DIDS BASED ON THE COMBINATION OF CUTTLEFISH ALGORITHM AND DECISION TREE

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ABSTRACT:
Different Distributed Intrusion Detection Systems (DIDS) based on mobile agents have been proposed in recent years to protect computer systems from intruders. Since intrusion detection systems deal with a large amount of data, keeping the best quality of features that represent the whole data and removing the redundant and irrelevant features are important tasks in these systems. In this paper, a novel DIDS based on the combination of Cuttlefish Optimization Algorithm (CFA) and Decision Tree (DT) is proposed. The proposed system uses an agent called Rule and Feature Generator Agent (RFGA) for reducing the dimensionality of the data by generating a subset of features with their corresponding rules. RFGA agent uses CFA to search for optimal subset of features, while DT is used as a measurement on the selected features. The proposed model is tested on the KDD Cup 99 dataset. The obtained results show that the proposed system gives a better performance even with a small subset of 5 features when compared with the using all 41 features.

KEYWORDS: Feature Selection Distributed Intrusion Detection System, Cuttlefish Optimization, Mobile agent.

1. INTRODUCTION
An Intrusion Detection System (IDS) is a security mechanism that gathers both user and system operations in computer and network systems and processes these information in order to determine the intrusive and attacker’s events and can take some actions to abort these dangerous events (Center, 2009). A new approach (Steven R. Snapp, 1991) is the development of DIDS, where sensors (host and network based) gathers data, pre-process it and send it to a centralized station which is able to analyse and process this input.

Recently, a new paradigm on the development of DIDS which is based on Mobile Agents (MA) has attracted many researchers (Donald G. Marks, 2004; E., 2005; Imen Brahmi, 2010; Manneet S, 2007; R. Sasikumar, 2012). MA is a composition of a software program and the data that can be defined as an autonomous program which is able to migrate and move from one node to another. It is commonly featured with autonomy, social ability and learning (Saidat Adebukola Onashoga, 2009). Keeping the best quality of features that represent the whole data and removing the noisy features, is an important function in IDS which can perform on the accuracy rate and computation time. In their previous study (Z. O, Adel Sabry Eesa, Adnan Mohsin Abdulazeez Brifcani, 2015), proposed a new feature selection model based on the combination of CFA and DT to reduce the dimensionality of the IDS dataset. This motivates us to reuse this model as an agent for designing a new DIDS in distributed environment. Some related previous studies in the literature can be found in (Chi-Ho Tsang, 2007; Hai Thanh Nguyen 2010; Jean-Louis Lassez 2008; Mohanabharathi R, 2012; N. Pratik Neelakantan 2011; Rupali Datti, 2012; Shih-Wei Lin, 2012; V. Bolón-Canedo, 2011).

This paper falls into 6 sections, as follows: Section 2 presents a brief introduction to MA, CFA and DT. The architecture, rule producer, and the mechanism of feature selection of the proposed system are discussed in detail in Section 3. Section 4 describes evaluation criteria for the proposed system. While section 5 highlights the experimental results and the discussion on the results reached. Lastly, a conclusion and some future works are listed in section 6.

2. BACKGROUND
2.1. Agents
Agent can be defined as an entity that can perform some tasks independently without any supervision. It can adapt itself, make decisions and collaborate with other agents. Besides working independently, the agent can perform some tasks with other agents and interact with the change of the environment (“The Agent-Oriented Software Engineering Handbook,” 2004). There are two types of agents static and mobile agents (Wang J., 2006).

Static agent is firstly applied in the field of intrusion detection as an agent technique. It is the agent that remains in a fixed position or some fixed platforms, while mobile agent is an agent that can migrate from one node to another through the network. It could be dynamically distribute on the server interfaces which can be monitored on different sites. It also ensures a big level of resistance to network breakdowns and provides bandwidth saving since communication between mobile agent and the server, only takes part in locally exchanged messages which are not passed by the network (Dallal Boughaci, 2006).

2.2. Cuttlefish Optimization Algorithm CFA
CFA is a new optimization algorithm (A. M. A. B. Adel Sabry Eesa, Zeypet Orman, 2013). It simulates the mechanisms used by cuttlefish to change its color. The shapes and colors seen in the skin of the cuttlefish are generated by the six cases of light reflection. The mechanism of light reflection is due to

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the collaboration of different layers of cells including (chromatophores, leucophores and iridophores) as shown in Figure 1.

