Intrusion Detection with Genetic Algorithms and Fuzzy Logic

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ABSTRACT

This paper describes two different ways of training an intrusion detection system about possible attacks to a system: genetic algorithms and fuzzy logic. I will describe how genetic algorithms are used in intrusion detection systems and compare the results to the winning entry of the KDD99 Classifier Learning Contest. I will then describe how fuzzy genetic algorithms are used and compare those results with a decision tree algorithm.

Categories and Subject Descriptors

[**Security and Privacy**]: Intrusion Detection Systems

General Terms

Security

Keywords

Intrusion detection, genetic algorithm, fuzzy logic, KDD99, RLD09, computer security

1. INTRODUCTION

An attack on important and confidential data is a concern for many people, so it is important to have a way to detect and analyze these attacks. A way of detecting attacks is by using an intrusion detection system. An intrusion detection system is a device that monitors network activities for malicious or abnormal behaviors and then produces reports and alerts [10]. There are various ways of training the intrusion detection system about possible threats. Two approaches that I will talk about in this paper are the use of genetic algorithms and fuzzy logic.

In Section 2 I will give some background on intrusion detection. I will describe the main types of networking attacks in Section 2.1, and ways of detecting attacks in Section 2.2. In Section 2.3 I will describe two data sets that are commonly used in intrusion detection. I will explain how *rules* are used to differentiate between normal connections and attacks in Section 2.4, and then give information on genetic algorithms in Section 2.5. After that, I will describe the measures that are used in determining the accuracy of an intrusion detection system in Section 2.6. In Section 3 I will describe the use of a genetic algorithm in an intrusion detection system, and in Section 4 I will describe the use of a fuzzy genetic algorithm. Section 5 has some conclusions about the use of genetic algorithms and fuzzy genetic algorithms in intrusion detection systems.

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2. BACKGROUND

2.1 Types of Networking Attacks

There are four main types of networking attacks that this paper will address: *denial of service*, *remote to user attacks*, *user to root attacks*, and *probing*. Each attack that happens on a network can be placed into one of these categories. [10]

Denial of service (DoS) attacks happen when an attacker makes a machine inaccessible to a user by making it too busy to serve legitimate requests. For example, many systems lock out a user from an account after a certain number of failed login attempts. An attacker would be able to use this to prevent legitimate users from logging in [1]. Remote to user (R2L) attacks happen when an attacker sends packets to a machine over the network in order to gain access to things a local user would have on the machine. An example is when an attacker tries to gain access to a machine by guessing possible usernames and passwords. User to root (U2R) attacks happen when an attacker starts out with access on the machine and then tries to gain root access to the system. For example, if a program expects a user to input their name, the programmer has to decide how many characters that name buffer will require. Assume the program allocates 20 characters for the name buffer. Suppose the user's name has 35 characters. The last 15 characters will overflow the buffer, which could then overwrite the instructions that are to be executed next. An attacker can cause commands to be executed by manipulating the data that overflows. Probing happens when an attacker examines a machine in order to collect information about weaknesses or vulnerabilities that in the future could be used to compromise the system. [10, 13]

2.2 Detection Methodologies

There are two different ways of detecting attacks: *signature-based detection* and *anomaly-based detection*.

A signature is a pattern that corresponds to a known attack. Signature-based detection compares well-known patterns of attacks that are already in the intrusion detection system against captured events in order to identify a possible attack. It is a simple and effective way to detect known attacks. Signature-based detection is also called *knowledge-based detection* or *misuse detection*. [14]

Anomaly-based detection looks for patterns of activity that are rare and uncommon. It is an effective way to detect new attacks. Anomaly-based detection is also called *behavior-based detection*. [10]

2.3 Data Sets

Two different data sets are used in this paper to evaluate the performance of intrusion detection systems: KDD99 and RLD09. The KDD99 data set is a benchmark data set that was generated by simulating a military network environment in 1999. It has long been a standard data set for intrusion detection. The data was processed into five million records. A record is a sequence of TCP packets, between which data flows to and from a source IP address to a target IP address. The data in the set is classified as either normal or attack activity. KDD99 uses 41 *features*, which are properties of a record that are used to describe the activity and help to distinguish normal connections from attacks. [9]

In research conducted by P. Jongsuebsuk, N. Wattanapongsakorn, and C. Charnsripinyo [11, 12], which will be discussed in Section 4, eight out of the 41 KDD99 features [9] were used. They decided on these 8 features based on research done in [8]. The features are:

1. duration: the length of the normal or attack activity in seconds.

