HookFinder: Identifying and Understanding Malware Hooking Behaviors

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Abstract

Installing various hooks into the victim system is an important attacking strategy employed by malware, including spyware, rootkits, stealth backdoors, and others. In order to defeat existing hook detectors, malware writers keep exploring new hooking mechanisms. However, the current malware analysis procedure is painstaking, mostly manual and error-prone. In this paper, we propose the first systematic approach for automatically identifying hooks and extracting hooking mechanisms. We propose a unified approach, fine-grained impact analysis, *to identify malware hooking behaviors. Our approach does not rely on any prior knowledge of hooking mechanisms, and thus can identify novel hooking mechanisms. Moreover, we devise a method using* semantics-aware impact dependency analysis *to provide a succinct and intuitive graph representation to illustrate hooking mechanisms. We have developed a prototype,* HookFinder*, and conducted extensive experiments using representative malware samples from various categories. We have demonstrated that HookFinder can correctly identify the hooking behaviors of all samples, and provide accurate insights about their hooking mechanisms.*

1 Introduction

The arms race between malware writers and malware defenders is escalating. In order to evade malware defense techniques, malware writers are always striving to explore novel attacking techniques. In response, malware defenders must accurately and responsively understand malware's attacking vectors to gain an upper hand.

One important malware attacking vector is its hooking mechanism. Malicious programs implant hooks for many different purposes. Spyware may implant hooks to get notified of the arrival of new sensitive data. For example, keyloggers may install hooks to intercept users' keystrokes; password thieves may install hooks to get notified of the input of users' passwords; network sniffers may install hooks to eavesdrop on incoming network traffic; and BHO-based adware may also install hooks to capture URLs and other sensitive information from incoming web pages. In addition, rootkits may implant hooks to intercept and tamper with critical system information to conceal their presence in the system. Malware with a stealth backdoor may also place hooks on the network stack to establish a stealthy communication channel with remote attackers.

Several tools [4, 13, 24] detect hooking behaviors by checking known memory regions for suspicious entries. However, they need prior knowledge of how existing malware implants hooks. Therefore, they become futile when malware uses new hooking mechanisms. This concern is not hypothetical. Recently, new stealthy kernel backdoors (deepdoor [26] and uay [30]) are reported to employ a novel hooking mechanism for intercepting the network stack. To set up hooks, they overwrite only a small portion in NDIS data block. Without knowing this particular hooking mechanism, we can hardly notice this kind of hooks. In fact, all existing hook detection methods have failed to detect this kind of hooks.

In response to rapidly evolving malware techniques, we need an effective and efficient mechanism, to discover new hooking behaviors and understand their hooking mechanisms. Unfortunately, the existing malware analysis procedure is painstaking, mostly manual and error-prone. Various code obfuscation techniques used in malware make this manual process even more difficult. In this paper, we propose the first systematic approach to this research problem. In particular, given an unknown malicious binary, we aim to identify if this code installs any hooks into the system, and if so, provide detailed information about how it installs the hooks.

The intuition of our approach is that a hook implanted by a piece of malicious code is one of the *impacts* (in terms of memory and registers) that the malicious code has made to the whole system, and this impact eventually affects the execution flow of the system to jump into the malicious code. In order to capture this distinct behavior, we propose a novel approach, *fine-grained impact analysis*. It works by identifying all the impacts made by the malicious code, and keeping track of the impacts flowing across the whole system. If the control flow is affected by one of these impacts to jump into the malicious code, then we determine that this transition is caused by a hook, which is installed by the malicious code. To understand how this hook is implanted, we devise a *semantics-aware impact dependency analysis* mechanism. It performs dependency analysis on the history of impact propagation, leveraged with OS-level semantics.

We have prototyped our approach into a tool called HookFinder, and evaluated it with eight malware programs. In the experiment, HookFinder identified hooking behaviors of each malware sample within minutes. For each identified hooking behavior, HookFinder gave valuable insights and details about the underlying hooking mechanism. The efficiency and effectiveness of HookFinder makes it possible to automatically categorize hooking behaviors of the large volume of malware samples received by anti-virus companies everyday, and instantly realize and respond to novel hooking mechanisms.

In summary, this paper makes the following contributions:

- We propose fine-grained impact analysis as a unified approach to identifying the hooking behavior of malicious code. Since it does not rely on any prior knowledge of hooking mechanisms, our approach is well suited for identifying novel hooking mechanisms.

- In order to provide valuable insights about how malware implants hooks, we devise a semantics-aware impact dependency analysis method, which provides a succinct and intuitive graphical representation to help malware analysts understand the hooking mechanism employed by a piece of malware.

- We have designed and developed HookFinder to demonstrate the feasibility of our approach. We have conducted extensive experiments with representative malware samples from various categories, and demonstrated that HookFinder could correctly identify their hooking behaviors, and provide accurate insights about their hooking mechanisms.

The paper is structured as follows. The next section gives an overview of our approach. Section 3 describes details on the design and implementation of HookFinder. Section 4 presents the experimental results. Section 5 discusses some related issues. Section 6 surveys related work and Section 7 concludes the paper.

2 Problem Statement and Our Approach

In this section, we formalize the problem of hooking behavior detection and analysis, and give a brief overview of our approach.

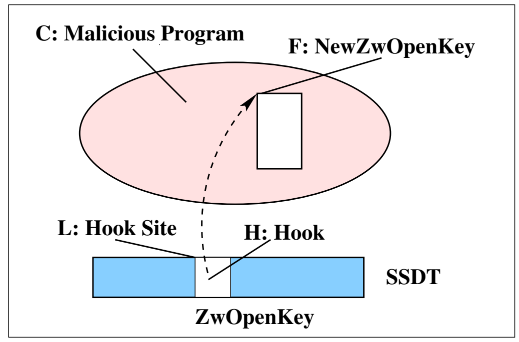
2.1 Problem Statement

Given a malware sample, our approach first determines whether it contains hooking behaviors. A hooking behavior can be formalized as follows. A malicious program C attempts to change a memory location L of the operating system, to implant a *hook* H. When a certain event happens, the operating system will load the hook H, and then starts to execute malicious code F in program C. We refer to the address of F as *hook entry*, and L as *hook site*. Figure 1(a) shows a piece of pseudo code that hooks an entry in the System Service Descriptor Table (SSDT) of Windows system. This hooking mechanism is used in many kernel-mode malware samples, such as the Sony Rootkit [27]. In this example, the hook entry F is `NewZwOpenKey`, and the hook site L is the entry for `ZwOpenKey` in the service descriptor table, and the hook H is the address of `NewZwOpenKey`, as illustrated in Figure 1(b).

