Senior Thesis Research Report

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1 Introduction

This report summarizes my work with the DEPEND research group as part of CS499 (senior thesis) from January 2015 through December 2015.

The paper is structured as follows. A brief discussion of performance counters work is provided in Section II. An overview of the userspace data is presented in Section III. In Section IV, the development of the kernel module and interaction with KVM is explained. Section V contains an overview of the data collection and architecture. Section VI analyzes the data that was collected, with areas for future work presented in Section VII. Finally, the conclusions from this work are available in Section VIII.

1.1 Timeline

This project took place over two semesters. In the first semester, the initial plan for the work was developed and several core components were engineered. This includes the user space counter collection tool and the kernel space tool.

The second semester of this work was mostly focused around understanding whether performance counters can be a useful invariant on thier own, or whetherother components would need to be used in order to detect execution irregularities. This involved collecting data, creating tools to analyze it, and graphing the data to understand its usefulness.

1.2 Background

This thesis was grown out of previous semsters I had spent working with the DEPEND research group. Specifically, in this work, I sought to answer the following question: *by constructing fingerprints from execution signatures (using performance counters) of a hypervisor (e.g., qemu-kvm) at different points in time, is it possible to detect compromised hypervisor execution by comparing them to known good ones?* This is a form of *dynamic analysis* because the detection is done at runtime and not at compile time (static analysis).

1.3 Hardware Performance Counters

Hardware performance counters (herein referred to as HPCs) allow for the collection of various low-level information about a processor's current state. The counters can provide valuable performance insights. Unfortunately, the first machine I attempted to use did not support HPCs, and it is not enabled by default on most machines. However, after switching to another machine, I was able to enable the counters and begin collecting data.

The counters available vary from machine to machine. The important counters are total retired instructions, conditional branch instructions, branch instructions, store instructions, and load instructions. The counters were collected with PAPI, which is described in the next section.

1.4 Motivation

To understand the motivation behind this project, it is important to have a good high-level understanding of the virtualized system topology. A visual overview of the topology is shown in Figure 1.

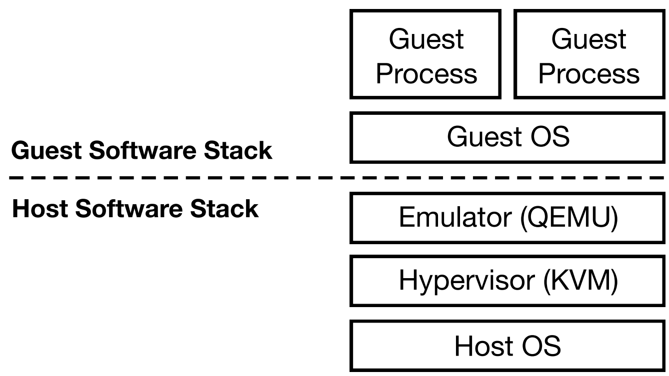


Figure 1: Virtual machine topology. Areas of focus include QEMU and KVM.

A search of the National Vulnerability Database shows that there are many reported vulnerabilities in QEMU. These range in severity, but can be as grave as allowing for arbitrary code execution by the virtual machine guest.[1] While there are research papers already published on dynamic analysis using hardware performance counters, these have not been applied towards virtualization[8][1][5].

The principal motivation for this work was to understand if we could feasibly develop a method of detecting a compromised hypervisor. Hypervisor security is very important, and because the hypervisor functions as the backbone of a virtualized system, its integrity is paramount for the virtual machine's security.

2 Related Work

There are a number of existing works which cover HPCs for security. These center around several concerns:

- Overhead in using HPCs

[1] `http://web.nvd.nist.gov/view/vuln/search-results?query=QEMU&search_type=all&cves=on`

- Accuracy and nondeterminism of the counters
- Accuracy of detection methods using counters
- Feasability of HPCs as a dynamic analysis invariant

2.1 Using Counters for Dynamic Analysis

The paper "Are Hardware Performance Counters a Cost Effective Way for Integrity Checking of Programs?" attempts to understand performance counter usage for integrity checking from a cost perspective, and concludes that HPCs are efficient for detecting program modification[4]. The NumChecker[8] paper presents a framework through which to detect kernel rootkits. It uses HPCs to verify system call execution.

