

# Generalization of the Ball-Collision Algorithm

**Violetta Weger**

joint work with Carmelo Interlando, Karan  
Khathuria, Nicole Rohrer and Joachim Rosenthal

University of Zurich



**University of  
Zurich<sup>UZH</sup>**

**SIAM AG 19**

**11 July 2019**

- 1 Motivation
- 2 Introduction
- 3 Prange's Algorithm
- 4 Improvements overview
- 5 Ball-collision Algorithm
- 6 New directions
- 7 Comparison of Complexities
- 8 Open questions

## Proposing a code-based cryptosystem

- Structural Attacks
- Nonstructural Attacks

Have to consider Information Set Decoding (ISD)

## Proposing a code-based cryptosystem

- Structural Attacks
- Nonstructural Attacks

**Have to consider Information Set Decoding (ISD)**

1978 Berlekamp, McEliece and van Tilborg: Decoding a random linear code is NP-complete

## Problem (Syndrome decoding problem)

*Given a parity check matrix  $H$  of a (binary) code of length  $n$  and dimension  $k$  and a syndrome  $s$ :*

$$s = Hx^\top \in \mathbb{F}_2^{n-k}$$

*and the error correction capacity  $t$ , we want to find  $e \in \mathbb{F}_2^n$  of weight  $t$  such that*

$$s = He^\top.$$

# ISD algorithms and syndrome decoding problem

- Syndrome decoding problem is equivalent to the decoding problem and

## Problem (Decoding problem)

*Given a generator matrix  $G$  of a (binary) code of length  $n$  and dimension  $k$  and a corrupted codeword  $c$ :*

$$c = mG + e \in \mathbb{F}_2^n$$

*and the error correction capacity  $t$ , we want to find  $e \in \mathbb{F}_2^n$  of weight  $t$ .*

- equivalent to finding a minimum weight codeword, since in  $\mathcal{C} + \{0, c\}$  the error vector  $e$  is now the minimum weight codeword.

## Notation

Let  $c \in \mathbb{F}_q^n$  and  $A \in \mathbb{F}_q^{k \times n}$ , let  $S \subset \{1, \dots, n\}$ , then we denote by  $c_S$  the restriction of  $c$  to the entries indexed by  $S$  and by  $A_S$  the columns of  $A$  indexed by  $S$ . For a code  $\mathcal{C} \subset \mathbb{F}_q^n$ , we denote by

$$\mathcal{C}_S = \{c_S \mid c \in \mathcal{C}\}.$$

## Definition (Informationset)

Let  $\mathcal{C} \subset \mathbb{F}_q^n$  be a code of dimension  $k$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that

$$|\mathcal{C}| = |\mathcal{C}_I|,$$

then we call  $I$  an information set of  $\mathcal{C}$ .

## Notation

Let  $c \in \mathbb{F}_q^n$  and  $A \in \mathbb{F}_q^{k \times n}$ , let  $S \subset \{1, \dots, n\}$ , then we denote by  $c_S$  the restriction of  $c$  to the entries indexed by  $S$  and by  $A_S$  the columns of  $A$  indexed by  $S$ . For a code  $\mathcal{C} \subset \mathbb{F}_q^n$ , we denote by

$$\mathcal{C}_S = \{c_S \mid c \in \mathcal{C}\}.$$

## Definition (Informationset)

Let  $\mathcal{C} \subset \mathbb{F}_q^n$  be a code of dimension  $k$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that

$$|\mathcal{C}| = |\mathcal{C}_I|,$$

then we call  $I$  an information set of  $\mathcal{C}$ .



## Definition (Informationset)

*Let  $G$  be the  $k \times n$  generator matrix of  $\mathcal{C}$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that  $G_I$  is invertible, then  $I$  is an informationset of  $\mathcal{C}$ .*

## Definition (Informationset)

*Let  $H$  be the  $n - k \times n$  parity check matrix of  $\mathcal{C}$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that  $H_{I^c}$  is invertible, then  $I$  is an informationset of  $\mathcal{C}$ .*

## Definition (Informationset)

*Let  $G$  be the  $k \times n$  generator matrix of  $\mathcal{C}$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that  $G_I$  is invertible, then  $I$  is an informationset of  $\mathcal{C}$ .*

## Definition (Informationset)

*Let  $H$  be the  $(n - k) \times n$  parity check matrix of  $\mathcal{C}$ . If  $I \subset \{1, \dots, n\}$  of size  $k$  is such that  $H_{I^c}$  is invertible, then  $I$  is an informationset of  $\mathcal{C}$ .*

1962 Prange proposes the first ISD algorithm.

Assumption: All  $t$  errors occur outside of the information set.

