One Picture is Worth a Thousand Words:
A New Wallet Recovery Process

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Abstract—We introduce a new wallet recovery process. Our solution associates 1) visual passwords: a photograph of a secretly picked object (Chabanne et al., 2013) with 2) ImageNet classifiers transforming images into binary vectors and, 3) obfuscated fuzzy matching (Galbraith and Zobernig, 2019) for the storage of visual passwords/retrieval of wallet seeds. Our experiments show that the replacement of long seed phrases by a photograph is possible.

Index Terms—Cryptographic Obfuscation, Imagenet Classifier, Application of Machine Learning to Cryptocurrency Wallets

I. INTRODUCTION

Cryptocurrency wallets store private keys and make use of them for performing transactions among blockchains. Their loss is identified in [14] as one of the three challenges associated to Bitcoin. Today, they mainly rely on a seed phrase for their recovery [27]. In 2021, the New York Times reported [1] that “20 percent of the existing 18.5 million Bitcoin or around 3.7 million BTCs appear to be lost due to forgotten passwords”.

To alleviate the burden of remembering this long password, we alternatively rely on the concept of visual passwords introduced in 2013 by Chabanne et al. [11].

The underlying principle of visual passwords is, in the context of authentication, the following:

• At the registration step, you choose an object and take a photograph of it. Your choice has to remain secret.
• When you want to authenticate yourself, you take another photograph of the same object for a comparison image vs image with the reference.

While [11] focuses on a single type of object: Hamiltonian circuits among a cube, with a design enabling many possible configurations; to ensure a good entropy, we here let the users choose among a great variety of different objects.

A special care is taken to the storage of references. We apply the work of Galbraith and Zobernig [17] to perform Hamming ball membership determining in an obfuscated way whether a binary vector lies close to a predetermined center.

Our main contribution is the introduction of a novel wallet recovery system. Moreover, we show its feasibility by our experiments transforming visual passwords by state of the art image processing algorithms into suitable binary vectors, called templates in the following, for secure storage/seed retrieval.

The rest of the paper is organized as follows: in Sec. II we recall the techniques and security properties of obfuscated Hamming distance comparisons and show how to deliver a payload in case of a matching. In Sec. III, we describe how to transform visual password pictures into binary vector templates thanks to deep learning algorithms. In Sec. IV, we report our experiments. Sec. V details our proposal. Sec. VI concludes.

A. Related Works

For a general introduction to wallets in the context of Bitcoin; see, for instance, chapter 4 of [24].

While there are numerous other attempts to replace passwords using graphical interfaces and images [8], visual passwords [11] share a lot with biometric recognition. For instance, we are using in Sec. IV the same tools to evaluate the accuracy of our proposal, namely:

• The False Acceptance Rate (FAR) measures the proportion of times an imposter can fool the system. FAR is directly related to the security level.
• On the opposite, the user’s convenience is gauged thanks to the False Reject Rate (FRR) which corresponds to genuine attempts dismissed.

As one cannot win both at the same time with FAR and FRR, the Detection Error Tradeoff (DET) curve which represents false rejection rate vs. false acceptance rate comes into consideration for determining the Equal Error Rate (EER) of the system where FAR and FRR are equal.

Major differences however differentiate biometrics and visual passwords. Biometrics are public and immutably linked to a person while visual passwords are secret and easy to renew. For instance, biometrics need liveness anti-spoofing countermeasures to thwart impersonation attacks and depending on their application, privacy enhancing technologies are necessary too.

Fuzzy matching has already been considered in the context of biometrics, around the notion of secure sketch introduced in [15]. Here the matching is realized thanks to
an underlying error correcting code. As indicated in [17], parameters of secure sketch are thus “strongly constrained by the need for an efficient decoding algorithm”. Moreover, when it comes to their implementation with real (biometric) data, their security is questionable [30], in particular regarding their reusability.

Cryptographic techniques such as a secret sharing mechanism [22] or multi-signature techniques [19] can also be envisaged for cryptocurrency wallets. Another solution [28] relies on a Diffie-Hellman exchange between hardware wallets with a human visual verification to thwart man-in-the-middle attacks.

II. OBSCURACATED FUZZY HAMMING DISTANCE MATCHING

In this section, we show how to store our reference binary vector templates in a way that enables Hamming distance comparisons while preserving their confidentiality. I.e. we retrieve the wallet’s seed when and only when a fresh template close to the reference is entered. For that, we make use of cryptographic obfuscation.

