How to Further Increase Leakage Exploitation Rate in Profiled Side-Channel Attacks?

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Abstract. Template Attack is widely accepted to be one of the most powerful side-channel attacks, because it is assumed that one has full knowledge of targeted crypto devices and thus be well capable of characterizing the side-channel leakages. However, whether or not Template Attack exploits side-channel leakages to the fullest is still not clear. In this paper, we present a negative answer to this central question, by introducing a normalization process into original Template Attack. We present Normalized Template Attack, which has the normalization process. Furthermore, we prove that Normalized Template Attack is better that its original counterpart in terms of leakage exploitation rate. We evaluate the key-recovery efficiency of Normalized Template Attack and original Template Attack as well under identical scenarios, by performing attacks against both simulated and real power traces. Our experimental results show that our method is valid end effective. Remarkably enough, this normalization process is of extremely low computation cost. Therefore, we argue that the normalization process should be integrated as a necessary part of profile attacks in order to better understand the practical threats of these attacks.

Keywords: Template Attack, leakage exploitation rate, normalization process, profiled side-channel attacks.

1 Introduction

Side-channel attacks belong to an important kind of cryptanalysis techniques on cryptographic implementations. As a matter of fact, many implementations of traditional cryptosystems even provably secure in black-box model were broken by side-channel attacks using electromagnetic radiation [1,5], running-time [2], fault detection [3], power consumption [4] and many more [6,7].

Among those side-channel attacks, Power Analysis Attack is the most studied one. Power Analysis Attack exploits the fact that the instantaneous power consumption of a cryptographic device depends on the data it processes and on the operation it performs. As an important attack method in Power Analysis Attack, S.Chari et al. presented Template Attack in [8]. Template Attack is a *two-stage* attack method. The first stage is a profiling stage and the second stage is an extraction stage. In the profiling stage, one builds templates for each key-dependent operation. In the extraction stage, one exploits one or a limited number of power traces and the templates to classify the correct key. Template Attack is widely accepted to be the strongest side channel attack possible from an information theoretic point of view [8]. Because it assumes that one knows all the details of the targeted device and possesses a device which is identical or similar to the targeted device. Therefore, one can accurately characterize signals and noises in different times and builds templates in the profiling stage. While such an assumption is limiting, it holds in many cases and has been used in other side-channel attacks [21,22]. Nowadays, with the development of embedded device, Template Attack becomes more practical. Template Attack is also an important tool to evaluate the security strength of a device.

In many real world settings, one can not classify the correct key with only a single power trace in the extraction stage due to noise and the accuracy of templates. Therefore, one needs a limited number of power traces to classify the correct key. According to different attack scenarios, one may apply maximum likelihood approach on the product or the sum of conditional probabilities obtained from power traces and the templates in the extraction stage to classify the correct key. When the power traces are statistically independent, one will apply maximum likelihood approach on the product of conditional probabilities [13]. Otherwise, when the key-dependent operation in different power traces are the same, one may apply maximum likelihood approach on the sum of conditional probabilities. The latter case is also called Amplified Template Attack [9]. Let's show some examples for the two attack scenarios respectively in the following.

When one can attack the output of the S-boxs in the first round of AES-128 with random message input choosing by himself, he will apply maximum likelihood approach on the product of conditional probabilities. Because the power traces are statistically independent due to the output of the S-boxs are random.

Amplified Template Attack can be used at least in the following two specific examples. *Example 1:* If one can not obtain any information about the input and output of some symmetric cipher, he can only attack the key scheduling mechanism of the symmetric cipher and obtains more than one power traces corresponding to the same key (key-dependent operation) in the extraction stage. Usually, this situation may be caused by the following two reasons. Reason one is that the adversary can not control the targeted device in the extraction stage and he can only measure the power consumption. Reason two is that the Hamming Weight of some sensitive intermediate value can not be recovered with probability 1 using a single power trace due to noise for some device whose leakage function is Hamming Weight leakage function [18]. *Example 2:* When one tries to attack some fixed substantial intermediate value such as the secret key of some asymmetric cryptosystem, he can only obtain more than one power traces with the same key-dependent operation and apply Amplified Template Attack. For instance, many public key encryption schemes and digital signature schemes are based on the Discrete Logarithm Problem or the Decisional Diffie-Hellman assumption. These schemes usually need to compute g^x, where g is an element of a group of prime order q and $x \in \mathbb{Z}_q$ is the secret key. Note that x is fixed in every invocation. When sliding-window exponentiation [19] is used to compute g^x, one could build templates for the window and applies Amplified Template Attack.

Motivations Maximizing leakage exploitation rate is an important method to improve side-channel attacks. Usually, a side-channel attack method with higher leakage exploitation rate will be more effective and efficient. In the above two attack scenarios, the adversary applies maximum likelihood approach on the product or the sum of conditional probabilities obtained from power traces and templates to classify the correct key. However, it is unknown that whether this way of exploiting power traces and templates maximize leakage exploitation rate and result in the highest Success Rate of attack[1] [10]. Therefore, a natural question is that does there exist a better way to exploit power traces and templates which has higher leakage exploitation rate and achieves higher Success Rate of attack than the classical way? In this paper, we try to answer this important question.

