The More You Know: Improving Laser Fault Injection with Prior Knowledge

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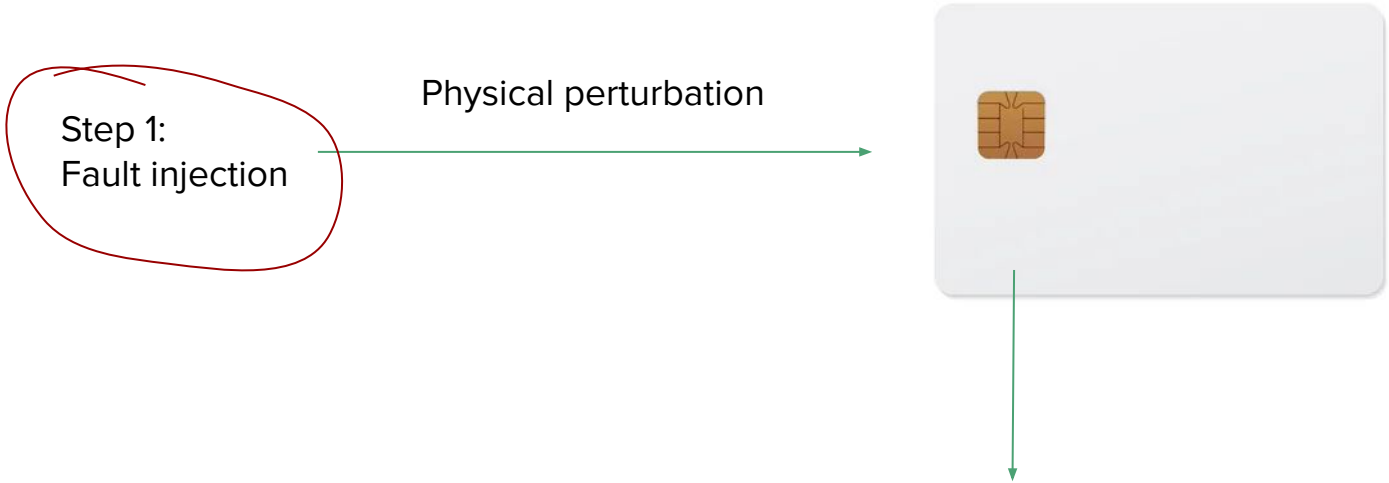
Fault Injection (FI) attacks

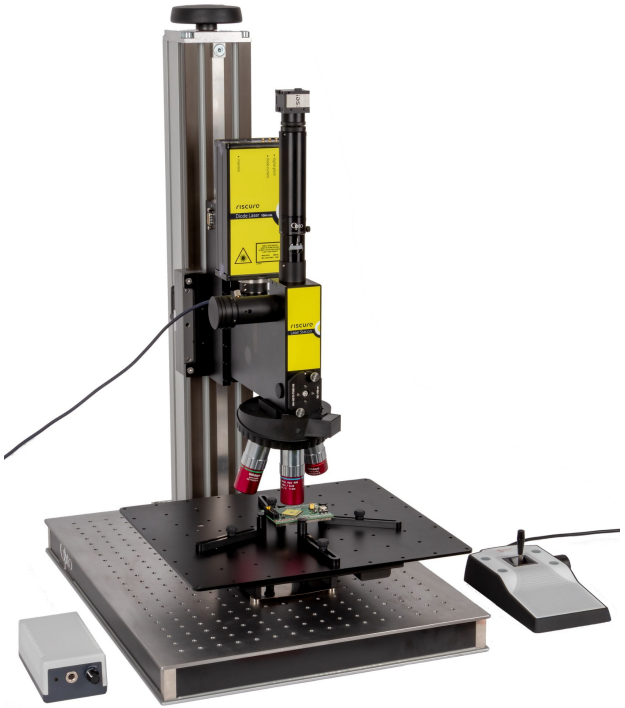


Laser Fault Injection (LFI)

Parameters

Location on the device: x, y

Laser pulse width, delay and intensity



LFI: 529 days with ≈ 0.15 seconds per point (parameter combination)

EMFI*: exhaustive search 29 203 years to conduct with ≈ 0.16 seconds per point (parameter combination)

* Maldini, Antun, et al. "Genetic algorithm-based electromagnetic fault injection." *2018 Workshop on Fault Diagnosis and Tolerance in Cryptography (FDTC)*. IEEE, 2018.