![Image of six cases of reflected light](image)

Figure 1. six cases of reflected light

Two main operations are designed for this algorithm the reflection operation and the visibility operation. Reflection is designed to mimic the mechanism of reflected light, while the visibility operation is designed to mimic the visibility of matched patterns. These two operations are designed to calculate the new solution or new point as in Equation 1.

\[
\text{newp} = \text{reflection} + \text{visibility} \quad (1)
\]

The main steps of CFA are described in Algorithm 1. The equations considered in Algorithm 1 are given as follows:

**Case (1,2):**

\[
\text{reflection}_j = R \ast G_i[i].\text{Points}[j] \quad (2)
\]

\[
\text{visibility}_j = V \ast (\text{Best}.\text{Points}[j] - G_i[i].\text{Points}[j]) \quad (3)
\]

**Case (3,4):**

\[
\text{reflection}_j = R \ast \text{Best}.\text{Points}[j] \quad (4)
\]

**Case (5):**

\[
\text{reflection}_j = R \ast \text{Best}.\text{Points}[j] \quad (5)
\]

\[
\text{visibility}_j = V \ast (\text{Best}.\text{Points}[j] - AV_{\text{Best}}) \quad (6)
\]

Where \(G_i\) is a group of cells, \(i\) is the \(i\)th cell in \(G_i.\text{Points}[j]\) is the \(j\)th point of \(i\)th cell. \text{Best}.\text{Points} represents the best solution points, \(R\) represents the rate of reflection, \(V\) represents the visibility rate of the general appearance of the pattern, while the \(AV_{\text{Best}}\) is the mean value of the \text{Best} solution points. \(R\) and \(V\) are found as follows:

\[
R = \text{random}() \ast (r_1 - r_2) + r_2
\]

\[
V = \text{random}() \ast (v_1 - v_2) + v_2
\]

Where, \text{random} is a function which is used to produce some small random numbers around zero such as between (0, 1), while \(r_1, r_2, v_1\) and \(v_2\) are four fixed constant values determined by the user such as (1, -1).

**Algorithm 1:**

1. Initialize population \((P[N])\) with random solutions. Assign the values of \(r_1, r_2, v_1, v_2\).
2. Evaluate \text{fitness} of the population, and keep the best solution in \text{Best}.
3. Divide population into 4 Groups: \(G_1, G_2, G_3\) and \(G_4\).

Repeat

1. Calculate average points of the best solution (\text{Best}), and store it in \(AV_{\text{Best}}\).
2. Case(1,2): for each cell in \(G_i\) generate the new solution by using \text{reflection} and \text{visibility}. Equation (2,3), and calculate the \text{fitness}. Replace current_fitness and Best_fitness with the new fitness if the new fitness is better.
3. Case(3,4): for each cell in \(G_i\) generate the new solution by using \text{reflection} and \text{visibility}. Equation (4,3), and calculate the \text{fitness}. Replace current_fitness and Best_fitness with the new fitness if the new fitness is better.
4. Case(5): for each cell in \(G_i\) generate the new solution using \text{reflection} and \text{visibility}. Equation (5,6), and calculate the \text{fitness}. Replace current_fitness and Best_fitness with the new fitness if the new fitness is better.
5. Case(6): for each cell in \(G_i\) generate a random solution and calculate the \text{fitness}. Replace current_fitness and Best_fitness with the new fitness if the new fitness is better.
6. Until stopping criteria
7. Return Best solution

**2.3. Decision Tree**

DT is one of the most well-known subfield of machine learning within the larger field of artificial intelligence. DTs are used widely by many researchers for classification problems. In addition, they are also assisting in uncovering features of data that were previously unrecognizable to the eye. therefore, they can be used successfully in data mining applications such as in (Lior Rokaeh, 2007). DTs are also work effectively in many different domains such as typical business scenarios for airline autopilots and medical diagnoses (Mihai Linteant, 2007; Nahla Ben Amor, 2004).

