Detection of Non-Content Based Attacks Using GA with Extended KDD Features

Edward Guillén, Jhordany Rodriguez, Rafael Páez, and Andrea Rodriguez

***Abstract*—Detection attack tools have a very wide range of solutions, from the applications of rules obtained by experience to the use of machine learning techniques, including multiple bioinspired methods. In order to analyze the results of research methods for attack detection, the DARPA KDD data set have been widely used but their data are outdated for various kinds of attacks. A software called *Spleen* designed to get data from a tested network with the same structure of DARPA data set is introduced. The application is used to complete the data set with additional features according to an attack analysis. In order to show advantages of an extended data set, two genetic methods in the detection of non-content based attacks are tested.**

***Index Terms*— Adaptative Algorithm, Genetic Algorithms, Information Security, Intrusion Detection, KDD, Machine Learning TCPIP.**

I. Introduction

SINCE the beginning of information transmission by means of computer network resources, the security threats have been raised with different approaches, being the most used the Intrusion Detection Systems –IDS [1]. The attacks have been detected with rules obtained by experience or with the use of machine learning algorithms according to data sets acquired from networking scenarios with normal traffic and with injected attacks to the same scenario [2-8]. The most widely used data set is DARPA data set developed by MIT [9,10] with a complete feature collection of attacks, unfortunately some authors have shown weaknesses on the data set either in the lack of important features for detecting some attacks as well as their outdated information [11,12].

In order to improve detection results, a new set of features have been proposed by some author, with a tool called TSTAT [13]. In the same way, it is possible to find tools supplied by MIT such as LARIAT. The tool simulates traffic generation and allows the aggregations of host and services with the programmed deploy of attacks [14].

This paper shows a software to obtain DARPA compatible features and the possibility of getting additional information in order to construct an updated data set with multiple networking scenarios.

With the obtained information, two genetic methods to detect non-content based attacks will be shown in order to analyze the results not only in a simulation scenario but also in the real world. The obtained results enforce the idea of making hybrid detection systems, according to the characteristics of identified groups of attacks.

In the part II, the database will be explained, as well as a brief introduction to *spleen* software which was used to obtain DARPA features with new variables.

A rules-based Genetic Algorithm –GA attack detection approach will be shown in part III. The weight-based genetic algorithm attack detection is analyzed in part IV to finally show the results in part V and discuss some conclusions at the end of the paper.

II. Data Base for Attack Analysis

In 1998 a well-known data set for intrusion detection evaluation was developed by the DARPA Intrusion Detection Evaluation Group at MIT Lincoln Laboratory. The data set is composed by 41 statistical, behavioral and status variables collected from network scenarios in presence of diverse attack types [9,10]. Although the collection of data was finished more than 10 years ago, the data handling standard is useful for analyze new approaches using Machine Learning or Computational Intelligence in order to find or evaluate intrusion detection methods [15]. However, the DARPA data set not only has the outdated problem but also their variables have shown not to be completed for trustable analysis purposes [11, 12]. In order to achieve better results and taking advantage of the MIT previous work, it was developed a software to obtain the results from DARPA data set plus additional variables including PDU content analysis according to the attack to be studied. The software is called *Spleen* and it is available under request at gissic.umng.edu.co website.

A. Intrusion Detection database description

Samples from DARPA, used for the training and testing process, are composed by two main components, the first one is a collection of features which describes the event and the

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second one is a class, which informs the type of the event, that is, if it is a normal or an abnormal behavior, all these samples are organized in a CSV file.

Descriptive features of a recorded event can be classified in three groups: discrete, continuous percentage and continuous count features.

B. Spleen Data Set Extractor Software

Spleen software is able to collect information from a network interface and gather them with the DARPA data set architecture. The features could be completed with additional information adaptable to the research requirements. Details about possible variables in *spleen* are not the subject of this paper but some of them are going to be used for detection purposes, they will be explained in section II D.

The diagram of spleen modules is shown in Fig. 1.