Contributions In this paper, we present a new way to exploit power traces and templates. This new way has higher leakage exploitation rate and achieves higher Success Rate of attack than the classical way and can be used in both the above two attack scenarios. The new way introduces a normalization process into original Template Attack and exploits normalized conditional probability (See section 3 for more details) instead of conditional probability. Our experiments verified that the Success Rate will be improved a lot in both the above two attack scenarios when our new way is used.

Related Work Template Attack was introduced in [8]. In [9], C.Rechberger et al. provided answers to some basic and practical issues of Template Attack, such as how to select points of interest in an efficient way, and how to preprocess noisy data. Amplified Template Attack was also presented in [9]. Subspace-based template attacks were investigated in [15,16]. In [17], Template Attack on an implementation of a block cipher that uses a masking scheme is introduced that retrieves the secret key. In [23], an efficient leakage characterization method in the profiling stage for Template Attack is introduced. Our work is different from their work, because we only consider the extraction stage but not the profiling stage. A simple pre-processing technique of Template Attack, normalizing the trace means and variances from the training and test devices is evaluated for various test data set sizes in [20]. However, our important discovery is not considered or neglected in these previous work.

In section 2, we review Template Attack and the above two attack scenarios. We show our new way and explain why it is more effective in section 3. Our new way can be used in the two attack scenarios yielding two new attack methods.

[1] Assume that the adversary executes *tot* times attack in the same attack scenario. In the *tot* times attack, the adversary successes *suc* times (For example, the secret key is recovered successfully *suc* times.). Then Success Rate is defined to be *suc*/*tot*.

The two new attack methods are verified by simulated and practical experiments in section 4. In section 5, we conclude this paper.

2 Preliminaries

In this section, we briefly review Template Attack. In Template Attack, there exists two stages. The first stage is a profiling stage and the second stage is a extraction stage. We will introduce the two stages in the following.

2.1 The Profiling Stage

In the profiling stage, one has a device which is identical or similar to the targeted device. One derives some power traces from this device. These power traces are used to build templates for each key-dependent operation. In the extraction stage, one uses these templates to classify the correct key.

Let us assume there exist K different key $key_i, i = 1, 2, \ldots, K$ which need to be classified. There also exist K different key-dependent operations O_i with $i = 1, 2, \ldots, K$. Usually, one will generate K templates, one for each key-dependent operation O_i. In each one of the templates, there exists two parts. The first part in a template estimates the data-dependent portion of the side channel leakage. It is the average signal M_i for each of the operations. The second part in a template estimates the probability density of the noise in the side channel leakage. One can exploit advanced techniques [9,14] to choose N selected instants $(P_1, P_2, \ldots, P_N)$ in each sample. It is assumed that the noise in the side channel leakage approximately has a multivariate normal distribution with respect to the selected N interesting points $(P_1, P_2, \ldots, P_N)$. A N dimensional noise vector $n_i(S)$ is extracted from each sample S (a power trace) representing the template's key dependency O_i as $n_i(S) = (S[P_1] - M_i[P_1], \ldots, S[P_N] - M_i[P_N])$. One computes the $(N \times N)$ covariance matrix C_i from these noise vectors. The probability density of the noise occurring under key-dependent operation O_i is then given by the N dimensional multivariate Gaussian distribution $p_i(\cdot)$ where the probability of observing a noise vector $n_i(S)$ is

$$p_i(n_i(S)) = \frac{1}{\sqrt{(2\pi)^N |C_i|}} exp\Big(-\frac{1}{2} n_i(S)^T C_i^{-1} n_i(S) \Big) \quad n_i(S) \in \mathbb{R}^N, \qquad (1)$$

where $|C_i|$ denotes the determinant of C_i, and C_i^{-1} its inverse.

2.2 The Extraction Stage

In this stage, one tries to classify the correct key with one or a limited number of power traces obtained from the targeted device. Usually, due to noise and the accuracy of templates, one can not recover the correct key with only a single power trace. When one obtains more than one power traces in the extraction stage, according to different attack scenarios, his strategy to classify the correct key is to apply maximum likelihood approach on the product or the sum of conditional probabilities obtained from power traces and templates.

Assume that one obtains t power traces (denoted by $S_1, S_2, \ldots, S_t$) in the extraction stage.

When the power traces are statistically independent, one will apply maximum likelihood approach on the product of conditional probabilities [13], i.e.

$$key_{ck} = argmax_{key_i}\Big\{\prod_{j=1}^{t} Pr(S_j|key_i), i = 1, 2, \ldots, K\Big\},$$

where $Pr(S_j|key_i) = p_{f(S_j,key_i)}(n_{f(S_j,key_i)}(S_j))$. The key_{ck} is considered to be the correct key. The output of the function $f(S_j, key_i)$ is the index of some key-dependent operation. For example, when one attacks the output of the first S-box of the first round of AES-128, one builds templates for each output of the S-box (The key-dependent operation is the output of the S-box.). In this case, $f(S_j, key_i) = Sbox(m_j \oplus key_i)$, where m_j is the plaintext of the power trace S_j. For convenience, we call this attack scenario "Product Case Template Attack".

