FMHash: Deep Hashing of In-Air-Handwriting for User Identification

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Abstract

Gesture biometrics are gaining popularity with gesture input interfaces on mobile and Virtual Reality (VR) platforms that lack a keyboard or touchscreen to type a password for user authentication. However, less attention is paid to the gesture-based user identification problem, which essentially requires indexing and searching the gesture motion templates in a large database efficiently. In this paper, we propose FMHash, a user identification framework that can generate a compact binary hash code from a piece of in-air-handwriting of an ID string, which allows fast search in a database of in-air-handwriting templates through a hash table. To demonstrate the effectiveness of the framework, we implemented a prototype and report preliminary results (∼98% precision and ∼93% recall). More detailed evaluation, comparison and improvement is working-in-progress.

The ability of hashing in-air-handwriting pattern to binary code can be used to achieve convenient sign-in and sign-up with in-air-handwriting gesture ID on future mobile and VR devices.

1. Introduction

People interact with Virtual Reality (VR) or Augmented Reality (AR) applications and mobile devices through gesture user interfaces [2][3]. Such interfaces can capture and track hand motions in the air, and allow a user to manipulate menus, dialogues, and other virtual objects directly by hand gesture. However, for security related tasks such as sign-up and sign-in, entering the user ID and password through a virtual keyboard on gesture interfaces become cumbersome due to the lack of keystroke feedback. Many existing research [21][11][17][5][9][24][20][19] exploit the rich information in native gestures, and esp., in-air-handwriting, to authenticate a user to access an account. Yet, a usually neglected function is user identification with gesture or in-air-handwriting. The former is a true or false question, i.e., answering whether the user owns the account that he or she claims to own. The latter is a multiple choice question, i.e., answering which account the user wants to login by a gesture given a database of many accounts. Consider an analogy of the sign-in procedure over the web on a traditional computer, the authentication task resembles typing and checking the password, while the identification task is searching the database given an ID number or ID string. Is it possible to construct a system that is capable of (1) taking a piece of information from a native gesture, or specifically, an in-air-handwriting of an ID string instead of typing, (2) search a potentially large database of accounts registered using the in-air-handwriting of the same ID string, and (3) return the matched identity or account with high accuracy and fast respond time?

Compared to gesture based user authentication, the user identification task is more challenging due to a few unique characteristics of the gesture. First, gestures have inherent fuzziness. Even if the same user writes the same string in the air twice, the generated two signals are not identical but contains minor variations. Yet, the system should be able to tolerate the fuzziness and identify the two signals as the same user, unlike typing an ID string of characters twice where not a single bit difference is tolerated. Second, it is difficult for many native gestures to provide enough information to enable a large account ID space as well as distinctiveness. Third, given the fuzziness of the gesture, it is challenging to design an efficient index of the gesture patterns of all users or accounts to enable fast identification.

In this paper, we propose a framework called FMHash, i.e., Finger Motion Hash, to efficiently obtain a user’s account ID from the hand motion of writing an ID string in the air. FMHash uses a deep convolutional neural network (called FMHashNet) to convert the in-air-handwriting signal to a compact binary code, and further enables indexing and searching the gesture patterns in the account database with a hash table. This is similar as face recognition, where a large database of identities are indexed using faces and an ID can be retrieved by an image of a unknown face. However, user identification with face has shortcomings. For example, one face is linked to one person, and a user can neither have multiple faces for multiple accounts nor change or revoke his or her own face. Moreover, if a website requires face image to register, the users will be worried about
privacy because it is impossible to stay completely anonymous. Yet, with in-air-handwriting of an ID string, the user can have multiple accounts with different ID strings, change or revoke the ID string, and stay anonymous by writing something unrelated to the true identity. In summary, our contributions in this paper are as follows:

1) We proposed a deep hashing framework of in-air-handwriting for user identification over gesture interface. Our method can accommodate gesture fuzziness by hashing multiple instances of the same handwriting by the same user to the same binary code with high probability of success (∼98% precision and ∼93% recall in our experiments).

