C&ESAR 2023 by DGA
Cybersecurity of Smart Peripheral Devices (Mobiles/IoT/Edge)

When Side-channel Meets Malware

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November 22^{th}

Outline

ANR-JCJC: Automated Hardware Malware Analysis (AHMA)

"Can side-channel play a role against Malware?"

CAPSULE

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Publications

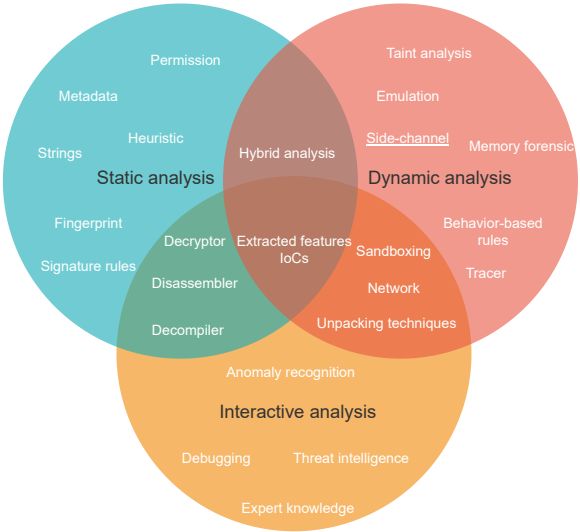
- Duy-Phuc Pham et al. "Obfuscation Revealed: Leveraging Electromagnetic Signals for Obfuscated Malware Classification". In: *Annual Computer Security Applications Conference (ACSAC)*. 2021.
  - Duy-Phuc Pham, Damien Marion, and Annelie Heuser. "Poster: Obfuscation Revealed-Using Electromagnetic Emanation to Identify and Classify Malware". In: *2021 IEEE European Symposium on Security and Privacy (EuroS&P)*. IEEE. 2021, pp. 710–712.
  - Extended version presented at hardware.IO USA (San Francisco) 2022.
- Duy-Phuc Pham, Damien Marion, and Annelie Heuser. "ULTRA: Ultimate Rootkit Detection over the Air". In: *25th International Symposium on Research in Attacks, Intrusions and Defenses (RAID)*. 2022.
- Duy-Phuc Pham's PhD thesis.

Why this topic?

- Trending of attacks on embedded devices.
- Difficulties for antivirus solutions on IoT devices: constraints, diversity, dataset.
- Malware detection bypasses

Malware analysis techniques

- Malware detection
- Malware similarities
- Malware classification



Malware-evasion techniques

Static analysis

- Malware obfuscation
- Packers

Dynamic analysis

- Anti-debugging
- "Side-channel information"

Side-channel

- Embeded device
- Side channel information
  - Power consumption
  - Electromagnetism (EM)
  - Cache, HPC (software)

- Anomaly detection using power consumption and EM.

RQ1

How can we build and setup an IoT malware classification and detection on embedded device using EM?

Contribution

Automated framework to automatically classify IoT malware by leveraging EM.

- Anomaly detection using power consumption and EM.
- Lack of research of side-channel detection for real-world malware.
- No variations regarding obfuscation and packers.

RQ2

If a malware analyst has a dataset of unlabeled binaries. Would it be possible to classify the dataset into labeled types, families, variants of malware or rootkits, obfuscation techniques used etc.?

Contribution

Real-world malicious and benign IoT dataset classification.

- Anomaly detection using power consumption and EM.
- Lack of research of side-channel detection for real-world malware.
- No variation regarding obfuscation and packers.
- Utilize benchmark software to detect rootkit.

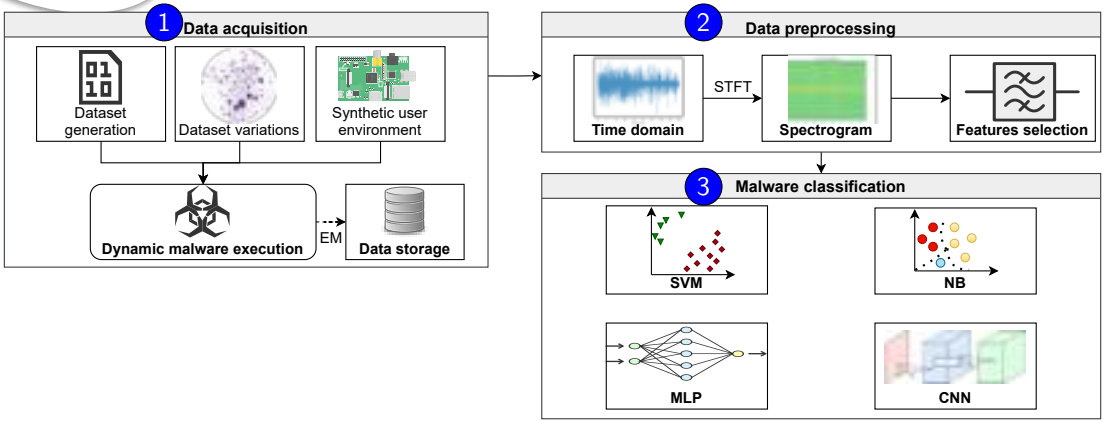
RQ3

Is it feasible to utilize EM for stealthy rootkit detection on embedded devices?

Contribution

Novel *baits* to detect rootkit in real-time.

