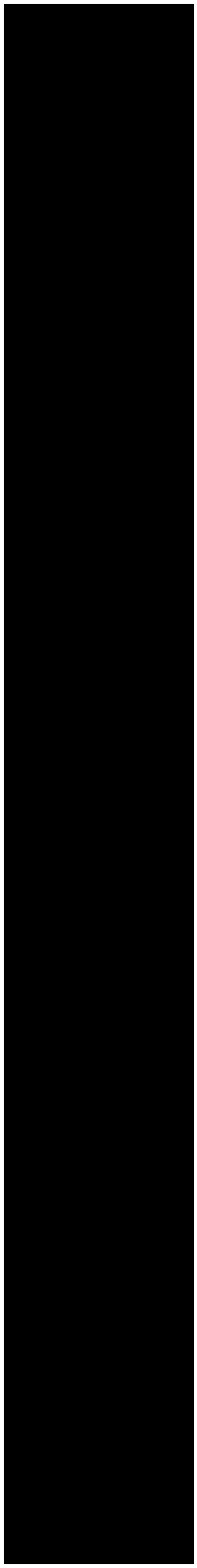

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The Use of Computational Intelligence in Intrusion Detection Systems: A Review

by

Shelly Xiaonan Wu* Wolfgang Banzhaf

Email: xiaonan@cs.mun.ca, banzhaf@cs.mun.ca

Department of Computer Science
Memorial University of Newfoundland
St. John's, NL, Canada A1B 3X5

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Shelly Xiaonan Wu * Wolfgang Banzhaf

Computer Science Department, Memorial University of Newfoundland, St John's, NL A1B 3X5, CA

Abstract

Intrusion detection based upon computational intelligence is currently attracting considerable interest from the research community. Characteristics of computational intelligence (CI) systems, such as adaptation, fault tolerance, high computational speed and error resilience in the face of noisy information fit the requirements of building a good intrusion detection model. Here we want to provide an overview of the research progress in applying CI methods to the problem of intrusion detection. The scope of this review will be on core methods of CI, including artificial neural networks, fuzzy systems, evolutionary computation, artificial immune systems, swarm intelligence, and soft computing. The research contributions in each field are systematically summarized and compared, allowing us to clearly define existing research challenges, and to highlight promising new research directions. The findings of this review should provide useful insights into the current IDS literature and be a good source for anyone who is interested in the application of CI approaches to IDSs or related fields.

Key words: Survey, Intrusion detection, Computational intelligence, Artificial neural networks, Fuzzy systems, Evolutionary computation, Artificial immune systems, Swarm intelligence, Soft computing

1. Introduction

Traditional intrusion prevention techniques, such as firewalls, access control and encryption, have failed to fully protect networks and systems from increasingly sophisticated attacks and malwares. As a result, intrusion detection systems (IDS) have become an indispensable component of security infrastructure used to detect these threats before they inflict widespread damage.

When building an IDS one needs to consider many issues, such as data collection, data pre-processing, intrusion recognition, reporting, and response. Among them, intrusion recognition is at the heart. Audit data are examined and compared with detection models, which describe the patterns of intrusive or benign behavior, so that both successful and unsuccessful intrusion attempts can be identified.

Since Denning first proposed an intrusion detection model in 1987 [74], the research efforts have been focused on how to effectively and accurately construct detection models. Between the late 1980s and the early 1990s, a combination of expert systems and statistical approaches was very popular. Detection models were derived from the domain knowledge of security experts. From the mid-1990s to the late 1990s, acquiring knowledge of normal or abnormal behavior had turned from manual to automatic. Artificial intelligence and machine learning techniques were used to discover the underlying models from a set of training data. Commonly used methods were rule based induction, classification and data clustering.

In fact, the process of automatically constructing models from data is not trivial, especially for intrusion detection problems. This is because intrusion detection faces such problems as huge network traffic volumes, highly imbalanced attack class distribution, the difficulty to realize decision boundaries between normal and abnormal behavior, and requiring continuous adaptation to a constantly changing environment. Artificial intelligence and machine learning have shown limitations to achieving high detection accuracy and fast processing times when confronted with these requirements. For example, the detection model in the winning entry of the KDD99 competition was composed of 50 $\times$ 10 C5 decision trees. The second-placed entry consisted of a decision forest with 755 trees [85]. Fortunately, computational intelligence techniques, known for their ability to

* Corresponding author. Tel.: +1 709 737 6947; fax: +1 709 737 2009.
Email addresses: xiaonan@cs.mun.ca (Shelly Xiaonan Wu), banzhaf@cs.mun.ca (Wolfgang Banzhaf).

adapt and to exhibit fault tolerance, high computational speed and resilience against noisy information, compensate for the limitations of these two approaches.

The aim of this paper is twofold. The first is to present a comprehensive survey on research contributions that investigate utilization of computational intelligence (CI) methods in building intrusion detection models. The scope of this survey is on the core methods in CI, which encompass artificial neural networks, fuzzy sets, evolutionary computation methods, artificial immune systems, and swarm intelligence. Applications of these methods reveal that each of them has pros and cons. Soft computing has the synergistic power to intertwine the pros of these methods in such a way that their weaknesses will be compensated. Soft computing, therefore, will be a part of this discussion, too. The second aim is to define existing research challenges, and to highlight promising new research directions.

The remainder of this review is divided into several sections, organized as follows. Section 2 defines IDSs and computation intelligence. Section 3 introduces commonly used datasets and performance evaluation measures, with the purpose of removing confusion found in some research work. Section 4 categories, compares and summarizes core methods in CI that have been proposed to solve intrusion detection problems. Section 5 compares the strengths and limitations of these approaches, and identifies future research trends and challenges. We end with concluding remarks in section 6.

2. Background

2.1. *Intrusion Detection*

An intrusion detection system dynamically monitors the events taking place in a monitored system, and decides whether these events are symptomatic of an attack or constitute a legitimate use of the system [71]. Figure 1 depicts the organization of an IDS where solid arrows indicate data/control flow while dotted arrows indicate a response to intrusive activities.

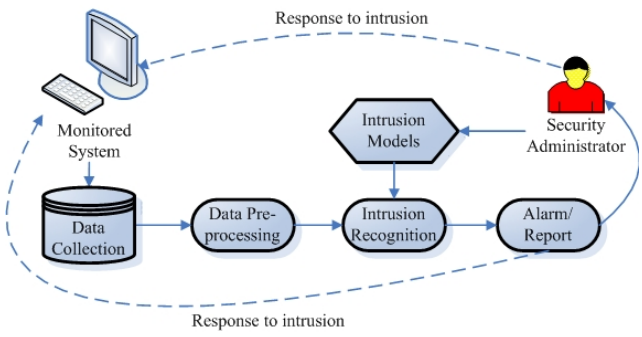


Fig. 1. Organization of a generalized intrusion detection system

In general, IDSs fall into two categories according to the detection methods they employ, namely (i) misuse detection and (ii) anomaly detection. Misuse detection identifies intrusions by matching observed data with pre-defined descriptions of intrusive behavior. So well-known intrusions can be detected efficiently with a very low false positive rate. For this reason, the approach is widely adopted in the majority of commercial systems. However, intrusions are usually polymorph, and evolve continuously. Misuse detection will fail easily when facing unknown intrusions. One way to address this problem is to regularly update the knowledge base, either manually which is time consuming and laborious, or automatically with the help of supervised learning algorithms. Unfortunately, datasets for this purpose are usually expensive to prepare, as they require labeling of each instance in the dataset as normal or a type of intrusion. Another way to address this problem is to follow the anomaly detection model proposed by Denning [74].

Anomaly detection is orthogonal to misuse detection. It hypothesizes that abnormal behavior is rare and different from normal behavior. Hence, it builds models for normal behavior and detects anomaly in observed data by noticing deviations from these models. There are two types of anomaly detection [48]. The first is static anomaly detection, which assumes that the behavior of monitored targets never changes, such as system call sequences of an Apache service; the second type is dynamic anomaly detection. It extracts patterns from behavior habits of end users or networks/hosts usage history. Sometimes these patterns are called profiles.

Clearly, anomaly detection has the capacity of detecting new types of intrusions, and only requires normal data when building the profiles. However, its major difficulty lies in discovering boundaries between normal and abnormal behavior, due to the deficiency of abnormal samples in the training phase. Another difficulty is to adapt to constantly changing normal behavior, especially for dynamic anomaly detection.

In addition to the detection method, there are other characteristics one can use to classify IDSs, as shown in Figure 2.

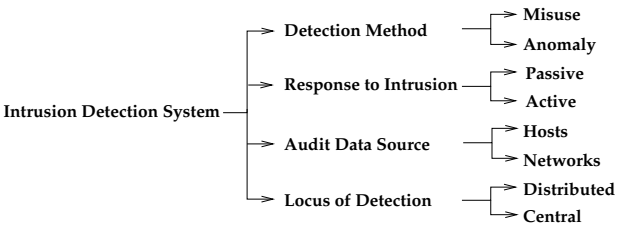


Fig. 2. Characteristics of intrusion detection systems

2.2. *Computational Intelligence*

Computational Intelligence (CI) is a fairly new research field with competing definitions. For example, in Computational Intelligence - A Logical Approach [234], the authors define CI as

"Computational Intelligence is the study of the design of intelligent agents. ... An intelligent agent is a system

that acts intelligently: What it does is appropriate for its circumstances and its goal, it is flexible to changing environments and changing goals, it learns from experience, and it makes appropriate choices given perceptual limitations and finite computation."

In contrast, Bezdek [34] defined CI as

"A system is computational intelligent when it: deals with only numerical (low-level) data, has pattern recognition components, does not use knowledge in the artificial intelligence sense; and additionally when it (begins to) exhibit i) computational adaptivity, ii) computational fault tolerance, iii) speed approaching human-like turnaround, and iv) error rates that approximate human performance."

We subscribe to the later definition. From this notion, and through the discussion of Craenen and Eiben [57], and Duch [82], we can summarize that computational intelligence systems possess the characteristics of computational adaptation, fault tolerance, high computational speed and less error prone to noisy information.

CI is different from the well-known field of Artificial Intelligence (AI). AI handles symbolic knowledge representation, while CI handles numeric representation of information; AI concerns itself with high-level cognitive functions, while CI is concerned with low-level cognitive functions; AI analyzes the structure of a given problem and attempts to construct an intelligent system based upon this structure, thus operating in a top-down manner, while the structure is expected to emerge from an unordered beginning in CI, thus operating in a bottom-up manner [57, 82].

Although there is not yet a full agreement on what computational intelligence exactly is, there is a widely accepted view on which areas belong to CI: artificial neural networks, fuzzy sets, evolutionary computation, artificial immune systems, and swarm intelligence. These approaches, except for fuzzy sets, are capable of the autonomous acquisition and integration of knowledge, and can be used in either supervised or unsupervised learning mode. The two learning schemes construct data-driven models in a training phase, and verify their performance in a testing phase.

In the intrusion detection field, supervised learning usually produces classifiers for misuse detection from class-labeled training data. Classifiers basically are a function mapping data points to corresponding class labels. Unsupervised learning distinguishes itself from supervised learning by the fact that no class-labeled data available in the training phase. It groups data points based upon their similarities. Unsupervised learning satisfies the hypothesis of anomaly detection, hence is usually employed in anomaly detection.

3. Datasets and Performance Evaluation

In this section, we will summary popular benchmark datasets and performance evaluation measures in intrusion detection domain, with the purpose of clarifying the misuse of these terms we have found during the review process.

3.1. *Datasets*

Since computational intelligence approaches build detection models from data, the quality of training datasets directly affects the quality of trained models. For the research works we survey here, data is normally collected from three sources: data packages from networks, command sequences from user input, or system low-level information, such as system call sequences, log files, system error logs, and CPU/memory usage. We list some commonly used benchmarks in Table 1. All of these datasets have been used in either misuse detection or anomaly detection.

The DARPA-Lincoln datasets and the KDD99 dataset In 1998, MIT's Lincoln laboratory conducted the first and most comprehensive research project to evaluate the performance of different intrusion detection methodologies, under the DARPA ITO and Air Force Research Laboratory sponsorship. This dataset contains seven weeks of training data and two weeks of testing data. The attack data include more than 300 instances of 38 different attacks launched against victim UNIX hosts, falling into one of the four categories: Denial of Service (DoS), Probe, U2R (Users to Root), and R2L (Remote to Local). For each week, inside and outside network traffic data, audit data recorded by Sun Microsystem's Basic Security Module(BSM) on Solaris hosts, and file system dumps from UNIX hosts were collected. In 1999, the evaluation was held by Lincoln laboratory again. Three weeks of training and two weeks of test data were generated this time. More than 200 instances of 58 attack types were launched against victim UNIX and Windows NT hosts and a Cisco router. In addition, host audit data were extended to Window NT systems. In 2000, three additional scenario-specific datasets were generated to address distributed DoS and Windows NT attacks. Detailed descriptions of these datasets can be found at http://www.ll.mit.edu/IST/ideval/data/data_index.html.

The KDD99 dataset was derived from the DARPA98 network traffic data in 1999 by a Bro program which assembled individual TCP packets into TCP connections. It was the benchmark dataset used in the International Knowledge Discovery and Data Mining Tools Competition, and also the most popular dataset ever used in the intrusion detection field. Each TCP connection has 41 features with a label which specifies the status of a connection as either being normal or a specific attack type [2]. There are 38 numeric features and 3 symbolic features, falling into the following four categories:

(i) Basic Features: 9 basic features were used to describe each individual TCP connection.

(ii) Content Features: 13 domain knowledge related features were used to indicate suspicious behavior having no sequential patterns in the network traffic.

(iii) Time-based Traffic Features: 9 features were used to summarize the connections in the past two seconds that had the same destination host or the same service

Table 1
Summary of Popular Datasets in Intrusion Detection Domain

Data Source	Dataset Name	Abbreviation
Network Traffic	DARPA 1998 TCPDump Files	DARPA98
	DARPA 1999 TCPDump Files	DARPA99
	KDD99 Dataset	KDD99
	10% KDD99 Dataset	KDD99-10
	Internet Exploration Shootout Dataset	IES
User Behavior	UNIX User Dataset	UNIXDS
System Call Sequences	DARPA 1998 BSM Files	BSM98
	DARPA 1999 BSM Files	BSM99
	University of New Mexico Dataset	UNM

as the current connection.

(iv) Host-based Traffic Features: 10 features were constructed using a window of 100 connections to the same host instead of a time window, because slow scan attacks may occupy a much larger time interval than two seconds,

The training set contains 4,940,000 data instances, covering normal network traffic and 24 attacks. The test set contains 311,029 data instances with a total of 38 attacks, 14 of which do not appear in the training set. This dataset is very large, so 10% of this KDD99 training set are frequently used.

McHugh [211] published an in-depth criticism of the DARPA dataset, arguing that some methodologies used in the evaluation are questionable and may have biased its results. For example, normal and attack data have unrealistic data rates; training datasets for anomaly detection are not adequate for its intended purpose; no effort have been made to validate that false alarm behavior of IDSs under test shows no significantly difference on real and synthetic data. Malhony and Chan [207] confirmed McHugh's findings by their experiments, which discovered that many attributes had small and fixed ranges in simulation, but large and growing ranges in real traffic.

As sharing the same root with the DARPA dataset, the KDD99 dataset inherits the above limitations. In addition, the empirical study conducted by Sabhnani *et al.* [239] stated that "KDD training and test data subsets represent dissimilar target hypotheses for U2R and R2L attack categories". According to their analysis, 4 new U2R attacks appear in test data, which constitutes 80% data of all U2R data in the test data. Similiarly, 7 new R2L attacks are presented in the testing data, and constitute more than 60% of R2L data in the test data. This may well explain why the detection results for U2R and R2L attacks are not satisfactory in most IDSs.

Despite all this criticism, however, both the DARPA Lincoln and the KDD99 datasets continue to be the largest publicly available and the most sophisticated benchmarks for researchers in evaluating intrusion detection algorithms or machine learning algorithms.

The Internet Exploration Shootout Dataset is another project that tries to evaluate various data exploration techniques. This dataset consists of an attack-free set and 4 sets containing IP spoofing attacks, guessing rlogin or ftp passwords, scanning attacks and network hopping attacks, respectively. The data was captured by TCPDump in about 16 minutes on the MITRE Corp. network. Only TCP and UDP packets with 13 attributes were collected. For detailed information about the packets and for downloading the dataset, please refer to http://ivpr.cs.uml.edu/shootout/network.html.

In our survey, this dataset was mainly used by Kim and Bentley, interested in research on artificial immune system-based IDSs. Balthrop *et al.*, however, questioned this dataset because "it only takes place over a period of about 16 minutes, not enough time to reasonably characterize normal behavior" [29].

Other Benchmarks include the University of New Mexico dataset and the UNIX user dataset. The former was provided by the team of Stephanie Forrest at the University of New Mexico. This team collected several datasets of system calls executed by different programs. For more information, please refer to http://www.cs.unm.edu/~immsec/systemcalls.htm. The later dataset contains 9 sets of sanitized user data drawn from the command histories of 8 UNIX computer users at Purdue University over the course of up to 2 years. For more information on this dataset please refer to http://kdd.ics.uci.edu/databases/UNIX_user_data/UNIX_user_data.html.

Self-produced Datasets Since these benchmarks have shown some shortcomings, researchers sometimes produce their own datasets. However, in a real network environment, it is very hard to guarantee that supposedly normal data are intrusion free indeed. The robust approach introduced by Rhodes *et al.* [237] is able to remove anomalies from training data. Another reason for using self-produced dataset is incomplete training sets, which would decrease the accuracy of IDSs. Therefore, artificial data are generated and merged into the training sets [17, 88, 109, 121, 137, 257].

3.2. *Performance Evaluation*

3.2.1. *Confusion Matrix*

The effectiveness of an IDS is evaluated by its ability to give a correct classification. According to the real nature of

a given event and the prediction from an IDS, four possible outcomes are shown in Table 2, which is known as the confusion matrix. True negatives as well as true positives correspond to a correct operation of the IDS; that is, events are successfully labeled as normal and attacks, respectively; false positives refer to normal events being classified as attacks; false negatives are attack events incorrectly classified as normal events.

Table 2
Confusion Matrix

		Predicted Class	
		Negative Class (Normal)	Positive Class (Attack)
Actual Class	Negative Class (Normal)	True Negative (TN)	False Positive (FP)
	Positive Class (Attack)	False Negative (FN)	True Positive (TP)

Based on the above confusion matrix, the evaluation mainly applies the following criteria to measure the performance of IDSs:

- True Negative Rate (TNR): $\frac{TN}{TN+FP}$, also known as Specificity.
- True Positive Rate (TPR): $\frac{TP}{TP+FN}$, also known as Detection Rate (DR) or Sensitivity. In information retrieval, this is called Recall.
- False Positive Rate (FPR): $\frac{FP}{TN+FP} = 1 - specificity$, also known as False Alarm Rate (FAR).
- False Negative Rate (FNR): $\frac{FN}{TP+FN} = 1 - sensitivity$.
- Accuracy: $\frac{TN+TP}{TN+TP+FN+FP}$
- Precision: $\frac{TP}{TP+FP}$, which is another information retrieval term, and often is paired with "Recall".

The most popular performance metrics is detection rate (DR) together with false alarm rate (FAR). An IDS should have a high DR and a low FAR. Other commonly used combinations include Precision and Recall, or Sensitivity and Specificity.

3.2.2. *Receiver Operating Characteristic*

The Receiver Operating Characteristic (ROC) has its origin in radar signal detection techniques developed during World War II, which was used to characterize the tradeoff between hit rate and false alarm rate over a noisy channel [211]. In intrusion detection, this method is used for counting detection costs or evaluating various detection learning schemes.

