Magnitude Squared Coherence based SCA

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Abstract. Magnitude Squared Coherence is a signal processing tool that indicates how well two time domain signals match one with the other by tracking linear dependencies in their spectral decomposition. This paper introduces different ways of using the Magnitude Squared Coherence for Side Channel Analysis. This distinguisher has several advantages over well-known distinguishers.

Keywords: Secure Circuit, Side Channel Attacks, Distinguisher

1 Introduction

Following [1], many Side-Channel Attacks have been proposed in the literature. Surprisingly, most of them directly work with time domain traces. Easy connection with engineering intuition could explain this trend despite some inherent drawbacks of such an approach. Among them, the impossibility of capturing the complete leakage scattered over many time samples of raw traces appears as a limitation.

By contrast, much less attention has been paid to Side-Channel Analysis performed in the frequency domain that could bring a solution to this problem. To the best of the authors' knowledge, Gebotys, Ho and Tiu first proposed to apply a differential attack after the application of a Fast Fourier Transform (FFT) [2]. This work was then extended towards CPA-like attacks in [3-4]. Various similar approaches were described in [5].

If [3-7] demonstrate the greater efficiency of power analyses carried out in the frequency domain, they do not propose a solution to the aforementioned limitation of time domain analyses. Indeed, all aim at disclosing the secret key by analyzing separately each harmonic of the signal spectrum. Doing so, only a part of the leakage which is scattered over several harmonics is exploited.

Within this context, this paper introduces different Magnitude Squared Coherence Analyses to overcome the aforementioned limitation. All the proposed techniques are more efficient (less traces are necessary to disclose the secret key) than the one introduced in our former works [6-7]. Moreover, some of them appear more generic because they rely on non-parametric statistical analyses of Coherence distributions. This latter point is not tackled in this paper; it is still the subject of on-going works.

The rest of the paper is organized as follows. Section 2 reminds some basics about Magnitude Squared Coherence and its first application [6-7] in the context of SCA. Sections 3, 4 and 5 introduce different parametric and non parametric analyses of Coherence distributions. These additional techniques complete our first proposal, the SCAN [6-7]. Experimental results are given in section 6. They demonstrate that the proposed attacks are more efficient (only a reduced set of traces is necessary to disclose the secret key manipulated by unprotected cryptographic circuits) but require more cpu-time to be completed. In Section 7, the impact of the different parameters involved in the setting of the MSC based analyses is discussed. Finally, a conclusion is drawn in section 8.

Preliminary Note

Note that it could have been interesting to evaluate, MSC based analyses, using the set of traces provided by the DPA contest 2. However, these traces correspond to AES power consumption measurements. They carry less information in the frequency domain because of the low cut-off frequencies of both power pad en supply network but also because of the low sampling rate used to collect them. We therefore preferred EM measurements.

2 Magnitude Squared Coherence

2.1 Theory

Magnitude Squared Coherence is a signal processing tool that returns real values between 0 and 1 to indicate how well two time domain signals *x(t) and y(t)* match one with the other. To estimate the similarity level, linear dependencies in the spectral decomposition of *x(t)* and *y(t)* are tracked by computing *MSC(f)* values at different frequencies according to:

$$MSC_{xy}(f) = \frac{|P_{xy}(f)|^2}{P_{xx}(f) * P_{yy}(f)} \tag{1}$$

In which, P_{xy} is the cross-power spectral density of *x(t)* and *y(t)* and, P_{xx} and P_{yy} the related power spectral densities.

To calculate power and cross-power spectral densities between *x(t)* and *y(t),* the Welch's averaged modified periodogram method [8] is typically used. It consists in first dividing the two signals in *w* time windows of the same length (i.e. with the same number of samples) and then calculating the power spectral densities of each window before averaging them to obtain final *MSC(f)* values at different frequencies.

2.2 MSC application to SCA

To retrieve the secret key by SCA, an adversary typically collects a set of n raw traces $\{T_1 \ldots T_n\}$ corresponding to a set of messages $\{m_1 \ldots m_n\}$ acquired during different cryptographic operations. Then, he applies a selection function that sorts traces in several subsets according to a hypothesis on the secret key. Finally, the adversary applies a distinguisher to identify among all possible keys the correct one. Among the known efficient distinguishers, he may adopt the Difference of Means [1], the Pearson [9], the Spearman or the Kendall correlation coefficients or even the mutual information [10].