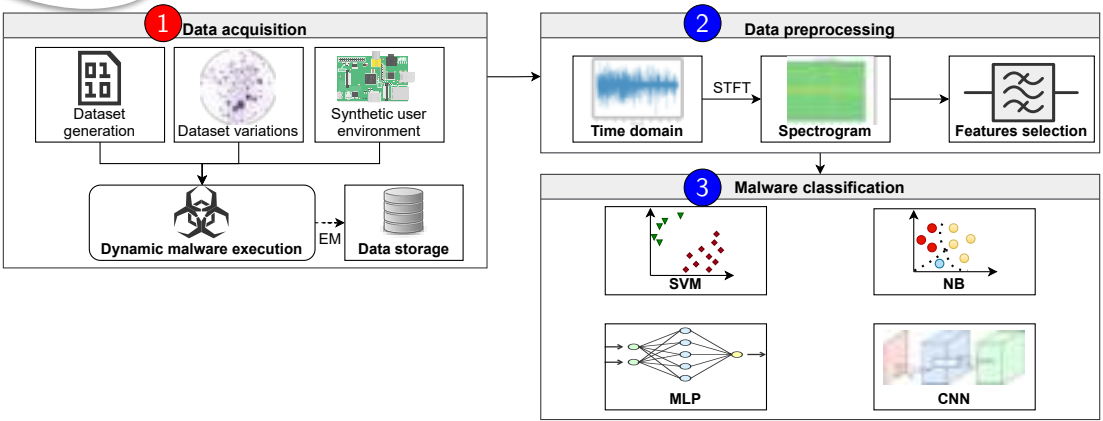
Frameworks overview



Open-source (code and dataset)

https://github.com/ahma-hub/analysis/wiki
https://gitlab.com/ultra-RK/ultra

Dataset divergences between AHMA and ULTRA



Dataset

1. AHMA focuses on malwares' variations, while ULTRA focuses on rootkits.

AHMA's malwares and benign

Samples

- **benign** **[5]:** random34, playaudio, recordcamera, takepicture, encodevideo
- **mirai** **[8]:** mirai, mirai_addopaque, mirai_virtualize, mirai_flatten, mirai_bcf, mirai_cfflatten, mirai_sub, mirai_upx
- **gonnacry** **[12]:** gonnacry, gonnacry_upx, gonnacry_aes_upx, gonnacry_aes, gonnacry_des, gonnacry_des_upx, gonnacry_virtualize, gonnacry_flatten, gonnacry_bcf, gonnacry_sub, gonnacry_cfflatten, gonnacry_addopaque
- **rootkits** **[2]:** maK_it, spy (kisni)
- **bashlite** **[8]:** bashlite, bashlite_bcf, bashlite_flatten, bashlite_upx, bashlite_addopaque, bashlite_cfflatten, bashlite_sub, bashlite_virtualize

Obfuscations and variations

obfuscations: _addopaque, _virtualize, _flatten, _cfflatten, _bcf, _sub, _upx.

encryption algorithm for gonnacry (by default blowfish): _aes, _des

ULTRA's rootkits and benign

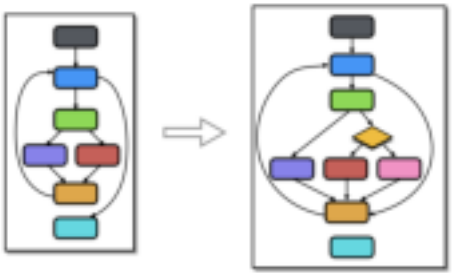
- Benign activities
  - User-space: Linux utilities, etc.
  - Kernel-space: Kernel drivers, firewalls, etc.
- Rootkit dataset

	Hide files	Network	Keylogger	RAT	LPE	Mode
*diamorphine**	✓				✓	Kernel
*m0ham3d**	✓	✓			✓	Kernel
adore-ng	✓	✓		✓		Kernel
spy			✓			Kernel
maK_it			✓			Kernel
beurk	✓	✓		✓		User
vlany	✓	✓		✓		User

* plus an obfuscated version.

Dataset: Variations

- UPX, Tigress, O-LLVM
- Opaque predicates, bogus control flow, instructions substitution, control-flow flattening; packer and code virtualization

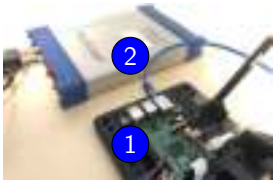


Same target devices

Specifications

- Multi-purpose embedded device.
- Prominent architecture: ARM and MIPS.

→ Raspberry Pi B+, Creator CI20



Raspberry Pi B+

Creator CI20

Acquisition divergences: Picoscope Vs SDR

Picoscope

- cheap oscilloscope, but not very cheap
- standard in side-channel
- **Setup:** EM monitoring during 2.5s at 2MHz sampling rate.
  - 200k traces [2TB]

SDR Advantages

- Flexible and adaptable
- Suitable for streaming mode
- Affordable and portable
- **Setup:** EM monitoring during 0.5s using HackRF SDR with 2MHz window
  - Centered in 1222MHz for Raspberry Pi B+ and 792MHz for the Creator CI20.
  - 800k traces [6.6TB]

