A Note on Processing Time of Biometric Identification

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ABSTRACT: *This paper evaluates an existing algorithm for biometric identification. In identification based on biometric images, the number of image comparisons is an important factor to estimate the total processing time in addition to the processing time of a single image comparison. Maeda et al. proposed an identification algorithm which reduces the number of image comparisons. This paper evaluates the algorithm in terms of the processing time and the accuracy with the features extracted by SIFT from palmprint images. The evaluation in this paper proves that the algorithm is applicable to the SIFT-based palmprint features.*

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1. Introduction

Personal authentication has been an essential issue in many social infrastructure systems. Especially, biometric authentication has attracted attention as a technology to compensate some weaknesses of token- and knowledge-based authentication [7]. With the spread of computers and networks, the scope of applications of personal authentication was extended into a wide area which includes behavioral tracing and access control, and moreover, the number of persons who use each application system is supposed to become huge. For authentication based on biometric information, there exist two possible procedures of matching, that is, verification and identification [7]. Identification searches who the target person is, while verification confirms that the target person is a particular person. Identification requires a longer processing time compared with verification, and it becomes more conspicuous in systems with a large number of users.

We focused on comparison-based approaches for the procedure of biometric identification. Identification with biometric information can be considered as the problem of the nearest neighbor search, that is, to search a set of vectors for the most similar vector to the input vector. Hence, an approach to accelerate identification is acceleration of the nearest neighbor search by a suitable data structure or an approximation [4, 6]. In some practical systems, however, the matching process of biometric information might be implemented as a distinct module and treated as a black box. In such a situation, identification should be conducted on the basis of comparisons between two pieces of biometric information.

Maeda et al. [10] proposed an efficient algorithm of comparison-based biometric identification, however it is not clear whether their algorithm is effective to general biometric traits. If we arrow some deterioration of the identification accuracy, we can consider searching for a vector whose similarity with the input vector is larger than a given threshold, instead of the most similar vector. In this method, the processing time of identification can be reduced by stopping the search when a vector with a large similarity is found. The algorithm by Maeda et al. reduced the number of comparisons between the input information and already registered information (template) by considering a similarity between any pair of templates in advance. They reported that the average number of comparisons was experimentally $O(\sqrt{N})$ for the number N of the templates, while the expectation of that in the linear search is $O(N)$.

However, the biometric features considered in the simulation were not described in detail, and the effect of their algorithm is considered to depend on the distribution of the biometric features.

We applied the identification algorithm by Maeda et al. into the features extracted by SIFT from palmprint images to evaluate the algorithm. This paper focused on palmprint as the biometric information for authentication because of the following reasons:

- Palmprint can be captured easily as an image by a general-purpose camera instead of a special device;
- Palmprint has a larger area for matching (hence, robust against usual noise) than fingerprint;
- Palmprint is difficult to be brought into connection with privacy compared with face.

In this paper, we considered Scale-Invariant Feature Transform (SIFT) [8, 9] which extracts image futures invariant to scale and rotation. The algorithm by Maeda et al. and the linear search algorithms are implemented, and then the number of image comparisons and the error rate are examined with the features. The sample set of palmprint images had been captured with a fixing guide [2], hence the robustness about scale and rotation was not evaluated in the experiments, although those were expected to be guaranteed by using SIFT.

The evaluation in this paper clarifies the possibility of application of the algorithm by Maeda et al. If the algorithm is applicable to the features extracted by SIFT from general biometric images, it implies that the acceleration can be realized without any special knowledge about biometric traits.

The rest of this paper is organized as follows. Section 2 clarifies the criteria for the processing time and the accuracy of personal identification with biometric images. Section 3 introduces the identification algorithm proposed by Maeda et al. Section 4 defines the similarity on palmprint images for identification and reports the experimental results.

2. Preliminaries

This section formalizes the problem of personal identification with biometric images and clarifies the criteria for evaluating identification algorithm in the sense of time and accuracy.

2.1 Identification

In personal identification with biometric images, each image corresponds to a person. In the rest of this paper, the problem is called simply *identification*. 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 predicted to correspond to the input image. We suppose that the idea of a similarity on biometric images is given. Then, the problem of identification is formalized to be

- To find the template whose similarity with the input image is the largest in the set of templates, or

- To find the template whose similarity with the input image is not less than a given threshold.

In the second formalization, the output can be "*null*" if the similarity is less than the threshold for any template in the set. Also for the first formalization, we can introduce the output "null" by considering a threshold. The target of this paper is the problem by the second formalization.

