A New Difference Method for Side-Channel Analysis with High-Dimensional Leakage Models

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CASCADE

CONSTRUCTIVE ATTACKS | SIDE CHANNEL ANALYSIS | SECURE DESIGN

Overview

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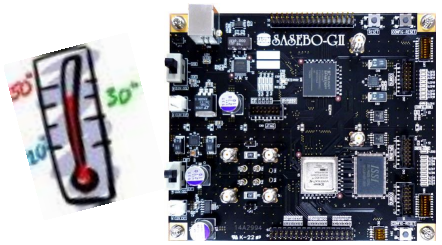
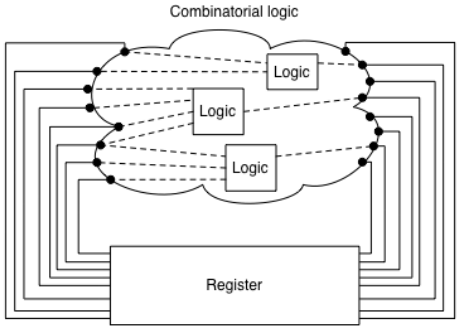
A New Difference Method for Side-Channel Analysis with High-Dimensional Leakage Models

New Difference Method



Leakage Models



illustrated by

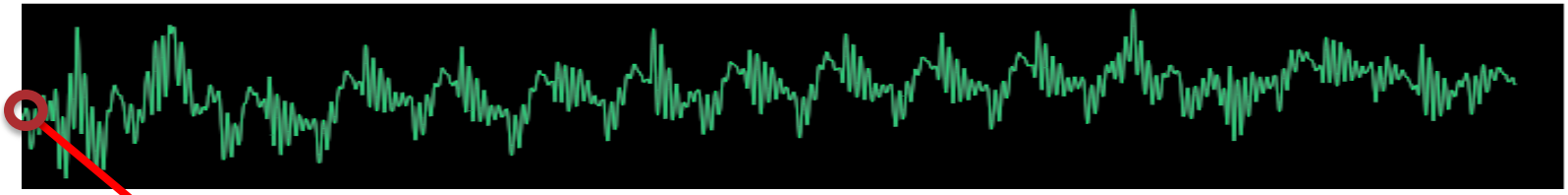
Dpacontest v2

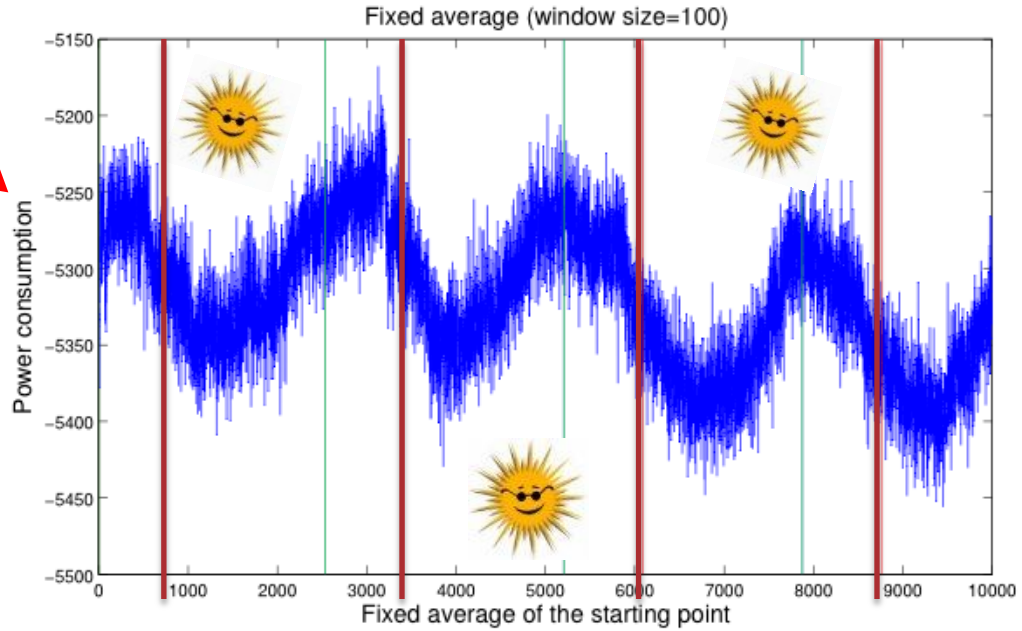
Dpacontest v2

- AES- 128 hardware implementation
- Public Access
  - Template Base
    - 1.000.000 measurements
    - Random keys / inputs
  - Public Base
    - 32 different fixed keys each 20.000 random inputs
- Organizers
  - Evaluation on a Private Base
  - Criteria: Partial Success Rate, Global Success Rate, Guessing Entropy