Obfuscation makes programs unintelligible while preserving their functionality. General obfuscation techniques are either impossible [7] or, despite major progress [21], ineffective. In 2014, [6] defines practical input-hiding obfuscation techniques for evasive functions including point functions “x == e”, which return 1 when the input is equal to a predetermined constant e and 0 otherwise.

Example 1: [35] describes how to obfuscate variable comparisons “ax + b == y” where a, b are two k-bits constants. Let H stand for a preimage-resistant hash function with n-bits outputs, n > k. Choose at random \( t \in \{0,1\}^{n-k} \) and \( r \in \{0,1\}^k \). Let \( h = H(r || t) \) and \( u = r + b \). Values \( a, u, h \) are published. The obfuscated program then checks

\[
H(ax + u - y || t) = h
\]

while keeping the value \( b \) hidden. Note that when \( (1) \) is verified by inputs \( (x, y, b) \), \( b \) can be retrieved as \( b = y - ax \).

Relying on a number-theoretic computational assumption called the Modular Subset Product (MSP) problem (see Fig. 1), [17] defines a Hamming distance obfuscator which checks whether an \( n \)-bits binary vector \( x \) is within Hamming distance \( r \) of a predetermined \( e \) for

\[
r \leq \frac{n}{2} - \sqrt{\log(2)n\lambda}
\]

where \( \lambda \) is a security parameter.

A vector \( c = (c_1, \ldots, c_n) \in \{0,1\}^n \) is encoded as

\[
\text{ENCODE}(c) = ((p_i)_{i=1,\ldots,n}, q, C)
\]

where

- \( C = \prod_{i=1}^{n} p_i^{c_i} \mod q \);
- \( (p_i)_{i=1,\ldots,n} \) are small distinct primes taken at random for each encoding;
- \( q \) is a small safe prime verifying \( \prod_{i \in I} q/2 < \) for all \( I \subset 1, \ldots, n \) with cardinality \(|I| < r\). Typically, \( q \sim (n \log n)^r \).

This encoding procedure keeps the vector \( c \) hidden when

\[
r > \log(2\sqrt{2\pi}e) \frac{n}{\log(n\log(n))}
\]

A procedure \( \text{DECODE} \) is then defined s.t.

\[
\text{DECODE}((p_i)_{i=1,\ldots,n}, q, C, x) = e \quad \text{for each vector } x \text{ which stands at Hamming distance } d(c,x) < r. \text{ This procedure returns } \perp \text{ for } x \text{ s.t. } d(c,x) \geq r \text{ except when a false acceptance occurs. Note that, when } r \text{ satisfies } (4), \text{ this false acceptance cannot happen, see Sec. IV-C and [17] for details.}

The obfuscated program with embedded data \((p_i)_{i=1,\ldots,n}, q, C\) is executed as follows for an input \( x \):

\[
\begin{align*}
1_1: \ c' &= \text{DECODE}((p_i)_{i=1,\ldots,n}, q, C, x) \\
1_2: \text{ If } c' = \perp \text{ Return } \perp \\
1_3: \text{ Return the obfuscated point function comparison to } c
\end{align*}
\]

In [17], the last line \( 1_3 \) eliminates false acceptances. Using the notations introduced in Example 1, write now \( c = \chi_1 || \chi_2 \) with \( n = 2k \), i.e. split the \( n \)-bits binary vector \( c \) in two parts and convert them into the integers \( \chi_i, i = 1, 2 \); and for \( b \) at random, let \( a\chi_1 + b = \chi_2 \). In our proposal, we replace \( 1_3 \) by:

\[
1_3': \text{ If } (1) \text{ stands for inputs } \chi_1 || \chi_2 = c' \text{ Return } b = \chi_2 - a\chi_1; \text{ else Return } \perp
\]

enabling us to retrieve the payload \( b \) when successful.

We then obtain the \( \text{RETRIEVESEED} \) program comprised of the three lines: \( 1_1, 1_2, 1_3' \).

III. PICTURES PROCESSING

In this section, we describe our choices for transforming photographs of visual passwords into binary vector templates. Our experiments are reported in the next section.

