On the Order of Search for Personal Identification with Biometric Images

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Abstract

The processing time of personal identification can be a critical problem in systems with a large number of users. This paper proposes an efficient algorithm for personal identification with biometric images. The algorithm reduces the number of image comparisons for the search of a similar image to the query image by preparing a suitable order of image comparison. The candidates of the order are decided based on the similarities between the registered images, and then the order is selected according to the results of comparisons between the query image and a small number of images. This paper also evaluates the algorithm by experiments with palmprint images in terms of the number of image comparisons and the error rate of personal identification. As the result, the algorithm reduces the number of comparisons to 30% of the standard linear search algorithm with no loss of the error rate.

Keywords: biometrics, personal identification, image comparison, palmprint.

1 Introduction

Dependability is an important factor for social infrastructure systems in addition to efficiency. The strength against malicious attacks can be regarded as a kind of dependability of the system. Personal authentication is one of the straightforward solutions to preserve the dependability at the level of social engineering. Especially, biometric authentication is expected to compensate some weaknesses of token- and knowledge-based authentication [1]. For example, verifying fingerprints of users prevents an ATM system from attacks by stolen smart cards and leaked passwords.

For authentication based on biometric information, there exist two possible procedures of matching, verification and identification [1]. Identification searches for the target person, and verification confirms that the target person is a particular person. The processing time of identification usually depends on the number of images registered for image matching (called "templates"), which can leads a critical problem in a large scale system. The aim of this paper is an acceleration of personal identification with biometric images. If biometric images are formalized as numerical vectors, identification can be reduced to the problem of nearest neighbor search which is solved fast by a suitable data structure [2] or an approximation [3]. In some practical systems, however, the process of image matching is implemented as a distinct module and treated as a black box whose input is a pair of two images and output is a similarity between the two images. In such a situation, identification should be conducted on the basis of some results of image comparison.

The naive "comparison-based" algorithm is the linear search algorithm. By stopping the search when a similar image is found, the number of image comparisons can be reduced with some deterioration of

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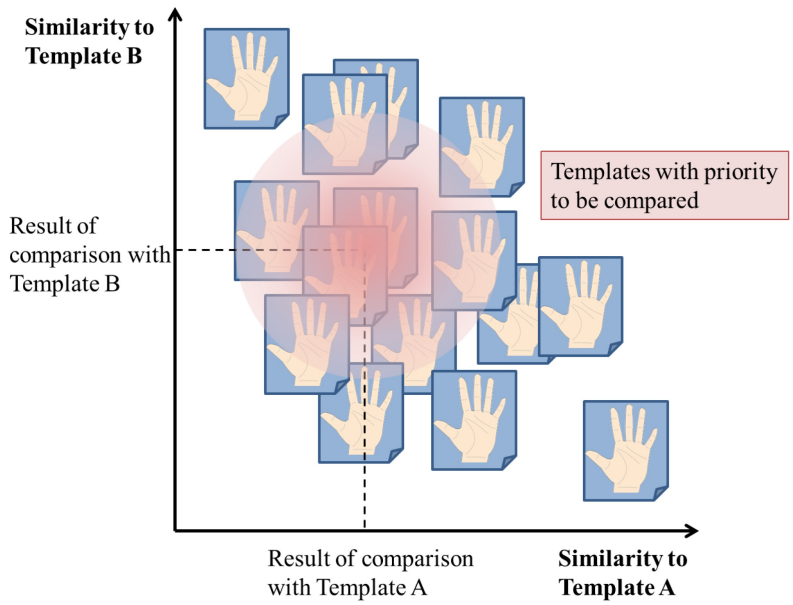

Figure 1: The main idea of our identification algorithm. The templates are plotted according to the results of comparisons with Templates A and B, and the order of comparison is decided on the basis of the distance from the point obtained by the results of comparisons between the query image and Templates A and B.

accuracy as compared with finding the most similar image. Maeda et al. [4] proposed an identification algorithm (MSM) that reduces the number of image comparisons in the linear search. The main idea of the algorithm is that the order of templates compared with the query image is decided according to the results of the conducted comparisons and the similarities between templates. They reported that the average number of comparisons is experimentally $O(\sqrt{N})$, while that in the linear search is $O(N)$. However, the process to decide the template requires $O(N)$ time for each comparison, and hence the total processing time is proportional to $N^{3/2}$ on the assumption that the number of comparisons is $O(\sqrt{N})$ [5].