Acquisition divergences: triggering

AHMA

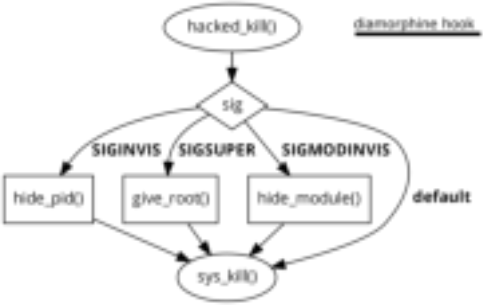
- recording start at the malware installation using a software trigger,

ULTRA

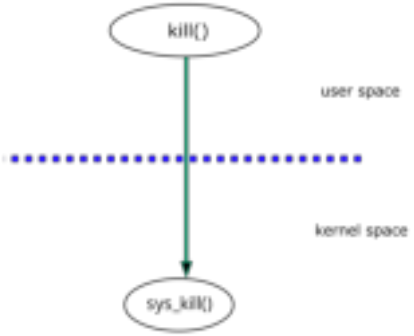
- record **baits** activities

Bait definition

A *bait* β, which is a software or hardware stimulus on a device δ, has the following requirements:
(i) The bait can trigger partial or full behavior of rootkits without knowing *modus operandi* of the rootkit in advance;
(ii) It has a variable duration time of execution activities that can be remotely controlled;
(iii) It cannot be distinguished from common benign behavior (e.g., it relies on unprivileged execution).

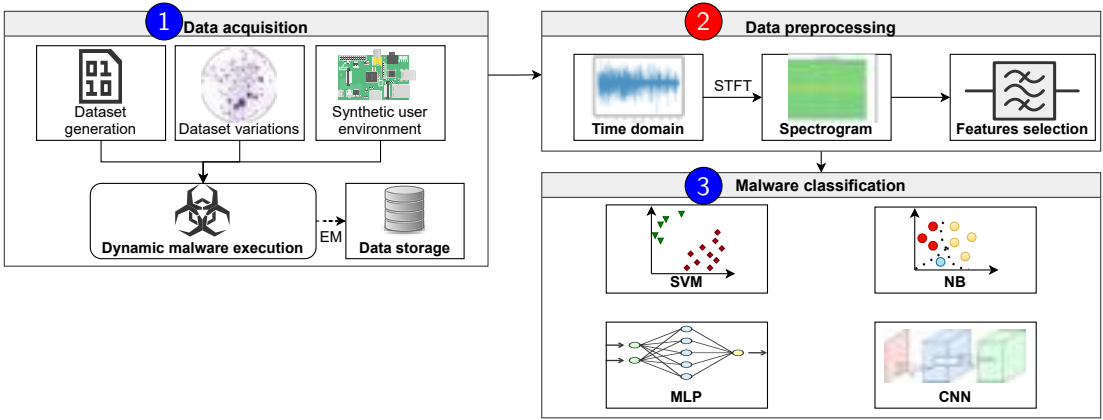


Diamorphine rootkit syscall hooking



kill() syscall flow

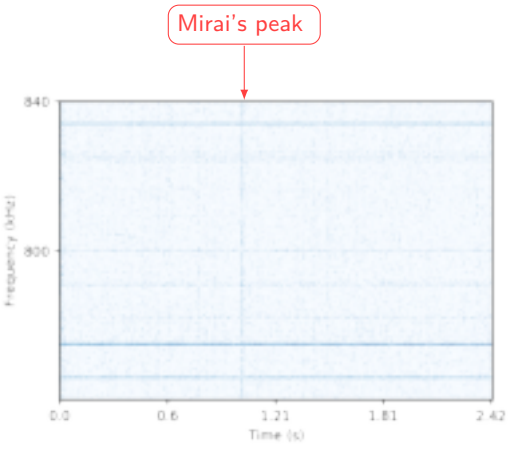
Frameworks overview: data acquisition



Data and pre-processing

- **Raw traces:**
  106k(traces) $\times$ 2(MS/s) $\times$ 2.5(s) [1.2TB]
- **Time-frequency representation:**
  Short-time Fourier transform
  $spectro\{x(n)\}(m,\omega) = |\sum_{n=0}^{N} x(n)w(n-m)e^{-j\omega n}|^2$

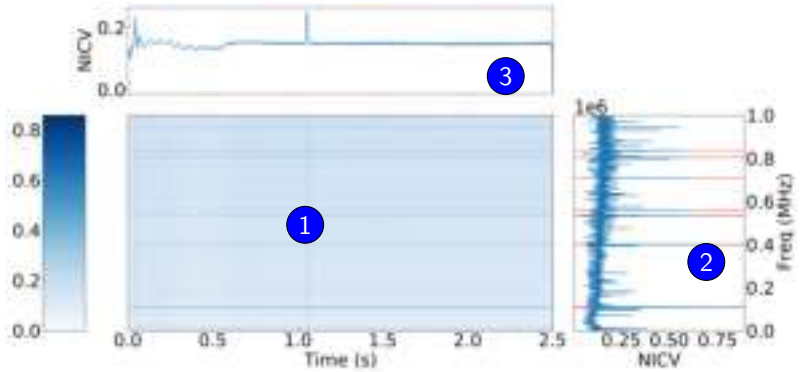
$$\begin{cases} \text{windows} & = 8192 \\ \text{overlap} & = 4096 \end{cases}$$



Features selection: Normalized Inter-Class Variance [Bha+14]

$$\mathrm{NICV}(X, Y) = \frac{\mathrm{Var}[\mathbb{E}[X|Y]]}{\mathrm{Var}[X]}$$

$$F_{\text{extract}} = \mathrm{argmax}_{\epsilon}\left(\left\{\max\left[\mathrm{NICV}(X, Y)_f^D\right]\right\}_{f<F}\right)$$