In many real world settings, one can only obtains more than one power traces with the same key-dependent operation in the extraction stage. Amplified Template Attack [9] can be used in this attack scenario. In Amplified Template Attack, the adversary can computes $\sum_{j=1}^{t} Pr(S_j|key_i)$ for each key $key_i, i = 1, 2, \ldots, K$ and apply maximum likelihood approach on the sum of conditional probabilities, i.e.

$$key_{ck} = argmax_{key_i}\Big\{\sum_{j=1}^{t} Pr(S_j|key_i), i = 1, 2, \ldots, K\Big\},$$

where $Pr(S_j|key_i) = p_{f(key_i)}(n_{f(key_i)}(S_j))$. The key_{ck} is considered to be the correct key. The output of the function $f(key_i)$ is the index of some key-dependent operation. In this case, the output of $f(key_i)$ only depends on key_i. For example, when one attacks the output of some S-box in the key expansion algorithm of AES-128, $f(key_i) = key_i$.

3 Our New Way to Increase Leakage Exploitation Rate for Template Attack

In this section, we will introduce our new way to increase leakage exploitation rate and explain why it is better. Our new way is different from the classical method only in the extraction stage. The profiling stage remains unchanged.

For simplicity, we rewrite $Pr(S_j|key_i)$ as $P(i, j), i = 1, 2, \ldots, K, j = 1, 2, \ldots, t$. Denote the natural logarithm of each conditional probability $P(i, j)$ as $H(i, j)$, i.e. $H(i, j) = lnP(i, j), i = 1, 2, \ldots, K, j = 1, 2, \ldots, t$. For every power trace

S_j $(j = 1, 2, \ldots, t)$, we compute $maxln(j) = max\{H(1, j), H(2, j), \ldots, H(K, j)\}$. Clearly, for each conditional probability $P(i, j), i = 1, 2, \ldots, K$ obtained from a single power trace S_j $(j = 1, 2, \ldots, t)$, there exists a real number $\alpha_{ij} \in [0, 1], i = 1, 2, \ldots, K$ such that $\alpha_{ij} = maxln(j)/H(i, j)$. Note that α_{ij} is proportional to the conditional probability $P(i, j)$ for a fixed j. Let

$$V(i, j) = e^{\frac{maxln(j)}{H(i,j)}} = e^{\alpha_{ij}}, i = 1, 2, \ldots, K, j = 1, 2, \ldots, t.$$

We call $V(i, j)$ the normalized conditional probability.

In the following, we will show a new way with higher leakage exploitation rate than the classical way. We consider Product Case Template Attack as an example. For Amplified Template Attack, we have similar result.

Assume that, for the correct key key_{ck}, we have

$$\prod_{j=1}^{t} V(ck, j) > \prod_{j=1}^{t} V(i, j), i \in \{1, 2, \ldots, K\}\backslash ck.$$

This assumption is reasonable. Because for the correct key key_{ck} and every power trace S_j $(j = 1, 2, \ldots, t)$, α_{ckj} is much closer to 1 than α_{ij} for the wrong keys $key_i, i \in \{1, 2, \ldots, K\}\backslash ck$ with high probability.

If

$$\prod_{j=1}^{t} P(ck, j) > \prod_{j=1}^{t} P(i, j), i \in \{1, 2, \ldots, K\}\backslash ck,$$

Product Case Template Attack will return the correct key key_{ck}. However, when noise is large and/or the templates are not very accurate, Product Case Template Attack may return a wrong key $key_{wk}, wk \in \{1, 2, \ldots, K\}\backslash ck$.

We divide the t power traces $\{S_1, S_2, \ldots, S_t\}$ into two sets. In the first set $Set1$, there are u samples $\{S_{i_1}, \ldots, S_{i_u}\}$ and $P(ck, i_1) > P(wk, i_1), \ldots, P(ck, i_u) > P(wk, i_u)$. In the second set $Set2$, there are $t-u$ samples $\{S_{j_1}, \ldots, S_{j_{t-u}}\}$ and $P(ck, j_1) \leq P(wk, j_1), \ldots, P(ck, j_{t-u}) \leq P(wk, j_{t-u})$. Let $P1_{ck} = \prod_{k=1}^{u} P(ck, i_k)$, $P2_{ck} = \prod_{k=1}^{t-u} P(ck, j_k)$, $P1_{wk} = \prod_{k=1}^{u} P(wk, i_k)$, and $P2_{wk} = \prod_{k=1}^{t-u} P(wk, j_k)$.

Let $V1_{ck} = \prod_{k=1}^{u} V(ck, i_k)$, $V2_{ck} = \prod_{k=1}^{t-u} V(ck, j_k)$, $V1_{wk} = \prod_{k=1}^{u} V(wk, i_k)$, and $V2_{wk} = \prod_{k=1}^{t-u} V(wk, j_k)$. According to the definition, we have $P1_{ck} > P1_{wk}$, $P2_{ck} \leq P2_{wk}$, $V1_{ck} > V1_{wk}$, and $V2_{ck} \leq V2_{wk}$. Due to

$$\prod_{j=1}^{t} V(ck, j) = V1_{ck}V2_{ck} > V1_{wk}V2_{wk} = \prod_{j=1}^{t} V(wk, j),$$

we have

$$\frac{V1_{ck}}{V1_{wk}} > \frac{V2_{wk}}{V2_{ck}}. \qquad (2)$$

However, if Product Case Template Attack return key_{wk} as the output, thus

$$\prod_{j=1}^{t} P(ck, j) = P1_{ck}P2_{ck} < P1_{wk}P2_{wk} = \prod_{j=1}^{t} P(wk, j).$$