In this paper, we propose an identification algorithm as an improvement of the algorithm proposed in our previous work [6]. The main idea of the previous version is to prepare the order of image comparison statically instead of the dynamic $O(N)$ computation in MSM. Fig. 1 illustrates the concept of our method. Our approach decides the order of comparison according to the distance statically on the fixed space, while MSM computes the distance dynamically and the space changes for each comparison. The algorithm can reduce the number of image comparisons as MSM although the time complexity is no more than $O(N)$. However, in the previous version we had to fix the templates for deciding the order in advance of identification. In the new version, the template can be selected at the point of identification, and hence we can examine the effect of the selected templates on the performance of the algorithm. We confirm that the novel algorithm reduces the number of image comparisons as the previous version and does not worsen the accuracy by experiments with palmprint images.

The rest of this paper is organized as follows. Section 2 formalizes the target problem and the criteria for the processing time and the accuracy of identification algorithms. Section 3 introduces the novel algorithm and shows the time complexity of the algorithm. Section 4 reports the experimental results with palmprint images.

2 Preliminaries

In this paper, the problem of personal identification with biometric images is simply called *identification*. In identification, each image corresponds to a person. The input of identification consists of an image (called an *input image*) and a set of images (called a set of *templates*). The output is the name of the person judged to correspond to the input image or "null" if the person of the input image is judged to be not included in the persons of the templates.

We suppose that an idea of similarity on biometric images is given. Then, the *linear search algorithm* is, for a given threshold,

- The input image is compared with each template in the set successively in an order;
- If a template whose similarity with the input image is not less than the threshold is found, then the algorithm outputs the person of the image and terminates;
- If the similarities with every templates are less than the threshold, then the algorithm outputs "null" and terminates.

For the accuracy of an identification algorithm, we consider "the rate that the person of the output is not the person of the input image" as the *error rate* of the algorithm.

3 Algorithm

We propose an identification algorithm which reduces the number of image comparisons in the linear search algorithm by preparing a suitable order of image comparison in advance.

3.1 Preparation

First, we prepare a set of orders of image comparison for the linear search algorithm which are the candidates of the suitable order for an efficient identification.

Let T be the set of templates, $N = |T|$, and t_i a template in T for $1 \leq i \leq N$. For a given idea of a similarity of images, we calculate the similarity m_{ij} between t_i and t_j for $1 \leq i, j \leq N$. An order of image comparison is expressed as a list of the N templates in T. Then, we prepare N lists $O_i = (o_i(1), o_i(2), \ldots, o_i(N))$ for $1 \leq i \leq N$ such that

- $o_i(j) \in T$ for $1 \leq j \leq N$, and $o_i(j) \neq o_i(k)$ if $j \neq k$,
- $o_i(1) = t_i$,
- $d(o_i(1), o_i(j)) \leq d(o_i(1), o_i(j+1))$ for $1 \leq j \leq N-1$, where $d(t_i, t_j)$ is the Euclidean distance between $(m_{i1}, m_{i2}, \ldots, m_{iN})$ and $(m_{j1}, m_{j2}, \ldots, m_{jN})$.

For example, for the matrix of the similarities between the templates t_1, t_2, and t_3

$$(m_{ij}) = \begin{pmatrix} 100 & 10 & 30 \\ 10 & 100 & 20 \\ 30 & 20 & 100 \end{pmatrix},$$

$d(t_1, t_3) < d(t_2, t_3) < d(t_1, t_2)$, and hence the orders are

$$O_1 = (t_1, t_3, t_2),\ O_2 = (t_2, t_3, t_1),\ O_3 = (t_3, t_1, t_2).$$

3.2 Identification

Next, we chose an order from the set in the preparation according to the results of some image comparisons with the input image (called *initial comparisons*).

Let $t_{r_1}, t_{r_2}, \ldots, t_{r_\ell}$ be the templates for the initial comparisons and $M_i^r = (m_{ir_1}, m_{ir_2}, \ldots, m_{ir_\ell})$ for $1 \leq i \leq N$. Then, the order of image comparison for the linear search algorithm is decided as follows.

1. The input image is compared with the ℓ templates and a vector of ℓ similarities is obtained;
2. We search the N ℓ-dimensional vectors M_i^r for $1 \leq i \leq N$ for the nearest vector to the vector obtained in the step 1;
3. The order of image comparison for identification is O_i if M_i^r is the nearest vector.

For example, in the example in Subsection 3.1, if the template for the initial comparison is t_1 and the result of the comparison is 12, then 10 is the nearest to 12 in $\{100, 10, 30\}$ and the order is decided to be O_2. If the templates for the initial comparisons are t_1 and t_2 and the results are 12 and 21, then $(30, 20)$ is the nearest to $(12, 21)$ in $\{(100, 10), (10, 100), (30, 20)\}$ and the order is O_3.