Input:  $H \in \mathbb{F}_2^{n-k \times n}$ ,  $s \in \mathbb{F}_2^{n-k}$ ,  $t \in \mathbb{N}$

Output:  $e \in \mathbb{F}_2^n$ ,  $wt(e) = t$  and  $He^T = s$ .

- 1 Choose an information set  $I \subset \{1, \dots, n\}$  of size  $k$ .
- 2 Find an invertible matrix  $U \in \mathbb{F}_2^{n-k \times n-k}$  such that  $(UH)_I = A$  and  $(UH)_{I^c} = \text{Id}_{n-k}$ .
- 3 If  $wt(Us) = t$ , then  $e_I = 0$  and  $e_{I^c} = Us$ .
- 4 Else start over.

- 1 Choose an information set  $I \subset \{1, \dots, n\}$  of size  $k$ .

Let us assume for simplicity that  $I = \{1, \dots, k\}$ .

# Prange's algorithm

- 1 Choose an information set  $I \subset \{1, \dots, n\}$  of size  $k$ .
- 2 Find an invertible matrix  $U \in \mathbb{F}_2^{n-k \times n-k}$  such that  $(UH)_I = A$  and  $(UH)_{I^c} = \text{Id}_{n-k}$ .

Let us assume for simplicity that  $I = \{1, \dots, k\}$ .

$$UH = (A \quad \text{Id}_{n-k}),$$

hence

$$UHe^\top = (A \quad \text{Id}_{n-k}) \begin{pmatrix} 0 \\ e_{I^c} \end{pmatrix} = Us.$$

# Prange's algorithm

- 1 Choose an information set  $I \subset \{1, \dots, n\}$  of size  $k$ .
- 2 Find an invertible matrix  $U \in \mathbb{F}_2^{n-k \times n-k}$  such that  $(UH)_I = A$  and  $(UH)_{I^c} = \text{Id}_{n-k}$ .
- 3 If  $wt(Us) = t$ , then  $e_I = 0$  and  $e_{I^c} = Us$ .

Let us assume for simplicity that  $I = \{1, \dots, k\}$ .

$$UH = \begin{pmatrix} A & \text{Id}_{n-k} \end{pmatrix},$$

hence

$$UHe^T = \begin{pmatrix} A & \text{Id}_{n-k} \end{pmatrix} \begin{pmatrix} 0 \\ e_{I^c} \end{pmatrix} = Us.$$

From which we get the condition  $e_{I^c} = Us$ .

The cost of an ISD algorithm is given by the product of

- the cost of one iteration,
- inverted success probability = average number of iterations needed.

The success probability is given by the weight distribution of the error vector.

Example (Success probability of Prange's algorithm)

$$\binom{n-k}{t} \binom{n}{t}^{-1}.$$

The cost of an ISD algorithm is given by the product of

- the cost of one iteration,
- inverted success probability = average number of iterations needed.

The success probability is given by the weight distribution of the error vector.

Example (Success probability of Prange's algorithm)

$$\binom{n-k}{t} \binom{n}{t}^{-1}.$$



The cost of an ISD algorithm is given by the product of

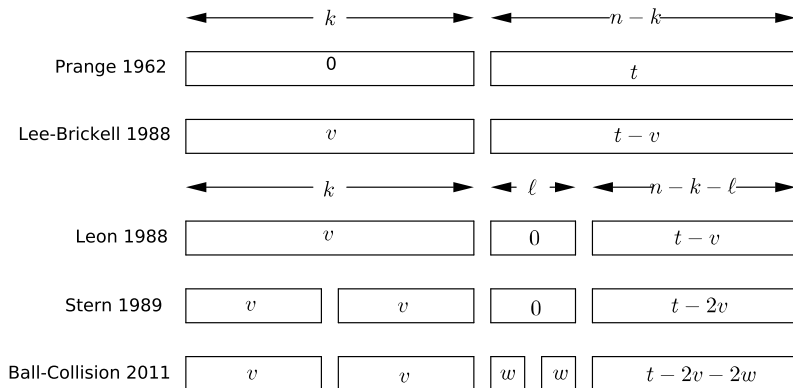
- the cost of one iteration,
- inverted success probability = average number of iterations needed.

