Using More Points in The Same Clock Cycle to Achieve Better Performance of Template Attacks

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Abstract. Template Attacks are widely accepted to be the most powerful side-channel attacks from an information theoretic point of view. For classical Template Attacks, several papers suggested that one should not choose more than one point as the interesting points per clock cycle when he conducts Template Attacks, since additional points in the same clock cycle do not provide additional information. Disobeying this constraint leads to poorer classification performance even if a higher number of interesting points is chosen. In this paper, we show that additional points in the same clock cycle do provide additional information when the condition of equal covariances does not hold by presenting a new way of conducting Template Attacks. Our new way achieves better classification performance compared with classical Template Attacks and Principal Component Analysis (PCA)-based Template Attacks. Using our new way, it is not necessary to consider the problem of choosing special points as the interesting points because our new way achieves the best classification performance when all the points in the clock cycles are used. Moreover, the computational price of the new way is low and practical. Therefore, we suggest that one should use this new way to better understand practical threats of Template Attacks when one want to use more than one point as the interesting points per clock cycle.

Keywords: Side-Channel Attacks, Power Analysis Attacks, Template Attacks.

1 Introduction

As an important method of Power Analysis Attacks, Template Attacks were firstly proposed by S. Chari et al. in 2002 [1]. Under the assumption that one has a reference device identical or similar to the targeted device, and thus be well capable of characterizing power leakages of the targeted device, Template Attacks are widely accepted to be the strongest side-channel attacks from an information theoretic point of view [1].

Principally, Template Attacks consist of two stages. The first stage is the profiling stage and the second stage is the extraction stage. In the profiling stage, one can accurately characterize signals and noises in different time samples and builds templates for each key-dependent operation with the reference device. In the extraction stage, one can exploit a small number of power traces measured from the targeted device and the templates to classify the correct (sub)key. We note that, Template Attacks are also important tools to evaluate the physical security of a cryptographic device.

Contributions Depending on the measurement setup and the data acquisition strategy, captured traces can be quite big (i.e. the number of sampled points is high). For Template Attacks to be practical, it is paramount that not all points of a trace are part of the templates. To reduce the number of points, one needs to choose some interesting points in traces. The interesting points are those time samples that contain the most information about the characterized key-dependent operation(s). For classical Template Attacks, the paper [2] suggested that the minimum distance between these points should be approximately a clock cycle or more. This constraint is used to avoid numerical problems when inverting the covariance matrix, since the authors believed that additional points in the same clock cycle *do not* provide additional information. Disobeying this constraint leads to poorer classification performance even if a higher number of interesting points is chosen [2]. Some other papers [3, 4, 14] also recommended to choose at most *one* interesting point per clock cycle. According to this accepted guideline, the number of interesting points is rather limited and depends on the number of clock cycles which are correspond to the key-dependent operation.

In this paper, we show that the previous accepted guideline of choosing interesting points is limited. Specifically speaking, we find that additional points in the same clock cycle *do* provide additional information which can not be neglected when the condition of equal covariances [5] (known as *homoscedasticity*) does not hold (Please see the section 2.1.1 for more details.) by presenting a new way of conducting Template Attacks. Furthermore, the new way possesses more advantages:

- Using our new way, one can achieve better classification performance[1] compared with classical Template Attacks and PCA-based Template Attacks.
- Using our new way, it is not necessary to consider the problem of choosing special points as the interesting points because one can achieve the best classification performance when all the points in the clock cycles are used.
- The computational price of the new way is low and practical.

Therefore, we suggest that one should use our new way to better understand practical threats of Template Attacks when one want to use more than one point as the interesting points per clock cycle to conduct this kind of attacks.