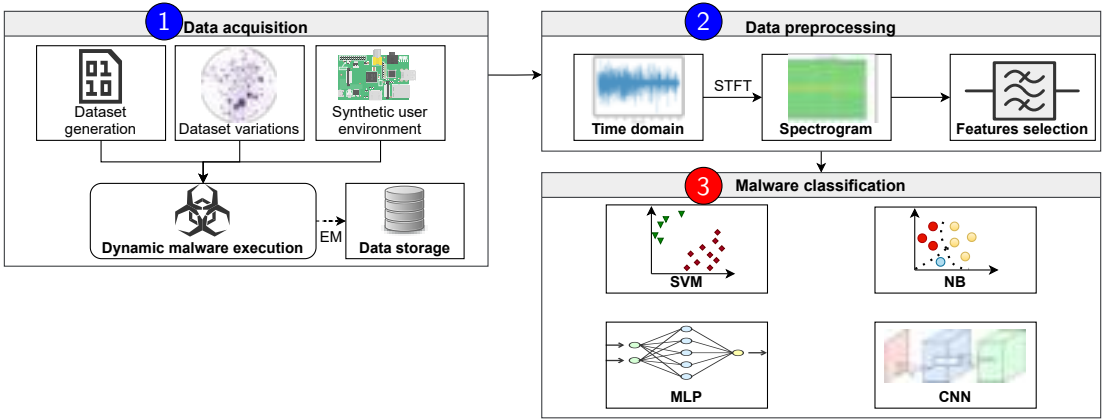


Iterative Vs hill-climbing for selection

Based on NICV's results

- AHMA: try from one to F bandwidth without rejections,
- ULTRA: hill-climbing process, with rejection process to select optimal bandwidth subspace.

Frameworks overview: classification



Machine Learning & Deep Learning models

Machine Learning

- (AHMA)Linear Discriminant Analysis (LDA) / (ULTRA)Kernel PCA + (AHMA + ULTRA) Naive Bayes (NB)
- (AHMA)Linear Discriminant Analysis (LDA) / (ULTRA)Kernel PCA + (AHMA + ULTRA) Support vector machine (SVM)

Deep Learning

- (AHMA + ULTRA) Multi-Layer Perceptron (MLP)
- (AHMA) Convolutional Neural Network (CNN)

Malware classification results

Scenarios	#	MLP	CNN	MLP	CNN
		Rasp.		ci20	
Family	6	98.00 [14]	**99.36** [11]	96.96 [11]	**96.99** [11]

Table 1. Accuracy obtained with MLP, CNN applied on several scenarios for the ci20 and raspberry.

Labels	*benign,*	*mirai,*	*gonnacry,*	*maK_it spy*	*bashlite*
Samples	`random34`, `encodevideo`, `takepicture`, `recordcamera`, `playaudio`	`mirai`, `mirai_cfflatten`, `mirai_virtualize`, `mirai_flatten`, `mirai_bcf`, `mirai_addopaque`, `mirai_sub`, `mirai_upx`	`gonnacry`, `gonnacry_upx`, `gonnacry_aes_upx`, `gonnacry_aes`, `gonnacry_virtualize`, `gonnacry_flatten`, `gonnacry_bcf`, `gonnacry_sub`, `gonnacry_cfflatten`, `gonnacry_addopaque`, `gonnacry_des`, `gonnacry_des_upx`	`maK_it`, `spy`	`bashlite`, `bashlite_bcf`, `bashlite_flatten`, `bashlite_upx`, `bashlite_addopaque`, `bashlite_cfflatten`, `bashlite_sub`, `bashlite_virtualize`

Malware classification results

	#	MLP	CNN	MLP	CNN
Scenarios			**Rasp.**		**ci20**
Novelty (family)	5	**96.65** [11]	89.04 [4]	**99.92** [25]	99.91 [11]

Table 1. Accuracy obtained with MLP, CNN applied on several scenarios for the ci20 and raspberry.

Labels	*benign,*	*mirai,*	*gonnacry,*	*rootkit,*	*bashlite*
Samples learning	`random34, encodevideo, takepicture, recordcamera, playaudio`	`mirai, mirai_cfflatten, mirai_bcf, mirai_upx`	`gonnacry, gonnacry_upx, gonnacry_virtualize, gonnacry_flatten, gonnacry_bcf, gonnacry_sub, gonnacry_addopaque,`	`maK_it,`	`bashlite, bashlite_bcf, bashlite_upx, bashlite_addopaque, bashlite_cfflatten, bashlite_sub`
Samples testing	`random34, encodevideo, takepicture, recordcamera, playaudio`	`mirai_virtualize, mirai_flatten, mirai_addopaque, mirai_sub`	`gonnacry_aes_upx, gonnacry_aes, gonnacry_cfflatten`	`spy (kisni)`	`bashlite_flatten, bashlite_virtualize`

Malware classification results

	#	MLP	CNN	MLP	CNN
Scenarios			**Rasp.**		**ci20**
Obfuscation	7	71.1 [11]	**78.9** [15]	42.8 [5]	**44.7** [5]

Table 1. Accuracy obtained with MLP, CNN applied on several scenarios for the ci20 and raspberry.

