Obfuscation with Turing Machine

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Abstract. Software security is a fundamental research domain in this threat emerging technology world. Control flow obfuscation one of important techniques to prevent hackers from understanding the program internal logic and leveraging software vulnerabilities to do damage. Hence, concealing important conditional branch logics are crucial for protecting software from being compromised. In this paper, we propose a novel control flow obfuscation method by leveraging the complexity of Turing machine. By entwining the original software programs with Turing machine execution, control transfers could be selectively obfuscated. Control flow graph and call graph could be significantly complicated. We implemented an obfuscation tool named Turing machine obfuscator with LLVM. Compared with previous works, our control flow obfuscation technique bears two distinct advantages:1.Complexity. Complicated implementation of Turing machine makes it hard for attackers to follow the control flow graph logic.2.Universality. Our obfuscation happens on intermediate representative level so the application scope is broadened to almost every language with a LLVM front-end compiler. We evaluate the obfuscator by potency, resilience, stealth and cost respectively. Experiment results show that Turing machine obfuscator could obfuscate programs in stealth with good performance and robustness.

Key words: software security, control flow obfuscation, Turing machine, LLVM

1 Introduction

Obfuscation derives from intellectual property protection. The Internet brings us unprecedented convenience along with idea plagiarism threat and copyright infringement. Concealing the algorithm of a software means a lot for the society especially for high-tech industry. Attackers could take advantage of the state-of-the-art techniques [21, 22, 23] to recover source code structure from binaries, exploit software vulnerabilities or to steal software ideas or algorithms. Obfuscation is mostly designed to impede such (malicious) reverse engineering process.

Recently, Software security research again draws people's attention because of infamous ransomware attack and severe vulnerabilities such as the "Wanncry" incidence and the OpenSSL heart bleeding bug. All of these malwares exploit vulnerabilities inside a software. To exploit vulnerabilities in the software, attackers usually need to recover the program control-flow structures first.

Dynamic code analysis is a popular and effective technique to explore inner logic of a program. *Concolic testing* is well-developed and widely-adopted technique which leverages both symbolic and concrete execution to exhaust the program path coverage [25]. A common reverse engineering flow with the help of concolic execution is shown in Fig. 1. The concolic testing engine yields new input which leads to new execution path by solving path conditions as constraints. Hence, a lot of anti-reverse engineering research has focused on preventing adversaries from analyzing important path conditions in a program[20, 5, 7, 8, 9]. Control flow obfuscation is one of these cutting-edge techniques. Control flow obfuscation aims at hiding path conditions and complicating the execution flow within a program. By rewriting or adding extra control flow components, the program path conditions become difficult or even impossible to analyze. Existing research (e.g., [2]) have successfully demonstrated the effectiveness of control flow obfuscation.

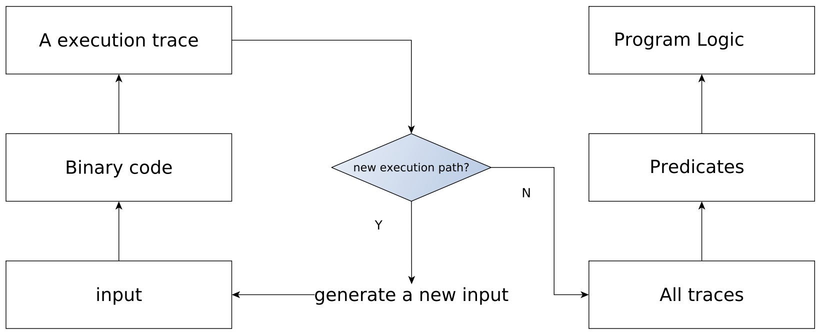


Fig. 1: Reverse engineering with concolic testing

In this paper, we propose a novel control flow obfuscation method which leverages Turing machine to compute path conditions. *Church—Turing thesis* has shown that any function is computable by a human being without resource limitation concerns if and only if this function is computable by a Turing machine [24]. This means any functional component of software can be reimplemented as a Turing machine; the replaced code component and its corresponding semantic equivalent Turing machine is called *Turing Equivalent.*

In this work, we propose to simulate important branch conditions in original source code with its *Turing Equivalent* Turing machine. A Turing machine behaves as a state machine so it would bring in a large amount of extra control flow transfers and basic blocks to the overall program control flow graph. A typical Turing machine leverages transition tables to guide the state transition, and such transition table-based execution would introduce additional computations to the target program. We believe the proposed Turing machine obfuscation would largely complicate the protected program, and also bring in new challenges for reverse engineering tasks.

To obfuscate a program through the proposed Turing machine obfuscation technique, we first translate the original program source code into a compiler intermediate representation. Our Turing machine obfuscator then selects path condition instructions for translation; the translated instruction will invoke its corresponding Turing machine component, which is semantically equivalent to the original path condition. After finishing the execution in the Turing machine "black box", the execution flow returns back to the original instruction, with a return value that indicates the branch selection. Inspired by previous work [4], we evaluate our obfuscator regarding four aspects which are potency, resilience, cost and stealth, respectively. Results indicate that Turing machine obfuscator could effectively obfuscate commonly-used software with acceptable performance penalty.