Therefore, we have

$$\frac{P1_{ck}}{P1_{wk}} < \frac{P2_{wk}}{P2_{ck}}. \tag{3}$$

Clearly, we have

$$P(i,j) = e^{H(i,j)} = V(i,j)^{\frac{H^2(i,j)}{maxln(j)}}, i = 1,2,\ldots,K, j = 1,2,\ldots,t.$$

We know that $V(i,j) \in [e^0, e]$. However, we can not bound the range of $H^2(i,j)/maxln(j), i = 1,2,\ldots,K, j = 1,2,\ldots,t$. Note that, if inequality (2) and inequality (3) hold simultaneously, we can say that $H^2(wk,j)/maxln(j)$ are much larger than $H^2(ck,j)/maxln(j)$, for some $S_j \in Set2$ with high probability. This case occurs due to the noise in each power trace and depends on the templates. Our new way exploits the normalized conditional probability $V(i,j)$ so that it is more accurate and effective.

Now, we can give out an improved attack method for Product Case Template Attack and Amplified Template Attack respectively. The two new attack methods are called "Normalized Product Case Template Attack" and "Normalized Amplified Template Attack" respectively and use the new way which has higher leakage exploitation rate. The two new attack methods are shown in Algorithm 1 and Algorithm 2 respectively. Note that we ignore the profiling stage of the two new attack methods here and only show the extraction stage of the two new attack methods. The profiling stage of two new attack methods are the same as the original Template Attack.

Algorithm 1 Normalized Product Case Template Attack

```
Input: $P(i,j), i = 1,2,\ldots,K, j = 1,2,\ldots,t$
Output: a candidate key $key_{ck}, ck \in \{1,2,\ldots,K\}$

Step 1 Computes the natural logarithm of each conditional probability $P(i,j)$, namely
    $H(i,j) = lnP(i,j), i = 1,2,\ldots,K, j = 1,2,\ldots,t.$
Step 2 Computes
    $maxln(j) = max\{H(1,j), H(2,j), \ldots, H(K,j)\}$
for each power traces $S_j, j = 1,2,\ldots,t$.
Step 3 Computes normalized conditional probability $V(i,j)$ for each power traces:
    $V(i,j) = exp(\frac{maxln(j)}{H(i,j)}), i = 1,2,\ldots,K, j = 1,2,\ldots,t.$
Step 4 Applying maximum likelihood approach on $\prod_{j=1}^{t} V(i,j)$. Let
    $key_{ck} = argmax_i\{\prod_{j=1}^{t} V(i,j), i = 1,2,\ldots,K\}.$
Step 5 Return $key_{ck}$.
```

Algorithm 2 Normalized Amplified Template Attack

```
**Input:** $P(i,j), i = 1,2,\dots,K, j = 1,2,\dots,t$
**Output:** a candidate key $key_{ck}, ck \in \{1,2,\dots,K\}$

**Step 1** Computes the natural logarithm of each conditional probability $P(i,j)$, namely
        $H(i,j) = lnP(i,j), i = 1,2,\dots,K, j = 1,2,\dots,t.$
**Step 2** Computes
        $maxln(j) = max\{H(1,j), H(2,j), \dots, H(K,j)\}$
for each power traces $S_j, j = 1,2,\dots,t$.
**Step 3** Computes normalized conditional probability $V(i,j)$ for each power traces:
        $V(i,j) = exp(\frac{maxln(j)}{H(i,j)}), i = 1,2,\dots,K, j = 1,2,\dots,t.$
**Step 4** Applying maximum likelihood approach on $\sum_{j=1}^{t} V(i,j)$. Let
        $key_{ck} = argmax_i\{\sum_{j=1}^{t} V(i,j), i = 1,2,\dots,K\}.$
**Step 5** Return $key_{ck}$.
```

Step 1-3 in Algorithm 1 and Algorithm 2 are called normalization process. Note that, the normalization process is of extremely low computation cost.

4 Experiments

In this section, we evaluate the key-recovery efficiency of our two new attack methods and the original Template Attacks by experiments. We analyze the effectiveness by using Success Rate [10]. On one hand, we will evaluate the performance of our new attack methods and the original Template Attacks under different noise level using simulated power traces. On the other hand, we will perform our new attack methods and the original Template Attacks against real power traces.

For simplicity, let np denotes the number of simulated power traces or real power traces used in the profiling stage and let ne denotes the number of simulated power traces or real power traces used in the extraction stage. In each figure showing an experiment result, our new attack method (such as Normalized Product Case Template Attack or Normalized Amplified Template Attack) is denoted by "Our Method" and the classical attack method (such as Product Case Template Attack or Amplified Template Attack) is denoted by "Classical Method".

4.1 Simulated Experiments

We will introduce simulated experiments about Normalized Product Case Template Attack at first. Then, simulated experiments about Normalized Amplified Template Attack will be shown. In all simulated experiments, the standard deviation of Gaussian noise is denoted by σ.

4.1.1 Simulated Experiments about Normalized Product Case Template Attack

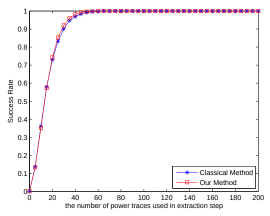
In simulated scenarios, we chose the output of the first S-box of the first round of unprotected AES-128 as the target intermediate value. The Hamming Weight power model [12] was adopted to test the effectiveness of Normalized Product Case Template Attack and Product Case Template Attack. We employed three different noise levels (Gaussian noise) to test the influence of noise on the performance of Normalized Product Case Template Attack and Product Case Template Attack. The standard deviation of the three noise levels were 2,4, and 6.

