MAIL: Malware Analysis Intermediate Language - A Step Towards Automating and Optimizing Malware Detection

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ABSTRACT

Dynamic binary obfuscation or metamorphism is a technique where a malware never keeps the same sequence of opcodes in the memory. Such malware are very difficult to analyse and detect manually even with the help of tools. We need to automate the analysis and detection process of such malware. This paper introduces and presents a new language named MAIL (Malware Analysis Intermediate Language) to automate and optimize this process. MAIL also provides portability for building malware analysis and detection tools. Each MAIL statement is assigned a pattern that can be used to annotate a control flow graph for pattern matching to analyse and detect metamorphic malware. Experimental evaluation of the proposed approach using an existing dataset yields malware detection rate of 93.92% and false positive rate of 3.02%.

Categories and Subject Descriptors

D.3 [**Programming Languages**]: Language Constructs and Features—*Patterns*; K.6 [**Management of Computing and Information Systems**]: Security and Protection—*Invasive software*

General Terms

Security, Languages

Keywords

Intermediate languages, Static binary analysis, Malware analysis, Malware detection, Control flow graph

1. INTRODUCTION

Detecting whether a given program is a malware is an undecidable problem [14, 27]. Antimalware detection techniques are limited by this theoretical result. Malware writers exploit this limitation to avoid detection.

In the early days the malware writers were hobbyists but now the professionals have become part of this group because of the financial gains [5] attached to it or for political and military reasons. One of the basic techniques used by a malware writer is obfuscation [26]. Such a technique obscures a code to make it difficult to understand, analyze and detect malware embedded in the code.

Initial obfuscators were simple and detectable by simple signature-based detectors. These signature-based detectors work on simple signatures such as byte sequences, instruction sequences and string signatures (pattern of a malware that uniquely identifies it). However, they lack information about the semantics or behavior of the malicious program. To counter these detectors the obfuscation techniques evolved, producing metamorphic malware that use stealthy mutation techniques such as *instruction reordering*, *dead code insertion*, and *register renaming* [29]. Likewise, to address effectively the challenges posed by metamorphic malware, we need to develop new methods and techniques to analyze the behavior of a program and make a better detection decision with few false positives. One such approach consists of translating the program into an intermediate language that provides an abstract format for analyzing and reasoning rigorously about the program behavior, in order to discover malicious occurrences.

Intermediate languages are used in compilers [1] to translate the source code into a form that is easy to optimize and increase portability. The term intermediate language also refers to the intermediate language used by the compilers of high level languages that do not produce any machine code, such as Java and C#.

The ability to translate programs written for different platforms, such as intel x86 and ARM architectures, to the same intermediate language provides portability to malware analysis and detection tools. An intermediate language can provide a general abstraction of the malicious code in a program and hence can be used as part of a tool to simplify and automate the process of malware analysis and detection. Different analysis techniques can be applied to the intermediate language to optimize malware detection, such as performing control flow analysis on the intermediate form and annotating the intermediate form with patterns that can be used by a pattern matching tool.

We propose, in this paper, a new intermediate language named MAIL (Malware Analysis Intermediate Language) for malware analysis that can enhance the detection of metamorphic malware.

Almost all the malware use binaries, instructions that a computer can interpret and execute, to infiltrate a computer system. There are hundreds of different instructions in any assembly language. We need to reduce and simplify these instructions considerably to optimize the static analysis of any such assembly program for malware detection. MAIL provides an abstract representation of an assembly program and hence the ability for a tool to automate malware analysis and detection. We want a common intermediate language that can be used with different platforms, so we do not have to perform separate static analysis for each platform. By translating binaries compiled for different platforms to MAIL, a tool can achieve platform independence. Each MAIL statement is annotated with patterns that can be used by a tool to optimize malware analysis and detection.

The rest of the paper is structured as follows. In Section 2, we discuss related research efforts in the development of intermediate languages for malware analysis and detection. In Section 3 we describe in detail the language design and components. In Section 4 we introduce our malware detection approach. In Section 5 we conduct an experiment to assess the properties of MAIL and our proposed malware detection approach. We finally conclude in Section 6.