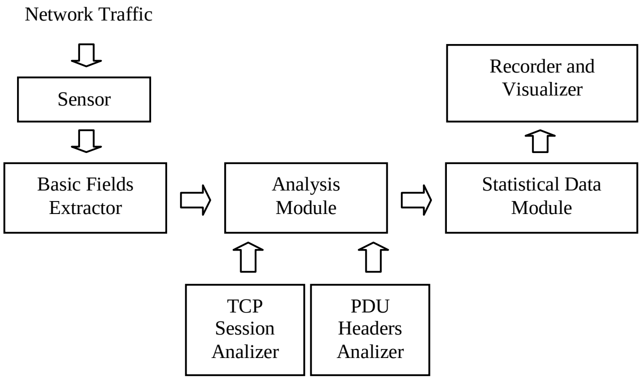


Fig 1. Diagram of *Spleen* modules

C. Non- Content based Attacks

In some attacks, information above to layer 4th is sending, in order to take advantage of an application vulnerability, so the payload length of layer fourth is different to zero. These kinds of attacks are usually called “content based attacks”[16].

In the other hand, there are some attacks which do not need to send information to the session layer or above, it means that the payload of a possible fourth layer packet is empty; these attacks will be called non-content based attacks and over them a genetic algorithm detection will be shown in order to probe advantages of additional features captured with *Spleen* software.

D. Variables Selection and Filtering

New database with the initial data architecture of the DARPA data set is created, and it is completed with some more features in the presence of different attacks with a lab network scenario similar to the one used by MIT[9,10].

In addition with the feature types presented in the original dataset –KDD99–, a new type of feature is obtained with *Spleen.* The new feature type is called Change Behavior Detector –CBD and it is obtained as follows: during a slot of time the events which match some conditions are counted; the process is made again in the next slot of time and its results are compared with previous value in last time period. The CBD feature is the difference between the counted events in actual period and in the last time period. It is able to detect abrupt changes in the network traffic behavior.

From the available set, it is necessary to establish the most significant variables in the detection of intrusive events according to the explained focus. The decision tree CHAID was used over the obtained data as the first feature filter [17]. From the 41 obtainable variables, 13 are content based features, it means that such data are not necessary to detect non-content based attacks, i.e. [18] presents a feature relevance analysis over DARPA set to detect attacks and it can be seen that the most important feature in non-content based attacks detection is the status flag of the connection, that is the 4th feature in the data set. The most important possible states of status flag are shown in Table I [19,20].

TABLE I.
STATUS FLAG OF THE CONNECTION

State	Meaning
SF	Normal SYN/FIN completion
REJ	Connection rejected, Initial SYN elicited a RST in reply
S0	State 0: initial SYN seen but no reply
S1	State 1: connection established (SYN's exchanged), nothing further seen
S2	State 2: connection established, initiator has closed their side
S3	State 3: connection established, responder has closed their side
RSTO	Connection reset by the originator
RSTR	Connection reset by the responder
OTH	Other, a state not contemplated here.

Another current event to be taken into account is the number of bytes sent to a layer upper than 4th by the originator of the connection –the client, making a two states discretization, when the sent bytes are less than 50B and when the sent bytes are more than 50B, because a non-content based attack is characterized by sending few information.

Historical events can help in the detection process because some attacks usually take various steps to be successful. By analyzing the steps, it is possible to know that something is wrong in the network traffic, for example in a portsweep attack, it is possible to find requests made to a not offered service, causing a REJ state connection; this fact by itself does not necessary mean that a portsweep attack is present, instead, it could be possible that someone is trying to get information about the services offered in the network.

Due to the nature of non-content based attacks, the characteristics 4, 25, 26, 27, 28, 29, 34, 39, 40 and 41 were selected to perform the classification [18, 21]. The descriptions of each feature can be found in [10] and [18]. As it can be seen, most of the selected features are refereed to statistical information about the TCP connection states.

In order to complete the DARPA data set and by means of statistical analysis, the database was completed using *spleen* software with the variables illustrated in table II.

III. RULES BASED GENETIC ALGORITHM ATTACK DETECTION

An algorithm to detect non- content based attacks was first implemented. With the approach, the main characteristics are focus in headers and behavior from layers third and fourth according to the features explained before. Rules based detection system has the characteristics explained by Holland [23,24].

