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# Differential Cluster Analysis

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#### Presentation Outline

- Introduction
- Differential Cluster Analysis
- Applications
- Experimental Results

## Conclusion



#### Adversary Success

The adversary is successful if she recovers the secret subkey  $k^{\circ}$ .

# Introduction: Differential Power Analysis in a Nutshell

## The DPA (Differential Power Analysis) Problem

Given measurements  $i_n$  ( $n \in \{1, ..., N\}$ ) while the crypto device computes function  $f_{k^0}$  with random inputs  $x_n$ :

 Does a statistics prove significant differences of the measurements according to a partitioning function g(f<sub>k</sub>(x<sub>n</sub>))?



## DPA Partitioning Functions g:

- Single-bit partitioning function (Kocher et al., 1999)
- Multi-bit partitioning/comparison function:
  - "All-or-Nothing" with a leakage model (e.g., Hamming weight) (Messerges *et al.*, 2000)
  - CPA (Correlation Power Analysis) with a leakage model (e.g., Hamming distance) (Brier *et al.*, 2002)

## The CA (Collision Analysis) Problem

Given measurements  $i_n$  ( $n \in \{1, ..., N\}$ ) while the crypto device computes the many-to-one function  $f_{k^0}$  with random inputs  $x_n$ :

 Does a statistics prove high similarity of measurements with two inputs x<sub>i</sub> ≠ x<sub>j</sub>?

#### Collision Detection:

• Euclidean distance of measurement vectors over some *t*. (Schramm *et al.*, 2003)

#### Objectives

- Combination of leakage detection functions for DPA (Separation) and CA (Cohesion).
- Sensitivity to general leakage features
- Multi-bit approach
  - using all measurements and
  - without the need for a good power model.
- Multivariate approach

#### Idea

- Our basic approach: Cluster Analysis
- Our basic question: Do clusters of measurements exist?

# Differential Cluster Analysis

#### Requirement

*f<sub>k</sub>* : {0,1}<sup>u</sup> → {0,1}<sup>w</sup> is a many-to-one collision function, i.e., at least two inputs *x<sub>i</sub>*, *x<sub>i'</sub>* ∈ {0,1}<sup>u</sup> with *x<sub>i</sub>* ≠ *x<sub>i'</sub>* collide in one state Δ ∈ {0,1}<sup>w</sup>.

## The DCA (Differential Cluster Analysis) Problem

Given measurements  $i_n$  ( $n \in \{1, ..., N\}$ ) while the crypto device computes the many-to-one function  $f_{k^0}$  with random inputs  $x_n$ :

 Does a cluster criterion function prove the existence of clusters of measurements according to partitioning function f<sub>k</sub>(x<sub>n</sub>)?



# Measuring Clustering Quality



# **Cluster Criterion Functions**

Sum-of-Squared-Error:

$$J_{SSE} = \sum_{i=1}^{c} \sum_{\boldsymbol{x} \in \mathcal{D}_i} \| \boldsymbol{x} - \boldsymbol{m}_i \|^2$$

 $J_{SSE}$  evaluates intra-cluster cohesion. The optimal partition minimizes  $J_{SSE}.$ 

Sum-of-Squares:

$$J_{SOS} = \sum_{i=1}^{c} n_i \parallel \boldsymbol{m}_i - \boldsymbol{m} \parallel^2$$

 $J_{SOS}$  evaluates inter-cluster separation. The optimal partition maximizes  $J_{SOS}.$ 

The sum of  $J_{SSE}$  and  $J_{SOS}$  is a constant.

# Special Cluster Criterion Functions

Variance criterion (Standaert et al.: ICISC 2008):

$$J_{VAR} = \frac{\parallel \mathbf{v} \parallel^2}{\frac{1}{N} \sum_{i=1}^c n_i \parallel \mathbf{v}_i \parallel^2}$$

 $J_{VAR}$  evaluates overall variance vs. intra cluster variances. The optimal partition maximizes  $J_{VAR}$ .

T-test criterion (Gierlichs et al.: CHES 2006):

$$J_{STT} = \sum_{i,j=1;i\neq j}^{c} \frac{\|\boldsymbol{m}_{i} - \boldsymbol{m}_{j}\|^{2}}{\sqrt{\frac{\|\boldsymbol{v}_{i}\|^{2}}{n_{i}} + \frac{\|\boldsymbol{v}_{j}\|^{2}}{n_{j}}}}$$

 $J_{STT}$  evaluates inter cluster separation, normalized by intra cluster variances and cluster sizes. The optimal partition maximizes  $J_{STT}$ .

#### Differential Cluster Analysis (General Approach)

- For each subkey hypothesis k:
  - Sort measurements into 2<sup>w</sup> clusters D<sub>0</sub>,..., D<sub>2<sup>w</sup>−1</sub> according to Δ<sub>i</sub> = f<sub>k</sub>(x<sub>n</sub>) (1 ≤ n ≤ N).
  - Compute a cluster criterion function:  $J_k$ .
- **2** Rank the pairs  $(k, J_k)$  according to  $J_k$ .
- Output subkey candidate that leads to the best clustering quality.