2. RELATED WORK

Several intermediate languages for malware analysis and detection have been proposed in the literature [6, 39, 38, 24, 4, 12, 19]. This Section discusses the academic and the commercial research efforts in the development of intermediate languages for malware analysis and detection. First we present one of the commercial efforts and then move to the academic efforts. The reasons for selecting these research efforts are: (1) information about them is available publicly; (2) they are well described, i.e. at least part of the syntax and semantics is either described or defined mathematically; (3) they are currently being used in either academic or commercial malware analysis and detection tools.

REIL is an intermediate language that is being used in a commercial reverse engineering tool named *BinNavi* [18, 35]. Although REIL is not specifically designed for malware analysis, it is used in *BinNavi* for manual malware analysis and detection. In [32], Sepp et al. proposed an extension of REIL with relational information by translating the flags (an instruction's side effects) calculations into arithmetic instructions. The extension also helps reduce the size of a REIL program. The core language has a very reduced instruction set and consists of only 17 different instructions, and uses a flat memory model. The native instructions are translated to REIL instructions using a map. Based on the experiments carried out by the authors, on average an original native instruction is translated into approximately 20 REIL instructions. Unknown native instructions are replaced with NOP instructions which may introduce inaccuracies in disassembling. There are no examples in the paper of translating an assembly program into REIL. Furthermore, REIL does not translate FPU, MMX and SSE instructions, privileged instructions like system calls, interrupts and other kernel-level instructions. The reason for not including these instructions is that the authors think that these instructions are not yet used in exploiting security vulnerabilities. REIL cannot translate instructions of the type that address registers by an index, as in PowerPC. REIL cannot handle self-modifying code. The reason for this is that the REIL instructions cannot be overwritten or modified during the interpretation of REIL code.

SAIL is an intermediate language presented in [13] that represents a control flow graph(CFG) [1] of the program under analysis, and is used in a prototype malware detection tool developed by the authors. Each instruction in SAIL is either an assignment statement or a call statement, and becomes a block [1] and a node in the CFG. The *operators* supported in SAIL are arithmetic, bit-vector, relational and the special memory addressing operator. A node in the CFG contains only a single SAIL instruction, which can make the number of nodes in the CFG extremely large and therefore can make the analysis excessively slow for larger binary programs.

The VINE Intermediate Language (VINE-IL) proposed by Song et al. [33] is the intermediate language of the static analysis framework VINE used in the *BitBlaze* project. *BitBlaze* provides an extensible binary analysis platform for security applications. It is not specifically designed for malware detection but for general security applications. *BitBlaze* is used in the tool *Panorama* [37] for malware analysis and detection. The authors chose simplicity over efficiency, so VINE first translates a binary to VEX, an intermediate language used in Valgrind [28] (a dynamic binary instrumentation tool) and then to VINE-IL. The reason for not using VEX intermediate language directly, is the presence of implicit side effects in VEX instructions. In VINE-IL the final translated instructions have all the side effects explicitly exposed as VINE instructions. While exposing all the side effects in VINE-IL may be appropriate for general security applications such as program verification, this may not be efficient for specific security applications such as malware detection. Different platforms have different number and type of flags. Exposing all the side effects makes this approach general but also makes it difficult to maintain platform independence. In contrast to SAIL, side-effects are avoided in MAIL, making the language much simpler and providing ground for efficient malware detection.

In [3], the authors use an intermediate language called CFGO-IL to simplify transformation of a program in the x86 assembly language to a CFG. After translating a binary program to CFGO-IL, the program is optimized to make its structure simpler. The optimizations also remove various malware obfuscations from the program. These optimizations include dead code elimination, removal of unreachable branches, constant folding and removal of fake conditional branches inserted by malware. The side effects of the assembly instructions are exposed explicitly in the instructions of the CFGO-IL. The authors developed a prototype malware detection tool using CFGO-IL that take advantage of the optimizations and the simplicity of the language. However, by exposing all the side effects of an instruction, the language faces the same problem of maintaining the platform independence like VINE-IL. Furthermore, the size of a CFGO-IL program tends to increase compared to the original assembly program.