If our approach detects hooking behaviors in a malware sample, it outputs a graph representation of the hooking mechanism, *hook graph*. The hook graph tells us two main characteristics of a hooking mechanism: *hook type* and *implanting mechanism*.

```
#define SYSTEMSERVICE(_function) \
  KeServiceDescriptorTable.ServiceTableBase \
  [*(PULONG)((PUCHAR)_function+1)]
void HookSyscalls() {
  ...
  OldZwOpenKey = SYSTEMSERVICE(ZwOpenKey);
  SYSTEMSERVICE(ZwOpenKey) = NewZwOpenKey;
  ...
}
```

(a)



(b)

Figure 1. An SSDT Hooking Example. This code attempts to hook `ZwOpenKey`, by writing the address of its own function `NewZwOpenKey` into the corresponding entry of the SSDT `KeServiceDescirptorTable`.

Hook Type Depending how it is interpreted by the CPU, a hook H can be either a *data hook* or a *code hook*. A data hook is interpreted as data by the CPU, and is used as the destination address of some control transfer instruction to jump into the hook entry F. For example, the hook in Figure 1 is a data hook, because it is the address of the hook entry, and is interpreted as the jump target. A code hook is interpreted as code by the CPU. A code hook contains a jump-like instruction (such as `jmp` and `call`), and is injected to overwrite some system code (such as kernel modules and common DLLs). When a code hook is activated, the execution is redirected into the malicious code F. We need to detect hooking behaviors in both cases, and we should be able to tell what kind of hook it is when we detect one. As we will see later, the policies used to detect hooking behaviors are different between these two categories due to their different nature.

Implanting Mechanism Malware has two choices to install H into L. First, it may directly write H into L using its own code. Second, it may call a function to achieve it on its behalf. Windows system provides several APIs for applications to register various event handlers (i.e., hooks). For example, `SetWindowsHookEx` allows an application to register a hook for certain Windows event, such as keystroke events. Whenever a keystroke is entered into the system, Windows will call the hook function provided by this application. In addition, functions like `memcpy` and `WriteProcessMemory` can overwrite a memory region on behalf of their callers. Thus, once we identify a hook, we need to determine which method the malware used to register the hook.

If the malware directly modifies L to install H, we need to understand where L is, and how the malware sample obtains L. Since L is usually not located in a fixed place, malware has to find it from some static point. This static point can be a global system symbol, or the result of a function call. After obtaining this static point, malware may walk through the data structures referenced by it to eventually locate L. The example in Figure 1 makes use of this method, and the hook site L is calculated from a global symbol `KeServiceDescriptorTable`. For this type of implanting mechanism, the hook graph answers the following questions:

- Where is the static point?
- How does the malware obtain the static point?
- How does it infer the final location L from the static point?

If the malware invokes an external function to register H, we need to identify the function's address and name. In addition, we need to know the actual arguments that are used to call this function. The function call and its argument list can give semantic information about how the hook and what kind of hook is registered. For example, if we identify that a malicious program calls `SetWindowsHookEx` to register a hook, we are able to tell from the first argument what type of hook is registered. For this type of implanting mechanism, the hook graph answers the following questions:

- What is the external function, including its entry address and its name?

- What arguments does the malware use to invoke this function?

2.2 Our Approach

Since most malware programs are equipped with various code obfuscation techniques to foil static analysis, our approach is based on dynamic analysis. That is, we actually monitor the execution of the malware in a special environment, and use the obtained information to derive how it implants the hook, and how the hook is activated by the operating system. Note that our approach is designed for analysis, not on-line detection. Our approach is divided into two steps: hook detection and hooking mechanism analysis.

Hook Detection: Fine-grained Impact Analysis Our approach is based on the following intuition. Malicious code makes changes, including memory and the other machine state changes, to the execution environment as it runs. We call these changes *impacts*. Obviously, a hook H is one of the impacts made by the malicious code, and this impact finally redirects the execution control flow into the malicious code. Hence, if we are able to identify all the impacts of the malicious code, and observe one of the impacts being used to cause the execution to be redirected into the malicious code, we can determine a hook installed by the malicious code. Furthermore, we are also interested in how an impact is formulated, for the purpose of understanding hooking mechanism. Therefore, we identify *initial impacts*, the newly introduced impacts by the malicious code, and then keep track of the impacts propagating over the system.

Based on this intuition, we propose *fine-grained impact analysis*. We mark all the initial impacts made by the malicious code at byte level. The initial impacts include data written directly by the malicious code, and data written by the external code (through function calls) on its behalf. Then we keep track of the impacts propagating through the whole system. During the execution, if we observe that the instruction pointer (i.e., `EIP` in x86 CPUs) is loaded with a marked impact, and the execution jumps immediately into the malicious code, then we identify a hook. Furthermore, in this case, we have determined that the jump target is the hook entry F, the memory location that the instruction pointer is loaded from is the hook site L, and the content within L is the hook H.

Hooking Mechanism Analysis: Semantics-aware Impact Dependency Analysis Once identifying a hook H, we want to understand the hooking mechanism. During the impact propagation, we record into a trace the details about how the impacts are propagated in the system. Therefore, from the trace entry corresponding to the detected hook H, we can perform backward dependency analysis on the trace. The result gives how the hook H is formulated and installed into the hook site L. However, such a result is difficult to understand, because it only provides hardware-level information and sometimes can be enormous. We combine OS-level semantics information with the result, and perform several optimizations to hide unnecessary details. The final output is a succinct and intuitive graphical representation, assisting malware analysts to understand its hooking mechanism.

Note that our approach would catch "normal" hooking behaviors. Windows provides a number of APIs, such as `CreateThread` and `CreateWindow`, for applications to register their callback functions. Windows will invoke these callbacks on certain events. These function calls that register normal hooks can be compiled into a white-list. Then if one of these normal hooks is captured by our detection step, we can classify it as normal, by extracting its hooking mechanism and comparing it with the white-list. In practice, we find this white-listing approach very effective. Note that "normal" hooks are not considered false positives in our case, since our goal is to extract and analyze any hooking mechanism which may be employed by the sample of interest.

3 System Design and Implementation

To demonstrate the feasibility of our approach, we design and implement a system, HookFinder, to identify the hooking behavior and understand the hooking mechanism. In this section, we give an overview of HookFinder and describe its components.

3.1 System Overview

The overview of HookFinder is illustrated in Figure 2. HookFinder is based on a *whole-system emulator*. It emulates an x86 computer and runs a Windows guest system on top of it. The malware to be analyzed is executed in the Windows guest system. There are two reasons why we employ a whole-system emulator. First, it facilitates instrumenting CPU instructions in a fine-grained manner. In particular, we are able to instrument every CPU instruction executed in the Windows guest system. Second, it provides an excellent protection line between the analysis environment and the malware.