TABLE II.
SOME ADDITIONAL FEATURES FROM SPLEEN SOFTWARE

ID	Name	Type	Description
Basic Features			
42	Unusual TCP flags	Boolean	True if this connection had received packets with unusual TCP flags configurations.
43	Out of sequence packets	Int	The number of packets of this connection that not arrived on time.
44	Payload Size average	Int	The size average of the payload length of the packets of this connection, including the retransmissions.
Host Traffic Features (with last 255 connections)			
45	Client count	Int	The number of connections from this client.
46	Not completed client rate	Double	% of connections from this client with the states S0 or S1
47	Same host and service	Double	% of connections from this client that have the same host and service.
48	Persistent connection rate	Double	% of connections to the current host which were not answered and other attempt to establish them was made.
Behavior Changes Detector (difference between two periods)			
49	Host rejected difference	Int	# of connections rejected by the current host.
50	Service rejected difference	Int	# of connections to this service that was rejected
51	Unanswered host count	Int	# of connections no answered by this host
52	Unanswered service count	Int	# of connections to the current service that have not been answered yet.

A. *Knowledge Representation*

Each line in the data base is represented as follows.

$$S = \{v_1, v_2, ..., v_n\}$$

With *n* number of variables.

Each feature could be represented only by three stages:

$$v_n : \begin{cases} 0 \\ 1 \\ \# Dontcare \end{cases}$$

If there is any continuous feature, they are always normalized between 0 and 1, and they are digitalized according to a variability analysis. In that way, v_n could contain more than one bit

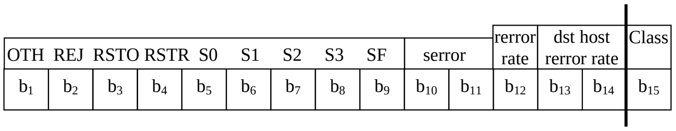
The rules has the {`if` v_1 `and` v_2 `and` v_n `then` class} structure.

The class only has two possible stages "1" or "0" meaning that exists or not an attack. Although the database makes distinction between different attacks such as Teardrope, DoS, Portsweep and so on, all non-content based attacks were merged with just one class.

At the end of each vector, a class of attack or not attack is putting according to database.

B. *The Chromosome*

The chromosome has the following structure (Fig. 2)



OTH	REJ	RSTO	RSTR	S0	S1	S2	S3	SF	serror		rerror rate	dst host rerror rate		Class
b_1	b_2	b_3	b_4	b_5	b_6	b_7	b_8	b_9	b_{10}	b_{11}	b_{12}	b_{13}	b_{14}	b_{15}

Fig. 2 Initial chromosome structure with just some features

Although the final structure is composed by some more features according to table II, a chromosome with classical KDD features was implemented in order to compare GA results with additional features obtained with *spleen.*

C. *The Algorithm*

The developed approach can be seen in the Fig. 3. The fitness function is a measure of effectiveness according to a comparison between each rule and the training data.

A classical mutation operator is used to create a new element based on parents by making a little change in some of its characteristics. To perform this task two parameters are important, the first one is the mutation probability, which defines the probability that any of the characteristics could change in new individuals, if it is the case, the second parameter, "deep mutation" defines how many characteristics could change.

The complete database is composed by 150.500 lines. The training data has 4.000 individuals and the validation data was probed with 2.000 individuals randomly selected from the main database. When the best rules were selected, they were tested in an IDS with real time traffic in an attacked network with ethical hacking techniques.

IV. WEIGHT BASED GENETIC ALGORITHM ATTACK DETECTION

Several features assume special values in presence of some normal or abnormal behaviors; the goal of this approach is to use these values to classify an event. Each feature is going to have an influence level according to its behavior when the event corresponds to a selected class. If the feature takes high values in the events which belong to a selected class, then its influence level is going to be high. Each feature of the event will contribute with a numerical value according to the product of its current value and its influence level. If the sum of all the contributions is bigger than a threshold, then the event is going to be classified as the indicated class. It is important to know that the influence levels can be positive or negative.

Most of the features refer to historical data; however their influence level depends on the current event, for that reason the influence level of each feature will be related with some current condition. Since the most significant feature that represents the current event is the status flag, all features influence levels will have a bonus when this flag is active.