Dpacontest v2

Template Base with 1.000.000 measurements, recorded during 3-4 days





Environmental Influences

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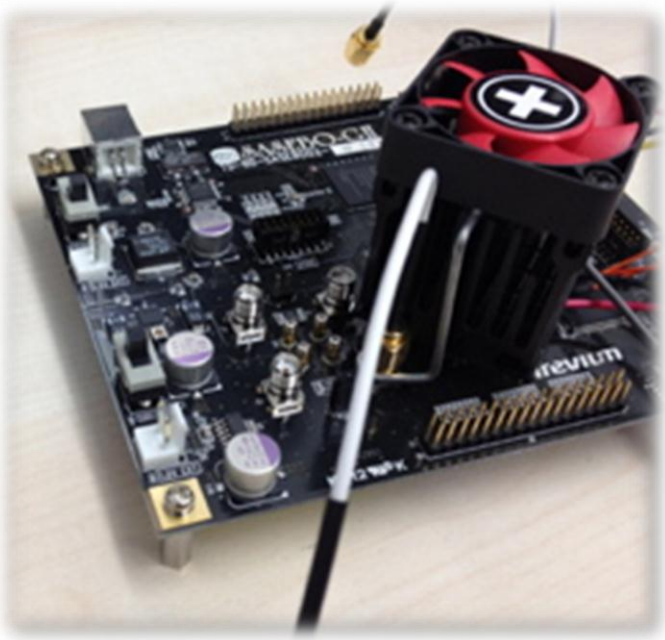

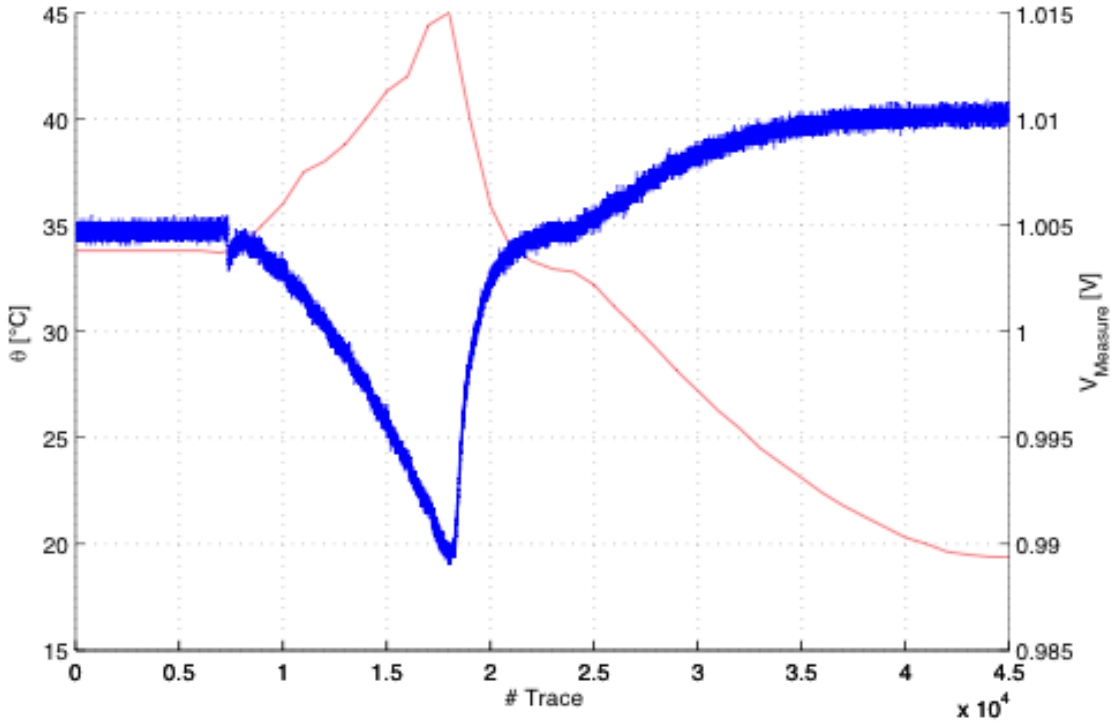

Temperature

Power consumption

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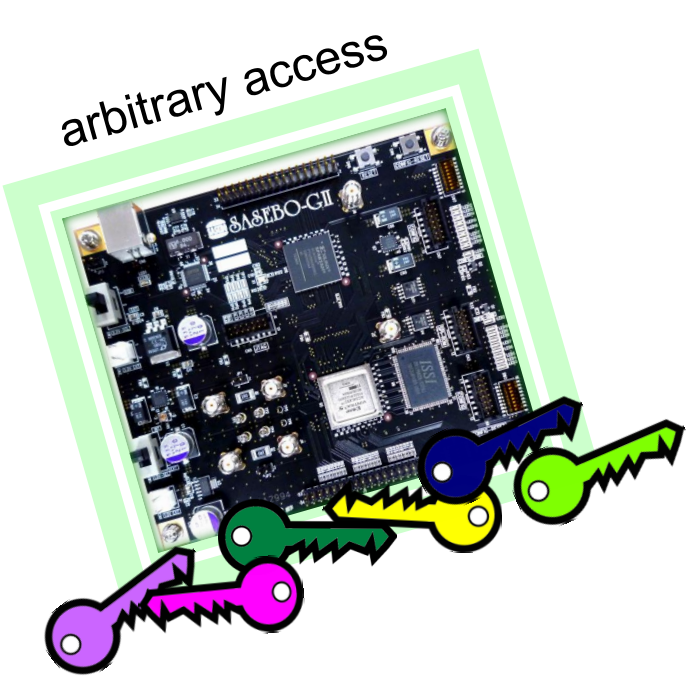
Profiled Side-Channel Attacks



- Classification: Template Attack [Chari03], + Model [AGH07]
- Model + Regression: Stochastic Approach [SLP05]