A. Templates Construction

Consider the architecture of an ImageNet classifier as in Fig. 2. It takes as an input an image from which its features are extracted thanks to a Convolutional Neural Network (CNN) to eventually output a classification. Similarly to the idea used in Face Recognition algorithms, the underlying representation is a good candidate feature for object recognition even if the objects were not in the training dataset. Consequently, in a first step, we remove the last classification layers to just keep floating point vectors of the internal representation. Finally, we binarize these vectors to obtain our templates.
B. Model Choice

We choose a model trained (with its parameters) among https://paperswithcode.com/sota/image-classification-on-imagenet. After different trials (see Annex A), we pick VGG-16 [31] as the underlying model to classify images. This leads to vectors with 4096 floating-point coordinates. To reduce the dimension to only 512 bits, we apply Locality Sensitive Hashing (LSH) [20]. For this, we generate a random sparse matrix of shape (4096, 512) thanks to the Scikit library: https://scikit-learn.org/stable/. We then multiply the generated matrix by the original coordinates. Lastly, we only keep the signs of the resulting vector elements so as to turn the floating values into binary ones. At the end, our overall architecture is similar to the perceptual hashing algorithm NeuralHash [2].

IV. Experiments

A. Test Dataset

To validate our experiments, we use the Amsterdam Library of Object Images (ALOI) [18]. The ALOI dataset is made of 1,000 objects recorded under various viewing angles, illumination angles, and illumination colors (Fig. 3), yielding a total of 110,250 images for the collection.

B. Accuracy

To test the accuracy of our system, we select, for each object, 3 different views – corresponding to rotation angles of 0, 15 and 35 degrees – which seems realistic in terms of noise for the target scenario. We then obtain the resulting DET curves shown in Fig. 4.

From our observations, our binarization process only slightly degrades our overall accuracy. Some more sophisticated methods as in [33] could be used for binarization but as the degradation is under control, our experiments stick to this simple method.

C. Implementation Details

With $n = 512$, we choose $r = 140$, placing ourselves at the rightmost part of Fig. 1. These parameters satisfy both inequalities (2) and (4).

Our implementation of the ENCODE (resp. RETRIEVESEED) procedure yields on our laptop an average encoding time (resp. decoding time) of 50 ms (resp. 10 ms). These timings are in line with the ones given by [17].

We obtain then an FAR around $4 \times 10^{-4}$ for a rotation angle of 15 degrees (resp. 35 degrees) and a corresponding FRR of 1.8% (resp. 7%). Note that, in our system – in opposition to biometric systems where a false reject can imply for a user to be blocked at a gate – a false reject simply demands for a new photograph of the referenced object to be taken.

Remark 1: A user can store different objects. For each of them, its encoding enables us to hide a new secret $k_i$, $i = 1, \ldots, m$. By taking the exclusive OR of all of them $k_1 \oplus \ldots \oplus k_m = k$, the resulting $k$ is obtained for an illegitimate user when each of the $m$ objects he had chosen leads to an encoding which matches with the genuine stored object (see the piling-up lemma of [23] for further analysis).

V. Our Proposal

As pointed out by [5], there is a huge gap, e.g. for VGG-16, regarding the intrinsic dimension – i.e. the minimal number of parameters needed to describe a representation – between input images and outputs of CNNs. We rely on that observation to mitigate the risk of an attack which looks for false positives by restricting the capacity of an adversary to compute templates corresponding to photos of objects.

We thus envisage to implement a proprietary algorithm on a dedicated server, i.e. with dedicated metaparameters and training. This way, template requests can be recorded and a security policy be established to limit their number, enforcing access control to templates.

To protect users against the server, we suggest sending visual passwords encrypted thanks to homomorphic encryption. Template computation is now possible directly in the encrypted domain [13] and new progress is announced [9], [29].

We now consider that a homomorphic encryption scheme is chosen [4] and that users generate their own private key for this scheme. Note that they do not have to keep them.

A. Detailed Description

Our system is made of:

- users;
- a dedicated server $S$ in charge of computing templates for users from their visual password.
Fig. 4: DET Curves

(a) Rotation of 35 degrees, EER=11%
(b) Rotation of 15 degrees, EER=2%

Fig. 5: Our Wallet Recovery Process

The different steps of our wallet recovery process are summarized in Fig. 5.

More specifically, a user $U$ is going to ENCODE his template (3) and perform RETRIEVESEED using his own device; e.g. his mobile phone. This device also enables him to capture and then, encrypt his visual password (resp. decrypt his template) before sending it to $S$ (resp. after receiving it from $S$). We consider that all these operations performed on the device of $U$ are safe from attacks.