2. src_bytes: the number of bytes sent from source to destination. Source is the user who may or may not be an attacker, and destination is the server being potentially attacked.

3. num_failed_logins: the number of failed login attempts.

4. root_shell: returns 1 if root shell is obtained, which means that the user is able to log in as root. This gives them the ability to do things like add accounts and change user passwords. If root shell is not obtained, 0 is returned.

5. num_access_files: the number of operations on access control files. Access control files specify which users are granted access to objects and what operations are allowed on the objects. An example would be (Alice, delete), which would give Alice permission to delete the file. [2]

6. srv_count: the number of connections to the same service as the current connection in the past two seconds.

7. serror_rate: the percentage of connections that have "SYN" errors. When a client attempts to connect to a server, it first sends a SYN (synchronize) message to the server. The server then acknowledges the request by sending a SYN-ACK to the client. The connection is established when the client sends an ACK back to the server. A SYN error is a failure that happens early in this process. [5]

8. same_srv_rate: the percentage of connections to the same service.

The KDD99 data set is 14 years old, and newer attack types are not included in it because of its age. Because of this, P. Jongsuebsuk, N. Wattanapongsakorn, and C. Charnsripinyo [11, 12] created their own data set, RLD09, to use in their experiments. To create the data set, the authors captured network data from a university in Bangkok, Thailand. RLD09 has 17 different types of attacks that can be divided into denial of service attacks and probe attacks. It also has normal network activity. RLD09 uses 12 features, which include the number of packets, source ports, and destination ports. For further information, see [11, 12]. RLD09 only has 12 features because the number of features affect the speed and memory consumption of the intrusion detection system.

2.4 Rules

A commonly used approach for detecting intrusions and to differentiate between normal connections and attacks is to use rules. Rules are represented by if-then statements in the following format: If (*condition*) then (*consequence*). The condition part of the rule is composed of one or more features, and the consequence of the rule says if it is an intrusion or not. For example: if (*duration* = 1, and *src_bytes* = 0, and *serror_rate* = 50) then *intrusion*. [8]

2.5 Genetic Algorithm

Genetic algorithms are a search technique used to find solutions to problems. Operations analogous to biological *mutation*, *selection*, and *crossover* are used to evolve and improve rules.

Mutation is where random bits in an *individual*, or possible solution, are changed. Selection is where individuals that have a better *fitness* are chosen over the other individuals. The fitness function determines the quality of a particular individual. Crossover is where two individuals swap one of their characteristics with the other to form two new individuals.

The solution to a problem is represented as a chromosome. First, a randomly generated population of chromosomes is created. According to the characteristics of the problem, the positions of each chromosome are encoded as bits, characters, or numbers. Then mutation, selection, and crossover are applied to each generation and eventually the best solution is found. [6]

2.6 Determining the Accuracy of an Algorithm

In a machine learning experiment, a common technique is to divide the data set into two subsets, a *training set* and a *testing set*. The given algorithm is then trained on the training set to look for patterns. These patterns are then verified using the test set. [15] Four different measures are then used to determine the accuracy of the algorithm in question.

A *false positive* (FP) happens when an intrusion detection system incorrectly identifies normal activity as being an attack. A *false negative* (FN) happens when an intrusion detection system fails to identify harmful activity. A *true positive* (TP) happens when an intrusion detection system correctly identifies activities to be attacks. A *true negative* (TN) happens when an intrusion detection system correctly identifies activities to be normal.

The *detection rate* (DR) of an intrusion detection system is the number of intrusions detected by the system divided by the total number of intrusions. [4]

3. USING GENETIC ALGORITHMS

3.1 Algorithm Overview

In research conducted by M. S. Hoque, M. A. Mukit, and M. A. N. Bikas [10], a genetic algorithm was used to make their intrusion detection system. The system is divided into two phases: a precalculation phase and a detection phase. In the precalculation phase, a set of chromosomes are created using training data. Then this set of chromosomes is used in the detection phase for comparison. Algorithm 1 is used in the precalculation phase. It initializes chromosomes for comparison. It takes the network data as an input and outputs a set of chromosomes.

Algorithm 1 Major steps in precalculation

```
range = 0.125
for each training data do
  if it has neighboring chromosome within range then
    Merge it with the nearest chromosome
  else
    Create new chromosome with it
  end if
end for
```

In the detection phase, the precalculated set of chromosomes is used to find the fitness of each chromosome in the population. Selection, crossover, and mutation occur, and then the type of the data (whether it is an attack or normal behavior) is predicted. Algorithm 2 is used in the detection phase. It takes the precalculated set of chromosomes as an input and outputs the type of data.