This paper is organized as follows. Section 2 discusses related works on obfuscation, especially control flow obfuscation. Section 3 presents the overall design of Turing machine obfuscator. Obfuscator implementation is discussed in section 4. Section 5 presents the evaluation result of our proposed technique. We further present discussion in section 6, and conclude the paper in Section 7.

2 Related Work

Generally speaking, reverse engineering techniques are categorized into static track and dynamic track. To battle static reverse engineering, researchers usually focus on hardening disassembling and decompiling process. To combat the dynamic reverse engineering techniques such as concolic testing, sensitive conditional transfer logic must be hidden from adversaries. Control flow obfuscation has been proved effective in this scenario.

Sharif et al. ([5]) identify conditions that could trigger malware execution then using a hash function to transform such condition outputs. Hence, corresponding conditional codes which would be run with the trigger value were encrypted with a key generated based on the instruction trigger value. By this means the obfuscation analyzer could never get a chance to get the expected "launching code" consequently planted malware could never be executed. This technology works on certain fixed trigger value but not in scenarios that trigger values are intervals. This limitation narrows the application scopes greatly since a large volume of branch conditions are comparison operations. In addition, the encryption and decryption process in this methodology also introduce non-negligible overhead.

Popov et al. ([7]) propose to leverage signals ("traps") to replace the unconditional control transfer instructions such as `jmp` and `call` to impede disassembly operation which is the first step of reverse engineering. Moreover, dummy control transfers and junk instructions are also inserted after signal replacements. This method seems to be effective in fooling disassemblers but it cannot be applied in scenarios that the conditional control flow transfers need to be protected.

Another related work proposes to cover branch information leveraging a remote trusted third party environment [8]. In general, their technique mostly introduces notable network overhead and also relies on trusted network accessibility which may not be feasible in practice.

Ma et al. ([2]) take advantage of neural network to replace certain branch condition statements in source programs; the propose technique is evaluated to conceal conditional instructions and dynamic analysis such as concolic testing would be trapped to cover the protected branches. Although the idea is promising and the experimental results indicate the effectiveness to certain degree, in general neural network-based solution may not be suitable for such scenarios. To the best of our knowledge, neural network works like a black box; it lacks a rigorous theoretical foundation to show a correct result can always to generated given an input. In other words, neural networks may yield results which lead to the selection of incorrect branches. Overall, neural networks not only introduce complexity but also unpredictability to the transformed programs. Trained models may behave very differently if given initial parameters with only some nuances, which means that it is very challenging to train an accurate enough model to simulate the conditional instruction. In addition, we notice that neural network usually consumes too much memory in the evaluations.

3 Turing machine obfuscation

3.1 Design Overview

In a program, a path condition statement compares two operands and select a branch for control transfer based on the comparison result. In theory, Turing machine has been proved to be able to simulate the semantics of any computer algorithm. Hence, any program path condition statement can be modeled by a Turing machine. Taking advantage of its powerful computation ability as well as execution complexity, we propose to employ Turing machine to obfuscate path condition statements in a program. The general workflow of a Turing machine obfuscated path condition statement is shown in Fig. 2. As shown in the figure, instead of directly computing a boolean value in the condition statement, we feed a Turing machine with the inputs (the value of operands) and let the Turing machine to simulate the execution.

3.2 Turing Machine

Turing Machine is a mathematical model which could simulate any computer program. As shown in Fig. 3, a typical Turing machine consists of four components:

- An infinite-long tape which consists of a sequence of cells. Each cell holds a symbol defined in the tape alphabet.
- A tape head which could conduct read, write, move left and move right operations.
- A state register used to record the state of the Turing machine. Turing machine states are finite.

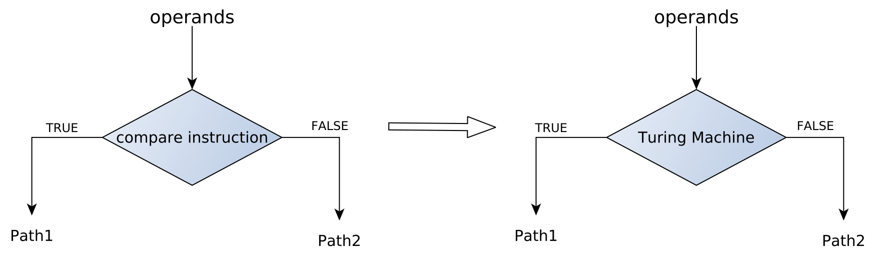


Fig. 2: Workflow of a Turing machine obfuscated path condition statement.

– A transcription table that consists of all the transition rules defining how a Turing machine transfers from one state to another.