Related Work Template Attacks were firstly introduced in [1]. The paper [2] provided answers to some basic and practical issues of Template Attacks, such

[1] In this paper, we use success rate of attacks [6] as a metric about classification performance.

as how to choose interesting points in an efficient way and how to preprocess noisy data. A more systematic approach of choosing interesting points, which relies on the data variability, is to choose the interesting points based on PCA. PCA-based Template Attacks were investigated in [3]. We will review PCA-based Template Attacks in Section 2.2. LDA-based Template Attacks were introduced in [11]. However, this kind of Template Attacks depends on the condition of equal covariances, which does not hold in most settings. Therefore, it is not a better choice compared with PCA-based Template Attacks in most settings [5] and we ignore this kind of attacks here. The paper [14] presented a variation of Template Attacks that can be applied to block ciphers when the plaintext and ciphertext used are unknown. In [8], Template Attacks were used to attack a masking protected implementation of a block cipher. Recently, a simple preprocessing technique of Template Attacks, normalizing the sample values using the means and variances was evaluated for various sizes of test data [7]. In [9], the assumption of Template based DPA was relaxed with machine learning techniques. Also, the paper [10] relaxed the assumption made in Template Attacks by using a method based on a semi-supervised learning strategy.

Organization of This Paper The rest of this paper is organized as follows. In section 2, we review classical Template Attacks as well as PCA-based Template Attacks. In section 3, we introduce and analyze our new way of conducting Template Attacks. The new way was verified by practical experiments which are introduced in section 4. In section 5, we conclude the whole paper.

2 Preliminaries

In this section, we briefly review classical Template Attacks and PCA-based Template Attacks.

2.1 Classical Template Attacks

We will introduce the two stages of classical Template Attacks in the following.

2.1.1 The Profiling Stage In the profiling stage, one has a reference device identical or similar to the targeted device. One can use power traces measured from the reference device to characterize power leakages of the targeted device.

Let us assume that there exist K different (sub)keys $key_i, i = 0, 1, \ldots, K-1$ which need to be classified. Also, there exist K different key-dependent operations O_i, $i = 0, 1, \ldots, K-1$. Usually, one will generate K templates, one for each key-dependent operation O_i. One can exploit advanced techniques [2, 11, 12] to choose N interesting points $(P_0, P_1, \ldots, P_{N-1})$. Each template is composed of a mean vector and a covariance matrix. Specifically, the mean vector is used to estimate the data-dependent portion of side-channel leakages. It is the average signal vector $\mathbf{M}_i = (M_i[P_0], \ldots, M_i[P_{N-1}])$ for each one of the key-dependent operations. The covariance matrix is used to estimate the probability density of the noises at different interesting points. It is assumed that noises at

different interesting points approximately follow the multivariate normal distribution. A N dimensional noise vector $\mathbf{n}_i(\mathbf{S})$ is extracted from each trace $\mathbf{S} = (S[P_0], \ldots, S[P_{N-1}])$ representing the template's key dependency O_i as $\mathbf{n}_i(\mathbf{S}) = (S[P_0] - M_i[P_0], \ldots, S[P_{N-1}] - M_i[P_{N-1}])$. One computes the $(N \times N)$ covariance matrix $\mathbf{C}_i$ from these noise vectors. The probability density of the noises occurring under key-dependent operation O_i is given by the N dimensional multivariate Gaussian distribution $p_i(\cdot)$, where the probability of observing a noise vector $\mathbf{n}_i(\mathbf{S})$ is:

$$p_i(\mathbf{n}_i(\mathbf{S})) = \frac{1}{\sqrt{(2\pi)^N |\mathbf{C}_i|}} exp\Big(-\frac{1}{2}\mathbf{n}_i(\mathbf{S})\mathbf{C}_i^{-1}\mathbf{n}_i(\mathbf{S})^T\Big) \quad \mathbf{n}_i(\mathbf{S}) \in \mathbb{R}^N. \qquad (1)$$

In equation (1), the symbol $|\mathbf{C}_i|$ denotes the determinant of $\mathbf{C}_i$ and the symbol $\mathbf{C}_i^{-1}$ denotes its inverse. We know that the matrix $\mathbf{C}_i$ is the estimate of the true covariance $\mathbf{\Sigma}_i$. The condition of equal covariances [5] means that the leakages from different key-dependent operations have the same true covariance $\mathbf{\Sigma} = \mathbf{\Sigma}_0 = \mathbf{\Sigma}_1 = \cdots = \mathbf{\Sigma}_{K-1}$. In most settings, the condition of equal covariances does not hold.