Labels	*addopaque,*	*virtulalize,*	*flatten*
Samples	`mirai_addopaque,`	`mirai_virtualize,`	`mirai_flatten,`
	`gonnacry_addopaque,`	`gonnacry_virtualize,`	`gonnacry_flatten,`
	`bashlite_addopaque`	`bashlite_virtualize`	`bashlite_flatten`

Labels	*cflatten,*	*upx,*	*sub,*	*bcf*
Samples	`mirai_cflatten,`	`mirai_upx,`	`mirai_sub,`	`mirai_bcf,`
	`gonnacry_cflatten,`	`gonnacry_upx,`	`gonnacry_sub,`	`gonnacry_bcf,`
	`bashlite_cflatten`	`bashlite_upx`	`bashlite_sub`	`bashlite_bcf`

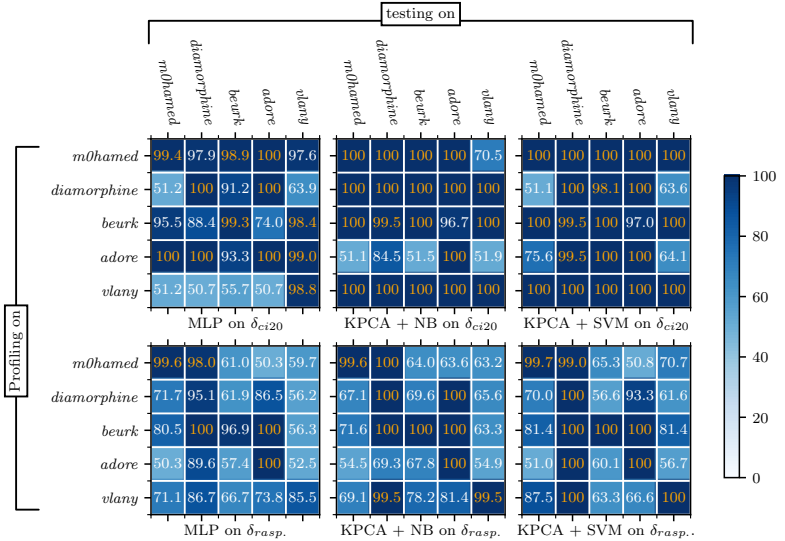
Malware classification results

	#	MLP	CNN	MLP	CNN
Scenarios			**Rasp.**		**ci20**
Executables	35	70.7 [5]	**77.1** [10]	29.9 [9]	**34.3** [6]

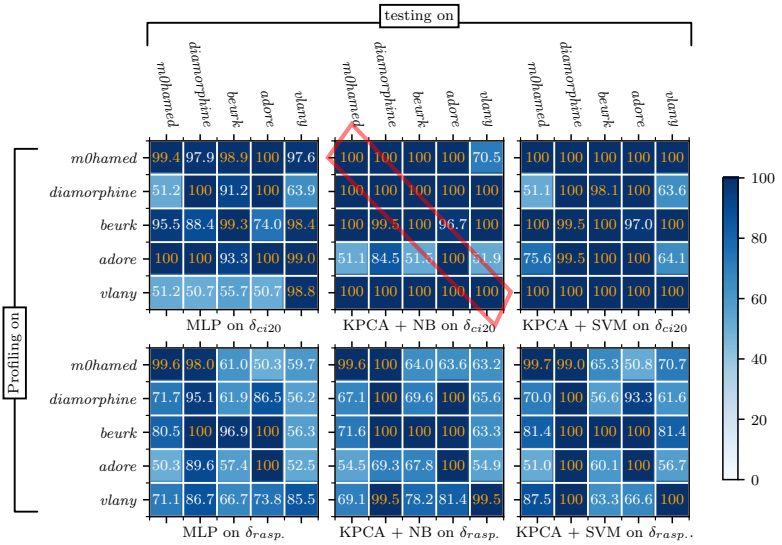
Table 1. Accuracy obtained with MLP, CNN applied on several scenarios for the ci20 and raspberry.

Labels: *random34, mirai, mirai_addopaque, mirai_virtualize, mirai_flatten, mirai_bcf, mirai_cfflatten, mirai_sub, mirai_upx, gonnacry, gonnacry_upx, gonnacry_aes_upx, gonnacry_aes, gonnacry_des, gonnacry_des_upx, gonnacry_virtualize, gonnacry_flatten, gonnacry_bcf, gonnacry_sub, gonnacry_cfflatten, gonnacry_addopaque, maK_it, spy (kisni), bashlite, bashlite_bcf, bashlite_flatten, bashlite_upx, bashlite_addopaque, bashlite_cfflatten, bashlite_sub, bashlite_virtualize, playaudio, recordcamera, takepicture, encodevideo*

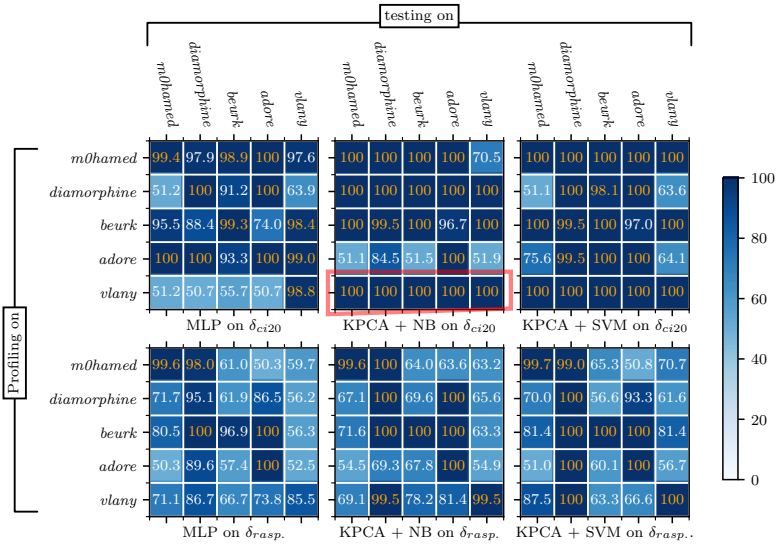
Rootkit detection: Novelty detection using getdents