In [10], Cesare and Xiang introduce a new intermediate language for malware analysis named WIRE. The language is currently being used in the *Malwise* tool [11] developed by the authors. To the best of our knowledge, this is the only research effort that has the same goals as the MAIL language. The language is formally defined using an incomplete set of BNF notations. The authors defined operational semantics of WIRE and provided manual examples to check the semantic equivalence of obfuscated code using these operational semantics. WIRE does not explicitly specify the indirect jumps, making malware detection more complicated. There is only one instruction *ijmp* in WIRE that uses register as the branch target. The register contents (address) can be known or unknown and hence can complicate the malware analysis, and may render an incorrect analysis. To simplify malware analysis, in MAIL, this information is made explicit in the instruction.

Furthermore, the authors mention side effects of the assembly instructions as one of the difficulties of using the native assembly, but do not say anything about the side effects of the WIRE instructions. It is not clear how the language is used in the *Malwise* tool to automate the malware analysis and detection process. None of the referred papers [9, 8, 7, 11, 10] covers the automation process using WIRE.

3. THE MAIL LANGUAGE

In this Section, we give an outline of the design of MAIL and introduce underlying elements.

3.1 Language Design

We believe a good language must start small and simple, and must give opportunities to the language developers to grow (extend) the language with the users. Therefore MAIL is designed as a small, simple, and extensible language. In this and next subsections we describe how MAIL is designed in detail.

The basic purpose of MAIL is to represent structural and behavioral information of an assembly program for malware analysis and detection. MAIL will also make the program more readable and understandable by a human malware analyst. An assembly program may consist of the following type of instructions (we use Intel x86-64 assembly instructions [16] as sample instructions):

Control instructions: include instructions that can change the control flow of the program, such as JMP, CALL, RET, CMP, CMPS, CMPPS, PCMPEQW, REP and LOOP instructions.

Arithmetic instructions: perform arithmetic operations, such as ADD, SUB, MUL, DIV, FSIN, FCOS, PADDW, PSUBW, ADDPS, ADDPD, PMULLD, PAVGW, DPPD, SHR and SHL.

Logical instructions: perform logical operations, such as AND, OR, and NOT.

Data transfer instructions: involve data moving instructions, such as MOV, CMOV, XCHG, PUSH, POP, LODS, STOS, MOVS, MOVAPS, MOVAPD, IN, OUT, INS, OUTS, LAHF, SAHF, PREFETCH, FLDPI, FLDCW, FXSAVE, LEA, and LDS.

System instructions: provide support for operating systems and include instructions such as LOCK, LGDT, SGDT, LTR, STR and XSAVE, etc.

Miscellaneous instructions: All other instructions that do not fit into any of the above groups are included in this group of instructions, such as NOP, CPUID, SCAS, CLC, STC, CLI, HLT, WAIT, MFENCE, PACKSSWB, MAXPS, and UD (undefined instruction).

Designing a language that is small and simple, and accurately represents all these instructions for structural and behavioral information is non-trivial. Our goal is to create as few statements as possible in the intermediate language and map as many instructions as possible to these statements. For example we do not translate (i.e. ignore) the following x86 instructions:

```
CLFLUSH:    Flush caches
CLTS:       Clear TLB)
SMSW:       Restore machine status word
VERR:       Verify if a segment can be read
WBINVD:     Writing back and flushing of external caches
XRSTOR:     Restore processor extended states from memory
XSAVE:      Save processor extended states from memory
```

The complete list of x86 instructions that are not translated into the MAIL statements is given in [2].

3.2 MAIL Statements

The MAIL statements are divided into the following 8 basic statements (the complete MAIL grammar is given in [2]):

```
statements    ::= ( statement* ) ;
statement     ::= assignment_s+ | control_s+
                | condition_s+ | function_s+
                | jump_s+ | lib_call_s+
                | 'halt' | 'lock' ;
```

Every statement in the MAIL language has a *type* also called a *pattern* that can be used for pattern matching during malware analysis and detection. These *patterns* are introduced and explained in Section 3.4. MAIL has its own registers but also reuses the registers present in the architecture that is being translated to the MAIL language. There are other special registers such as:

- **Flag registers:** ZF (zero flag), CF (carry flag), PF (parity flag), SF (sign flag) and OF (overflow flag). These flag registers are of size one byte and are used in conditional statements.
  e.g. if (ZF == 1) jmp 0x405632;
- **eflags:** stores the flag registers.
- **sp:** to keep track of the stack pointer.
- **gr and fr:** these are infinite number of general purpose registers for use in integer and floating point instructions, respectively, and as they are used they are appended by a number, such as gr1, gr2, gr3, fr1, fr2, and fr3 etc.

