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# Evaluation of a Fingerprint Identification Algorithm with SIFT Features*

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## Abstract

In fingerprint identification, the short identification time is a crucial need. The identification time can be estimated according to the number of conducted matching processes multiplied by the consumed time by a single matching process. The Matching Score Matrix is an existing identification algorithm that reduces the number of matching processes. This paper evaluates the algorithm with the features extracted from fingerprint images by SIFT. The processing time and the accuracy are compared with those of the straightforward method based on the linear search. The evaluation results prove the applicability of the algorithm to fingerprint identification using SIFT features.
**Keywords:** biometrics; personal identification; fingerprint; SIFT.

## 1 Introduction

Biometric authentication compensates some weaknesses of token- and knowledge-based authentication. Fingerprint is one of the dominant biometrics traits that keeps spreading out because its uniqueness, acceptability, and low cost [5]. Due to the high demand on fingerprint deployments, fingerprint database is supposed to contain a huge number of enrolled users. The identification process searches for the person's identity inside the database. In the large scale identification deployment, the database size becomes larger and the identification time will be much longer. Due to related system's performance issues, reducing the identification time is a highly demanding problem.

The reduction of identification time can be achieved by managing two factors, that is, "the processing time of a single matching process" and "the number of matching processes". For the latter one, Maeda et al. [8] proposed an identification algorithm (MSM) that needs little matching processes compared to the linear search. MSM reduces the number of matching processes between the input image and already registered information (templates) by considering a similarity between templates. It is reported that the average number of matching is proportional to $\sqrt{N}$ for the database size $N$, while the expectation of that in the linear search is $O(N)$.

The aim of this paper is to evaluate the applicability of MSM to general biometric images. Although MSM has been evaluated with fingerprint images in [8], the information about the extracted features is missing. As a first step, we focus on Scale Invariant Feature Transform (SIFT) [6, 7] as a method of feature extraction. SIFT is one of the popular methods for image matching and object recognition. It efficiently extracts reliable features, therefore, it is used to overcome different fingerprint image degradations such as noise, partiality, and rotations. Since SIFT does not need any specified knowledge about biometric treat, the results of an evaluation with SIFT features are expected to show general properties. Some researchers have already used SIFT for biometric-based authentication with applications on fingerprints [4, 11] and palmprints [1, 10]. To show the applicability of SIFT is not the aim of this paper.

In this paper, we apply MSM to the SIFT features extracted from fingerprint images. The processing time and the accuracy are reported and compared against the linear search. Our evaluation results confirm that the number of matching processes is reduced and the error rate for identification is not increased by MSM from the linear search. The contribution of this paper is to clarify the applicability of MSM as a speed-up method for standard comparison-based identification algorithms.

The reminder part of this paper is organized as follows. Section 2 clarifies the criteria for the processing time and the accuracy of personal identification using fingerprint images. Section 3 introduces the MSM algorithm proposed by Maeda et al. The experimental results are shown in Section 4. Conclusions and future work are reported in Section 5.

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# 2 Preliminaries

This section clarifies the criteria for evaluating the identification time and the identification accuracy. In this paper, we consider personal identification with biometric images.

## 2.1 Identification Time

For the evaluation of the identification time, "the number of image comparisons" and "the processing time of a single image comparison" will be considered in addition to "the total identification time". In the rest of the paper, the number of templates is described by $N$. The number of image comparisons in the linear search is $O(N)$. Although a classification of images with $c$ classes decreases the number of matching processes to about $1/c$, it is still considered as $O(N)$. The number in the target algorithm (MSM) of the evaluation in this paper was reported in [8] to be proportional to $\sqrt{N}$.

## 2.2 Identification Accuracy

For measuring the accuracy of an identification algorithm, we will 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 verification error rates [5]. The *false rejection rate* (*FRR*) is calculated as the rate that the similarity between two images of the same person is less than the threshold, and the *false acceptance rate* (*FAR*) is the rate that the similarity between the images of different persons is not less than the threshold. FRR and FAR depend on the similarity threshold. 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. [8] proposed an identification algorithm for general biometric information 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 comparison 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 $1 \leq i \leq N$.

1. At the first comparison, the matching score $v_1$ between the input image and $t_{r_1}$ is calculated.
2. 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 $t_{r_2}$ 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 $r_1 \neq r_2$.
3. Inductively, if $v_n$ is not less than the threshold, then the algorithm outputs $r_n$ and terminates. Otherwise, the next comparison is operated with $t_{r_{n+1}}$. $r_{n+1}$ is decided as $j$ such that
$$W_{j,n} = \frac{V_n \cdot U_{j,n}}{\|V_n\| + \|U_{j,n}\|}$$
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
$$U_{j,n} = (M(j, r_1), M(j, r_2), \ldots, M(j, r_n)).$$
4. If the similarity between the input image and any template is less than the threshold, then the algorithm outputs "null" and terminates.

In [8], Maeda et al. performed a simulation of MSM with fingerprints and reported that the average number of comparisons is experimentally proportional to $\sqrt{N}$, while the expectation of that in the linear search is $(N+1)/2$. However, the processing time for computing $W_{j,n}$ for any possible $j$ still depends on $N$. Therefore, the time for this process might be significant for a large $N$.