2.2 Overhead

As the name implies, hardware performance counters were initially designed to aid in performance instrumentation of low-level software. Using HPCs is attractive because they are built into the processor, meaning that they add a negligible amount of hardware overhead to program execution. However, storing this information and analyzing it dynamically can introduce overhead. The NumChecker[8] paper reveals that the amount of overhead varies significantly with the frequency of collection, presumably due to I/O; for a sampling rate of 5 seconds, the overhead introduced by NumChecker was 2.8%[8]. Another work shows that the overhead incurred in that situation was less than 10%[4].

2.3 Counter Accuracy and Nondeterminism

Using HPCs as an invariant has proved a controversial topic, as they appear to be nondeterministic. This is because there are many events happening on the processor, which cause small fluctuations in the counter values.

However, some metrics are more consistent than others. From [4]: "The shortlisted events include the total number of instructions retired, the number of branch instructions retired, cache stores (they are better measures than loads because loads can be speculative), completed I/O operations, and number of floating point operations."[4]

There are many sources of nondeterminism, and it appears to vary from chip to chip. The paper "Non-determinism and overcount on modern hardware performance counter implementations" explores these sources and attempts to make sense of which counters are best. It comes to the conclusion that total instructions retired is one of the most consistent counters[10].

2.4 Detection Accuracy from Using HPCs

HPCs only provide the data. From this data, is important to conduct proper statistical analysis to achieve meaningful results. Specifically, in integrity check-

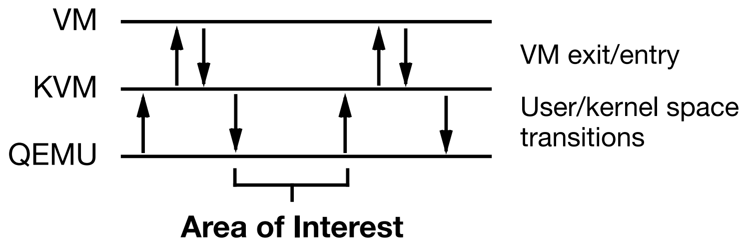


Figure 2: Diagram of the various transfers of control between QEMU, KVM, and the host virtual machine. When KVM returns to QEMU, it provides an exit reason which can be used by QEMU to take appropriate action. However, KVM may transfer control to the virtual machine (and back) before returning to QEMU. The arrows represent transfer of control. The duration for which HPCs were recorded is also displayed. The area of interest highlighted was chosen because it focuses solely on QEMU while allowing for collection of the exit reason from KVM.

ing, the most important metric is a low false positive rate.

The HPC data is best interpreted as a matrix of feature vectors. From this, a number of very interesting analytical techniques arise, including (but not limited to): linear regression, support vector machines, random forests, nearest neighbors, and clustering. Principally, nearest neighbors is the most popular of these choices, but each approach has different advantages[3]. It is also possible to build simple classification simply by looking within a threshold of all known values[8]. In one paper, artificial neural networks were used[1].

3 QEMU

QEMU is a machine emulator which allows for the emulation of a platform so that a full operating system/hypervisor may run on top of it. QEMU provides emulation of both entire machines and external I/O devices (e.g., hard-drives, network devices, and keyboards). However, when the host and guest operating system are the same architecture[2], native virtualization can be accomplished by using KVM, a Linux kernel feature which allows for hardware-assisted virtualization. KVM leverages processor support for virtualization to expose an API for running guest virtual machines. In this configuration, QEMU only emulates I/O devices. Because both pieces of software play crucial roles in running the guest virtual machine, execution frequently traps from one to another. This is explained in Figure 2.

[2] An `x86` machine may also be virtualized on an `x86_64` architecture

3.1 Modifications

In order to collect HPC data from QEMU, some modifications were required. QEMU does not have a plugin architecture, so a custom build of QEMU was created for instrumentation purposes.

The modifications were fairly simple: using the PAPI performance counter library, I was able to output HPC measurements across a known path of execution. Furthermore, with the KVM hypercall extension, I was able to make markings in the data collection from within the guest VM. With this toolset, it became trivial to mark the beginning and ending of a program in the guest VM and observe the QEMU data for this period.