2.2 Processing Time

In this paper, we focus on comparison-based algorithms for identification. Therefore, the processing time T of an identification algorithm is formalized to be

$$T = T_c \times N_c;$$

where T_c is the processing time of a single image comparison and N_c is the number of image comparisons conducted for a single identification.

The straightforward algorithm of identification is the linear search, that is, comparing the input image with each template in the set successively in an order. Let N be the number of the templates. Then, the linear search algorithm requires $O(N)$ times of image comparisons, that is, $N_c = O(N)$. The processing time of a single image comparison can be regarded as a constant, that is, T_c does not depend on N. Therefore, the processing time of the linear search is estimated to be $O(N)$ on the formalization. Although a classification of biometric images with α classes decreases N_c to about $1/\alpha$, it is still $O(N)$.

2.3 Accuracy

For measuring the accuracy of an identification algorithm, we consider "*the rate that the person who corresponds to the output image is different from the person of the input image*", and this rate is called the error rate (ER) of the identification algorithm.

We also consider the standard error rates in verification [7]. The input of a verification algorithm is a pair of an image and the name of a person, and the output is "*accept*" or "reject". Then, the false rejection rate (FRR) is defined to be the rate that the output is "*reject*" and the person who corresponds to the input image is same as the person of the input, and the false acceptance rate (FAR) the rate that the output is "*accept*" and the person of the input image is different from the input person. FRR and FAR depend on the threshold for the similarity, and then the equal error rate (EER) is the value of FRR and FAR at the point of the threshold where the two error rates are identical.

3. Matching Score Matrix Algorithm

Maeda et al. [10] proposed an identification algorithm with general biometric information, that is, images in the argument of this paper, which reduces the number of image comparisons in the linear search. The main idea of the algorithm is that the similarity (called the *matching score*) between any pair of the templates is calculated in advance, and then the order of the comparisons with the input image is decided according to the matching scores.

Let t_i be a template for $1 \leq i \leq N$ and $M(i, j)$ the matching score between t_i and t_j for $1 \leq i, j \leq N$. Then, the matching score matrix algorithm (MSM) is described as follows, where r_i is the index of the i^{th} template in the order of image comparison for $1 \leq i \leq N$.

• At the first comparison, the matching score v_1 between the input image and t_{r1} is calculated.

• If v_1 is not less than the threshold, then the algorithm outputs r_1 and terminates. Otherwise, the next comparison is done with the template t_{r2} such that $M(r_2, r_1)$ is the nearest to v_1 in $M(j, r_1)$ for $1 \leq j \leq N$ and $r_1 \neq r_2$.

• Inductively, if v_n is not less than the threshold, then the algorithm outputs rn and terminates. Otherwise, the next comparison is operated with t_{rn+1}. r_{n+1} is decided as j such that

$$W_{j,n} = \frac{V_n, \mathrm{U}_{j,n}}{\| V_n \| + \| \mathrm{U}_{j,n} \|}$$

is the maximal for $j \in \{1, 2, \ldots, N\} \setminus \{r_1, r_2, \ldots, r_n\}$, where $V_n = (v_1, v_2, \ldots, v_n)$ and $U_{j,n} = (M(j, r_1), M(j, r_2), \ldots, M(j, r_n))$. N

• If the similarity between the input image and any template is less than the threshold, then the algorithm outputs "*null*" and terminates.

In [10], Maeda et al. performed a simulation of MSM with fingerprints and reported that the average number of comparisons is experimentally proportional to $\sqrt{N}$, that is, N_c is proportional to $\sqrt{N}$ in the sense of the formalization in Subsection 2.2. By the previous description of the algorithm, however, the processing time for computing $W_{j,n}$ for any possible j still depends on N, that is, $T_c = O(N)$. Therefore, the total processing time is estimated to be proportional to $N^{3/2}$.

4. Evaluation

The identification algorithm in Section 3 was applied to practical palmprint images and evaluated in terms of the criteria in Section 2.

4.1 Image Matching

We considered a matching of SIFT features for the comparison of palmprint images. This subsection defines the similarity on palmprint images for identification.

Prior to applying SIFT feature extraction to palmprint images, the region of interest (ROI) on each palmprint was extracted. The accuracy of identification can be affected considerably by this process, especially when we suppose contactless images. In the SIFT-based verification by Chen and Moon [3], the ROI on a palmprint was extracted as a square based on the method in [13]. In this paper, we took account of the difficulty of capturing the landmarks for the method in [13] on contactless palmprint images, and then extracted the ROI as the circle which covers the maximal part on a palm. Fig. 1 is an example of the extraction of the ROI. The palmprint image is a sample taken from [2].