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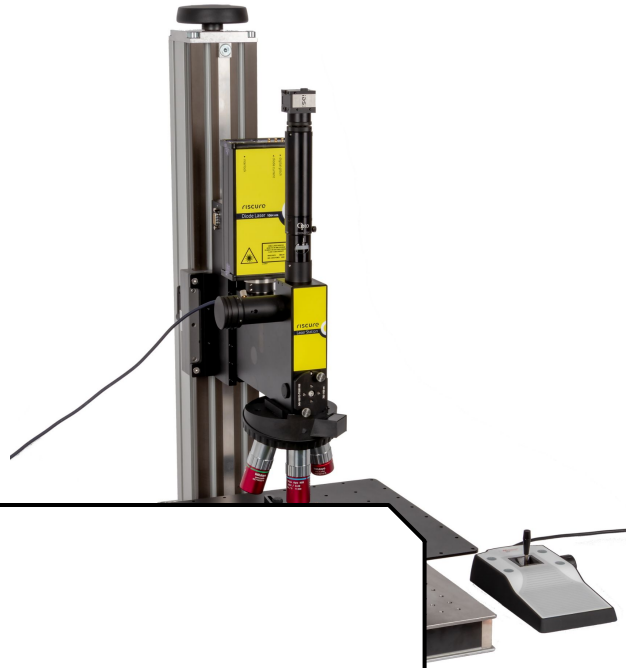

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EM
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Issue! Large search space

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Algorithms for FI parameter search

Grid search and Random search

Evolutionary approach - memetic algorithms

Reinforcement learning

Hyperparameter tuning - Successive Halving Algorithm

- Carpi, Rafael Boix, et al. "Glitch it if you can: parameter search strategies for successful fault injection." *International Conference on Smart Card Research and Advanced Applications*. Springer, Cham, 2013.
- Maldini, Antun, et al. "Genetic algorithm-based electromagnetic fault injection." *2018 Workshop on Fault Diagnosis and Tolerance in Cryptography (FDTC)*. IEEE, 2018.
- Krček, Marina, Daniele Fronte, and Stjepan Picek. "On the Importance of Initial Solutions Selection in Fault Injection." *2021 Workshop on Fault Detection and Tolerance in Cryptography (FDTC)*. IEEE, 2021.
- Moradi, Mehrdad, et al. "Exploring fault parameter space using reinforcement learning-based fault injection." *2020 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W)*. IEEE, 2020.
- Werner, Vincent, Laurent Maingault, and Marie-Laure Potet. "Fast Calibration of Fault Injection Equipment with Hyperparameter Optimization Techniques." *International Conference on Smart Card Research and Advanced Applications*. Springer, Cham, 2021.

Algorithms for FI parameter search

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Issue! Any change with the FI setup or sample's behavior - the process has to be repeated anew

- Carpi, ...ranced *Applica*
- Maldin... 018.
- Krček, ...rance in *Crypto*...
- Moradi, Mehrdad, et al. "Exploring fault parameter space using reinforcement learning-based fault injection." *2020 50th Annual IEEE/IFIP International Conference on Dependable Systems and Networks Workshops (DSN-W)*. IEEE, 2020.
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Proposed method