Thus, the identification is completed by the linear search algorithm with the chosen order of image comparison.

The initial comparisons require ℓ comparisons of images. Generally, searching the nearest vector from N ℓ-dimensional vectors needs $O(N^{1-1/\ell})$ time with a kd-tree although the processing time is practically expected to be about $\log N$. The linear search clearly needs $O(N)$ image comparisons. Therefore, the total processing time of the proposed algorithm is no more than $O(N)$.

The difference of this algorithm from the old version in [6] is the definition of the distance between two templates in Subsection 3.1. The distance in the old version is calculated from ℓ-dimensional vectors that correspond to the templates for the initial comparisons, hence the templates have to be fixed at the point of the preparation.

4 Experiments

The number of image comparisons and the error rate of the proposed algorithm are examined with practical palmprint images.

4.1 Similarity of Images

We consider a matching of SIFT features for the comparison of palmprint images. This subsection defines the similarity on palmprint images. In this paper, the region of interest on each palmprint was extracted as the circle that covers the maximal part on a palm as [5].

SIFT is one of the popular methods for image matching and object recognition. The detailed mechanism can be found in [7, 8]. SIFT translates an image into a set of key points and each key point has a vector as its feature. Then, a comparison of two images is done by matching two sets of key points. There exist several possible procedures for the matching of key points. In this paper, the similarity between images (that is, sets of key points) is defined as follows. Let P and Q be two sets of key points and $v(p)$ the feature vector of a key point p. We consider q_p, p_q, and m such that

- For any $p \in P$, $q_p \in Q$ satisfies that $\|v(q_p) - v(p)\|$ is the smallest in Q.
- For any $q \in Q$, $p_q \in P$ satisfies that $\|v(p_q) - v(q)\|$ is the smallest in P.
- m is the number of the pairs of $p \in P$ and $q \in Q$ such that $q_p = q$ and $p_q = p$.

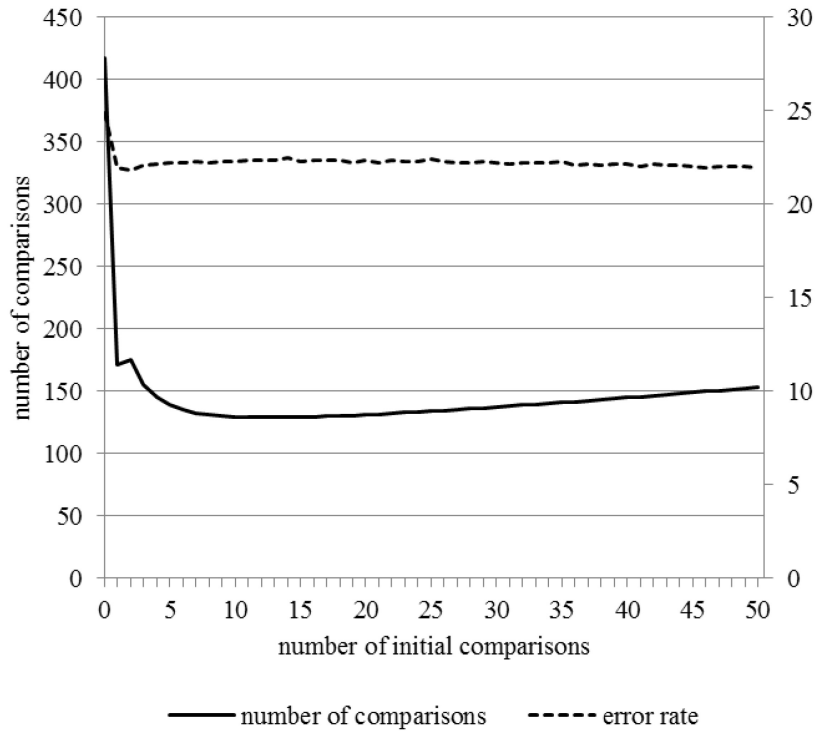

Figure 2: The optimum error rates and the numbers of image comparisons at the optimum error rates of the proposed algorithm.

Then, the similarity of two images whose features are respectively P and Q is defined to be

$$\frac{m}{\max\{|P|,|Q|\}}.$$

For the practical process of SIFT in our experiments, the function "`SiftFeatureDetector`" in OpenCV [9] was used. The parameter "`threshold`" of the function was fixed at 0.01 and the other parameters were set to the default values according to the results of some preparatory experiments about the processing time and the error rate of matching.