SIFT extracts image futures which are invariant to scale and rotation. SIFT is one of the popular methods for image matching and object recognition, and there already exist some researches which apply SIFT into verification on biometric images such as fingerprints [5, 12] and palmprints [3, 11]. The scope of this paper is not any examination of SIFT feature extraction but an evaluation of an identification algorithm. Therefore, this subsection concentrates to aspects about application of SIFT, and the detailed mechanism of SIFT can be found in [8, 9].

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 on images (that is, sets of key points) was defined as follows. Let P and Q be two sets of key points and $v(p)$ the feature vector of a key point p.

- 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 $p_q = p$.

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

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

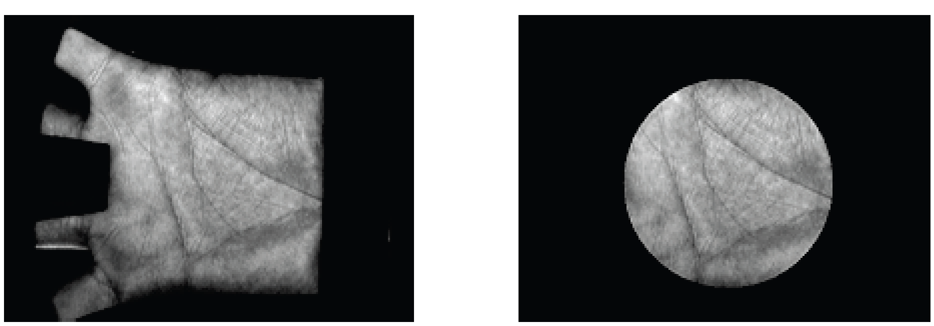

Figure 1. An example of a palmprint image (left) and the extracted ROI (right).

4.2 Methods

The experiments in this paper were conducted on the PolyU Palmprint Database [2]. For the practical process of SIFT, the function "*SiftFeatureDetector*" in OpenCV [1] was used. We used the computer with Intel ® Core^{TM} 2 Duo CPU E8500 3.16GHz and 3GB RAM.

First, to set the parameters of the SIFT function and examine the processing time of a single image comparison, we conducted a preparatory experiment with 11 sets of 50 palmprint images (10 persons with 5 images for each). The processing time for the matching of key points and the EER were examined. Then, by considering the trade-off of the two values, the parameter "*threshold*" of the function was fixed at 0:01, and the other parameters were set to the default values. The processing time for the matching of key points was 75 msec at the point of the threshold.

Next, MSM and the linear search algorithm were applied to a sample set of palmprint images. The set contains 1; 200 images which consists of 150 persons times 8 images. We conducted 2-fold cross-validation. We separated the set into two sample sets of 150×4 images, then an experiment was conducted with one set for templates and another set for input images, and repeated by swapping the sets. The number of image comparisons in MSM depends on the choice of the pair of images for the first comparison, and that in the linear search depends on the order of templates in addition to the choice. Therefore, identification was repeated for any combination of the initial pair (600×600 patterns), and a cyclic order was fixed for the repetition in the linear search. Thus, any value of the experiments is the average of $600 \times 600 \times 2$ trials.