An optimal IDS should maximize the DR and minimize the FAR. Normally, the tradeoff between DR and FAR is decided by various parameters of the IDS, such as detection threshold, or the size of a sliding window. The ROC curve plots DR on the Y-axis, against the FAR on the X-axis at different parameter settings. As depicted in Figure 3, by

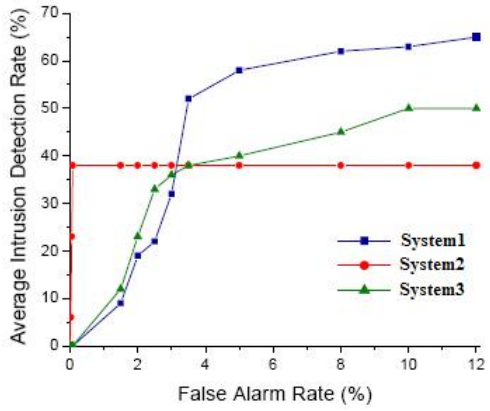


Fig. 3. ROC curves showing the average intrusion detection rates of 3 systems.

changing the values of some parameters, one can obtain the rates shown on the lines. The ROC curves provide us an effective way to compare the performance of systems derived from different parameter settings or the performance of different systems. Figure 3 shows that system1 averagely outperforms the other two systems in this example.

4. Algorithms

In this section, we will review the core computational intelligence approaches that have been proposed to solve intrusion detection problems. These include artificial neural networks, fuzzy sets, evolutionary computation, artificial immune systems, swarm intelligence and soft computing.

4.1. *Artificial Neural Networks*

An Artificial Neural Network (ANN) consists of a collection of processing units called neurons that are highly interconnected according to a given topology. ANNs have the ability of learning-by-example and generalization from limited, noisy, and incomplete data. They have been successfully employed in a broad spectrum of data-intensive applications. In this section, we will review their contributions and performance on intrusion detection domain. This section is organized by the types of ANNs illustrated in Figure 4

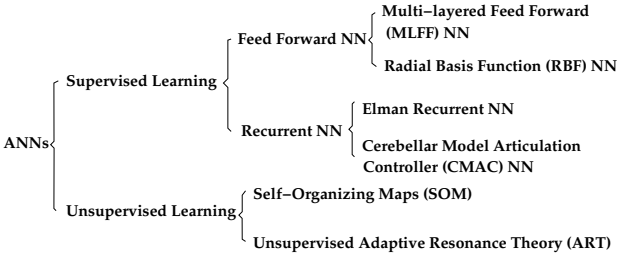


Fig. 4. Types of ANNs reviewed in this section.

4.1.1. *Supervised Learning*

4.1.1.1. *Feed Forward Neural Networks* Feed forward neural networks are the first and arguably the simplest type of artificial neural networks devised. Two types of feed forward neural networks are commonly used in modeling either normal or intrusive patterns.

Multi-layered Feed Forward (MLFF) Neural Networks MLFF networks use various learning techniques, the most popular being back-propagation (MLFF-BP). In the early development of intrusion detection, MLFF-BP networks were applied primarily to anomaly detection on the user behavior level, e.g. [257] and [238]. [257] used information, such as command sets, CPU usage, login host addresses, to distinguish between normal and abnormal behavior, while [238] considered the patterns of commands and their frequency.

Later, research interests shifted from user behavior to software behavior described by sequences of system calls. This is because system call sequences are more stable than commands. Ghosh *et al.* built a model for the *lpr* program [109] and the DARPA BSM98 dataset [108] using MLFF-BP, respectively. A leaky bucket algorithm provided some memory of anomalous events diagnosed by the network, resulting in the temporal characteristics of program patterns being accurately captured.

Network traffic is another indispensable data source. Cannady *et al.* [40] applied MLFF-BP on 10,000 network packets collected from a simulated network environment for misuse detection purpose. Although the training/testing iterations required 26.13 hours to complete, their experiments showed the potential of MLFF-BP as a binary classifier to correctly identify each of the embedded attacks in the test data. MLFF-BP can also be used as a multi-class classifier (MCC). MCC neural networks can either have multiple output neurons [218] or assemble multiple binary neural network classifiers [287]. Apparently, the latter is more flexible than the former when facing a new class.

Except for the BP learning algorithm, there are many other learning options in MLFF networks. [219] compared 12 different learning algorithms on the KDD99 dataset, and found that resilient back propagation achieved the best performance among the neural networks in terms of accuracy (97.04%) and training time (67 epochs).

Radial Basis Function Neural Networks Radial Basis Function (RBF) neural networks are another widely used type of feed forward neural networks. Since they perform classification by measuring the distances between inputs and the centers of the RBF hidden neurons, they are much faster than time consuming back-propagation, and more suitable for problems with large sample size [46].

Research work, such as [144], [197], [236], [288], employed RBF to learn multiple local clusters for well-known attacks and for normal events. Other than being a classifier, the RBF network was also used to fuse results from multiple classifiers [46]. It outperformed five different decision fusion functions, such as Dempster-Shafer combination and Weighted Majority Vote.

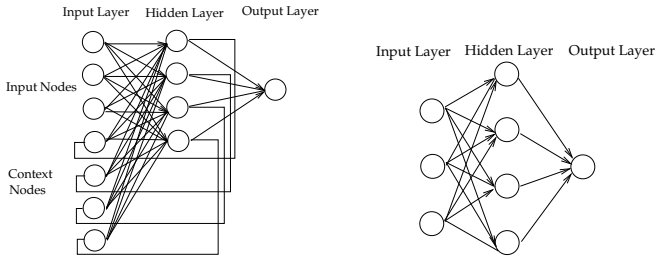
Jiang *et al.* [160] reported a novel approach which integrates both misuse and anomaly detections in a hierarchical RBF network framework. In the first layer, an RBF anomaly detector identifies whether an event is normal or not. Anomaly events then pass an RBF misuse detector chain, with each detector being responsible for a specific type of attack. Anomaly events which could not be classified by any misuse detectors were saved to a database. When enough anomaly events were gathered, a C-Means clustering algorithm clustered these events into different groups; a misuse RBF detector was trained on each group, and added to the misuse detector chain. In this way, all intrusion events will automatically and adaptively be detected and labeled.

Comparison between MLFF-BP and RBF networks Since RBF and MLFF-BP networks are widely used, a comparison between them is naturally required. [160] and [288] compared the RBF and MLFF-BP networks for misuse and anomaly detection on the KDD99 dataset. Their experiments have shown that for misuse detection, BP has a slightly better performance than RBF in terms of detection rate and false positive rate, but requires longer training time, while for anomaly detection, the RBF network improves the performance with a high detection rate and a low false positive rate, and requires less training time (cutting it down from hours to minutes). All in all, RBF networks achieve better performance. The same conclusion was drawn by Hofmann *et al.* on the DARPA98 dataset [143, 144].

Another interesting comparison has been made between the binary and decimal input encoding schemes of MLFF-BP and RBF [197]. The results showed that binary encoding has lower error rates than decimal encoding, because decimal encoding only computes the frequency without considering the order of system calls. Decimal encoding, however, handles noise well and the classifiers can be trained with fewer data. Furthermore, there are fewer input nodes in decimal encoding than in binary encoding, which decreases the training and testing time and simplifies the network structure.

4.1.1.2. *Recurrent Neural Networks* Detecting attacks spread in a period of time, such as slow port scanning, is important but difficult. In order to capture the temporal locality in either normal patterns or anomaly patterns, some researchers used time windows or similar mechanisms [108, 144, 197, 289], or chaotic neurons [281] to provide BP networks with external memory. However, window size should be adjustable in predicting user behavior. When users perform a particular job, their behavior is stable and predictable. At such times a large window size is needed to enhance deterministic behavior; when users are changing from one job to another, behavior becomes unstable and stochastic, so a small window size is needed in order to forget quickly the meaningless past [72]. The incorporation

of memory in neural networks has led to the invention of recurrent links, hence the name Recurrent Neural Networks (RNN) or Elman network, as shown in Figure 5.



(a) RNN (b) MLFF

Fig. 5. Compared with MLFF, parts of the output of RNN at time *t* are inputs in time *t+1*, thus creating internal memories of the neural network.

Recurrent networks were initially used as a forecaster, where a network predicted the next events in an input sequence. When there is a sufficient deviation between the predicted output and the actual events, an alarm is issued. Debar *et al*. [70, 72] modified the traditional Elman recurrent model by giving input at both time *t-1* and time *t*. The learning process used standard back propagation. The authors showed that the accuracy of predicting the next command, given a sequence of previous commands, could reach up to 80%. Ghosh *et al*. [107] compared the recurrent network with an MLFF-BP network as a forecaster on program system call sequences. The results showed that recurrent networks achieved the best performance with a detection accuracy of 77.3% and zero false positives.

Recurrent networks are also trained as classifiers. Cheng *et al*. [51] employed a recurrent network to detect network anomalies in the KDD99 dataset, since network traffic data have the temporal locality property. A truncated-Back-Propagation Through Time (T-BPTT) learning algorithm was chosen to accelerate training speed of an Elman network. They argued for the importance of payload information in network packets. Retaining the information in the packet header but discarding the payload leads to an unacceptable information loss. Their experiment indicated that an Elman network with payload information outperformed an Elman network without such information. Al-Subaie *et al*. [17] built a classifier with an Elman network for the UNM system calls dataset. Their paper is a good source of the comparison of ELMAN and MLFF networks in terms of network structure, computational complexity, and classification performance. The two research works both confirmed recurrent networks outperform MLFF networks in detection accuracy and generalization capability. Al-Subaie *et al*. in addition pointed out a performance overhead being associated with the training and operation of recurrent networks.

The Cerebellar Model Articulation Controller (CMAC) neural network is another type of recurrent networks, who has the capability of incremental learning. It avoids retraining a neural network every time when a new intrusion appears. This is the main reason that Cannady [41, 42] applied CMAC to autonomously learn new attacks. The author modified the traditional CMAC network by adding a feedback from the environment. This feedback would be any system status indicators, such as CPU load or available memory. A modified least mean square learning algorithm was adopted. A series of experiments demonstrated the CMAC effectively learned new attacks in real time based on the feedback from the protected system, and generalized well to similar attack patterns.

4.1.2. *Unsupervised Learning*

Self-Organizing Maps and Adaptive Resonance Theory are two typical unsupervised neural networks. Similar to statistical clustering algorithms, they group objects by similarity. They are suitable for intrusion detection tasks in that normal behavior is densely populated around one or two centers, while abnormal behavior and intrusions appear in sparse regions of the pattern space outside of normal clusters.

4.1.2.1. *Self-Organizing Maps* Self-organizing maps (SOM), also known as Kohonen maps, are single-layer feed forward networks where outputs are clustered in a low dimensional (usually 2D or 3D) grid. It preserves topological relationships of input data according to their similarity.

SOMs are the most popular neural networks to be trained for anomaly detection tasks. For example, Fox *et al*. first employed SOMs to detect viruses in a multiuser machine in 1990 [103]. Later, other researchers [147, 270] used SOMs to learn patterns of normal system activities. Nevertheless, SOMs have been found in the misuse detection, too, where a SOM functioned as a data pre-processor to cluster input data. Other classification algorithms, such as feed forward neural networks, were trained using the outputs from the SOM [35, 43, 161].

Sometimes SOMs map data from different classes into one neuron. Therefore, in order to solve the ambiguities in these heterogeneous neurons, Sarasamma *et al*. [240] suggested to calculate the probability of a record mapped to a heterogeneous neuron being of a type of attack. A confidence factor was defined to determine the type of record that dominated the neuron.

These previous works are all single layer SOMs. Rhodes *et al*. [237], after examining network packets carefully, stated that every network protocol layer has a unique structure and function, so malicious activities aiming at a specific protocol should be unique too. It is unrealistic to build a single SOM to tackle all these activities. Therefore, they organized a multilayer SOM, each layer corresponding to one protocol layer. Sarasamma *et al*. [240] drew a similar conclusion that different subsets of features were good at detecting certain attacks. Hence, they grouped the 41 features of the KDD99 dataset into 3 subsets. A three-layer SOM model was built, accepting one subset of features and heterogeneous neurons from the previous SOM layer. Results showed that false positive rates were significantly re-

duced in hierarchical SOMs compared to single layer SOMs on all test cases.

Lichodzijewski *et al*. employed a two-layer SOM to detect anomaly user behavior [193] and anomaly network traffic [192]. The first layer comprised 6 parallel SOMs, each map clustering one feature. The SOM in the second layer combined the results from SOMs in the first layer to provide an integrated view. Kayacik *et al*. [162, 164, 165] extended Lichodzijewski's work by introducing the third SOM layer, while keeping the first two layers unchanged. The SOM in the third layer was intended to resolve the confusion caused by heterogeneous neurons. In both Kayacik's and Lichodzijewski's work, a Potential Function Clustering method was used between the first and second layer. This clustering algorithm significantly reduced the dimensions seen by neurons in SOMs from the second layer. When comparing their results with best supervised learning solutions, their methods have shown a similar detection rate but a higher FP rate. The major reason, in their perspective, is the availability of suitable boosting algorithms for unsupervised learning, which may be a direction for future research.

Zanero [283, 285] was another supporter who suggested to consider payload of network packets in the analysis. He proposed a multi-layer detection framework, where the first layer used a SOM to cluster the payload, and compressed it into a single feature. This compressed payload feature was then passed on to the second layer as input, together with other features in packet headers. Most classification algorithms can be used in the second tier. Unfortunately, the high dimensional (from 0 to 1460 bytes) payload data greatly decreased the performance of the first layer. Zanero later conceived the *K-means+* [284] algorithm to avoid calculating the distance between each neuron, thus greatly improving the runtime efficiency of the algorithm.

Unlike other unsupervised approaches, SOMs are useful to visualize the analysis. Girardin introduced a visual approach for analyzing network activities [111], which best took advantage of topology-preserving and dimensionality-reducing properties of SOMs. Network events are projected onto a two dimensional grid of neurons, and then each neuron is portrayed as a square within the grid. The foreground color of the square indicates the weights of each neuron. Thus similar network events have similar foreground color, and are grouped together closely. The background color indicates the quality of the mapping. The size of the square identifies the number of events mapped to the unit. Therefore, users can easily tell the rare and abnormal events from the graph, which facilitates users to explore and analyze anomaly events.

If we are using SOMs to visualize the structural features of the data space, SOMs discussed in the previous work would be inappropriate, because they contain small numbers of neurons, which prohibits the emergence of intrinsic structural features in the data space on a map. Emergent SOMs (ESOM), based on simple SOMs, contain thousands to tens of thousands of neurons. The large number of neurons in ESOM is necessary in order to achieve emergence, observe the overall structures and disregard elementary ones. An ESOM with U-Matrix was employed in [214, 215, 216], focusing on the detection of DoS attacks in KDD99 data. Although their work showed very high accuracy (between 98.3% to 99.81%) and a low false alarm rate (between 2.9% to 0.1%), the training procedure suffered from a high computational overhead, especially when the size of the training set was over 10,000.

4.1.2.2. *Adaptive Resonance Theory (ART)* The Adaptive Resonance Theory (ART) embraces a series of neural network models that perform unsupervised or supervised learning, pattern recognition, and prediction, since it has been invented by Stephen Grossberg in 1976. Unsupervised learning models include ART-1, ART-2, ART-3, and Fuzzy ART. Various supervised ones are named with the suffix "MAP", such as ARTMAP, Fuzzy ARTMAP, and Gaussian ARTMAP. Compared with SOMs who cluster data objects based on the absolute distance, ARTs cluster objects based on the relative similarity of input patterns to the weight vector.

Amini *et al*. compared the performance of ART-1 (accepting binary inputs) and ART-2 (accepting continuous inputs) on KDD99 data in [19]. They concluded that ART-1 has a higher detection rate than ART-2, while ART-2 is 7 to 8 times faster than ART-1. This observation is consistent with results in [197]. Later, Amini *et al*. in [20] further conducted their research on self-generated network traffic. This time they compared the performance of ARTs and SOMs. The results showed that ART nets have better intrusion detection performance than SOMs on either offline or online data.

Fuzzy ART nets combine fuzzy set theory and adaptive resonance theory. This combination is faster and more stable than ART nets alone in responding to arbitrary input sequences. Liao *et al*. [190] and Durgin *et al*. [83] are two examples of using Fuzzy ART to detect anomalies. Liao *et al*. deployed Fuzzy ART in an adaptive learning framework which is suitable for dynamic changing environments. Normal behavior changes are efficiently accommodated while anomalous activities can still be identified. Durgin *et al*. investigated in detail the capabilities of SOMs and Fuzzy ARTs. Both SOMs and Fuzzy ARTs show promise in detecting network abnormal behavior. The sensitivity of Fuzzy ARTs seems to be much higher than that of SOMs.

4.1.3. *Summary*

In this section, we reviewed previous research contributions on artificial neural networks in intrusion detection. Various supervised and unsupervised ANNs were employed in misuse and anomaly detection tasks. All these research works took advantage of ANNs' ability to generalize from limited, noisy, and incomplete data. Some researchers attempted to address disadvantages of ANNs as well. For example, [51, 218, 283, 288] tried to reduce the long training time; [160, 237, 287] used the ensemble approach to solve

the retraining problem of ANNs when facing a new class of data; for the black box nature of ANNs, [144] extracted attack patterns from the trained ANNs in comprehensible format of if-then rules.

To improve detection accuracy, the following practices have been proven useful in ANNs:

– Temporal locality property. Studies [107, 108] have confirmed that the temporal locality property exists in normal as well as in intrusive behavior in the intrusion detection field. In ANNs time can be represented either explicitly or implicitly. [20] and [193] concluded that explicit representation of time does not accurately identify intrusions. When it comes to implicitly represent time, researchers either adopted neural networks with short-term memory, such as recurrent nets, or mapped temporal patterns to spatial patterns for networks without memory. Most of the works chose sliding windows, which gather n successive events and then form one input vector from them (e.g., [35, 40, 144, 147, 165, 181, 192, 197]). Other mechanisms include the leaky bucket algorithm [108], layer-window statistical preprocessors [289], chaotic neurons [281], and using the time difference between two events [20]. All these results confirm that designing a detection technique that capitalizes on the temporal locality characteristic of the data can contribute to better results.
– Network structure. Intrusions are evolving constantly. Sometimes attacks are aiming at a specific protocol, while sometimes they are aiming at a specific operating system or application. Therefore it would be unreasonable to expect a single neural network to successfully characterize all such disparate information. Previous research reminds us that networks with ensemble or hierarchical structure achieve better performance than single layer ones, no matter whether they are supervised or unsupervised ([40, 160, 165, 185, 240, 287]).
– Datasets and features. Neural networks only recognize whatever is fed to them in the form of inputs. Although they have the ability of generalization, they are still unable to recognize unseen patterns sometimes. One cause of this difficulty is incomplete training sets. To address this problem, randomly generated anomalous inputs ([17, 109, 257]) are inserted into the training set with the purpose of exposing the network to more patterns, hence making the training sets more complete. Selecting good feature sets is another way to improve performance. [240] identified that different subsets of features are good at detecting certain types of attacks. [165] conducted a series of experiments on a hierarchical SOM framework on KDD99 data. They found that 6 basic features are sufficient for recognizing a wide range of DoS attacks, while 41 features are necessary to minimize the FP rate. Among the 6 basic features, protocol and service type appear to be the most significant.

4.2. *Fuzzy Sets*

The past decades have witnessed a rapid growth in the number and variety of applications of fuzzy logic. Fuzzy logic, dealing with the vague and imprecise, is appropriate for intrusion detection for two major reasons. First, the intrusion detection problem involves many numeric attributes in collected audit data, and various derived statistical measures. Building models directly on numeric data causes high detection errors. For example, an intrusion that deviates only slightly from a model may not be detected or a small change in normal behavior may cause a false alarm. Second, the security itself includes fuzziness, because the boundary between the normal and anomaly is not well defined. This section will spell out how fuzzy logic can be utilized in intrusion detection models.