Stochastic Approach in a Nutshell

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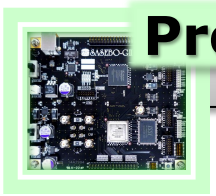

Profiling Phase

Stochastic Model

$$I_t(x,k) = \boxed{\begin{array}{c}\text{Leakage Model}\\ + \\ \text{Regression}\end{array}} + R_t$$

Power consumption at time t

Deterministic part

Noise

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Stochastic Approach in a Nutshell

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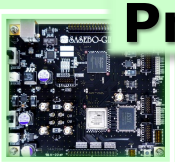
Profiling Phase



$$I_t(x,k) = h_t(x,k) + R_t$$

$$\begin{pmatrix} i_t(x_1,k) \\ i_t(x_2,k) \\ i_t(x_3,k) \\ \vdots \\ i_t(x_{N_1},k) \end{pmatrix} = \begin{pmatrix} 1 & g_{1,t;k} & \cdots & g_{u-1,t;k} \\ 1 & g_{1,t;k} & \cdots & g_{u-1,t;k} \\ \vdots & \vdots & \ddots & \vdots \\ 1 & g_{1,t;k} & \cdots & g_{u-1,t;k} \end{pmatrix} \beta^* + \epsilon$$

Leakage Model

Least Square Estimation $\widetilde{\beta^*} = (A^T A)^{-1} A^T \mathbf{i_t}$

Estimated Approximator $\widetilde{h}^*_{t;k}(\cdot,k) = \sum_{j=0}^{u-1} \widetilde{\beta}^*_{j,t;k} \cdot g_{j,t;k}(\cdot,k)$

Stochastic Approach in a Nutshell

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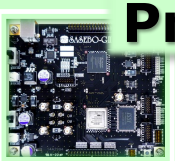

Profiling Phase

$$I_t(x,k) = h_t(x,k) + R_t$$

$$R_{\mathbf{t}} = I_{\mathbf{t};k}(X,k) - h_{\mathbf{t};k}(X,k)$$

$$\mathbf{R_t} \sim \mathcal{N}(0,C)$$

$$f_C\colon \mathbb{R}^m \to \mathbb{R} \qquad f_C(\mathbf{z}) = \frac{1}{\sqrt{(2\pi)^m \det C}} e^{-\frac{1}{2}\mathbf{z}^T C^{-1}\mathbf{z}}$$

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Stochastic Approach in a Nutshell

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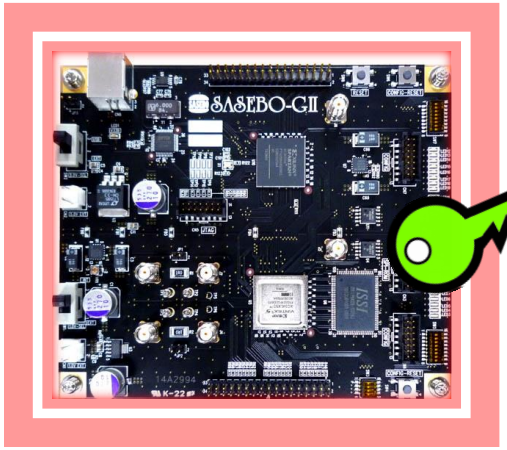
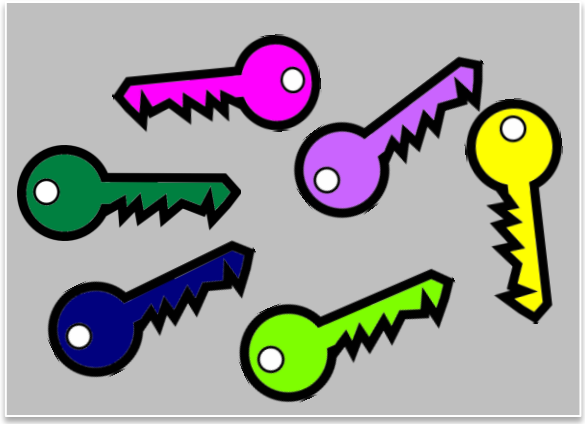
Attack Phase



Attacker gains N_3 measurements

with a secret key $k^\dagger$



Maximum Likelihood

$$\prod_{l=1}^{N_3} f_C\left(\mathbf{i_t}(x_l, k^\dagger) - \widetilde{\mathbf{h}}^*_{\mathbf{t};k}(x_l, k)\right)$$

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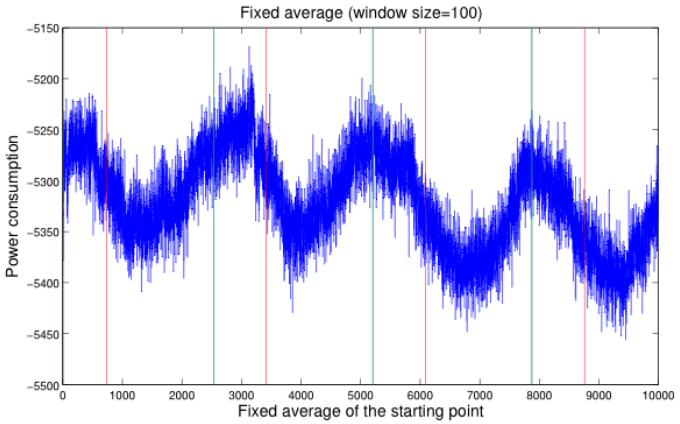
Drifting Offset



$$I_t(x,k) = h_t(x,k) + R_t$$

'normal' SA

OTM

$$I_t(x_l,k) = h_t(x_l,k) + \tau_{t;l} + R_t$$

$$\tau_{t;l} - \tau_{t;l+1} \approx 0$$

Consider differences of consecutive power consumptions!