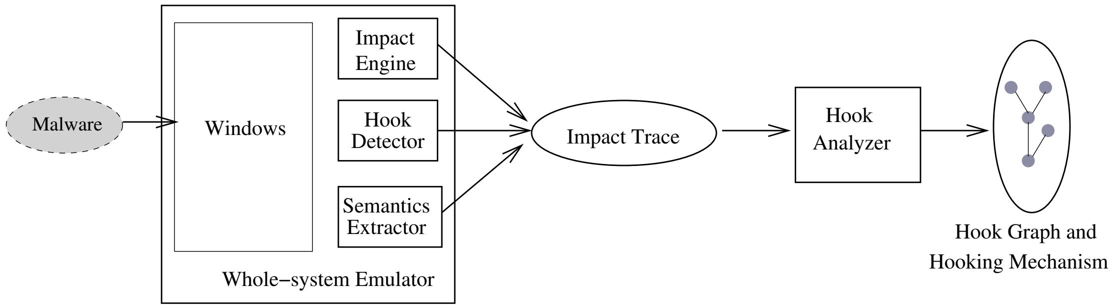


Figure 2. System Overview

Therefore, it is relatively more difficult for malicious code to interfere with our detection and analysis procedure and affect the analysis results. In the implementation, we develop HookFinder on top of TEMU [29], which is the dynamic analysis component in the BitBlaze project [2].

Within the emulator, we build three components: *impact analysis engine*, *semantics extractor*, and *hook detector*. The impact analysis engine is a central component, which performs fine-grained impact analysis. It marks the impacts made by the malware, and keeps track of impacts propagating over the whole system. A whole-system emulator only provides a hardware-level view of the system, such as the states of CPU registers, physical memory, and I/O devices. However, malware analysts need to understand the malware and system behaviors at the operating-system level. The semantics extractor implements the functionality of extracting OS-level semantics information from the emulated environment. For example, it provides process and module information of the current instruction executed. It can also provide information about external function calls. The hook detector behaves like a controller, cooperating with the impact analysis engine and the semantics extractor to identify hooks.

To analyze hooking mechanisms, the impact propagation events, as well as necessary OS-level semantics information, are recorded into a trace, called the *impact trace*. The *hook analyzer* analyzes the impact trace and generates a succinct and intuitive graphical representation, *hook graph*. The hook graph conveys essential information for malware analysts to easily understand the hooking mechanism.

3.2 Impact Analysis Engine

The impact analysis engine performs fine-grained impact analysis, and is composed of two sub-components: *impact marker* and *impact tracker*. The impact marker is responsible for marking the initial impacts made by the malicious code, and the impact tracker keeps track of the impacts propagation.

Impact Marker In the impact marker, we aim to identify all the initial impacts that can be used to install hooks. This is important, because if we fail to mark some initial impacts, malware writers may exploit this fact to evade our detection.

First, we consider that an instruction from malicious code directly makes an impact. When an executable binary is loaded into the system, a module space is allocated for it, and the code and data segments from the binary are copied into this module space and initialized. The semantics extractor mentioned in Section 3.3 is able to tell which module space belongs to the sample under analysis. Then, for an instruction located in that module, we need to mark its impact accordingly. That is, we mark the destination operand, either a memory location or a CPU register, if it is not marked already.

In addition, we consider that malicious code may make an impact by calling an external function. For example, it may call `ReadFile` to obtain the address of the hook entry F from a configuration file, and then install it as the hook H into the hook site L by calling `memcpy`. If we do not consider this situation, H will not be marked. Therefore, we need to mark the output of that external function too. Again, we will discuss in Section 3.3 how the semantics extractor determines if an instruction is executed under the context of an external function call.

To identify the impacts made in an external function, we treat memory writes and register writes differently. For memory writes, we mark a memory location if it is written under the context of the external function call, and it is not a local variable on the stack. To determine a local variable, we obtain the stack range for the current thread from the semantics extractor, and compare the memory location with the value of ESP on the entry of the external function call: if the memory location is smaller than the value of ESP and within the stack range, then it is a local variable. For register writes, we only need to consider EAX. According to the function calling conventions (i.e., _cdecl and _stdcall) in Windows, EAX contains the return value when applicable, while the other general-purpose registers (except the stack pointer ESP) remain unchanged. Now we need to determine if EAX contains the return value and mark it accordingly. We save the value of EAX on the entry of an external function call, and then on the exit of the function, check if EAX is changed. If so, we mark this EAX.

Furthermore, malware may dynamically generate new code. Since self-generated code is also part of impacts made by the malicious code, the memory region occupied by it must have already been marked. Thus, we can determine if an instruction is generated from the original malicious binary by simply checking if the memory region occupied by that instruction is marked. If so, we also treat that code region as malicious code, and mark the inputs taken by the self-generated code too.

Impact Tracker The impact tracker keeps track of the impacts propagating throughout the system. It tracks data dependencies between source and destination operands. That is, if any byte of any source operand is marked, the destination operand is also marked. In addition, for a memory source operand, if its address becomes marked, we also mark the destination operand. This policy enables us to track how the malicious code walks through a data structure, starting from a marked pointer to the data structure. These two policies are similar to those in the dynamic taint analysis systems [7, 10, 11, 22, 33]. Note that the impact tracker keeps track of impacts propagating over the whole system, including the disk. It still keeps track of the impacts that are swapped out to disk, or written to the registry and filesystem. Therefore, HookFinder is able to detect the hooks that are registered through the registry and filesystem.

What makes the impact tracker different from dynamic taint analysis is the way it checks immediate operands. That is, if an instruction has an immediate operand, the impact tracker checks if the memory region occupied by this immediate is marked and if so, propagates the impact accordingly. In contrast, the dynamic taint analysis systems treat immediate operands as clean. In our scenario, the malicious code may overwrite the system code with manipulated immediate numbers in the instructions. For example, in the code hook case, the malicious code may inject into the system code a jump instruction with a hard-coded target address, to redirect the execution to the malicious code. This immediate operand is a crucial impact that is deliberately injected by the malicious code to set up a hook. Therefore, we need to check immediate operands.

To enable dependency analysis, the impact tracker performs an extra operation during the impact propagation. That is, we assign a unique identifier to each marked byte of the destination operand. We refer to this identifier as *dependency ID*. Then for each instruction that creates or propagates the marked data, we write a record into the impact trace. The record contains the relationships between the dependency IDs of marked source and the destination operand, associated with other detailed information about that instruction.

3.3 Semantics Extractor

The semantics extractor bridges the semantic gap between the hardware-level view and the software-level view. Specifically, the purposes of the semantics extractor are three-fold: (1) determine the process, thread, and module information for the current instruction; (2) determine if an instruction is executed in the context of an external function call, and if so, resolve its function name and arguments; and (3) determine the symbol name if a memory read is to a symbol.

Several previous systems [10, 14–16, 33] have discussed extracting OS-level semantics from a virtual machine monitor or a whole-system emulator. There are mainly two types of approaches. First, we can directly examine the guest system states from outside, with complete knowledge of crucial data structures [10, 14, 15]. Second, we can insert a kernel module into the guest system to collect the necessary information [16, 33]. Our implementation is based on TEMU, which combines these two approaches.

Process, Thread, and Module Information The other two systems [16, 33] that are also based on TEMU have described how we extract process, thread and module information. To summarize, the kernel module loaded in the guest system registers several callback routines. Whenever a process is created or deleted or a module is loaded into a process memory space, the corresponding callback routine is invoked. The callback routines gather the information such as the value of CR3 for each process and the memory region for each module, and then pass it to the underneath emulator via a predefined I/O port. Obtaining thread information is fairly straightforward, as the data structure for the current thread is mapped into a well-known virtual address in Windows. We can simply read the thread information, such as the thread ID and stack base and size, directly from outside.