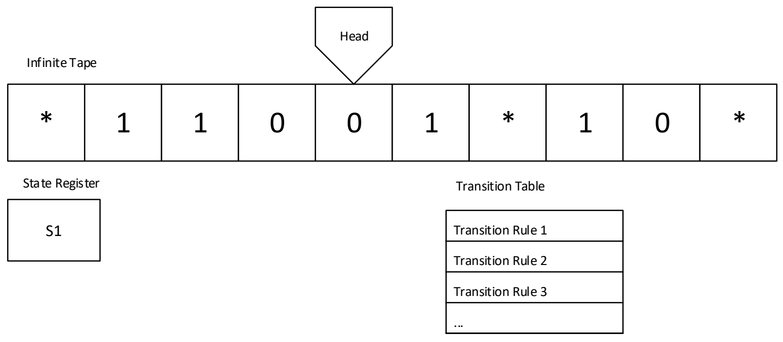


Fig. 3: Turing Machine Components

Although simple, Turing machine model includes all necessary parts of a modern computer. The head is I/O device. The infinite tape acts as the computer memory. The transition table acts as a computer processor which embeds the algorithm of a piece of program. Hence, Turing machine is also deemed as the foundation of modern computer science development.

Turing machine initialization TODO this paragraph needs to be rephrased. difficult to understand the point.

Initially, Turing machine is in "start" (S_0) state and tape records the Turing machine input. Blank symbol is symbolized as Char "*" on tape. Consistent with existing Turing machine simulator project [6], we use the length of "·" to represent an operand of integer type. For instance, integer 5 is represented as five continuous "·" on tape. Turing machine tape alphabet is $\{\cdot, *\}$. The tape in Fig. 3 displayed an initial state of Turing machine. The head of Turing machine is placed on the leftmost cell. Different integer operands are separated by a single blank symbol "*". Operands encoded on the tape of Fig. 3 are 5 and 1. When Turing machine starts to run, the head reads the current tape cell, combining with current state register value it could locate one and only one match transition rule in the transition table. Mathematically a transition rule could be represented by a 5 element tuple:

$$(S_c, T_c, S_n, T_n, D)$$

where:

- S_c is the current Turing machine state
- T_c is the current tape cell symbol read by the head
- S_n is the new Turing machine state
- T_n is the symbol head writes to current tape cell
- D is the direction the head should move (i.e., "left" or "right")

Turing machine running The Turing machine keeps running step by step directed by the transition table until it reaches a `Halt` state. On the other hand, Turing machine may keep running forever since the process of solving some problems cannot terminate. In our research, we implement Turing machine to do simple algebra computations so it would always reach a `Halt` state. When reaching the `Halt` state, the machine stops running and the computation result is shown on the tape. Table 1 shows a transition table example, which supports a Turing machine to conduct the `add` operation in our implementation.

Current State	Current Symbol	New State	New Symbol	Direction
S_0	*	S_0	*	Right
S_0	.	S_1	.	Right
S_1	*	S_2	.	Right
S_1	.	S_1	.	Right
S_2	*	S_3	*	Left
S_2	.	S_2	.	Right
S_3	*	S_3	*	Left
S_3	.	S_4	*	Left
S_4	*	$Halt$	*	-
S_4	.	S_4	.	Left

Table 1: Transition table of the `add` operation in a Turing machine.

Addition Turing Machine TODO this paragraph needs to be rephrased. difficult to understand the point. In this section, we elaborate the design of "add" Turing machine which simulates the semantics of the addition operation. Other Turing machines used in this research are designed in a similar way. Through constructing this transition table, we essentially realize rules which could concatenate two integer dot cells together. After a sequence of reading and writing operations based on the transition table, two operand dot strings are merged into one long string on tape; the length of result string is the sum of two inputs. Adding Turing Machine Transition table encodes the running algorithm which is simplified in Algorithm 1. When Turing machine completes execution process, the sum of left and right operand is yield on the tape. The length of the result is exactly the sum of two operands because Turing machine erase one dot cell of right operand and complement with one dot cell between the two input operands.

Algorithm 1 Transition table algorithm for the "add" Turing machine.

```
1: procedure RUNNING PROCEDURE
2:     head ← blank cell before left operand starting cell
3:     while head != blank cell after right operand do move right
4:     move left
5:     last dot cell of right operand ← blank symbol
6:     while head != blank cell isolator of two operands do move left
7:     blank cell isolator ← dot
8:     while head != blank cell befor left operand do move left
9:     Halt;
```

Turing Machine of other operations As previously discussed, given any program algorithm, there must exist a corresponding Turing machine. Since our Turing machine obfuscator concentrates on obfuscating integer control transfer instruction, Turing machine obfuscator need to contain transition tables which is capable of doing arithmetic operations such as $+, -, \times, \div$ and all the involved comparison operations like $\leq, \geq, \neq$, etc.

To implement the arithmetic operations, besides the addition table shown in Table 1, we construct three more tables for subtraction, multiplication and division operations. Their transition tables are relatively more complex than Table 1. Actually in our implementation, we build transition table of 16, 34 and 80 transition rule entries for subtraction, multiplication and division Turing machines, respectively.

As for the comparison operations, XXX

In sum, we construct XXX transition tables, with overall XXX transition table entries.

By design, our Turing machine could dynamically allocate new tape cells to construct an infinite tape used to store intermediate results.