In a first attempt to exploit *MSC* within the context of SCA, we formerly proposed the SCAN [7] for Squared Coherence ANalysis. The basic idea of the SCAN is to simply replace, in the original DPA, the Difference operation of two mean values by the computation of a *coher* value (2), between two mean EM traces.

However, MSC could also be used in a less straightforward manner requiring an additional preprocessing of traces. Indeed, the adversary can first compute the *MSC(f)* coefficients between each pair of traces for frequency values falling into the bandwidth of its SCA platform. He may finally apply the aforementioned distinguishers to one or several *MSC(f)* samples to retrieve the secret key. However, this procedure suffers from the same limitation as the procedures of [2, 3, 4]; it does not allow capturing the whole leakage which is scattered over several harmonics. An alternative, to overcome this limitation, is to compute, as SCAN does, the mean Coherence coefficient of *MSC(f)* values on a given frequency bandwidth:

$$coher(T_i, T_j) = \frac{1}{m} \sum_{f=f_{\min}}^{f_{\max}} MSC_{T_i,T_j}(f) \tag{2}$$

where T_i and T_j denote time domain traces.

At the end of this preprocessing, the adversary obtains a set *Coher* of $1/2 \cdot n \cdot (n-1)$ *coher* values ranging between 0 and 1. Compared to the procedures associated to DPA, CPA, MIA, or SCAN the adversary have thus at disposal $1/2 \cdot (n-1)$ times more informers to retrieve the secret. This is an interesting advantage of working with pairs of traces rather than analyzing traces one by one. Such an advantage could be of prime importance while attacking systems in which key is regularly refreshed. The remaining question is then how to efficiently extract, from the resulting *Coher* distribution, the secret key.

3 Mean and Variance Analyses

Many statistical SCA procedures aim at analyzing the first or second moment of specific distributions sorted according to the values provided by a selection function f_k^w:

$$
\begin{aligned}
f_k : \{0,1\}^n \times \{0,1\}^p &\rightarrow \{0,1\}^w \\
(m_i, k) &\mapsto f_k(m_i, k) = c_i
\end{aligned}
\tag{3}
$$

If the Hamming Weight (HW) model is chosen, f_k^w predicts the value c_i of w bits processed by the cryptographic algorithm according to the value of a clear/ciphered message m_i and to a guess $k \in K$ of the key. If the Hamming Distance (HD) model is preferred, $f_{k^*}^w$ rather outputs a word c_i of w bits indicating which of the w bits have switched during a given clock cycle.

An adversary adopting *MSC* for SCA may analyze the Means and the Variances of some subsets of *Coher*. Indeed, he may sort the coher values by selecting pairs of traces according to one of the two following functions:

$$
\begin{aligned}
\Delta f_k^w : \{0,1\}^w \times \{0,1\}^w &\rightarrow \{0,1\}^w \ or \ N \\
(c_i, c_j) &\mapsto \left| \begin{array}{l} \Delta f_k(c_i, c_j) = f_k(m_i, k) \oplus f_k(m_j, k) \\ or \\ \Delta f_k(c_i, c_j) = HW(f_k(m_i, k) \oplus f_k(m_j, k)) \end{array} \right.
\end{aligned}
\tag{4}
$$

As shown, Δf_k^w is the xor or the hamming weight of the xor of two words c_i and c_j computed by the function f_k^w according to the HW or to the HD model and to a guess k on the key.

3.1 Mean analysis

Following (3), let us define $C_{k^*} / \Delta f_{k^*}^1 = 0$ and $C_{k^*} / \Delta f_{k^*}^1 = 1$ as two subsets of *Coher* with $w=1$. Because $C_{k^*} / \Delta f_{k^*}^1 = 0$ gathers *coher* values associated to pairs of traces with a given bit having the same HW or HD, the expectation $E(C_{k^*} / \Delta f_{k^*}^1 = 0)$ should be greater than $E(C_{k^*} / \Delta f_{k^*}^1 = 1)$ for the right guess of the key while, for wrong hypotheses the expectations must have nearly the same value. Extending this reasoning to several bits as in [13], an adversary may therefore expect disclosing the secret key $k_g \in K$ using the following DoM distinguisher:

$$
\underset{k^* \in K}{ArgMax} \left\{ \sum_{bit=1}^{w} \left| E(C_{k^* | \Delta f_{k^*}^1 = 0}) - E(C_{k^* | \Delta f_{k^*}^1 = 1}) \right|_{bit} \right\}
\tag{5}
$$