External Function Call Previous systems [10, 33] have also discussed how to determine external functions called by the malicious code, by comparing the stack pointers. The intuition is that the malicious code has to push the arguments and the return address onto the stack to call an external function. Thus by comparing the stack pointer when the execution enters the malicious code, and the one when the execution leaves, we can determine if the execution jumping out of the malicious code is because of an external function call.

Then given the entry address of an external function, we want to resolve its function name. We achieve this by parsing the PE header of a module whenever it is loaded into the system. Each binary in the PE format contains an export table that for each of its exported functions maps its name with its offset within the binary. Combining the offset with the base address that the module is actually loaded in, we can infer the actual address of an external function.

Symbol Name When an instruction reads a memory location, we want to determine if it is reading a symbol, and if so, resolve the symbol name. This is useful in generating an OS-level hook graph. Similarly to resolving external function name, we parse the PE header of a module whenever it is loaded into the system. We extract symbol names with their offsets in both export table and import Table, and infer the actual address of a symbol using the module base address and its offset.

3.4 Hook Detector

The hook detector works by checking if the control flow is affected by some marked value, which redirects the execution into the malicious code. More precisely, we observe whether the instruction pointer `EIP` is marked, and the execution jumps immediately from the system code into the malicious code region, or the code region generated from the malicious code. If the conditions are satisfied, we identify a hook: the jump target is the hook entry F, the memory location that EIP is loaded from is L, and the content in L is H.

The above policy functions properly for identifying data hooks, but is problematic for code hooks. This is because a code hook is a piece of code generated by the malicious code, and thus is treated as malicious code by the above policy. Therefore when the code hook redirects the execution to the malicious code, the above policy will not raise an alarm because it sees the execution being transferred from malicious code to malicious code. To solve this problem, we extend the above policy such that the execution transitions from a code hook region into malicious code will raise an alert.

Then the question is how to distinguish code hook regions with other self-generated code regions. Self-generated code usually remains in the module space of the malicious code, or stays in a region that is not occupied by any module (such as in heap), whereas a code hook region is a piece of code that overwrites a code region in a different module. Therefore, during execution, if the currently executed basic block is marked and from a different module, and EIP is marked and jumps into the malicious code, we identify it as a code hook.

3.5 Hook Analyzer

Once a suspicious hook is identified, the hook analyzer is able to extract essential information about its hooking mechanism by performing *semantics-aware dependency analysis* on the impact trace. The procedure consists of the following three steps: (1) from the hook H, perform backward dependency analysis on the impact trace, and generate hardware-level hook graph; (2) with the OS-level semantics information, transform the hardware-level hook graph into an OS-level hook graph; and (3) if necessary, simplify the hook graph by hiding unnecessary details and merging similar nodes. We detail these steps respectively.

Hardware-level Hook Graph A hook graph represents dependencies among malware's instructions that are used to implant a hook. A node of a hook graph corresponds to an instruction involving hooking behavior; an edge of a hook graph points from an instruction setting an operand to an instruction using the operand as source.

Recall that each record in the impact trace has dependency information. With the hook H identified by our hook detector, we create the first node in our hook graph, representing the instruction that activates H. We then obtain the hook's dependency ID ID_h, and locate the record that defines ID_h in the impact trace. Finally, we search backwards in the impact trace to add depen-

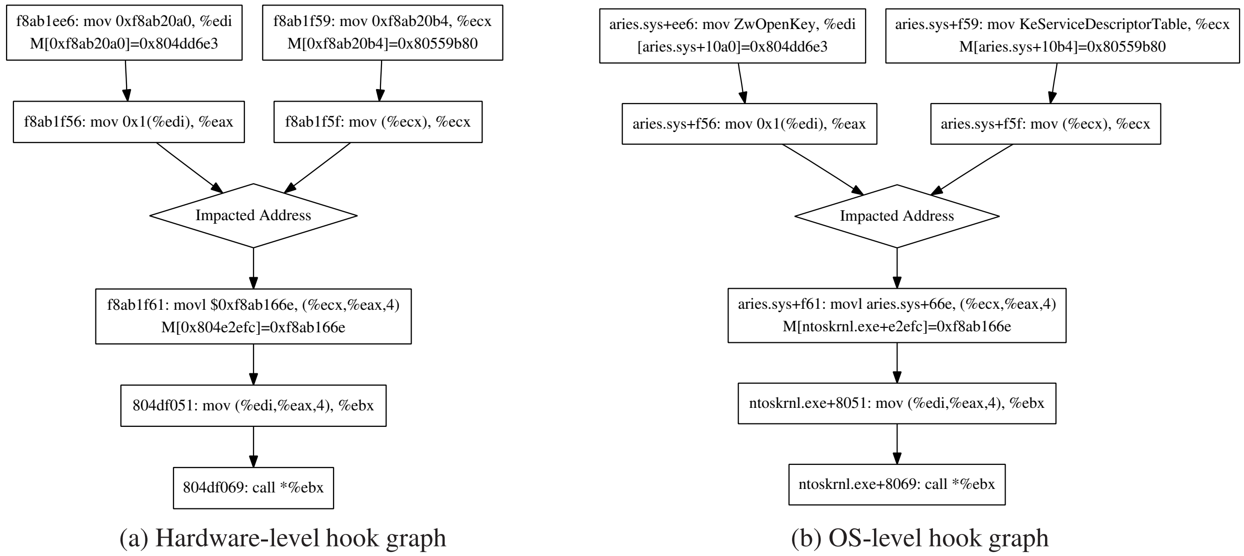


Figure 3. Hardware-level and OS-level hook graphs for a hook in Sony Rootkit.

dency information. Specifically, for each record R in the impact trace, if it creates a new dependency ID id that is used in the hook graph, we added a node N representing the instruction corresponding R, and add edges from N to other nodes that uses id as source operands in their corresponding instructions. We perform this backward search recursively until we reach the beginning of the trace. Besides the dependency information, each record contains detailed information about an instruction, such as its address and the values of its operands. If the instruction is executed under the context of an external function, the record also contains the entry address of that external function, and the value of `ESP` on the entry of call. We also put these details into the corresponding nodes. The resultant graph is the hardware-level hook graph.

Figure 3(a) shows a hardware-level hook graph built from a hook in Sony Rootkit [27], which employs the same hooking mechanism as the sample shown in Figure 1. A rectangle node denotes an instruction propagating malware's impacts. A diamond node denotes that its successor's destination address is affected by the malware's impacts. Note that to save space, we only display really important information for each node, such as the instruction address and the disassembled instruction. For each memory operand, we show its address and value. If the instruction is executed under the context of an external function call, we also show the entry of the function call and the ESP value on the entry.