3.3 Universal Turing Machine

While a Turing machine could perform powerful algorithm simulation, its computation ability is predetermined by its embedded transition table. For instance, a Turing machine capable of doing addition operation could only simulate the "add" operation since other operations would have very distinct transition rules; a "add" Turing machine could not represent "subtract" operations. To some degree, each Turing machine is encoded with a fixed algorithm. However, in non-trivial programs, path conditions could be any kind of operation such as $x + 5$ or 6×7. Many of these algebra expressions would correspond to different Turing machines. Hence, we need an unified translator to represent arbitrary computations. Universal Turing machine is designed to simulate arbitrary Turing machines. It stores and interprets arbitrary Turing machines on a single tape. As shown in Fig. 4, both the inputs and the transition tables are written on the tape of the universal Turing machine. In some sense, a universal Turing machine acts as the interface for us to employ Turing machines of different semantics.

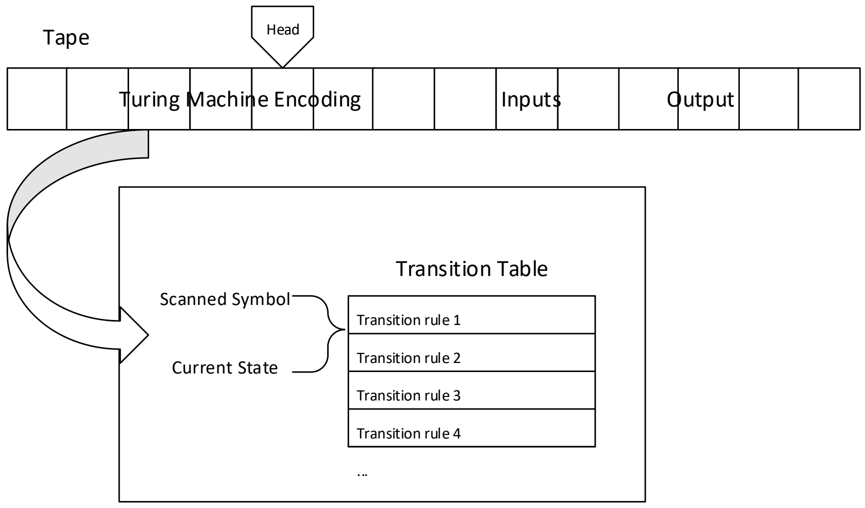


Fig. 4: Overall workflow of a universal Turing machine.

Tape construction Before universal Turing machine execution, a tape which contains the inputs and Turing machine transition tables is generated. For each operation of "+", "−", "×" and "÷", there is a corresponding transition table. As aforementioned, integer inputs are encoded as strings of "." with different lengths. Following the standard tape formatting protocol, we then concatenate transition tables and inputs to form a tape for the universal Turing machine. In this way, all the information needed for computations exists on the tape. During the execution of universal Turing machine, it would first extract a proper transition table then perform one step computation.

please see the notes in the tex file Universal Turing machine bears the essence of the modern computer which is being programmable. Through storing different transition tables on a sequence of cells on the tape, an universal Turing machine can actually perform semantic equivalent computation to arbitrary programs; as aforementioned, such Universal Turing Machine and the replaced algebra expression are *Turing Equivalent*. In our Turing machine obfuscator, we can invoke a Universal Turing machine function call on interested control transfer instructions.

Negative Integer Operand Preprocess please see the notes in the tex file In software programs, integer operands comprise both positive and negative cases. Turing machine could only dispose of positive operands in consequence of we use the length of dot cell on tape to represent a integer. This means we have to preprocess the invalid operands in Turing machine obfuscator. In the preprocessing stage, Turing machine obfuscator could convert invalid operands to its opposite number to run Turing machine. Calculate result from Turing machine is also changed before returning. For instance, $-4+(-6)$ is preprocessed to $4+6$, afterwards -10 which is the opposite number of 10 is returned.

4 Implementation

We implemented Turing Obfuscator on Intermediate Representation(IR) level with the help of LLVM [18]. In general Turing obfuscator employed three phases to generated target obfuscated binary as shown in Figure 5. The first is to compile both target source program and obfuscator source code to IR, then the obfuscator processes IR instructions with several passes. At last these instrumented IR codes are compiled again and linked to the final obfuscated binary. Turing machine obfuscator is implemented with C.

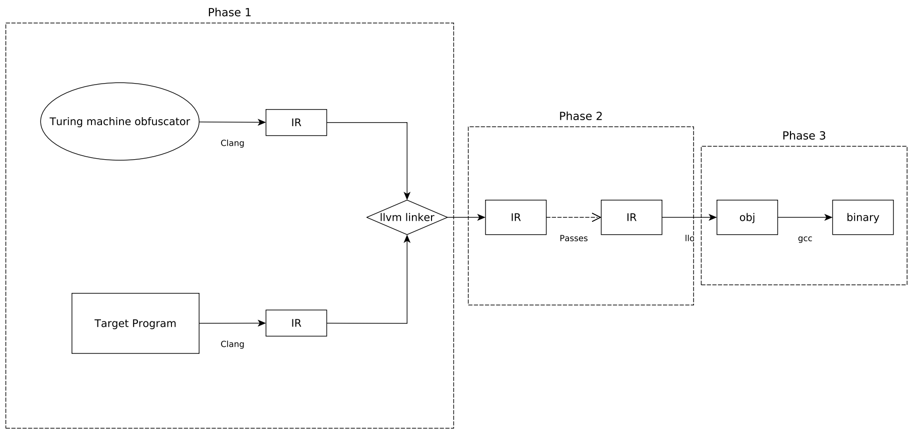


Fig. 5: Turing Machine Obfuscator work flow

4.1 Translating Source code to IR

Turing machine obfuscator converts target source program to LLVM IR in phase 1. The reason behind this is LLVM could generalize our Turing machine obfuscator in consequence of the abundance of LLVM front end compilers. LLVM provides many front end compilers which could turn source programs written in C, C++, Python and other languages into LLVM IR. Since obfuscation transformation takes place in IR level, the applicable range of Turing obfuscator is significantly broadened compared to previous works [2, 8]. In experiments, we use software programs in C as target source codes so Clang-5.0 is the front end compiler.

