

Physical Security of Code-based Cryptosystems based on the Syndrome Decoding Problem

Séminaire Creach Labs “Sécurité des composants” 2023

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**LABORATOIRE
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Context

2016 NIST called for proposals for **post-quantum cryptography** algorithms

2017 Round 1: 69 candidates,

2019 Round 2: 26 candidates,

2020 Round 3: 7 finalists (+8 alternate).

2022 **Round 4**

- Selected: CRYSTALS-KYBER
- Candidates: BIKE, **Classic McEliece** [1], HQC and ~~SIKE~~.

Research challenges

- *“More hardware implementations”*
- *“Side-channel attacks”*
- *“Side-channel resistant implementations”*

Dustin Moody (NIST), PKC 2022

[1] M. R. Albrecht, D. J. Bernstein, T. Chou, et al. **Classic McEliece: conservative code-based cryptography: cryptosystem specification**. Tech. rep. National Institute of Standards and Technology, 2022.

Classic McEliece

Classic McEliece is a **Key Encapsulation Mechanism**, based on the **Niederreiter cryptosystem** [2].

- $\text{KeyGen}() \rightarrow (\mathbf{H}_{\text{pub}}, k_{\text{priv}})$
- $\text{Encap}(\mathbf{H}_{\text{pub}}) \rightarrow (\mathbf{s}, k_{\text{session}})$
- $\text{Decap}(\mathbf{s}, k_{\text{priv}}) \rightarrow (k_{\text{session}})$

The Encapsulation procedure establishes a **shared secret**.

- $\text{Encap}(\mathbf{H}_{\text{pub}}) \rightarrow (\mathbf{s}, k_{\text{session}})$

Generate a random vector $\mathbf{e} \in \mathbb{F}_2^n$ of Hamming weight t

Compute $\mathbf{s} = \mathbf{H}_{\text{pub}}\mathbf{e}$

Compute the hash: $k_{\text{session}} = H(1, \mathbf{e}, \mathbf{s})$

[2] H. Niederreiter. "Knapsack-Type Cryptosystems and Algebraic Coding Theory". In: **Problems of Control and Information Theory** 15.2 (1986), pp. 159–166.

The security of the Niederreiter cryptosystem relies on the **syndrome decoding problem**.

Syndrome decoding problem

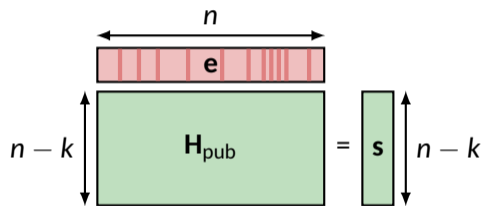
Input: a binary matrix $\mathbf{H} \in \mathbb{F}_2^{(n-k) \times n}$
a binary vector $\mathbf{s} \in \mathbb{F}_2^{n-k}$
a scalar $t \in \mathbb{N}^+$

Output: a binary vector $\mathbf{x} \in \mathbb{F}_2^n$ with a Hamming weight $\text{HW}_2(\mathbf{x}) \leq t$ such that : $\mathbf{H}\mathbf{x} = \mathbf{s}$

Known to be a **hard** problem [3].

[3] E. R. Berlekamp, R. J. McEliece, and H. C. A. van Tilborg. "On the inherent intractability of certain coding problems (Corresp.)". In: *IEEE Transactions on Information Theory* 24.3 (1978), pp. 384–386.

Classic McEliece parameters



n	k	$(n - k)$	t
3488	2720	768	64
4608	3360	1248	96
6688	5024	1664	128
6960	5413	1547	119
8192	6528	1664	128

The public key H_{pub} is **huge!** Up to 1.7 MB.

Hardware implementations

Implementations on embedded systems are now feasible : [4] [5] [6]

Reference hardware target : Arm[®] Cortex[®]-M4

Several **strategies** to store the (very large) keys :

- Streaming the public key from somewhere else,
- Use a structured code,
- Use a very large microcontroller.

