

Exact Template Attacks with Spectral Computation

M. MAHAR M. OULADJ S. GUILLEY H. BELBACHIR F.
MOKRANE

Université Paris 8, LAGA, UMR 7539, Paris, France.

CERIST, Algiers, Algeria.

Secure-IC S.A.S. , Rennes, France,
and École Normale Supérieure (ENS), Paris, France.

CATI, RECITS Laboratory, USTHB, Algiers, Algeria.

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Plan

- Introduction;

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- Formal proof;

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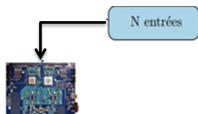
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- Spectral expression;

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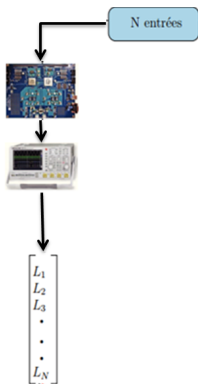
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- Conclusion and perspectives.

Introduction: Side-Channel attacks



Introduction: Side-Channel attacks



Side-Channel attack

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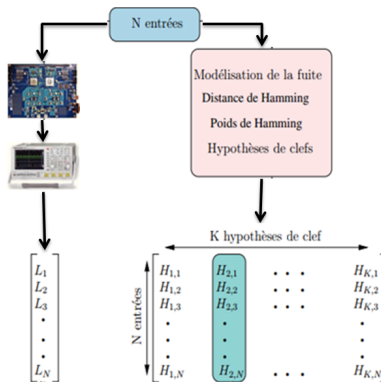
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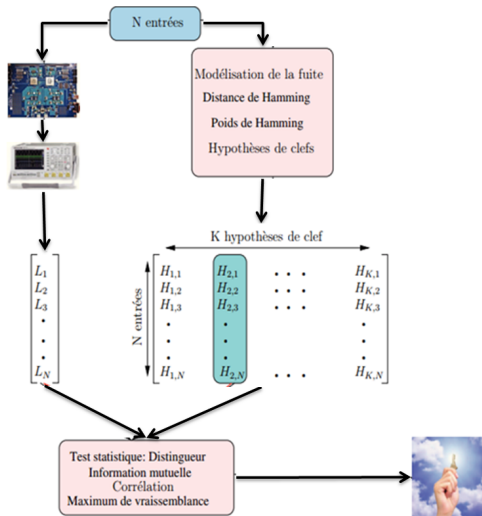
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Introduction: Side-Channel attacks



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Introduction: Correlation Power Attack

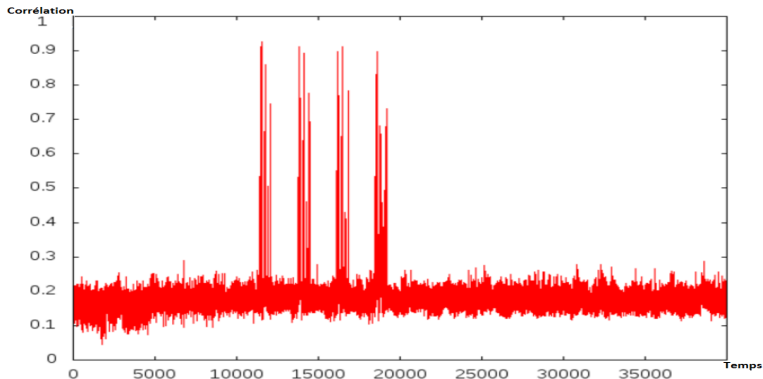
The correlation between the real leakage M and the leakage model V applied to the key k is:

$$\rho_{M,V_k} = \frac{\text{cov}(M, V_k)}{\sigma_M \cdot \sigma_{V_k}} = \frac{\langle M, V_k \rangle}{\|M\| \|V_k\|}$$

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Result of a Correlation Power Attack

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- Σ : the $D \times D$ covariance matrix of the noise.

