# Using the Joint Distributions of a Cryptographic Function in Side Channel 

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## Introduction

Context: Side channel attacks on embedded software cryptographic algorithm.

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- without plaintext or ciphertext
- without profiling phase



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- ( $a_{i}$ ) and $\left(b_{i}\right)$ have not independent distributions.
- ( $a_{i}$ ) and $\left(b_{i}\right)$ have a joint distribution that could depend on some key bits. Example: the couples $\left(a, b_{1}\right)$ with $b_{1}=\mathrm{SB}(a)$ and $\left(a, b_{2}\right)$ with $b_{2}=\mathrm{SB}(a \oplus 0 x f f)$ have different distributions.


## The idea



Remarks:

- ( $a_{i}$ ) and $\left(b_{i}\right)$ have not independent distributions.
- ( $a_{i}$ ) and $\left(b_{i}\right)$ have a joint distribution that could depend on some key bits.
$\Rightarrow$ Choice of a targeted function.
Example: $g(a, k)=\mathrm{SB}(a \oplus k)$


## The attack principle

- Acquisitions of couples (leakage of $a_{i}$, leakage of $b_{i}$ ). $\Rightarrow$ Empirical distribution $S_{d}$.
- Precomputations of theoretical distributions $S(g, k)$ of $\left(a_{i}, g\left(a_{i}, k\right)\right)$ for each possible key $k$.
- Comparison of $S_{d}$ to each $S(g, k)$.
$\Rightarrow$ The nearest determines the correct key value.


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## Compare an exact value to a leakage one

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## Compare an exact value to a leakage one

- Intermediate data $a_{i}$ and $b_{i}$ are reduced to a leakage model $\varphi\left(a_{i}\right)$ and $\varphi\left(b_{i}\right)$ (Hamming weigth, identity,...)
- Signal amplitudes are mapped to this leakage model too. Leakage estimation

Example: Classification method for a Hamming weight model of 4 bits:

| HW value | number |
| :---: | :---: |
| 0 | 1 |
| 1 | 4 |
| 2 | 6 |
| 3 | 4 |
| 4 | 1 |
| Total | 16 |



## Compare two distributions

Notations:

- $p_{i j}$ is the probability $\varphi(a)=i$ and $\varphi(g(a, k))=j$
- $f_{i j}$ is the frequency of couple $\left(\varphi(a), \varphi\left(g\left(a, k^{\star}\right)\right)\right)=(i, j)$

Example the $\chi^{2}$ distance:

$$
\begin{gathered}
\chi^{2}\left(S(g, k), S_{d}\right)=\sum_{i} \sum_{j} \delta\left(p_{i j}, f_{i j}\right) \\
\delta\left(p_{i j}, f_{i j}\right)= \begin{cases}\frac{\left(p_{i j}-f_{i j}\right)^{2}}{p_{i j}} & , p_{i j} \neq 0 \\
0 & , p_{i j}=f_{i j} \\
\infty & , p_{i j}=0 \neq f_{i j}\end{cases}
\end{gathered}
$$

$\Rightarrow$ The smallest distance between $S_{d}$ and all the $S(g, k)$ reveals the correct key $k$.

## But...

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Solution: Others distances from the paper:
S.-H. Cha. Comprehensive survey on distance/similarity measures between probability density functions. International Journal of Mathematical Models and Methods in Applied Sciences, 2007.

- Classical distances over $\mathbb{R}^{n}$
- Distances based on scalar product
- Distances based on Shannon entropy


## Simulations

■ 100,000 simuled attacks

- Targeted function: $g(a, k)=\operatorname{SB}(a \oplus k)$
- Leakage model: Hamming weight of 8 bits
- Two kinds of error for the leakage estimation:
- small errors : correct value $\pm 1$
- random errors : random value
- Chosen distance : 33 different distances


## Simulations for different distances and 50\% small errors



## Simulations for different distances and 50\% random errors



## Best distances

- Pearson $\chi^{2}$ distance: $\sum_{i} \sum_{j} \frac{\left(p_{i j}-f_{i j}\right)^{2}}{f_{i j}}$
- Product scalar distance: $1-\sum_{i} \sum_{j} p_{i j} \cdot f_{i j}$

■Kullback-Leiber distance: $\sum_{i} \sum_{j} p_{i j} \cdot \ln \left(\frac{p_{i j}}{f_{i j}}\right)$

- Harmonic mean distance: $1-2 \sum_{i} \sum_{j} \frac{p_{i j} \cdot f_{i j}}{p_{i j}+f_{i j}}$
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$\Rightarrow$ With these distances the attack succeeds even in presence of errors.
$\Rightarrow$ The estimation may be approximative. No profiling phase is needed.

## ATMega2561 : experimental conditions

- First round of a software AES-128
- Targeted function: $g(a, k)=\operatorname{SB}(a \oplus k)$
- Selection of the points of interest thanks to the variance
- Hamming weigth estimation by classification
- Chosen distance: Scalar product


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- $4 \times 4$ instants with the higher variance:
- The top 16 reveals 3 key bytes
- No position information for these bytes: it remains $\approx 2^{107}$ keys to test
- The probability for randomly finding 3 bytes is less than $2^{-24}$
- Time $<1$ second


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- The top 16 reveals 3 key bytes
- No position information for these bytes: it remains $\approx 2^{107}$ keys to test
- The probability for randomly finding 3 bytes is less than $2^{-24}$
- Time $<1$ second
- $50 \times 50$ instants with the higher variance:
- The top 16 reveals 10 key bytes
- No position information for these bytes: it remains $\approx 2^{70}$ keys to test
- The probability for randomly finding 10 bytes is less than $2^{-80}$
- Time $<2$ minutes


## Conclusion

- Without the knowledge of the plaintext or the ciphertext
- Many cryptographic functions
- Good stability in case of weak leakage estimation
- Easy and fast
- Difficulty for identifying of the position of the recovered key bytes


## Perspectives

- Improve the attack thanks to the next rounds
- Apply this attack to protected implementations
- Try others methods to model and/or estimate the leakage

■ Find others methods for points of interest detection without the knowledge of plaintext or ciphertext

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## Questions?

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## DPAContest V4: experimental conditions

- First round of a software AES-256 with a RSM countermeasure
- Traces with the same unknown offset $i$
- Targeted function: $g(a, k)=\mathrm{SB}\left(a \oplus k \oplus M_{i}\right) \oplus M_{i+1}$
- Selection of the points of interest thanks to the variance
- Hamming weigth estimation by classification
- Chosen distance: Scalar product


## DPAContest V4: attack and results

- The attack is repeated on each pair of interest points
- Occurence number of the resulting key bytes
- Instants where the variance is 5 times the mean variance:
- 28,000 points of interest
- The top 16 for occurence numbers reveals 7 key bytes
- These bytes are well-ordered: it remains $\approx 2^{92}$ keys to test
- The probability for randomly finding these bytes is less than $2^{-40}$
- Time: 5 days