For each noise level, we did as follows. We used 5000, 7500, and 10000 simulated power traces to build the 256 templates respectively (Because the output of the first S-box of the first round of unprotected AES-128 is 8 bits long, we need to build 256 templates.). The three groups of simulated power traces were generated with a fixed key and random plaintext input. We generated additional 20000 simulated power traces which were used in the extraction stage with a fixed key and random plaintext input. We tested the Success Rate of Normalized Product Case Template Attack (denoted by $SR_{(ne,NPCTA)}$) and the Success Rate of Product Case Template Attack (denoted by $SR_{(ne,PCTA)}$) when one can use ne traces in the the extraction stage as follows. We executed 32 groups of the two attacks simultaneously. In each of the 32 groups, we repeated the two attacks 128 times. For each time, we chose ne traces chosen from the 20000 simulated power traces uniformly at random. Both Normalized Product Case Template Attack and Product Case Template Attack used the same templates and the same ne traces in the extraction stage. For the ith group, we respectively recorded how many times the two attacks can successfully recover the correct key (denoted by $num_{(ne,i,NPCTA)}$ for Normalized Product Case Template Attack and $num_{(ne,i,PCTA)}$ for Product Case Template Attack). Then, for each group, we computed the Success Rate $sr_{(ne,i,NPCTA)}$ ($sr_{(ne,i,NPCTA)} = num_{(ne,i,NPCTA)}/128$) and $sr_{(ne,i,PCTA)}$ ($sr_{(ne,i,PCTA)} = num_{(ne,i,PCTA)}/128$). The Success Rate of the two attacks for the case one using ne traces in the extraction stage were computed by

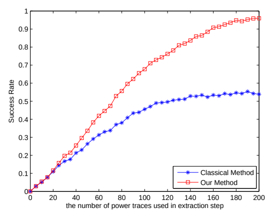
$$SR_{(ne,NPCTA)} = \frac{\sum_{i=1}^{32} sr_{(ne,i,NPCTA)}}{32}, SR_{(ne,PCTA)} = \frac{\sum_{i=1}^{32} sr_{(ne,i,PCTA)}}{32}.$$

We will show $SR_{(ne,NPCTA)}$ and $SR_{(ne,PCTA)}$ for different ne in Figure 1. Note that, in Figure 1, each subtitle represents that the two attacks (Normalized Product Case Template Attack and Product Case Template Attack) are executed when the number of simulated power traces used in the profiling stage equals to np and the standard deviation of Gaussian noise equals to σ.

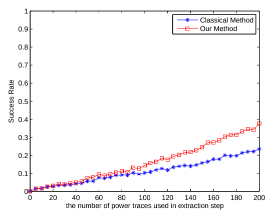
From Figure 1, we can see that Normalized Product Case Template Attack is more effective than Product Case Template Attack when the templates are not very accurate (The templates are built with less simulated power traces.) and the noise level is high. For example, when $np = 5000$, $\sigma = 4$, and $ne = 200$, the



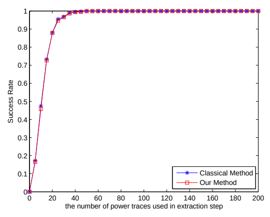
(a) np =5000,σ =2



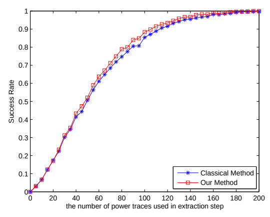
(b) np =5000,σ =4



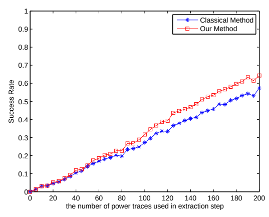
(c) np =5000,σ =6



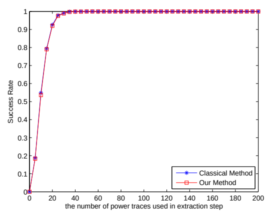
(d) np =7500,σ =2



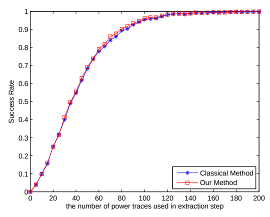
(e) np =7500,σ =4



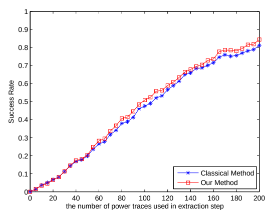
(f) np =7500,σ =6



(g) np =10000,σ =2



(h) np =10000,σ =4



(i) np =10000,σ =6

Fig. 1. Simulated Experiments Results of Normalized Product Case Template Attack and Product Case Template Attack ($SR_{(ne,NPCTA)}$,$SR_{(ne,PCTA)}$)

$SR_{(200,NPCTA)}$ equals to 0.96 while $SR_{(200,PCTA)}$ equals to 0.54. In all the cases, the Success Rate of Normalized Product Case Template Attack are not lower than that of Product Case Template Attack. When one uses more simulated power traces to build the templates in the profiling stage, the Success Rate of Normalized Product Case Template Attack are not lower than that of Product Case Template Attack. Hence, we only consider the case that one can only use less simulated power traces to build the templates in the profiling stage.

