# Non-interactive inner products in privacy-preserving biometric identification using secure multiparty computation

## Intro

Inner products are fundamental operation in privacy-preserving applications. In addition to this paper, which focus on LWE implementation based on (Couteau & Zarezadeh, Non-Interactive Secure Computation of Inner-Product from LPN and LWE, 2023), my submission for the "Secure and Private Computing" 3 ECTS course at HSG also includes a presentation about biometric identification, a presentation about the status of the code and various reviews on other papers that were presented by peers.

## Protocol Description

Here some questions and answers to understand the protocol which will be implemented. Please note that all pictures in this chapter are from slides from (Couteau, Geoffroycouteau, 2022) and the explanations are founded on (Couteau, Youtube, 2022).

1. What does the protocol do?

The protocol is used to exchange shares of vectors among different parties. Assuming there are two parties, Bob and Alice, each holding a vector, x1 and x4. Then this protocol can be used to securely exchange shares of the locally computed vector encoding.

A diagram of different people

Description automatically generated with medium confidenceA diagram of a person's face

Description automatically generated

1. How does the protocol work?

The exact working of the protocol is quite complex. It is based on alekhnovich’s key exchange (AKE). In AKE there is natively an inner product calculation. Does this allow to embed an inner product computation of x1 and x4 onto AKE? Yes! Inner product computation plus some noise term e. That is exactly how the protocol works. A secure inner product computation is done on top of AKE which itself is also an inner product computation. Support of homomorphic property!

A diagram of a complex equation

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Its correctness can be proved by looking at AKE. It is t2/n << 1 (t refers to the Hamming weight). In MPC, correctness errors translate to leakage when a “detectable” error occurs. Still secure but of course with a loss. But when using LWE then the error is negligible. That is why LWE is used.

A screenshot of a computer

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1. Where can such a protocol be used?

It can for example be used to exchange securely fingerprint, iris scans, any other biometric data or in general secured data. Another example would be authentication from a user to a server.

A black and white symbols

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1. How can it be used for biometric identification?

By combining LWE with MPC, biometric identification can be performed in a way that respects the privacy and security of the individual's sensitive biometric data, while still allowing for accurate and secure comparisons.

1. What advantage does the protocol provide (over other protocols) for biometric identification?

It provides post quantum security. It is very efficient. The error tolerance makes the protocol more robust. Ahead of time, each party can publish the shares. That makes the protocol more efficient.

## Non-Interactive Key Exchange

Works between n parties. Each party broadcasts its public key pkn. When two parties decide to communicate among each other, they get (by calculating one) a shared private key K. Let’s make an example how two parties (Alice and Bob) can get a shared private key K:

The great thing about this interaction pattern is that it avoids n2 pairwise key exchange among all the parties.

## Non-interactive secure computing

It would be nice if there exist a pattern to securely exchange encodings. Works between n parties. Parties are broadcasting an encoding of their input:

Two parties can than compute and from their own state plus the other party’s encoding.

This interaction pattern avoids as above n2 pairwise key exchange among all the parties.

## Non-interactive multi party computation (MPC)

The goal of the implementation is to do non-interactive MPC for shares of inner products. So instead of encoding some xi or xj, shares of are calculated.

Parameters throughout the paper

|  |  |
| --- | --- |
| Security parameter |  |
| Upper case letters denote matrices |  |
| Bold lower-case letters denote row vectors |  |
| Transpose on row vectors denote column vectors |  |
| Horizontal concatenation of horizontal vectors |  |
| Vertical concatenation of vertical vectors |  |
| x is uniformly sampled from the set X |  |
| Finite set S uniform distribution is denoted by |  |
| Bernoulli distribution with parameter |  |

Example

means that the random variable evaluates to 1 with probability and to 0 with probability . More generally, denotes the distribution that outputs a uniformly random element of with probability , and 0 otherwise.

According to (Couteau & Zarezadeh, Non-Interactive Secure Computation of Inner-Product from LPN and LWE, 2023) in section 3, there exists a “general non-interactive protocol for securely computing the inner product between two vectors over , with correctness error (independent of the value of the inputs).”The great thing is that the protocol can either be instantiated under LPN (learning parity with noise, the error will be noticeable but arbitrary small) or under the LWE (learning with errors, the error can be made negligible) assumption.

But what data is been used? The tutors provided two a .npy arrays with shape 13’232x128 (data) and 13’232x1 (labels). After having quickly looked at the arrays and with some research done, it turns out that the data must be LFW (labeled faces in the wild). The LFW dataset contains 13,233 images of faces collected from the web. This dataset consists of the 5749 identities with 1680 people with two or more images.[[1]](#footnote-1)

### Implementation

Implementation is done according to (Couteau & Zarezadeh, Non-Interactive Secure Computation of Inner-Product from LPN and LWE, 2023) in section 3.3 (non-interactive inner product from LWE) as described in Figure 1. A white background with black text

Description automatically generated

Figure 1: LWE-based non-interactive inner-product

So the first step is to implement the setup method. The output will be .

|  |  |  |
| --- | --- | --- |
| Description | Parameter | Value |
| Generator matrix of linear code |  | 512x384 |
| Dimension (eg. row dimension of u |  | 128 |
| Dimension |  | 4n |
| Dimension |  | 2n |
| Dimension |  | 2^15 |
| Dimension |  | 2^14 |

Setup is normally done by an trusted party but here it is done in directly in the code. Dimension of is . So an matrix with the dimension 512x384

In two further steps, encode and decode are implemented. Plese refer directly to the code. Please note that some matrices had to be padded with zeros or random values according to the describtion of the algorithms in Figure 1.

### Validation 1

So the next step will be to apply the encode and decode algorithms accordingly.

A math equations and formulas

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Figure 2: Application of Encode and Decode

Alright lets say we have two parties, X and Y. Now calucaltion of pkx, skx, pky and sky is performed with Encode function.

We want to validate if . If so, we are done!

### Validation 2

Another possible way to validate according to (Couteau & Zarezadeh, Non-Interactive Secure Computation of Inner-Product from LPN and LWE, 2023) from page 9:

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Figure 3: Validation as in LPN (Learning Parity with Noise)

## Further Reading

Please note that the distances are either Euclidean or Hamming distance calculations. According to (Couteau & Zarezadeh, Non-Interactive Secure Computation of Inner-Product from LPN and LWE, 2023) computing the Hamming distance between two vectors x and y is where HW denotes the Hamming weight.

1. https://paperswithcode.com/dataset/lfw [↑](#footnote-ref-1)