Algorithm 2 Major steps in detection

```
Initialize the population
while number of generation is not reached do
  for each chromosome in the population do
    for each precalculated chromosome do
      Find fitness // Fitness function is the standard de-
      viation equation with distance
    end for
    Assign optimal fitness as the fitness of that
    chromosome
  end for
  Remove some chromosomes with worse fitness
  Apply crossover to the selected pair of chromosomes of
  the population // crossover rate = 0.15
  Apply mutation to each chromosome of the
  population // mutation rate = 0.35
end while
```

3.2 Experimental Design and Results

The authors of [10] used the KDD99 data set. They used only the numerical features of the KDD99 data set (34 out of 41 total features). For the training data set, the KDD99 10% version file was used. This is a 10% subset of the full KDD99 data set. For the test data set, the KDD99 corrected version file was used. This file corrects various typos that were in other files. [9] The training set has a total of 494,021 records, and 396,741 of them are attacks. The test set has a total of 311,029 records, and 250,436 of them are attacks. Table 1 shows the number of records of normal and attack activity in the training and test sets.

Table 1: Number of records

	Training	Testing
Normal	97,280	60,593
Probe	4,107	4,166
DoS	391,458	229,853
U2R	52	228
R2L	1,124	16,189
Total	494,021	311,029

In the detection phase, an initial population is created and then is compared with each chromosome that was created in the precalculation phase. Crossover and mutation happen in the detection population in order to create a new population. The results from running the genetic algorithm are shown in Tables 2 and 3. The detection rate was 94.9%. The false positive rate was 30.5%. The false negative rate was 5%. The true negative rate was 69.5%.

The authors of [10] compared their results with the winning entry of the KDD99 Classifier Learning Contest [7]. The winning entry used a decision tree algorithm, which is another common algorithm that is used. For further information on decision trees, see [3]. The authors of [10] found that they had a better detection rate for denial of service and user to root attacks than the winning entry. For the winning entry, the detection rate of denial of service was 97.1%, and for user to root it was 13.2%. In [10] the detection rate of denial of service was 99.4% and for user to root it was 18.9%.

4. USING FUZZY GENETIC ALGORITHMS

The focus of [11, 12] is on detecting new or unknown types of attacks in a network. The intrusion detection system used is able to identify normal network activity as well as attacks using a fuzzy genetic algorithm. This kind of algorithm is able to learn new attacks, and has a high detection rate.

4.1 Fuzzy Logic Rules and Algorithm

Attacks on systems do not always have a fixed pattern, so fuzzy logic is used to detect patterns that have a behavior that is between normal and unusual. Fuzzy logic rules are similar to the rules described in Section 2.4, except that *consequence* is a certainty factor. For example, if (*duration* = 6) then (*probability of it being an attack is 50%*).

In order to measure the probability that a record is an attack, a trapezoidal shape was used in [11, 12]. This is shown in Figure 1. The trapezoidal shape has four parameters: a, b, c, and d. Algorithm 3 calculates the probability of a record being an attack.

An example of using the fuzzy shape and algorithm is: suppose that the feature is duration, and suppose it is 6 seconds. Suppose that $a = 1$, $b = 3$, $c = 5$, $d = 7$. Then the probability of an attack is equal to

$$\frac{d - \text{data}}{d - c} = \frac{7 - 6}{7 - 5} = 0.5.$$

Table 2: Results for Genetic Algorithm Experiment

		Predicted label					
		Normal	Probe	DoS	U2R	R2L	% Correct
Actual class	Normal	42138	1421	15835	486	713	69.5
	Probe	398	2963	654	2	149	71.1
	Dos	921	432	228489	1	10	99.4
	U2R	146	21	8	43	10	18.9
	R2L	11191	578	3398	141	881	5.4
% Correct		76.9	54.7	92.0	6.4	50.0	

Table 3: Results for Genetic Algorithm Experiment

		Predicted label	
		Normal	Intrusion
Actual class	Normal	True Negative (42,138)	False Positive (18,455)
	Probe	False Negative (12,528)	True Positive (237,908)