4 KVM and `kprof`

The KVM kernel module was modified for use in this project. This section aims to explain the changes that were made and elaborate on the design of the additional data collection module that was developed.[3]

4.1 KVM Exits

When execution is transferred to the KVM context, the hypervisor will return what is known as an *exit reason* when execution transfers back. The exit reason is related to the hardware VM exit provided by VT-x. There is a long list of exit reasons spanning many different explanations for what occurred while KVM had control of execution. [4]

4.2 The `kprof` Module

In order to be able to collect the data from user space, I developed a device driver. This allows the usage of the `ioctl` function from the user space program (useragent) and for data to be transferred out of the kernel.

In the device driver, called `kprof`, a set of internal buffers in constructed so that the data may be continuously populated in memory and then flushed to disk at an interval (this is the same technique used in the hprobe kernel module). This helps keep the performance impact of this double buffer solution manageable in addition to providing a lock-free mechanism for reading the data from multiple code paths.

The current module exposes two simple symbols:

1. `start_record()`, which starts the recording of events.
2. `stop_record(exit_reason)`, which stops the recoding, records the difference since the last call to `start_record`, and records the exit reason given for this data entry.

[3] A full list of modifications to the module is available in the README of the project.

[4] A full list of the exit reasons for KVM is available at `http://lxr.free-electrons.com/source/arch/x86/include/uapi/asm/vmx.h#L30`

I then modified the KVM kernel module to make these calls around exits. Specifically, the counter values recorded represent execution across the KVM code path. When an exit returns, the counters are started until the next exit comes in.

As discussed above, the counters are placed into a series of buffers. Finally, the useragent program is run in user space to flush these buffers and reset the internal state of the `kprof` module. Because a single run of the VM may result in the collection of millions of entries (resulting in some buffers being overwritten), the useragent program is run simultaneously while the VM is running. One major benefit of this multi-part solution is that the module does not need to be re-installed for additional runs. An API for resetting the internal state of the module is exposed via the `ioctl` interface.

5 Data Collection

Data for this project was collected using both the `kprof` kernel module and the userspace QEMU extensions. The data was collected from runs of a CentOS 7 virtual machine when using Linux. For Windows, the VM was a Windows 7 VM. Details of the userspace data collection are available in [6]. An overview of the entire system is shown in Figure 3.

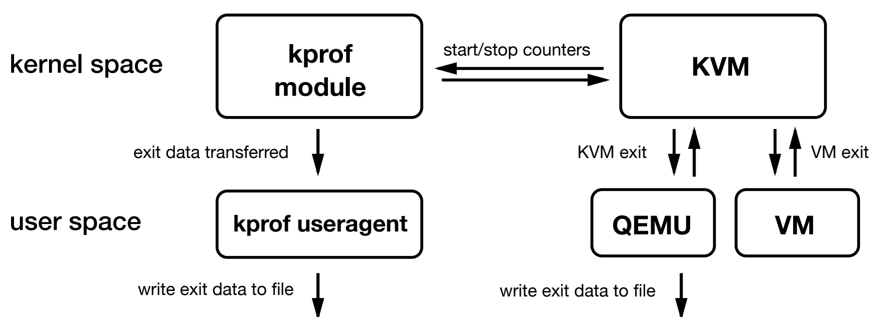


Figure 3: System architecture overview composing both userspace and kernel space data collection mechanisms.

6 Analysis

6.1 iozone and Workload Distribution

A visual evaluation of the data as presented in Figure 4 shows that we cannot make an accurate judgement of whether we are seeing a new wokload purely based on the performance counter data. From this graph, we observe that the workload manifests as a change in the graph. Additionally, this graph gives some insights into how the operating system uses the hypervisor. We observe