Stochastic Approach + OTM

Consider differences of consecutive power consumptions!

OTM

Profiling Phase I

$$\widetilde{h}^*_{t;k}(\cdot,k) = \widetilde{\beta}^*_{0,t,k} + \sum_{j=1}^{u-1} \widetilde{\beta}^*_{j,t,k} g_{j,t;k}(\cdot,k)$$

Stochastic Approach + OTM

CASED

Consider differences of consecutive power consumptions!

OTM

Profiling Phase II

‘normal’ SA

$$R_{\mathbf{t}} \sim \mathcal{N}(0, C) \qquad R_{\mathbf{t}} = I_{\mathbf{t};k}(X, k) - h_{\mathbf{t};k}(X, k)$$

SA - OTM

$$\mathbf{I_t}(x_l, k) - \mathbf{h_t}(x_l, k) - \tau_{\mathbf{t};l}$$
$$-(\mathbf{I_t}(x_{l+1}, k) - \mathbf{h_t}(x_{l+1}, k) - \tau_{\mathbf{t};l+1}) \sim N(0, 2C)$$

Stochastic Approach + OTM

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Consider differences of consecutive power consumptions!

OTM

Attack Phase

Maximum Likelihood

$$\prod_{l=1}^{N_3} f_C\left(\mathbf{i_t}(x_l, k^\dagger) - \widetilde{\mathbf{h}}^*_{\mathbf{t};k}(x_l, k)\right)$$

Independence → additional mathematical difficulties (details: paper)

Results: SA vs. SA-OTM

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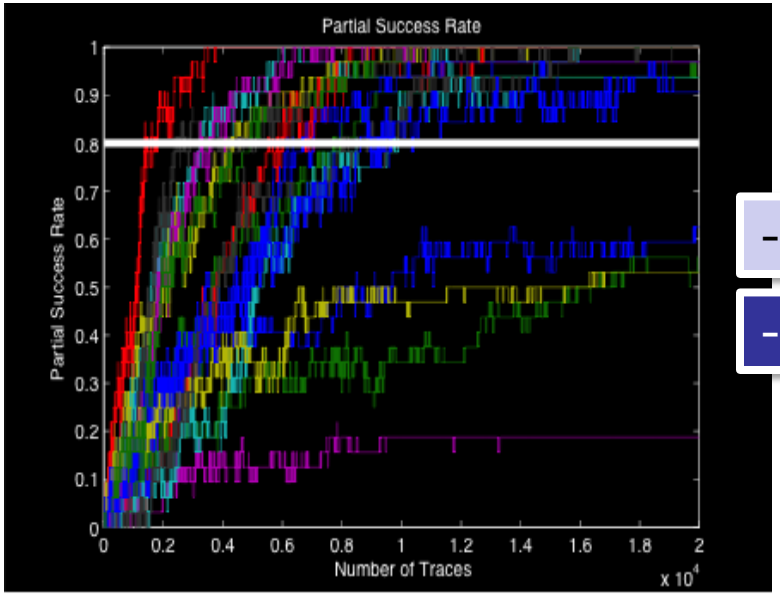
Stochastic Approach



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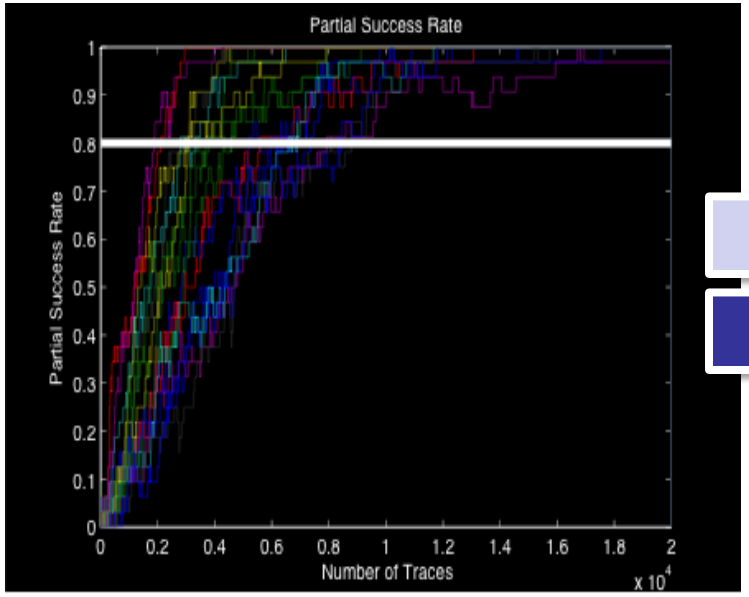
Stochastic Approach + OTM