The majority of the assembly instructions are data moving instructions, as shown above. We introduce in the following, two MAIL assignment statements covering the data transfer, arithmetic, logical and some of the system instructions. We use EBNF [17] notation to define these statements:

```
assignment_s  ::= register_s
                  | address_s ;
register_s    ::= register '=' (math_operator)? expr
                  | register '=' (expr)? math_operator expr
                  | register '=' lib_call_s ;
address_s     ::= address '=' (math_operator)? expr
                  | address '=' (expr)? math_operator expr
                  | address '=' lib_call_s ;

expr          ::= register | address | digit+ ;
register      ::= 'eflags'
                  | 'gr_' digit+ | 'fr_' digit+ | 'sp'
                  | register_name (':' register_name)? ;
register_name ::= letter+ ['0' - '9']?
                  | 'ZF' | 'CF' | 'PF' | 'SF' | 'OF' ;
address       ::= '[' digit+ ']' | reg_address
                  | 'UNKNOWN' ;
```

Control instructions are very important because they can change the behavior of a program, and they can be changed or added by polymorphic and metamorphic malware to avoid detection. The following MAIL control statement represents the control instructions:

```
control_s     ::= ('if' condition_s
                          (jump_s | assignment_s))
                  ('else' (jump_s | assignment_s))? ;
jump_s        ::= 'jmp' address ;
lib_call_s    ::= letter+ '(' address (, args)* ')' ;
function_s    ::= 'start_function_' digit+ statement
                  'end_function_' digit+ ;
condition_s   ::= (expr rel_operator expr)+ ;
```

3.3 MAIL Library

The current MAIL library contains 22 functions. The following are some of the examples of MAIL library functions:

- *compare(op1, op2):* compares two values *op1* and *op2* and then set the flag register.
- *max(op1, op2) and min(op1, op2):* returns the maximum and minimum of the parameters *op1* and *op2* respectively.
- *swap(op1, op2):* swap the bits in *op2* and write back in *op1*.

Details about all these library functions are given in [2]. These library functions can help in translating most of the complex assembly instructions present in current processor architectures. The purpose of these functions is not to capture the exact functionality of the assembly instruction(s) but to help in analysing the structure and behavior of the assembly program, and capturing some of the patterns in the program that can help detect malware.

3.4 MAIL Patterns for Annotation

MAIL can also be used to annotate a CFG of a program using different patterns available in the language. The purpose of these annotations is to assign patterns to MAIL statements that can be used later for pattern matching during malware detection. There are total 21 patterns in the MAIL language as follows:

ASSIGN: An assignment statement, *e.g.* EAX=EAX+ECX;

ASSIGN_CONSTANT: An assignment statement including a constant, *e.g.* EAX=EAX+0x01;

CONTROL: A control statement where the target of the jump is unknown, *e.g.* if (ZF == 1) JMP [EAX+ECX+0x10];

CONTROL_CONSTANT: A control statement where the target of the jump is known. *e.g.* if (ZF == 1) JMP 0x400567;

CALL: A call statement where the target of the call is unknown, *e.g.* CALL EBX;

CALL_CONSTANT: A call statement where the target of the call is known, *e.g.* CALL 0x603248;

FLAG: A statement including a flag, *e.g.* CF = 1;

FLAG_STACK: A statement including flag register with stack, *e.g.* EFLAGS = [SP=SP-0x1];

HALT: A halt statement, *e.g.* HALT;

JUMP: A jump statement where the target of the jump is unknown, *e.g.* JMP [EAX+ECX+0x10];

JUMP_CONSTANT: A jump statement where the target of the jump is known, *e.g.* JMP 0x680376