2.1.2 The Extraction Stage In the extraction stage, one tries to classify the correct (sub)key with a small number of traces obtained from the targeted device. Assume that one obtains t traces (denoted by $\mathbf{S}_1, \mathbf{S}_2, \ldots, \mathbf{S}_t$) in the extraction stage. For example, when the traces are statistically independent, one will apply maximum likelihood approach on the product of conditional probabilities [13], i.e.

$$key_{ck} = argmax_{key_i}\Big\{ \prod_{j=1}^{t} \mathsf{Pr}(\mathbf{S}_j | key_i), i = 0, 1, \ldots, K-1 \Big\},$$

where $\mathsf{Pr}(\mathbf{S}_j|key_i) = p_{f(\mathbf{S}_j, key_i)}(n_{f(\mathbf{S}_j, key_i)}(\mathbf{S}_j))$. The key_{ck} is considered to be the correct (sub)key. The output of the function $f(\mathbf{S}_j, key_i)$ is the index of a key-dependent operation. For example, when the output of the first S-box (denoted by $Sbox$) in the first round of AES-128 is chosen as the targeted intermediate value, one builds templates for each output of the S-box. In this case, $f(\mathbf{S}_j, key_i) = Sbox(m_j \oplus key_i)$, where m_j is the plaintext corresponding to the power trace $\mathbf{S}_j$.

2.2 PCA-based Template Attacks

PCA-based Template Attacks [3] which were accepted to be optimal before [5] exploit a continual point fragment correspond to the targeted intermediate value in traces (We assume the length of the continual point fragment is N.). One first computes the empirical covariance matrix, which is given by

$$\mathbf{ECM} = \frac{1}{K}\sum_{i=0}^{K-1}(\mathbf{M}_i - \overline{\mathbf{M}})(\mathbf{M}_i - \overline{\mathbf{M}})^T.$$

The quantity $\overline{\mathbf{M}} = \sum_{i=0}^{K-1} \mathbf{M}_i/K$ is the average of the mean vectors. Let us denote the matrixes of eigenvectors and eigenvalues of $\mathbf{ECM}$ by $\mathbf{U}$ and Δ, i.e.

$$\mathbf{ECM} = \mathbf{U}\Delta\mathbf{U}^T.$$

The principal directions $\{w_i\}_{i=1}^{L}$ are the columns of $\mathbf{U}$ that correspond to the L largest eigenvalues of Δ. The corresponding matrix of principal directions is denoted $\mathbf{W} \in \mathbb{R}^{N\times L}$. The *Cumulative Percentage of Total Variation* [15] is often used to determine how many principal directions should be exploited (i.e. to determine the concrete value of L). One uses projected mean vectors $\{\mathbf{W}^T\mathbf{M}_i^T\}_{i=0}^{K-1}$ and projected covariance matrices $\{\mathbf{W}^T\mathbf{C}_i\mathbf{W}\}_{i=0}^{K-1}$ to conduct the attacks. Specifically speaking, the probability of observing a noise vector when one assumes the key-dependent operation is O_i is computed by

$$p_i(\mathbf{n}_i(\mathbf{S})) = \frac{exp(-\frac{1}{2}\mathbf{n}_i(\mathbf{S})\mathbf{W}(\mathbf{W}^T\mathbf{C}_i\mathbf{W})_i^{-1}(\mathbf{n}_i(\mathbf{S})\mathbf{W})^T)}{\sqrt{(2\pi)^L|\mathbf{W}^T\mathbf{C}_i\mathbf{W}|}} \quad \mathbf{n}_i(\mathbf{S}) \in \mathbb{R}^N. \qquad (2)$$

One classifies the correct (sub)key based on the probability computed by equation (2).

3 Our New Way

In this section, for the purposes of comparison, we will introduce three different strategies to conduct Template Attacks. The first strategy and the second strategy are the classical way of conducting Template Attacks but with different number of interesting points per clock cycle. The third strategy is our new way of conducting Template Attacks. Finally, we evaluate the computational prices of the second strategy, the third strategy, and PCA-based Template Attacks.

Assume that, in one trace, there is a *continual* point fragment $(P_0, P_1, \ldots, P_{N-1})$ which is correspond to the key-dependent operation and has length N. We also assume that these N points are in c continual clock cycles. Therefore, there are N/c points per clock cycle. Let the symbol $P_{(i,j)}$ denotes the j^{th}, $j \in \{1, \ldots, N/c\}$ interesting point in the i^{th}, $i \in \{1, \ldots, c\}$ clock cycle.