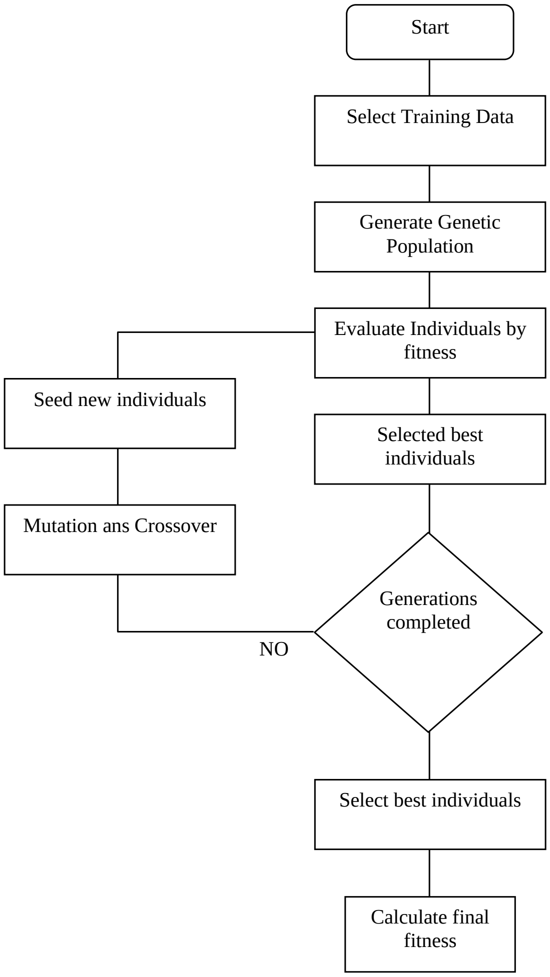


Fig. 3 Rules based genetic algorithm

A. Knowledge Representation

The goal of this genetic algorithm –GA is to find the correct influence level for each feature and to establish what value of status flag is going to give the bonus condition to each feature. With that bonus value is wanted to establish how much the influence level of a feature is going to be incremented in the presence of its bonus status flag, this value is going to be called the bonus value and it is set to 50% in order to make a significant difference when the bonus status flag is present.

TABLE III.
POSSIBLE BONUS STATUS FLAGS

Bonus state	Meaning	Bonus State	Meaning
0000	SF	1000	OTH
0001	S3	1001	S0 or S1
0010	S2	1010	RST events
0011	S1	1011	No S0 or S1
0100	S0	1100	No RST events
0101	RSTO	1101	No SF
0110	RSTR	1110	None
0111	REJ	1111	Any

Each influence level is going to be an integer value from -7 to 8 which is going to be represented by 4 bits. The status flag which gives the bonus condition is represented by 4 bits assuming the values shown in Table III.

Another important component of the GA is the threshold value; it is initially set to the number of selected features for the evaluation, allowing each feature has a relevant role in the detection.

B. The Chromosome

Each one of selected features, except the status flag of the connection, corresponds to a gene and it is composed by two fields: *influence level* (Weight) and *bonus status* flag (Bonus). The threshold value is the same for all the individuals in order to reduce the GA search space. Chromosome structure for this approach is shown in figure 4.

Chromosome																	
Gene 0								...	Gene (n-1)								threshold
Weight				Bonus					Weight				Bonus				
b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	b	Int

Fig 4. Chromosome Structure for weight based GA

C. The Algorithm

The Weight based GA algorithm is similar to the rules based GA, (Fig 3) the main difference is the way the events are evaluated for classification. With the chromosome structure of Fig 4, the weighted sum is evaluated with the equation 1. The result is then compared with the threshold value. If the threshold is exceeded then the event is labeled according to the class that is wanted to be detected.

$$a = \sum_{i=0}^{n-1} f_i * W_i * \left(1 + BFS_i * BP\right) \qquad (1)$$

Where n is the number of selected characteristics, f is the feature value obtained from the training data element, W is the assigned weight to the feature, BFS is the status of the bonus flag assigned for that characteristic “1” or “0”, and BP is the bonus value, (BP is the same for all features and elements) Note that the term in parentheses is 1 when the bonus condition –BFS-is 0.

V. RESULTS

The algorithm was tested with an initial population P of 50 individuals and with 20 generations g. The number of generations and population were tested with different values in order to obtain the best value with the minimal computational cost.

Examples of the best obtained rules with the first 14 bits and the class bit with the fitness value F in the training and test stages can be seen in Figure 5.

Chromosomes															*F* train	*F* test
#	#	0	#	0	0	0	0	0	0	0	#	#	#	1	0,91572	0,97974
#	#	#	#	0	0	0	0	#	0	0	1	#	#	1	0,91069	0,99263
0	#	#	#	#	#	#	0	#	#	0	1	#	#	1	0,91069	1

Fig. 5. Example of best rules with some features and the fitness results in training and test process

With the data set obtained with *spleen*, the two GA approaches were trained. Every non-content based attack was labeled in just one class. Table IV shows the results of weight based GA with just Darpa data set.