OS-level Hook Graph With the OS-level semantics information provided by the semantics extractor, we can transform a hardware-level hook graph into an OS-level hook graph. Given the address of an instruction, we can show which module it belongs to and its offset to the module base. Similarly for memory access, we can determine if it falls into any module space. If the memory access is to a symbol, we can even resolve its symbol name. Given the entry address of an external function, we can resolve its function name. Then, the resulting graph is an OS-level hook graph. Figure 3(b) illustrates the OS-level hook graph transformed from Figure 3(a). We can see that Figure 3(b) correctly reflects the hook registration procedure shown in Figure 1. That is, symbols `ZwOpenKey` and `KeServiceDescriptorTable` are used to calculate the hook site L (shown in the diamond-shaped node), and an address (aries.sys+66e) is written into L. This is the hook H, the address of the hook entry F.

In addition to resolving function names, HookFinder also extracts function arguments from an impact trace. Since pushing arguments onto the stack is also part of the impacts made by a malware sample, the information about these arguments is already recorded in the impact trace. To extract a function's arguments, HookFinder locates the first record R of the activation of the function. The records preceding R contain function arguments, but may also contain other non-argument impacts made by the malware. As the impacts trace has information about the value of register `ESP` at the beginning of the function's activation, we only include the impacts within a certain distance to the value of `ESP`. In the current implementation, we search for up to 10 four-byte words following the location of `ESP` as arguments.

Graph Simplification The resulting hook graph can be very complex in some cases. For better readability and clarity, we simplify it using the following criteria: (1) if two adjacent nodes belong to the same external function call, we merge them into a single virtual node; (2) if two adjacent nodes are direct-copy instructions, such as `mov`, `push`, and `pop`, we merge them into a single node, because these instructions propagate the same value without modification. We apply these two criteria repeatedly on our hook graph until no nodes can be merged. The result is often a graph much clearer to be interpreted.

4 Evaluation

In this section, we present details on the experimental results of HookFinder, by evaluating it with real-world malware samples. We first give a summary of the experimental results over these samples, and then present details on two of them. In all our experiments, we run HookFinder on a Linux machine with a dual-core 3.2 GHz Pentium CPU and 2GB RAM. On top of HookFinder, we install Windows XP Professional SP2 with 512M of allocated RAM as the guest operating system.

4.1 Overview

Our sample set consists of eight malware samples, which are obtained from public resources (such as [20, 23]) and collaborative researchers. In Table 1, we characterize these samples according to whether they are packed, whether they are kernel or user threats, and which categories they belong to. We include Uay backdoor to verify the capability of HookFinder in identifying novel hooks [1].

In the experiment, HookFinder has successfully identified hooks for all the samples. We summarize the results in Table 2. In the second column of Table 2, we list the elapsed time for each sample. It breaks down into two parts: the runtime for running the sample in the emulated environment (shown as the first number), and the runtime for generating hook graphs (as the second number). After executing a sample, we wait for 2-3 minutes to make sure it has fully started. In order to trigger potential hook behavior, we then perform a series of simple interactions with the emulated system, including listing a directory, and pinging a remote host, which may cost another 2 or 3 minutes. The runtime for generating hook graphs varies from 2 seconds to 33 minutes, depending on the trace size, the number of hooks, and other factors. In total, HookFinder spends up to 39 minutes on a sample during the evaluation, which is efficient compared to manual malware analysis that can last hours or days.

The third column lists the size of the impact trace for each sample. As we can see, the maximum size in the table is 14G, which is acceptable for a complex program executing millions of instructions.

The fourth and fifth column shows the number of suspicious hooks and the total number of identified hooks, for each sample. We found some normal hooks registered by the following functions: *EVENT_SINK_AddRef*, *FltDoCompleteProcessingWhenSafe*, *StartServiceDispatcherA*, *CreateThread*, *CreateRemoteThread*, and *PsCreateSystemThread*. Note that our approach does not distinguish the intent of a hooking behavior. Thus, we will identify all hooks in the first place; then we check normal hooks by comparing them with our white-list.

The last column gives essential information about the hooking mechanism. We found that three samples installed code hooks. All three samples derive the hook sites by calling *GetProcAddress*. Vanquish directly writes the hooks into the hook sites, whereas AFXRootkit and Hacker Defender call *WriteProcessMemory* and *NtWriteVirtualMemory* respectively to achieve it. The other six samples installed data hooks, four of which call external functions to install the hooks. In particular, CFSD calls *FltRegisterFilter*, and Trojan/Keylogg-LF and Troj/Thief call *SetWindowsHookEx*. We also extracted arguments for these function calls, and we found that Trojan/Keylogg-LF installed a WH_KEYBOARD_LL hook, and Trojan/Thief installed a WH_CALLWINDPROC hook. The remaining two samples directly write hooks into hook sites. The static points are *KeServiceDescriptorTable* and *NdisRegisterProtocol* for Sony Rootkit and Uay Backdoor, respectively.

4.2 Detailed Analysis

Here we present detailed results for two malware samples: Uay Backdoor and Vanquish.

Uay backdoor HookFinder identified five data hooks in total for this sample. We reviewed the generated hook graphs, and we found that three of them were installed by *PsCreateSystemThread*. This kernel function creates

[1] Since deepdoor is not released by its author, we cannot include it in our experiment.

Sample	Size	Packed?	Kernel/User	Category
Troj/Keylogg-LF	64KB	Y	User	Keylogger
Troj/Thief	334KB	N	User	Password Thief
AFXRootkit [1]	24KB	Y	User	Rootkit
CFSD [6]	28KB	N	Kernel	Rootkit
Sony Rootkit [27]	5.6KB	N	Kernel	Rootkit
Vanquish [31]	110KB	N	User	Rootkit
Hacker Defender [12]	96KB	N	Both	Rootkit
Uay Backdoor [30]	212KB	N	Kernel	Backdoor

Table 1. Malware Samples in Our Experiment

Sample	Runtime	Trace	Hooks		Hooking Mechanism
			Total	Mal	
Troj/Keylogg-LF	6m+9m	3.7G	2	1	Data, Call:`SetWindowsHookEx(WH_KEYBOARD_LL,...)`
Troj/Thief	4m+3s	143M	1	1	Data, Call:`SetWindowsHookEx(WH_CALLWINDPROC,...)`
AFXRootkit	6m+33m	14G	4	3	Code, Call:`WriteProcessMemory`
CFSD	4m+2m	2.8G	5	4	Data, Call:`FltRegisterFilter`
Sony Rootkit	4m+2s	25M	4	4	Data, Direct, Static Point:`KeServiceDescriptorTable`
Vanquish	6m+12m	4.4G	11	11	Code, Direct, Static Point:`GetProcAddress`
Hacker Defender	5m+27m	7.4G	4	1	Code, Call:`NtWriteVirtualMemory`
Uay backdoor	4m+25s	117M	5	2	Data, Direct, Static Point:`NdisRegisterProtocol`

Table 2. Summarized experimental results

a system thread with the thread entry provided by the caller. Thus, these three hooks are normal hooks. The other two are suspicious, and their hook graphs are similar. We show one graph in Figure 4. We also show the original hardware-level graph in Figure 6 in the Appendix.