Note that, there are many methods about how to choose interesting points. For example, difference of means based method [1], sum of squared differences based method [9], Signal to Noise Ratio based method [13], SOST [9], and DPA based method [13] etc. It turns out that an approach that works well in practice is to choose points that lead to high correlation coefficients in DPA attacks as interesting points [16]. However, in this paper, we do not investigate the question about how to choose a point as the interesting point. In other words, we assume one can choose interesting points efficiently and effectively.

3.1 Strategy 1

In this strategy, one only uses one point as the interesting point per clock cycle and chooses c points

$$\left\{P_{(1,1)}, P_{(2,1)}, \ldots, P_{(c,1)}\right\}$$

from the N continual points as the c interesting points. Then, one conducts classical Template Attacks with templates which are built with the c interesting points. We call the attack with this strategy as "ATTACK-1".

3.2 Strategy 2

In this strategy, one uses more than one point as the interesting points per clock cycle. In order to show this strategy more clearly, we take the simplest case as an example (i.e. We assume that one uses two points as the interesting points per clock cycle). Therefore, $2c$ points are chosen from the N continual points as the interesting points:

$$\big\{(P_{(1,1)}, P_{(1,2)}), (P_{(2,1)}, P_{(2,2)}), \ldots, (P_{(c,1)}, P_{(c,2)})\big\}.$$

Then, one conducts classical Template Attacks with templates which are built with the $2c$ interesting points. This means that one needs to compute a $(1 \times 2c)$ mean vector and a $(2c \times 2c)$ covariance matrix for each template. We call the attack with Strategy 2 as "ATTACK-2".

Note that, the success rate of Strategy 2 will reduce when one uses more points as the interesting points per clock cycle to conduct Template Attacks [2,5]. Our experiments in the next section also verified this fact.

3.3 Strategy 3 (Our New Way)

Strategy 3 is our new way of conducting Template Attacks. In our new way, during the profiling stage, one uses more than one point as the interesting points per clock cycle. In order to show our new way more clearly, we also take the simplest case as an example (i.e. We assume that one uses two points as the interesting points per clock cycle.). Therefore, $2c$ points are chosen from the N continual points as the interesting points:

$$\big\{(P_{(1,1)}, P_{(1,2)}), (P_{(2,1)}, P_{(2,2)}), \ldots, (P_{(c,1)}, P_{(c,2)})\big\}.$$

One divides the $2c$ interesting points into two sets. In the first set, there are c interesting points:

$$\mathsf{Set1} = \big\{P_{(1,1)}, P_{(2,1)}, \ldots, P_{(c,1)}\big\}.$$

The rest c interesting points are in the second set:

$$\mathsf{Set2} = \big\{P_{(1,2)}, P_{(2,2)}, \ldots, P_{(c,2)}\big\}.$$

Note that, in each set, any two points of the c interesting points are not in the same clock cycle. But the two points $(P_{(i,1)}, P_{(i,2)})$, $i = 1, 2, \ldots, c$ are in the same clock cycle and contain very similar information. In the following, one builds templates in the same way as classical Template Attacks with the c interesting points in $\mathsf{Set1}$ and obtains a group of templates denoted by $\mathsf{G1}$. Similarly, with the same traces used for obtaining $\mathsf{G1}$, one builds templates with

the c interesting points in $\mathsf{Set2}$ and obtains another group of templates $\mathsf{G2}$. At this point, the profiling stage is finished.

In the extraction stage, one first computes a sequence

$$\big\{\mathsf{Pr}(1,0), \mathsf{Pr}(1,1), \ldots, \mathsf{Pr}(1,K-1)\big\},$$

where the value $\mathsf{Pr}(1,i)$ represents the probability of the i^{th} (sub)key is the correct (sub)key (In the example of section 2.2, $\mathsf{Pr}(1,i)$ equals to $\prod_{j=1}^{t} \mathsf{Pr}(S_j|key_i)$.) using $\mathsf{G1}$ with some traces obtained from the targeted device in the same way as classical Template Attacks. Then, one sorts the sequence in decreasing order and computes $\mathsf{Index}(1,i),\ i=0,1,\ldots,K-1$ for each (sub)key. The value $\mathsf{Index}(1,i)$ represents the sequence number of $\mathsf{Pr}(1,i)$ in the sorted sequence. Similarly, one computes another sequence

$$\big\{\mathsf{Pr}(2,0), \mathsf{Pr}(2,1), \ldots, \mathsf{Pr}(2,K-1)\big\}$$

using $\mathsf{G2}$ with the same traces obtained from the targeted device. Then, he computes $\mathsf{Index}(2,i),\ i=0,1,\ldots,K-1$ for each (sub)key. The candidate value of the correct key is computed by

$$key_{ck} = argmin_i\big\{\mathsf{Index}(1,i) + \mathsf{Index}(2,i), i \in \{0,1,\ldots,K-1\}\big\}.$$

We call the attack with our new way as "ATTACK-3".

