Vulnerability Assessment of Ciphers To Fault Attacks Using Reinforcement Learning

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Abstract. A fault attack (FA) is one of the most potent threats to cryptographic applications. Implementing a FA-protected block cipher requires knowledge of the exploitable fault space of the underlying crypto algorithm. The discovery of exploitable faults is a challenging problem that demands human expertise and time. Current practice is to rely on certain predefined fault models. However, the applicability of such fault models varies among ciphers. Prior work discovers such exploitable fault models individually for each cipher at the expense of a large amount of human effort. Our work completely replaces human effort by using reinforcement learning (RL) over the huge fault space of a block cipher to discover the effective fault models automatically. Validation on an AES block cipher demonstrates that our approach can automatically discover the effective fault models within a few hours, outperforming prior work, which requires days of manual analysis. The proposed approach also reveals vulnerabilities in the existing FA-protected block ciphers and initiates an end-to-end vulnerability assessment flow.

Keywords: Reinforcement Learning · Fault Attack

1 Introduction

A fault attack (FA) is a class of active implementation-based attacks in which an adversary deliberately perturbs the computation to extract secrets through the faulty system response or bypass some security mechanism. FAs are applicable over a wide range of computing platforms starting from small embedded systems (e.g., RFID tags) running 8-bit processors [BBB+10, SJR+20], medium-scale 32-bit ARM processors [RRB+19, HPP21a], to high-end cloud applications running Intel chips and GPUs [SFK20, BM16, QWLQ19, MOG+20]. Hardware circuits such as FPGA and ASIC are also vulnerable [SBR+20, BLMR19, CML+11] to FAs. Some popular and recent exploits of FAs include Sony Playstations [Lu19], bitcoin wallets [bit22], Starlink User Terminal [att22], deep neural nets [HFK+19], and many more. The that FAs can be launched on such commercial products at very low cost makes them extremely potent threats.

While applicable to symmetric and public-key cryptosystems, FAs have seen significant progress for keyed symmetric-key primitives (e.g., block ciphers). This is attributed to the widespread applicability of such primitives, even in modern post-quantum schemes [HPP21b]. Therefore, protecting and testing symmetric-key cryptosystems for potential FA threats remains one of the most active research areas in hardware security.

Even though FAs in block ciphers are well-explored, developing protected implementations (even for well-known attacks) remains challenging. This is partly because FAs are often algorithm-specific. Secondly, FAs require logical abstraction of physical faults,
called fault models, to perform the attacks. In general, the attacks have to be discovered separately for each block-cipher algorithm and each fault model, which requires (mathematically intense) expertise and time. For instance, it took roughly 8 years (after the introduction of faults attacks) to find out the most optimal approach to attacking AES [TMA11]. While finding out a single attack instance is sufficient for an adversary, a defender has to find all of them. Such a process is extremely tedious and error-prone, and depends on the considered fault models. Research in this area has seen numerous failures, mainly for not considering proper fault models. For example, Statistical Ineffective Fault Analysis (SIFA) [DEG+18, DEK+18] in 2018 and Fault Template Attacks (FTA) in 2020 have rendered most of the existing FA countermeasures ineffective [SBR+20]. In summary, the interaction between a fault model and a cipher is often complex and cipher-specific, which could only be explored with manual effort to date.

Quite evidently, designing and especially certifying FA countermeasures is not something that can be performed manually. Given that the attacks are complex, the first step is to understand the exploitable fault space (and, therefore, the exploitable fault models) in an unprotected cipher algorithm. Then, the design and testing of the countermeasures should proceed based on the exploitable faults in the unprotected version. Also, in the end, one should verify whether or not the inclusion of countermeasures adds some vulnerability. Surprisingly, only a handful of work have addressed this problem to date. Existing tools in this regard aim to discover vulnerabilities in either unprotected or protected algorithms. However, most of them work on a given fault-list based on some well-known fault model (byte/bit). The main problem with this approach is that it can be highly specific to certain fault models and may eventually result in a false sense of security. In particular, there is no guarantee that if a fault model is unexploitable for one cipher, it will not be exploitable for the other one.

1.1 Our Goals and Contributions

This work aims to address the problem of automated exploitable fault model identification in a block cipher or its protected implementation. This bridges one of the major gaps in the automation efforts for fault analysis. In order to mimic human expertise in this regard, we propose using reinforcement learning (RL) combined with a t-test [SKP+19]. While ALAFA maybe effective in analyzing the leakage due to a fault, the identification of the effective fault space remains an open problem. We note that the proposed approach is based on simulation data, and therefore, easy to realize for any block cipher without spending much time behind formalization (this is clearly an advantage over developing a formal approach in this regard). The simplicity of a simulation-based approach also leaves the scope for integrating several implementation-based constraints, eventually leading to application-specific security guarantees. As a potential example, we demonstrate that all the known exploitable fault models for AES (including the target rounds) can be identified automatically by the RL agent. Finally, the RL-based framework scales for analyzing protected implementations without significant changes. We establish this by exploring vulnerabilities in an FA countermeasure. The major contributions of this work are as follows.

