Control Flow Graphs as Malware Signatures
Guillaume Bonfante, Matthieu Kaczmarek, Jean-Yves Marion

To cite this version:

HAL Id: inria-00176235
https://inria.hal.science/inria-00176235
Submitted on 3 Oct 2007

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L’archive ouverte pluridisciplinaire HAL, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d’enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.
Control Flow Graphs as Malware Signatures

Guillaume Bonfante, Matthieu Kaczmarek and Jean-Yves Marion
Nancy-Université - Loria - INPL - Ecole Nationale Supérieure des Mines de Nancy
B.P. 239, 54506 Vandœuvre-lès-Nancy Cédex, France

Abstract
This study proposes a malware detection strategy based on control flow graphs. It carries out experiments to evaluates the false-positive ratios of the proposed methods. Moreover, it presents some insight to establish detection methods sound with respect to some obfuscation techniques.

Introduction
In this paper, we propose a detection strategy based on control flow graphs (CFGs). More precisely, we show how flow graphs can be used as signatures. This is the first step of a broader semantics based approach to detection. For the last twenty years, commercial software has treated this problem with the help of detection strategies based on string signatures. This method requires a database of signatures continuously updated. To maintain the database, some experts analyse every new malicious programs and try to reverse engineer a corresponding signature, with the constraint to produce as least as possible false-positives. The complexity of such an analysis is illustrated by [7]. The amount of time and manpower induced by this strategy is now challenged by advanced obfuscation techniques [5, 1, 2].

In order to enhance this strategy, current detection research interest in detecting semantic aspects. Different approaches have been proposed. In [14, 15], assembler instructions are specified in an equational logic and a prover is used to identify malicious behaviour. The methods exposed in [4, 6] are based on abstract interpretation, the considered signatures are built on control flow graphs and on traces of system states. In [13, 10], CFGs and data flow are used to detect malware.

This study follows the same vein. It carryes out some experiments using CFGs as signatures. This detection strategy is motivated by the fact that the domain of CFGs is at least as complex as the domain of strings. That is for any integer $n$, there are more than $2^n$ different CFGs composed of $n$ nodes. It is worth to mention that the CFG extraction is fully automatic.

This paper goes through the following roadmap. The Sect. 1 defines some notions about detection and places this work in a sound theoretical context. The Sect. 2 describes the CFGs induced by x86 assembler which is the architecture target by our experiment. The experiments are presented in the Sect. 3. Finally, we question some problems opened by this work in the Sect. 4.
1 Detection

**Detectors.** We consider the detection notion defined in [6]. Let $P$ be the set of programs and $M \subset P$ the set of malicious programs. We associate $M$ to a set of signatures $M$. A detector on $M$ is a function $D : P \times M \rightarrow \{0, 1\}$. Then we say that a program $p$ is detected if there is a signature $m \in M$ such that $D(p, m) = 1$.

Applying this definition on the classical signature scanning method, the set $M$ would consist in the list of all known malware string signatures and the associated detector would be defined by $D(p, m) = 1$ if $m$ is a substring of $p$ and $D(p, m) = 0$ otherwise.

**Evaluation.** A detector aims at the discrimination of sane programs from malware. As a result a detector can only be evaluated w.r.t a set of sane programs $S \subset P$ and set of malicious programs $M \subset P$. We suppose that $M \cap S = \emptyset$. We define w.r.t $D$, $M$ and $S$ the set of false-positives $F^+ = \{p \mid p \in M \land \forall m \in M : D(p, m) = 0\}$. We associate to $F^+$ the false-positive ratio defined by the ratio between the cardinals of $F^+$ and of $S$.

2 CFGs in assembler x86

**Description.** A control flow graph (CFG) is composed of linked nodes. We define six kinds of node jmp, jcc, call, ret, inst and end which correspond to the control flow structure. First, x86 assembler programs have four kinds of flow instruction: non-conditional jumps (jmp), conditional jumps (jcc), function calls (call) and function returns (ret). Then, we abstract any contiguous sequence of instructions without flow modification as a node of kind inst. Finally, the kind end corresponds to the end of the program.

This induces the following properties on the graph. Any CFG has a unique node of kind end. Nodes of kind jmp, call and inst have only one successor. Nodes of kind jcc have exactly two successors. Nodes of kind call and ret are well parenthesised. If a node of kind ret has no corresponding node of kind call then it is linked to the node of kind end. We present two examples of CFG extraction in Figure 1.

We use the following structure to represent nodes.

```c
typedef struct node_t{
    add_t node_add;
    add_t ret_add;
    kind_t kind;
    node_t *children;
} node_t;
```

**Reduction.** While experimenting, we have observed that nodes of kind jmp and inst do not really provide information about the control flow. Indeed, they have a unique successor and they do not influence the succeeding flow – as do call nodes. Then, we propose to also experiment with reduced graph.