JUMP_STACK: A return jump, *e.g.* JMP [SP=SP-0x8]

LIBCALL: A library call, *e.g.* compare(EAX, ECX);

LIBCALL_CONSTANT: A library call including a constant, *e.g.* compare(EAX, 0x10);

LOCK: A lock statement, *e.g.* lock;

STACK: A stack statement, *e.g.* EAX = [SP=SP-0x1];

STACK_CONSTANT: A stack statement including a constant, *e.g.* [SP=SP+0x1] = 0x432516;

TEST: A test statement, *e.g.* EAX and ECX;

TEST_CONSTANT: A test statement including a constant, *e.g.* EAX and 0x10;

UNKNOWN: Any unknown assembly instruction that cannot be translated.

NOTDEFINED: The default pattern, *e.g.* all the new statements when created are assigned this default value.

4. MALWARE ANALYSIS USING MAIL

4.1 Approach Overview

Almost all the malware use binaries to infiltrate a computer system, which can be a desktop, a server, a laptop, a kiosk or a mobile device. Binary analysis is the process of automatically analysing the structure and behavior of a binary program. We use binary analysis for malware detection.

A binary program is first disassembled and translated to a MAIL program. In [2], we expalin in detail with examples of translating a x86 and an ARM assembly program into a MAIL program. The MAIL program is then annotated with patterns. We then build a CFG of the annotated MAIL program. This annotated CFG becomes part of the signature of the program and is matched against a database of known malware samples to see if the program contains a malware or not. This approach is very useful in detecting **known malware** but may not be able to detect unknown malware.

It is difficult to write a new metamorphic malware [34] and in general malware writers reuse old malware. To hide detection the malware writers change the obfuscations (syntax) more than the behavior (semantic) of such a new metamorphic malware. If an unknown metamorphic malware uses all or some of the same class of behaviors as are used by the training dataset (set of old metamorphic malware) then it is possible to detect these type of malware using machine learning techniques. On this assumption and motivation, we train our detector (classifier) on the training dataset and detect **unknown malware** as follows:

After a program sample is translated to MAIL, an annotated CFG for each function in the program is built. Instead of using one large CFG as signature, we divide a program into smaller CFGs, with one CFG per function. A program signature is then represented by the set of corresponding (smaller) CFGs. A program that contains part of the control flow of a training malware sample, is classified as a malware, i.e. if a percentage (compared to some predefined threshold) of the number of CFGs involved in a malware signature match with the signature of a program then the program is classified as a malware.

4.2 Subgraph Matching

Before explaining the subgraph matching technique used in this paper for malware detection, we first define *graph isomorphism* [23] as follows:

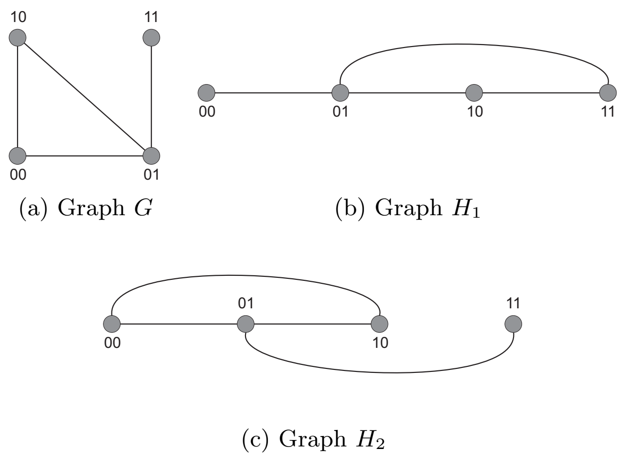
Let $G = (V_G, E_G)$ and $H = (V_H, E_H)$ be any two graphs, where V_G, V_H and E_G, E_H are the sets of vertices and edges of the graphs, respectively.

DEFINITION 1: A vertex bijection (one-to-one mapping) denoted as $f_V = V_G \rightarrow V_H$ and an edge bijection denoted as $f_E = E_G \rightarrow E_H$ are **consistent** if for every edge $e \in E_G$ f_V maps the endpoints of e to the endpoints of edge $f_E(e)$.