8781

4638

PSR = average % of obtaining the correct key byte

PGE = average ranking of the correct key byte

min stable PSR > 80%

max PGE stable < 10

Overview

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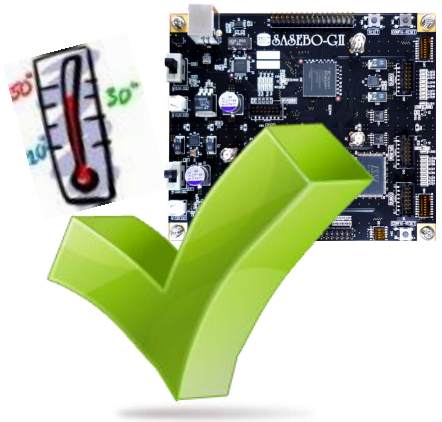
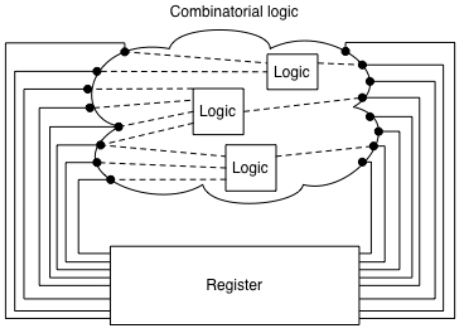
New Difference Method



Leakage Models



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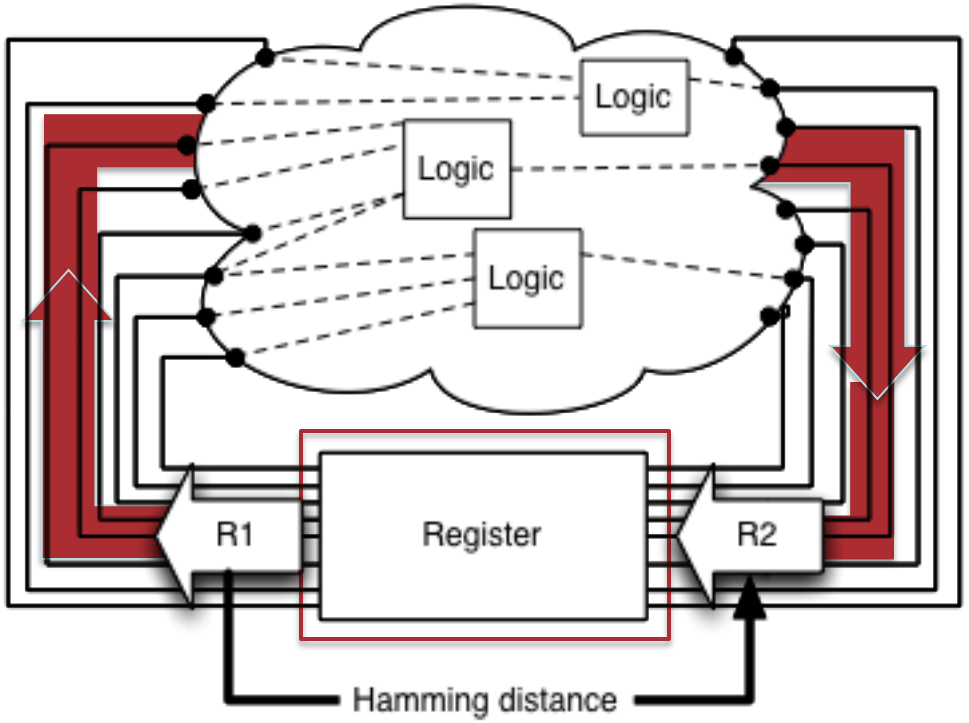
Leakage Models

Common Models:

- HD Register transitions
- bitwise HD transitions [KSS09]

High-dimensional Models:

- bitwise HD transitions + interactions between bit lines



Results: Stochastic Approach + OTM

Public Base

Dim	Interactions	PSR > 80%	PGE < 10
8	1	6781	4637
36	1,2	5876	2308
92	1,2,3	5195	2139
162	1,2,3,4	4353	1690
218	1,2,3,4,5	3552	1504
246	1,2,3,4,5,6	3769	1477
254	1,2,3,4,5,6,7	3720	1476
255	1,2,3,4,5,6,7,8	3718	1479

-13 % / -50 %

-23 % / -53 %

-35 % / -63 %

-47 % / -67 %

-44 % / -68 %

-45 % / -68 %

-45 % / -68 %

Results: Private Base

Dim	Interactions	PSR > 80%	PGE < 10
92	1,2,3	4358	1894
255+alignment	1,2,3,4,5,6,7,8	2748	1356

‘official winner’	5890	2767

unknown type attack

[LNOS11]	2155	3181

clockwise collision attack
additionally considers information from Round 9

Conclusion

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A New Difference Method for Side-Channel Analysis with High-Dimensional Leakage Models

New Difference Method

- ❑ Environmental influences
- ❑ Tolerates drifting offsets

Leakage Models

- ❑ More precise models
- ❑ Captures also interactions between circuit elements

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Clockwise Collision Analysis -- Overlooked Side-Channel Leakage Inside Your Measurements
Cryptology ePrint Archive, Report 2011/579

Getting more from PCA: First results of using Principal Component Analysis for extensive power analysis

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[3] KPMG Advisory

[4] Riscure

Session ID: CRYP-402

Session Classification: Side Channel Attacks III

RSA CONFERENCE 2012

Outline

- Introduction
- Workings of PCA
- Previous works
- PCA for side-channel analysis
  - Motivating examples
- Experiments
  - Noise reduction
  - PCA transformation
  - PCA on misaligned traces
- Conclusions and Future work