4.2.1. *Fuzzy Misuse Detection*

Fuzzy misuse detection uses fuzzy models, such as fuzzy rules or fuzzy classifiers to detect various intrusive behavior. When fuzzy logic was initially introduced to the intrusion detection domain, it was integrated with expert systems. Fuzzy rules substituted ordinary rules so as to map knowledge represented in natural languages more accurately to computer languages. Fuzzy rules were created by security experts based on their domain knowledge. For example, the Fuzzy Intrusion Recognition Engine (FIRE) proposed by Dickerson *et al.* used fuzzy rules to detect malicious network activities [80, 81]. Although the fuzzy sets and their membership functions were decided by a fuzzy C-means algorithm, hand-encoded rules were the main limitation of their work.

Avoiding hand-coded fuzzy rules is the one main research topic in fuzzy misuse detection. Commonly employed methods are generating rules based on the histogram of attribute values [10, 11], or based on partition of overlapping areas [10, 11, 184], or based on fuzzy implication tables [291], or by fuzzy decision trees [194], or by association rules [84] or by SVMs [279]. Due to the rapid development of computational intelligence, approaches with learning and adaptive capabilities have been widely used to automatically construct fuzzy rules. These approaches are artificial neural networks, evolutionary computation, and artificial immune systems. We will investigate them in detail in Section 4.6 on "Soft Computing".

Another application of fuzzy logic is decision fusion, which means that fuzzy logic fuses the outputs from different models to present a final fuzzy decision. For instance, Cho *et al.* trained multiple HMMs to detect normal behavior sequences. The evaluations from HMMs were sent to the fuzzy inference engine, which gave a fuzzy normal or abnormal suggestion [56]. Similar fuzzy inference systems were used to combine the decisions of multiple decision trees [259], multiple neuro-fuzzy classifiers [261], and other models [241].

4.2.2. *Fuzzy Anomaly Detection*

Fuzzy logic plays an important role in anomaly detection, too. Current research interests are to build fuzzy normal behavior profiles with the help of data mining.

Bridges *et al.* suggested to use fuzzy association rules and fuzzy sequential rules to mine normal patterns from audit data [36, 37]. Their work was an extension of the fuzzy association rule algorithm proposed by Kuok *et al.* [180] and the fuzzy sequential rule algorithm by Mannila and Toivonen [208]. To detect anomalous behavior, fuzzy association rules mined from new audit data were compared with rules mined in the training phase. Hence, a similarity evaluation function was developed to compare two association rules [202, 203]. Florez *et al.* [94] later described an algorithm for computing the similarity between two fuzzy association rules based on prefix trees, so better running time and accuracy were achieved. El-Semary *et al.* compared the test data samples against fuzzy association rules directly by a fuzzy inference engine [84].

Fuzzy logic also worked with another popular data mining technique, outlier detection, on anomaly detection. According to the hypothesis of IDSs, malicious behavior is naturally different from normal behavior. Hence, outliers should be considered as abnormal behavior. Therefore, the fuzzy C-Medoids algorithm [246] and the fuzzy C-Means algorithm [52, 53, 54, 141] are two common clustering approaches to identify outliers. As all clustering techniques, they are affected by the "curse of dimensionality", thus suffering performance degradation when confronted with datasets of high dimensionality. Feature selection is a necessary data pre-processing step. For example, Principal Component Analysis [141, 246] and Rough Sets [52, 53, 54] can be applied on datasets before being clustered.

4.2.3. *Summary*

Fuzzy logic, as a means of modeling the uncertainty of natural language, constructs more abstract and flexible patterns for intrusion detection, thus greatly increasing the robustness and adaptation ability of detection systems. Two research directions are active in the fuzzy logic area. Algorithms with learning and adaptive capabilities are investigated on the issue of automatically designing fuzzy rules. Popular methods include but not limited to: association rules, decision trees, evolutionary computation, artificial neural networks. In turn, fuzzy logic helps to enhance the understandability and readability of some machine learning algorithms, such as SVMs or HMMs. The use of fuzzy logic smoothes the abrupt separation of normality and abnormality. From the research work reviewed in this section, and the work will be mentioned later in the Soft Computing section, the popularity of fuzzy logic clearly demonstrates the successfulness of fuzzy logic in fulfill these two roles. We believe that fuzzy logic will remain an active research topic in the near future.

4.3. *Evolutionary Computation*

Evolutionary Computation (EC) in computer science, as creative as the evolution in nature, is capable of addressing real-world problems with great complexity. These problems normally involve randomness, complex nonlinear dynamics, and multimodal functions, which are difficult for traditional algorithms to conquer [95]. In this section, we will review the role of EC in the intrusion detection field. Some important issues, such as evolutionary operators, niching, and fitness functions will be discussed.

This survey focuses on Genetic Algorithms (GA) [148] and Genetic Programming (GP) [179]. GA and GP differ with respect to several implementation details, but conceptually they are nearly identical. Generally speaking, evolution in them can be described as a two-step iterative process, consisting of random variation and selection [95], as shown in Figure 6.

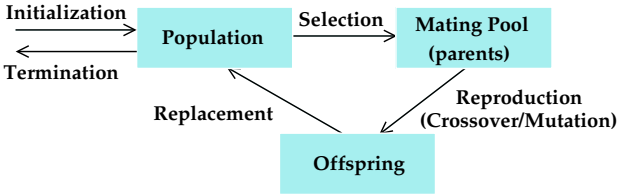


Fig. 6. The flow chart of a typical evolutionary algorithm

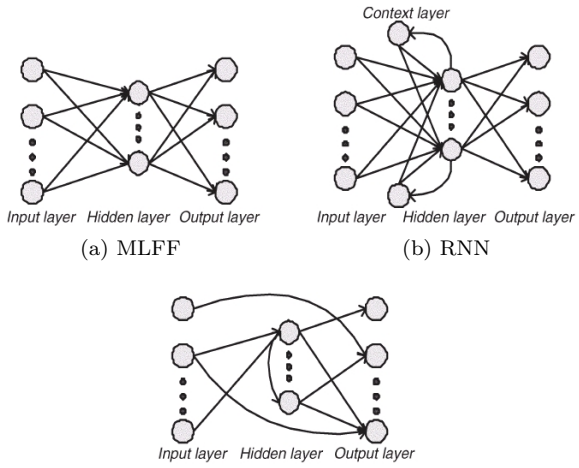
4.3.1. *The Roles of EC in IDS*

4.3.1.1. *Optimization* Some researchers are trying to analyze the problem of intrusion detection by using a multiple fault diagnosis approach, which is analogous to the process of human beings being diagnosed by a physician when they are suffering from a disease. For a start, an events-attacks matrix is defined, which is known as pre-learned domain knowledge (analogous to knowledge possessed by a physician). The occurrence of one or more attacks is required to be inferred from newly observed events (analogous to symptoms). Such a problem is reducible to a zero-one integer problem, which is NP-Complete. [64] and [212] both employed GA as an optimization component, but [212] used a standard GA, while [64] used a micro-GA in order to reduce the time overhead normally associated with a GA. Both works coded solutions in binary strings, where the length of a string was the number of attacks, and 1's or 0's in a genome indicated if an attack was present. The fitness function in both works were biased to individuals who can predict a maximum number of intrusion types (number of 1's in chromosomes), while avoiding to warn of attacks that did not exists (unnecessary 1's in chromosomes). Diaz-Gomez *et al.* corrected the fitness definition used in [212] after careful analysis [77, 78] and mathematical justification [76], and further refined it in [79].

4.3.1.2. *Automatic Model Structure Design* ANNs and clustering algorithms are two popular techniques to build

intrusion detection models. The problematic side of them is that one has to decide an optimal network structure for the former, and the number of clusters for the latter. To remedy these drawbacks, evolutionary algorithms are introduced for automatic design purpose.

[144] evolved an RBF neural network to classify network traffic for the DARPA98 dataset. The GA was used to select an optimal feature set and to learn the structure of RBF net, such as the type of basis function, the number of hidden neurons, and the number of training epochs. Evolving Fuzzy Neural Network (EFuNN) is another example of this kind. It implements a Mamdani-type fuzzy inference system where all nodes are created during learning [47, 190]. In contrast to evolving networks with fixed topologies and connections, Han *et al*. [133] proposed a Evolutionary Neural Network (ENN) algorithm to evolve an ANN which detected anomaly system call sequences. A matrix-based genotype representation was implemented, where the upper right triangle was the connectivity information between nodes, and the lower left triangle described the weights between nodes. Consequently, this network has no structural restrictions, and is more flexible, as shown in Figure 7. [278]



(a) MLFF (b) RNN

(c) ENN

Fig. 7. Comparing structures of different artificial neural networks [133].

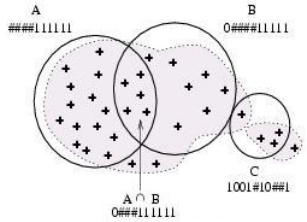
presented a misuse detection model constructed by the understandable Neural Network Tree (NNTree). NNTree is a modular neural network with the overall structure being a decision tree, and each non-terminal node being an expert neural network. The GA recursively designed these networks from the root node. The designing process was, in fact, a multiple objective optimization problem, which kept the partition ability of the networks high, and the size of trees small. [50] investigated the possibility of evolving neural networks by an Estimation of Distribution Algorithm (EDA), a new branch of EC. A floating point coding scheme was adopted to represent weights, thresholds and flexible activation function parameters. The modeling and sampling step in the EDA improves search efficiency, because sampling is guided by global information extracted through modeling to explore promising areas.

The experiment results of the above works all confirmed that automatically designed networks outperformed conventional approaches in detection performance. [133] further verified evolutionary approaches reduced the training time.

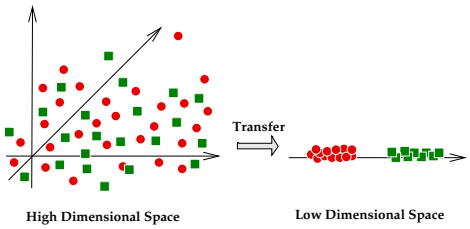
As for clustering algorithms, evolutionary algorithms shorten the tedious and time-consuming process of deciding appropriate cluster centers and number of clusters. Leno *et al*. [186] first reported their work of combining unsupervised niche clustering with fuzzy set theory for anomaly detection and applied it to network intrusion detection. Here "unsupervised" means that the number of clusters is automatically determined by a GA. An individual, representing a candidate cluster, was determined by its center, an n-dimensional vector with n being the dimension of the data samples, and a robust measure of its scale (or dispersion) δ^2. The scale was updated every generation based on density of a hypothetical cluster. In [198, 200] by Lu *et al*., a GA was applied to decide the number of clusters based upon a Gaussian Mixture Model (GMM). This model assumed that the entire data collection can be seen as a mixture of several Gaussian distributions, each potentially being a cluster. An entropy-based fitness function was defined to measure how well the GMMs approximated the real data distribution. Thereafter, a K-means clustering algorithm was run. In contrast, [290] reversed the order of the K-means and evolutionary approaches. K-means was used to decide potential cluster centers, followed by the GA refining cluster centers. The authors integrated a simulated annealing algorithm as selection operator.

4.3.1.3. *Classifiers* There are two streams of applying evolutionary algorithms as classifiers: classification rules and transformation functions. A classification rule is the rule with if-then clause, where a rule antecedent (IF part) contains a conjunction of conditions on predicting attributes, and the rule consequent (THEN part) contains the class label. As depicted in Figure 8a, the task of EC is to search for classification rules (represented as circles) who cover the data points (denoted as "+") of the unknown concept (represented as shaded regions). In this sense, evolving classification rules is regarded as conception learning. Classification can also be achieved by a transformation function, which transforms data into a low dimensional space, i.e. 1D or 2D, such that a simple line can best separate data in different classes (shown in Figure 8b).

A GA uses fixed length vectors to represent classification rules. Antecedents and class label in if-then rules are encoded as genes in a chromosome (shown in Figure 9a). Either binary [159, 213, 222] or real-number [117, 188, 189, 233, 248] encoding schemes are conceived. A "don't care" symbol, $*$, is included [117, 159, 188, 189, 213, 222, 233, 248] as a wild card that allows any possible value in a gene, thus improving the generality of rules. GP, on the other hand, often uses trees illustrated in Figure 9b [199, 280],



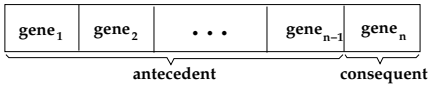
(a) Classification Rules [149]



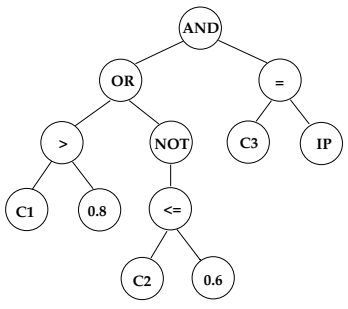
(b) Classification Transformation Functions

Fig. 8. Two streams of applying evolutionary algorithms as classifiers.

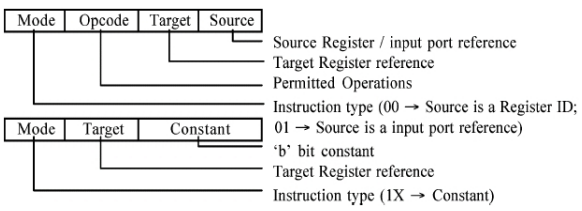
or decision trees [96, 97] to represent classification rules. Compared with a GA which connects conditions in the antecedent only by the AND operator, GP has richer expressive power as it allows more logic operators, such as OR, NOT, etc. Further, if the logic operators in Figure 9b are replaced by arithmetic operators, the tree then represents a transformation function [89]. Linearly structured GP is another way to represent the transformation function with a sequence of operators acting on operands (shown in Figure 9c). A GA, in contrast, represents the transformation function in a linear vector containing coefficients or weights of input attributes.



(a) GA Chromosome



(b) Tree GP Chromosome



(c) Linear GP Chromosome [254]

Fig. 9. Chromosome structures of GA, Tree GP and Linear GP.

Research works that explored the evolution of classifiers by GAs for intrusion detection have been summarized in Table 3. Among them, [55] and [275] are two research works on searching for transformation functions by GAs. The function has the following format: $C(\chi) = \sum_{j=1}^{n}(w_j \times \chi_j)$, where n is the number of attributes, w_j is a weight [275] or coefficient [55] of attribute χ_j. A threshold value or a separation line is established. When $C(\chi)$ exceeds this threshold value, input χ is flagged as malicious attacks [55] or normal [275].

The rest works shown in Table 3 employed GA to evolve classification rules. One difference between binary and multiple classification rules lies in representation. In binary classification, since all rules have the same class label, the "output" part can be left out of the encoding. Researchers

Table 3
Classifiers Evolved by GA

Type	Research Works
Binary Classifiers	[55], [159], [188], [189], [213], [222], [248], [274], [275]
Multi-classifiers	[32], [59], [114], [117], [233], [242], [243], [244], [245]

in [32, 117, 159, 188, 189, 233, 248] all suggested to consider niching in basic GAs when evolving classification rules. Niching helps to cover all data samples with a minimum set of accurate rules. Some sophisticated GAs were investigated, too. [213] and [222] used REGAL to model normal network traffic on IES and DARPA98 data. REGAL [110] is a distributed GA system, designed for learning First Order Logic concept descriptions from examples. Another group in Australia reported initial attempts to extend XCS, an evolutionary Learning Classifier System (LCS), to intrusion detection problems. The GA was responsible for introducing new rules into the population, and its role had been examined by experiments in [245]. The authors proposed several modifications on XCS to improve detection accuracy, such as mutation and deletion operator, and a distance metric for unseen data in the testing phase [59]. They further presented an analysis and comparison of two classifier systems (XCS and UCS), and other machine learning algorithms on intrusion detection [245]. Experiments showed that XCS was significantly better than UCS, but both XCS and UCS were competitive approaches for intrusion detection. For the overall framework, please refer to [243].

Research on evolving classifiers by GP is summarized in Table 4. Among these, Lu *et al.* [199], Yin *et al.* [280] and Folino *et al.* [96, 97] evolved classification rules, while the rest evolved transformation functions. Every contributions has its own flavor in solving intrusion detection problems; for example, Crosbie *et al.* [58] used Automatically Defined Function to ensure type safety in tree-based GP; Folino *et al.* evolved decision trees for multi-classification purposes;

Table 4
Classifiers Evolved by GP

Type		Research Work
Binary Classifiers	Tree-based GP	[58], [199], [280]
	LGP	[8], [9], [131], [138], [182], [183], [220], [252], [253], [254]
Multi-classifiers	Tree-based GP	[89], [96], [97]
	LGP	[191]

Lu *et al*. seeded the initial population with patterns of known attacks.

Crosbie [58] and Folino *et al*. [96, 97] both stressed the cooperation among individuals. The former organized the system by autonomous agents, each of which was a GP-evolved program detecting intrusions from only one data source. The latter deployed their system in a distributed environment by using the island model. Each node was an island and contained a GP-based learning component enhanced with a boosting algorithm. Islands evolved independently, but the best individuals were asynchronously exchanged by a migration process, after a fixed number of generations.

Abraham and his research team [8, 9, 131, 220] and Song *et al*. [252, 253, 254] are two research groups working on LGP and its application in intrusion detection. Abraham's group focused on investigating basic LGP and its variations, such as Multi-Expression Programming (MEP) [224] and Gene Expression Programming (GEP) [93], to detect network intrusion. Experiments, in comparing LGP, MEP, GEP and other machine learning algorithms, showed that LGP outperformed SVMs and ANNs in terms of detection accuracy at the expense of time [219, 220]; MEP outperformed LGP for Normal, U2R and R2L classes and LGP outperformed MEP for Probe and DoS classes [8, 9, 131]. Although LGP and MEP both outperformed GEP in all classes, GEP still reached a classification accuracy greater than 95% for all classes [9]. Song *et al*. implemented a page-based LGP with a two-layer subset selection scheme to address the binary intrusion detection classification problem. Page-based LGP meant that an individual was described in terms of a number of pages, where each page had the same number of instructions. Page size was dynamically changed when the fitness reached a "plateau" (fitness does not change for several generations). Since intrusion detection benchmarks are highly skewed, they pointed out that the definition of fitness should reflect the distribution of class types in the training set. Two dynamic fitness schemes, dynamic weighted penalty and lexicographic fitness, were introduced. The application of their algorithms to other intrusion detection related research can be found in [182, 183].

The above mentioned transformation functions evolved by GPs were for binary classification. Therefore, Faraoun *et al*. [89] and Lichodzijewski *et al*. [191] investigated their applications in multi-category classification. Faraoun *et al*. implemented multi-classification in two steps. In the first step, a GP mapped input data to a new one-dimensional space, and in the second step, another GP mapped the output from the first step to class labels; Lichodzijewski *et al*. proposed a bid-based approach for coevolving LGP classifiers. This approach coevolved a population of learners that decomposed the instance space by way of their aggregate bidding behavior.

Besides GA and GP, Wilson *et al*. [274] investigated the possibility of evolving classifiers by Grammatical Evolution (GE). GE utilized a separate genotypic and phenotypic representation. The genotypic representation was translated into the phenotypic form using a Context Free Grammar (CFG), typically of a Backus-Naur Form (BNF) [225]. In their work, an SQL selection statement in BNF form was firstly designed; then a binary string in the genotype was eventually translated into an SQL selection statement in the phenotype. Such a phenotypic representation accelerates fitness evaluation because a simple SQL query takes no time. The authors achieved favorable results for classifying both normal and abnormal traffic on the KDD99 dataset.

4.3.2. *Niching and Evolutionary Operators*

4.3.2.1. *Niching* Most EC applications have focused on optimization problems, which means that individuals in the population compete with others for a global optimum. However, pattern recognition or concept learning is actually a multimodal problem in the sense that multiple rules (see Figure 8a) or clusters ([186]) are required to cover the unknown knowledge space (also known as "set covering" problem). In order to locate and maintain multiple local optima instead of a single global optimum, niching is introduced. Niching strategies have been proven effective in creating subpopulations which converge on local optima, thus maintaining diversity of the population [102].