The success probability is given by the weight distribution of the error vector.

Example (Success probability of Prange's algorithm)

$$\binom{n-k}{t} \binom{n}{t}^{-1}.$$

# Improvements Overview



# Ball-collision Algorithm

---

**Algorithm 1** Ball-collision over  $\mathbb{F}_q$

---

Input: The  $(n - k) \times n$  parity check matrix  $H$ , the syndrome  $s \in \mathbb{F}_q^{n-k}$  and the positive integers  $p_1, p_2, q_1, q_2, k_1, k_2, \ell_1, \ell_2 \in \mathbb{Z}$ , such that  $k = k_1 + k_2$ ,  $p_i \leq k_i$ ,  $q_i \leq \ell_i$  and  $t - p_1 - p_2 - q_1 - q_2 \leq n - k - \ell_1 - \ell_2$ .

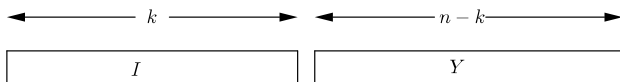
Output:  $e \in \mathbb{F}_q^n$  with  $He^T = s$  and  $w(e) = t$ .

- 1: Choose an information set  $I \subseteq \{1, \dots, n\}$  of  $H$  of size  $k$ .
  - 2: Partition  $I$  into two disjoint subsets  $X_1$  and  $X_2$  of size  $k_1$  and  $k_2 = k - k_1$  respectively.
  - 3: Partition  $Y = \{1, \dots, n\} \setminus I$  into disjoint subsets  $Y_1$  of size  $\ell_1$ ,  $Y_2$  of size  $\ell_2$  and  $Y_3$  of size  $\ell_3 = n - k - \ell_1 - \ell_2$ .
  - 4: Find an invertible matrix  $U \in \mathbb{F}_q^{(n-k) \times (n-k)}$ , such that  $(UH)_Y = \text{Id}_{n-k}$  and  $(UH)_I = \begin{bmatrix} A_1 \\ A_2 \end{bmatrix}$ , where  $A_1 \in \mathbb{F}_q^{(\ell_1 + \ell_2) \times k}$  and  $A_2 \in \mathbb{F}_q^{\ell_3 \times k}$ .
  - 5: Compute  $Us = \begin{bmatrix} s_1 \\ s_2 \end{bmatrix}$ , where  $s_1 \in \mathbb{F}_q^{\ell_1 + \ell_2}$  and  $s_2 \in \mathbb{F}_q^{\ell_3}$ .
  - 6: Compute  $S = \{(A_1(\pi_I(x_1)) + \pi_{Y_1 \cup Y_2}(y_1), x_1, y_1) \mid x_1 \in \mathbb{F}_q^n(X_1), wt(x_1) = v_1, y_1 \in \mathbb{F}_q^n(Y_1), wt(y_1) = w_1\}$ ,
  - 7: Compute  $T = \{(-A_1(\pi_I(x_2)) + s_1 - \pi_{Y_1 \cup Y_2}(y_2), x_2, y_2) \mid x_2 \in \mathbb{F}_q^n(X_2), wt(x_2) = v_2, y_2 \in \mathbb{F}_q^n(Y_2), wt(y_2) = w_2\}$ .
  - 8: **for**  $(v, x_1, y_1) \in S$  **do**
  - 9:     **for**  $(v, x_2, y_2) \in T$  **do**
  - 10:         **if**  $w(-A_2(\pi_I(x_1 + x_2)) + s_2) = t - p_1 - p_2 - q_1 - q_2$  **then**  
           Output:  $e = x_1 + x_2 + y_1 + y_2 + \sigma_{Y_3}(-A_2(\pi_I(x_1 + x_2)) + s_2)$
  - 11:         **else** go to Step 1 and choose new information set  $I$ .
-

# Ball-collision Algorithm

- 1 Choose an information set  $I$ .

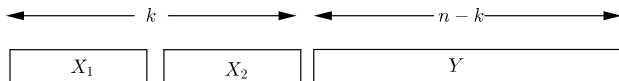
Let us assume for simplicity that  $I = \{1, \dots, k\}$ .



# Ball-collision Algorithm

- 1 Choose an information set  $I$ .
- 2 Partition  $I$  into  $X_1$  and  $X_2$ .

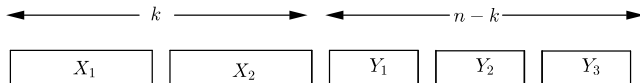
Let us assume for simplicity that  $I = \{1, \dots, k\}$ .