Discussions In our new way, we do not build templates with interesting points in the same clock cycle simultaneously. Therefore, the new way avoids the numerical problems when inverting the covariance matrix. The new way will has higher success rate of attacks because it exploits information from more points in a trace in spite of the points in the same clock cycle provide very *similar* information. The paper [2] claimed that *"additional points in the same clock cycle do not provide additional information".* Our experiments in the next section show that the claim of paper [2] is incorrect when the condition of equal covariances does not hold. If additional points in the same clock cycle do not provide additional information, the success rate of our new way should approximately equal to that of ATTACK-1. However, evaluation results in the next section show that the success rate of our new way is obviously higher than that of ATTACK-1. Note that, in our new way, we do not classify the correct (sub)key like this: $key_{ck} = argmin_i\{\mathsf{Pr}(1,i) + \mathsf{Pr}(2,i), i \in \{0,1,\ldots,K-1\}\}$. The reason is that the probability obtained by templates $\mathsf{G1}$ may not be in the same rang as the probability obtained by templates $\mathsf{G2}$. This may lead to poorer classification performance.

There are two generalizations about our new way of conducting Template Attacks. The first generalization is to use more points as the interesting points per clock cycle to conduct our new way of Template Attacks. Assume that one uses s $(2 < s \leq N/c)$ points as the interesting points per clock cycle, he will divide the cs interesting points into s sets and build s groups of templates in the profiling stage similarly to the way introduced above. In the extraction stage, one classifies the correct (sub)key by computing

$$key_{ck} = argmin_i\big\{\mathsf{Index}(1,i) + \ldots + \mathsf{Index}(s,i), i \in \{0,1,\ldots,K-1\}\big\}.$$

Note that, if one uses all the points as the interesting points per clock cycle, he will not need to choose special points as the interesting points. In many cases, using all the points as the interesting points is practical due to the low computational price of our new way.

The second generalization is as follows. One can use s ($2 \leq s \leq N/c$) points as the interesting points per clock cycle. For a fixed number of points used as the interesting points per clock cycle, one uses more than s sets of interesting points to build templates and conducts our new way similarly as long as any two points in each set are not in the same clock cycle.

The success rate of our new way will be higher when the two generalizations are used but the computational price will also be higher. In this paper, we only consider the first generalization and do not further consider the second generalization.

3.4 Computational Prices

We evaluate the computational prices of ATTACK-2, ATTACK-3, and PCA-based Template Attacks (short for PCA-TA) in this subsection. For Template Attacks, the computational price mainly depends on the size of the mean vector and the covariance matrix. Therefore, we compare the sizes of the mean vectors and the covariance matrixes to show the computational prices of the three attacks. We show the sizes of the mean vectors and the covariance matrixes for the three attacks in Table 1. For ATTACK-2 and ATTACK-3, we assume one uses s ($2 \leq s \leq N/c$) points as the interesting points per clock cycle. Hence, for ATTACK-3, one needs to compute s different ($1 \times c$) mean vectors and s different ($c \times c$) covariance matrixes for a key-dependent operation.

For PCA-based Template Attacks, one can use the method introduced in paper [5] to compute the projected mean vectors and projected covariance matrices. Using this method, one can avoid both numerical problems and the computation of large covariance matrices. We uses this advanced method to conduct PCA-based Template Attacks in this paper.

From Table 1, we find that the computational price of our new way (ATTACK-3) is much lower than that of classical Template Attacks (Attack-2), especially when the value of c is large. The reason is that the size of the covariance matrix grows quadratically with the number of interesting points. However, the computational price of our new way is higher than that of PCA-based Template Attacks (We ignore the computational price of computing the matrixes $\mathbf{ECM}$, $\mathbf{U}$, and Δ.). To sum up, the computational price of our new way is low and practical.