Within the context of intrusion detection, both sharing and crowding are applied to encourage diversity. [163, 188, 189] employed fitness sharing, while [248] employed crowding and [186] employed deterministic crowding (DC). DC is an improved crowding algorithm, which nearly eliminates replacement errors in De Jong's crowding. Consequently, DC is effective to discover multiple local optima compared to no more than 2 peaks in De Jong's [206]. Unfortunately, there is no experimental result available in [248], so we cannot estimate the limitations of De Jong's crowding in intrusion detection problems. Hamming distance [188, 189, 248] or Euclidean distance [163] were used to measure the similarity between two individuals in both niching schemes.

However, defining meaningful and accurate distance measures and selecting an appropriate niching radius are difficult. In addition, computational complexity is an issue for these algorithms. The shared fitness evaluation requires, at each generation, a number of steps proportional to M^2, with M being the cardinality of the population [110]. So, Giordana *el al*. introduced a new selection operator in REGAL, called *Universal Suffrage*, to achieve niching [110]. The individuals to be mated are not chosen directly from

the current population, but instead indirectly through the selection of an equal number of data points. It is important to notice that only individuals covering the same data points compete, and the data points (stochastically) "vote" for the best of them. In XCS, the niching mechanism was demonstrated via reward sharing. Simply, an individual shares received rewards with those who are similar to them in some way [59].

[199] implemented niching neither via fitness sharing nor via crowding, but via token competition [187]. The idea is as follows: A token is allocated to each record in the training dataset. If a rule matches a record, its token will be seized by the rule. The priority of receiving the token is determined by the strength of the rules. On the other hand, the number of tokens an individual acquires also helps to increase its fitness. In this way, the odds of two rules matching the same data is decreased, hence the diversity of the population is maintained.

4.3.2.2. *Evolutionary Operators* In EC, during each successive generation, some individuals are selected with certain probabilities to go through crossover and mutation for the generation of offspring. Table 5 summarizes commonly used selection, crossover and mutation operators employed in intrusion detection tasks.

Table 5
Evolutionary Operators Employed in Intrusion Detection Tasks

Operators		Research Work
Selection	Roulette wheel	[59], [89], [159]
	Tournament	[64], [79], [138], [252]
	Elitist	[144], [117]
	Rank	[133], [274]
Crossover	Two-point	[59], [64], [89], [117], [159], [199], [213], [222], [280]
	One-point	[32], [133], [186], [274], [278]
	Uniform	[144], [213], [222]
	Arithmetical	[144]
	Homologous	[138], [183], [182], [252], [253], [254]
Mutation	Bit-flip	[59], [64], [144], [159], [186], [213], [222], [274], [278]
	Inorder mutation	[233]
	Gaussion	[144]
	One point	[89], [199], [280]

Some special evolutionary operators were introduced to satisfy the requirements of representation. For example, page-based LGP algorithms [183, 182, 252, 253, 254] restricted crossover to exchanging pages rather than instructions between individuals. Mutation operators took two forms: in the first case the mutation operator selected two instructions with uniform probability and performed an EX-OR on the first instruction with the second one; the second mutation operator selected two instructions in the same individual with uniform probability and then exchanged their positions. Hansen *et al*. [138] proposed a homologous crossover in LGP attempting to mimic natural evolution more closely. With homologous crossover, the two evolved programs were juxtaposed and the crossover was accomplished by exchanging sets of continuous instruction blocks having the same length and the same position between the two evolved programs.

Most researchers have confirmed the positive role mutation played in the searching process. However, they held different opinions about crossover in multimodal problems whose population contains niches. A mating restriction was considered when individuals of different niches were crossed over. Recombining arbitrary pairs of individuals from different niches may be conducive to the formation of unfit or lethal offspring. For example, if crossover were conducted on the class label part, which means rules in different classes exchange their class labels, it would cause a normal data point to be anomalous or vice versa. [233] applied mutation, but not crossover, to produce offspring; [64] only applied mutation and crossover to the condition-part of rules; [186] introduced an additional restriction on the deterministic crowding selection for restricting the mating between members of different niches.

Except for these three operators, many other operators were conceived for improving detection rate, maintaining diversity or other purposes. Among them, seeding and deletion are two emerging operators that are adopted by many EC algorithms in intrusion detection applications.

- Seeding [59, 110]. As discussed earlier, evolving classification rules can be regarded as a "set covering" problem. If some instances are not yet covered, seeding operators will dynamically generate new individuals to cover them. Normally, this method is used to initialize the first population at the beginning of the searching.
- Deletion [59]. EC works with a limited population size. When a newly generated individual is being inserted into the population, but the maximum population size is reached, some old individuals have to be removed from the population. In traditional EC, where a global optimum is targeted, the less fit individuals are preferably replaced. However, for multimodal problems, other criteria in addition to fitness, such as niches or data distribution, should be considered to avoid replacement errors. [59] extended the deletion operator of XCS by considering class distribution, especially for highly skewed datasets. For example, normal instances constitute approximately 75% of total records in the KDD99 dataset. Therefore, rules which cover normal data points will have a higher fitness than others, which implies that rules for the normal class have a much lower chance to be deleted compared to rules for other classes. So integrating class distribution into the deletion operator allows it to handle minority classes.
- Adding and Dropping. These two operators are variations of mutation. When evolving rules, dropping means re-

move a condition from the representation, thus resulting in a generalized rule [199, 280]. On the contrary, adding conditions results in a specialized rule. [133] employed adding and dropping to add a new connection between neurons, and delete the connection between neurons, respectively.

4.3.3. *Fitness Function*

An appropriate fitness function is essential for EC as it correlates closely with the algorithm's goal, thus guiding the search process. Intrusion detection systems are designed to identify intrusions with accuracy. Therefore, accuracy should be a major factor when yielding a fitness function. In Table 6, we categorize the fitness function from research work we surveyed. The categorization is based on three terms: detection rate (DR), false positive rate (FPR) and conciseness.

The research contributions in the first row are all devoted to anomaly detection problems. Since no attack is presented in the training phase, DR is not available. Their fitness functions may vary in format, but they all look for models which cover most of the normal data. In this example, $H(C_i)$ represents the entropy of data points who belong to cluster C_i, and $H_{max}(C_i)$ is the theoretical maximum entropy for cluster C_i.

Accuracy actually requires both the DR and FPR. Ignoring either of them will cause misclassification errors. A good IDS should have a high DR and a low FPR. The first example in the second row directly interprets this principle. α stands for the number of correctly detected attacks, A the number of total attacks, β the number of false positives, and B the total number of normal connections. As we know, patterns are sometimes represented as if-then clause in IDSs, so in the second example, the support-confidence framework is borrowed from association rules to determine the fitness of a rule. By changing weights w_1 and w_2, the fitness measure can be used for either simply identifying network intrusions or precisely classifying the types of intrusion [117]. The third example considers the absolute difference between the prediction of EC (φ_p) and the actual outcome (φ).

Conciseness is another interesting property that should be considered. This is for two reasons: concise results are easy to understand, and concise results avoid misclassification errors. The second reason is less obvious. Conciseness can be restated as the space a model, such as a rule, or a cluster, uses to cover a dataset. If rule A and rule B have the same data coverage, but rule A is more concise than B, so A uses less space than B does when covering the same dataset. Therefore the extra space of B is more prone to cause misclassification errors. Apparently the first example of this kind considers all three terms, where length correlates with conciseness. The second example of this type considers the number of counterexamples covered by a rule (w), and the ratio between the number of bits equal to 1 in the chromosome and the length of chromosome (z), which is the conciseness of a rule. A is a user-tunable parameter. The fitness function in [186] also preferred clusters with small radius if they covered the same data points.

4.3.4. *Summary*

In this section, we reviewed the research in employing evolutionary computation to solve intrusion detection problems. As is evident from the previous discussion, EC plays various roles in this task, such as searching for an optimal solution, automatic model design, and learning for classifiers. In addition, experiments reasserted the effectiveness and accuracy of EC. However, we also observed some challenges in EC, as listed below. Solving these challenges, to some degree, will further improve the performance of EC-based intrusion detection.

- No reasonable termination criterion. Most current works simply set the termination criterion as a pre-specified number of iterations, or a threshold of fitness. Such a criterion may be helpful when searching for the global optimum, but inappropriate for multiple local optima. The experiment of [244] showed that it is necessary to stop evolution in LCS using a stopping criterion other than the maximum number of generations. Therefore, more research work is required to investigate a reasonable termination criterion.
- Niching. Sharing and crowding are two commonly used niching schemes, with the purpose of maintaining the diversity of a population. In the context of intrusion detection, some researchers advocate that fitness sharing is more suitable, such as [189], while others support crowding. Hence, the question arises: are they equally useful for intrusion detection? If not, which one is better? Learning intrusion behavior is equivalent to conception learning, which is always looking for multiple solutions. Although niching is capable of discovering and maintaining multiple local optima, there is no guarantee that a complete set of solutions will be returned.
- Distributed EC models. Training sets in intrusion detection are normally generated from network traffic dumps and event logs, which have large volume. This makes evaluating the validity of a candidate solution in EC even more expensive and time consuming. In contrast to monolithic architectures, distributed models [97, 110, 144] have the advantage of assigning each node a portion of the data, hence they put less burden on fitness evaluation. In addition, islands are trained simultaneously and independently, so they can be added to and removed from the system dynamically. However, there are many issues deserving careful investigation, such as evolutionary models or communication mechanisms in a distributed environment.
- Unbalanced data distribution. One important feature of intrusion detection benchmarks is their high skewness. Take the KDD99-10% dataset as an example: there are 391,458 instances in the DoS class while only 52 instances are in the U2R class. Both [59] and [252] pointed out in-

Table 6
Fitness Summary

Factors			Examples	References
DR	FPR	Conciseness		
×	√	×	$\frac{H(C_i)}{H_{max}(C_i)}$	[133], [186], [200], [198]
√	√	×	$\frac{\alpha}{A} - \frac{\beta}{B}$	[55], [79], [89], [159], [183], [233], [248], [275], [290]
			$w_1 \times support + w_2 \times confidence$	[32], [117], [199], [274], [280]
			$1 - \lvert\varphi_p - \varphi\rvert$	[27], [58], [131], [188], [189], [252]
√	√	√	$w_1 \times sensitivity + w_2 \times specificity + w_3 \times length$	[114]
			$(1 + Az) \times e^{-w}$	[64], [213], [222]

dividuals which had better performance on frequently occurring connection types would be more likely to survive, even if they performed worse than competing individuals on the less frequent types. Therefore, when designing an intrusion detection system based on EC approaches, one should consider how to improve the accuracy on relatively rare types of intrusion without compromising performance on the more frequent types.

4.4. *Artificial Immune Systems*

The *human immune system* (HIS) has successfully protected our bodies against attacks from various harmful pathogens, such as bacteria, viruses, and parasites. It distinguishes pathogens from self tissues, and further eliminates these pathogens. This provides a rich source of inspiration for computer security systems, especially intrusion detection systems. According to [167, 251], features gleaned from the HIS satisfy the requirements of designing a competent IDS [146, 167]. Hence, applying theoretical immunology and observed immune functions, its principles, and its models to IDS has gradually developed into a new research field, called *artificial immune system* (AIS).

AIS based intrusion detection systems perform anomaly detection. Instead of building models for the normal, they generate non-self (anomalous) patterns by given normal data only, as Figure 10 illustrated. Any matching to non-self patterns will be labeled as an anomaly.

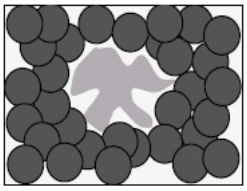


Fig. 10. The goal of AIS-based IDSs is to generate all patterns, denoted as black circles, which match none of the normal data. The shaded region represents a space containing only normal data [146].

In this section, we will review research progress on immune system inspired intrusion detection. Although review work for AISs [22, 61, 67, 98, 153] and their application to the intrusion detection domain [16, 170] exist, our review is different in that it focuses on two perspectives: tracking the framework development of AIS based IDSs and investigating key elements shown in Figure 11 when engineering an AIS-based intrusion detection system [67]. In recent years, research on AIS is extended to the study of innate immune systems, in particular to the danger theory proposed by Matzinger [209, 210]. Hence, the last part of this section will present intrusion detection motivated by danger theory.

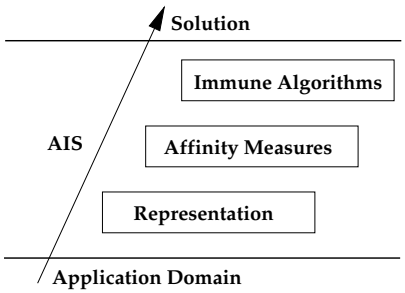


Fig. 11. The framework to engineer an AIS. Representation creates abstract models of immune cells and molecules; affinity measures quantify the interactions among these elements; algorithms govern the dynamics of the AIS [67].

4.4.1. *A Brief Overview of Human Immune System*

Before we start the discussion of AIS models, a brief overview of the HIS will be necessary. A more detailed introduction of the HIS can be found elsewhere, see [68]. Our human immune system has a multi-layered protection architecture, including physical barriers, physiologic barriers, an innate immune system and an adaptive immune system. Compared to the first three layers, the adaptive immune system is capable of adaptively recognizing specific types of pathogens, and memorizing them for accelerated future responses [146]. It is the main inspiration for AISs.

The adaptive immune system is a complex of a great variety of molecules, cells, and organs spread all over the body, rather than a central control organ. Among its cells, two lymphocyte types, T cells and B cells, cooperate to distinguish self from non-self (known as antigens). T cells

recognize antigens with the help of *major histocompatibility complex* (MHC) molecules. *Antigen presenting cells* (APC) ingest and fragment antigens to peptides. MHC molecules transport these peptides to the surface of APCs. Receptors of T cells will bind with these peptide-MHC combinations, thus recognizing antigens. On the contrary, the receptors of B cells directly bind to antigens. The bindings actually are chemical bonds between receptors and epitopes/peptides. The more complementary the structure and the charge between receptors and epitopes/peptides are, the more likely the binding will occur. The strength of the bond is termed "affinity".

T cells and B cells are developed and matured within the thymus and bone marrow tissues, respectively. To avoid autoimmunity, T cells and B cells must pass negative selection stage, where lymphocytes who match self cells are killed. Prior to negative selection, T cells undergo positive selection. This is because in order to bind with the peptide-MHC combinations, they must recognize self MHC first. So the positive selection will eliminate T-cells with weak bonds to self MHC. T cells and B cells which survive the negative selection become mature, and enter the blood stream to perform the detection task. These mature lymphocytes have never encountered antigens, so they are naive.

Naive T cells and B cells can still possibly autoreact with self cells, because some peripheral self proteins are never presented during the negative selection. To prevent self attack, naive cells need two signals in order to be activated: one occurs when they bind to antigens, and the other is from other sources, as a "confirmation". Naive T helper cells receive the second signal from innate system cells. In the event that they are activated, T cells begin to clone. Some of the clones will send out signals to stimulate macrophages or cytotoxic T-cells to kill antigens, or send out signals to activate B cells. Others will form memory T cells. The activated B-cells migrate to a lymph node. In the lymph node, a B cell will clone itself. Meanwhile, somatic hypermutation is triggered, whose rate is 10 times higher than that of the germ line mutation, and is inversely proportional to the affinity. Mutation changes the receptor structures of offspring, hence offspring have to bind to pathogenic epitopes captured within the lymph nodes. If they do not bind they will simply die after a short time. If they succeed in binding, they will leave the lymph node and differentiate into plasma or memory B-cells. This process is called affinity maturation. Note clonal selection affects both T cells and B cells, while somatic mutation has only been observed in B cells. As we can see, by repeating selection and mutation, high affinity B cells will be produced, and mutated B cells adapt to dynamically changing antigens, like viruses.

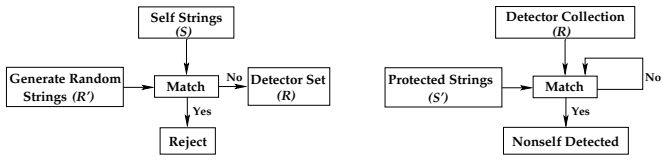
The immune response caused by activated lymphocytes is called primary response. This primary response may take several weeks to eliminate pathogens. Memory cells, on the other hand, result in quick reaction when encountering pathogens that they have seen before, or that are similar to previously seen pathogens. This process is known as secondary response, which may take only several days to eliminate the pathogens.

In summary, the HIS is a distributed, self-organizing and lightweight defense system for the body [167]. These remarkable features fulfill and benefit the design goals of an intrusion detection system, thus resulting in a scalable and robust system.

4.4.2. *Artificial Immune System Models for Intrusion Detection*

The HIS is sophisticated, hence researchers may have different visions for emulating it computationally. In this section, we will review the development of AIS models for solving intrusion detection problems.

4.4.2.1. *A self-non-self discrimination AIS model* The first AIS model suggested by Forrest *et al.* was employed in a change-detection algorithm to detect alterations in files [101] and system call sequences [100]. This model simulated the self-non-self discrimination principle of the HISs, as illustrated in Figure 12. Negative selection was the core of this model, by which invalid detectors were eliminated when they matched self data. Although not many immune features were employed, it reflected some initial steps toward a greater intellectual vision on robust and distributed protection systems for computers [99].



(a) Censoring (b) Detecting

Fig. 12. The self-non-self discrimination model. A valid detector set will be generated, and then monitor protected strings [101].

4.4.2.2. *An AIS model with lifecycle* Hofmeyr and Forrest later extended the above prototype with more components and ideas from the HISs. The new AIS model (shown in Figure 13) considered the lifecycle of a lymphocyte: immature, mature but naive, activated, memory, and death. The finite detectors' lifetime, plus costimulation, distributed tolerance and dynamic detectors result in eliminating autoreactive detectors, adapting to changing self sets, and improving detection rates through signature-based detection. As an application of this model, a system called LISYS (Lightweight Immune SYStem) was developed to detect intrusions on a distributed environment. Williams *et al.* employed this model to detect computer viruses [139] and network intrusion [273], but extended it with an affinity maturation step to optimize the coverage of the non-self space of antibodies [140, 273].

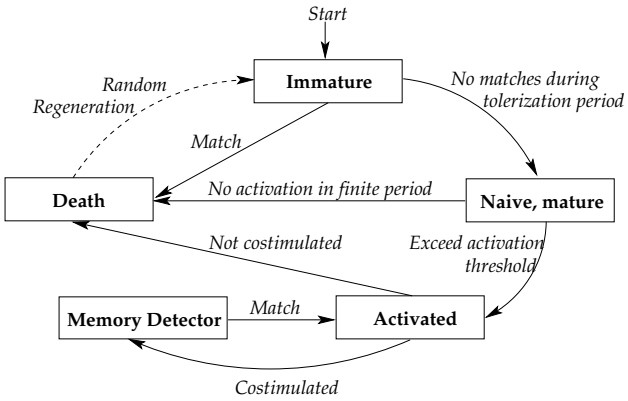


Fig. 13. The lifecycle of a detector. A set of detectors are generated randomly as immature detectors. An immature detector that matches none of normal data during its tolerization period becomes mature; otherwise it dies. When a mature detector matches sufficient input data, this detector will be activated. Alternatively, a mature detector that fails to become activated eventually dies. Within a fixed period of time, if an activated detectors receive no co-stimulation, e.g. responses from system security officers, it will die too; otherwise it becomes a memory detector [112].

4.4.2.3. *An evolutionary AIS model* Kim and Bentley proposed an AIS model [167] based on three evolutionary stages: gene library evolution, negative selection and clonal selection, shown in Figure 14. The gene library stores potentially effective genes. Immature detectors are created by selecting useful genes and rearranging them, rather than generated randomly. Genes in successful detectors are added to the library, while those in failed detectors are deleted. In a sense, the library evolves; the negative selection removes false immature detectors by presenting self without any global information about self; the clonal selection detects various intrusions with a limited number of detectors, generates memory detectors, and drives the gene library evolution. Hofmeyr's lifecycle model was adopted in their model.