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- $N_q = X_q - Y_{q,k}$

- $p_{N_q}(X_q - Y_{q,k}) = \frac{1}{\sqrt{(2\pi)^Q |\Sigma|}} e^{-\frac{1}{2}(X_q - Y_{q,k})^T \Sigma^{-1} (X_q - Y_{q,k})}$

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A scalability Problem!

the guessed key can be carried out by [5, 3]:

$$\hat{k} = \underset{k}{\operatorname{argmin}} \sum_{x=0}^{2^n-1} n_x (\tilde{L}_x - \tilde{M}_{x,k})^T \Sigma^{-1} (\tilde{L}_x - \tilde{M}_{x,k}) . \quad (1)$$

Such that:

- n_x is the number of times the message x is involved,
- \tilde{L}_x is the average trace over over all the traces corresponding to the same message x ,
- $\tilde{M}_{x,k}$ is leakage model corresponding to the couple (x, k) .
- $\Sigma = \frac{1}{N} L L^T - \frac{1}{2^n} \tilde{M} \tilde{M}^T$
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Formal proof

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The attack (1) is more efficient in terms of computation, and memory space, than the theorem 1, as soon as the number of traces N is greater than the number of plaintexts involved in the leakage model (e.g. for AES it is $2^n = 256$).

To compute (1) without using the approximation by the LLN, contrary to the state of the art, one can consider.

Proposition (Exact Template Attack – Expression of the Maximum Likelihood Distinguisher)

$$\hat{k} = \underset{k}{\operatorname{argmin}} \sum_{x=0}^{2^n-1} n_x \tilde{M}_{x \oplus k}^T \Sigma^{-1} \tilde{M}_{x \oplus k} - 2 \sum_{x=0}^{2^n-1} (n_x \tilde{L}_x^T) (\Sigma^{-1} \tilde{M}_{x \oplus k}) .$$

Recalling that, for any pair of pseudo-Boolean functions f and g , we have:

$$\sum_{x=0}^{2^n-1} f(x) \cdot g(x \oplus k) = (f \otimes g)(k) = WHT(WHT(f) \bullet WHT(g))(k),$$

where

- ① “ \bullet ” denotes the direct product between two pseudo-Boolean functions (that is, the term-to-term product),
- ② “ \otimes ” denotes the convolution product between two pseudo-Boolean functions,
- ③ WHT denotes the Walsh-Hadamard Transform.

$$WHT(f)(u) = \sum_x (-1)^{u \cdot x} f(x).$$

Spectral expression

$$\begin{aligned}\hat{k} &= \underset{k}{\operatorname{argmin}} \sum_{x=0}^{2^n-1} n_x \tilde{M}_{x \oplus k}^T \Sigma^{-1} \tilde{M}_{x \oplus k} - 2 \sum_{x=0}^{2^n-1} (n_x \tilde{L}_x^T) (\Sigma^{-1} \tilde{M}_{x \oplus k}) \\ &= \underset{k}{\operatorname{argmin}} n(\cdot) \otimes \mathcal{M}(\cdot)(k) - 2 \sum_{u=1}^D L_{\text{cumul}}[u] \otimes \tilde{\mathbb{M}}[u](k) \\ &= \underset{k}{\operatorname{argmin}} WHT \left[WHT(n) \bullet WHT(\mathcal{M}) - 2 \sum_{u=1}^D WHT(L_{\text{cumul}}[u]) \bullet WHT(\tilde{\mathbb{M}}[u]) \right]\end{aligned}$$

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So, we can carry out an exact template attack, by pre-processing $WHT(\mathcal{M})$, $WHT(\tilde{\mathbb{M}}[u])$ (for each u value), during the profiling phase, then guessing the key \hat{k} accordingly.

Results and experimental validation

- We employed raw traces from the SCA database (ASCAD) of the French National Agency for Information Systems Security (ANSSI) [2].
- The encryption algorithm target is a protected software implementation of AES running on an ATMEGA-8515 μ -processor.

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- The target variable is $Z = \text{SBox}(x[2] \oplus k[2])$.