4 Experiments

In this section, we experimentally evaluate the three strategies introduced in Section 3 as well as PCA-based Template Attacks. For implementation of cryptographic algorithms with countermeasures, one usually first uses some methods

Table 1. The Sizes of Mean Vectors And Covariance Matrixes

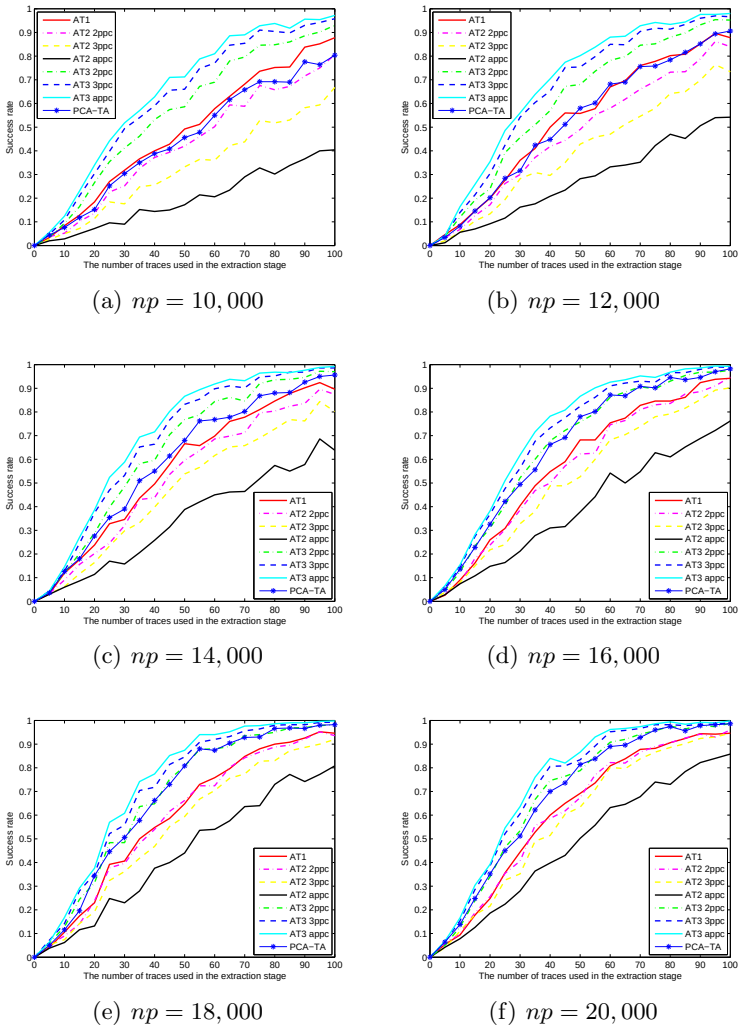
	the sizes of mean vectors	the sizes of covariance matrixes
ATTACK-2	$1 \times sc$	$sc \times sc$
ATTACK-3	$s \times (1 \times c)$	$s \times (c \times c)$
PCA-TA	$1 \times L$	$L \times L$

to delete the countermeasures and then tries to attack the implementation using classical attacks (Such as Template Attacks) against unprotected implementation. For example, if one has traces with random delays [18]. He may first use the method proposed in [17] to remove the random delays and then use classical attacks to recover the correct (sub)key. The methods of deleting countermeasures are beyond the scope of this paper. Therefore, we take unprotected AES-128 implementation as example. We tried to attack the output of the first S-box in the first round of unprotected AES-128 software implementation on an typical 8-bit microcontroller STC89C58RD+ whose operating frequency is 11MHz. The real power traces were acquired with a sampling rate of 50MS/s. The average number of real power traces during the sampling process was 10 times. We used the same device for both the profiling and the extraction stage, which provides a good setting for the focus of our research. In all the practical experiments, we chose the continual point fragment using classical DPA based method [13]. The correlation coefficient of each point in the continual point fragment was larger than 0.7. We chose the points with high correlation coefficient as the interesting points per clock cycle. For our device, the condition of equal covariances does not hold. This means that the differences between different covariance matrixes $\mathbf{C}_i$ are very evident (can easily be observed from visual inspection).