4.2 Static Analysis Pass

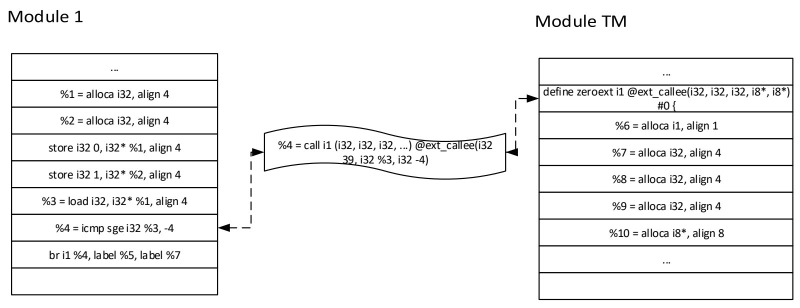
After preparation phase 1, Turing machine obfuscator does some static analysis on source program IR to locate all transformation candidates. LLVM Pass framework is a core module of LLVM to conduct instruction granularity analysis, transformation or other compiler level optimization. We built a Pass with this framework to iterate and analyze every IR instruction in each module of a source program. Instructions of Turing machine are filtered out and prevented from being obfuscated to avoid endless recursion.

Locate Candidate Predicates Currently we only extract control transfer instructions with integer operands as obfuscation candidates. These candidates comprise 10 kinds of instructions including : equal, not equal, unsigned greater than, unsigned greater or equal, unsigned less than, unsigned less or equal, signed greater than, signed greater or equal, signed less than, signed less or equal.

4.3 Transformation Pass

After the static analysis Pass we got all eligible instruction candidates. Afterwards, we built another Transformation pass to transform some or all of these candidate control transfers to a function call to universal Turing machine interface. Result of universal Turing machine call is stored to a register inside LLVM which is used to direct following path label.The essence of Turing obfuscator is to hide important control transfers inside IR codes. Turing machine obfuscator could obfuscate any designated control transfer inside a target program. In experiments we randomly select a portion of the candidates and do the transformation.

We noticed that if Obfuscation could cover branch information further if we could jump back to a caller function basic block based on the Turing machine running result like in [2], but essentially it still expose branch trace since we need to record the basic block addresses of each branch. To the best of our knowledge, perfecting branch hiding technique does not exist since there is always a way to figure out inner logic of a certain program given enough time and energy. We need to harden this process as much as possible. Currently we adopt the IR replacement way to invoke Turing machine.



```
...
%1 = alloca i32, align 4
%2 = alloca i32, align 4
store i32 0, i32* %1, align 4
store i32 1, i32* %2, align 4
%3 = load i32, i32* %1, align 4
%4 = icmp sge i32 %3, -4
br i1 %4, label %5, label %7
```

```
%4 = call i1 (i32, i32, i32, ...) @ext_callee(i32
39, i32 %3, i32 -4)
```

```
...
define zeroext i1 @ext_callee(i32, i32, i32, i8*, i8*)
#0 {
%6 = alloca i1, align 1
%7 = alloca i32, align 4
%8 = alloca i32, align 4
%9 = alloca i32, align 4
%10 = alloca i8*, align 8
...
```

Fig. 6: Transformation Pass

Obfuscation Level Similar with [3], Obfuscation level is an indicator which weighs how much of a program is transformed by the transform pass. We defined obfuscation level as the percentage between obfuscated instruction and total eligible instructions:

$$O = M/N$$

- M is the number of instructions replaced by transformation pass.
- N is the number of all instruction candidates filtered by static analysis pass.

5 Evaluation

Inspired by previous research [4, 2], we evaluate our Turing machine obfuscator based on four metrics which are *potency*, *resilience*, *stealth* and *cost*, respectively. Potency weighs the complexity of the obfuscated programs, which is straightforward to show how competent an obfuscator is. A good obfuscator also needs to protect itself from being deobfuscated; to measure how well an obfuscated program is resilient to automatic deobfuscation techniques, we evaluate the resilience of our Turing machine obfuscator. Moreover, in the battle against experienced attackers, obfuscated programs should not be too distinguishable from its origins otherwise it would be easy to be recognized. Hence, we measure the stealth to show how well an obfuscated program resembles the original one. Cost is naturally employed to measure the execution overhead of a software program.

While obfuscation would inevitably introduce performance penalty, we measure the execution time of the obfuscated code to show the overall cost is acceptable.