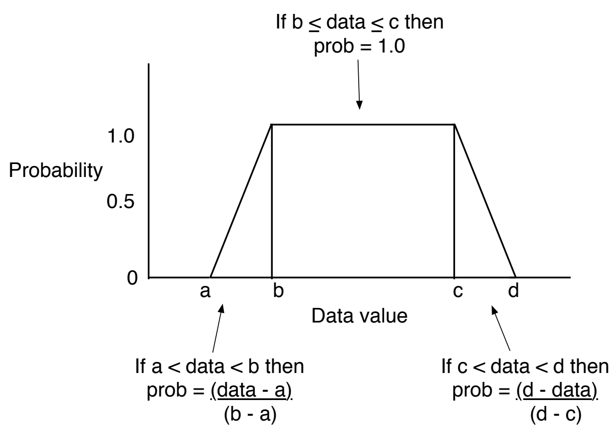

Figure 1: Used to measure the probability that a record is an attack

Algorithm 3 Fuzzy Algorithm

if data value is between b and c **then**
  prob $= 1.0$
else if data value is between a and b **then**
  prob $= (\text{data} - a)/(b - a)$
else if data value is between c and d **then**
  prob $= (d - \text{data})/(d - c)$
else
  prob $= 0.0$
end if

Figure 2: Fuzzy encoding for a feature

010	011	100	101
a=2	b=3	c=4	d=5

The four parameters a, b, c, and d are encoded into blocks of binary strings, where each block is a feature with values between 0.0 and 7.0. See Figure 2 for an example of a block. A rule has 12 blocks of features, and at the end of the string is the type of attack. An example of this is Figure 3.

4.2 Algorithm Overview

The algorithm that is used in [11, 12] first randomly generates rules. Then the rules are improved in the training phase, which can be seen in Algorithm 4. After that, the rules are used to classify the data in the testing phase. Algorithm 4 describes the fuzzy genetic algorithm that is used. One record (either an attack or normal activity) is passed into a rule. Each feature in a record is matched to one block of the rule. The parameters of each block measure the probability of an attack using the trapezoidal fuzzy rule shape. The probabilities of each block are then compared with a threshold to determine if the record represents an attack or normal behavior.

The fitness function to be maximized is:

$$\text{fitness function} = \frac{\alpha}{A} - \frac{\beta}{B}$$

A is total number of attack records. B is total number of normal records. α is total number of attack records correctly identified as attack. β is total number of normal records incorrectly classified as attack.

A population size of 10 was used for each generation. An individual in the population represents a possible detection rule. The two best individuals from a present generation are preserved for the next generation. The other individuals in the new generation come from mutation and single-point crossover.

4.3 Experimental Design and Results

Figure 3: A rule with 12 blocks of features

010	011	100	101	......	010	011	101	111	DoS
a=2	b=3	c=4	d=5	......	a=2	b=3	c=5	d=7	
		Block 1				Block 12			Type

Algorithm 4 Fuzzy Genetic Algorithm

```
for each record do
  for each rule do
    for each feature do
      prob = fuzzy(); // Algorithm 3
      totalprob = totalprob + prob;
    end for
    if totalprob > threshold then
      class is attack;
    else
      class is normal;
    end if
  end for
  compare the predicted result with actual result
  find A, B, α, and β
  // A is total number of attack records. B is total number of normal records. α is total number of attack records correctly identified as attack. β is total number of normal records incorrectly classified as attack.
end for
calculate fitness
//create next generation
preserve_best()
crossover() // single-point crossover
mutation() // mutation rate = 0.30
```

A variety of experiments were run in [11, 12]. Two experiments used just RLD09, and three experiments used KDD99 and RLD09 together.

4.3.1 Experiments using Only RLD09

The experiments using only RLD09 that the authors of [11, 12] performed used a total of 16,000 records of normal activity and 10,500 records of attack activity. Of the attack records, 4,000 of them were denial of service attacks and 6,500 were probe attacks.

In the first experiment, the fuzzy genetic algorithm was used to create denial of service and probe detection rules and then the rules were verified with known attack types. 10,000 records were used for the training set and all 26,500 records were used for the testing set. The two steps in the training process were to find a denial of service rule, and find a probe rule. Both of these rules were then used together in the testing process to identify attacks from the testing data set.

The detection rate of denial of service attacks in training was 91.64% and the detection rate of probe attacks in training was 94.79%. The detection rate of the testing data set increased to 97.92%. Results from this experiment are shown in Table 4.

In the second experiment, [11, 12] pulled some types of attacks out of the training set and kept them for unknown data testing. This was to test that the fuzzy genetic algorithm could detect unknown attacks. In this experiment, seven tests were run. For each test case there were 13 attack types plus normal activity that were in the training data set. Three attack types were used for the unknown testing data set. For example, test case 1 used the training data set that does not have Advance Port Scan, Ack Scan, and Xmas Tree, which are all probe attacks. These three attacks were then used for the testing data set. Table 5 shows some of the results from the fuzzy genetic algorithm and a decision tree algorithm, which is another common way of addressing these problems. For further information on decision trees, see [3], and for further information on the types of denial of service and probe attacks, see [13]. When compared with the decision tree algorithm, the fuzzy genetic algorithm has a higher detection rate in all cases except 3 and 5.

