# On the Optimal Pre-processing for Non-profiling Differential Power Analysis

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- Introduction
- Optimal Pre-processing of the Power Traces
- Experimental Evaluation
- Comparison with profiling Stochastic attack
- Conclusion

#### Introduction





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• Univariate distinguisher is applied on a selected sample point

#### Multivariate DPA

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#### • Existing Pre-processing techniques

- Comb filter
- 2 FFT
- Ø Multiband filter
- Wavelet transform etc
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• The output leakage  $l_o$  of a linear FIR of order T applied to the traces  $I = \{l_0, \dots, l_{T-1}\}$ 

$$l_o = \sum_{t=0}^{T-1} h_t l_t$$
 (1)

where  $\boldsymbol{h} = \{h_0, \cdots, h_{\mathcal{T}-1}\}$  is the impulse response of the filter

- Let centered (w.r.t. mean leakage) trace  $I = \{l_0, ..., l_{T-1}\}$ =  $\{d_0 + n_0, \cdots, d_{T-1} + n_{T-1}\} = d + n$
- SNR of *l<sub>o</sub>* is given by

$$SNR^{\prime_o} = \frac{|\mathbf{h}'\mathbf{d}|^2}{E[|\mathbf{h}'\mathbf{n}|^2]} = \frac{|\mathbf{h}'\mathbf{d}|^2}{\mathbf{h}'\Sigma_{\mathbf{N}}\mathbf{h}}$$

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 Both Σ<sub>N</sub> and d need the secret key to estimate, thus are not feasible in non-profiling DPA • The impulse response of the matched filter for the trace I is given by ([3, 4])

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#### • We introduce Signal Ratio (SR) of the output signal Io:

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- The SNR of the output leakage *l<sub>o</sub>* reaches its maximum if and only if SR of that also reaches its maximum
- Impulse response of the optimum linear filter which maximizes the SR of the output signal  $l_o$

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- Extension of the conventional leakage model over multiple time instants [1]:
  - Conventional leakage model

$$L_{t^*} = a_{t^*} \Psi(S_{k^*}) + N_{t^*}$$

Multivariate leakage model

$$a_{t} = a_t \Psi(S_{k^*}) + N_t, \qquad \qquad t_0 \le t < t_0 + \tau$$

Incorporating algorithmic noise

$$L_t = a_t (\Psi(S_{k^*}) + U + c) + N_t$$

$$= a_t (I + c) + N_t,$$

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- $\bullet~$  Estimation of  $\Sigma_L$  requires large number of power traces
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• Approximation of  $\mathbf{h}_{opt}$ :  $\mathbf{h}_{appr} = diag(\Sigma_{\mathsf{L}})^{-1}\mu_{\mathsf{L}}$  i.e.

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- The approximate optimum filter **h**<sub>appr</sub> neglects the correlation between the leakages of two different sample points
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#### • The performed attacks are:

- CPA on the unprocessed traces
- CPA on the output of the Optimum filter (OF)
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- The attacks are performed in the following domains:
  - Time domain.
  - Frequency domain
  - Eigenvector domain
- Experiments are performed in four scenarios:
  - Scenario (a): on the acquire power traces
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## Experimental Result: Scenario (a)



Figure: Results on Acquired Traces of AES Encryption

## Experimental Result: Scenario (b)



Figure: Results on Acquired Traces adding Uncorrelated Noise

## Experimental Result: Scenario (c)



Figure: Results on Acquired Trace adding Correlated Noise

## Experimental Result: Scenario (d)



Figure: Results on Acquired Traces adding both the Correlated Noise and Uncorrelated Noise

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### Comparison with profiling Stochastic attack



Figure: Results of Profiling Stochastic Attack using HD model and CPA using AOF in Frequency Domain

- Two linear filters have been proposed for optimal pre-processing in non-profiling DPA
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