As we can see in Figure 4, there are two branches at the bottom. The left branch describes how the hook site L was inferred, and the right branch presents how the hook H was formulated. From the top of the right branch, we can see that H originated from the output of a function call *NdisAllocateMemoryWithTag*. This kernel function is used to allocate a memory region in the kernel space. According to the function's semantics, this output has to be the address of the allocated memory region. This address is finally implanted into the hook site L.

From the top of the left branch, we observe that L is derived from the output of a function call *NdisRegisterProtocol*. This kernel function registers a network protocol. According to the function semantics, we believe this output is the protocol handle in the second argument. This handler points to an internal data structure maintained by the Windows kernel. Then we can see the instruction (at uay.sys+1695) reads a field with the offset 0x10 in this data structure. The obtained value (v_1) is then used as a pointer to read another value (v_2) from the offset 0x10 in the data structure pointed by v_1, in the subsequent instruction (at uay.sys+16a0). Then, the instruction (at uay.sys+1589) adds v_2 with 0x40, and the resulting value is eventually used as the hook site L. We believe that this sample actually walks into this internal data structure that it obtains from *NdisRegisterProtocol*, and locates the designated hook site L. Interestingly, the definition of the data structure for the protocol handle created from *NdisRegisterProtocol* is not released in any documentation from Microsoft, but this malware sample seems to be able to understand this data structure, and knows how to locate the desired hook site from it.

The hook graph for another suspicious hook is very similar to this one, except that it adds v_2 with 0x10. With the knowledge of how this internal structure is defined, we would be able to tell which two functions this malware sample actually hooked.

By analyzing this sample using HookFinder, we are able to unveil a novel mechanism for intercepting the

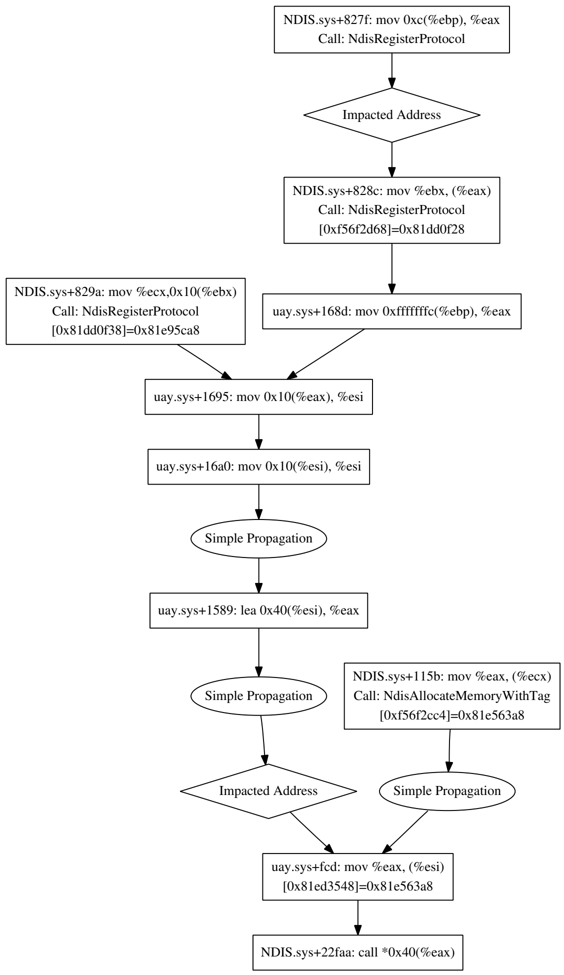


Figure 4. Hook Graph for Uay

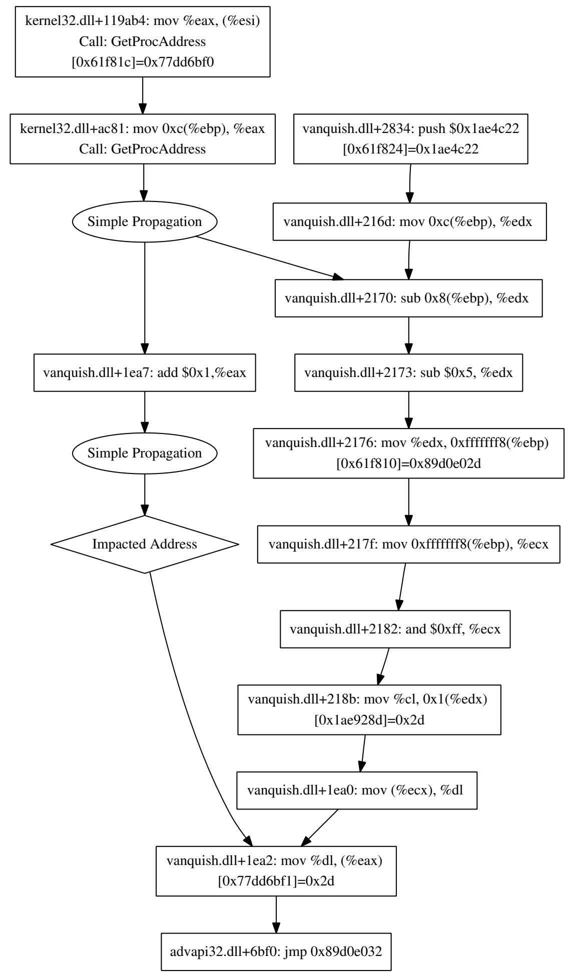


Figure 5. Hook Graph for Vanquish

network stack employed by malware. That is, malware can tamper with the function pointers in some kernel data structures associated with registered network protocols. With this important understanding, we can verify and protect the integrity of these data structures, to defend against this kind of hooking mechanism.

Vanquish HookFinder identified 11 code hooks in total for Vanquish. After reviewing the hook graphs, we found that Vanquish hooked four unique APIs: *RegCloseKey*, *LoadLibraryExW*, *RegEnumKeyW* and *RegEnumKeyExW*. Thus, multiple hooks may correspond to one API hooking, because Vanquish installs one hook per process for that API.

We show a hook graph for hooking *RegCloseKey* in Figure 5. The other hook graphs are similar. First, we can see the bottom node. This is the actual instruction Vanquish injected into the system code to set up the hook. It is a `jmp` instruction, and its address is the entry point of *RegCloseKey*. The rest of the graph shows how the jump target of this instruction is formulated. Here the address of this jump target (i.e., 0x77dd6bf1) is the hook site L, and the content in L is H (i.e., 0x89d0e032). Again, the left branch represents how L was inferred, and the right branch indicates how H was formulated.