2) We designed a regularizer called the pq-regularizer and a progressive training procedure for our neural network model to ensure good separation, i.e., hashcode of in-air-handwriting signals of different accounts are separated more than two bits in over 99% of the change. Meanwhile, we can maintain a reasonably fast training speed (∼10 minutes for a full training on our dataset).

3) We provided an analysis on the hash code fuzziness by evaluating our framework with a dataset of 200 accounts.

The remainder of the paper is organized as follows. Related works on gesture-based authentication and deep hashing are discussed in section 2. In section 3, the architecture of the proposed framework is presented. Then we show the empirical evaluation results in section 4. Finally we draw the conclusion and discuss future work in section 5.

2. Related Works

Most 3D hand gesture based authentication systems use a combination of password and behavioral biometrics, i.e., different users differ in either the gesture content or the convention of hand motion, or both. The hand motion is usually captured by a handheld device [17][5], wearable device [21][20] or a camera [9][24][19], and the authentication service compares the captured motion signal with a template [17][24][19] or runs a pipeline of feature extractors and statistical pattern classifiers [5][20] to make a decision. The gesture content can be simple movements like shaking [21] or complex in-air-handwriting of a password or signature [9][24][23]. Most in-air-handwriting password-based authentication systems [9][24][19][8][20] only focus on the difference in the motion signals generated by different users without understanding the meaning of the writing content. This feature allows the user to write freely in an arbitrary language instead of only clearly legible letters, and hence, enables a large password space, which further builds the foundation of our work that asks users to write distinct account ID strings of arbitrary content. However, identification is different from authentication. Existing systems need to exhaustively check every account in the database using the authentication procedure, which is impractical with large account database. Instead, we employ deep hashing method to convert the in-air-handwriting signal to a binary hash code and identify the user in constant time regardless the number of accounts.

Deep hashing has been extensively investigated in the computer vision, pattern recognition, and machine learning community mainly for image retrieval [25][14][26][27][28][16][15][7][10][18]. Such systems build a deep convolutional neural network (CNN) to convert 2D images to compact binary hash codes, and use the hash code to index the image database. To search similar images, a query image is converted to a hash code with the same neural network, and images in the database with the exact same or neighboring hash code are returned. Existing works mainly utilize the label of training images through pairwise supervision [25][16], triplet supervision [26][14], or ranking list supervision [27], with various regularization and quantization loss [16] to train the network to hash images of the same class to the same code. Although we are also utilizing CNN to generate hash code, our work has differences. First, the features of in-air-handwriting motion signal is inherently different from the features of image. Second, identification has different goals from image retrieval. For an identification system, it is desired to maintain the sparsity of the Hamming space to avoid wrong identification instead of maintaining smooth similarity change of the hash code in image retrieval, and the fuzziness in the signal should not propagate to the hash code to increase identification accuracy. Meanwhile, secret key can be generated from the hash code.
code to protect the account information and long hash code is preferred due to the difficulty to guess. Third, considering that new accounts are registered from time to time, our network is optimized with smaller number of parameters and faster training speed.

3. The FMHash Framework

The proposed FMHash framework (shown in Figure 1) contains five components:

1. An in-air-handwriting motion capture device (e.g., a Leap Motion controller [1] in our implementation);
2. A preprocessing module smoothing and normalizing the captured motion signal (detailed in section 3.1);
3. A deep CNN that takes preprocessed motion signal x as input and generate a high dimensional floating point latent vector h (denoted as a function \( f(x) = h \), explained in detail in section 3.2);
4. An additional neural network layer that project the latent vector h to low dimensional space and quantize the projected result to B-bit binary hash code b ∈ \{−1, +1\}^B (denoted as another function \( g(h) = b \), and B is usually 16, 32, 64, etc., explained in detail in section 3.2);
5. An account database that stores a hash table index of account tuples <ID, b\(I^D\), h\(I^D\)>, where ID is the account ID (usually a unique number generated by the system at registration), b\(I^D\) and h\(I^D\) are the hash code and latent vector corresponding to the account (detailed in section 3.3).