3.2 Variance analysis

Similarly, because $C_{k^*} / \Delta f_{k^*}^1 = 0$ gathers *coher* values associated to pairs of traces with the same HW or HD, one may expect that the variances $V(C_{k^*} / \Delta f_{k^*}^1 = 0)$ or $V(C_{k^*} / \Delta f_{k^*}^1 = 1)$ have greater values for wrong guesses than for the secret key. An adversary may thus apply the following Difference of Variances (DoV) distinguisher:

$$\underset{k^*\in K}{ArgMin}\left\{\sum_{bit=1}^{w}\left|V(C_{k^*|\Delta f_{k^*}^1=0})\right|_{bit}\right\} \tag{6}$$

4 Correlation Analysis

From engineering intuition and empirical observations, let us assume that the expectations $E(C_{k^*}/\Delta f_{k^*}{}^w=q)$ ($\Delta f_{k^*}{}^w$ corresponding to the second equation of (4)) are decreasing with increasing values of q, i.e with the HW or HD difference associated to a pair of traces. Considering this statement, an adversary may analyze the correlation between the *coher* and the $\Delta f_{k^*}{}^w$ values. One effective manner is to adopt the Pearson's coefficient to quantify the linear relationship between them. The associated distinguisher is in that case:

$$\underset{k^*\in K}{ArgMax}\left\{\frac{P\cdot\sum_{p=1}^{P} coher|_p\cdot\Delta f_{k^*}^{w>1}\big|_p-\sum_{p=1}^{P} coher|_p\cdot\sum_{p=1}^{P}\Delta f_{k^*}^{w>1}\big|_p}{\sqrt{P\cdot\sum_{p=1}^{P} coher|_p^2-\left(\sum_{p=1}^{P} coher|_p\right)^2}-\sqrt{P\cdot\sum_{p=1}^{P}\Delta f_{k^*}^{w>1}\big|_p-\left(\sum_{p=1}^{P}\Delta f_{k^*}^{w>1}\big|_p\right)^2}}\right\} \tag{7}$$

where $coher/_p$ denotes the p^{th} coherence value and $\Delta f_{k^*}{}^w>1/p$ the p^{th} Hamming Distance value (3).

Note that one may also consider the Spearman coefficient to capture a monotonic but non linear variation of *coher* values with Δf_k or even use the Kendall's coefficient for more generic analyses.

5 Non-Parametric Tests

If the Kendall rank correlation is a non parametric distinguisher, its use remains cpu-time consuming when applied to large sets of data. For generic and more efficient MSC based analyses, an adversary may exploit well known statistical tests such as the Kolmogorov-Smirnov (KS), the Cramer-Von-Mises (CVM) tests or even more sophisticated and adaptive tests, e.g. [11]. Indeed, such tools allow comparing the cumulative density functions (CDF) of two empirical samples in a non-parametric manner, i.e. without any assumption on the underlying distribution law.

For sake of simplicity let us consider only the KS-test even if slightly better experimental results were obtained with [11]. In that case, the comparison of two empirical CDF, F_1 and F_2, is based on the calculus of $\Delta(F_1,F_2)$, the maximum distance between the two CDF defined by

$$\Delta(F_1,F_2)=\sqrt{\frac{g_1\cdot g_2}{g_1+g_2}}\cdot\underset{x}{Sup}\left|F_1(x)-F_2(x)\right| \tag{8}$$

where g1 and g2 are the number of samples of F_1 and F_2.

Assuming (a) that the CDF associated to the secret key is unique and different from that of wrong key guesses and (b) that the distributions of wrong guesses are similar in shape, the KS test can be used according to the following distinguisher:

$$\underset{k^* \in K}{ArgMax}\left\{\sum_{q}\sum_{k \neq k^*}\Delta\left(C_{k^*|\Delta f_{k^*}^{w}=q}, C_{k|\Delta f_{k}^{w}=q}\right)\right\} \tag{9}$$

It aims at identifying the key guess associated to the CDF differing the most from all the others.