4.1.2 Simulated Experiments about Normalized Amplified Template Attack

To verify the Normalized Amplified Template Attack, we attacked the key expansion algorithm of unprotected AES-128 as an example. Algorithm 3 in Appendix A describes the key expansion algorithm of unprotected AES-128.

RotWord in Algorithm 3 performs a one-byte circular left shift on a word. This means that an input word [b0,b1,b2,b3] is transformed into [b1,b2,b3,b0]. SubWord in Algorithm 3 performs a byte substitution on each byte of its input word, using the S-box. If the adversary can recover w[3],w[7],w[11], and w[15], then he can recover the main key key[0],key[1],…,key[15] using the algorithm structure of the key expansion algorithm easily. Note that w[3],w[7],w[11], and w[15] are the input of RotWord. And the output of RotWord is the input of SubWord. Therefore, one can try to attack the output of S-box in SubWord and recover w[3],w[7],w[11], and w[15] completely if he obtains the output of S-box successfully. In all of our experiments for Normalized Amplified Template Attack, we attacked the output of S-box in SubWord and tried to recover key[15] in w[3] as an example. The processes of attacking other byte in w[3],w[7],w[11], and w[15] are similar.

We adopted ID power model [11] to test the effectiveness of Normalized Amplified Template Attack and Amplified Template Attack. If the intermediate value computed by the device is *mid*, the ID power model will leak *mid* itself as the simulated power consumption. For Hamming Weight power model [12], different intermediate values with the same Hamming Weight will have the same simulated power consumption. Therefore, it is very difficult to classify a specific intermediate value accurately when the intermediate values for different power traces are fixed. Hence, we used ID power model. We used 10000, 15000, and 20000 simulated power traces to build 256 templates respectively. The value of key[15] of each simulated power trace was generated randomly. We employed three different noise levels (Gaussian noise) to test the influence of noise on the performance of Normalized Amplified Template Attack and Amplified Template Attack. The standard deviation of the three noise levels were 2, 4, and 8.

In our simulated experiments, we chose 32 random value for key[15]. For each one of the 32 values of key[15], we generated 400 simulated power traces. We tested the Success Rate of Normalized Amplified Template Attack (denoted by $SR_{(ne,NATA)}$) and the Success Rate of Amplified Template Attack (denoted by $SR_{(ne,ATA)}$) when one can use ne traces in the the extraction stage as follows. For the ith ($i = 1, 2, \ldots, 32$) value of key[15], we repeated the two attacks 128 times. For each time, we chose ne simulated power traces uniformly at random from the corresponding 400 simulated power traces. Both Normalized Amplified Template Attack and Amplified Template Attack used the same templates and the same ne traces in the extraction stage. For the ith ($i = 1, 2, \ldots, 32$) value of key[15], we respectively recorded how many times the two attacks can recover the output of S-box successfully (denoted by $num_{(ne,i,NATA)}$ for Normalized Amplified Template Attack and $num_{(ne,i,ATA)}$ for Amplified Template Attack). For the ith ($i = 1, 2, \ldots, 32$) value of key[15], we use $sr_{(ne,i,NATA)}$ and $sr_{(ne,i,ATA)}$ to denote the Success Rate (i.e. $sr_{(ne,i,NATA)} = num_{(ne,i,NATA)}/128$ and $sr_{(ne,i,ATA)} = num_{(ne,i,ATA)}/128$). The Success Rate of the two attacks for the case one using ne traces in the extraction stage were computed by

$$SR_{(ne,NATA)} = \frac{\sum_{i=1}^{32} sr_{(ne,i,NATA)}}{32}, SR_{(ne,ATA)} = \frac{\sum_{i=1}^{32} sr_{(ne,i,ATA)}}{32}.$$

We will show $SR_{(ne,NATA)}$ and $SR_{(ne,ATA)}$ for different ne in Figure 2. Note that, in Figure 2, each subtitle represents that the two attacks (Normalized Amplified Template Attack and Amplified Template Attack) are executed when the number of simulated power traces used in the profiling stage equals to np and the standard deviation of Gaussian noise equals to σ.

From Figure 2, we can see that Normalized Amplified Template Attack is much more effective than Amplified Template Attack when the noise level is high. For example, when $np = 15000$, $\sigma = 4$, and $ne = 100$, the Success Rate of Normalized Amplified Template Attack equals to 0.77 while the Success Rate of Amplified Template Attack equals to 0.34. When $np = 15000$, $\sigma = 8$, and $ne = 100$, the Success Rate of Normalized Amplified Template Attack equals to 0.45 while the Success Rate of Amplified Template Attack equals to 0.16.

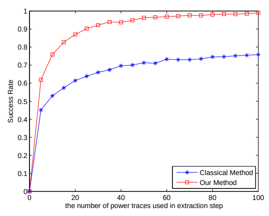
4.2 Practical Experiments

We performed our two new attack methods against real power traces. The real power traces of all the practical experiments were sampled from PowerSuite 4.0. PowerSuite 4.0 is a software benchmark evaluation board we designed and developed by ourselves, and its CPU is an 8-bit microcontroller STC89C58RD+. The real power traces were acquired with a sampling rate of 50M sample/s from PowerSuite 4.0 board. The average number of real power traces during the sampling process was ten times.