Let "AT1" denote Attack-1. Let "AT2 2ppc" and "AT3 2ppc" respectively denote the case of ATTACK-2 and ATTACK-3 using the same two points as the interesting points per clock cycle. Let "AT2 3ppc" and "AT3 3ppc" respectively denote the case of ATTACK-2 and ATTACK-3 using the same three points as the interesting points per clock cycle. Let "AT2 appc" and "AT3 appc" respectively denote the case of ATTACK-2 and ATTACK-3 using all the points as the interesting points per clock cycle. Let "PCA-TA" denote PCA-based Template Attacks using the first 6 principal directions (i.e. $L = 6$ Please see Section 2.2 for more details.). For our device, the first 6 principal directions are sufficient to ensure the success rate of PCA-based Template Attacks. The Cumulative Percentage of Total Variation equals to 0.996 when the first 6 principal directions are used. The next few principal directions only *slightly* increase the power of this kind of attacks and it is not necessary to use all the principal directions [3,5].

We conducted the eight attacks with same traces both in the profiling stage and the extraction stage. For simplicity, let np denote the number of traces used in the profiling stage and let ne denote the number of traces used in the extraction stage. We used 10,000, 12,000, 14,000, 16,000, 18,000, and 20,000 traces to build the 256 templates respectively. The traces were generated with a fixed main key and random plaintext inputs. We generated additional 20,000

traces with another fixed main key and random plaintext inputs. The 20,000 traces were used in the extraction stage. We tested the success rates of the eight attacks when one uses ne traces in the extraction stage as follows. We repeated



(a) $np = 10,000$ (b) $np = 12,000$

(c) $np = 14,000$ (d) $np = 16,000$

(e) $np = 18,000$ (f) $np = 20,000$

Fig. 1. The Practical Experiments Results

the eight attacks 500 times. For each time, we chose ne traces from the 20,000 traces uniformly at random and the eight attacks were conducted with the same ne traces. We respectively recorded how many times the eight attacks can successfully recover the correct subkey. The success rates of the eight attacks are

shown in Figure 1. From Figure 1, we can see that the success rate of ATTACK-3 is higher than the success rates of ATTACK-1, ATTACK-2, and PCA-based Template Attacks. We note that, when more points are used as the interesting points per clock cycle, the success rate of our new way will be higher while the success rate of ATTACK-2 will be lower. These results indicate that additional points in the same clock cycle *do* provide additional information. We also prove that PCA-based Template Attacks are not optimal.

When one uses all the points as the interesting points per clock cycle, our new way achieves the best classification performance. Therefore, we suggest that our new way should be used to avoid the problem of choosing special points in the clock cycles as the interesting points. One cannot expect that the success rate of ATTACK-3 will be much higher than those of ATTACK-1 and PCA-based Template Attacks. The reasons are as follows. First, ATTACK-3 only uses very similar information from the additional points in the same clock cycle. Second, essentially, our new way *does not* depend on more advanced technology compared with classical Template Attacks.

For other S-boxes in the first round of the unprotected AES-128 software implementation, similar evaluation results were obtained by us. The result of the paper [5] shows that additional points in the same clock cycle provide additional information when the condition of equal covariances holds. Our evaluation results combine with the result of the paper [5] show that one can not ignore the additional information provided by the additional points in the same clock cycle because the additional information can also be exploited to achieve better classification performance of Template Attacks.

5 Conclusion and Future Work

In this paper, we find that additional points in the same clock cycle do provide additional information when the condition of equal covariances does not hold by presenting a new way of conducting Template Attacks. This new way achieves better classification performance compared with classical Template Attacks and PCA-based Template Attacks. Using our new way, it is not necessary to consider the problem of choosing special points as the interesting points because one can achieve the best classification performance when all the points in the clock cycles are used. Moreover, the computational price of the new way is low and practical. Therefore, we suggest that one should use this new way to better understand practical threats of Template Attacks when one want to use more than one point as the interesting points per clock cycle to conduct this kind of attacks. In the future, it would be interesting to find quantitative factors about why classical Template Attacks have poorer classification performance when one uses more than one point as the interesting points per clock cycle. It is also very necessary to further verify our new way in other devices such as FPGA, ASIC, and the devices in which the condition of equal covariances holds.

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