6 Experimental Results & Discussion

To confirm the relevance of MSC based SCA, including SCAN, this section reports experimental results obtained by application of different analyses against an unprotected DES implementation, mapped into an FPGA, and operating at 50 MHz. For this purpose, we selected a list of distinguishers that are representative of the state-of-the-art and adopted both the Hamming Weight and Distance models. In addition to multi-bit SCAN we first proposed in [7], we considered:

- Correlation analysis in the time domain as the reference. This test is usually the first one considered in the literature for evaluating a leaking device. In the present context, it allowed us to confirm experimentally that a Hamming Distance leakage model was a reasonable abstraction to predict the DES electromagnetic emissions.
- Second, we applied the multi-bit DPA of Bevan and Knudsen [13] in the time domain (MB-DPA).
- Third, we applied the Correlation Power Frequency Analysis (CPFA) described in [4] and further analyzed in [3], to provide a comparison with previous attempts to exploit frequency-based attacks.
- Finally, we implemented two types of MIA attacks [10], one estimating the probability density functions with histograms, and one based on a Gaussian assumption that turned out to be a quite accurate approximation in our experiments.

Our evaluations followed the framework in [12] and, in particular, we computed a global Success Rate (SR) taken over the 8 DES last round sub-keys. These metrics have been estimated for a reduced set of traces (5000) per attack, and sampled over 50 independent attacks. EM traces were acquired using a Lecroy scope featuring a 20 GS/s sampling rate and using a low noise 63db amplifier with a 1 GHz bandwidth.

Additionally, we measured the cpu-times spent to run the different analyses, coded in C, to process EM traces. Note that all our experiments were conducted on PC including an Intel Duo Core operating at 3 GHz and 8 Go of RAM.

Note that MSC coefficients were computed considering a time window of 512 samples (i.e. 25.6 ns to be compared to clock period 20 ns) centered on the last round. According to the Welch's method, this window was divided into 127 sub-windows (*w=127*) of 8 samples (400ps) overlapping with its two neighboring windows by 4 samples (200ps). Note that the width of the sub-windows was chosen in order to be equal to the typical delay value of FPGA's LUT. Power and cross-power spectral densities were obtained by applying an FFT to the 127 sub-windows. The FFT were carried out considering 64 points i.e. using zero padding [8,14]. Only the spectral harmonics falling into the -3db bandwidth (f_{min} = 50MHz, f_{max} = 1GHz) of our acquisition platform were kept to compute the final *coher* values (2).

6.1 Number of traces required

Table 1 gives, for each attack applied considering the HD model, the number of traces required to obtain a Global Success Rate of 10%, 20%, 40%, 60%, 80% and 100%. Shaded cells highlight analyses providing a given success rate with less than 1k EM traces.

As shown, all considered distinguishers disclose the secret key. This confirms that the Hamming Distance model was, as expected, a reasonable abstraction of EM radiations of the iterative and unprotected DES implementation. However, the main conclusion that we may draw from table I is that MSC based analyses including SCAN require clearly less EM traces than standard distinguishers to disclose the key. As an evidence, the distinguishers of eq. 5 (mean analysis), eq. 7 (correlation analysis) and eq. 9 (KS test) give a success rate of 100% with roughly 750 traces while CPA gives for the same number of traces only a score of 10%. MSC based analyses, including SCAN, are thus more efficient than standard distinguishers. Generally speaking one may conclude that MSC based analyses (eq. 5, 7 and 9) require 6 times less EM traces to disclose the key with a Success Rate of 100% than CPA and 2 times less traces than SCAN.