Improve performance when a change is introduced

Decision tree (DT) to learn the behavior/responses of the target

Prior knowledge

Combination with **Memetic Algorithm (MA)**

Existing algorithm

- Initial population uses the knowledge
- Other operators remain unchanged

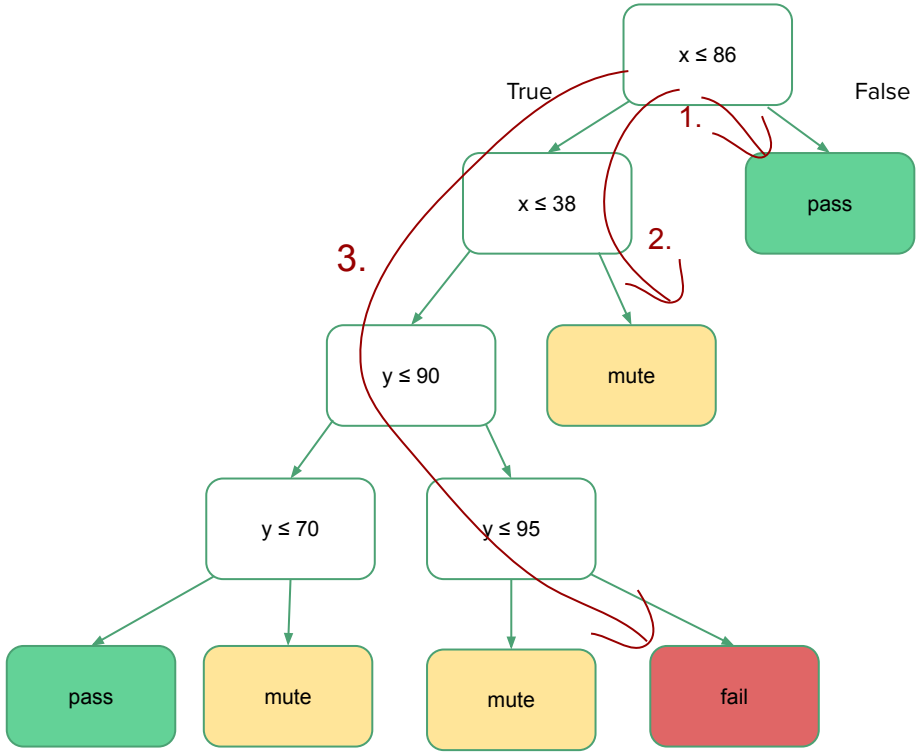
Use on **different samples of the same target**

Decision Tree (DT)

if-then rules:

1. if $x > 86$ then *pass*
2. if $x \in \langle 38, 86]$ then *mute*
3. if $x \leq 38$ *and* $y > 95$ then *fail*
4. ...

CART* algorithm



* Breiman, Leo, et al. *Classification and regression trees*. Routledge, 2017.

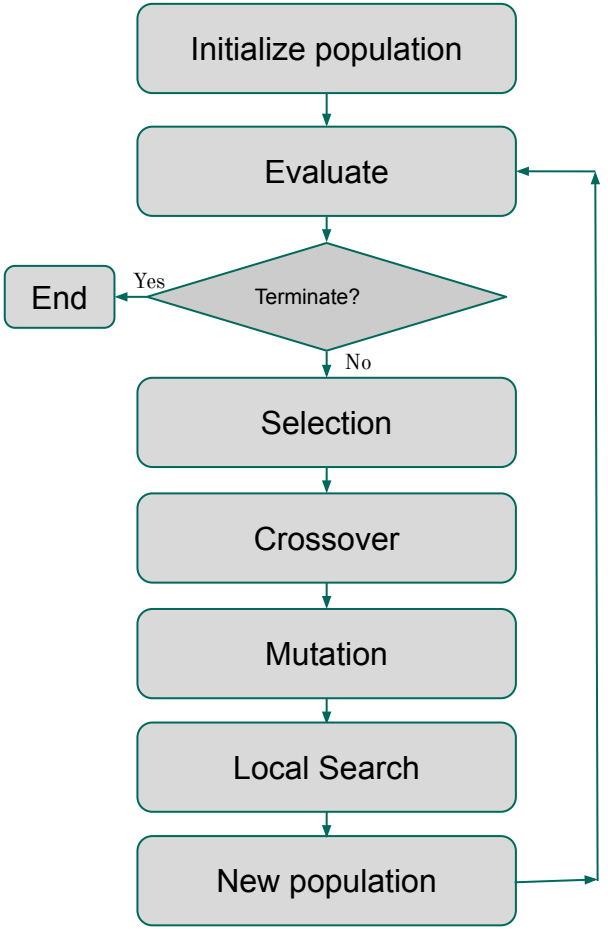
Memetic Algorithm (MA)