4.4.2.4. *A multi-level AIS model* T cells and B cells are two primary but complex immunological elements in the HIS. Dasgupta *et al*. proposed a multilevel immune learning algorithm (see Figure 15), focusing on their functions and interactions [63]. This model considers detecting intrusion and issuing alarms in a multi-level manner. T-cells recognize the peptides extracted from foreign proteins, while B-cells recognize epitopes on the surface of antigens. Therefore, in their computational model, T-detectors (analogous to T cells) performed a low-level continuous bitwise match, while the B-detectors (analogous to B cells) performed a high-level match at non-contiguous positions of strings. To prevent the system from raising false alarms, T-suppression detectors (analogous as T-suppression cells) are introduced, which decide the activation of T-detectors. Activated T-detectors will further provide a signal to help activate B-detectors. This model further simulated negative selection, clonal selection and somatic hypermutation of mature T cells and B cells.

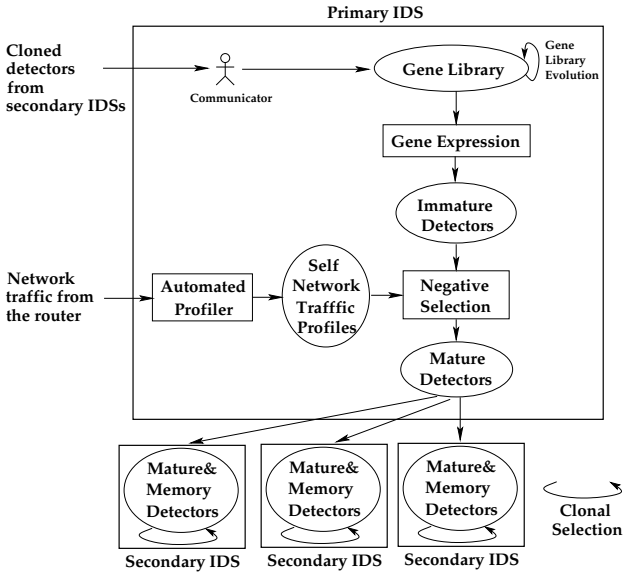


Fig. 14. Conceptual architecture of Kim and Bentley's AIS Model. The central primary IDS generates valid detectors from gene library, and transfers unique detector subsets to distributed secondary IDSs. Secondary IDSs execute detection task, as well as proliferate successful detectors [167].

4.4.2.5. *Artificial Immune Network Model* Artificial Immune Networks (AIN) are based on the immune network theory proposed by Jerne [150]. This theory hypothesizes the immune system maintains an idiotypic network of interconnected B cells for antigen recognition. These B cells stimulate or suppress each other to keep the stabilization of the network. In AIN, antigens are randomly selected from the training set and presented to B cells. The stimulation effects between B-cells and antigens (binding) are calculated. Meanwhile, the stimulation and suppression effects between B cells are also calculated. B-cells will be selected to clone and mutate based on the total interaction effects. Useless B cells are removed from the network, while new B cells are created randomly and incorporated into the network, and links among all B cells are reorganized. A network is returned for detection when the stopping criterion is met. Based on Jerne's work, many AIN models were developed [105], as shown in Figure 16. AINs have been proposed for problem solving in areas such as data analysis, pattern recognition, autonomous navigation and function optimization.

4.4.2.6. *Other AIS models* Millions of lymphocytes circulate in the blood stream and lymph nodes performing the role of immune surveillance and response. Therefore, Dasgupta [60] and Hamer [139] both proposed a model for mapping the mobility of cells into an AIS by mobile agents. Lymphocytes, antibodies and other cells are mapped into agents roaming around a protected system to perform sensing, recognizing, deleting and cleaning jobs. Luther *et al*. [205] presented a cooperative AIS framework in a P2P environment. Different AIS agents collaborate by sharing their detection results and status. Twycross *et al*. [266] incorpo-

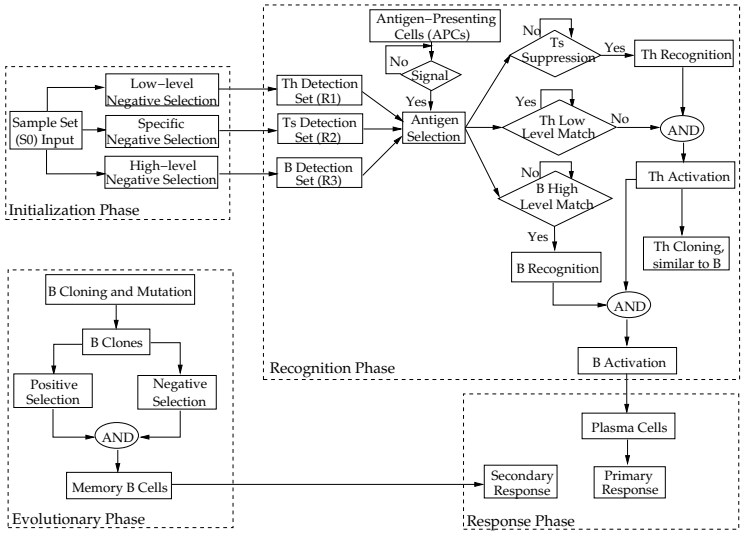


Fig. 15. A multi-level AIS model proposed by Dasgupta *et al.* [63].

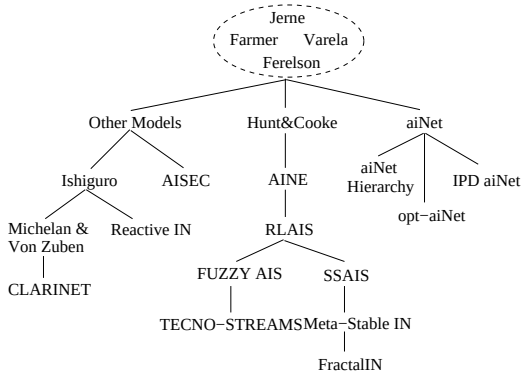


Fig. 16. Genealogical tree of AIN models: each model is a modification or is based on its parent [105].

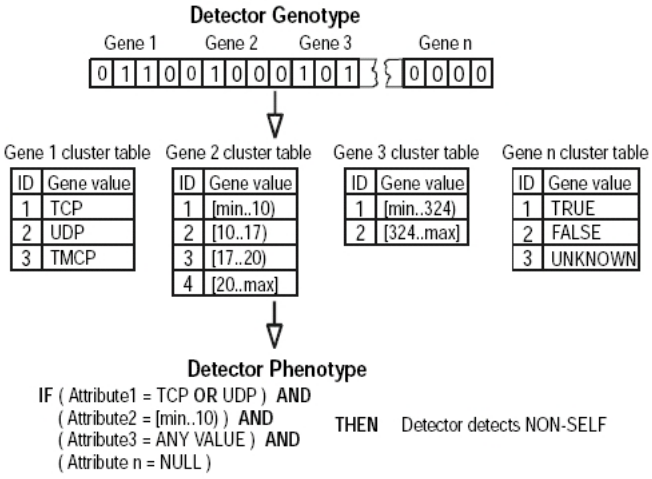


Fig. 17. Detector genotype and phenotype [167].

rated ideas from innate immunity into artificial immune systems (AISs) and presented an *libtissue* framework.

4.4.3. *Representation Scheme and Affinity Measures*

The core of the HIS is self and non-self discrimination performed by lymphocytes. To engineer such a problem in computational settings, appropriately representing lymphocytes and deciding the matching rules are key steps.

Antibodies are generated by random combinations of a set of gene segments. Therefore a natural way to represent detectors is to encode them as gene sequences, comparable to chromosomes in genetic algorithms. Each gene represents an attribute in the input data. Normally, a detector is interpreted as an if-then rule, such as Figure 17 shown. The affinity, when mapped into the intrusion detection domain, means the similarity between detectors and data.

Binary strings are the most commonly adopted coding schemes. There are two ways to represent detectors in binary strings. The difference lies in how to determine the number of nucleotides. Suppose the number of nucleotides in a gene is denoted as N_n, and the number values of an attribute is denoted as N_a. N_n can either equal to N_a [172, 167] or be the minimum integer which satisfies $2^{N_n} >= N_a$ [22, 101, 112, 139, 146, 273]. The first representation allows a single attribute of each detector to have more than one value, but requires more space. Affinity measures in binary strings are r-contiguous bits matching (rcb) [101], r-chunks matching [28], landscape-affinity matching [139], Hamming distance and its variations. Compared to perfect matching, these partial matchings provide generalization for a learning algorithm. Homer compared rcb, landscape-affinity matching, Hamming distance and its variations on a randomly generated dataset [139]. The results showed that the *Rogers and Tanimoto* ($R\&T$), a variation of the Hamming distance, produced the best performance.

González [120] further compared $R\&T$ with r-chunks, rcb and Hamming distance on two **real-valued** datasets. Although r-chunks outperformed others, it still showed a very high false positive rate. This can be explained by the intrinsic meaning of difference or similarity in numeric data. Affinity measures suitable for binary strings do not correctly reflect the distance in numeric meanings.

Therefore, two real-valued representations were suggested by Dasgupta's research group to encode numeric information. In the first coding scheme, a gene in a detector has two nucleotides: one saves the lower bound value of an attribute, and the other one saves the upper bound [62]. Hence, a chromosome actually defines a hypercube. In the second coding scheme, a detector has n+1 genes, where the first n genes represent the center of an n-dimensional hypersphere, and the last gene represents the radius [121]. Major matching rules used in real-valued representation include: Euclidean distance, generalized distances of different norms in Euclidean space (including special cases: Manhattan distance (1-norm), Euclidean distance (2-norm), λ-norm distance for any λ, and infinity norm distance), interval-based matching, and other distance metrics [158].

Representations combining the two approaches were adopted, too [136]. Numeric attributes are encoded in real-valued format, and category attributes are encoded in strings. Matching rules were accordingly applied.

4.4.4. *Negative Selection Algorithms*

The *negative selection* (NS) algorithm simulates the process of selecting nonautoreactive lymphocytes. Consequently, given a set of normal data, it will generate a set of detectors which match none of these normal data samples. These detectors are then applied to classify new (unseen) data as self (normal) or non-self (abnormal). In this section, various NS algorithms will be summarized; then some key issues, such as detector generation, controlling the FP rate and FN rate, and coverage estimation will be discussed.

4.4.4.1. *Development of Negative Selection Algorithms*

The negative selection algorithm was firstly suggested by Forrest *et al.*, already shown in Figure 12. This algorithm started with a population of randomly generated detectors. These potential detectors, analogous to immature lymphocytes, were exposed to normal data. Those which matched normal data were removed from the population immediately and replaced by new detectors. Detectors survived this selection process were used in the detection phase (shown in 12b). In this model, self data and detectors were encoded as binary string, and *rcb* matching rules decided the affinity.

Since the empirical study [120] supported the advantages of real-valued representations on numeric data, Dasgupta and his group extended the initial negative selection algorithm to a series of real-valued NS algorithms. Figure 18 lists NS algorithms proposed by that group and by other researchers. Dasgupta *et al.* hypothesized that each self sample and its vicinity is normal, so they considered a variability range (called *vr*) as the radius for a normal point. Obviously, representing normal data points by a hypersphere achieved generalization for unseen data. An example showing how a self region might be covered by circles in 2-dimension is given in Figure 19a.

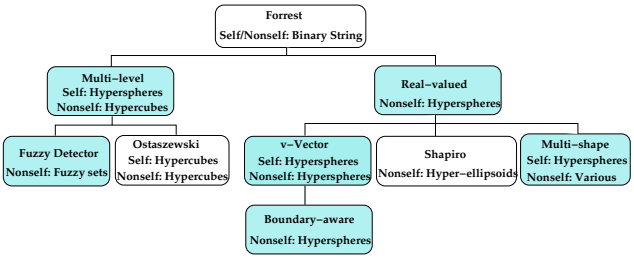
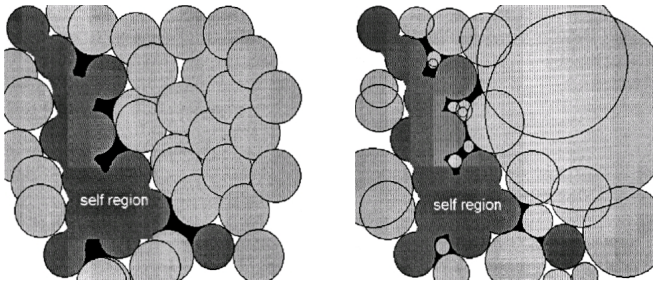


Fig. 18. Genealogical tree of real-valued NS algorithms: each model is a modification or is based on its parent. Dark rectangulars denote research work by Dasgupta groups, and white ones by other researchers.

Features of these NS algorithms can be summarized as follows:

- Multi-level: By changing the parameter *vr* of self hypersphere, a set of detectors with hierarchical levels of deviation were generated. Such a hierarchical detector collection characterized a noncrisp description for the non-self space [62]. A variation of this algorithm integrated fuzzy systems to produce fuzzy detectors [123].
- Real-valued: Instead of inefficiently throwing away detectors who match self samples, this algorithm gave these detectors a chance to move away from the self set during a period of adaptation. Detectors would eventually die if they still matched self sets within a given time frame. Meanwhile, detectors moved apart from each other in order to minimize the overlap in the non-self space [119]. In the end, this algorithm generated a set of constant-sized (because of constant radius) hypersphere detectors covering non-self space, as demonstrated in Figure 19a for a 2-dimensional space. Shapiro *et al.* expressed detectors by hyper-ellipsoids instead of hyperspheres [247].
- v-Vector: Clearly in real-valued NS algorithms, large numbers of constant-sized detectors are needed to cover the large area of non-self space, while no detectors may fit in the small area of non-self space, especially near the boundary between self and non-self. Hence a variable radius was suggested in the v-Vector algorithm [154, 155]. The core idea of this algorithm is illustrated in Figure 19b in a 2-dimensional space.
- Boundary-aware: Previous algorithms took each self sample and its vicinity as a self region, but deciding vicinity is difficult, especially for self samples that are close to the boundary between self and non-self. This algorithm aims to solve the "boundary dilemma" by considering the distribution of self samples.
- Multi-shape: Different geometric shapes, such as hyper-rectangles [62, 123], hyper-spheres [119, 154, 155] and hyper-ellipses [247], were used for covering the non-self space. This algorithm thus incorporated these multiple hyper-shape detectors together [24, 25]. Detectors with suitable size and shape were generated according to the space to be covered. As an application, this algorithm was used to detect intrusions in Ad-Hoc networks [26].
- Ostaszewski: Ostaszewski *et al.* argued that detectors generated by the multi-level NS algorithm cannot completely cover the non-self space, due to the shape conflict

between the structures used for self (hypersphere) and non-self (hypercubes). Hence, in their algorithm, both self and non-self patterns were hypercubes. Self patterns, instead of self data, were used in the NS algorithm. The conversion of large self data space into comparatively small schemata space was effective, and the conversion compressed the number of inputs of the NS algorithm. A similar conversion was also suggested by Hang and Dai [135, 137].



(a) Constant-sized detectors (b) Variable-sized detectors

Fig. 19. The main concept of v-Vector. The dark area represents self region. The light gray circles are the possible detectors covering the non-self region [155].

New NS algorithms are continuously being published. For example, a NS algorithm, enhanced by state graphs [204], is able to locate all occurrences of multi-patterns in an input string by just one scan operation; a feedback NS algorithm was proposed to solve the anomaly detection problem [286].

However, concerns were raised recently on the applicability of NS Algorithms. Garrett [106] concluded that NS algorithms are distinct, and are suitable for certain application only. Freitas *et al.* [104] have criticized the use of NS algorithms in classification. However, NS algorithms were proven useful in generating non-self data, which could be mixed with self data to train classifiers. For details, refer to [121, 137]. Stibor *et al.* pointed out that a real-valued NS algorithm, defined over the hamming shape-space, is not well suited for real-world anomaly detection problems [255, 256]. To tackle these issues, Ji *et al.* [157] clarified some confusions that may have mislead the applicability of negative selection algorithms.

4.4.4.2. *Detector Generation* The typical way of generating detectors in NS algorithms is random or exhaustive, as described in the model (Figure 12) originally proposed by Forrest *et al.*, later being frequently adopted in other research work, e.g. [63, 118, 119, 146, 152, 155].

Instead of inefficiently throwing away detectors who match self samples, Ayara *et al.* [23] and González *et al.* [119] both decided to give these detectors a chance to move away from the self set in a period of time before eliminating them. Ayara *et al.* further compared their algorithm (NSMutation) with exhaustive, linear [75], greedy [75], binary template [272] detector generating algorithms in terms of time and space complexities. The results can be found in [23]. They concluded that though NSMutation was more or else an exhaustive algorithm, it eliminated redundancy and provided tunable parameters that was able to induce different performance.

Recent trends are applying evolutionary algorithms to evolve detectors to cover the non-self space, since a similar evolution process was observed in antibodies. The evolutionary negative selection algorithm (ENSA) is shown in Figure 20, where a negative selection algorithm is embedded in a standard evolutionary process as an operator. Sometimes the NS affects individuals' fitness, and hence results in generating more qualified detectors. Sometimes it is the only way to evaluate fitness. Detectors who pass through the negative selection will either be removed from or stay in the population. Removed ones are replaced by newly generated detectors.

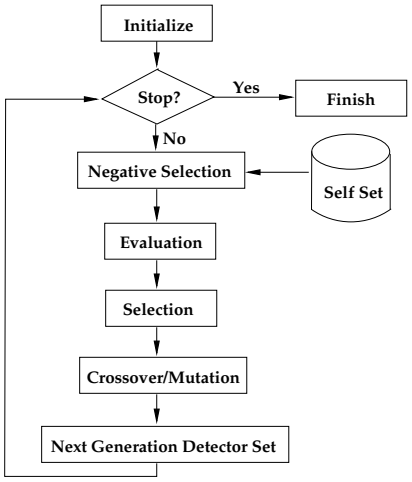


Fig. 20. Generating Detectors by Evolutionary Algorithms.

Kim *et al.* [168] introduced niching to the ENSA so as to maintain diversity. Diversity is necessary for ENSA because a set of solutions (detectors) collectively solves the problem (covering non-self space). Niching has been proved to be an effective way to solve multimodal problems [102, 206]. Kim implemented niching in the way similar to the token competition. A self sample and several detectors were randomly selected. Only the detector which showed least similarity with the self sample had the chance of increasing its fitness.

Dasgupta's group claimed the detector generation was not only a multimodal optimization problem, but also a multiobjective problem [62]. Hence, they used sequential niching to achieve multimodal, and defined three reasonable criteria to evaluate a detector: a good detector must not cover self space; it should be as general as possible; and it has minimum overlap with the rest of the detectors. Therefore, the fitness function was defined as:

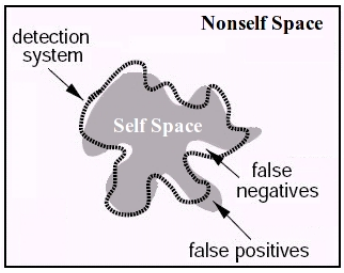
$$f(x) = volume(x) - (C \times num\_elements(x) + overlapped\_volume(x)) \quad (1)$$

where $volume(x)$ is the space occupied by detector x; $num\_elements(x)$ is the number of self samples matched

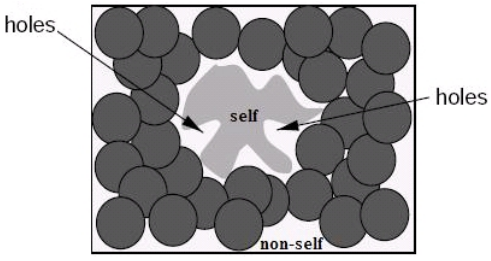
by x; C is the coefficient. It specifies the penalty x suffers if it covers normal samples; $overlapped\_volume(x)$ is the space x overlaps with other detectors. Obviously, the first part is the reward, while the second part is the penalty. This multi-objective multimodal ENSA was applied in their multi-level NS [62], fuzzy NS [123] and multi-shape NS algorithms [24, 25]. Ostaszewski *et al.* also used this fitness definition in their work. The multi-shape NS used a structure-GA while the rest used standard GAs.