Table 1. Number of processed traces vs Success Rate (HD model)

Success Rate	10%	20%	40%	60%	80%	100%
CPA [9]	775	1075	1525	2150	4475	5000
DPA [13]	850	1175	1750	2800	4250	4975
MIA histo [10]	3350	3775	4375	4850	4975	5000
MIA pdf [10]	1150	1400	1775	2150	2600	4575
CPFA [4]	1110	1205	1410	1630	2025	3150
SCAN [7]	260	320	430	660	910	1725
Eq. 5	230	260	310	440	495	650
Eq. 6	440	450	535	670	780	1135
Eq. 7	320	410	480	532	660	730
Eq.9 (1 bit)	350	370	440	455	540	690
Eq.9 (4 bits)	495	550	630	750	830	1060

Table 2. Number of processed traces vs Success Rate (HW model)

Success Rate	10%	20%	40%	60%	80%	100%
CPA [9]	Fail	Fail	Fail	Fail	Fail	Fail
DPA [13]	Fail	Fail	Fail	Fail	Fail	Fail
MIA histo [10]	Fail	Fail	Fail	Fail	Fail	Fail
MIA pdf [10]	Fail	Fail	Fail	Fail	Fail	Fail

CPFA [4]	Fail	Fail	Fail	Fail	Fail	Fail
SCAN [7]	1510	1800	2270	2690	3220	4600
Eq. 5	2430	2510	2685	3460	3980	4855
Eq. 6	4250	4400	Fail	Fail	Fail	Fail
Eq. 7	2375	2515	2705	3495	3990	4810
Eq.9 (1 bit)	2120	2580	3310	3710	4070	4495
Eq.9 (4 bits)	2750	3025	3635	3895	4085	4300

Table 2 gives the results of the same analyses as Table 1 while the opponent prefers the HW model. 'Fail' in a cell indicates that the key was not found after the processing of 5k traces. As shown, DPA, CPA, MIA, CPFA do not succeed in disclosing the secret with such a reduced set of measurements. This was an expected result because the HW model is a really rough abstraction of the EM radiations of our DES implementation. Indeed, it does not require any RAM access or any transfer of data via a pre-charged bus. Despite the limited relevance of HW model, and in contrast with standard distinguishers, most MSC based analyses allow disclosing the 8 sub-keys with a success rate of 100% with less than 5k traces.

6.2 CPU times

If MSC based analyses disclose the secret-key with few measurements, they involve the computation of many FFT on short length vectors. One may thus wonder if such analyses are cpu-time consuming or not. Tables 3 and 4 report the normalized cpu-times required, using different distinguishers, to obtain a given success rate considering both HW and HD models. The normalization was done with respect to the time necessary to obtain a Success Rate of 10% with a HD based CPA. With the equipment described in the first paragraph of section 6, the time unit is equal to 20 seconds. Note that all these cpu-time analyses were conducted so that to obtain a guess of the key only after the processing of the number of traces leading to the targeted success rate value.

Table 3. Normalized CPU-time vs Success Rate (HD model)

Model ↓		**Success Rate**	**10%**	**40%**	**80%**	**100%**
HD	**Time Domain**	CPA [9]	**1.0**	2.0	5.8	6.4
		DPA [13]	1.2	2.5	6.0	7.0
		MIA histo [10]	16.95	23.9	28	28.4
		MIA pdf [10]	19	29	43	76
	Frequency domain	Eq. 5	43	78	197	341
		Eq. 6	156	231	489	1038
		Eq. 7	84	185	354	430
		Eq.9 (1 bit)	98	155	236	386
		Eq.9 (4 bits)	198	320	556	900
		CPFA [4]	1.43	1.82	2.61	4.07
		SCAN [7]	1.05	1.25	1.9	3.05

Table 4. Normalized CPU-time vs Success Rate (HW model)

Model ↓		Success Rate	10%	40%	80%	100%
HW	Time Domain Analyses	CPA [9]	Fail	Fail	Fail	Fail
		DPA [13]	Fail	Fail	Fail	Fail
		MIA histo [10]	Fail	Fail	Fail	Fail
		MIA pdf [10]	Fail	Fail	Fail	Fail
	Frequency Domain Analyses	Eq. 5	4761	5823	12803	19051
		Eq. 6	14606	fail	fail	Fail
		Eq. 7	4552	5915	12842	18692
		Eq.9 (1 bit)	3626	8845	13382	16309
		Eq.9 (4 bits)	6095	10674	13468	14917
		CPFA [4]	Fail	Fail	Fail	Fail
		SCAN [7]	2.7	3.8	5.1	6.9

From Tables 3 and 4, one may conclude that MSC based analyses, excluding SCAN, are cpu-time consuming. This is especially true when incoherence values are computed for all pairs of traces. The cpu-time of these analyses range from 50 (eq.9) to 160 (eq.5) times the cpu-time spent by a CPA. Note however that (a) the cpu-time required (1 min 01s) to obtain, with a Success Rate of 100%, the secret key with a SCAN is only half the one spent to run a CPA and (b) that only MSC based analyses are able to disclose the secret key, using the HW model, with such a reduced set of curves (5k traces). Note that running MSC based analyses with Matlab is extremely long and that proper C codes are mandatory to obtain such cpu-time costs.