TABLE IV
RESULTS OF WEIGHT BASED GA ONLY WITH DARPA

Figure of merit	Training phase	Testing Phase
True positives	0.98122	0.9788
True Negatives	0.99643	0.98620
False positives	0.00356	0.01379
False Negatives	0.01877	0.02111
Fitness	0.98986	0.97985

With the same data set but with the additional features the results in Table V were obtained.

TABLE V
RESULTS OF WEIGHT BASED GA WITH THE ADDITIONAL DATA

Figure of merit	Training phase	Testing Phase
True positives	0.99530	0.98204
True Negatives	1.0	1.0
False positives	0.0	0.0
False Negatives	0.00469	0.01795
Fitness	0.99797	0.98443

Obtained results were made with next GA parameters: Population of 120, 15% of mutation probability and a deep of 2.

The same process was performed with the rules based GA, and results appears in Tables VI and VII.

TABLE VI
RESULTS OF RULE BASED GA USING DARPA FEATURES.

Figure of merit	Training phase	Testing Phase
True positives	0.9788	0.97465
True Negatives	0.99643	0.97241
False positives	0.00356	0.02534
False Negatives	0.02112	0.02758
Fitness	0.98885	0.97435

TABLE VII
RESULTS OF RULE BASED GA USING THE ADITIONAL DATA

Figure of merit	Training phase	Testing Phase
True positives	0.99530	0.99310
True Negatives	1.0	1.0
False positives	0.0	0.0
False Negatives	0.00469	0.00689
Fitness	0.99797	0.999084

In figure 6, it is shown a comparison of results with GA weight based approach with KDD and with proposed additional features. On the other hand the figure 7 shows the results obtained by the rule based GA approach.

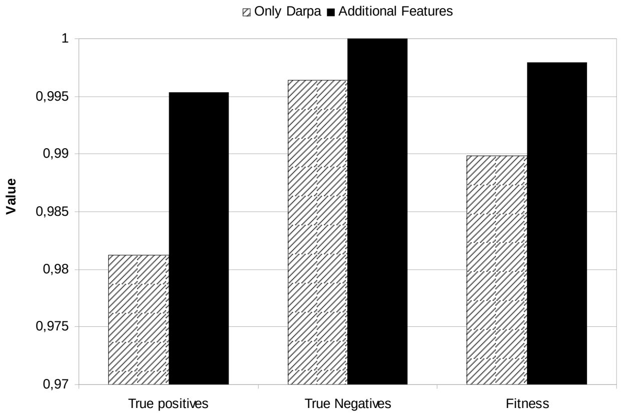


Fig 6. Comparison of results with GA weight based approach with KDD99 classical features and with proposed additional features.

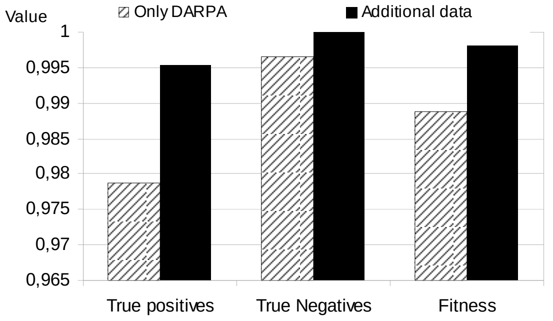


Fig 7. Comparison of results with GA rules based approach with KDD99 classical features and with the addition of proposed features.

VI. CONCLUSIONS

Spleen provides the possibility to change the way the features are obtained, for example extending the time window or the number of considered connections in statistical measurements. It represents a bigger range of possibilities for research purposes.

The definition of “normal traffic” can differ from network to network; *Spleen* allows the construction of particular datasets which describe the behavior of tested networks. It makes easier the work of IDS schemes to detect abnormal activity.

Future studies about intrusions behavior could possibly give information about what data are useful for their detection, then modifications to *Spleen* and machine learning algorithms can be made in order to improve detection results.

The new type of feature –change behavior detector-provides a way to detect abrupt changes on network traffic, but it must be implemented carefully according to network traffic distribution. The most important parameter to the change behavior detector variables is the observation time, the longer this period, the more descriptive the measure.

Since intrusions get more sophisticated day after day, *spleen* software could be used to getting new features in order to detect attacks, but it is still necessary to construct a new complete database each time a feature is discovered, that is why it is important to construct a very large data set with as many variables as possible continuously updated.

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