DEFINITION 2: G and H are **isomorphic graphs** if there exists a vertex bijection f_V and an edge bijection f_E that are consistent. This relationship is denoted as $G \cong H$.

An example of isomorphism is shown in Figure 1. The edges of graphs G and H_1 are not consistent, e.g. edge $\{00, 10\}$ in graph G is not mapped to any edges in graph H_1, therefore graphs G and H_1 are not isomorphic. Whereas the edges of graphs G and H_2 are consistent, therefore graphs G and H_2 are isomorphic.

In our malware detection approach, graph matching is defined in terms of **subgraph isomorphism**. Given the input of two graphs, *subgraph isomorphism* determines if one of the graphs contains a subgraph that is isomorphic to the other graph. Generally, *subgraph isomorphism* is an NP-Complete problem [15]. A CFG of a program is usually a sparse graph, therefore it is possible to compute the isomorphism of two CFGs in a reasonable amount of time.



(a) Graph G (b) Graph H_1

(c) Graph H_2

Figure 1: Example of *graph isomorphism*. Graphs G and H_2 are *isomorphic* but not G and H_1.

Based on the definition of *graph isomorphism* presented above we formulate our CFG matching approach as follows:

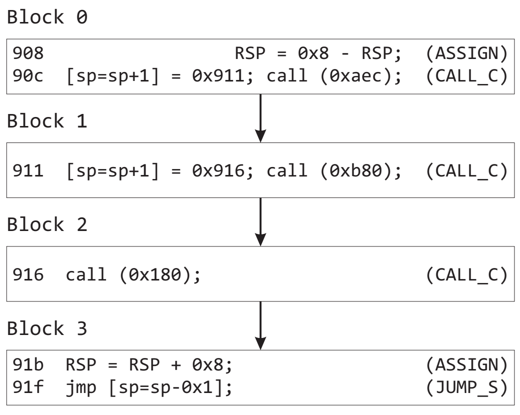
Let $P = (V_P, E_P)$ denote a CFG of the *program* and $M = (V_M, E_M)$ denote a CFG of the *malware*, where V_P, V_M and E_P, E_M are the sets of vertices and edges of the graphs, respectively. Let $P_{sg} = (V_{sg}, E_{sg})$ where $V_{sg} \subseteq V_P$ and $E_{sg} \subseteq E_P$ (i.e. P_{sg} is a subgraph of P). If $P_{sg} \cong M$ then P and M are considered as matching graphs.

After the binary analysis performed we obtain a set of CFGs (each corresponding to separate function) of a program. To detect if a program contains a malware we compare the CFGs of the program with the CFGs of known malware samples from our training database. If a percentage of the CFGs of the program, greater than a predefined threshold, match one or several of the CFGs of a malware sample (from the database) then the program will be classified as a malware.

4.3 Pattern Matching

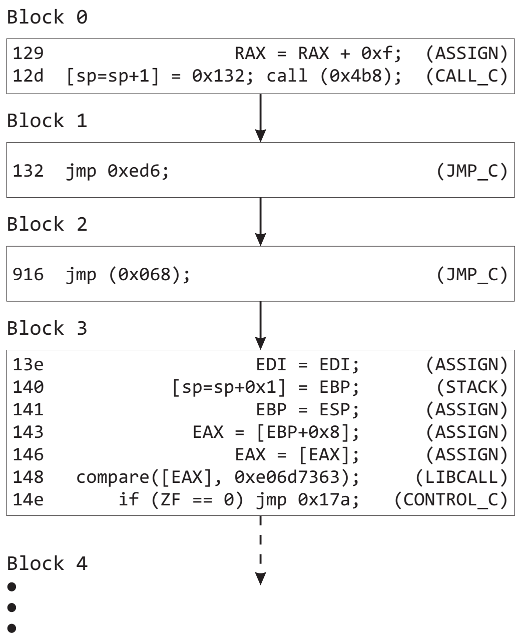
Very small graphs when matched against a large graph can produce a false positive. Likewise to alleviate the impact of small graphs on detection accuracy, we integrate a *Pattern Matching* sub-component within the *Subgraph Matching* component. Every statement in MAIL is assigned a *pattern* as explained in Section 3.4. If a CFG of a malware sample matches with a CFG of a program (i.e. the two CFGs are *isomorphic*), then we further use the *patterns*, assigned to MAIL statements, to match each statement in the matching nodes of the two CFGs. A successful match requires all the statements in the matching nodes to have the same (exact) patterns, although there could be differences in the corresponding statement blocks.