As an additional observation, we compared the cpu-times required to run HW based DPA, CPA and SCAN with one shot EM traces, i.e. without using the averaging capabilities of the scope. 150k one shot traces were processed to disclose the key using HW model based CPA and DPA while, with an HW based SCAN, 65k traces only are sufficient. The CPA and SCAN took 42 min and 22 min, respectively.

6.3 Discussion

Considering Tables 1 to 4 that give evidence of the efficiency and costs of MSC based analyses, several conclusions may be drawn. Firstly, among all considered MSC based analyses, SCAN offers the most interesting trade-offs between efficiency and cpu-time. Secondly, MSC based analyses (excluding SCAN) are interesting candidates for SCA when only reduced set of measurements are available (less than 5k to 10k traces). This is typically the case when secret keys are frequently refreshed and derived from a master key.

Secondly, all considered frequency domain analyses, i.e. MSC based analyses including SCAN and CPFA [4], allow disclosing the key with a smaller number of EM traces than time domain analyses. To our opinion, (a) the associated reduction of noise thanks to the analysis of a reduced set of harmonics and (b) the gathering, on these harmonics of leakages scattered over several time domain samples may explain this observation.

Thirdly, working with pair of traces, here with MSC based analyses excluding SCAN, allows obtaining $1/2\cdot(n-1)\cdot n$ informers with n measurements. This is a really interesting advantage that allows disclosing key with few traces. However, less cpu-time consuming techniques to compare traces should be envisaged to process, in a reasonable time, large sets (>10k traces) of measurements.

7 Setting parameters of a SCAN and MSC based Analyses

All aforementioned MSC based analyses, including SCAN, were conducted with the same setting of parameters. More precisely, a time window of 512 samples (25.6ns) was analyzed. This time window was divided into $w=127$ sub-windows of 8 samples overlapping with the two neighboring ones by 4 samples accordingly to the Welch's method. 64 points FFT were conducted for each sub-window using zero-padding and only harmonics between 50 MHz and 1 GHz were kept to compute $MSC(f)$.

If these settings were applied considering the unit delay of FPGA luts (~500ps), one may wonder if modifying these settings reduces or increases the efficiency of the MSC based analyses. We thus analyzed the impact of these different parameters on the efficiency of the SCAN (which offers the best trade-off between efficiency and cpu-time) considering that all results hold for all MSC based analyses.

The impact of the number of points, *NFFT*, of conducted FFT was analyzed because it allows tuning the number of harmonics falling into the frequency bandwidth of interest i.e. between f_{min} and f_{max}. Table 5 gives the number of traces required to reach a Success Rate value of 80% and the cpu-times necessary to process 5k traces for the SCAN attack based on a HD model. The bandwidth *BW* was set so that f_{min}=50 MHz and f_{max}=1.5 GHz. As shown, increasing *NFFT* improves significantly the efficiency of the SCAN without increasing the cpu-time required to disclose the key (the latter being mainly fixed by the time spent to read traces on the disk). This enhancement is due to the increased number of harmonics falling into the considered frequency bandwidth *BW*. Note that the computation of the *coher* values at the end of the required traces represents a small amount of time compared to the reading and the sorting of the traces which explains the small impact of the *NFFT* parameter on the cpu-time. The impact should be much greater for the others MSC based attacks.