New threats

That makes them vulnerable to **physical attacks** (fault injection & side-channel analysis)

[4] S. Heyse. “Low-Reiter: Niederreiter Encryption Scheme for Embedded Microcontrollers”. In: **International Workshop on Post-Quantum Cryptography**. Vol. 6061. Darmstadt, Germany: Springer, May 2010, pp. 165–181.

[5] J. Roth, E. G. Karatsiolis, and J. Krämer. “Classic McEliece Implementation with Low Memory Footprint”. In: **CARDIS**. vol. 12609. Virtual Event: Springer, Nov. 2020, pp. 34–49.

[6] M. Chen and T. Chou. “Classic McEliece on the ARM Cortex-M4”. In: **IACR TCHES 2021.3** (2021), pp. 125–148.

A “modified” syndrome decoding problem

Binary syndrome decoding problem (Binary SDP)

Input: a binary matrix $\mathbf{H} \in \mathbb{F}_2^{(n-k) \times n}$
a binary vector $\mathbf{s} \in \mathbb{F}_2^{n-k}$
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Syndrome decoding problem

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\mathbb{N} syndrome decoding problem (\mathbb{N} -SDP)

Input: a binary matrix $\mathbf{H} \in \{0, 1\}^{(n-k) \times n}$
a ~~binary~~ vector $\mathbf{s} \in \mathbb{N}^{n-k}$
a scalar $t \in \mathbb{N}^+$

Output: a binary vector $\mathbf{x} \in \{0, 1\}^n$ with a Hamming weight $\text{HW}(\mathbf{x}) \leq t$ such that : $\mathbf{H}\mathbf{x} = \mathbf{s}$

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\mathbb{N} syndrome decoding problem (\mathbb{N} -SDP)

Input: a binary matrix $\mathbf{H} \in \{0, 1\}^{(n-k) \times n}$
a ~~binary~~ vector $\mathbf{s} \in \mathbb{N}^{n-k}$ ← How do we get this integer syndrome?
a scalar $t \in \mathbb{N}^+$

Output: a binary vector $\mathbf{x} \in \{0, 1\}^n$ with a Hamming weight $\text{HW}(\mathbf{x}) \leq t$ such that : $\mathbf{H}\mathbf{x} = \mathbf{s}$

Physical attack #1: Fault injection

Syndrome computation

We target the **syndrome computation**: $\mathbf{s} = \mathbf{H}_{\text{pub}} \mathbf{e}$

Matrix-vector multiplication performed over \mathbb{F}_2

Algorithm Schoolbook matrix-vector multiplication over \mathbb{F}_2

```
1: function MAT_VEC_MULT_SCHOOLBOOK(matrix, vector)
2:   for row  $\leftarrow$  0 to  $n - k - 1$  do
3:     syndrome[row] = 0 ▷ Initialisation
4:   for row  $\leftarrow$  0 to  $n - k - 1$  do
5:     for col  $\leftarrow$  0 to  $n - 1$  do
6:       syndrome[row]  $\hat{=}$  matrix[row][col] & vector[col] ▷ Multiplication and addition
7:   return syndrome
```

Laser fault injection attack on the schoolbook matrix-vector multiplication

Targeting the XOR operation, considering the Thumb instruction set.

bits	15	14	13	12	11	10	9	8	7	6	5	4	3	2	1	0
EORS: $Rd = Rm \oplus Rn$	0	1	0	0	0	0	0	0	0	1	Rm		Rdn			
EORS: $R1 = R0 \oplus R1$	0	1	0	0	0	0	0	0	0	1	0	0	0	0	0	1

Laser fault injection in flash memory : **mono-bit, bit-set fault model** [7].

[7] A. Menu, J.-M. Dutertre, J.-B. Rigaud, et al. "Single-bit Laser Fault Model in NOR Flash Memories: Analysis and Exploitation". In: **FDTC**. Milan, Italy: IEEE, Sept. 2020, pp. 41-48.

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Laser fault injection in flash memory : **mono-bit, bit-set fault model** [7].