The way his wallet’s seed is used after its retrieval is out-of-scope of this paper.

Server $S$ is considered honest-but-curious regarding the requests from the users. It protects the implementation of the proprietary model $M$ and restricts templates computation.

B. Security Discussion

We consider three factors to be taken into account for the security of our wallet seeds recovery process:

- Storage of the obfuscated template;
- Access to a templates construction algorithm;
- Choice diversity for visual passwords.

Our threat model is simple: we want to protect against an adversary who tries to retrieve the wallet’s seed by presenting a binary vector close to the stored reference template.

Having access to the know-how for transforming visual passwords into templates enables this adversary to attempt to obtain a false acceptance. Otherwise, we rely on the security provided by the obfuscated fuzzy Hamming distance matching. Searching in $\{0,1\}^n, n = 512$ leads to a probability of $1/2^\lambda$ with $\lambda = 87$ for $r = 140$ (see (2)) to find by chance a vector in the targeted Hamming ball. In contrast, the knowledge of the underlying templates subspace enables the adversary to drastically reduce his efforts with a FAR of $4.10^{-4}$ (see also Annex B). The confidentiality of the model $M$ is paramount for our wallet recovery process.

Regarding that point, besides server compromise, given oracle access to a neural network as in our proposal, model extraction attacks can be launched [32]. Today, the best attacks [10], [12], [25], [26], [34] against ImageNet classifiers seem unpractical. Note also that a first defense strategy keeping the model’s accuracy has been introduced.
VI. Conclusion

We are confident that there is room for improvement of the accuracy of our system. For instance, facial recognition which is an image processing problem of roughly the same difficulty as ours obtains less than 1% of FRR at FAR of $10^{-6}$ with systems working all around the world [3]. Our performances of Sec. IV-B look poor in comparison. As usual in big data, a huge dataset might enable us to improve our model. We are currently looking for a larger database of objects to work with. For instance, regarding the FAR we obtained, the presence of various objects which look similar – see, for instance, Fig. 6 – among the 1,000 within ALOI, tends to increase this rate in our experiments. A user does have a much larger choice at his disposal. For instance, a museum collection often counts more than a million objects while offering a long term storage for them.

APPENDIX A

Selected Model

To turn images into binary vectors, we use an NN. We opt for the VGG architecture after various trials. For instance, we tried the pretrained EfficientNet architecture, which has a higher accuracy on ImageNet (see https://paperswithcode.com/sota/image-classification-on-imagenet). However, it yields a higher FRR for a given FAR on ALOI, as can be seen in Fig. 7.

Similarly, in order to reduce the number of bits from 4,096 to 512, we select LSH even though other methods, such as Principal Component Analysis (PCA) exist. However, PCA depends on the training data, when LSH is independent of it. If the PCA is determined on Imagenette data rather than ALOI images, the resulting accuracy is lower than LSH, as can be seen in Fig. 8.

APPENDIX B

Probability of Randomly Selecting a Template in the Hamming Ball

[17] determines an upper bound for the probability of randomly selecting an element $y \in \{0,1\}^n$ in $B_x(r)$, the Hamming ball of radius $r$ and center $x$, taking also into account a security parameter $\lambda$.

In our case, for $n = 512$, $r = 140$ and $\lambda = 87$, we have: $Pr_{y \in \{0,1\}^n} \left[ y \in B_x(140) \right] \leq \frac{1}{2^{87}}$.

Exploiting the inherent correlation between coordinates of templates, we are now going to estimate an upper bound for

$Pr_{y \in \{0,1\}^n \cap \text{Templates subspace}} \left[ y \in B_x(r) \right]$ corresponding to when an adversary restricts himself to search among the templates subspace. This is the case when he has access to the model $M$.

Moreover in our experiments, we restrict ourselves to image inputs and we compute the templates of the 13,394 images coming from the Imagenette dataset (https://github.com/fastai/imagenette) searching for a false acceptance with one of the 1,000 templates of the ALOI dataset (without any rotation). We obtain that 4 among these 1,000 ALOI templates get a false acceptance – a distance less than 140 – with respectively 2, 12, 1 and 2 templates coming from the other dataset. This leads to a ratio of $1.27 \times 10^{-6}$ of the comparisons. We lose two orders of magnitude from the FAR of Sec. IV-C due to the fact that we are here looking at images that can be quite different than the objects from ALOI.

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