

Accurate fault detection & classification based on embedded machine learning algorithms

Smart Monitor

Sylvain Guilley, CTO Tuesday May 29, 2018.



#### Presentation Outline

#### General introduction on trends in embedded systems security

Innovative product 1: Digital sensor v2

Innovative product 2: Smart monitor

Conclusions



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#### It is *machine* against *machine*

Attackers get smart:

- Automatic generation of specialized fault attacks
- Machine learning assisted pattern recognition in traces
- Deep learning in side-channel analysis

In response, protections must be smart

	Rich information		big data
_	Clever analysis	artificial	intelligence



#### Similar situation in IT security

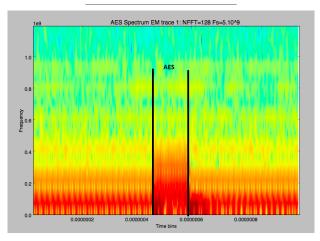


<u>Source:</u> http://archive.darpa.mil/cybergrandchallenge/.



#### Noisy EM analysis

Side-channel analysis and machine learning: A practical perspective (IJCNN 2017  $[PHJ^+17]$ )

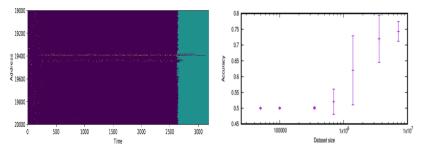


## SECURE-IC

#### Microarchitectural Analysis Cachyzr (tool in CTZ)

#### DYNAMIC ANALYSIS: ML-ENHANCED CACHE-TIMING ATTACK

- · Cache miss & Cache hit patterns could reveal sensitive information (leakage)
- Deep-learning on cache access patterns
- E.g. OpenSSL ECDSA Nonce LSB recovery using convolutional neural networks





#### How we handle smart attacks?

#### Security by design

- Formal models of protection rationale
- Validation by VTZ tool (Virtualyzr [DGN+17]), throughout the design flow
- Evaluation in rich platform

Machine learning (ML)

- Sensors fusion
- Embedded ML
- Nice byproduct: allows to tolerate noise, e.g., technology dispersion



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[GP17]



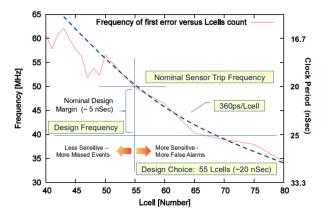


- Centered status: can see as well speed decrease as speed increase
- More fine: delta temperature/bit, etc.
- History (internal oscilloscope)
- Spatial efficiency (= smart monitor)



(illustration)

#### New feature: finer resolution

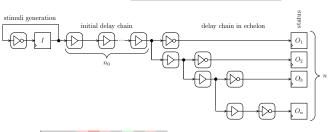


Objective: by proper selection of buffers, make the slope more steep.



(illustration)

#### New features: history



I	0	1	0	1	0	1	0	1	0	1	0
$O_1$	1	0	1	0	1	0	1	0	1	0	1
$O_2$	1	0	1	0	1	0	1	0	1	0	1
÷ .	1	0	1	0	0	0	1	0	1	0	1
$O_{th}$	1	0	1	1	0	1	1	0	1	1	1
$O_{th+1}$	0	1	0	1	0	1	0	0	0	1	0
$O_{th+2}$	0	1	0	1	0	1	0	1	0	1	0
:	0	1	0	1	0	1	0	1	0	1	0
$O_n$	0	1	0	1	0	1	0	1	0	1	0

A unique signature: Fig. 14, page 189, of [SBGD11]

## SECURE-IC

#### The Digital Sensor V2: new usages

- As always: fully digital, i.e., using precharacterized standard cells from the PDK
  - Can replace analog sensors (see below)
  - Less costly than analog sensors for small technological nodes (7 nm, 5 nm, etc.)
- One *single* instance is sufficient for:
  - low clock frequency: have  $n_0$  set to a large value
  - high clock frequency: have  $n_0$  set to 0
  - low / high temperature: increase n / decrease  $n_0$  (see slide 19)
  - better voltage (higher than nominal): increase n beyond 32 bits (see slide 20)
- Multiple instances are needed for local attacks, such as:
  - EM pulse injection attack
  - laser injection attack
  - Number and location of sensors: spread by supply net of P/G network, close to sensitive registers



#### Experimental results

Dimensioning on SAKURA G, SPARTAN 6 FPGA:

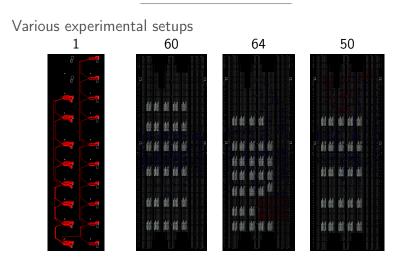
FIFO depth: 40

- Status: 16 to 32 chain length:  $n_0 = 70 + 16-32$
- ➡ Number of instances: ≈ 50
- Sensitivity (see next slides):
  - **0.04 bit**/°C
  - 0.18 bit/mV
- Without and with crypto running in parallel (AES core)

Big data: 64000 bits ready to be analyzed at each clock cycle.