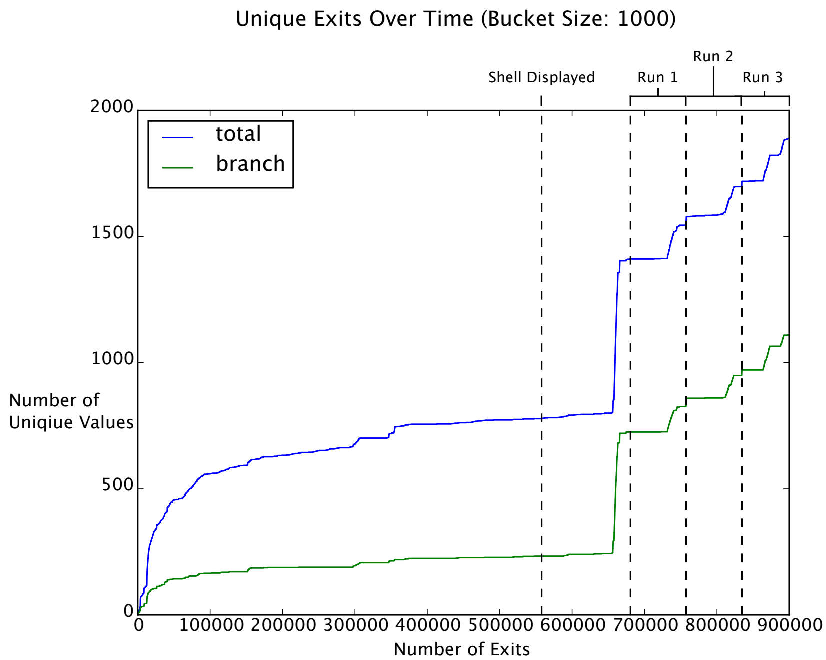


Figure 4: Plot of the unique counter values observed over time. The workload consists of initial boot of a Linux machine, followed by three succesive runs of the iozone filesystem benchmark. Here, *bucket size* refers to a smoothing factor applied to the data. Numbers are placed into buckets of this size. A bucket size of 1000 means there are buckets of values 0-999, 1000-1999, etc. Numbers in the same bucket are treated as the same for the creation of this graph.

a high level of entropy at boot and shortly after the shell is displayed to the user. Runs of the filesystem benchmark increase the number of unique counters observed, but successive runs do not show an increase by a lesser delta. From this, we can conclude that while the performance counters are a valuable metric, they cannot stand alone in detecting certain executions.

This is just one view of the data. Another is to separate the graphs by observed exit reason. This allows us to interpret the specific nature of the workload. For the iozone dataset, if we separate the data according to exit reason, there are many `HALT` exit reasons occuring during the iozone runs (this exit reason indicates that the CPU has been paused until the next interrupt occurs). However, these are sparse during the boot of the operating system. In this case, the halt instructions might be a sign that there is an IO-heavy operation occurring or some other device-related operation. These sorts of observations are interesting for understanding more about the workload.

6.2 Windows and Linux

One of the interesting applications of the counter data is to better understand how Linux and Windows use the hypervisor. We can do this by collecting a sample of counter values through the kprof module from booting a virtual machine of both systems.

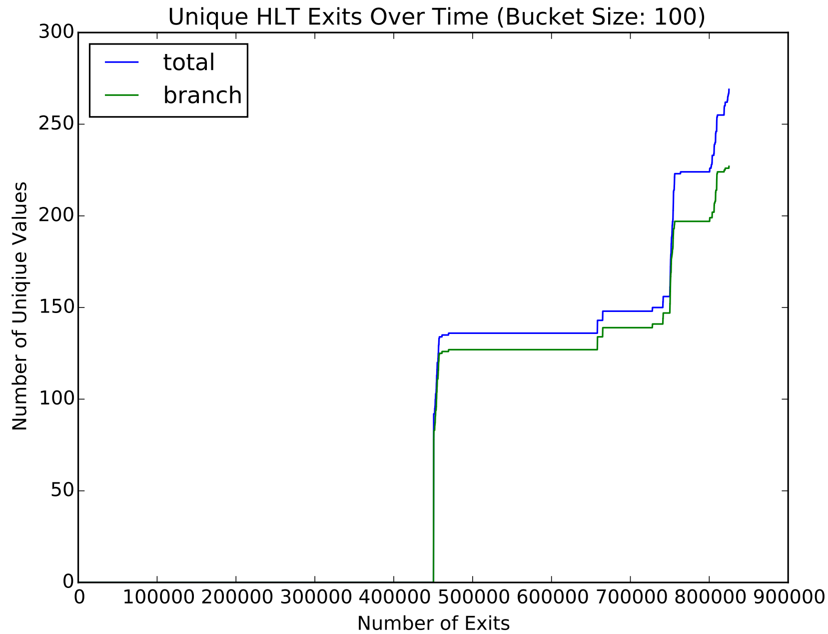
I collected this data from the aforementioned CentOS VM and a Windows 7 VM, both running on the same bare metal machine with the same hypervisor and custom QEMU fork. [5] The data was then fed through a series of scripts to split it out by exit reason and observe how the number of unique exit reasons grow over time. This script used a bucket size of 1000 (refer to Figure 4 for more information on bucket size).