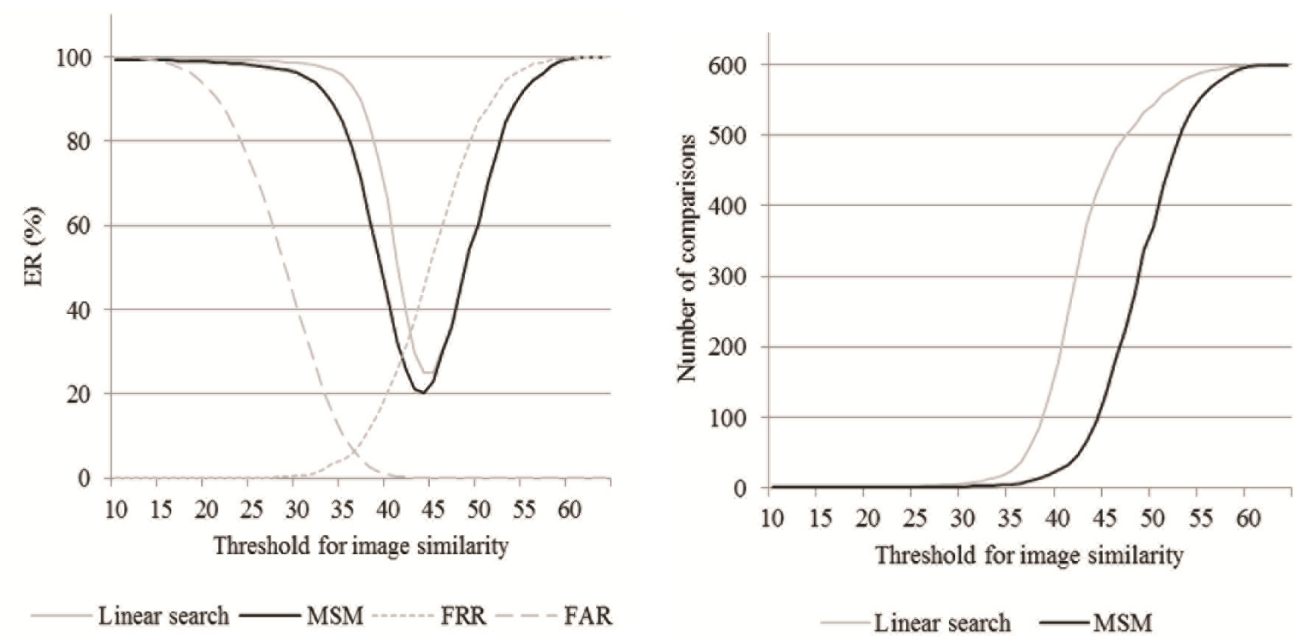

Figure 2. The ERs with FRR and FAR (left) and the number of image comparisons (right) of MSM and the linear search algorithm.

4.3 Results

The left-hand of Figure 2 shows the ERs of MSM and the linear search algorithms at the different values of the threshold for the image similarity with the FRR and FAR. The experimental result reports that MSM slightly decreased the ER compared to the linear search algorithm. The optimum ER was 20:3%for MSM and 24:9%for the linear search algorithm respectively at the threshold 44.

The right-hand of Figure 2 shows the number of image comparisons in MSM and the linear search algorithms at the different values of the threshold for the image similarity. The number of the image comparisons was drastically reduced by MSM. The number at the point of the optimum ER was 94:6 for MSM and 417:3 for the linear search algorithm.

Additionally, for MSM, the processing time of deciding the order of image comparison was examined. The processing time of the search for the next template was 3.0 msec at the point of the optimum ER. Therefore, the processing time of a single search is 0.032 msec. Although this time should be considered as an overhead of MSM against the linear search (and it is proportional to N as we mentioned in Section 3), it is extremely short compared with the processing time (75 msec) for the matching of key points.

We also examined the number of image comparisons in MSM with a limit for the number. MSM terminates if the number of image comparisons reaches the limit. The limitation is effective in identification where the person of the input image is not included in the templates. Figure 3 shows the ER and the number of image comparisons in MSM with several limits at the threshold of the optimum ER. By the results, the number of image comparisons can be reduced to half with little deterioration of the accuracy by the limit of about 30% of the number of the templates.

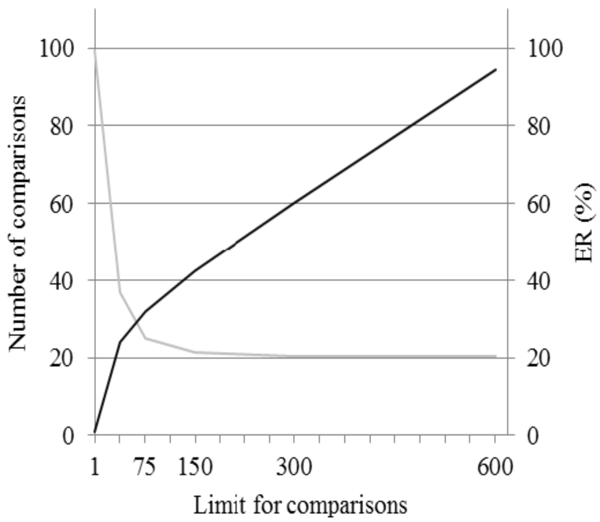

Figure 3. The ER and the number of image comparisons in MSM with limit for the number of image comparisons.

5. Conclusion

This paper evaluated the existing identification algorithm with biometric information by Maeda et al. [10]. The algorithm was implemented and evaluated in terms of the processing time and the accuracy with the features extracted by SIFT from practical palmprint images. By the conducted experiments, we can conclude that the algorithm by Maeda et al. can reduce the number of image comparisons from the linear search algorithm also for the features extracted by SIFT from palmprint images.

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