With the development of EC, ENSA is gradually strengthened by new evolutionary features. González and Cannady [124] implemented a self-adaptive ENSA, where the mutation step size was adjustable in a Gaussian mutation operator. Their method avoided trial and error when determining the values of tunable parameters in NSMutation; Ostaszewski *et al.* [226, 227, 228] employed co-evolution in their ENSA. A competitive co-evolutionary model helped detectors to discover overlooked regions. The anomaly dataset and the detector set took their turn as predators and preys. Detectors were trying to beat down anomaly data points by covering them. The fitness of data points not covered by any detector were increased, thus resulting in a high possibility of these points to be presented to detectors again. Haag *et al.* [132] employed a multi-objective evolutionary algorithm to measure the tradeoff among detectors with regard to two independent objectives: best classification fitness and optimal hyper-volume size.

4.4.4.3. *Controlling False Positive and False Negative Errors* Inaccurate boundaries between self and non-self space (see Figure 21a), and incomplete non-self patterns (see Figure 21b) are two main causes of false positive and false negative errors in AISs.



(a) Inaccurate Boundaries



(b) Incomplete Non-self Patterns

Fig. 21. Reasons for FPR and FNR in AISs [146].

Self samples in training sets are never complete. As a result, some autoreactive detectors cannot be eliminated during the negative selection. These detectors fail to recognize unseen normal data, thus causing false positives, as shown in Figure 21a. To avoid false positive errors, Hofmeyr [146] introduced the activation threshold (τ), sensitivity level (δ) and costimulation. Instead of signaling an alarm every time a match happens, a detector has to wait until it is matched at least τ times within a limited time period. However, if attacks are launched from different sources, a single detector cannot be matched repeatedly. Therefore, δ is intended to consider the matches of all detectors in a host. An alarm will be triggered when the contributions of multiple detectors exceeds δ within a limited time period. Costimulation requires a confirmation from a human operator whenever an activated detector raises an alarm.

Giving generality to self samples is another way to address incomplete self samples problem. As previously discussed, Dasgupta's group used a hyper-sphere area around self samples in the NS algorithm. Although their methods successfully avoid overfitting, it unfortunately produces an over-generalization problem. Over-generalization will cause false negative errors as shown in Figure 21a. Therefore, Ji *et al.* proposed a boundary-aware algorithm [151]; Ostaszewski *et al.* presented the self samples by variable-sized hyper-rectangles; Hang *et al.* [135, 137] employed a co-evolutionary algorithm to evolve self patterns.

Incomplete non-self patterns in AISs are mainly caused by holes, which are the undetectable negative space (shown in 21b). They are desirable to the extent that they prevent false positives if unseen self samples are falling into them. They are undesirable to the extent that they lead to false negatives if non-self samples are falling into them. Balthrop *et al* [28] and Esponda *et al.* [86, 87] pointed out that matching rules are one reason of inducing holes. For example, the r-contiguous bit matching rule induces either length-limited holes or crossover holes, while the r-chunks matching rule only induces crossover holes. Their analysis is consistent with the D'haeseleer's suggestion: using different matching rules for different detectors can reduce the overall number of holes [75]. Alternatively, using different representations helps to avoid holes, too. Hofmeyr [146] introduced the concept of permutation masks to give a detector a second representation. Permutation masks are analogous to the MHC molecules in HIS. In fact, changing representation is equivalent to changing "shape" of detectors. Dasgupta and other researchers [226] then suggested variable-sized [154, 155, 227, 228] and variable-shaped detectors (e.g. hyper-rectangular [62, 123], hypersphere [119, 155], hyper-ellipsoid [247], or a combination of them [24, 25]). Niching sometimes contributes filling holes, because it attempts to maximize the space coverage and minimize the overlaps among them.

Holes bring another issue. Hofmeyr explained in [146] that the longer the period of time over which holes remain unchanged, the more likely an intruder will find gaps, and once found, those gaps can be exploited more often. There-

fore, he proposed a combination of rolling coverage and memory cells to solve this problem. Each detector is given a finite lifetime. At the end of its lifetime, it is eliminated and replaced by a new active detector, thus resulting in a rolling coverage. Memory detectors ensure that what has been detected in the past will still be detected in the future.

4.4.4.4. *The Estimation of Coverage* No matter whether detectors are generated exhaustively or by using evolutionary algorithms, a measure is required to decide when to stop the generation process. Estimating the coverage ratio, which is also called detector coverage, is one major research subject of NA algorithms.

Forrest [101] and D'haeseleer [75] estimated the number of detectors for a given failure probability when the exhaustive generation and the r-continuous matching rule were used; later Esponda *et al.* [87] discussed the calculation of the expected number of unique detectors under the r-chunks matching rule for both the positive and negative selection algorithm.

Dasgupta *et al.* [62] and Ji [155] estimated the coverage by retry times. Later Ji used hypothesis testing to estimate the detector coverage in v-vector NS algorithm [156]. González [122] and Balachandran [25] used the Monte Carlo estimation to calculate the detector coverage.

4.4.5. *Affinity Maturation and Gene Library Evolution*

As described previously, the affinity maturation is the basic feature of an immune response to an antigenic stimulus. Clonal selection and somatic hypermutation are essentially a Darwinian process of selection and variation, guaranteeing high affinity and specificity in non-self recognition in a dynamically changing environment. Computationally, this leads to the development of evolution inspired clonal selection algorithms. These algorithms rely on the input of non-self data (antigens), whereas negative selection algorithms need self data as input.

Forrest *et al.* [102] first used genetic algorithm with niching to emulate clone selection. Kim and Bentley in [172] embedded the NS algorithm as an operator into Forrest's work. This operator filtered out invalid detectors generated by mutation. Since this algorithm only works on a static dataset, it was named static clonal selection algorithm. Later same authors introduced Hofmeyr's lifecycle model to this algorithm to cope with dynamic environment. This new algorithm was called dynamic clonal selection [169]. Although this algorithm was able to incrementally learn normal behavior by experiencing only a small subset of self samples at one time, it showed high FP errors owing to the infinite lifespan of memory cells. The next step was naturally to define a lifecycle for memory cells. When an antigen detected by a memory cell turned out to be a self-antigen, this memory cell would be deleted. Such a confirmation was equivalent to the co-stimulation signal in Hofmeyr's model [173, 175]. Dasgupta *et al.* also employed the clone selection in their multi-level model [63]. Both mature B-detectors and T-detectors proliferated and were mutated depending on their affinity with antigens.

The clonal selection algorithm implementing affinity maturation is now gradually developed into a new computational paradigm. CLONALG (CLONal selection ALGorithm) [69], ARIS (Artificial Immune Recognition System) [271], and opt-aiNet [66] are well known clonal selection algorithms. These algorithms are used in performing machine-learning and pattern recognition tasks, and solving optimization problems. Although they employ the generation-based model and evolutionary operators when generating offspring, they distinguish themselves from other evolutionary algorithms by the following: firstly, cloning and mutation rate are decided by an individual's affinity. The cloning rate is proportional to the affinity, while the mutation rate is inversely proportional to the affinity. There is no crossover in clonal selection algorithms; secondly, it is a multi-modal preserving algorithm. The memory cell population (P_m) incrementally saves the best solution in each generation. P_m will be returned as the final solution when the algorithm is terminated; thirdly, the population size is dynamically adjustable. Applications of these algorithms to intrusion detection can be found in [116, 195, 196, 276]

In the biological immune system, antibodies are generated by combining fragments from gene libraries. Gene libraries, shaped by evolution, are used to guide the creation process to create antibodies with a good chance of success, while preserving the ability to respond to novel threats [45].

Perelson *et al* [232] and Cayzer *et al.* [44, 45] showed that gene libraries can enhance coverage. Cayzer *et al.*, in addition, investigated the role of gene libraries in AIS [44, 45]. Their empirical experiments suggest that gene libraries in AIS provide combinatorial efficiency, reduce the cost of negative selection, and allow targeting of fixed antigen populations.

Kim and Bentley [174, 175] employed gene library evolution to generate useful antibodies. A problem found in their extended dynamic clonal selection algorithm was that a large number of memory detectors require costimulations in order to maintain low FP rates. This was because new detectors were generated randomly, thus increasing the possibilities of generating invalid detectors. The authors suggested taking feedbacks from previously generated detectors, such as using deleted memory detectors as the virtual gene library. They argued that these deleted memory detectors still held valid information about antibodies, so new detectors were generated by mutating the deleted detectors. Further finetuning of these detectors would generate a useful detectors with high probabilities.

4.4.6. *Danger Theory*

The fundamental principle that guides the development of AIS is the self non-self discrimination. Immune responses are triggered when the body encounters non-self antigens. Therefore, negative selection acts an important filter to eliminate autoreactive lymphocytes. However, questions

have been raised regarding this classical theory, because it cannot explain transplants, tumors, and autoimmunity, in which some non-self antigens are not eliminated, while some self antigens are destroyed. Matzinger, therefore, proposed the Danger Model [209, 210], and claimed that immune responses are triggered by unusual death of normal tissues, not by non-self antigens. Unusual death would indicate that there was a dangerous situation.

This theory is still debated within the immunology field. Nevertheless, it provides some fresh ideas that may benefit the design of an AIS. For example, it avoids the scaling problem of generating non-self patterns. Aickelin and his research group started to work on a "Danger Project" [1] in 2003, intended to apply Danger Theory to intrusion detection systems. The authors emphasis the crucial role of the innate immune system for guiding the adaptive immune responses. Their research specifically focuses on building more biologically-realistic algorithms which consider not only adaptive, but also innate immune reactions [13, 14]. Their work so far can be mainly summarized as one innate immunity architecture, and two danger theory based algorithms.

Before we discuss their work, the biological inspiration should be explained in more detail. Danger Theory is based on the difference between healthy and stressed/injured cells. It suggests that cells do not release alarm signals when they die by normally planned processes (known as apoptosis), whereas cells do release alarm signals when they are stressed, injured, or die abnormally (known as necrosis). A type of cells known as Dendritic Cells (DC) act an important media, passing the alarm signal to the adaptive immune system. DCs have three distinct states: immature (iDC), semimature (smDC), and mature (mDC). iDCs exist in the extralymphoid compartments, where they function as macrophages: clear the debris of tissue, degrade their proteins into small fragments, and capture alarm signals released from necrose cells using toll-like receptors (TLR). Once iDCs collect debris and are activated by an alarm signal, they differentiate into mDCs, and migrate from the tissue to a lymph node. However, if iDCs do not receive any activation in their lifespan but collect debris, they differentiate into smDCs, and also move to a lymph node. Once in a lymph node, mDCs and smDCs present those fragments collected in the immature stage as antigens at their cell surface using MHC molecules. When a naive T cells in the lymph node binds to these antigens, it will be activated only if the antigens it bonds to are presented by an mDC; it will not response if the antigens are presented by an smDC. This is because mDCs secrete a type of cytokines called IL-12 which activate naive T cells, while smDCs secrete a type of cytokines called IL-10 which suppress naive T cells. In summary, DCs act as a bridge between the innate and adaptive immune system. They will trigger an adaptive immune response when danger has been detected [127, 128, 267].

From the above discussion, we can see that tissues provide an environment that can be affected by viruses and bacteria, so that signals are sent out and an immune response is initiated. Both Aickelin and Bentley proposed the idea of artificial tissues, because real-world problems sometimes are very difficult to be connected, compared, and mapped to artificial immune algorithms. Similar to the function of tissues, artificial tissues form an intermediate layer between a problem and an artificial immune algorithm, for example, providing data pre-processing for artificial immune algorithms. However, they held different perspectives about artificial tissues.

Bentley *et al.* [33] introduced two tissue growing algorithms for anomaly detection. Artificial tissue grows to form in a specific shape, structure and size in response to specific data. When data does not exist to support a tissue, the tissue dies. When too much or too diverse data exist for a tissue, the tissue divides. Danger signals are released when a tissue dies. In a sense, artificial tissues provide generic data representations, enabling them to function as an interface between a real-world problem and an artificial immune algorithm. Twycross and Aickelin, on the other hand, proposed a *libtissue* architecture in [266], which allowed researchers to implement, analyze and test new AIS algorithms, as shown in Figure 22. *libtissue* has a client/server architecture. *libtissue* clients represent the data collected from the monitored systems as antigens and signals, and then transmit them to the *libtissue* server. The client also responds to outputs from the *libtissue* server, and changes the state of the monitored system. On the *libtissue* server, one or more tissue compartments are defined. Compartments provide an environment, where immune cells, antigens and signals interact. Immune cells, which are embodied by the artificial immune algorithms, perform analysis and detection. The final decision will be sent back to the client.

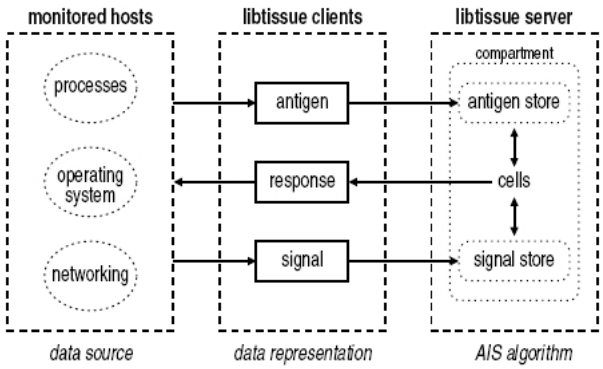


Fig. 22. The architecture of *libtissue* [266].

Another observation from the introduction of the Danger Theory is the role of DCs and their interaction with T-cells. Hence, the Dendritic Cell algorithm (DCA) [125, 126, 127, 128, 129, 130] and TLR algorithm (TLRA) [267, 268, 269] were proposed by Greensmith *et al.* and Twycross *et al.*, respectively.

DCA attempts to simulate the power of DCs which are able to activate or suppress immune responses by correlation of signals representing their environment, combined

with locality markers in the form of antigens [128]. To emulate DCs, representing signals and antigens is the core of the algorithm. Antigens are the input data. Based on immunological observation, Greensmith *et al.* defined four input signals in the DCA: pathogen associated molecular patterns (PAMPs), safe signals, danger signals and inflammatory cytokines [127]. These signals describe the context or environment of an antigen, derived either from input data or the indices of monitored system, such as CPU usage or errors recorded by log systems. The DCA starts with creating a population of immature DCs. Each iDC collects antigens and signals, and transforms them by an equation to three output concentrations: costimulatory molecules (*csm*), smDC cytokines (*semi*) and mDC cytokines (*mat*). *csm* tracks the maturation of a DC. When this quantity is larger than a pre-defined threshold, this DC is said to be mature, and will be moved to the lymph node. The other two outputs, *semi* and *mat*, will determine if this DC will develop to be an smDC or mDC. Matured DCs are ready for intrusion detection. In summary, the maturation phase in the DCA actually correlates signals and antigens to normal or danger context. The DCA is deployed in the *libtissue* framework to detect port scan intrusions, specifically ping scans [125, 128] and SYN scans [126]. Kim *et al.* applied this algorithm to detect misbehavior in sensor networks [171].

TLRA focuses on the interaction between DCs and T-cells, which replaces the classical negative selection algorithm. TLRA are completed in a training and testing phase. In training, only normal data is presented to DCs. Accordingly, all DCs will develop to smDCs. smDCs in a lymph node will match with randomly generated T-cells. If a match happens, which means smDCs activate naive T-cells, then these T-cells will be killed. In the testing phase, anomaly is detected when naive T-cells are activated by antigens. Compared to the classical negative selection algorithms, TLRA considers the environment of the input data, not only the antigen itself, thus increasing the detection rate and decreasing the false positive rate. The TLRA was deployed in the *libtissue* framework to detect process anomaly [267, 268, 269]. Kim *et al.* in [177] emulated interactions between DCs and T cells in the CARDINAL (Cooperative Automated worm Response and Detection ImmuNe ALgorithm), too. However, T cells in CARDINAL will differentiate into various effector T cells, such as helper T cells and cytotoxic T cells. These effector T cells are automated responsers that react to worm-related processes. They also exchange information with effector T cells from other hosts when they respond.

In summary, both the DCA and TLRA employ the model of DCs, which is an important element in the innate immune system. Experimental results of both algorithms showed good detection rate, thus further confirming that incorporating innate immune response benefits the development of an AIS. The implementation of these two algorithms focuses on the different aspects of the DC model. The DCA relies on the signal processing aspect by using multiple input and output signals, while the TLRA emphasizes the interaction between DCs and T-cells, and only uses danger signals. The DCA does not require a training phase, but needs to assign input signals to the appropriate categories. The TLRA uses two types of cells, while DCA only uses one type of cells. As shown in [128], the DCA depends on few tunable parameters, and is robust to changes in the majority of these parameters. However, choosing good signals should not be trivial, and might affect the performance of both algorithms.

4.4.7. *Summary*

In this section, we reviewed the progress in artificial immune systems and their applications to intrusion detection domain. The successful protection principles in the human immune system have inspired great interest for developing computational models mimicking similar mechanisms. Reviewing these AIS-based intrusion detection systems or algorithms, we can conclude that the characteristics of an immune system like uniqueness, distribution, pathogen recognition, imperfect detection, reinforcement learning and memory capacity compensate weaknesses of the traditional intrusion detection methods, thus resulting in dynamic, distributed, self-organized and autonomous intrusion detection.

The HIS has a hierarchical structure consisting of various molecules, cells, and organs. Therefore, researchers may have their own perspective and versions when starting to model. Table 7 summarizes the similarities between the approaches.

From this table, it is evident that NS algorithms are more thoroughly investigated and widely used than other AIS approaches in intrusion detection. This is because NS algorithms lead anomaly detection into a new direction: modeling non-self instead of self patterns. We also notice the quick emergence of Danger Theory, which provides some fresh ideas that benefit the design of AISs. The lifecycle of detectors has been proven as an effective way to avoid holes and adapt to the changes in self data. Few of the research reviewed use immune networks.

Although AIS is a relatively young field, it has received a great deal of interest, and there has been some significant developments recently. Meanwhile, researchers have shown an interest in not only developing systems, but have started to think more carefully about why and how to develop and apply these immune inspired ideas. As a result, a number of AISs research groups published state-of-the-art reviews of AIS research in 2006 and 2007, attempting to reorganize the research efforts, to clarify terminology confusion and misunderstandings, and to reconsider the immunological metaphors before introducing more new ideas, specifically [61] by Dasgupta, [98] by Forrest, [158] by Ji and Dasgupta, [170] by Kim, Bentley, Aickelin *et al.* and [260] by Timmis. This also implies that anomaly detection is getting more attention.

Despite many successes of AIS-based IDSs, there remain

Table 7: Summary of Artificial Immune System

HIS		AIS		
Layers	Immune Mechanism	Algorithm	Training Data	Research Work
Adaptive	Negative Selection (T cells and B cells)	Negative Selection	Self	[24][b], [25], [63], [100], [101], [118][a], [119], [122], [151], [154], [157] [152][a], [155], [168], [286], [247], [228], [226], [227], [136], [135], [137]
	Clonal Selection (B cells)	Clonal Selection	Nonself	[172], [169], [174], [173], [167][a], [175], [276], [196], [116], [195]
	Idiotypic Network	Immune Network	Nonself	[194]
	Cell Lifecycle	Detector Lifecycle	Self	[146][a], [145], [29], [112], [273], [139][b], [140], [174], [175]
Innate	Dendritic Cells	DC Algorithm	Self and nonself	[15], [129], [127], [130], [125], [128], [126], [176], [258]
	T Cells and Dendritic Cells	TLR Algorithm	Self	[177], [267], [269], [157], [268][a]

[a] Ph.D Thesis
[b] Master Thesis

some open questions:

- **Fitting to real-world environments**. Currently most of the algorithms were tested on the KDD99 dataset. However, real-world environments are far more complicated. Hence, improving the efficiency of the current AIS algorithms is necessary. To take NS algorithms as an example, one needs to consider how to avoid the scaling problem of generating non-self patterns; how to detect and fill holes; how to estimate the coverage of rule sets; and how to deal with a high volume and dimensional data.
- **Adapting to changes in self data**. Normal behavior is constantly changing, and so should normal patterns. Although the concept of a detector's lifecycle contributes to adaption, co-stimulation signals from system administrators are required, which is infeasible in reality. Hence, related mechanisms from the human immune system should be further explored, and carefully mapped to solve anomaly detection problems.
- **Novel and accurate metaphors from immunology**. Current AIS algorithms oversimplify their counterparts in immunology. One needs to carefully exploit all known useful features of immune systems, as well as consider the latest discoveries in immunology. A better understanding of immunology will provide informative insight into designing completely new models of AIS.
- **Integrating immune responses**. The HIS not only recognizes nonself antigens, but also removes these antigens after recognition. Current AIS-based IDSs focus on self and nonself recognition. Few research so far discussed the response mechanism after detection. A response within an IDS context does not simply mean the generation of an alert, but an implemented change in the system as the result of a detection.