ADCS: $R1 = R0 + R1$	0	1	0	0	0	0	0	1	0	1	0	0	0	0	0	1
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Outcome: switching from \mathbb{F}_2 to \mathbb{N}

The exclusive-OR (addition over \mathbb{F}_2) is turned into an **addition with carry** (addition over \mathbb{N})

[7] A. Menu, J.-M. Dutertre, J.-B. Rigaud, et al. "Single-bit Laser Fault Model in NOR Flash Memories: Analysis and Exploitation". In: **FDTC**. Milan, Italy: IEEE, Sept. 2020, pp. 41-48.

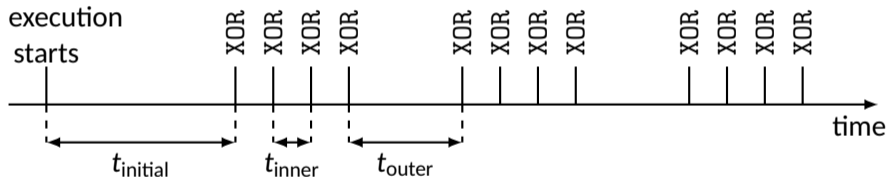
Multiple faults

Three independent delays must be tuned to fault the full matrix-vector multiplication:

t_{initial} : **initial** delay before the multiplication starts

t_{inner} : delay in the **inner** for loop

t_{outer} : delay in the **outer** for loop



Outcome

After $n \cdot (n - k)$ faults, we get a **faulty syndrome** $\mathbf{s} \in \mathbb{N}^{n-k}$ [8]

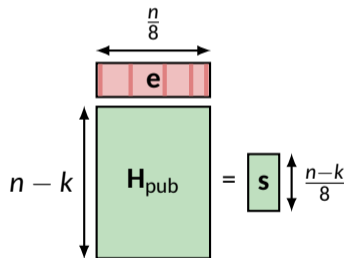
[8] P.-L. Cayrel, B. Colombari, V. Dragoi, et al. "Message-Recovery Laser Fault Injection Attack on the Classic McEliece Cryptosystem". In: **EUROCRYPT**. vol. 12697. Zagreb, Croatia: Springer, Oct. 2021, pp. 438–467

Packed matrix-vector multiplication

Objection: the schoolbook matrix-vector multiplication algorithm is **highly inefficient!**
Each **machine word** stores only **one bit**: a **lot** of memory is wasted.

Algorithm Packed matrix-vector multiplication

```
1: function Mat_vec_mult_packed(matrix, vector)
2:   for row  $\leftarrow$  0 to  $((n - k)/8 - 1)$  do
3:     syndrome[row] = 0                                 $\triangleright$  Initialisation
4:   for row  $\leftarrow$  0 to  $(n - k - 1)$  do
5:     b = 0
6:     for col  $\leftarrow$  0 to  $(n/8 - 1)$  do
7:       b ^= matrix[row][col] & vector[col]
8:       b ^= b >> 4
9:       b ^= b >> 2                                 $\triangleright$  Exclusive-OR folding
10:      b ^= b >> 1
11:      b &= 1                                        $\triangleright$  LSB extraction
12:      syndrome[row/8] |= b << (row % 8)           $\triangleright$  Packing
13:   return syn
```



Physical attack #2: Side-channel analysis

Side-channel analysis to obtain the integer syndrome

Algorithm Packed matrix-vector multiplication

```
1: ...  
2: for col  $\leftarrow$  0 to  $(n/8 - 1)$  do  
3:   b ^= matrix[row][col] & vector[col]  
4: ...
```

b = 00000000

b = 00000000

b = 0000**1**000

b = 0000**1**000

b = 0000**1010**

Side-channel analysis to obtain the integer syndrome

Algorithm Packed matrix-vector multiplication

```
1: ...  
2: for col  $\leftarrow$  0 to  $(n/8 - 1)$  do  
3:   b ^= matrix[row][col] & vector[col]  
4: ...
```