Introduction and Motivation

- We know a lot about side-channel analysis, but...
- Many open problems and research directions
- Similar research questions as in other communities i.e. privacy, machine learning, image processing, etc.
- Various countermeasures makes the key-recovery ever challenging
- PCA considered very powerful tool for data reduction/approximation

Principal Component Analysis (PCA)

- Multivariate technique, known since ~1900
- Finds major patterns in data variability
- Used to reduce the noise or the dimensionality in a data set, while retaining the most variance
- Given data points in n-dimens. space, project into a subspace while preserving max info
- Transforms data to a new set of Principal Components (PCs) by means of eigenvectors
- Used e.g. in gene analysis and face recognition

PCA in side-channel terminology

- Useful for template attacks i.e. interesting points selection
- Used for new distinguishers (variance dependency)
- Reducing the dimensionality of data
- Learning about leakage model

PCA: finding projections

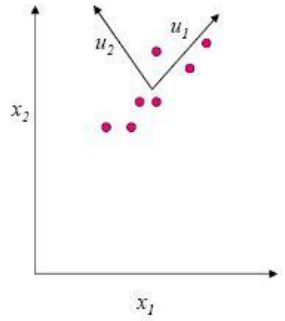
- Assume data is set of n-dimensional vectors, where m-th vector is: $x^m = (x_1^m, \cdots, x_n^m)$.
- We can represent these in any n-dim orthogonal basis vectors

$$x^m = \sum_{i=1}^{n} \alpha_i^m u_i, \quad u_i^T u_j = \delta_{ij}.$$

- PCA: for given $d < n$, find $(u_1, \ldots, u_d)$ that minimizes

$$E_d = \sum_{m=1}^{N} \left\| x^m - \hat{x}^m \right\|^2$$

$$\hat{x}^m = \frac{\sum_{i=1}^{N} x^m}{N} + \sum_{i=1}^{d} \alpha_i^m u_i.$$



PCA: finding projections to minimize the error

- Then:

$$E_d = \sum_{i=d+1}^{n} \sum_{m=1}^{N} \left[u_i^T \left(x^m - \bar{x} \right) \right]^2 = \sum_{i=d+1}^{n} u_i^T \sum u_i = \sum_{i=d+1}^{n} \lambda_i$$

$$\left(\hat{x}^m = \bar{x} + \sum_{i=1}^{d} \alpha_i^m u_i \right)$$

- E_d -> min for u_i eigen vectors of covariance matrix Σ, where:

$$\Sigma = (x_m - \bar{x})(x_m - \bar{x})^T$$

$$\Sigma u_i = \lambda_i u_i$$

PCA algorithm

1. Create a matrix of data Nxn (each row is one vector)
2. Subtract mean from all data points: $x_m - \bar{x}$
3. Compute covariance matrix Σ
4. Find eigenvectors and eigenvalues of Σ
5. Principal components are n eigenvectors with largest eigenvalues

$$\Sigma = U \Lambda U^{-1}$$

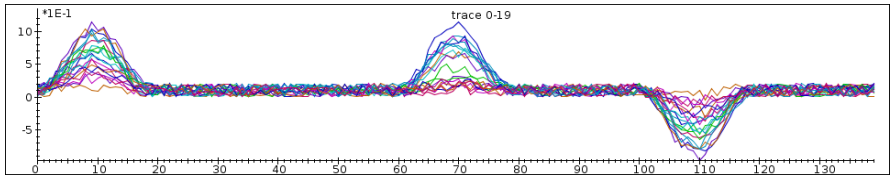
Previous works

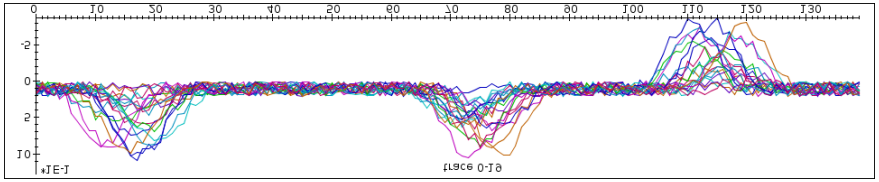
- [BN+03] first investigation
- [AP+06], [HG+11] PCA for templates
- [SN+10] PCA for key recovery
  - First Principal component as the side-channel distinguisher