3.1. Signal Acquisition and Preprocessing

The in-air-handwriting of an ID string is captured by the Leap Motion controller in our implementation as a raw signal containing the 3D position coordinates of the center of the palm sampled at about 110 Hz. Once this raw signal is obtained, we further obtain the 3D velocity, and 3D acceleration by calculating the difference of adjacent position samples. Then the signal is normalized in pointing direction (making the average hand pointing direction as x-axis) and amplitude (mean subtraction and division by standard deviation). Finally it is resampled to a fixed length of 256 data points in each dimension to form the 256×9 input vector x. An example of the motion signal and the trajectory of in-air-handwriting is shown in Figure 2.

![Figure 2. An example of the motion signal (left) and trajectory in the 3D space (right) obtained by writing “FMhash” in the air.](image)

3.2. FMHashNet

The deep CNN and the additional projection-quantization layer are implemented together and collectively called the FMHashNet. There are multiple design goals we want to achieve with FMHashNet. First, for a pair of in-air-handwriting signals \((x_1, x_2)\), if they are generated by the same user writing the same ID string, the corresponding hash codes \((b_1, b_2)\) should be the same in most cases or differ only in one or two bits sometimes due to the fuzziness of the signals; if they are generated from different ID strings (regardless of the same user or different users), \((b_1, b_2)\) should differ at least three bits. Second, the neural network should learn contrastive representations \(h\) to facilitate the projection. Third, it should be easy to train and fast to converge.

To achieve these goals, we design the FMHashNet in the following way, as shown in Table 1. First, we apply 5 convolutional and maxpooling layers with simple VGG-like kernel [22] and a fully connected layer to map input signal x to latent vectors h. Both the convolutional layer and the fully connected layer have leaky ReLU activation. Next, the projection layer project the latent vector h to a space with the same dimension as the final hash code, i.e., \(z = Wh + c\), where z is the projected vector whose size is B. After that, the hash code is generated by taking the sign of the projected vector \(b_i = \text{sign}(z_i), 1 \leq i \leq B\). This is essentially partitioning the latent space by B hyperplanes to obtain at most \(2^B\) regions associated with different hash code. Additionally, a softmax layer is added in parallel with the projection layer to help training.

| layer | kernel | output | #para |
|-------|--------|--------|-------|
| input: 256 * 9 |
| conv-pool1 | 3→1 conv, 2→1 max pool | 128 * 48 | 1.3k |
| conv-pool2 | 3→1 conv, 2→1 max pool | 64 * 96 | 14k |
| conv-pool3 | 3→1 conv, 2→1 max pool | 32 * 128 | 37k |
| conv-pool4 | 3→1 conv, 2→1 avg pool | 16 * 192 | 74k |
| conv-pool5 | 3→1 conv, 2→1 avg pool | 8 * 256 | 147k |
| fc (latent) | fully connected | 512 | 1,048k |
| softmax | 200 | 102k projection B | 512×B |
| cross-entropy loss | pairwise loss |

Table 1. FMHashNet Architecture
Second, we train the network using the projection layer with the following pairwise loss \( L \), and minibatches of 2M pairs of signals \((x_1^{(i)}, x_2^{(i)})\), \(1 \leq i \leq 2M\). Half of the minibatch is pairs of signals from the same class \((y^{(i)} = 0)\), and half is pairs of signals from different classes \((y^{(i)} = 1)\),

\[
L = \frac{1}{2M} \sum_{i=1}^{2M} L^{(i)},
\]

\[
L^{(i)} = (1-y^{(i)})\|z_1^{(i)} - z_2^{(i)}\| + y^{(i)} \max(m - \|z_1^{(i)} - z_2^{(i)}\|, 0) + \alpha(P(z_1^{(i)}) + P(z_2^{(i)})) + \beta(Q(z_1^{(i)}) + Q(z_2^{(i)})).
\]