Two widely-used open source programs are employed in our evaluation: compress tool BZIP2 [10] and regular expression engine slre [11]. In Turing machine obfuscator, we collect all path condition instructions (e.g., `cmp` and `test` instructions), variables and expressions which could affect the value of the conditional branch as transformation candidates. Obfuscation level is an index which represents the ratio between obfuscated instructions and all candidates. In our experiments, the ratio is set as 50% which means half of all conditional transfer candidates are *randomly* selected and obfuscated.

5.1 Potency

Control flow graph (CFG) and call graph provide insights on the general structure of a program and they are the foundation for most static software analysis. With the help of IDA Pro [13] which is a well-known commercial disassembler and debugger, we recover CFG and call graph information from both original and obfuscated binaries. By traversing the graph, we further calculate the number of basic blocks, number of call graph and control graph edges. We use such information to measure the complexity of a program, which is aligned with previous research [12]. Analysis result are shown in Table 2. Comparing the original and obfuscated programs, it can be observed that program complexity is increased in terms of each metric.

Table 2: Potency evaluation in terms of program structure-level information.

Program	**# of CFG Edges**	**# of Basic Blocks**	**# of Function**
BZIP2	3942	2647	78
obfuscated BZIP2	4195	2828	134
REGEXP	906	619	25
obfuscated REGEXP	1122	773	43

We further quantify the Turing machine obfuscated programs w.r.t. the cyclomatic number and knot number (these two metrics are introduced in [14, 15]). Cyclomatic metric is defined as

$$Cyclomatic = E - N + 2$$

where E and N represent the number of edges and the number of nodes in a CFG, respectively. Knot number shows the number of edge crossings in a CFG. These two metrics intuitively weighs how complicated a program is in terms of logic diversion number. Results in Table 3 shows that both knot number and cyclomatic number notably increase after Turing machine obfuscation. Overall, we interpret Table 2 and Table 3 as promising results to show program becomes more complex after the Turing machine obfuscation.

Table 3: Potency evaluation in terms of knot and cyclomatic number.

Program	**# of Cyclomatic**	**# of Knot**
BZIP2	1297	5596
obfuscated BZIP2	1369	5720
REGEXP	289	478
obfuscated REGEXP	351	1068

Besides picking 50% as the obfuscation level in evaluating potency, we also conduct experiments with obfuscation levels as 30%, 80% and 100%. Fig. 7 shows the number of call graph edges regarding different obfuscation levels. Observation shows that with a higher obfuscation level, the number of call graph edge increases. We interpret the results that the obfuscated program become more complicated with the obfuscation level increases.

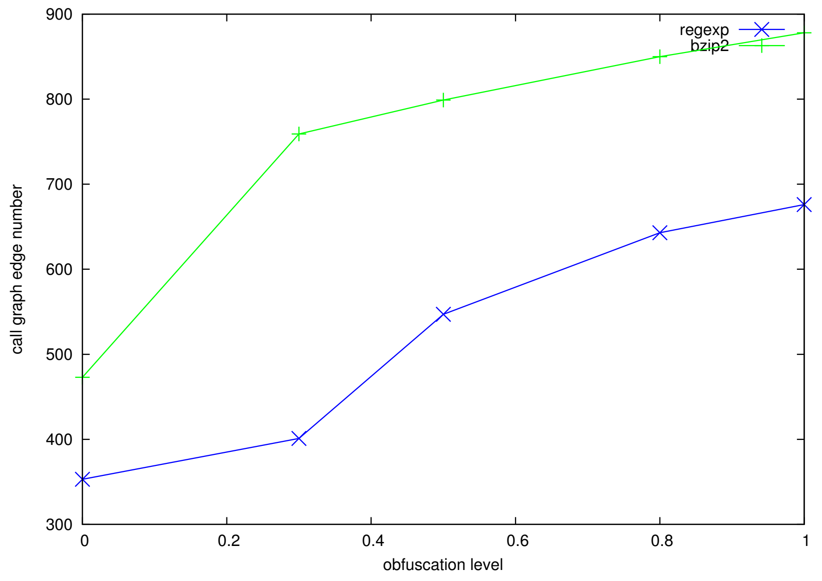


Fig. 7: Number of Call graph edges in terms of different obfuscation levels.

5.2 Resilience

A good obfuscation technique should resist deobfuscation tools as well. Concolic testing is an advanced deobfuscation technique aiming at finding bugs or vulnerabilities in software through the mixture of symbolic execution and concrete execution. Whereas, it is also used by adversaries to analyze or restore software inner logic control flow graph[27, 25, 26]. KLEE [19] is static analysis tool based on LLVM platform and it could generate enough test cases to ensure a code coverage threshhold. With the help of KLEE, it would be easy to conduct automated deobfuscation by concolic testing. We chose KLEE as the deobfuscation tool to evaluation resilience of Turing Machine obfuscator. We used a piece of sample code from KLEE [19] as the subject program (the sample code is shown in Fig. 8). The subject program need to be converted to IR codes since KLEE works on IR level.

```
int get_sign(int x) {
  if (x == 0)
    return 0;

  if (x < 0)
    return -1;
  else
    return 1;
}

int main() {
  int a;
  klee_make_symbolic(&a, sizeof(a), "a");
  return get_sign(a);
}
```

Fig. 8: KLEE sample code used in our evaluation. All the path conditions are obfuscated.

