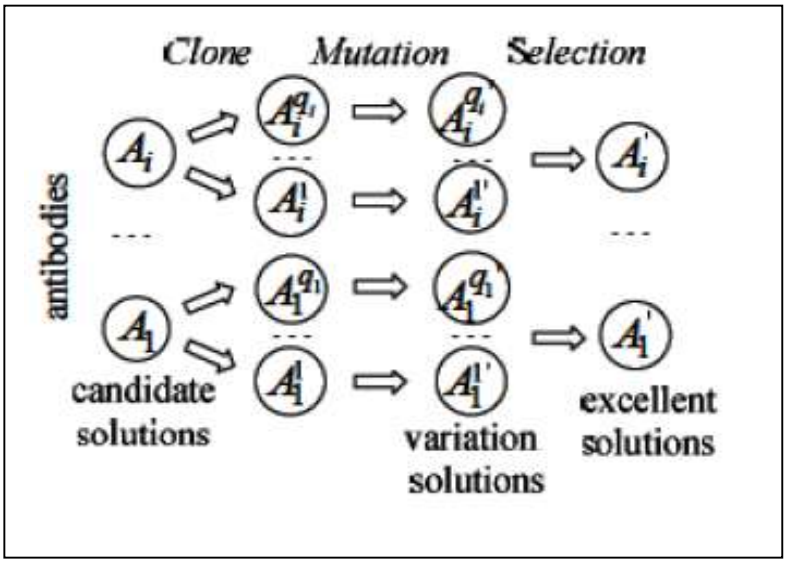
A study conducted by Greensmith *et al.* (2010) indicate that the earliest idiotypic network-based system, namely Jisys has fully utilized the stimulation and suppression effects concept throughout a

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.



(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).

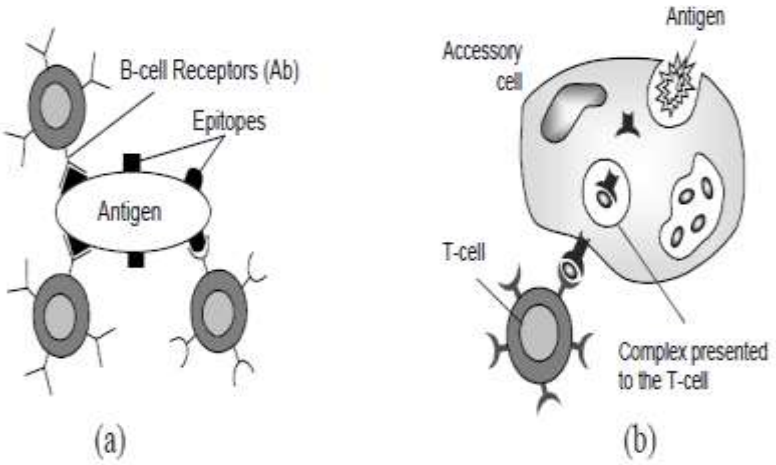


Figure 6: The Recognition Process in B-cells and T-cells (Source: de Castro & Timmis, 2002)

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.

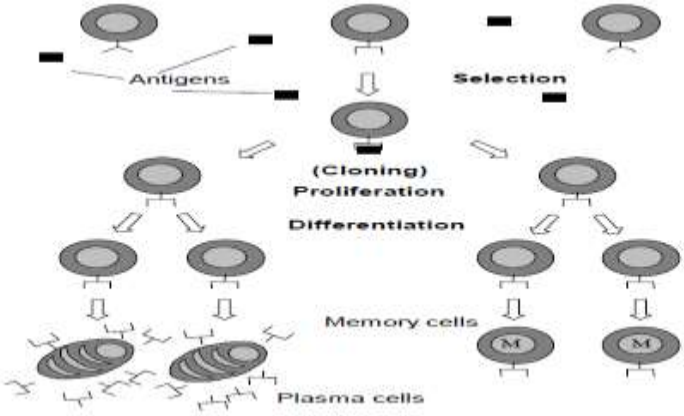


Figure 7: Principles of CSA
(de Castro & Timmis, 2002)

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.

Table 1: Summarization of AIS Techniques with Respected Application Areas

Criteria	NSA	INA	CSA
Types of Data	▪ Binary data.	▪ Binary data. ▪ Real numbers.	▪ Binary data. ▪ 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. ▪ Antigen.	▪ B lymphocytes. ▪ Y shaped antibodies.	▪ Epitopes. ▪ Plasma cells. ▪ Memory cells.
Generation	▪ T-cells	▪ B-cells	▪ Operates both on B-cells and T- cells.
Operation	▪ Matching and binding process/probabilities. ▪ Pseudo-random genetic rearrangement process. ▪ Censoring process of the thymus called negative selection. ▪ Switching of generated T-cells in the system to accomplish the immunological job.	▪ Cloning and mutating process (based on the imitation of clonal selection principle). ▪ Rowing or pruning of edges among nodes based on affinity (similarity in the problems representation space). ▪ Stimulation and suppression to stabilize the network. ▪ Key-and-lock relations that exist among different species of	▪ 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

		antibodies.	autoimmunity.
Characteristics	▪ 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). ▪ Inherent parallel characteristic enables the distribution to multiple sites when the process of generating detectors is	▪ 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 adapting itself to maintain a steady state that reflects the global results of environment interaction. ▪ A flexible selection mechanism, autonomous and completely decentralized (perfectly suits for	▪ 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

	costly (Ji & Dasgupta, 2007). ▪ 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).	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.	itself, but also to any structurally related antigen (de Castro & von Zuben, 2000). ▪ 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	▪ 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). ▪ Monitoring tools (Hart & Timmis, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ Binary classification (Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ Computer security (Hart & Timmis, 2008). ▪ Change/anomaly detection (Hart & Timmis, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015; Gonzalez & Cannady, 2004; Aydin *et al.,* 2010; Gong *et al.,* 2012). ▪ Fault / imperfect detection (Hart & Timmis, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ Rapid response detection system (Hart	▪ Control (Bian & Qiu, 2006; 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;). ▪ Data mining / data analysis / data visualization (Hart & Timmis, 2008). ▪ DNA classification (Hart & Timmis, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ Text classification (Secker *et al.*, 2003; Hart & Timmis, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ Pattern recognition (Luo *et al.,* 2007;	▪ Pattern recognition (Dabrowski & Kubale, 2008; Khaled *et al.,* 2010; Prashant & Mamta, 2015). ▪ 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

	& 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).	combinatorial optimization problems, as it has the capability to enlarge the solution space (Hart & Timmis, 2008; Ruochen *et al.,* 2003; Peng & Lu, 2015).
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).

	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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