Solutions in the population are LFI parameters:

x, y, delay, laser pulse width and intensity

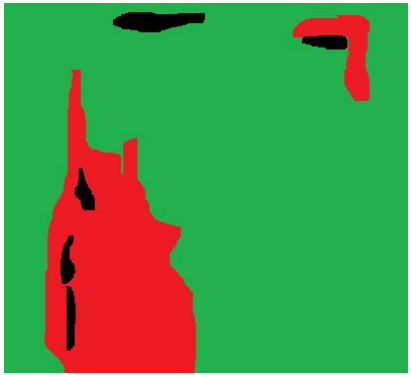
Population of size n

x_1, y_1, d_1, pw_1, i_1	f_1
x_2, y_2, d_2, pw_2, i_2	f_2
...	...
x_n, y_n, d_n, pw_n, i_n	f_n



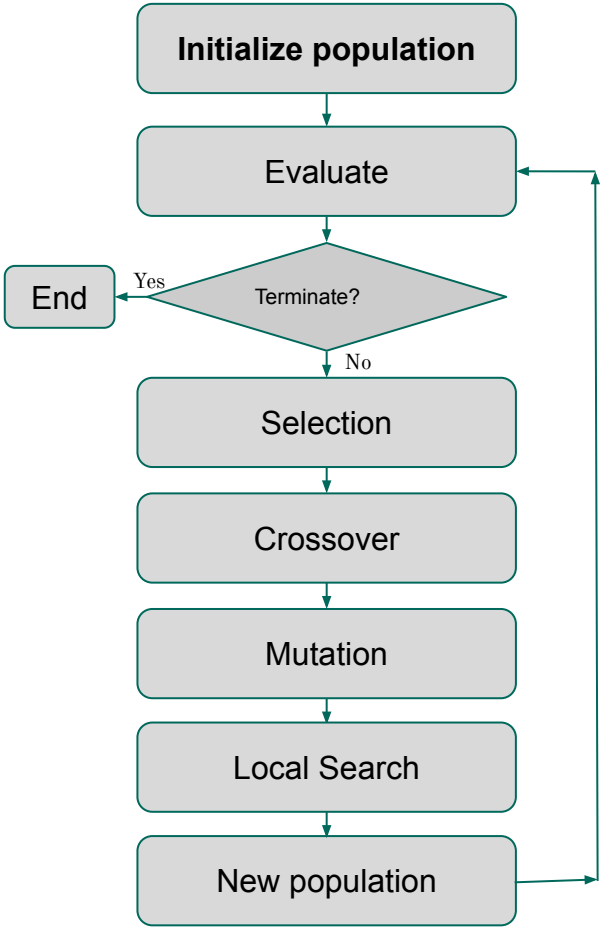
Krček, Marina, Daniele Fronte, and Stjepan Picek. "On the Importance of Initial Solutions Selection in Fault Injection." *2021 Workshop on Fault Detection and Tolerance in Cryptography (FDTC)*. IEEE, 2021.

Combining DT rules with MA



Rules for *fail*

1. $x \in \langle x_1, x_2] \; and \; y \in \langle y_1, y_2]$
2. $i \in \langle i_1, i_{max}]$
3. ...