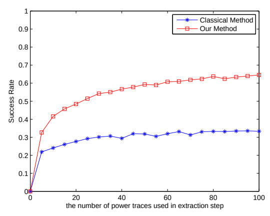
We will introduce practical experiments about Normalized Product Case Template Attack at first. Then, practical experiments about Normalized Amplified Template Attack will be shown.

4.2.1 Practical Experiments about Normalized Product Case Template Attack

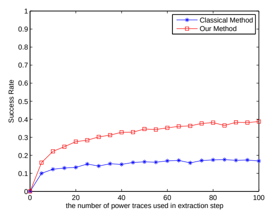
We tried to attack the output of the first S-box of the first round of an unprotected software AES-128 implementation over PowerSuite 4.0 as an example.



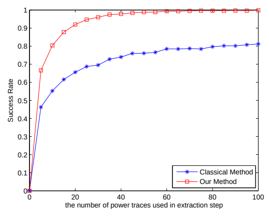
(a) np =10000,σ =2



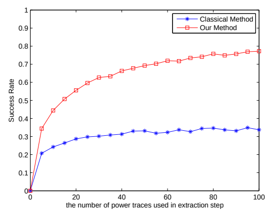
(b) np =10000,σ =4



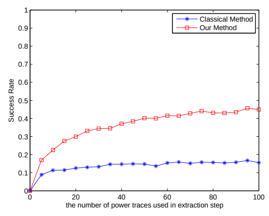
(c) np =10000,σ =8



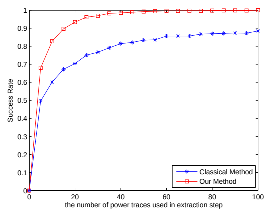
(d) np =15000,σ =2



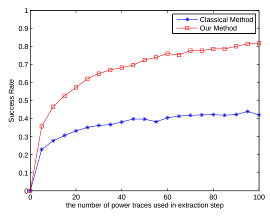
(e) np =15000,σ =4



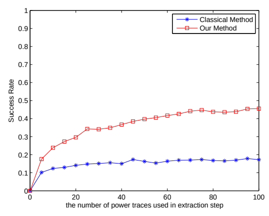
(f) np =15000,σ =8



(g) np =20000,σ =2



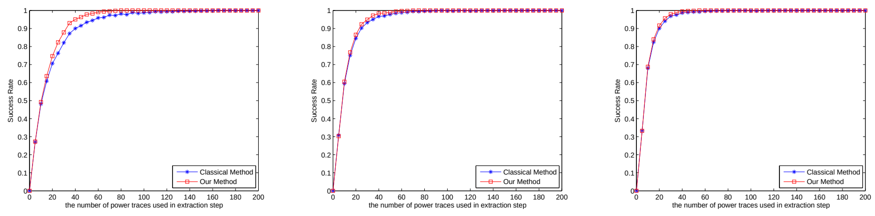
(h) np =20000,σ =4



(i) np =20000,σ =8

Fig. 2. Simulated Experiments Results of Normalized Amplified Template Attack and Amplified Template Attack ($SR_{(ne,NATA)}$,$SR_{(ne,ATA)}$)

Similarly to the simulated experiments of Normalized Product Case Template Attack and Product Case Template Attack, we used 5000, 7500, and 10000 real power traces to build the 256 templates respectively. The three groups of real power traces were generated with a fixed main key and random plaintext input. We generated additional 20000 real power traces with a fixed main key and random plaintext input. The 20000 real power traces were used in the extraction stage. We also computed $SR_{(ne,NPCTA)}$ and $SR_{(ne,PCTA)}$ similarly to that in the simulated experiments of Normalized Product Case Template Attack and Product Case Template Attack but with real power traces. We will show $SR_{(ne,NPCTA)}$ and $SR_{(ne,PCTA)}$ for different ne in Figure 3. In Figure 4, we show the Success Rate of recovering the whole main key in the first round of the unprotected software AES-128 implementation over PowerSuite 4.0 for Normalized Product Case Template Attack and Product Case Template Attack (denoted by $GSR_{(ne,NPCTA)}$ and $GSR_{(ne,PCTA)}$). Note that, in Figure 3 and Figure 4, each subtitle represents that the two attacks (Normalized Amplified Template Attack and Amplified Template Attack) are executed when the number of real power traces used in the profiling stage equals to np. Table 1 shows the minimum number of the real power traces needed by one in the extraction stage of our practical experiments to recover the correct key successfully with probability 1 for Normalized Product Case Template Attack and Product Case Template Attack respectively.