Rootkit detection: Novelty detection using getdents



Rootkit detection: Novelty detection using getdents



Rootkit detection: Different types and locations of probes

Probe type

Scenario	MLP BA	MLP TPR	MLP TNR	KPCA + NB BA	KPCA + NB TPR	KPCA + NB TNR	KPCA + SVM BA	KPCA + SVM TPR	KPCA + SVM TNR
$\{0,0\} \rightarrow \{0,0\}$	$100_{[2]}$	100	100	$100_{[2]}$	100	100	$100_{[2]}$	100	100
$\{0,0\} \rightarrow \{1,0\}$	$100_{[2]}$	100	100	$100_{[2]}$	100	100	$100_{[2]}$	100	100
$\{0,0\} \rightarrow \{2,1\}$	$60.6_{[2]}$	21.4	99.9	$50.0_{[2]}$	0.0	100	$50.0_{[2]}$	0.0	100
$\{1,0\} \rightarrow \{1,0\}$	$100_{[2]}$	100	100	$100_{[3]}$	100	100	$100_{[2]}$	100	100
$\{2,1\} \rightarrow \{2,1\}$	$100_{[1]}$	100	100	$100_{[4]}$	100	100	$100_{[4]}$	100	100

- **More scenarios available:** sample classification, keyloggers detection with software and hardware baits, influence of benign kernel activities, effect of background noise, influence of obfuscation.

ULTRA with a cheap probe
beurk vs. *open* bait

Rootkit detection: Different types and locations of probes

Probe location

Scenario	MLP BA	MLP TPR	MLP TNR	KPCA + NB BA	KPCA + NB TPR	KPCA + NB TNR	KPCA + SVM BA	KPCA + SVM TPR	KPCA + SVM TNR
$\{0,0\} \rightarrow \{0,0\}$	$100_{[2]}$	100	100	$100_{[2]}$	100	100	$100_{[2]}$	100	100
$\{0,0\} \rightarrow \{1,0\}$	$100_{[2]}$	100	100	$100_{[2]}$	100	100	$100_{[2]}$	100	100
$\{0,0\} \rightarrow \{2,1\}$	$60.6_{[2]}$	21.4	99.9	$50.0_{[2]}$	0.0	100	$50.0_{[2]}$	0.0	100
$\{1,0\} \rightarrow \{1,0\}$	$100_{[2]}$	100	100	$100_{[3]}$	100	100	$100_{[2]}$	100	100
$\{2,1\} \rightarrow \{2,1\}$	$100_{[1]}$	100	100	$100_{[4]}$	100	100	$100_{[4]}$	100	100

- **More scenarios available:** sample classification, keyloggers detection with software and hardware baits, influence of benign kernel activities, effect of background noise, influence of obfuscation.

ULTRA with a cheap probe

beurk vs. *open* bait

Conclusion

Achievement

- (fully open-source) AHMA framework: classification in presence of obfuscation
- (fully open-source) ULTRA framework: Wave-and-Play solution.
- Investigation of various experiments and real-world scenarios.
- Promising solution (detection accuracy up to 100%) and handy: tested with multiple probes and probe relocation with affordable SDR.

Media Coverage

- The Hacker News, Schneier on Security, 01 net...
- ...But be Careful to the fake news, we **never** used raspberry to detect malware on your computer!

Perspctives

What next?

- Is it possible to reverse the classification?
- Larger dataset and upcoming threats (*eg.* hypervisor, eBPF rootkits)
- A standalone solution that uses electromagnetic waves to detect malware and similar threats for other platforms (PLC, Linux servers, etc.)
- Portable solution with GPU (*e.g.* Nvidia Jetson Nano)

Thank you!
and

CAPSULE

is hiring!

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Balanced Accuracy

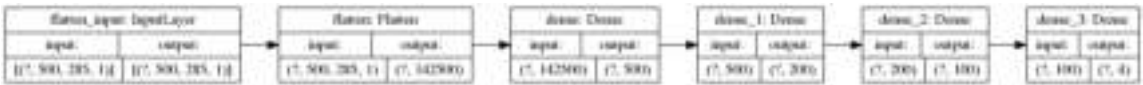
Consider a dataset that contains 99 negative samples and 1 positive sample. Classifying all values as negative yields a 0.99 accuracy score.
Balanced Accuracy is not affected by this issue. It normalizes true positive and true negative predictions by the number of positive and negative samples, respectively, and divides their sum by two:

$$\textbf{BA} = \frac{TPR + TNR}{2} \tag{1}$$

Monitor device(s)

- Picoscope 6000
- Keysight Infiniium
- HackRF SDR

- Multi-Layer Perceptron (MLP)
- Convolutional Neural Network (CNN)