Device under test

Target: STMicroelectronics product - confidential, 40nm technology

Test program: loading a data word from the non-volatile memory (NVM) into a register

Fault classes: *fail*, *mute*, *pass*, *changing*

Limited bounds for parameters:

305 017 650 possible parameter combinations

exhaustive would take ≃ 529 days where one laser shot takes ≃ 0.15 seconds

Experimental Setup

Different samples of the same target - IC1, IC2, IC3

- Changes in the focus: IC3 > IC1 > IC2
- FGS: 3.7 times more *fails* with IC3 then IC1
- RS: 2.7 times more *fails* with IC3 then IC1
- Both have more than IC2 with the worst focus

Fast Grid Search (FGS)	IC1	IC2	IC3
Tested parameters	12 350	12 350	12 350
fail	9 (0.07%)	0 (0%)	33 (0.27%)

Random Search (RS)	IC1	IC2	IC3
Tested parameters	5 920	5 920	5 920
fail	7 (0.12%)	3 (0.05%)	19 (0.32%)

Training data on IC1

880 DT models with different hyperparameters

On both datasets separately

Select the models based on the F1-score

	MA with random init. (10 runs)	Random Search (1 run)
Tested combinations	6 150.5	50 000
fail	366.5 (6.12%)	58 (0.12%)
changing	548.6 (8.92%)	451 (0.9%)
mute	182.6 (2.89%)	226 (0.45%)
pass	5 052.8 (82.08%)	49 265 (98.53%)

More examples for *fail* class!

Experiments on IC2

MA with random initialization: similar to IC1 results (more than FGS and RS results)

MA with DT found more fails: ≃ 61 % (64%, 55%, 52%, 72%) more

	RS	MA with random init.	MA with DT F1: 0.1776 MA data	MA with DT F1: 0.0999 MA data	MA with DT F1: 0.1999 RS data	MA with DT F1: 0.1756 RS data
Tested combinations	5920	6389.6	5059.3	5284.2	5581.3	5507.9
fail	3 (0.05%)	304.7 (5.03%)	848.4 (16.86%)	676.5 (12.48%)	633 (11.38%)	**1072.7 (19.39%)**
changing	27 (0.46%)	250 (3.88%)	234.6 (4.61%)	216.9 (4.11%)	160.2 (2.89%)	198.7 (3.6%)
mute	12 (0.2%)	147.9 (2.28%)	37.3 (0.74%)	81.7 (1.53%)	16 (0.29%)	33 (0.58%)
pass	5878 (99.29%)	5687 (88.82%)	3939 (77.79%)	4309.1 (81.51%)	4772.1 (85.44%)	4203.5 (76.43%)

Experiments on IC3

Two orders of magnitude more *fails* compared to RS

	RS	MA with DT F1: 0.1776 MA data	MA with DT F1: 0.0833 MA data	MA with DT F1: 0.1756 RS data
Tested combinations	5920	5262.7	5495.1	5554.5
fail	19 (0.32%)	1662.8 (31.53%)	**2688.8 (48.85%)**	2325.7 (41.83%)
changing	66 (1.11%)	221.9 (4.23%)	210.1 (3.81%)	153.4 (2.76%)
mute	99 (1.67%)	126 (2.37%)	74.1 (1.35%)	101.5 (1.82%)
pass	5736 (96.89%)	3252 (61.86%)	2522.1 (45.98%)	2973.9 (53.58%)

Highest F1-score did not lead to the best overall results

Rules from MA data were more specific and resulted in more *fails* in initial population

Conclusions and future work

DT rules improve the MA for FI parameter search on different samples of the same target

Number of *fail* responses found:

- Two orders of magnitude more than random search
- Up to 60% more than memetic algorithm with random initialization

Future work

- Extend the idea to manage other transferability cases, e.g., different bench or target