Table 5. Impact of NFFT on SCAN efficiency and cpu-time *(w=63, overlap=8, fmin=50 MHz fmax=1.5 GHz)*

NFFT	# of traces to reach a SR of 80%	CPU-times (s) for processing 5k traces	# of harmonics in BW
16	2450	2min 22s	1
32	1975	2min 23s	2
64	1350	2min 24s	4
128	1175	2min 26s	9

Table 6. Impact of f_{max} on SCAN efficiency and cpu-time *(w=63, overlap=8,* f_{min}*=50MHz, NFFT =128)*

fmax	# of traces to reach a SR of 80%	CPU-times (s) for processing 5k traces	# of harmonics in BW
1.5 GHz	1175	2min 26s	9
3.0 GHz	950	2min 26s	19
4.0 GHz	750	2min 26s	25
6.0 GHz	700	2min 26s	38
8.0 GHz	675	2min 26s	51
10 GHz	670	2min 26s	65

Considering the results of Table 5, we analyzed the impact of the f_{max} value on the SCAN efficiency considering NFFT=128. Results and parameter settings are reported Table 6. Note that 10 GHz is the maximum value that can be imposed due to the sampling rate of the scope (20GS/s). We observed an increase of the SCAN efficiency with the number of harmonics falling between f_{min} and f_{max}. Note however that after 4 GHz the increase is moderated. This was an expected result. Indeed, the cut-off frequency of our scope is 3.5 GHz while our low noise amplifier has a 3db cut-off frequency of 1 GHz. No valuable EM information is captured after 3.5 GHz.

Finally, we analyzed the impact of the number of sub-windows *(w)* on the SCAN efficiency. Note that the overlapping (overlap) between neighboring windows was fixed to be half the width of sub-windows. Results and related parameters are reported table 7. As shown, there is an optimal number of sub-windows w_{opt}=63. This optimum, which is relatively flat, corresponds to a sub-window width of 800 ps. This result confirms our intuition according to which EM traces must be analyzed over time intervals corresponding, at first order, to the unit delay of CMOS cells used to design the IC. In our case, the FPGA Lut delay is about 500 ps.

Table 7. Impact of the number of sub-window on SCAN efficiency and cpu-time *(overlap=50%,* f_{min}*=50MHz,* f_{max}*=10 GHz, NFFT =128)*

# of sub-windows	Sub-windows width (in ps)	# of traces to reach a SR of 80%	CPU-times (s) for processing 5k traces
127	400ps =8×50ps	1175	2 min 32s
63	800ps =16×50ps	1020	2 min 24s
31	1600ps =32×50ps	1175	2 min 21s
15	3200ps =64×50ps	1625	2 min 19s
7	6400ps =128×50ps	3350	2 min 18s

All above results define two guidelines for MSC based analyses. The first one is to fix *w* so that the sub-window width matches the unit delay of CMOS cells used to design the IC. This value changes with the CMOS technology but also with the nature of the IC: ASIC or FPGA. Cell delays are typically smaller in an ASIC than in FPGA for a given technology.

The second guideline is to increase as far as possible the number of harmonics falling into the frequency bandwidth *BW* of interest, typically the one of the used SCA platform or scope. The easiest way, but not the cheaper one, is to use a scope with high cut-off frequency and sampling rate.

However, this number should be maximized under cpu-time constraints i.e. according to the *n* number of traces to be processed. Indeed, the cpu-time of MSC based analyses (5, 6, 7 and 9), excluding SCAN, quadratically increases with *n*.

8 Conclusion

SCA in the frequency domain has been recently proposed as an alternative to usual time domain analyses. Within this context, several Magnitude Squared Coherence based analyses have been introduced and evaluated here considering an unprotected DES implementation. Some guidelines to use Magnitude Squared Coherence within the context of SCA have also been identified.

The experimental results reported in this paper demonstrate that Magnitude Squared Coherence based analyses offer several advantages. Among them, the main one is their ability to disclose the secret key with really reduced set of traces compared to standard distinguishers. This may represent an advantage if the secret key is regularly refreshed. A second advantage is their limited sensitivity to the accuracy of the considered power consumption model (HW or HD). For all MSC based analyses considered in this paper, these advantages arise at the cost of greater cpu-times except for one attack: the SCAN.

Several additional advantages should still be demonstrated. Among them, one may identify the opportunity of tuning the frequency bandwidth of interest. This may allow increasing Signal to Noise Ratio or, may allow tracking leakages on modulated signals. All these results and perspectives clearly highlight the interest of frequency domain analyses and especially the interest of Magnitude Squared Coherence as a tool for SCA.

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