Deep Learning models (MLP)

Table: Proposed MLP architecture of ULTRA framework

Layer	Size	Filter	Activation
Flatten	spectrogram_size	_	leaky relu
Dense	500	_	leaky relu
Dense	200	_	leaky relu
Dense	100	_	leaky relu
Dense	N	_	softmax (multi-class) or sigmoid (two-class)

Deep Learning models (CNN)

Layer	**Size**	**Filter**	**Activation**
Convolution	64	7×7	relu
Max Pooling	64	2×2	_
Convolution	128	3×3	relu
Convolution	128	3×3	relu
Max Pooling	128	2×2	_
Convolution	256	3×3	relu
Convolution	256	3×3	relu
Max Pooling	256	2×2	_
Dense	128	_	relu
Dense	64	_	relu
Dense	nb_labels	_	softmax

State of the art (1)

Article	Year	Techniques
WattsUpDoc: Power SC to Nonintrusively Discover Untargeted MW on Embedded Medical Devices	2013	- Detection of 12 MW variants - Power & MLP & 3NN &RF
Detecting crypto-ransomware in IoT networks based on energy consumption footprint	2017	- MW detection of Ransomware - PowerTutor & KNN
Deep learning-based classification and anomaly detection of side-channel signals	2018	- Anomaly detection of botnet - Power & MLP & LSTM
HLMD: a signature-based approach to HW-level behavioral MW detection and classification	2019	- MW classification of 14 variants - HPC & singular values

State of the art (2)

Article	Year	Techniques
EDDIE: EM-based detection of deviations in program execution	2017	- Code Inj. detection - EM & STFT & KS
MW detection in embedded systems using NN model for EM SC signals	2019	- MW detection of DDoS, Ransomware, CF Hijack - EM & MLP

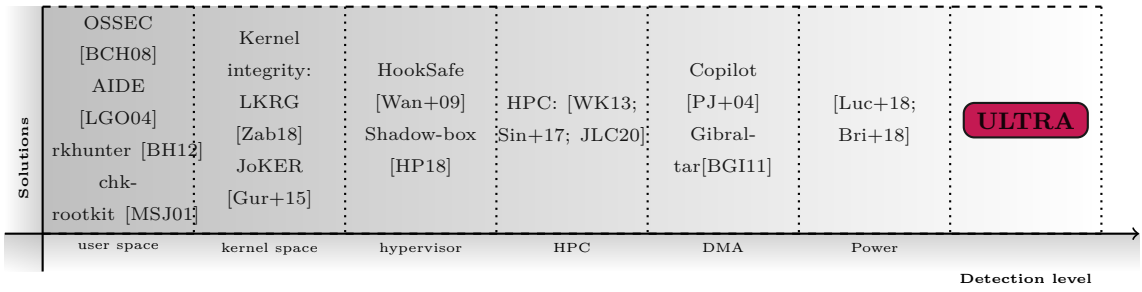
→ Real world malware.

State of the art (3)

Table: Comparison with related works on side-channel malware (SCM) analysis using EM or power consumption.

Article	SCM detection	Anomaly detection	SCM classification	Real-world SCM	Real-world analysis environment	Samples size	Variations	Benign dataset	Window size	Open data, source code	Device under test
WattsUpDoc [Cla+13]	✓	-	-	✓	-	15	-	-	5s	-	Windows XP Embedded 664 MHz
IDEA [Kha+19]	-	✓	-	-	-	3	-	-	$<40\mu$s	-	AT328p 16MHz, Cortex A8
REMOTE [Seh+20]	-	✓	-	✓	-	3	-	-	<10ms	-	Single-core ARM 1Ghz
Wang *et al.* [Wan+18]	-	✓	-	-	-	1	-	-	10s	-	Raspberry Pi, Arduino, Siemens PLC
Khan *et al.* [Kha+19]	✓	-	-	-	-	3	-	-	$<150\mu$s	-	Cyclone II FPGA & NIOS II soft-processor
DeepPower [Din+20]	✓	-	✓	✓	-	5	-	-	1s	-	MIPS/ARM OpenWRT
Chawla *et al.* [CKM21]	✓	-	✓	✓	-	137	-	✓	10s	-	Android Intrinsyc Open-Q 820
Chapter ??	*(✓)**	-	✓	✓	✓	35	✓	✓	2.5s	✓	Multi-core, 900 Mhz ARM

State of the art (4)



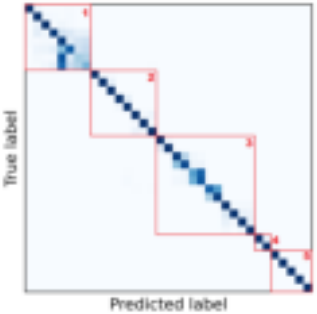
Taxonomy of rootkit detection approaches and positioning our approach in the state of the art and open source tools.

State of the art (5)

Table: Comparison with related works on rootkit (RK) detection using different side-channel analysis techniques: HPC, DMA, Power consumption (Power) and EM.