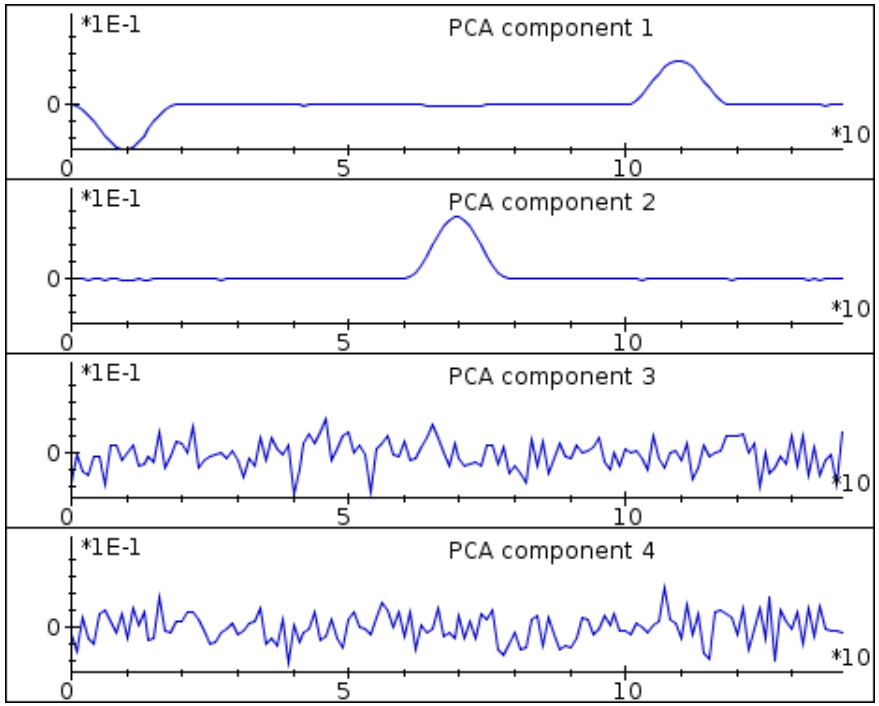
Multiple leakage points and PCA

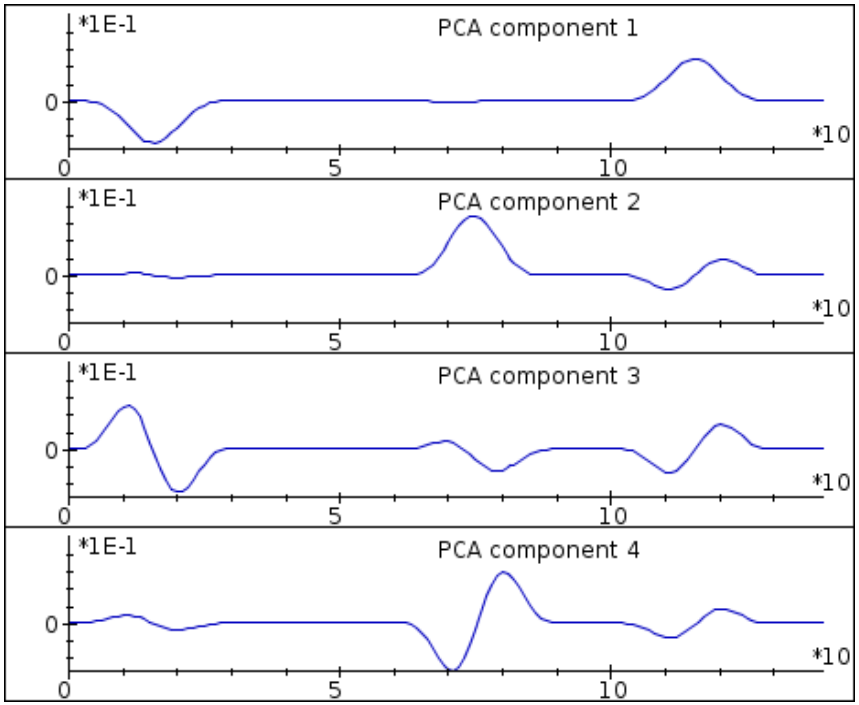
aligned

misaligned









PCA and noise reduction

- U is the feature vector

$$Y = U^T * X^T = (X * U)^T$$

- The PCA approximation with only p components

$$\hat{x} = \sum_{j=1}^{p} (u_j^T * x) * u_j$$

- The squared error

$$\sum_{i=p+1}^{n} \lambda_i$$

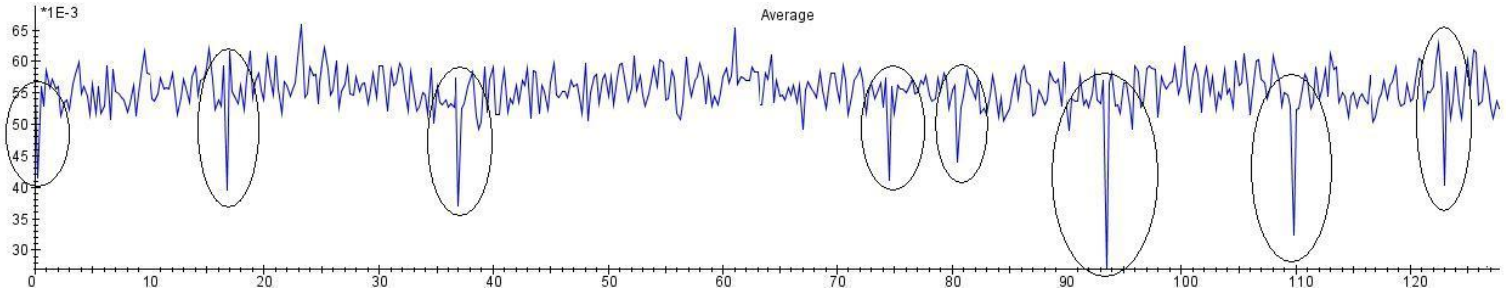
Experiments

Experiment 1: Noise reduction

- Key-related information shifts for various implementations and platforms
- Best strategy: PCA-> remove some PCs-> transform the data set back
- For a software implementation of DES
  - Different component keep different information related to specific S-boxes
  - In general, largest components contained a lot of (useless) noise
  - Templates could be made for a specific implementation/platform – which PCs should be kept