4.2 Results

The experiments were conducted on the PolyU Palmprint Database [10]. The sample set contains $1,200$ images that consists of 8 images times 150 persons. We separated the set into two sets of 4×150 images for templates and input images, and repeated each experiment with swapping the sets.

Fig. 2 shows the number of image comparisons and the error rate of the proposed algorithm against the number of initial comparisons. The error rate is the optimum value in the different values of the threshold for the image similarity. The number of image comparisons is the value at the optimum error rate and it contains the number of the initial comparisons. The templates for the initial comparisons were chosen randomly, and each value is the average of 100 trials with different sets of templates. The values for the number of initial comparisons 0 correspond to that of the normal linear search algorithm with a randomly chosen order.

The optimum error rate was about 22% for the numbers of initial comparisons more than 0. The average number of image comparisons was optimum for the number of initial comparisons 10 and the

Table 1: The optimum error rates and the numbers of image comparisons at the point of the optimum error rates for the linear search algorithm, MSM, the previous version of the proposed algorithm, and the proposed algorithm. $*$ is the rate against the number for the linear search algorithm.

	Error rate	♯Comparisons ($*$)
Linear search	24.9%	417.3 (1)
MSM [4]	20.3%	94.6 (0.23)
Old version [6]	20.2%	123.4 (0.30)
New version	22.3%	129.4 (0.31)

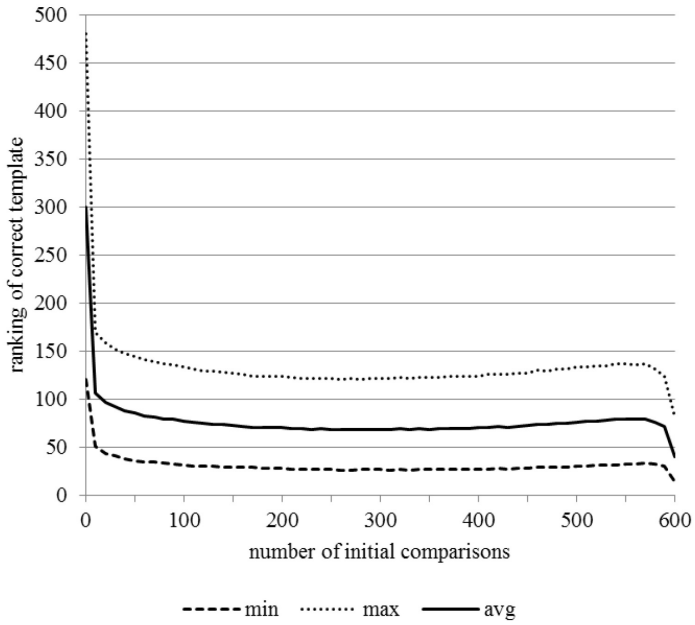

Figure 3: The ranking of correct templates in the orders chosen by initial comparisons. “min”, “max”, and “avg” are respectively the highest, the lowest, and the average rankings in the four correct templates for each persons.

value was 129.4. The average of the optimum number of initial comparisons for each trial was 11.9. Table 1 shows a comparison with the results in [6] which are for the same experiment with the normal linear search algorithm, MSM [4], and the old version of the proposed method [6]. By the results, the proposed method is confirmed to reduce the number of image comparisons with no loss of the accuracy similarly to the old version.

4.3 Discussion

In the proposed algorithm, the number of image comparisons mainly depends on the ranking of the correct templates (that is, the templates of the target person) in a selected order of comparisons. If a correct template is ranked high, the number of image comparisons for a search can be small. Fig. 3 shows the relation between the ranking of correct templates and the number of initial comparisons. In the result the ranking is rising rapidly until about 10 initial comparisons. Therefore, we estimate that an ideal feature of the images for personal authentication would be expressed as about 10-dimentional vectors.

5 Conclusion

An efficient algorithm for personal identification with biometric images was proposed. The algorithm reduces the number of image comparisons for finding a similar image by preparing a suitable order of the linear search according to the results of a small number of image comparisons. The algorithm was evaluated with practical palmprint images in terms of the number of image comparisons and the error rate. By the evaluation, the algorithm was confirmed to be able to reduce the number of image comparisons with no loss of the error rate from the normal linear search algorithm. With 600 images for templates, the number of image comparisons for a search was reduced into about 30% by extra 10 comparisons for deciding the order of the search.

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