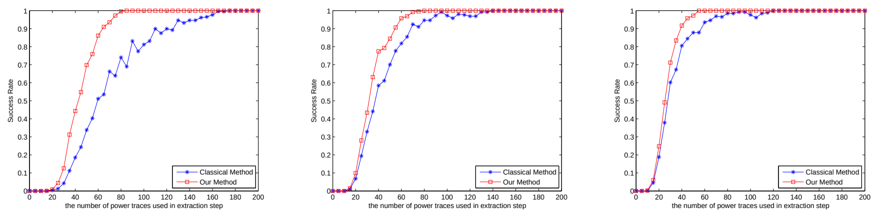


(a) np =5000 (b) np =7500 (c) np =10000

Fig. 3. Practical Experiments Results of Normalized Product Case Template Attack and Product Case Template Attack ($SR_{(ne,NPCTA)}$,$SR_{(ne,PCTA)}$)

Table 1. The Minimum Number of The Real Power Traces Needed by One to Recover The Correct Key Successfully With Probability 1 for Normalized Product Case Template Attack And Product Case Template Attack

	np =5000	np =7500	np =10000
Our Method	85	80	55
Classical Method	175	140	120



(a) np =5000 (b) np =7500 (c) np =10000

Fig. 4. Practical Experiments Results of Normalized Product Case Template Attack and Product Case Template Attack ($GSR_{(ne,NPCTA)}$,$GSR_{(ne,PCTA)}$)

From Figure 3, Figure 4 and Table 1, we can see that Normalized Product Case Template Attack is more effective than Product Case Template Attack. For example, when $np = 10000$, Normalized Product Case Template Attack only needs 55 real power traces to recover the correct key with probability 1 while Product Case Template Attack needs 120 real power traces.

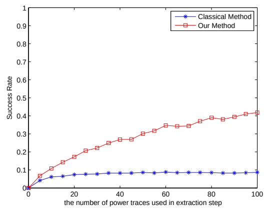
4.2.2 Practical Experiments about Normalized Amplified Template Attack

We attacked the same intermediate value as the simulated experiments of Normalized Amplified Template Attack in the key expansion algorithm of an unprotected software AES-128 implementation over PowerSuite 4.0 as an example.

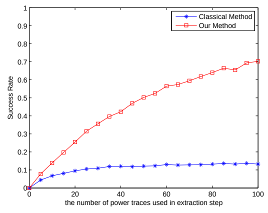
Similarly to the simulated experiments, we used 20000, 40000, and 60000 real power traces with random main key to build the 256 templates respectively. In our practical experiments, we also chose 32 random main key (Thus there are 32 random key[15].). For each main key, we generated 250 real power traces with the fixed main key. Similarly to the simulated experiments, we computed $sr_{(ne,i,NATA)}$ and $sr_{(ne,i,ATA)}, i = 1, 2, \ldots, 32$ for the 32 random key[15] but the ne traces used in the extraction stage were chosen from the 250 real power traces uniformly at random each time of the 128 times of attacks. Then we computed $SR_{(ne,NATA)}$ and $SR_{(ne,ATA)}$. The value of $SR_{(ne,NATA)}$ and $SR_{(ne,ATA)}$ are shown in Figure 5. In Figure 5, the subtitles represent how many real power traces are used in the profiling stage.

Table 2 shows the ratio of the Success Rate of Normalized Amplified Template Attack to the Success Rate of Amplified Template Attack for different number of real power traces used in the profiling stage and in the extraction stage.

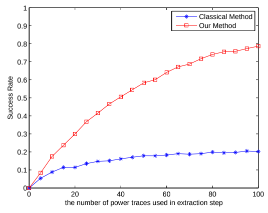
From Figure 5 and Table 2, we can see that the Success Rate of Normalized Amplified Template Attack is much higher than the Success Rate of Amplified Template Attack. For example, when $np = 40000$ and $ne = 100$, the Success Rate of Normalized Amplified Template Attack is 5.30 times higher than the Success Rate of Amplified Template Attack.



(a) np =20000



(b) np =40000



(c) np =60000

Fig. 5. Practical Experiments Results of Normalized Amplified Template Attack and Amplified Template Attack ($SR_{(ne,NATA)}$,$SR_{(ne,ATA)}$)

Table 2. The Ratio of The Success Rate of Normalized Amplified Template Attack to The Success Rate of Amplified Template Attack in Practical Experiments

np / ne	20000	40000	60000
20	2.33	2.68	2.62
60	3.93	4.35	3.51
100	4.81	5.30	3.89

5 Conclusion and Future Work

In this paper, we find a new way to increase leakage exploitation rate in Template Attack. The new way can be used in both Product Case Template Attack and Amplified Template Attack. We present Normalized Product Case Template Attack and Normalized Amplified Template Attack which have the normalization process and exploit normalized conditional probability instead of conditional probability. We also verified the two new attack methods by simulated and practical experiments. Remarkably enough, the normalization process in both our attack methods is of extremely low computation cost. Therefore, we argue that the normalization process should be integrated as a necessary part of profile attacks in order to better understand the practical threats of these attacks.

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Appendix A: The Key Expansion Algorithm of Unprotected AES-128

In this section, we introduce the key expansion algorithm of unprotected AES-128 in Algorithm 3.

The AES-128 key expansion algorithm takes as input a 4-word (16-byte) key (main key) and produces a linear array of 44 words (176 bytes). This is sufficient

Algorithm 3 Key Expansion Algorithm of AES-128

```
KeyExpansion (byte key [16], word w[44])
{
    word temp
    for (i = 0; i < 4; i++)
        w[i] = (key[4*i],key[4*i+1],key[4*i+2],key[4*i+3]);

    for (i = 4; i < 44; i++)
    {
        temp = w[i − 1];
        if (i mod 4 = 0)
            temp = SubWord(RotWord(temp)) ⊕ Rcon[i/4];
        w[i] = w[i − 4] ⊕ temp;
    }
}
```

to provide a 4-word round key for the initial AddRoundKey stage and each of the 10 rounds of the cipher.