DT classifier can be described as a recursive partition of the samples domain. It composes of nodes that create a rooted tree. Each inner node divides the instance domain into two or more subdomains based on some discrete functions of the input feature values. Each tested case is considered as a single feature, such that the instance domain is divided base on the attribute’s value (Yacine Bouzida, 2006). Samples are classified by directing them from the root node to a leaf nodes, based on the result of the tests along the path. The classification task starts from the root of a tree. It is considered the characteristic that corresponds to the root, and it determines which branch the value of the given characteristic is corresponded to. After that, the node where the given branch appears is evaluated. These processes will be repeated for each node until reaching a leaf node. Minimizing the entropy or information gain are two classical approaches of attribute selection are considered with the most famous algorithms such as ID3 and C4.5 (Quinlan, 1993).

**3. PROPOSED DIDS DESIGN**

The proposed system consists of several components which are: Collector Mobile Agent (CMA), Rule and Feature Generator Agent (RFGA), Controller Agent (CA), Action Mobile Agent (AMA), User Interface Agent (UIA), and several Nods (local networks) each with Sniffer Agent (SA) which works on the server as shown in Figure 2.

The work of the proposed system is described as follows: each node contains an agent called Sniffer Agent (SA). The goal of the SA is to collect connection information of incoming Internet packets and save them on a file, while CMA will migrate through the network moving from one node into another and gathers the information that is previously stored by SA. When CMA reaches the RFGA agent, it will pass its information to it.
and the RFGA agent will use this information to generate and mine a subset of features with their corresponding rules. CFA is used to produce a subset of features while DT is considered as a measure on the produced features and generates a set of corresponding rules, both the generated rules and the generated features will be passed to CA. CA can then decide whether these features are a type of attacks or they constitute a normal behavior. The decision is based on the generated rules that are provided by RFGA agent. If controller finds out that there is an attack on one of the nodes, it then will take an action through the AMA agent such as shutting down the computer, or alerting the user through the UIA agent.

The generated tree will be used as a judgment on the selected features by using the test dataset. These two steps will be repeated until the best subset of features is found. After that, both the generated features and the generated rule will be passed to CA.

### 3.2. Hierarchy of the Proposed System

Hierarchy of the proposed DIDS consists of five levels: in the first level, SA will gather connection information of the incoming packets from the network traffic and save them on a file, and this task will occur at each node in the network. In the second level, CMA will migrate through the networks and collect information that is stored by SA from each node by moving from a node into another until it reaches the RFGA and then it will pass its information about the visited nodes to the RFGA. In level 3, RFGA provides a subset of features with their corresponding rules which are produced by using the combination of the CFA and DT. The features subset and their corresponding rules are provided to be passed to CA. At level 4, the controller decides whether this information is a normal connection or an attack. The decision depends on several rules that are generated previously by DT. CA classifies each subset to one of the five classes resident in the KDD Cup 99 dataset: Normal, DoS, Probing, R2L, and U2R (Sandhya Peddabachigari, 2007). If CA agent finds that there is an attack, it will take an action through the AMA and the UIA in level 5.

The hierarchy of the proposed DIDS is illustrated in Figure 4.

### 3.1. Rule and Feature Generator Agent

The general principle of the proposed agent using the combination of CFA and DT is shown in Figure 3. RFGA generates a subset of features by using CFA which are used to build a decision tree.

For the evaluation process, the most known criteria used for KDD Cup 99 is the Cost Per Test (CPT) which is calculated by a confusion matrix and a given cost matrix (Elkan, 2000). A confusion matrix shown in Table 1, each column in this table is corresponding to the predicted class, while rows of this matrix are corresponding to the actual classes. The values of $CM(i, j)$, are the number of false classified samples that are actually belonging to class $i$, although falsely determined as a class $j$. The diagonal of this matrix $CM(i, i)$ is the number of truly detected samples.