Some interesting trends arise in the data. The two systems have a different distribution of total exit reasons, with Windows having more EPT_MISCONFIG and PENDING_INTERRUPT exits than Linux. Both boot sequences have high levels of IO_INSTRUCTION exits compared other reasons. There are also some differences in how the exits occur over time.

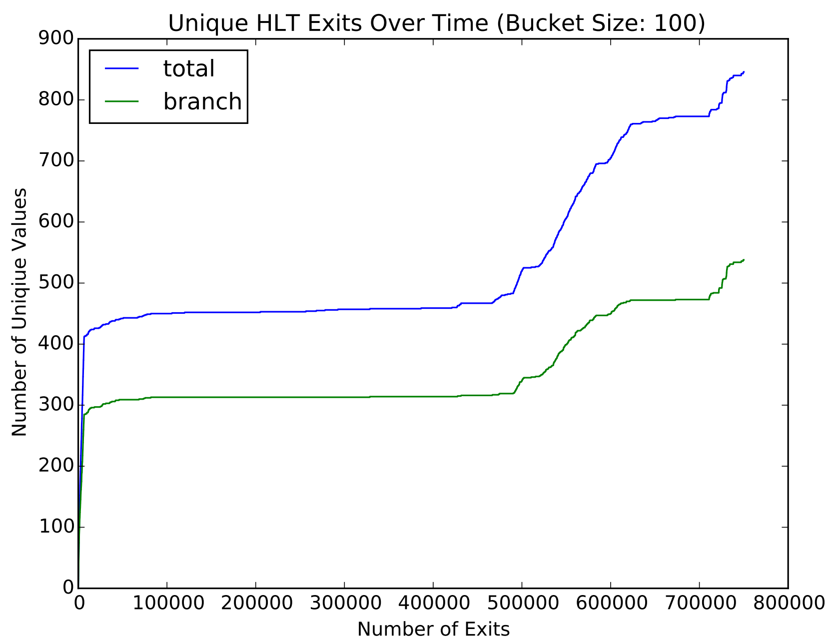
7 Future Work

Future work will involve building tools around the workload analysis component of this work. Since the API is already there, this is not too difficult to do for other developers. They can easily grab the counter data and manipulate it. I envision many interesting tools stemming from this. One example is a quick tool to capture the current hypervisor state and graph the next 30 seconds of data to see if there are any interesting phenomena occurring.

[5] Note: on boot, the Linux VM is able to make a hypercall so as to exactly mark when startup is complete, but this is not possible with the Windows machine.



(a) Windows



(b) Linux

Figure 5: Distribution of HLT (halt) exits for Windows and Linux virtual machine boots. Observe that the number of HLT exits quickly climbs and stabilizes for Linux, but does so much later in the Windows process. It is difficult to explain this discrepancy, but it does give some insight that we can use the counter instrumentation tools to observe differences in how these two operating systems use the hypervisor when running in a virtual machine.

7.1 Open Questions

The primary open question is: how can we leverage this existing performance counter infrastructure and data to create security tools? This is largely the focus of the hshield paper, which aims to build a new counter containing multiple input sources of data (such as information about the basic blocks being executed, performance counter data, and more). From there, a hardware unit can be built to continuously monitor integrity. Since the overhead of the performance counters is relatively minimal (due to native support in the CPU), this could be a viable application of this work.

8 Conclusion

Personally, I have learned many interesting things about how virutal machines operate and how other subsystems of Linux work.

HPCs are an interesting avenue to explore for security purposes, but ultimately they are more immediately useful as a method of observing how a workload is distributed and how different systems leverage the hypervisor.

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