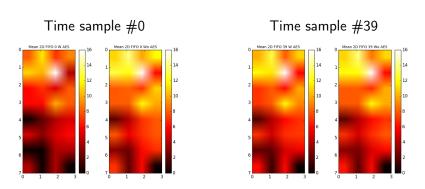








#### Natural variability

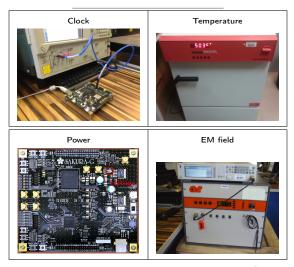


In a threshold-based approach, the threshold is not easy to set
 Depends on the location, depends on the internal activity



(LBZ)

#### Characterization & attack means





#### Experiments at Rennes SSF Security Science Factory



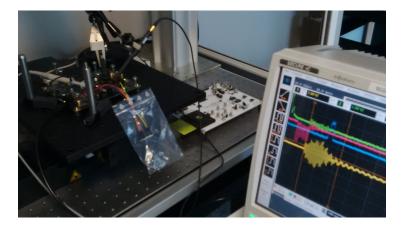


#### Experiments at Rennes SSF Security Science Factory





#### Experiments at Rennes SSF Security Science Factory

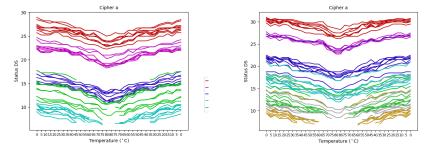




#### ■ Variability is by techno dispersion, not P&R

Automatic routing

#### Manual routing



#### Characterization: 0.04 bit/°C

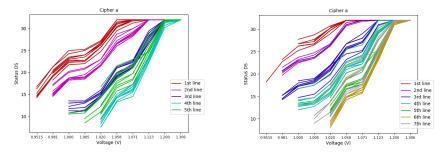
Saturation at ≤ 32 can be leveraged by increasing n
 Saturation at ≥ 0 can be leveraged by decreasing n<sub>0</sub>
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#### ■ Variability is by techno dispersion, not P&R

Automatic routing

#### Manual routing



#### Characterization: 0.18 bit/mV

- Saturation at  $\leq$  32 can be leveraged by increasing *n* 



Innovative product 1: Digital sensor v2 Summary

Security feature innovation ("big data" allowing "analytics"):

- Captures complete waveforms
- Monitors when conditions get worse but also when they unexpectedly get more favorable
- Increased environmental condition sampling resolution

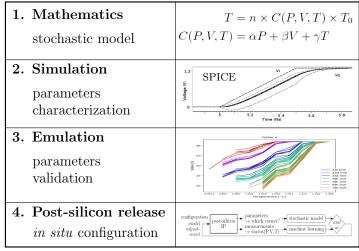
Demonstration / proof of maturity:

- ➡ Show-case of an FPGA board with a matrix of DS V2
- Illustration of sensitivity even to internal activity change
- Illustration of sensitivity when external conditions change



#### Robust design-for-security and -for-yield approach

DfS and DfY for the DS V2





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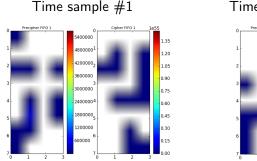
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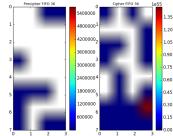
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# Distinguishing internal activity, with T-Test [Wel47]



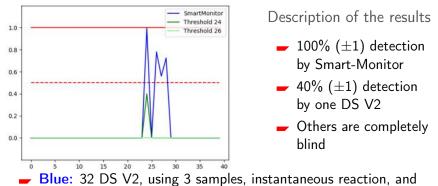
Time sample #36 (EM inj)



Normalized difference between with and without EM injection
 Those figures require multiple measures to be computed



#### Distinguishing internal activity, with ML [Vap98]



- accurate damping
- Green: threshold at each DS V2, equal to: normalized mean(with EM) - mean(w/o EM).



#### Radial Basis Function (RBF) kernel

#### Radial basis function kernel

From Wikipedia, the free encyclopedia

In machine learning, the **radial basis function kernel**, or **RBF kernel**, is a popular kernel function used in various kernelized learning algorithms. In particular, it is commonly used in support vector machine classification.<sup>[1]</sup>

The RBF kernel on two samples  $\mathbf{x}$  and  $\mathbf{x}$ ', represented as feature vectors in some *input space*, is defined as<sup>[2]</sup>

$$K(\mathbf{x}, \mathbf{x}') = \exp\left(-rac{\|\mathbf{x} - \mathbf{x}'\|^2}{2\sigma^2}
ight)$$

 $\|\mathbf{x} - \mathbf{x}'\|^2$  may be recognized as the squared Euclidean distance between the two feature vectors.  $\sigma$  is a free parameter. An equivalent, but simpler, definition involves a parameter  $\gamma = \frac{1}{2\sigma^2}$ :

$$K(\mathbf{x}, \mathbf{x}') = \exp(-\gamma \|\mathbf{x} - \mathbf{x}'\|^2)$$

#### Our best fit is for $\gamma \approx \frac{1}{4}$ .



Innovative product 2: Smart monitor Summary

Security feature innovation:

Can be fed by DS V2, but also other sensors, incl. CyberEU
 Pobust honign (malicious observation classification)

Robust benign / malicious observation classification

Demonstration / proof of maturity:

- Detection before the AES is faulted
- Model robustness w.r.t. device architecture



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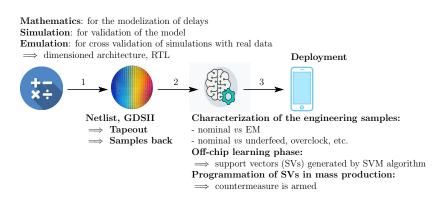
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# Flow for Smart-Monitor management of chip fabrication uncertainties





#### Bibliographical references I

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In David Atienza and Giorgio Di Natale, editors, *Design, Automation & Test in Europe Conference & Exhibition, DATE* 2017, Lausanne, Switzerland, March 27-31, 2017, pages 1129–1134. IEEE, 2017.

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