Here \(\|.\|\) is Euclidean norm. In this loss function, the first term forces the projected vectors of the same classes to the same value, and the second term forces the projected vectors of different classes to separate at least \(m\) in Euclidean distance. The remaining terms \(P(z)\) and \(Q(z)\) are the so-called \(pq\)-regularizer which is specially designed to help place all registered accounts into different regions and avoid ambiguity in quantization. These two terms are defined as follows:

\[
P(z^{(i)}) = \sum_{j=1}^{B} \max(\|z_j^{(i)}\| - p, 0),
\]

\[
Q(z^{(i)}) = \sum_{j=1}^{B} \max(q - \|z_j^{(i)}\|, 0),
\]

where \(p\) and \(q\) are hyperparameters, \(\|z_j^{(i)}\|\) is taking absolute value of the \(j\)th component of \(z^{(i)}\). This regularizer forces each element of the projected vector \(z\) to reside in the region \([-p, -q]\) or the region \([+q, +p]\), which corresponds to the bit -1 and bit +1 in the hash code \(b_i\) after quantization. With a careful choice of \(m\), we can push a pair of \((z_1, z_2)\) of different accounts to opposite regions, and hence, hash them to different binary codes, as shown in Figure 3. One example choice of \(m\) as in our experiment is \(p\sqrt{B}\), which is Euclidean distance from the origin to the point \(z^* = (p, p, ..., p)\). This forces the hash code of signals of different accounts differ at least one bit. Our experience shows larger \(m\) helps separation, but hurt convergence. The hyperparameter \(\alpha, \beta\) controls the portion of contribution of the regularizer in the total loss and gradients. Our design philosophy of the deep hashing network differs from most related works that try to minimize quantization loss (i.e., forces the projected vector to be close to the nodes of Hamming hypercube). Instead, we map the input to a bounded Euclidean space and push them away from the decision boundary \(z_j = 0\), where a relatively large region that can be quantized to the same bit value regardless of the quantization error. Meanwhile, it reduces the difficulty of training since the gradient of loss respect to \(z\) is easy to compute compared to the commonly used saturation method such as tanh or sigmoid relaxation.

3.3. Account Database and Procedures

As mentioned previously, each account contains a tuple of \(<ID, b^{(ID)}, h^{(ID)}>\). At registration time, the system generates a unique ID number for the registered account. The user is asked to create an ID string and write it \(K\) times. The obtained \(K\) in-air-handwriting signals \(\{x^{(1)}, x^{(2)}, ..., x^{(K)}\}\) are utilized to train the FMHashNet. Once the training is finished, we can use the training signals to construct \(b^{ID}\) and \(h^{ID}\) as follows:

\[
h^{ID} = \sum_{i=1}^{K} h^{(i)} = \sum_{i=1}^{K} f(x^{(i)}),
\]

\[
b^{ID} = g(h^{ID}) = \text{sign}(Wh^{ID} + c),
\]

where \(f()\) is the deep CNN \(g()\) is the projection and quantization process, and \(\text{sign}()\) is element-wise sign function. A hash table is also constructed to index all account tuples using the hash codes \(b^{ID}\).