Table 5: Unknown Attack Experiment, using only RLD09

Test Case	Unknown Attacks	Decision Tree DR (%)	Fuzzy Genetic DR (%)
1	Adv Port Scan (Probe) Ack Scan (Probe) Xmas Tree (Probe)	Avg = 98.33	Avg = 100
2	UDP Flood (DoS) Host Scan (Probe) UDP Scan (Probe)	Avg = 46.65	Avg = 99.80
3	Jping (DoS) Syn Scan (Probe) Fin Scan (Probe)	Avg = 99.70	Avg = 98.75
4	UDP Flood (DoS) RCP Scan (Probe) Fin Scan (Probe)	Avg = 70.35	Avg = 98.15
5	Http Flood (DoS) RCP Scan (Probe) Fin Scan (Probe)	Avg = 99.94	Avg = 97.50

4.3.2 Experiments using Both RLD09 and KDD99

The authors of [11, 12] also ran experiments that used both the RLD09 data set and the KDD99 data set in order to compare how the fuzzy genetic algorithm would perform on both. They used the KDD99 10% version file [9] for both the training dataset and testing dataset.

The first experiment used the fuzzy genetic algorithm to classify normal activity and attacks from both data sets. The authors of [11, 12] first trained and tested the fuzzy genetic algorithm (Algorithm 4) with the KDD99 data set. There were 6 different types of denial of service attacks and 4 different types of probe attacks. The detection rate of the KDD99 data set was 98.72%. Then 26,500 records of the RLD09 data set were used as the training set. The detection rate was 97.97%. The results of this experiment are shown in Table 6.

The next experiment used the fuzzy genetic algorithm to classify types of attacks in the KDD99 data set. They used the KDD99 training set, with 158,597 records of denial of service attacks and 1,500 records of probe attacks. Ten tests

Table 4: Results from Experiment 1, using only RLD09

	Attack	Normal	Total Records	FP (%)	FN (%)	DR (%)
DoS Training	1499	8501	10000	1.46	47.50	91.64
Probe Training	2496	7504	10000	1.83	15.38	94.79
Testing	10500	16000	26500	1.13	4.10	97.92

Table 6: KDD99 and RLD09 Results

Data set	Attack	Normal	FP (%)	FN (%)	DR (%)
KDD99	160,117	39,337	0.13	1.55	98.72
RLD09	10,500	16,000	1.14	3.39	97.97

Table 7: Results for KDD99 with Certain Attacks

Test	Attack	Type	FP (%)	FN (%)	DR (%)
1	Back	DoS	85.33	0.00	16.56
2	Smurf	DoS	0.76	0.10	99.73
3	Portsweep	Probe	6.40	0.00	93.66
4	Satan	Probe	0.74	3.75	99.22

were run, and Table 7 shows the accuracy of detecting some of the cases. The results showed that the detection rate of most of the cases were greater than 93%. There were only two cases that had low detection rates, one of which is case 1 in Table 7.

The final experiment that was run used only the RLD09 data set with the fuzzy genetic algorithm to classify types of attacks. 17 tests were run, and Table 8 shows the accuracy of detecting some of the cases. The results showed that the detection rate of a majority of the cases were greater than 97.5%. Again, there were only two test cases that had low detection rates, one of which is case 2 in Table 8.

5. CONCLUSIONS

This paper showed that the use of genetic algorithms and fuzzy logic in intrusion detection are effective ways of detecting attacks. The genetic algorithm that was used in [10] had a high detection rate for denial of service attacks. When compared with the winning entry of the KDD99 Classifier Learning Contest, it was shown to have a better detection rate for both denial of service and user to root attacks. The fuzzy genetic algorithm that was used in [11, 12] had a higher detection rate than a decision tree algorithm in most cases. It was also shown that fuzzy genetic algorithms are good at detecting unknown attacks.

6. REFERENCES

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Table 8: Results for RLD99 with Certain Attacks

Test	Attack	Type	FP (%)	FN (%)	DR (%)
1	Smurf	DoS	0.02	0	99.98
2	UDP Flood	DoS	11.06	0	89.59
3	Ackscan	Probe	0.03	0	99.97
4	Synscan	Probe	0.65	4.2	99.24

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