1. We bridge the gap in state-of-the-art FA automation by devising an automated fault-model discovery methodology.

2. To the best of our knowledge, for the first time, RL has been utilized in the context of FAs. We note that RL is an appropriate choice in this, given its exploration power through complex search spaces. We note that one of the major challenges in FA testing is the size and complexity of the search space, which can be efficiently explored with RL.
3. We present two distinct use cases: unprotected AES and one protected version of AES. The success of RL on two use cases establishes that FA testing for both protected and unprotected implementations is feasible under a unified framework.

2 Methodology

In this section, we formulate the intricacies of the fault space exploration problem as a Markov decision process and introduce its five critical components \((X, A, P, R, \gamma)\). \(X\) is the set of states. State \(s_t\) represents the current state of AES with injected faults. \(A\) is the set of actions. Action \(a_t\) is the bit location where RL selected to inject a fault according to policy \(\pi\). For State transition \(P\), we can identify the next state \(s_{t+1}\) in a deterministic manner by flagging the bits in the current state \(s_t\) according to action \(a_t\). Thus, the transition probability function reduces to a deterministic mapping \(P: S \times A \rightarrow S\). The reward function is \(r_{t+1} = R(x_t, a_t)\). Reward \(r_t\) relies on the t-test statistic (denoted as \(t\)), which is based on the current faulty state of AES. The t-test examines whether a faulty state is distinguishable from the uniform distribution [SMD18]. If t-test value is larger than a given threshold \(t_{th}\), \(r_t\) is 1, otherwise, it’s 0. Discount rate \(\gamma\), \(0 \leq \gamma \leq 1\), discounts future rewards to their present value.

State vector \(s_0\) is initialized to zeros. At time step \(t\), the RL agent makes the current action \(a_t\) of selecting \(i_{th}\) bit in AES state to inject a fault. This changes the \(i_{th}\) entry of next state vector \(s_{t+1}\) to be flagged as a 1. Once fault injection is completed, we collect 10,000 faulty ciphertexts and their correct ciphertexts and calculate the t-test value based on these faulty ciphertexts, followed by obtaining reward \(r_t\). In this way, the RL agent explores the fault space by taking actions and acquiring the corresponding reward. After certain interactions, the RL agent can obtain an optimal policy \(\pi^*\) in the end.

Figure 1 illustrates the reward recorded during the training of RL. As the training episodes increase, the RL agent learns to make a sequence of actions that favor the t-test statistic and finally converges to an optimal policy. We can get a t-test statistic of around

<table>
<thead>
<tr>
<th>Bit selected by RL</th>
<th>Location</th>
</tr>
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<tbody>
<tr>
<td>21, 23</td>
<td>Byte 2</td>
</tr>
<tr>
<td>60, 62, 63</td>
<td>Byte 7</td>
</tr>
<tr>
<td>66</td>
<td>Byte 8</td>
</tr>
</tbody>
</table>

Table 1: Bits selected by RL

Figure 2: Fault Induced in 8\(^{th}\) round of AES
267 for the discovered fault model. Table 1 lists the fault model derived according to the converged optimal policy, and Figure 2 depicts the fault model presenting in the 8th round of AES. This fault model is called the diagonal fault model, which was found by Saha et al. [SMC09]. Furthermore, the RL agent also discovers the bit fault model and byte fault model while exploring the fault space. This demonstrates that the RL agent can figure out all fault models researchers have discovered previously in the context of DFA of AES.

3 Experimental Results

3.1 Experiments Setup

We implement our work using Python 3.8.10 and conduct experiments on a 20.04 Ubuntu machine with an AMD 32-core 3.5GHz CPU processor and an NVIDIA A5000 24GB GPU. We select Proximal Policy Optimization [SWD+17] as our reinforcement learning algorithm. The custom RL environment and PPO algorithm were implemented based on the framework provided by Stable-Baselines3 and PyTorch1.6 packages. We employ vectorized environment in this package to compute multiple episodes of the RL pipeline in parallel, drastically reducing our training time. We set the parameter $t_{th}$ as 4.5.

3.2 Evaluation on AES block Cipher with Redundancy Countermeasure

We first evaluated the proposed framework on unprotected AES. Figure 3 shows the reward plot. It demonstrated that the proposed RL architecture could tackle an unprotected AES. We then investigated RL’s capability of fault space exploration on AES with one countermeasure in [SKP+19]. The countermeasure utilizes a redundant cipher computation creating two computational branches. The ciphertexts in these two branches are compared at the end of the computation. If they are different, the leakage can be observed by examining those ciphertexts. To evade this countermeasure, RL learned to inject the same set of faults sampled at those two computational branches automatically. The reward plot in Figure 3 demonstrates that our proposed framework can be extended to protected AES.

4 Conclusion

To the best of our knowledge, we report the first work in utilizing RL for fault space exploration in the context of FA of block cipher. Instead of relying on a human expert, our RL can achieve the same outcome by prior work but automatically. We demonstrated our proposed framework on two distinct use-cases: unprotected AES and AES with one countermeasure. This advancement can greatly reduce design effort for exploring effective fault space for FA of block cipher.
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References