HD = 0	b = 00000000	HW=0
HD = 1	b = 00000000	HW=0
HD = 0	b = 0000 1 000	HW=1
HD = 1	b = 0000 1 000	HW=1
HD = 1	b = 0000 1 0 1 0	HW=2

Side-channel analysis to obtain the integer syndrome

Algorithm Packed matrix-vector multiplication

```
1: ...  
2: for col ← 0 to (n/8 - 1) do  
3:   b ^ = matrix[row][col] & vector[col]  
4: ...
```

HD = 0	⌋	b = 00000000	HW=0
		b = 00000000	HW=0
HD = 1	⌋	b = 00001000	HW=1
		b = 00001000	HW=1
HD = 0	⌋	b = 00001000	HW=1
		b = 00001010	HW=2

Integer syndrome from Hamming distances or Hamming weights

$$s_j = \sum_{i=1}^{\frac{n}{8}-1} \text{HD}(\mathbf{b}_{j,i}, \mathbf{b}_{j,i-1})$$
$$= \sum_{i=1}^{\frac{n}{8}-1} | \text{HW}(\mathbf{b}_{j,i}) - \text{HW}(\mathbf{b}_{j,i-1}) | \text{ if } \text{HD}(\mathbf{b}_{j,i}, \mathbf{b}_{j,i-1}) \leq 1$$

HD = 2	⌋	b = 00001000	HW=1
		b = 00000100	HW=1

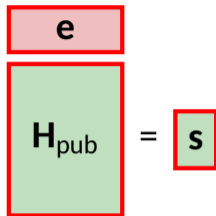
Happens if:

$\text{HW}(\text{mat}[r][c] \& \text{vec}[c]) > 1$

Unlikely, since $\text{HW}(\mathbf{e}) = t$ is low.

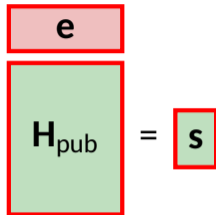
Side-channel analysis for Hamming weight recovery

$$\mathbf{s} = \mathbf{H}_{\text{pub}} \mathbf{e}$$



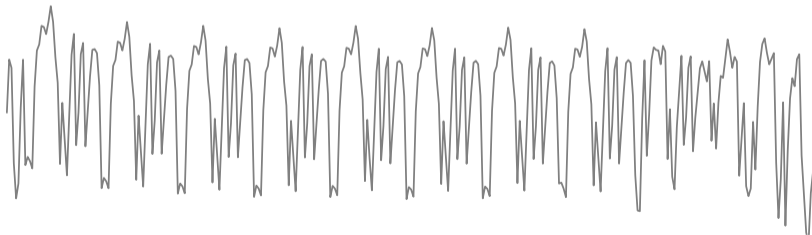
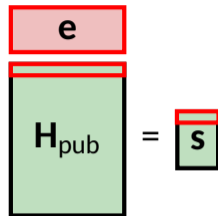
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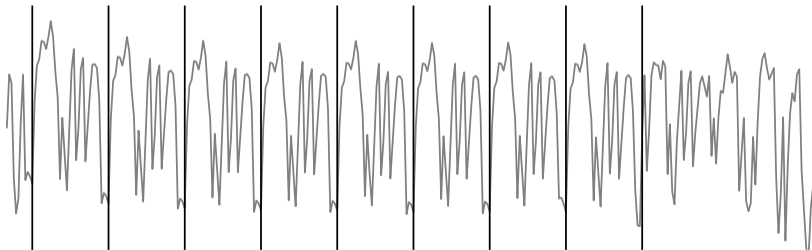
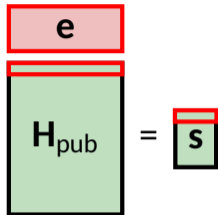
Side-channel analysis for Hamming weight recovery