At identification time, given a preprocessed in-air-handwriting signal \(x'\), the following steps are proceeded to obtain the account ID. First, we run the forward path of FMHashNet to obtain a latent vector \(h'\) and \(b'\). Second, we search the hash table using \(b'\) with a fuzziness tolerance of \(l\) bit. If \(l\) is 0, we just search the hash table using \(b'\). If \(l\) is not 0, we search the the hash table multiple times with each element of a collection of hash code \(S\), where \(S\) contains all possible hash codes with a Hamming distance less or equal than \(l\) bits from \(b'\). The rationale is that the fuzziness in the writing behavior eventually lead to errors that make \(b'\) differ from the hash code of its real account, but this difference should be smaller than \(l\) bits. In practice, we usually set \(l\) to 1 or 2 to limit the total number of searches for prompt response. In this way, a collection of candidate accounts will be obtained. The third step is compare \(h'\) with the latent vector of every candidate account to find the nearest neighbor. Finally, the account ID of this nearest neighbor is returned as the identified ID.
4. Experimental Evaluation

4.1. Dataset

We collected our own dataset of 200 accounts with 200 distinct in-air-handwriting ID strings. They are created by 100 users with exactly two accounts per user. For each account, the user wrote an ID string five times as registration and then five times as five independent identification tests. Roughly half of the users are college students (including both undergraduate and graduate students), and the other half are people of other various occupations (including both office workers and non-office workers). The contents of the ID strings are determined by the users and no two ID strings are identical. Most users chose a meaningful phrase for memory easiness and they wrote the ID strings very fast in an illegible way for convenience. The average time of writing a ID string in the air is around 3 to 8 seconds, depending on the complexity of the ID string.

4.2. Implementation Detail

We implement the FMHashNet in TensorFlow [4] on a Nvidia GTX 1080 Ti GPU. The weight parameters are initialized with the Xavier method [12] and the Adam optimizer [13] with a initial learning rate of 0.001 is used. The leaky ReLU negative slope is set to 0.2. The regularizer hyperparameter $p$ is set to 10, $q$ is set to 5. Based on our experience, reasonably good results can be achieved with a wide range of different $p$ and $q$ values as long as $p - q$ is larger than one. The inter-class distance $m$ is set to $p \sqrt{B}$, the hash code size $B$ is 16, 32, 48 or 64. For the training protocol, we first use the softmax layer and cross-entropy loss with 1,000 iterations. Then we use the projection layer and pairwise loss with pq-regularizer for another 10,000 iterations. During these 10,000 iterations, $\alpha$ is set to 0.1, and $\beta$ is initially set 0.0001 for the first 4,000 iterations, and gradually increased 10 times per every 2,000 iterations until 0.1. The training pairs are selected online, and $M$ is set to 200 in a minibatch. For the pairs of the same account, we randomly select an account and two training signals of that account; for the pairs of different accounts, we calculate the account hash code $b_{1ID}$ for each account every 20 iterations, and select pairs from those accounts whose hash codes differs less than three bits. If no such account exists, we randomly choose two signals from two different accounts as a pair.

Another major challenge we encountered is the limited amount of training data (only five signals per account). To overcome this challenge, we augment the training dataset in two steps. First, given $K$ signals $\{x^{(1)}, x^{(2)}, ..., x^{(K)}\}$ obtained at registration, for each $x^{(k)}$ in this set, we align all the other signals to $x^{(k)}$ to create $K - 1$ additional signals using Dynamic Time Warping [6], and in total we can obtain $K^2$ signals (in our case 25 signals). Second, we randomly picks two aligned signals and exchanges a random segment to create a new signal, and this step is repeated many times. Finally each account has 125 training signals.

4.3. Empirical Results

We ran experiments with different hash code size $B = 16, 32, 48, 64$ and fuzziness tolerance $l = 0, 1, 2$. For a single experiment, we trained the FMHashNet and ran the identification procedure with all 200×5 testing signals from
Table 2. Performance Comparison (with hash code side $B=16$)