An example of *Pattern Matching* of two *isomorphic* CFGs is shown in Figure 2. One of the CFGs of a malware sample, shown in Figure 2 (a), is *isomorphic* to a subgraph of one of the CFGs of a benign program, shown in Figure 2 (b). Considering these two CFGs as a match for malware detection will produce a wrong result, a false positive. The statements in the benign program do not match with the statements in the malware sample. To reduce this false positive we have two options: (1) we can match each statement exactly with each other or (2) assign patterns to these statements for matching. Option (1) will not be able to detect unknown malware samples and is time consuming, so we use option (2) in our approach, which in addition to reducing false positives has the potential of detecting unknown malware samples.



```
Block 0
908                   RSP = 0x8 - RSP;  (ASSIGN)
90c  [sp=sp+1] = 0x911; call (0xaec);  (CALL_C)
Block 1
911  [sp=sp+1] = 0x916; call (0xb80);  (CALL_C)
Block 2
916  call (0x180);                      (CALL_C)
Block 3
91b  RSP = RSP + 0x8;                   (ASSIGN)
91f  jmp [sp=sp-0x1];                   (JUMP_S)
```

(a) One of the CFGs of a malware sample



```
Block 0
129                   RAX = RAX + 0xf;  (ASSIGN)
12d  [sp=sp+1] = 0x132; call (0x4b8);  (CALL_C)
Block 1
132  jmp 0xed6;                          (JMP_C)
Block 2
916  jmp (0x068);                        (JMP_C)
Block 3
13e                     EDI = EDI;      (ASSIGN)
140              [sp=sp+0x1] = EBP;      (STACK)
141                     EBP = ESP;      (ASSIGN)
143               EAX = [EBP+0x8];      (ASSIGN)
146                   EAX = [EAX];      (ASSIGN)
148   compare([EAX], 0xe06d7363);     (LIBCALL)
14e      if (ZF == 0) jmp 0x17a;    (CONTROL_C)
Block 4
•
•
•
```

(b) One of the CFGs of a benign program

Figure 2: Example of *pattern matching* of two *isomorphic* CFGs. The CFG in (a) is *isomorphic* to the subgraph (blocks 0 - 3) of the CFG in (b).

For a successful *pattern matching* we require all the statements in the matching *blocks* to have the same patterns. In Figure 2, only the statements in *block 0* satisfy this requirement. The statements in all the other blocks do not satisfy this requirement, therefore these CFGs fail the *pattern matching*.

5. EXPERIMENTS

We conducted an experiment to evaluate the performance of our malware detection technique. The evaluation was carried out using 10-fold cross validation, and prototype implementation of our detector named MARD (for Metamorphic malware Analysis and Real-time Detection). MARD fully automates the malware analysis and detection process, without any manual intervention during a complete run. We present, in this section, the evaluation metrics, the experimental settings and obtained results.

5.1 Performance Metrics

To measure the performance of the malware detection technique we compute the detection rate (DR) and false positive rate (FPR). The **DR** metric indicates the number of samples correctly recognized as malware out of the total malware dataset. The **FPR** metric indicates the number of samples incorrectly recognized as malware out of the total benign dataset. These performance metrics are defined as follows:

$$DR = \frac{Number\ of\ correct\ malware\ detected}{Total\ number\ of\ malware\ in\ the\ dataset} \quad (1)$$

$$FPR = \frac{Number\ of\ incorrect\ malware\ detected}{Total\ number\ of\ benign\ programs\ in\ the\ dataset} \quad (2)$$

5.2 Dataset

The dataset used for the experiments consisted of total 1387 sample Windows programs collected from two different resources [30, 31]. Out of the 1387 programs, 250 are metamorphic malware samples, and the other 1137 are benign programs. The dataset distribution based on the size of the CFG after normalization is shown in Table 1. The dataset contains a variety of programs with CFGs, ranging from simple to complex for testing. As shown in Table 1, the size of the CFG of the malware samples range from 3 nodes to 129 nodes, and the size of the CFG of the benign programs range from 17 nodes to 15343 nodes. This variety in the samples provides a good testing platform for the graph and pattern matching techniques used in our tool.