# Detailed Comparison with CA and DPA

	DPA	СА	DCA	
Many-to-one function	not required	required	required	
Leakage model	<ul> <li>none for single- bit DPA</li> <li>required for</li> </ul>	none	not required, can be inte-	
	• required for multi-bit DPA		grated	
Statistics	based on differ- ences	based on simi- larity	based on both separation and cohesion	
Detected Leakage Features	<ul> <li>differences of two states for single-bit and "all-or-nothing" multi-bit DPA</li> <li>linearity of differences for CPA</li> </ul>	general features	general features	
Multivariate Leakage	original approach can be extended	yes	yes	

# Comparison with DPA: An Example

#### Example

Assume  $f_k : \{0,1\}^u \mapsto \{0,1\}^2$  is a many-to-one function.

- Single-bit DPA fails and
- Multi-bit DPA (with Hamming weight model) fails.

Does this assure that there is no leakage at all?

# Comparison with DPA: An Example

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Does this assure that there is no leakage at all?

## No. Counter-Example:



Algorithmic Collisions:

- $f_k$  emerges from an abstract concept (e.g., cryptographic standard).
- $f_k$  is implementation independent (despite of masking ...).

#### Example: DES

• DES S-box function is 4-to-1:  $f_k : \{0,1\}^6 \mapsto \{0,1\}^4$  yields  $2^4$  clusters.

## Example: AES

- AES S-box is not a collision function.
- Targeting only r-bit  $(1 \le r < 8)$  of AES S-box outcome:  $f_k : \{0, 1\}^8 \mapsto \{0, 1\}^r$  yields  $2^r$  clusters.
- AES MixColumns transformation is  $2^{24} to 1$ :  $f_k : \{0, 1\}^{32} \mapsto \{0, 1\}^8$  yields  $2^8$  clusters.

Implementation specific collisions:

- $f_k$  emerges from implementation properties.
- $f_k$  is not obvious in the algorithmic description.

#### Example: AES Hardware Module

Differential of two adjacent data cells in the studied AES hardware architecture:  $f_k : \{0, 1\}^{16} \mapsto \{0, 1\}^8$  yields  $2^8$  clusters.

$$f_k(x) = S(x_i \oplus k_i) \oplus S(x_{i'} \oplus k_{i'})$$
(1)

General DCA Approach requires 2<sup>16</sup> subkey hypotheses.

# Application: AES Hardware Module



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# AES Hardware Module: A New Attack Strategy

If  $f_k(x) = 0$  then  $f_k(x) = S(x_i \oplus k_i) \oplus S(x_{i'} \oplus k_{i'})$  simplifies to

 $S(x_i \oplus k_i) = S(x_{i'} \oplus k_{i'}) \Rightarrow x_i \oplus k_i = x_{i'} \oplus k_{i'} \Rightarrow k_i \oplus k_{i'} = x_i \oplus x_{i'}.$ 

The elements of one cluster are identical if  $k_i \oplus k_{i'} = k_i^{\circ} \oplus k_{i'}^{\circ}$ .

#### A new two-step key recovery attack:

- Determine the correct xor-difference  $k_i^{\circ} \oplus k_{i'}^{\circ}$  based on  $2^8$  hypotheses.
  - This is the difficult step that checks whether a special (small) cluster for  $f_k(x) = 0$  exists.
- 2 Determine the correct pair  $(k_i^{\circ}, k_{i'}^{\circ})$  based on 2<sup>8</sup> hypotheses.
  - This is the easy step that checks whether up to 2<sup>8</sup> clusters exist.

Attack strategy can also be applied with DPA.

# DES Implementation in Software: Univariate DCA Results

## Target Device: AVR Microcontroller



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Table: Success rates in % for various univariate and multivariate attack scenarios.

Test	Model	Time	N=15	N=20	N=25	N=30	N=40	N=50
CPA	LSB	overall	3	15	37	62	95	98
CPA	LSB	A	42	64	69	77	93	96
CPA	LSB	В	64	77	83	93	98	99
CPA	LSB	С	17	28	29	38	55	65
J <sub>SSE</sub>	LSB	overall	3	15	37	62	95	98
J <sub>SSE</sub>	LSB	A	42	64	70	77	93	96
J <sub>SSE</sub>	LSB	В	64	78	82	93	98	99
<b>J</b> <sub>SSE</sub>	LSB	С	18	28	31	38	56	65
CPA	LSB	AB	70	85	90	96	100	100
$J_{SSE}$	LSB	AB	70	83	91	97	100	100
CPA	LSB	ABC	76	90	96	99	100	100
$J_{SSE}$	LSB	ABC	78	94	96	99	100	100

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**Target Device:** Prototype chip which implements an AES-128 co-processor in 0.13  $\mu m$  sCMOS technology without countermeasures.

## General Approach with DCA:

- 2<sup>16</sup> key hypotheses
- key recovery with approx. 5000 measurements

# Two-Step Attack Strategy with DCA:

- 2<sup>9</sup> key hypotheses
- key recovery with approx. 50 000 measurements
  - Step 1: 50000 measurements
  - Step 2: 5000 measurements

- Introduction of Differential Cluster Analysis (DCA) a new technique bridging the gap between Collision Analysis (CA) and Differential Power Analysis (DPA).
- Introduction of implementation specific collisions.
- Confirmation of DCA on both software (DES) and hardware (AES) implementation.
- New two-step attack strategy for an AES hardware module.

Collision attacks on AES are not constrained to 8-bit software implementations on simple controllers anymore...