The left branch starts with the output of function call *GetProcAddress*. This function returns the actual function address, given a function name. Therefore, the source of the left branch is the address of a function call, and the actual value is 0x77dd6bf0, which is the address for *RegCloseKey*. As we follow the links down, we can see this address is added by 1 and used as L. Obviously, the offset 1 is for the opcode of `jmp`. Now for the right branch, we can see that it originates from an immediate (0x1ae4c22) pushed onto the stack. This value is first subtracted by the address for *RegCloseKey*, and then subtracted by 5. Then the value is "and" with 0xff to get the lowest byte, and this byte is written to the hook site L directly. Obviously, these steps are used to calculate the relative address for the `jmp` instruction.

5 Discussion

In this section, we discuss the resilience of our system to various evasion techniques that malware writers may exploit.

Exploiting Control Dependency The basis of our approach is to identify all impacts made by the malicious code, and keep track of the impact propagation via data dependency. It is natural for malware writers to think of exploiting control dependency, to evade our detection. For example, the malicious code may embed a complex switch statement like below to cut the data dependency between a and b.

```
switch(a) {
case 1: b=1; break;
case 2: b=2; break;
...
}
```

This evasion is not viable. This is because in the impact marker, we thoroughly mark all the initial impacts (i.e., memory and register writes) made by the malicious code. Thus, the output b will be marked anyway.

Not Exhibiting Hooking Behaviors When Tested Malware may not exhibit hooking behavior during our dynamic analysis. It may detect that it is running in our analysis environment and stay inactive if indeed. For example, it may run a redpill test [25], observe considerable slowdown on performance, or perform more sophisticated methods to determine this fact. Moreover, some malware only performs malicious behavior under certain conditions, such as on a specific date. This is a common shortcoming of dynamic analysis. The current implementation of HookFinder can deal with some common detection methods. We specially instrument several instructions like `sidt` to return deceitful results to malware, in order to bypass the redpill test. We also slow down the frequency of the PIT timer in QEMU to disguise the performance slowdown of our emulated system. A more comprehensive solution to this problem would be to explore multiple execution paths that depend upon certain conditions. Some research work has been done in this direction. Moser *et al.* [17] and Brumley *et al.* [3] also used QEMU to build malware analysis systems, which are able to uncover hidden behaviors of malware by exploring multiple execution paths. We will leave incorporating these techniques into HookFinder as future work.

Evading through "return-into-libc" In this paper, we consider that malware registers a function in its own code as a hook. Potentially, malware may not necessarily register its own function. It can put the address of certain function in system code into the hook site, exploiting the functionality of that function to perform some tasks, without being detected by HookFinder. This potential evasion resembles "return-into-libc" in buffer overflow attacks [18]. We do not consider this kind of evasion in the current implementation of HookFinder, as it is generally difficult to realize, in terms of finding good candidate functions and preparing compatible stack layout. We would like to extend our detection strategy to cope with this potential evasion in our future work.

Subverting or Misleading HookFinder Built on top of an emulator, HookFinder provides strong isolation such that it is unlikely for the malware running inside to interfere with HookFinder and the host system. However, some study shows the possibility of subverting the entire emulated environment by exploiting buffer overflows and integer bugs [21]. This problem can be addressed by fixing these bugs. HookFinder may also be misled. HookFinder identifies and analyzes hooks by examining both hardware-level and OS-level information. Hardware-level information can be trustworthy, because the underlying hardware relies on it to run the guest system. However, OS-level information can be spurious. Malware can find numerous methods to hijack the semantics extractor. Especially, the kernel module inserted into the guest system can be an obvious target. In the future release of HookFinder, we are going to develop a more robust and secure semantics extractor. More specifically, we will reason about OS-level semantics completely from outside, using reliable and faithful states of the emulated system.

6 Related Work

Hook Detection Researchers have developed several tools, such as VICE [4], System Virginity Verifier [24], and IceSword [13], to detect the existence of hooks in the system. With prior knowledge how malicious code usually set hooks, these tools examine known memory regions for suspicious entries. The common examined places are system service descriptor table (i.e., SSDT) exported by the OS kernel, interrupt descriptor table (i.e., IDT) that stores interrupt handlers, import address tables (i.e., IAT) and export address tables (i.e., EAT) of important system modules. Assuming that important system modules do not modify their code (with a few exceptions), System Virginity Verifier checks if code sections of important system DLLs and drivers remain the same in memory as those in the corresponding binaries on disk. In nature, these tools fall into misuse detection, and thus cannot detect hooks in previously unknown memory regions. In comparison, our approach captures the intrinsic characteristics of hooking behaviors: one of the malware's impacts has to be used to redirect the system execution into the malicious code. Therefore, it can identify unknown hooking behaviors. Moreover, it also provides insights about the hooking mechanisms.

Dynamic Taint Analysis The fine-grained impact analysis resembles the dynamic taint analysis technique, which is proposed to solve and analyze many other security related problems. Many systems [8, 9, 19, 22, 28] detect exploits by tracking the data from untrusted sources such as the network being misused to alter the control flow. Other systems [7, 10, 33] make use of this technique to analyze how sensitive information is processed by the system. Chow *et al.* applies dynamic taint analysis to understand the lifetime of sensitive information (such as password) in operating systems and large programs [7]. Egele *et al.* utilize this technique to analyze BHO-based spyware behavior [10]. Yin *et al.* also make use of dynamic taint analysis to detect and analyze privacy-breaching malware [33]. Moreover, dynamic taint analysis is used for other applications, such as automatically extracting protocol message formats [5], and preventing cross-site scripting attacks [32].

7 Conclusion

In this paper, we presented a novel dynamic analysis approach, *fine-grained impact analysis*, to identify malware hooking behaviors. This approach characterizes malware's impacts on its system environment, and observes if one of the impacts is used to redirect the system execution into the malicious code. Since it captures the intrinsic characteristics of hooking behavior, this technique is able to identify novel hooks. Moreover, we devised a *semantics-aware impact dependency analysis* method to extract the essential information about the hooking mechanisms, which is represented as hook graphs. We developed a prototype, HookFinder, and conducted extensive experiments using representative malware samples from various categories. The experimental results demonstrated that HookFinder can correctly identify the hooking behaviors for all the samples, and the generated hook graphs provide accurate insights about their hooking mechanisms.