# Ball-collision Algorithm

- 1 Choose an information set  $I$ .
- 2 Partition  $I$  into  $X_1$  and  $X_2$ .
- 3 Partition  $Y$  into  $Y_1, Y_2, Y_3$ .

Let us assume for simplicity that  $I = \{1, \dots, k\}$ .



# Ball-collision Algorithm

- 1 Choose an information set  $I$ .
- 2 Partition  $I$  into  $X_1$  and  $X_2$ .
- 3 Partition  $Y$  into  $Y_1, Y_2, Y_3$ .
- 4 Bring  $H$  in systematic form.

$$UHe^T = \begin{pmatrix} A_1 & \text{Id}_{\ell_1+\ell_2} & 0 \\ A_2 & 0 & \text{Id}_{\ell_3} \end{pmatrix} \begin{pmatrix} e_1 \\ e_2 \\ e_3 \end{pmatrix} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = Us.$$

We get the conditions

$$A_1 e_1 + e_2 = s_1,$$

$$A_2 e_1 + e_3 = s_2.$$

# Ball-collision Algorithm

- 1 Choose an information set  $I$ .
- 2 Partition  $I$  into  $X_1$  and  $X_2$ .
- 3 Partition  $Y$  into  $Y_1, Y_2, Y_3$ .
- 4 Bring  $H$  in systematic form.

$$UHe^T = \begin{pmatrix} A_1 & \text{Id}_{\ell_1+\ell_2} & 0 \\ A_2 & 0 & \text{Id}_{\ell_3} \end{pmatrix} \begin{pmatrix} e_1 \\ e_2 \\ e_3 \end{pmatrix} = \begin{pmatrix} s_1 \\ s_2 \end{pmatrix} = Us.$$

We get the conditions

$$A_1e_1 + e_2 = s_1,$$

$$A_2e_1 + e_3 = s_2.$$



Conditions:

$$A_1 e_1 + e_2 = s_1,$$

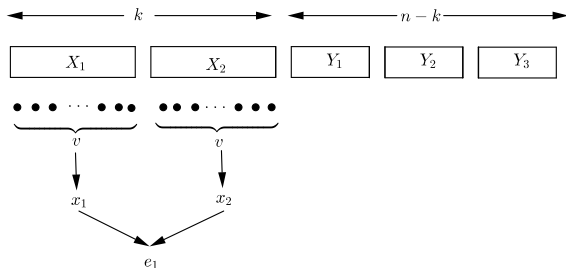
$$A_2 e_1 + e_3 = s_2.$$

Assumptions:

- a  $e_1$  has support in  $I = X_1 \cup X_2$  and weight  $2v$
- b  $e_2$  has support in  $Y_1 \cup Y_2$  and weight  $2w$
- c  $e_3$  has support in  $Y_3$  and weight  $t - 2v - 2w$

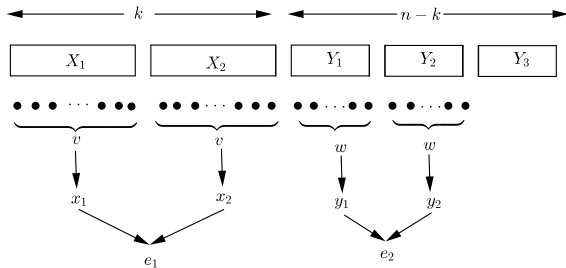
# Ball-collision Algorithm

a  $e_1$  has support in  $I = X_1 \cup X_2$  and weight  $2v$



# Ball-collision Algorithm

- a  $e_1$  has support in  $I = X_1 \cup X_2$  and weight  $2v$
- b  $e_2$  has support in  $Y_1 \cup Y_2$  and weight  $2w$



$$A_1 e_1 + e_2 = s_1, \quad (1)$$

$$A_2 e_1 + e_3 = s_2. \quad (2)$$

For condition (1):

go through all choices of  $e_1$  and  $e_2$  and check with collision if (1) is satisfied.

For condition (2):

define  $e_3 = s_2 - A_2 e_1$  and check if  $e_3$  has weight  $t - 2v - 2w$ .