4.5. *Swarm Intelligence*

Swarm Intelligence (SI) is an artificial intelligence technique involving the study of collective behavior in decentralized systems [3]. It computationally emulates the emergent behavior of social insects or swarms in order to simplify the design of distributed solutions to complex problems. Emergent behavior or emergence refers to the way complex systems and patterns arise out of a multiplicity of relatively simple interactions [3]. In the past few years, SI has been successfully applied to optimization, robotics, and military applications. In this section, we will review its contributions into the intrusion detection domain by discussing two swarm motivated research methods.

4.5.1. *Swarm Intelligence Overview*

We can observe various interesting animal behavior in nature. Ants can find the shortest path to the best food source, assign workers to different tasks, or defend a territory from neighbors; A flock of birds flies or a school of fish swims in unison, changing directions in an instant without

colliding with each other. These swarming animals exhibit powerful problem-solving abilities with sophisticated collective intelligence.

Swarm intelligence approaches intend to solve complicated problems by multiple simple agents without centralized control or the provision of a global model. Local interactions among agents and their environment often cause a global pattern of behavior to emerge. Hence, emergent strategy and highly distributed control are the two most important features of SI, producing a system autonomous, adaptive, scalable, flexible, robust, parallel, self organizing and cost efficient [223].

Generally speaking, SI models are population-based. Individuals in the population are potential solutions. These individuals collaboratively search for the optimum through iterative steps. Individuals change their positions in the search space, however, via direct or indirect communications, rather than the crossover or mutation operators in evolutionary computation. There are two popular swarm inspired methods in computational intelligence areas: *Ant colony optimization* (ACO) and *particle swarm optimization* (PSO). ACO simulates the behavior of ants, and has been successfully applied to discrete optimization problems; PSO simulates a simplified social system of a flock of birds or a school of fish, and is suitable for solving nonlinear optimization problems with constraints.

4.5.2. *Ant Colony Optimization*

Ants are interesting social insects. Individual ants are not very intelligent, but ant colonies can accomplish complex tasks unthinkable for individual ants in a self-organized way through direct and indirect interactions. Two types of emergent behavior observed in ant colonies are particularly fascinating: foraging for food and sorting behavior.

A colony of ants can collectively find out where the nearest and richest food source is located, without any individual ant knowing it. This is because ants lay chemical substances called pheromones to mark the selected routes while moving. The concentration of pheromones on a certain path indicates its usage. Paths with a stronger pheromone concentration encourages more ants to follow, thus in turn these additional ants reinforce the concentration of pheromones. Ants who reach the food first by a short path will return to their nest earlier than others, so the pheromones on this path will be stronger than other longer paths. As a result, more ants choose the short path. However, pheromones slowly evaporate over time. The longer path will hold less or even no traces of pheromone after a same time, further increasing the likelihood for ants to choose the short path [223].

Researchers have applied this ant metaphor to solve difficult, discrete optimization problems, including the traveling salesman problem, scheduling problems, the telecommunication network or vehicle routing problem, etc. Its application to the intrusion detection domain is limited but interesting and inspiring. He *et al.* [142] proposed an Ant-classifier algorithm, which is an extension of the Ant-Miner for discovering classification rules [230]. Artificial ants forage paths from the rule antecedents to the class label, thus incrementally discovering the classification rules, as shown in Figure 23. He *et al.* noticed that using only one ant colony to find paths in all classes was inappropriate, because the pheromone level updated by a certain ant would confuse successive ants interested in another class. So more than one colony of ants (i.e. red ants and blue ants in Figure 23) were applied to find solutions for multi-class classification problems simultaneously with each colony to focus on one class. Each colony of ants deposited a different type of pheromone, and ants were only attracted by pheromones deposited by ants in the same colony. In addition, a repulsion mechanism prevented ants of different colonies from choosing the same optimal path. Banerjee *et al.* [30, 31]

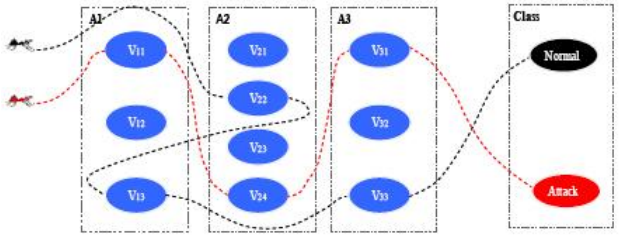


Fig. 23. A multi-class classification algorithm based on multiple ant colonies [142].

suggested to use ACO to keep track of intruder trails. The basic idea is to identify affected paths of intrusion in a sensor network by investigating the pheromone concentration. This work also emphasizes the emotional aspect of agents, in that they can communicate the characteristics of particular paths among each other through pheromone updates. Therefore, in a sensor network if the ants are placed, they could keep track the changes in the network path, following certain rules depicting the probabilities of attacks. Once a particular path among nodes is detected by the spy emotional ant, it can communicate the characteristics of that path through pheromone balancing to other ants; thereafter network administrators could be alerted.

In addition to finding the shortest path, ants also exhibit amazing abilities to sort objects. Ants group brood items at similar stages of development (e.g. larvae, eggs, and cocoons) together. In order to do sorting, ants must sense both the type of element they are carrying, and the local spatial density of that type of element. Specifically, each ant must follow some local strategy rules: it wanders a bit; if it meets an object which has a different type of objects around it and if it does not carry one, it takes that object; if it transports an object and sees a similar object in front of it, it deposits the object. By executing these local strategy rules, ants display the ability of performing global sorting and clustering of objects.

Deneubourg *et al.* [73] in 1990 first related this biological observation to an ant-based clustering and sorting algorithm. The basic ant algorithm started with randomly

scattering all data items and some ants on a toroidal grid. Subsequently, the sorting phase repeated the previously mentioned local strategy rules. Deneubourg introduced a "short-term memory" concept in ant-based clustering algorithms. The short-term memory saved the position of the last data item encountered, but it only permitted discrimination between a limited number of classes of data items. This limitation had been overcome later by Lumer and Faieta [201] who allowed their ants to remember the last few data items carried and their dropping positions. When a new data item was picked up, the position of the "best matching" data item memorized was used to bias the direction of the ant's random walk. The authors also were able to generalize this basic model to other problems in numeric data analysis.

An ant deciding whether to pick up or drop an item i considers the average similarity of i to all items j in its local neighborhood. The local density of similarity ($f(o_i)$) is calculated by Equation 2a, where j denotes the neighborhood of an object o_i; function $d(o_i, o_j)$ measures the similarity of two objects; δ^2 is the size of the local neighborhood; $\alpha \in [0, 1]$ is a data-dependent scaling parameter. The probability of picking up ($P_{pick}(o_i)$) and dropping an object ($P_{drop}(o_i)$) is shown in Equation 2b and Equation 2c, respectively, where k_1 and k_2 are scaling parameter.

$$f(o_i) = max\left\{0, \frac{1}{\delta^2}\sum_j (1 - \frac{d(o_i, o_j)}{\alpha})\right\} \tag{2a}$$

$$P_{pick}(o_i) = (\frac{k_1}{k_1 + f(o_i)})^2 \tag{2b}$$

$$P_{drop}(o_i) = \begin{cases} 2f(o_i) & \text{if } f(o_i) < k_2 \\ 1 & \text{if } f(o_i) \geq k_2 \end{cases} \tag{2c}$$

Romos and Abraham [235] applied this ant-based clustering algorithm to detect intrusion in a network infrastructure. The performance was comparable to the Decision Trees, Support Vector Machines and Linear Genetic Programming. The online processing ability, dealing with new classes, and the self-organizing nature of this approach make ant-based clustering algorithms an ideal candidate for IDSs. Similar work done by Feng *et al.* can also be found at [90, 91, 92]

Tsang and Kwong [262, 263] evaluated the basic ant-based clustering algorithm and an improved version [134] on the KDD99 dataset. They found that these two algorithms suffer from two major problems on clustering large and high dimensional network data. First, many homogeneous clusters are created and are difficult to be merged when they are large in size and spatially separated in a large search space. Second, the density of similarity measures only favors cluster formation in locally dense regions of similar data objects but cannot discriminate dissimilar objects with any sensitivity. The authors made further improvements on these algorithms, such as combining information entropy and average similarity in order to identify spatial regions of coarse clusters, and to compact clusters and incorrectly merged clusters; cluster formation and object searching were guided by two types of pheromones, respectively; local regional entropy was added to the short-term memory; a tournament selection scheme counterbalanced the population diversity and allowed to find optimal values for control parameters, e.g. α-value, or perception radius. Experiments on the KDD99 dataset showed strong performance in that their algorithm obtained three best and two second best results in five classes, when compared with KDD99 winner, K-means, [73] and [134].

4.5.3. *Particle Swarm Optimization*

Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Kennedy and Eberhart [166], inspired by social behavior such as bird flocking or fish schooling.

A high-level view of PSO is a collaborative population-based search model. Individuals in the population are called particles, representing potential solutions. The performance of the particles is evaluated by a problem-dependent fitness. These particles move around in a multidimensional searching space. They move toward the best solution (global optimum) by adjusting their position and velocity according to their own experience (local search) or the experience of their neighbors (global search), as shown in Equation 3. In a sense, PSO combines local search and global search to balance exploitation and exploration.

$$\begin{aligned} v_i(t) = {} & w \times v_i(t-1) \\ & + c_1 \times r_1(p_i^l - x_i(t-1)) \\ & + c_2 \times r_2(p_i^g - x_i(t-1)) \end{aligned} \tag{3a}$$

$$x_i(t) = x_i(t-1) + v_i(t) \tag{3b}$$

where $i = 1, 2, \ldots, N$, population size N; $v_i(t)$ represents the velocity of particle i, which implies a distance traveled by i in generation t; $x_i(t)$ represents the position of i in generation t; p_i^l represents the previous best position of i; p_i^g represents the previous best position of the whole swarm; w is the inertia weight which balances the local and global searching pressure;c_1 and c_2 are positive constant acceleration coefficients which control the maximum step size of the particle; r_1 and r_2 are random number in the interval [0,1], and introduce randomness for exploitation.

PSO has shown good performance in solving numeric problems. In the context of intrusion detection, PSO algorithms have been used to learn classification rules. Chen *et al.* [49] demonstrated a "divide-and-conquer" approach to incrementally learning a classification rule set using a standard PSO algorithm. This algorithm starts with a full training set. One run of the PSO is expected to produce the best classifier, which is added to the rule set. Meanwhile, data covered by this classifier are deleted from the training dataset. This process is repeated until the training dataset is empty. Abadeh *et al.* [5] embedded a standard PSO into their fuzzy genetic algorithm. The GA searches for the best individual in every subpopulation. The PSO was applied

to the offspring generated by crossover and mutation, aiming to improve the quality of fuzzy rules by searching in their neighborhood. Age was assigned to individuals before the start of local search. Fitter individuals live longer, thus having a longer time to perform local search. In their algorithm, the population consists N subpopulations, where N is the number of classes. Steady-state strategy was employed to update populations.

The classification task usually involves a mixing of both continuous and categorical attribute values. However, a standard PSO does not deal with categorical values: category values do not support the "+" and "-" operations shown in Equation 3. Hence Chen *et al*. mapped category values to integers. The order in mapped sequences sometimes makes no sense in the context of original nominal values, and mathematical operations applied to this artificial order may generate counter-intuitive results. Abadeh *et al*. then redefined the meaning of "+" and "-" operators in Equation 3 by the Rule Antecedent Modification (RAM) operator. The RAM operator can be explained by a simple example. Suppose a linguistic variable R has five fuzzy sets: $\{S, MS, M, ML, L\}$. Antecedent A and B in two particles may contain $\{S, M\}$ and $\{S, L\}$ respectively. $B - A = RAM(2, 3)$, which means B can be converted to A if the 2nd fuzzy set in B is replaced with the 3rd fuzzy set in R. Here $RAM(2, 3)$ is a RAM operator. $B + RAM(2, 3) = A$ means applying RAM operator $RAM(2, 3)$ to B will result in A.

4.5.4. *Summary*

In this section, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) and their applications to intrusion detection domain were reviewed. They either can be used to discover classification rules for misuse detection, or to discover clusters for anomaly detection, or even can keep track of intruder trails. Experiments results have shown that these approaches achieve equivalent or better performance than traditional methods.

ACO and PSO both have their roots in the study of the behavior of social insects and swarms. Swarms demonstrate incredibly powerful intelligence through simple local interactions of independent agents. Such self-organizing and distributed properties are especially useful for solving intrusion detection problems, which are known for their huge volume and high dimensional datasets, for real-time detection requirement, and for diverse and constantly changing behavior. Swarm Intelligence would offer a way to decompose such a hard problem into several simple ones, each of which is assigned to an agent to work on in parallel, consequently making IDSs autonomous, adaptive, parallel, self organizing and cost efficient.

4.6. *Soft Computing*

Soft computing is an innovative approach to construct a computationally intelligent system which parallels the extraordinary ability of the human mind to reason and learn in an environment of uncertainty and imprecision [282]. Typically, soft computing embraces several computational intelligence methodologies, including artificial neural networks, fuzzy logic, evolutionary computation, probabilistic computing, and recently also subsumed artificial immune systems, belief networks, etc. These members neither are independent of one another nor compete with one another. Rather, they work in a cooperative and complementary way.

The synergism of these methods can be tight or loose. Tightly coupled soft computing systems are also known as hybrid systems. In a hybrid system, approaches are mixed in an inseparable manner. Neuro-fuzzy systems, genetic-fuzzy systems, genetic-neuro systems and genetic-fuzzy-neuro systems are the most visible systems of this type. Comparatively, loosely coupled soft computing systems, or ensemble systems, assemble these approaches together. Each approach can be clearly identified as a module.

In this section, we will discuss how to learn uncertain and imprecise intrusive knowledge using soft computing. Hence, neuro-fuzzy and genetic-fuzzy hybrid approaches are introduced first. The discussion about the genetic-neuro and genetic-fuzzy-neuro hybrid systems can be found in Section 4.3.1.2. The last part of this section will examine the role of ensemble approaches played in intrusion detection.

4.6.1. *Artificial Neural Networks and Fuzzy Systems*

Artificial neural networks model complex relationships between inputs and outputs and try to find patterns in data. Unfortunately, the output models are often not represented in a comprehensible form, and the output values are always crisp. Fuzzy systems have been proven to be effective for dealing with imprecision and approximate reasoning. However, constructing a well-performed fuzzy system is not trivial. For example, determining appropriate membership functions and fuzzy rules is often a trial and error process.

Obviously, the fusion of neural networks and fuzzy logic benefits both sides: neural networks perfectly facilitate the process of automatically developing a fuzzy system for a given task by their learning and adaptation ability. This combination is called neuro-fuzzy systems; fuzzy systems make ANNs robust and adaptive since the output is no longer crisp. This combination is called fuzzy neural networks (FNN). For example, Zhang *et al*. [287] employed FNNs to detect anomalous system call sequences to decide whether a sequence is "normal" or "abnormal".

Neuro-fuzzy systems are commonly represented as a multilayer feed forward neural network, as illustrated by Figure 24. The neurons in the first layer accept input information. The second layer contains neurons which transform crisp values to fuzzy sets, and output the fuzzy membership degree based on associated fuzzy membership function. Neurons in the third layer represent the antecedent part of a fuzzy rule. Their outputs indicate how well the prerequisites of each fuzzy rule are met. The fourth layer

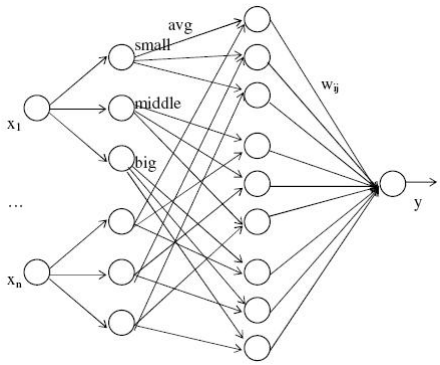


Fig. 24. A generic model of a neuro-fuzzy system [21].

performs defuzzification, and associates an antecedent part with an consequent part of a rule. Sometimes more than one defuzzification layer is used. The learning methods work similarly to that of ANNs. According to the errors between output values and target values, membership functions and weights between reasoning layer and defuzzification layer are adjusted. Through learning, fuzzy rules and membership function will be automatically determined. The common learning method is back propagation.

Intrusion detection systems normally employ neuro-fuzzy systems for classification tasks. For example, Toosi *et al.* [261] designed an IDS by using five neuro-fuzzy classifiers, each for classifying data from one class in the KDD99 dataset. The subtractive clustering method was utilized to determine the number of rules and initial membership functions. The neural network helped to further adapt and fine-tune the membership functions. Other similar neuro-fuzzy based IDSs can be found in [21] and [217].

In order to avoid determining the number of rules before training, the NEFCLASS system has been introduced. The NEFCLASS system is created from scratch and starts with no rule reasoning layer at all. Rules (neurons in the rule reasoning layer) are created by using of the reinforcement learning algorithm in the first run through the training data (rule learning). In the second run, a fuzzy back propagation algorithm adapts the parameters of membership functions (fuzzy set learning). Hofmann [143] and Alshammari [18] used this method for misuse detection on the DARPA98 and DARPA99 datasets, respectively. Hofmann *et al.* compared the performance of four neural and fuzzy paradigms (multilayer perceptrons, RBF networks, NEFCLASS systems, and classifying fuzzy-k-means) on four attack types. The NEFCLASS is the first runner-up after the RBF. Alshammari *et al.* pointed out that the performance of the NEFCLASS depends on the heuristics' learning factors. Through their experiments they found that a trapezoid membership function using the weight as an aggregation function for the ANN extensively reduces the number of false positive alerts with fewer mistakes. In addition, providing more background knowledge about network traffic provided better results on classification.

Another interesting type of neuro-fuzzy systems is the Fuzzy Cognitive Map (FCM). FCM is a soft computing methodology developed by Kosko as an expansion to cognitive maps which are widely used to represent social scientific knowledge [178]. They are able to incorporate human knowledge, adapt it through learning procedures, and provide a graphical representation of knowledge that can be used for explanation of reasoning. Xin *et al.* [277] and Siraj *et al.* [249, 250] both used FCM to fuse suspicious events to detect complex attack scenarios that involve multiple steps. As Figure 25 shows, suspicious events detected by misuse detection models are mapped to nodes in FCM. The nodes in the FCM are treated as neurons that trigger alerts with different weights depicting on the causal relations between them. So, an alert value for a particular machine or a user is calculated as a function of all the activated suspicious events at a given time. This value reflects the safety level of that machine or user at that time.

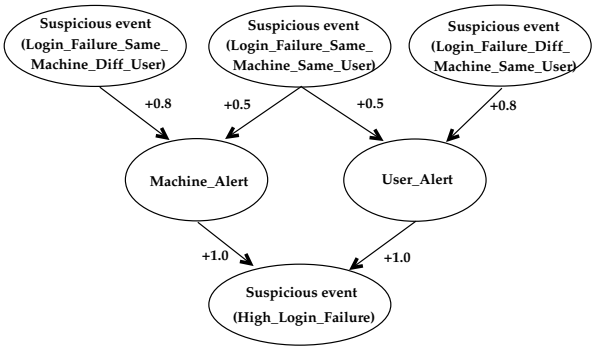


Fig. 25. A FCM to fuse suspicious events to detect complex attack scenarios that involve multiple steps [249].