Table 1: Dataset distribution for the experimental study

250 Malware Samples		1137 Benign Programs	
Size of CFG	**Number of Samples**	**Size of CFG**	**Number of Samples**
3	200	17	127
88	1	30	44
91 – 99	38	44 – 998	412
100 – 104	10	1000 – 9765	535
129	1	10118 – 15343	19

5.3 Evaluation Methodology and Results

The experiment was run on the following machine: Intel Core 2 Quad (4 Cores) CPU Q6700 @ 2.67 GHz with 4GB RAM, operating system Windows 7 professional.

We conducted 10-fold cross validation by selecting 25 malware samples out of the 250 malware to train our detector. The remaining 225 malware samples along with the 1137 benign programs in our dataset were then used to test the detector. These two steps were repeated 10 times and each time different set of 25 malware samples were selected for training and the remaining samples for testing. The overall performance results were obtained by averaging the results obtained in the 10 different runs.

As explained above, to classify a program as benign or malware we compare to some predefined threshold (value) the percentage of its CFGs that match malware CFGs from the training set. To determine this threshold value empirically, we ran the above experiments with different values of the threshold ranging from 20% to 90%. Table 2 lists the obtained results. As it can be noted the best results are obtained for threshold values of 20% – 25%.

Table 2: Malware detection performance by varying the detection threshold value.

Threshold	DR	FPR
20	99.2%	3.07%
25	99.2%	3.07%
30	93.2%	3.07%
40	86.4%	3.07%
50	82.8%	3.07%
60	76%	3.07%
70	76%	3.07%
80	76%	3.07%
90	76%	3.07%

Using a threshold value of 25%, we conducted further evaluation by increasing the size of the training set from 25 samples to 100 and 200 malware samples, respectively. The obtained results are listed in Table 3. The DR improved from 93.92% when the size of the training set is 25 to 99.6% and 100% when we used a training dataset of 100 and 200 samples, respectively.

Table 3: Malware detection performance by varying the training sample size, and setting the threshold value to 25%.

Training set size	DR	FPR	Real-Time
25	93.92%	3.02%	✓
100	99.6%	3.43%	✓
200	100%	3.43%	✓

Real-time here means the detection is fully automatic and finishes in a reasonable amount of time.

6. CONCLUSION

We have developed MAIL as a new intermediate language, and shown through experimental evaluation its effectiveness in malware analysis and detection.

It is important to note that a program translated to MAIL when executed may not produce the same output as the original program. MAIL is designed to perform static binary analysis and is not suitable for performing dynamic binary analysis.

The patterns developed if used with a behavioral signature of a binary program such as a CFG have the capability to produce useful classifications for malware analysis and detection, as shown by the results of the above experiments. But if the patterns are used alone, it may not produce the desired results.

The side effects of an assembly instruction are not directly translated to the MAIL statement. With the presence of various flag registers in the MAIL language it is possible for a malware analysis tool to include the side effect(s) of an assembly instruction by generating more statements and updating the affected flag registers.

The MAIL language is most useful in capturing the behavior (including structural and functional) of a binary program and can be used as part of different malware detection techniques such as the ones described in this paper and in [25, 22, 21, 20]. These techniques require behavioral, structural or functional information about a program. In its current form, MAIL cannot be used as part of other signature-based malware detection techniques, such as [36, 31, 30]. These techniques build the signatures using the opcodes of a binary program.

Currently we are carrying out further research into optimizing the tool to increase its accuracy and efficiency for detecting unknown metamorphic malware. We are collecting more metamorphic malware samples to use in our research and carry out experiments to further improve malware classification and detection.

Our future work will consist of strengthening our existing algorithms by investigating and incorporating more powerful pattern recognition techniques.

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