	Article	WnP	Classificat	Baits	ML	DL	Sample size	Open source	Benign	User RK	Window size	Device under test
HPC	Numchecker [WK13]	-	-	✓	-	-	8	-	-	-	262.3 ms	32-bit Ubuntu PC
HPC	[Sin+17]	-	-	-	✓	-	5	-	-	-	45s	VMWare Windows 7 Intel
HPC	[JLC20]	-	-	✓	✓	-	4	-	-	-	2.91s	ARM Cortex-A53
DMA	Copilot [PJ+04]	-	-	-	-	-	12	-	-	-	30s	PCI-compatible Intel PC Linux
DMA	Gibraltar [BGI11]	-	-	-	-	-	23	-	✓	-	20s	PCI-compatible Intel PC Linux
Power	[Luc+18]	-	-	-	✓	✓	5	-	-	✓	>5m	PC Windows 10 & Ubuntu 14
Power	[Bri+18]	-	-	-	✓	-	5	-	-	-	>1m	Dell OptiPlex 755 Windows 7
EM	**ULTRA**	✓	✓	✓	✓	✓	9	✓	✓	✓	1.3s	ARM Raspberry Pi & MIPS Ci20

Confusion matrix of a CNN classification into 35 binaries



Confusion matrix of a CNN classification into 35 binaries from left to right (with and without obfuscation).
(1) *bashlite_cfflatten, bashlite_upx, bashlite_bcf, bashlite, bashlite_addopaque, bashlite_sub, bashlite_flatten, bashlite_virtualize*;
(2) *mirai_sub, mirai_bcf, mirai_cfflatten, mirai, mirai_upx, mirai_addopaque, mirai_flatten, mirai_virtualize*;
(3) *gonnacry_des, gonnacry_des_upx, gonnacry, gonnacry_aes, gonnacry_aes_upx, gonnacry_upx, gonnacry_flatten, gonnacry_virtualize, gonnacry_addopaque, gonnacry_bcf, gonnacry_sub, gonnacry_cfflatten*;
(4) *spy, maK_It*;
(5) *benign:* encode video, play audio, take picture, record camera, random.

Dataset: Benign

- Binaries from fresh Linux installation
- Random activities

Activities	Executables			
Linux Utilities	mknod	vdir	more	find
	zgrep	ls	cat	findmnt
	zmore	as	ed	rm
	touch	dmesg	sleep	cd
	less	grep	objdump	
Network	wget	hostname	ss	ip
Compression	gunzip	bunzip2	bzip2	tar
	uncompress			
Data backup	dd			
Scripting	python			
Photo & Video	raspistill	raspivid		
Video Encoding	MP4Box			
Audio player	mpg321			

ULTRA's targeted devices specification

Table: ULTRA's targeted devices specification, architectures (Arch.), and their targeted frequency leakage (Fc) and CPU in MHz.

Device δ	Arch.	CPU	RAM	OS	Fc
Raspberry Pi B+	ARM32	700	512MB	Linux 4.1.7	1222
Creator CI20	MIPS32	1200	1GB	Linux 3.18.3	792

ULTRA's bill of materials

Table: ULTRA's bill of materials

Equipment	Rate/Unit	Count	Amount (Euro)
HackRF One SDR	309	1	309
Adapter SMA Male BNC Female RG316	5	1	5
Amplifier Langer PA-303 BNC	375	1	375
*Probe Langer RF-U 5-2**	250	1	250
Total			939

* *This can be omitted in the case of using a hand-crafted probe.*

Table: Performance evaluation of rootkit (RK) and their obfuscated variants(*) detection results, and execution latency. List of indicators: (✓) RK detected; (-) Not detected; (†) Malicious behavior trigger required; (⚠) Kernel panicked; Executed on (‡) CPU ; (§) GPU.

RK	AV solutions			
	rkhunter	*chkrootkit*	*LKRG*	*ULTRA*
diamorphine	✓	-	✓†	✓
diamorphine(*)	-	-	✓†	✓
m0ham3d	✓	-	✓†	✓
m0ham3d(*)	-	-	✓†	✓
adore-ng	-	-	✓† ⚠	✓
spy	-	-	-	✓
maK_it	-	-	-	✓
beurk	-	-	-	✓
vlany	-	-	-	✓
Latency *(sec)*	1326.6‡	44.3‡	2.6‡	1.3§-1.5‡

Rootkit Classification

Table: Classification by family and by activity obtained with MLP, LDA + NB and LDA + SVM. The column "#" gives the number of classes per scenario.

			MLP	LDA + NB	LDA + SVM
Scenario		**#**	**AC** $_{[\epsilon_{opt}]}$ $^{PR}/_{RC}$	**AC** $_{[\epsilon_{opt}]}$ $^{PR}/_{RC}$	**AC** $_{[\epsilon_{opt}]}$ $^{PR}/_{RC}$
δ_{ci20}	family	19	$91.3_{[65]}$ $^{83.0}/_{83.0}$	$76.0_{[10]}$ $^{65.6}/_{65.4}$	$85.6_{[8]}$ $^{76.1}/_{76.3}$
	activity	46	$82.5_{[45]}$ $^{83.0}/_{82.5}$	$62.5_{[10]}$ $^{63.2}/_{62.4}$	$76.0_{[10]}$ $^{75.8}/_{76.0}$
$\delta_{rasp.}$	family	19	$82.1_{[50]}$ $^{79.1}/_{76.5}$	$54.7_{[10]}$ $^{53.9}/_{55.3}$	$66.2_{[10]}$ $^{66.9}/_{60.1}$
	activity	46	$75.0_{[40]}$ $^{75.4}/_{75.0}$	$50.6_{[10]}$ $^{51.5}/_{55.6}$	$59.2_{[9]}$ $^{59.4}/_{59.2}$