4.6.2. *Evolutionary Computation and Fuzzy Systems*

Evolutionary computation is another paradigm with learning and adaptive capabilities. Hence, EC became another option for automatically designing and adjusting fuzzy rules. In Section 4.3.1, we discussed how to use EC approaches, especially GAs, to generate crisp rules to classify normal or intrusive behavior. Here, evolving fuzzy rules can be regarded as an extension of this research.

Compared with crisp rules, fuzzy rules have the following form:

$$if\ x_1 = A_1\ and\ \ldots\ and\ x_n = A_n\ then\ Class\ C_j\ with\ CF = CF_j$$

where x_i is the attribute of the input data; A_i is the fuzzy set; C_j is the class label; CF_j is the degree of certainty of this fuzzy if-then rule belonging to class C_j. Given input data, there are several defuzzification techniques to determine the class label. The winner-takes-all approach and majority vote are two commonly used defuzzification techniques. Winner refers to the rule with maximum CF_j. When using fuzzy logic, it is difficult for an expert to provide a "good" definition of membership functions. Genetic algorithms have been proven [36, 261] to be successful at tuning membership functions.

Building models for misuse detection essentially is a multi-class classification problem. In previous research,

crisp classification rules for all classes were evolved in one population. Each individual represented a partial solution to the overall learning task. They cooperatively solve the target problem. Niching was used to maintain the diversity or multimodality in a population. This approach sometimes is called Michigan approach, which is one commonly used method in classifier systems. The XCS mentioned in Section 4.3.1 is an example of this kind. The Pittsburgh approach and the iterative rule learning are another two methods. In the Pittsburgh approach, each individual is a set of rules, representing a complete solution for the target problem. Crossover exchanges rules in two individuals, and mutation creates new rules. The iterative rule learning basically is a divide-and-conquer method. Individuals are defined in the same way as in the Michigan approach. After a pre-defined number of generations, the best classification rule is added to a population which keeps track of the best individuals found so far. The data covered by this best rule is either removed from the training dataset or decreased the probability of being selected again. Work done by Chen *et al.* in Section 4.5 explained this method.

Gómez *et al.* first showed evolving fuzzy classifiers for intrusion detection in [113, 114]. Complete binary trees enriched the representation of GA by using more logic operators, such as "AND", "OR", and "NOT". The authors defined a multi-objective fitness function, which considered sensitivity, specificity and conciseness of rules. Because of their background in the AIS, they later integrated a negative selection algorithm in evolving fuzzy rules in non-self space [115, 123]. Here, the fitness function considered the volume of the subspace represented by a rule and the penalty a rule suffered if it covered normal samples.

Recent works conducted by Tsang *et al.* [264, 265], Abadeh *et al.* [4, 6, 7] and Özyer *et al.* [229] further developed Gómez's research in the following way:

- **Parallel learning**. Tsang *et al.* and Abadeh *et al.* both suggested a parallel learning framework. Tsang *et al.* used multiple fuzzy set agents (FSA) and one arbitrator agent (AA). A FSA constructed and evolved its fuzzy system. The AA evaluated the parent and offspring FSAs by accuracy and interpretability criteria. Abadeh *et al.* [6] divided the training dataset by class labels, and sent subsets to different hosts, where a GA worked on each sub-dataset in parallel.
- **Seeding the initial population**. Instead of generating the initial population randomly, Abadeh *et al.* randomly selected a training data sample, and determined the most compatible combinations of antecedent fuzzy sets. The consequent part was decided by a heuristic method. If the consequent part was consistent with the class label of data samples it covered, then this rule was kept, otherwise the generation process was repeated. Özyer *et al.* [229] ran the fuzzy association rule algorithm first. The strongest association rules were used as seeds to generate the initial population.
- **Representation**. All these research works represent fuzzy if-then rules as string. "don't care" (∗) symbol is included in their representation as a wild card that allows any possible value in a gene, thus improving the generality of rules.
- **Dynamically changing training data weights**. Abadeh *et al.* [4] and Özyer *et al.* [229] associated a weight to every training sample. Initially, the weights were the same. Weights of misclassified samples remained the same, while weights of correctly classified samples were decreased. Therefore, hard samples had higher probabilities to be exposed in the training algorithms.

These three contributions, of course, were different in many other ways. Mostly, they had different goals. Tsang *et al.* emphasized the importance of interpretability of fuzzy rules. Abadeh *et al.* tried to improve fuzzy rules by using local search operators to search their neighborhood [6]. Özyer *et al.* integrated boosting genetic fuzzy classifiers and data mining criteria for rule pre-screening. These three works also employed different classifier learning methods. Tsang *et al.* employed the Pittsburgh approach; Abadeh *et al.* [4] the Michigan approach; Özyer *et al.* the iterative learning approach. Classification rates of the three approaches are better than the winning entry at the Normal, DoS and Probe classes. Özyer *et al.* and Tsang *et al.* have slightly better or comparable results to the winning entry in the other two classes. Abadeh *et al.* achieved 84.7% and 92.4% compared to 13.2% and 8.4% in the winning entry on U2R and R2L classes, respectively.

4.6.3. *Ensemble Approaches*

Misuse intrusion detection is a very active and well-studied research area. Many classification approaches, from artificial intelligence, machine learning, or computational intelligence, have been applied to improve the detection accuracy, while reducing false positive errors.

Every approach has its strengths and weaknesses, however, resulting in various accuracy levels on different classes. The winning entry for the KDD99 cup, for instance, assembled 50 × 10 C5 decision trees by cost-sensitive bagged boosting. This indicated that even models built by the same algorithm can show differences in misclassification. Different methods provide complementary information about the patterns to be classified. Hence, ensemble approaches improve the overall performance of IDS. Techniques such as majority vote, winner-takes-all and others, combine outputs from classifiers built by different methods to produce a final prediction.

Abraham and his co-workers conducted a number of studies on the ensemble approach for intrusion detection [10, 12, 11, 48, 221, 231]. After individual, hybrid and ensemble models were trained and tested, the best model for each class was selected, and then was combined in order to maximize both computational efficiency and detection accuracy. Majority vote was finally used to decide the output of ensemble methods. In [12, 231], the authors assembled SVM, Decision Tree (DT) and hybrid SVM-DT approaches (denoted as E_1), as illustrated in Figure 26; in [221], they

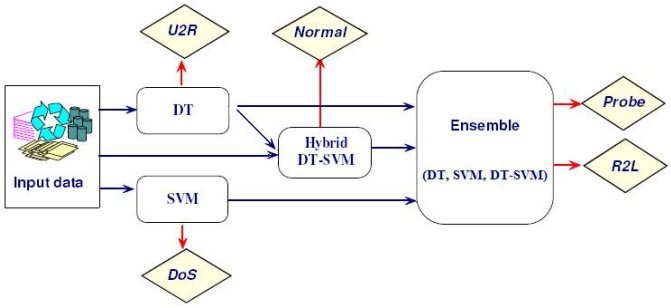


Fig. 26. A exemplar of ensemble models [12].

assembled SVM, MARS (Multivariate Adaptive Regression Splines), an ANN with resilient back propagation, an ANN with scaled conjugate gradient and an ANN with one-step-secant (denoted as E_2); in [48], they assembled CART (classification and regression trees) and Bayesian Networks with different feature sets (denoted as E_3); in [10, 11], they assembled DT, LGP, and fuzzy rules generated by partition of overlapping areas.

Results produced by these methods on test sets are shown in Table 8. Results are not comparable to the winning entry because different data were used: the winning entry used the complete KDD99 training and testing datasets, while Abraham *et al*. conducted experiments on the dataset containing only 11,982 records randomly generated from the KDD99 dataset, with 5,092 and 6,890 records for training and testing, respectively. However, it can be seen that computational intelligence approaches (LGP and fuzzy rules) detect attacks with high accuracy while only using 12 attributes.

4.6.4. *Summary*

Soft computing exploits tolerance for imprecision, uncertainty, low solution cost, robustness, and partial truth to achieve tractability and better correspondence to reality [282]. Their advantages, therefore, boost the performance of intrusion detection systems. Evolutionary computation and artificial neural networks automatically construct fuzzy rules from training data, and present knowledge about intrusion in a readable format; evolutionary computation designs optimal structures of artificial neural networks. These methods in soft computing collectively provide understandable and autonomous solutions to IDS problems. In addition, research has shown the importance of using ensemble approach for modeling IDS. An ensemble helps to combine the synergistic and complementary features of different learning paradigms indirectly, without any complex hybridization. Both the hybrid and ensemble systems indicate the future trends of developing intrusion detection systems.

5. Discussion

Over the past decade intrusion detection based upon computational intelligence approaches has been a widely studied topic, being able to satisfy the growing demand of reliable and intelligent intrusion detection systems.

In our view, these approaches contribute to intrusion detection in different ways. Since fuzzy sets represent and process numeric information in linguistic format, they make system complexity manageable by mapping a large numerical input space into a smaller search space. In addition, the use of linguistic variables is able to present normal or abnormal behavior patterns in a readable and easy to comprehend format. The uncertainty and imprecision of fuzzy sets smoothes the abrupt separation of normal and abnormal data, thus enhancing the robustness of an IDS.

Methods like ANNs, EC, AISs, and SI, are all developed with inspiration from nature. Through the "intelligence" introduced via the biological metaphor, they can infer behavior patterns from data without prior knowledge of regularities in these data. The inference is implemented by either learning or searching. Meanwhile, there remain differences (see also [65]):

- **Structures**. All approaches mentioned are composed of a set of individuals or agents. Individuals are neurons in ANNs; chromosomes in EC; immune cells or molecules in AISs; ants and particles in SI. The collection of these individuals form a network in ANNs; a population in EC; repertories in AISs; colonies and swarms in SI.
- **Performance Evaluation**. The performance of individuals is evaluated. In ANNs, the goal is to minimize the error between actual and desired outputs; in EC and SI, the fitness function defines how good an individual is; in AISs, the goodness of an individual is measured by the affinity between antibodies and antigens.
- **Interactions within the collection** Individuals inside the collection interact with each other. In ANNs, neurons are connected with each other directly. The weights associated with these connections affect the input to a neuron. In the other methods, interaction between individuals is indirect. For example, in AISs, interactions can be the suppression or stimulation within artificial immune networks, or the comparison of affinities between detectors in negative selection and in clonal selection; in SI, ants interact indirectly with pheromone, and particles interact with neighboring particles.
- **Adaptation**. All of these methods demonstrate the ability of adaptation, but in different ways. In EC, adaptation is achieved by evolution. Through crossover and mutation, the genetic composition of an individual can be changed. Selection weeds out poor individuals and conserves fit individuals. As a result, the entire population will converge to an optimum. Similar selection processes are at work in negative and clonal selection in AISs. SI and ANNs achieve adaptation by learning. Weights in ANNs, pheromones in ACO and positions in PSO are updated according to feedback from the environment or from other individuals.

These methods shows strengths and weaknesses. Hence, soft computing either tightly (hybrid) or loosely (ensemble) couple them together in a way that they supplement each

Table 8
Experiments results of Ensemble Approach conducted by Abraham *et al.*

		[12, 231]	[221]	[48]	[10, 11]	Wining Entry [85]
Normal	Number of Attribute	41	41	12	12	41
	Approach	DT+SVM	E2	CART	DT	Ensemble DT
	Accuracy	99.7%	99.71%	100%	100%	94.5%
DoS	Number of Attribute	41	41	17	12	41
	Approach	SVM	E2	E3	LGP	Ensemble DT
	Accuracy	99.92%	99.97%	100%	99.96%	97.1%
Probe	Number of Attribute	41	41	17	12	41
	Approach	E1	E2	CART	LGP	Ensemble DT
	Accuracy	100%	99.85%	100%	99.93%	83.3%
U2R	Number of Attribute	41	41	19	12	41
	Approach	DT	E2	CART	FR2	Ensemble DT
	Accuracy	68%	76%	84%	99.64%	13.2%
R2L	Number of Attribute	41	41	12	12	41
	Approach	E1	E2	E3	LGP	Ensemble DT
	Accuracy	97.16%	100%	99.47%	99.98%	8.4%

other favorably. The resulting synergy has been shown to be an effective way for building intrusion detection systems with good accuracy and real-time performance.

In order to have a global picture of research work carried out under the heading of CI, publication statistics according to the year of appearance is given in Figure 27. One can see clearly that the increasing number of research work indicates that intrusion detection systems are a growing research area in the computational intelligence field, notably since 2005. The approaches also exhibit diversity. ANN, AIS and EC are three main research directions. Consistent research efforts are shown in these directions each year. Investigation into their applicability to intrusion detection problems began as early as 1997. Research attention gradually focused on enhancing performance to achieve higher detection accuracy and lower false alarm rates, while improving capabilities for learning or adaptation to changes in events or behavior.

From this figure, it becomes easy to note a number of trends in the surveyed work. The first trend we encounter is the popularity of EC. Among 193 papers surveyed, 85 are related to evolutionary computation. Although EC methods were introduced into IDS as early as 1997, they became popular only in recent years. There seems to be a decline in 2006 and 2007, but in fact, the practice of EC in these years merges with fuzzy sets to generate fuzzy classification rules, research classified to be in the SC category. Besides, EC plays an important role in other computational intelligence approaches, such as in negative selection or clonal selection algorithms from AISs. The PSO algorithm does not belong to EC, since no reproduction and selection is involved.

The appearance of Swarm Intelligence is another trend. SI is a pretty new research direction for intrusion detection problems. It decomposes a hard problem into several simple sub-problems, assigning agents to work on smaller sub-problems in parallel, thus making IDSs autonomous, adaptive, self organizing and cost efficient. Currently, SI methods are mainly employed to learn classification rules and clusters. More research work in this area is expected in the near future.

We also see a trend to applying Soft Computing to intrusion detection problems. Tightly or loosely assembling different methods in a cooperative way definitely improves the performance of an IDS. The most popular combinations are genetic-fuzzy and genetic-neuro systems. The interest in integrating fuzzy sets as a part of these solutions is noticed. In our survey, 23 out of 26 research contributions in SCs utilize fuzzy sets.

Although some promising results have been achieved by current computational intelligence approaches to IDSs, there are still challenges that lie ahead for researchers in this area. First and foremost, good benchmark datasets for network intrusion detection are needed. The KDD99, and the DARPA98&99 datasets are main benchmarks used to evaluate the performance of network intrusion detection systems. However, they are suffering from a fatal drawback: failing to realistically simulate a real-world network [39, 207, 211]. An IDS working well on these datasets may demonstrate unacceptable performance in real environments. In order to validate the evaluation results of an IDS on a simulated dataset, one has to develop a methodology to quantify the similarity of simulated and real network traces, see for instance the research conducted by Brugger [38].

These datasets possess some special characteristics, such as huge volume, high dimension and highly skewed data distribution. Such features can hardly be found in other benchmarks, so they have been widely used for another purpose: challenging and evaluating supervised or unsupervised learning algorithms. However, this purpose is also under criticism [39]. For instance, i) the DARPA datasets include

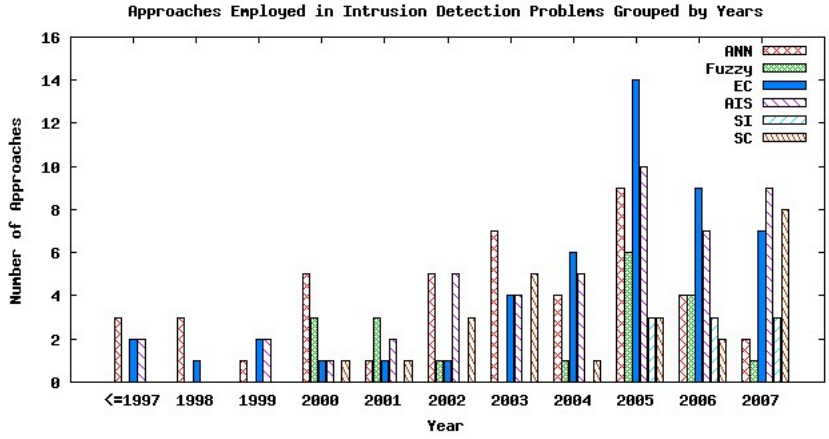


Fig. 27. Publication statistics according to the year of appearance.

irregularities, such as differences in the TTL for attacks versus normal traffic, so that even a simplistic IDS could achieve a good performance [207], ii) the KDD99 training and testing datasets have dissimilar target hypotheses for U2R and R2L classes [239]. Hereby, using these datasets alone is not sufficient to demonstrate the efficiency of a learning algorithm. Other benchmark datasets are recommended to use as well.

It is also worthwhile to note that the datasets shown in Table 1 were collected about 10 years ago. Maybe it is time to produce a new and high-quality dataset for the intrusion detection task. Such a dataset would also be meaningful for machine learning tasks in general. When recollecting data from networks, in addition to storing information in the header of individual packets, payload information [18, 51, 283, 285] and temporal locality property [107, 108] have been proven beneficial.

Secondly, an important aspect of intrusion detection is the ability of adaptation to constantly changing environments. Not only the intrusive behavior evolves continuously, but also the legitimate behavior of users, systems or networks shifts over time. If the IDS is not flexible enough to cope with behavioral changes, detection accuracy will dramatically decrease. Although adaptation is an important issue, only few research has addressed it so far. Recurrent networks introduced context nodes to remember clues from the recent past [17, 41, 42, 51, 70, 72, 107]; in AIS, the lifecycle of immune cells and molecules provides a rolling coverage of nonself space, which guarantees adaptation [146, 175]. The Dendritic Cell Algorithm in Danger theory fulfills adaptation requirements by considering signals from the environment [127, 128]. A focus on adaptation in IDSs is highly recommended.

Another challenge to confront in IDS is the huge volume of audit data that makes it difficult to build an effective IDS. For example, the widely used KDD99 training benchmark comprises about 5,000,000 connection records over a 41-dimensional feature set. Song *et al.* suggested the combination of Random Data Subset Selection and Dynamic Data Subset Selection so that linear genetic programming could process the data within an acceptable time [253, 254]. A similar method is to dynamically adjust the weights of data samples according to classification accuracy, hence changing the probability of data being selected [4, 229]. Other researchers have applied divide-and-conquer algorithms to the dataset. Data that have been classified correctly are removed from the training set. Consequently, the size of the dataset exposed to the learning algorithm shrinks. Another good way to exploit this problem is to utilize a distributed environment. Folin *et al.* [97] and Abadeh *et al.* [7] both examined distributed intrusion detection models, where each node was only assigned part of the data. An ensemble method was used to fuse decisions. Although AISs and SI have properties of self-organization and parallelism, their application to distributed IDS is not thoroughly examined.

Most of the methods discussed in this survey have their roots in the field of biology. However, the analogy between algorithms and their counterpart in biology is still relatively simple. This survey clearly shows that some researchers in this field have begun to adopt a more detailed understanding of biology to intrusion detection, for instance the danger theory, swarm intelligence, or advanced topics in evolutionary computation and artificial neural networks. It is expected that new discoveries and a deepened understanding of biology suitable for the intrusion detection task will be the subject of future work.

6. Conclusion

Intrusion detection based upon computational intelligence is currently attracting considerable interest from the research community. Its characteristics, such as adaptation, fault tolerance, high computational speed and error resilience in the face of noisy information, fit the requirement of building a good intrusion detection system.

This paper presents the state-of-the-art in research progress of computational intelligence (CI) methods in intrusion detection systems. The scope of this review was on core methods in CI, including artificial neural networks, fuzzy systems, evolutionary computation methods, arti-

ficial immune systems, and swarm intelligence. However, the practice of these methods reveals that each of them has advantages and disadvantages. Soft computing has the power to combine the strengths of these methods in such a way that their disadvantages will be compensated, thus offering better solutions. We therefore included soft computing as a topic in this survey. The contributions of research works in each method are systematically summarized and compared, which allows us to clearly define existing research challenges, and highlight promising new research directions. It is hoped that this survey can serve as a useful guide through the maze of the literature.

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