Experiment 2: PCA transformation

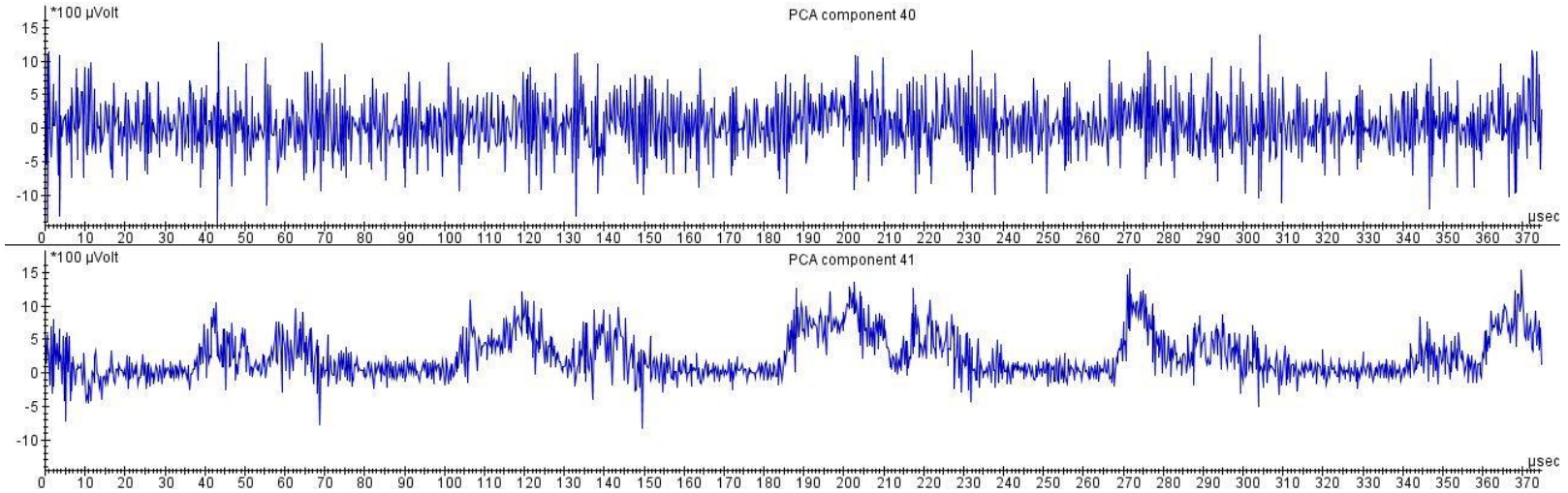
- CPA absolute average distinguisher – y-axis



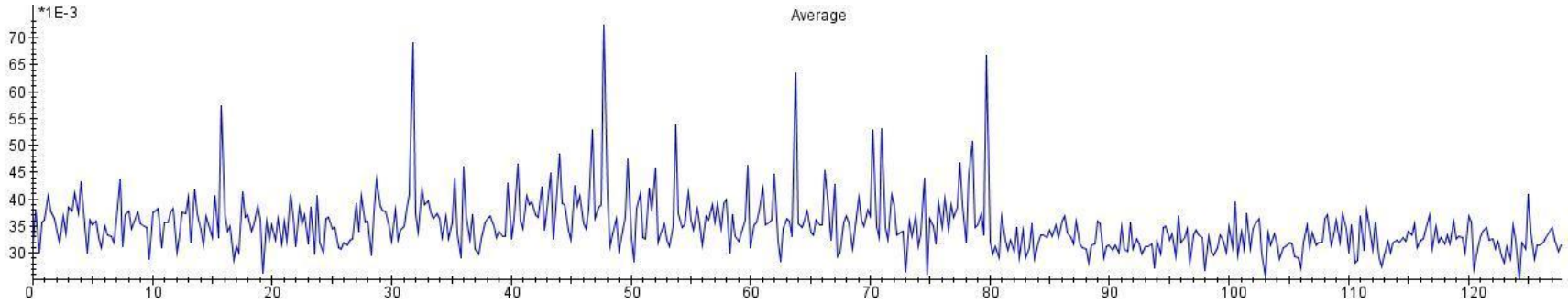
Key guesses for all S-boxes

Experiment 3: PCA and misalignment

- Specific PCs are more sensitive to exploitable leakage (e.g. 41-57)
- Absolute average distinguisher



Experiment 3: PCA and misalignment



Correct key guesses for 5 S-boxes

Comparison to other distinguishers and alignment techniques

- Computational issues:
  - Covariance matrix is typically very large (nxn)
  - Singular Value Decomposition (SVD)
- Comparison to static alignment
  - Due to the specifics of the PCA-based distinguisher, hard to compare with common methods

Conclusions

- PCA can be used for pre-processing
  - De-noising the data
  - Handling the countermeasures causing misalignment
- PCA for noise reduction: after removing noise-containing components, the key recovery improved
- PCA for key recovery: DPA on PCA-transformed data
- Our findings are confirmed on various platforms and algorithms

Some more reasoning + Future directions

- The linearity of PCA results in preserving leakage although spread over many time instances
- Kernel PCA: extracting also non-linear features
- Connection to clustering

Thanks

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