KLEE could detect three paths in the original subject program as expected. Based on different value of x, this program may traverse branches in which x equals 0, x is less than 0 and x is greater than 0, repectively. In contrast, after subject program is obfuscated by our Turing machine obfuscator, KLEE could only figure out one path. We interpret the evaluation result that Turing machine obfuscator can impede automated deobfuscation tools from restoring the structure of a program.

Due to limited information released by KLEE, we could not figure out the underlying reason that leads the failure of KLEE. Since Turing machine obfuscator make the conditional branches more complicated, our guess is that the internal constraint solver employed by KLEE is unable to yield proper symbolic input which "drill" into the branches protected by our Turing machine obfuscator.

5.3 Stealth

As mentioned in the beginning, software obfuscation technique should not only combat automated deobfuscation tools, but also manual deobfuscation methods. In the evaluation of stealth, [3] compares the instruction distributions of original and obfuscated programs. If instruction distribution of the obfuscated program is distinguishable from its original program (e.g `call` or `jmp` instruction proportions are abnormally high), it would be an obvious indicator that the program is manipulated. We adopted this metric to evaluate our Turing obfuscator. Obfuscation level for stealth evaluation is set to 50%.

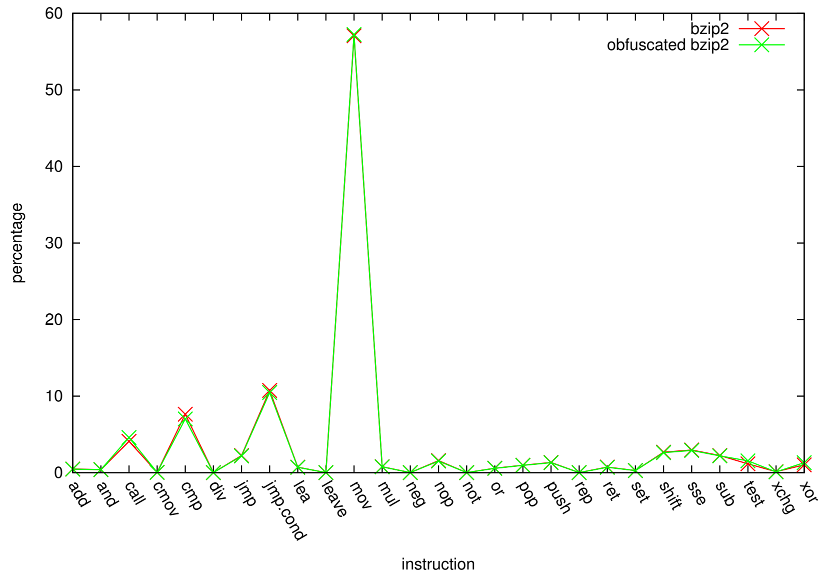


Fig. 9: BZIP2 instruction distribution comparison

Consistent with previous research ([3]), we put assembly instructions into 27 different categories. Fig. 9 and Fig. 10 present the instruction distribution of the original and obfuscated programs (BZIP2 and REGEXP). Experiment results indicate that the instruction distribution after obfuscation is very close to the origin distribution. Comparing these two figures together, we noticed that instruction diststribution variance of REGEXP is bigger than BZIP2, it makes sense since REGEXP consists of 8117 lines of Code and REGEXP contains only 1391 lines of C code. In sum, small instruction distribution variation is a promising result to show the proposed technique would obfuscate programs in a stealthy way.

5.4 Cost

Software running cost is another critical factor in evaluating an obfuscation technique. In most obfuscation research work, execution cost is inevitably increased because obfuscation would bring in extra instructions. Measuring the execution time is a convincing way to evaluate to the cost.

In our evaluation, both original and obfuscated programs are executed on a server with 2 Intel(R) Xeon(R) E5-2690 2.90GHz processors and 128GB system memory. BZIP2 is used to compress three different sample files and regular expression engine SLRE runs 149 test cases provided by its shipped test cases. We

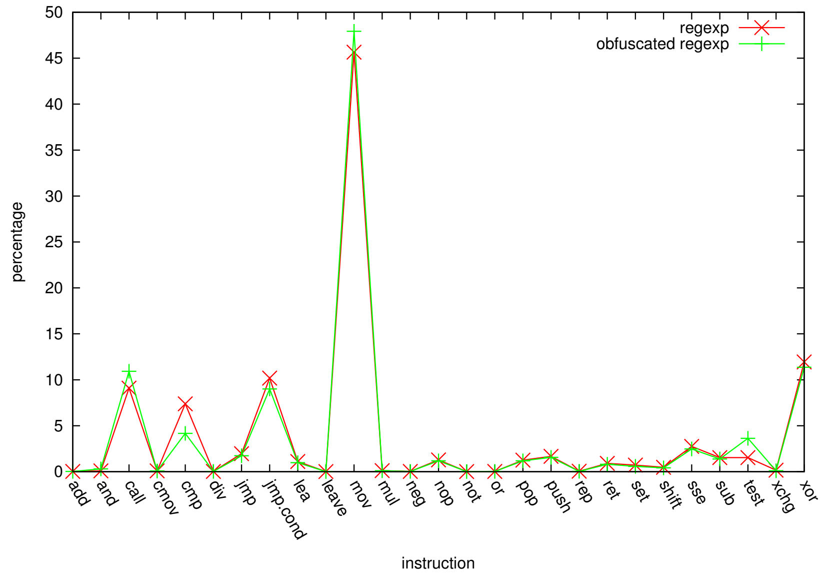


Fig. 10: regexp instruction distribution comparison

ran each program three times and recorded the average time cost as the final result.