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**Figure 2. Proposed design of DIDS base MA**

**Figure 3. Flowchart of the combination of CFA and DT**

The generated tree will be used as a judgment on the selected features by using the test dataset. These two steps will be repeated until the best subset of features is found. After that, both the generated features and the generated rule will be passed to CA.
Cost matrix can be similarly defined, as well, and \( C(i, j) \) is the cost penalty when a sample is falsely classified as class \( j \) which is actually belonging to class \( i \). There are a standard values of Cost matrix shown in Table 2. These values are specially designed for the KDD Cup 99 (Eesa, 2011).

\[
\text{Cost matrix can be similar defined as well, and } C(i, j) \text{ is the cost penalty when a sample is falsely classified as class } j \text{ which is actually belonging to class } i. \text{ There are standard values of Cost matrix shown in Table 2. These values are specially designed for the KDD Cup 99 (Eesa, 2011).}
\]

\[
\begin{array}{|c|c|c|c|}
\hline
\text{True positive label} & a & b \\
\hline
\text{True negative label} & c & d \\
\hline
\end{array}
\]

\[
a = \text{true positive, } b = \text{false negatives, } c = \text{false positive, } d = \text{true negative}
\]

In addition to PSP and CPT, Detection Rate (DR) and Correct are as measurement were also used. DR is the ratio of the number of correctly classified samples as an attack to the total number of this attack in the test dataset. Correct criterion is the ratio of the number of correct classified instance to the total number of correct and incorrect instances and they can be calculated as follows:

\[
\text{DR} = \frac{\text{no. of correctly classified instances as an attack}}{\text{total no. of this attack in test dataset}} \times 100\%
\]

\[
\text{Correct} = \frac{\text{no. of correctly classified instances as class } i}{\text{total no. of correct and incorrect instances classified as class } i} \times 100\%
\]

Table 4. Confusion matrix related to the DR, PSP, CPT and Correct using subset of five features

| Predicted | Normal | Prob | DoS | U2R | R2L | %D| R |
|-----------|-------|-----|-----|-----|-----|---|---|
| Actual    | 600306 | 167 | 241 | 0   | 147 | 99.1 |
| Normal    | 436    | 298 | 9   | 222 | 147 | 71.7 |
| Probing   | (4,166)| (229,853) | 7274 | 100 | 222 | 96.6 |
| DoS       | (228) | (16,189) | 206  | 0   | 22  | 95 |
| U2R       | 14592 | 0   | 74  | 0   | 1523| 9.41 |
| R2L       | 72.8  | 91.8| 99.9| 71.8| 0   | 71.8 |

5 features \( \text{PSP} = 92.177\% \quad \text{CPT} = 0.2489\)
Table 5. Confusion matrix related to the DR, PSP, CPT and Correct using complete 41 features

| Predicted Actual | Normal | Prob | DoS | U2R | R2 | L | %DR |
|------------------|--------|------|-----|-----|----|---|-----|
| Normal           | 6023   | 243  | 109 | 9   | 5  | 99.4 |
| (60,591)         |        |      |     |     |    |    |     |
| Probing          | 461    | 2862 | 700 | 0   | 3  | 68.7 |
| (1,166)          |        |      |     |     |    |    |     |
| DoS              | 7124   | 300  | 222431 | 0   | 0  | 96.77 |
| (229,853)        |        |      |     |     |    |    |     |
| U2R              | 191    | 0    | 36  | 1   | 15.8 |
| (228)            |        |      |     |     |    |    |     |
| R2L              | 15646  | 13   | 514 | 11  | 5  | 0.03 |
| (16,189)         |        |      |     |     |    |    |     |
| Correct          | 71.88  | 83.73| 99.41| 64.28| 35.03| 71 |
| 41 features      | PSP = 91.811% | CPT = 0.2613 |

6. CONCLUSION

The combination model of CFA and DT as an agent for feature selection in DIDS is investigated and tested on the benchmark KDD Cup 99 dataset. In addition, the migration of the CMA through the networks was simulated and tested successfully. After many experiments the best five features produced with CFA was \{f_1, f_6, f_21, f_3, f_15\}. The performance of these five features was compared with the performance of the complete 41 features in the KDD Cup 99 dataset. The obtained results show that with the only five features, the proposed system performs better than the complete 41 features.

The investigation of using CFA as a rule generator for IDS can be suggested as a future work. Moreover, the use of other techniques such as support vector machines, neural networks, clustering methods instead of using DT remains an open issue. Comparisons of feature selection techniques will also provide clues for constructing more effective models for intrusion detection.

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