$$s_j = H_{pub[j,]} e$$



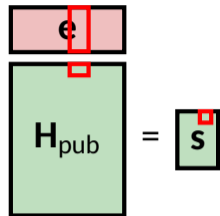
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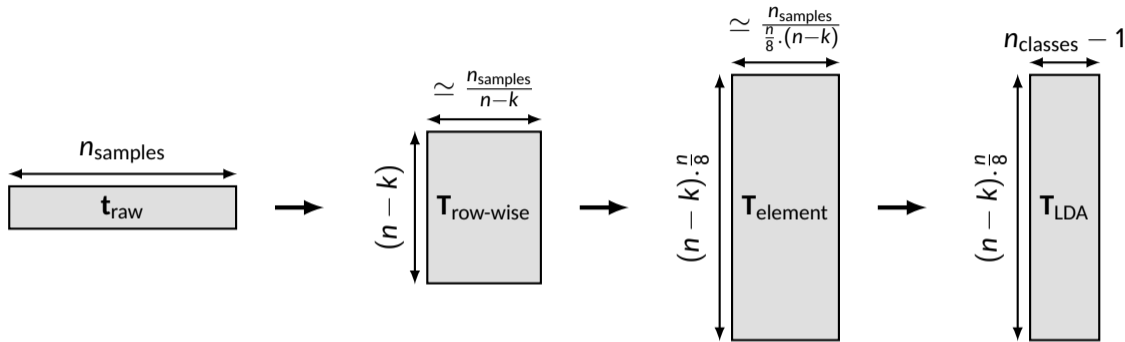


Side-channel analysis for Hamming weight recovery

$$\hat{b} = \mathbf{H}_{pub_{[j,i]}} \mathbf{e}_i$$



Trace(s) reshaping process



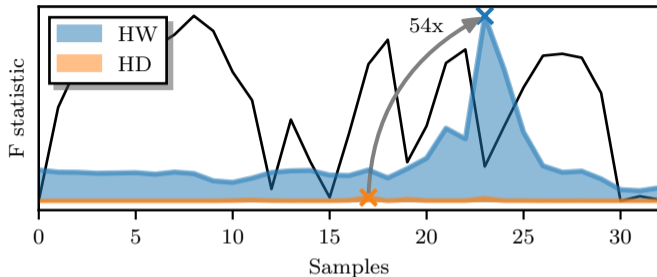
Training phase

- Linear Discriminant Analysis (LDA) for **dimensionality reduction**,
- From a **single** trace, we get $(n-k) \times \frac{n}{8}$ **training samples** $n = 8192 \rightarrow$ more than 1.7×10^6
- Fed to a **single** Random Forest classifier (`sklearn.ensemble.RandomForestClassifier`)

Random Forest classifier

Random Forest classifier training:

- Hamming weight:
 - $> 99.5\%$ test accuracy,
- Hamming distance:
 - $\approx 80\%$ test accuracy.



Outcome

- We can recover the **Hamming weight** very accurately,
- but **not the Hamming distance**...
- We can compute a *slightly inaccurate* integer syndrome. [9]

[9] B. Colombier, V. Dragoi, P. Cayrel, et al. "Profiled Side-Channel Attack on Cryptosystems Based on the Binary Syndrome Decoding Problem". In: **IEEE TIFS** 17 (2022), pp. 3407–3420

Exploiting the integer syndrome

Exploiting the integer syndrome

Option 1: Consider $\mathbf{H}_{\text{pub}}\mathbf{e} = \mathbf{s}$ as an **optimization problem** and solve it.

\mathbb{N} syndrome decoding problem (\mathbb{N} -SDP)

Input: a matrix $\mathbf{H}_{\text{pub}} \in \mathcal{M}_{n-k,n}(\mathbb{N})$ with $h_{i,j} \in \{0, 1\}$ for all i, j
a vector $\mathbf{s} \in \mathbb{N}^{n-k}$
a scalar $t \in \mathbb{N}^+$

Output: a vector \mathbf{e} in \mathbb{N}^n with $x_i \in \{0, 1\}$ for all i
and with a Hamming weight $\text{HW}(\mathbf{x}) \leq t$ such that : $\mathbf{H}_{\text{pub}}\mathbf{e} = \mathbf{s}$

ILP problem

Let $\mathbf{b} \in \mathbb{N}^n$, $\mathbf{c} \in \mathbb{N}^m$ and $\mathbf{A} \in \mathcal{M}_{m,n}(\mathbb{N})$

We have the following optimization problem:

$$\min\{\mathbf{b}^T \mathbf{x} \mid \mathbf{A}\mathbf{x} = \mathbf{c}, \mathbf{x} \in \mathbb{N}^n, \mathbf{x} \geq 0\}$$

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Can be solved by **integer linear programming**.