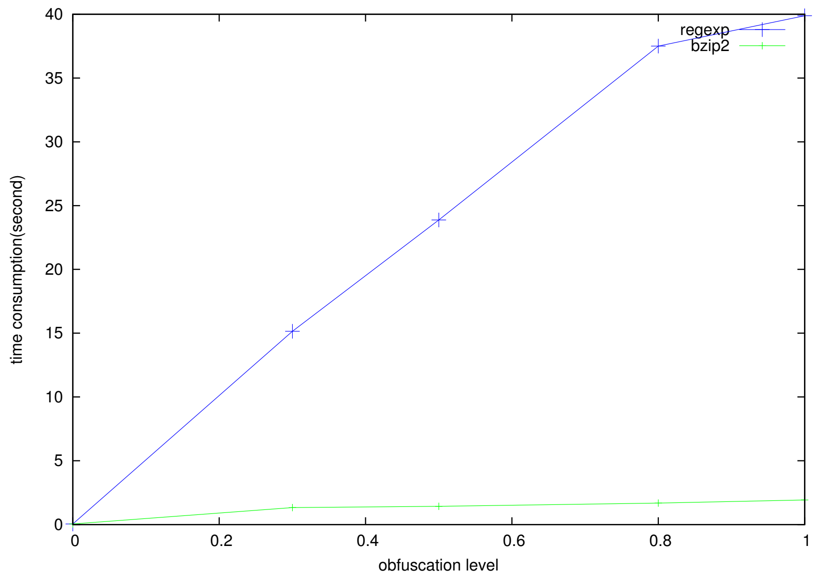


Fig. 11: Execution overhead in terms of different obfuscation levels.

Fig. 11 shows that for both test cases, the execution slowly grows w.r.t the increase of obfuscation levels. As expected, program takes more time to execute with more instructions are obfuscated. On the other hand, we interpret the overall time cost is still confined to a reasonable level. We also notice that there exists a difference between slopes of the two curves. Turing obfuscator randomly obfuscates candidate instructions within the program before execution. Hence the transformed instructions may not be indeed executed in the runtime. Difference between two curve slopes is probably due to such uncertainty of execution. In addition, the regexp program employs more recursive calls than BZIP2, thus may contribute to the relatively higher cost grow as well.

6 Discussion

To provide more insights and guideline for further adoption of our proposed technique, we discuss the strengths and weakness of Turing machine technique in this section.

6.1 Strength

Complexity In general, Turing machine model is a powerful calculator that is capable of solving any algorithm problem. Note that even a simple operation (e.g., "add") may lead to the change of Turing machine states for hundreds of times; every "move left" and "move right" operation lead to the tape modification and "read" or "write" operations.

Considering Turing machine as a state machine, it is hard—if possible at all—for adversaries with manual reverse engineering to follow the calculation logic without understanding the transition table rules and state variables. In addition, the intrinsic Turing machine complexity can also defeat automated deobfuscation tools (e.g., KLEE). As reported in our resilience evaluation (Sec. 5.2), the constraint solver of KLEE failed to yield proper inputs to cover two of three execution paths.

Opaque Obfuscation Enhanced Opaque obfuscation enhanced

Application Scope Previous obfuscation work [5] usually targets one or several specific kinds of predicate expressions. Also, most of them performs source code level transformations for specific kind of program languages [3]. Turing obfuscator broadens the application scope to any kind of conditional expression. In addition, it works for programs written in any language as long as they could be transformed into the LLVM IR. Considering a large portion of programming languages have been supported by LLVM, we envision Turning machine obfuscator would serve to harden many commonly used programming languages.

6.2 Weakness

During the Turing machine computation, frequent state change would indicate lots of read and write operations. Also, since tape is infinite in Turing machine model, it needs to allocate enough memory to accommodate complex computations. In general, the complexity of Turing machine is a double edge sword; it impedes adversaries and increases execution overhead at the same time. As reported in the cost evaluation (Fig. 11), we observed non-negligible performance penalty for both cases. One solution is to perform selective obfuscation; users can mark sensitive program components and Turing machine obfuscator would only harden those parts. Such strategy would improve the overall execution speed without sacrificing the major security requirements.

Moreover, our current implementation rewrites path condition instructions to invoke the Turing machine component. While it is mostly impossible for attackers to reason the functionality of the Turing machine code, return value of executing the Turing machine component is observable (since the return value is used to select branches). Certain amount of information leakage may become feasible at this point. We leave it as one future work to study the potential information leakage and countermeasures.

Operand number

7 Conclusion

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