| methods   | average precision | average recall | miss-rate | fail-rate | training time |
|-----------|-------------------|----------------|-----------|-----------|---------------|
|           | 0 bit  | 1 bit  | 2 bit  | 0 bit  | 1 bit  | 2 bit  | 0 bit  | 1 bit  | 2 bit  | 0 bit  | 1 bit  | 2 bit  | 648 s   |
| DSH-like  | 0.995  | 0.916  | 0.636  | 0.918  | 0.892  | 0.632  | 0.004  | 0.081  | 0.362  | 0.078  | 0.026  | 0.005  |          |
| tanh     | 0.970  | 0.821  | 0.494  | 0.443  | 0.638  | 0.474  | 0.014  | 0.139  | 0.484  | 0.544  | 0.223  | 0.042  |          |
| Ours     | 0.999  | 0.995  | 0.979  | 0.944  | 0.972  | 0.975  | 0.001  | 0.005  | 0.021  | 0.055  | 0.023  | 0.004  | 610 s    |

Figure 8. Distribution of the Hamming distance between the account hash code and the hash code of a testing signal for the same account (left) and different accounts (right). The left figure is obtained by counting the Hamming distances of all $200 \times 5$ pairs of $b^{t(i)}$ and $b^{1D}$, where $b^{t(i)}$ and $b^{1D}$ are from the same account. The right figure is obtained by counting the Hamming distances of all $200 \times 199 \times 5$ pairs of $b^{t(i)}$ and $b^{1D}$, where $b^{t(i)}$ and $b^{1D}$ are from different accounts. The hash code size is 16 bits.

Figure 5 shows the performance of five repetitions of the same experiment on our dataset with different hash code sizes. In general, longer hash code size provides better security because it is more difficult to guess the hash code without knowing the writing, but it is also more difficult to train due to the added parameters. Hence, there is slight performance drop. Also, a larger fuzziness tolerance $l$ leads to less failure of identification, but more misidentification as well as improved recall. In practical identification system, we recommend to set $l=1$ for best performance.

Next we evaluate the hash code fuzziness caused by the inherent fuzziness in the in-air-handwriting. As shown in Figure 5 (left), only 1.6% of the testing signals are hashed more than 2 bits away from the hash code of their real accounts. Such fuzziness is mitigated by the separation of the hash codes of different classes, as shown in Figure 5 (right). In most cases the hash code of a signal is at least three bits far away from the hash code of a wrong account.

We further compare our approach with the DSH regularizer [16], which resembles FMHashNet most among all existing deep hashing methods for image retrieval. The results are shown in Table 2. For the DSH-like method, the regularizer scalar is empirically chosen to be 0.1 (best result achievable), and pair margin $m$ is set to $2B$ as suggested in the original paper. Although the DSH-like method can be seen as an specific case of FMHashNet with $\alpha = \beta$ and $p = q = 1$, the underline design philosophy is completely different as mentioned in section 3.2. Another common variant is using saturating activation such as tanh in the last layer instead of our $pq$-regularizer, which is also compared in Table 2. In this configuration, pair margin $m$ is set to 6 (separation of at least 3 bits), and the initial learning rate is set to 1e-5 to avoid gradient explosion or vanishing. For fair comparison, all compared works have the same network architecture, the same training method, the same pair selection strategy, and the same testing protocol. They only differ in regularizer and loss function. Thus, technically speaking our DHS-like implementation is not exactly the original DHS method for hashing images because the original DHS cannot be directly used without modification. The major drawback of compared methods is that they are not optimized to achieve hash space sparsity and fuzziness tolerance at the same time. As a result, with these scheme, a considerable amount of hash codes from different accounts collide or only differ 1 or 2 bits.

5. Conclusion and Future Work

In this paper, we proposed a user identification framework named FMHash that can generate a compact binary hash code and efficiently locate an account in a database given a piece of in-air-handwriting of an ID string. We also implement and evaluate the proposed framework with a dataset of 200 accounts, and the performance is reasonably good with 98% precision and 93% recall. The ability to convert an in-air-handwriting gesture to hash code gives FMHash great potential for sign-in over gesture input interface. However, it has certain limitations such as requirement of retraining on the creation of new account and ID updating. In the future, we will continue improving the FMHash framework, investigating the long term performance, and possible key generation scheme.
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