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Appendix: Hardware-level Hook Graphs

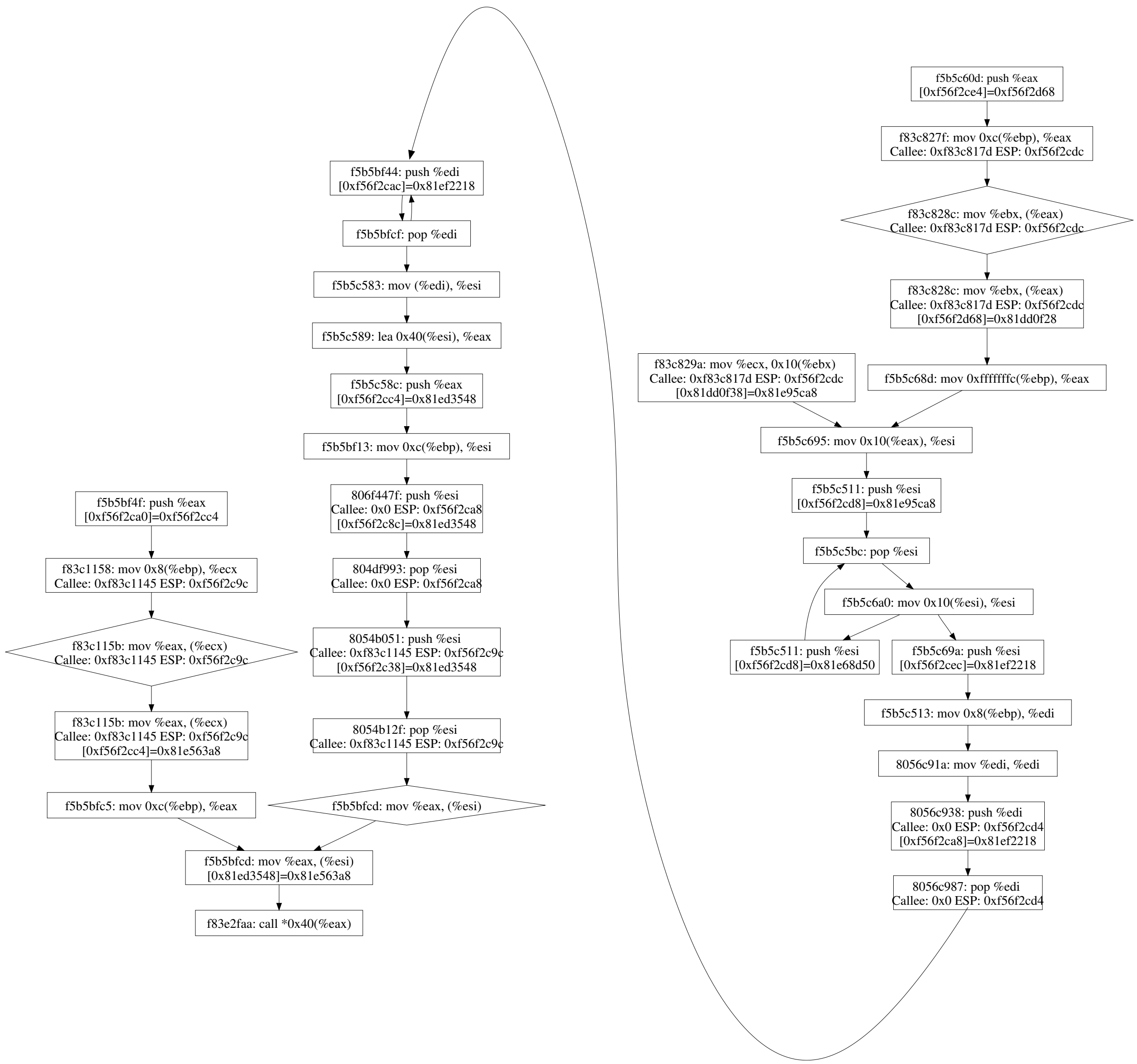

Figure 6. Hardware-level hook graph for Uay backdoor

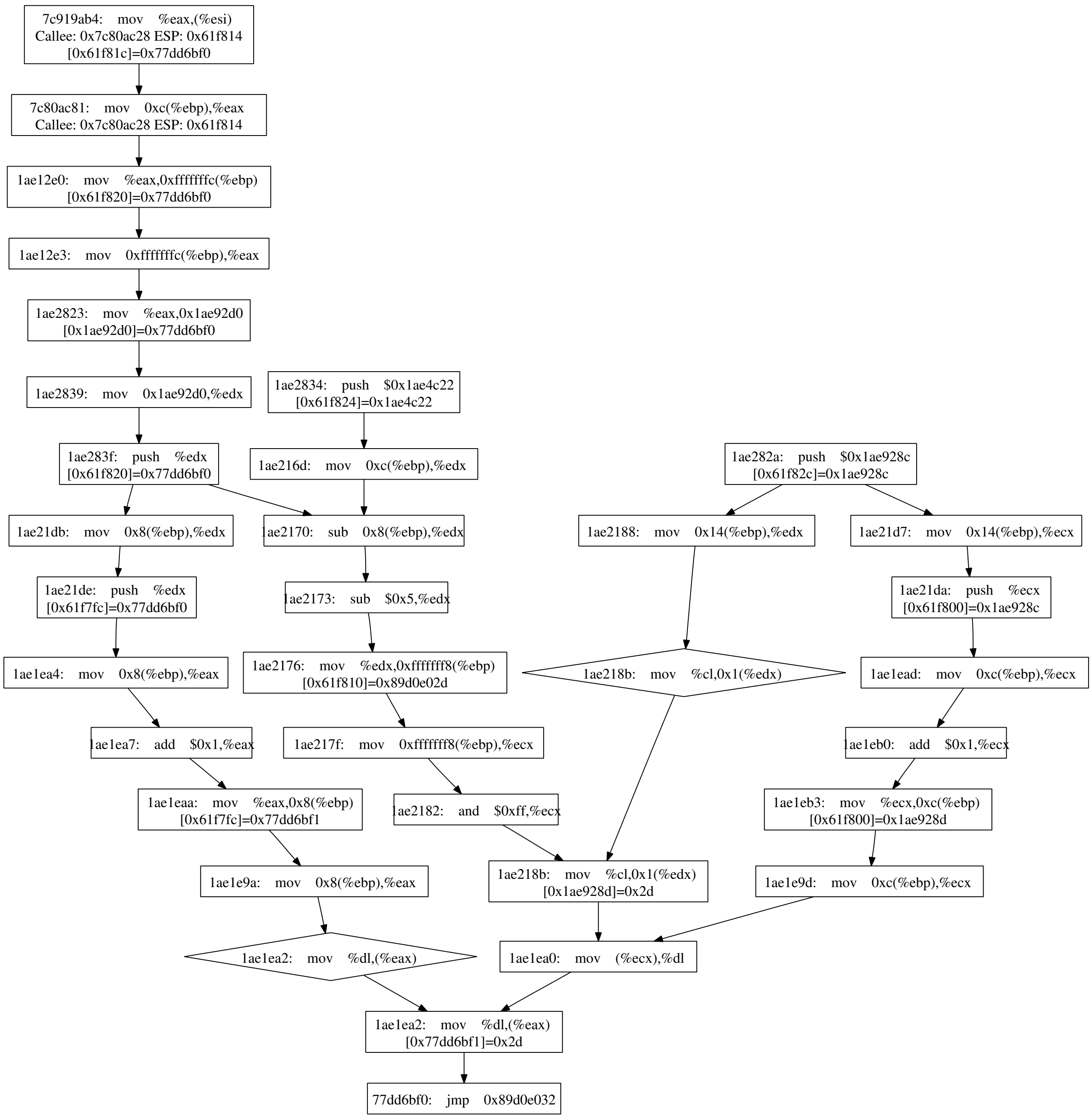

Figure 7. Hardware-level hook graph for Vanquish