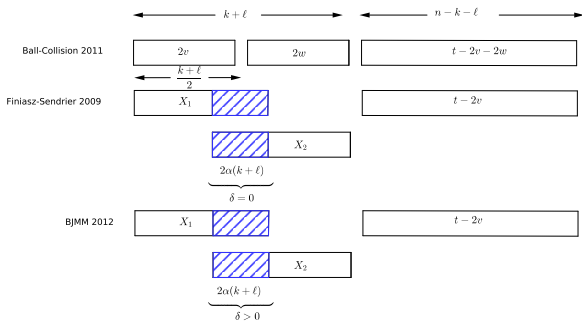
Success probability:

$$\binom{\lfloor k/2 \rfloor}{v} \binom{\lceil k/2 \rceil}{v} \binom{\lfloor \ell/2 \rfloor}{w} \binom{\lceil \ell/2 \rceil}{w} \binom{n-k-\ell}{n-2v-2w} \binom{n}{t}^{-1}.$$

Idea of overlapping sets:

2009 Finiasz and Sendrier:  $X_1$  and  $X_2$  can overlap

2012 Becker, Joux, May and Meurer: can add redundant errors in the overlap



# New directions

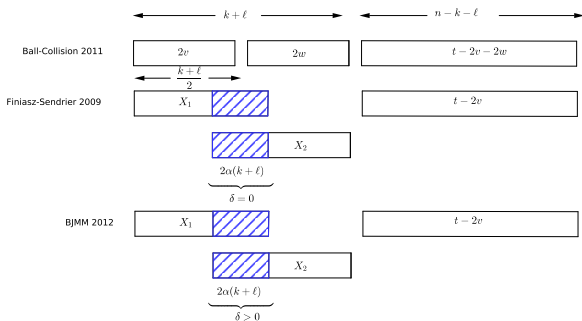
New parameters:

$\alpha$  overlap-ratio

$\delta$  amount of redundant errors

2009 Finiasz and Sendrier:  $\alpha = 1/2, \delta = 0$

2012 BJMM:  $\alpha = 1/2, \delta > 0$



# Comparison of Complexities

Let  $F(q, R)$  be the exponent of the optimized asymptotic complexity. The asymptotic complexity of half-distance decoding at rate  $R$  over  $\mathbb{F}_q$  is then given by  $q^{F(q,R)n+o(n)}$ .

$q$	$q$ -Stern	$q$ -Stern-MO	$q$ -Ball-collision	$q$ -BJMM-MO
2	0.05563	0.05498	0.055573	0.04730
3	0.05217	0.05242	0.052145	0.04427
4	0.04987	0.05032	0.049846	0.04294
5	0.04815	0.04864	0.048140	0.03955
7	0.04571	0.04614	0.045697	0.03706
8	0.04478	0.04519	0.044770	0.03593
11	0.04266	0.04299	0.042656	0.03335



# Comparison of Complexities

If preferred in base 2: The asymptotic complexity of half-distance decoding at rate  $R$  over  $\mathbb{F}_q$  is then given by  $2^{F(q,R)n+o(n)}$ .

$q$	$q$ -Stern	$q$ -Stern-MO	$q$ -Ball-collision	$q$ -BJMM-MO
2	0.05563	0.05498	0.055573	0.04730
3	0.08269	0.08308	0.082648	0.07017
4	0.09974	0.10064	0.099692	0.08588
5	0.11180	0.11294	0.111778	0.09183
7	0.12832	0.12953	0.128288	0.10404
8	0.13434	0.13557	0.13431	0.10779
11	0.14758	0.14872	0.147566	0.11537

- Is partitioning into more sets giving us better asymptotic complexities?
  - With new code-based cryptographic schemes, e.g. using rank-metric codes, can we adapt these ideas to these metrics?
  - Or if we know that in a certain metric ISD algorithms are difficult then, they could be interesting for code-based cryptography?
- 
- Can we use some structure, e.g. of cyclic codes, to improve the ISD algorithms in these cases?

- Is partitioning into more sets giving us better asymptotic complexities?
- With new code-based cryptographic schemes, e.g. using rank-metric codes, can we adapt these ideas to these metrics?
- Or if we know that in a certain metric ISD algorithms are difficult then, they could be interesting for code-based cryptography? **some self advertisement:**  
*Horlemann-Trautmann and Weger: Information Set Decoding in the Lee Metric with Applications to Cryptography*
- Can we use some structure, e.g. of cyclic codes, to improve the ISD algorithms in these cases? **solved by Tillich and Canto-Torres: Speeding up decoding a code with a non-trivial automorphism group up to an exponential factor**

Thank you!