Results and experimental validation: Success rate / #traces

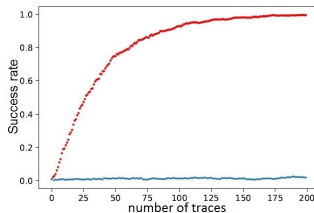


Figure: $D = 1$

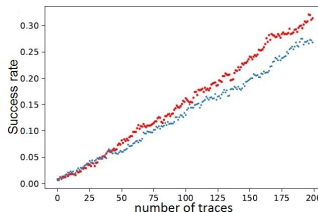


Figure: $D = 2$

Results and experimental validation: Success rate / #traces

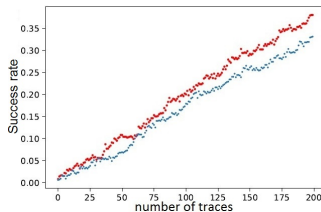


Figure: $D = 3$

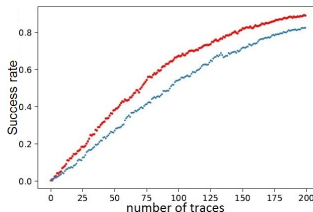


Figure: $D = 4$

Results and experimental validation: Success rate / #traces

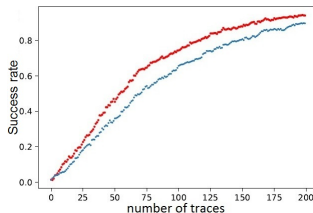


Figure: $D = 5$

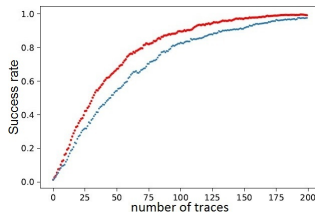


Figure: $D = 10$

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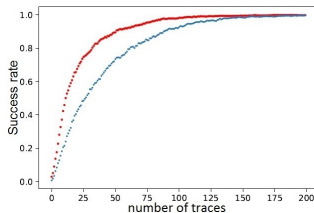


Figure: $D = 20$

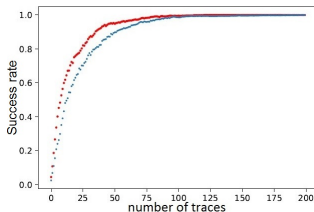
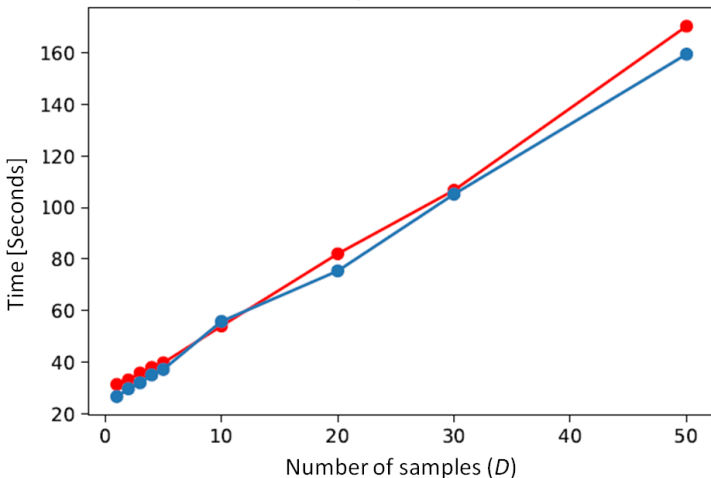


Figure: $D = 50$

Results and experimental validation: Computation time



Conclusions and perspectives

Conclusions:

- new improvement in template attacks' success rate, thanks to a spectral computation;
- Can be applied to any algorithms that involve SBox whose input is the *XOR*;
- A quasilinear instead of a quadratic time complexity (32x faster);
- Considerable gain in success rate comes at the expense of a marginal loss in computation time, which is explained in terms of complexity.

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- How these improvements behave with countermeasures,
- This approach should be extended to the Linear Regression Analysis (LRA) in [4].

Thank you for your attention



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