We propose the following graph reduction. For any node of kind inst or jmp remove the node from the graph and link all its predecessors to its unique successor. The Figure 2 presents a CFG and its reduction.
Figure 1: CFG extraction

3 Experiments

Methodology. These experiments examines CFGs as signatures for malware detection. Our experiment target win32 x86 architecture. A collection of 750 programs has been gathered and the ClamAV scanner has been used to check that they are sane programs. Then, a collection of 2278 has been collected from public sources. CFGs have been automatically extracted from malware and constitute the signatures. Finally, two algorithm detection have been implemented, we evaluates their false-positive ratios.

Detection based on CFGs. The first algorithm computes the detector $D$ defined by $D(p, m) = 1$ if $m$ if $m$ is isomorphic to the CFG of $p$ and $D(p, m) = 0$ otherwise. Informally speaking, the detector $D$ search for an exact malware CFG. We divide our collections of sane programs and malware in four category depending on the size of the CFGs. In the first category the CFGs of the programs have less that 50 nodes, in the second they have between 50 and 100 nodes, in the third they have between 100 and 5000 nodes, and in last category they have more that 5000 nodes. We interest in false-positives for each category. The Table 1 presents the results.

We observe that the false-positive ratio decrease w.r.t the size of CFGs. Under 100 nodes the CFG is not reliable to discriminate malware from sane programs, but over 100 nodes the results are much better. This is really encour-
Figure 2: CFG reduction

Table 1: Results of the experiments

<table>
<thead>
<tr>
<th>Size of CFGs</th>
<th>&lt; 50</th>
<th>50 - 100</th>
<th>100 - 5000</th>
<th>&gt; 5000</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sane programs (S)</td>
<td>15</td>
<td>51</td>
<td>383</td>
<td>301</td>
<td>750</td>
</tr>
<tr>
<td>Malware (M)</td>
<td>440</td>
<td>635</td>
<td>1033</td>
<td>170</td>
<td>2278</td>
</tr>
<tr>
<td>False-positives (F⁺)</td>
<td>10</td>
<td>15</td>
<td>7</td>
<td>1</td>
<td>33</td>
</tr>
<tr>
<td>Ratios</td>
<td>66.7%</td>
<td>29.4%</td>
<td>1.8%</td>
<td>0.3%</td>
<td>4.4%</td>
</tr>
</tbody>
</table>

Table 2: Results of the experiments with reduction

<table>
<thead>
<tr>
<th>Size of CFGs</th>
<th>&lt; 50</th>
<th>50 - 100</th>
<th>100 - 5000</th>
<th>&gt; 5000</th>
<th>Overall</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sane programs (S)</td>
<td>74</td>
<td>39</td>
<td>528</td>
<td>109</td>
<td>750</td>
</tr>
<tr>
<td>Malware (M)</td>
<td>1138</td>
<td>228</td>
<td>850</td>
<td>62</td>
<td>2278</td>
</tr>
<tr>
<td>False-positives (F⁺)</td>
<td>26</td>
<td>0</td>
<td>8</td>
<td>0</td>
<td>34</td>
</tr>
<tr>
<td>Ratios</td>
<td>35.1%</td>
<td>0.0%</td>
<td>1.5%</td>
<td>0.0%</td>
<td>4.5%</td>
</tr>
</tbody>
</table>

This detection method adds one new false-positive, but it has the advantage to group most of false-positives under 50 nodes. Over 50 nodes the accuracy is good. This experiment corroborates the hypothesis that nodes of kind `inst` and `jmp` do not provide information about control flow.

Moreover, using reduced graph, the detection becomes sound with respect to some obfuscation techniques such as code reordering. By code reordering, we consider...
the technique that consists in three steps. Split the program in blocks, permutes them and link the block with jumps to recover the original flow.

**Comparison.** For comparison, statistical methods used in [9] induce false-positive ratios between 0,5% and 34%. A detector based on artificial neural networks developed at IBM [12] presents a false-positive ratio lower than 1%. The data mining methods surveyed in [11] present false-positive ratios between 2,2% and 47,5%. Heuristics methods from antivirus industry tested in [8] present false-positive ratios lower than 0,2%.

4 Further Research

We have not considered host infection. In our framework, this detection would be associated to sub-graph search. In [3], such a study has been carried out for the virus MetaPHOR. The exposed results are promising.

It would be interesting to face our methods to metamorphic engines in order to evaluate the soundness w.r.t program obfuscation. We already know that the detector R is sound w.r.t code permutation, but it would be of worth to study the obfuscation techniques described in [11, 1, 2].

We should also consider the specific problem of packed and encrypted malware. In our study the signature of packed malware only target the decompression procedure. As a result if the used packer is public, such as UPX, this cause false-positive.

References