With `Scipy.optimize.linprog`:

➤ $n = 8192 : \approx 5 \text{ min} \dots$

Does not handle errors in \mathbf{s} well...

Exploiting the integer syndrome

Option 2 (*Quantitative Group Testing* [10]): which columns of \mathbf{H}_{pub} “contributed” to the syndrome.

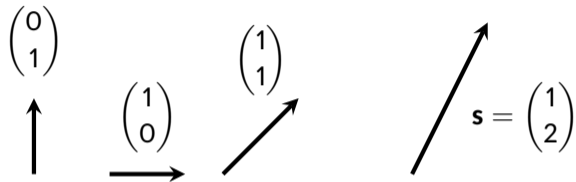
[10] U. Feige and A. Lellouche. “Quantitative Group Testing and the rank of random matrices”. In: **CoRR** abs/2006.09074 (2020). arXiv: 2006.09074.

Exploiting the integer syndrome

Option 2 (*Quantitative Group Testing* [10]): which columns of \mathbf{H}_{pub} “contributed” to the syndrome.

Example: $t = 2 = \text{HW}(\mathbf{e})$

$$\mathbf{H}_{\text{pub}} \mathbf{e} = \begin{pmatrix} 0 & 1 & 1 \\ 1 & 0 & 1 \end{pmatrix} \cdot \mathbf{e} = \begin{pmatrix} 1 \\ 2 \end{pmatrix}$$



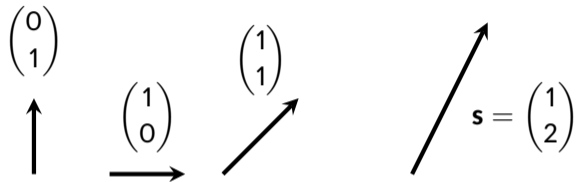
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Score function

The dot product can be used to compute a “score” for every column:

$$\psi(i) = \mathbf{H}_{\text{pub}[i]} \cdot \mathbf{s} + \bar{\mathbf{H}}_{\text{pub}[i]} \cdot \bar{\mathbf{s}} \quad \text{with } \bar{\mathbf{H}} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \end{pmatrix} \quad \text{and } \bar{\mathbf{s}} = \begin{pmatrix} 1 \\ 0 \end{pmatrix}$$

➤ $\psi(0) = 1 \times 0 + 2 \times 1 + 1 \times 1 + 0 \times 0 = 3$

➤ $\psi(1) = 1$

➤ $\psi(2) = 3$

[10] U. Feige and A. Lellouche. “Quantitative Group Testing and the rank of random matrices”. In: *CoRR* abs/2006.09074 (2020). arXiv: 2006.09074.

Score function : advantages

The **score** of the columns of \mathbf{H}_{pub} identifies which columns were **involved** in the computation.

From that we can derive the support of the secret vector \mathbf{e} .

Computational complexity

- Computing the dot product of two vectors is **very fast**,
- Overall cost for all columns of \mathbf{H}_{pub} : $\mathcal{O}((n - k) \times n) = \mathcal{O}(n^2)$
- $n = 8192 : \approx 0.2 \text{ s}$

Conclusion

Evaluation of post-quantum cryptography algorithms is a long process.

Work is needed in the following areas:

- Efficient implementations,
- Physical security of implementations,
- Protected implementations.

Bring together mathematicians, computer scientists, electrical engineers: SESAM team at LabHC.