# 4 Evaluation

MSM in Section 3 has been applied to a standard fingerprint database, and evaluated with regard to the time and the accuracy.

## 4.1 Experimental Environment

Applying SIFT feature extraction translates the fingerprint image into a set of key points according to the detected local maxima. Each extracted key point is represented by a number of descriptors related to the pixel orientation around it. The default SIFT feature extraction [6] produces key points with 128 descriptors as a features vector as 16 cell × 8 orientations. Then, a comparison of two images was done by matching the

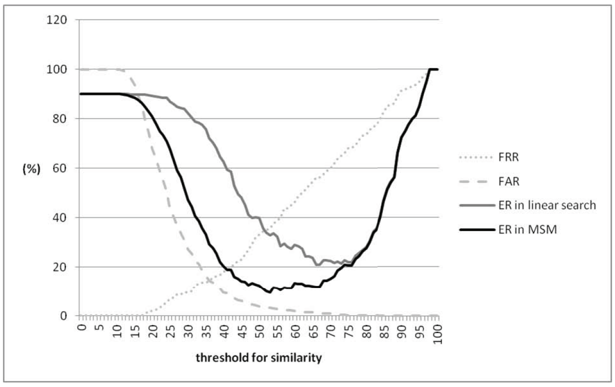


Figure 1: The ERs of the linear search and MSM with FRR and FAR.

two sets of descriptors. In this paper, SIFT features have been extracted and matched using the VLFeat library [12]. The output of matching process is the similarity score between the two input images.

Fingerprint Verification Competition 2002 (FVC2002) [9] DB2_B subset includes 80 fingerprint images (8 images $\times$ 10 persons). The set has been further divided into two sets of 40 images (4 images $\times$ 10 persons) for computing the matching score matrix and testing identification by MSM, respectively. The experiments were repeated after swapping the two sample sets, and each result is the average of the two trials. The region of interest (ROI) that includes a valuable ridge structure has been separated from the background area. Furthermore, the RANSAC algorithm [3] has been used to filter out the false matching points between the two input images.

Some primary experiments have been conducted to select the optimum SIFT parameters. The conducted experiments led to set the SIFT threshold to be 0.01. The selected threshold achieves the optimum ERR 14.4%. The matching score matrix has been created by computing the similarity scores between all images of the enrollment set. Therefore, the size of the matrix is 40 $\times$ 40.

### 4.2 Experimental Results

The total processing time and the ER depend on the threshold for similarity. Fig. 1 shows the ERs of the linear search and MSM with FRR and FAR calculated over the 80 fingerprint images. In the experiment, the identification was repeated 1,600 times which is the number of the combination of the initial pair (40 $\times$ 40) for the image comparison (and this process was repeated twice for the two image sets). By Fig. 1, MSM has an advance point over the linear search as its identification error is 9.41% compared to 20.9% for the linear search.

Table 1 shows the time characterization of the linear search and MSM. "Number of Comparisons" is the number of image comparisons conducted until the algorithm terminated, "Time for a Comparison" is the processing time required to conduct a single image comparison which includes feature extracting by SIFT, and "Time for a Search" is the processing time required to find the best template for the next comparison in the process 3 of the algorithm description in Section 3. The processing time for a single image comparison was computed separately from the experiment of identification, and it is the completely same process in the linear search and MSM. The other values are computed from the results on the threshold of the optimum error rate and respectively the average of the 1,600 $\times$ 2 times repetition.

The total processing time $T$ for an identification can be estimated by

$$T = M \times (T_1 + T_2),$$

where $M$ is the number of comparisons, $T_1$ is the processing time of a single comparison, and $T_2$ is the processing time for a search of the next candidate. $T_1$ is a constant (about the number of templates $N$) and has the same value for the linear search and MSM. $T_2$ should be regarded as almost 0 for the linear search. Table 2 shows the total processing time of a single identification estimated by the formalization and the error rate of the linear search and MSM at the threshold of the optimum ER. By Table 2, MSM consumes a shorter identification time compared to the linear search with the number of templates.

In the formalization of the processing time, $M$ is proportional to $N$ for the linear search, and Maeda et al. claims that $M$ is proportional to $\sqrt{N}$ for MSM [8]. By the algorithm description in Section 3, $T_2$ for MSM should be proportional to $N$. Therefore, $T$ is considered to be proportional to $N^{\frac{3}{2}}$ which is worse than the linear search. By Table 1, however, the processing time for finding the next template is extremely short compared with that for comparing images.

## 5 Conclusion

This paper evaluated one of the available algorithms, MSM, for identification time reduction with fingerprint SIFT features. The conducted evaluation proved the applicability of MSM for fingerprint identification using SIFT features. The superiority of MSM over the linear search with respect to the identification time and accuracy has been confirmed.

In MSM, if we assume that the number of comparisons is proportional to $N^{\frac{1}{2}}$ according to the report of [8], the total processing time for a single identification is proportional to $N^{\frac{3}{2}}$ [2] because the process to search

Table 1: The number of image comparisons, the processing time of a single image comparison, and the processing time for finding the next template of the linear search and MSM.

| | Number of Comparisons | Time for a Comparison (sec) | Time for a Search (sec) |
|---|---|---|---|
| Linear Search | 19.3 | 0.858 | – |
| MSM | 6.78 | 0.858 | 0.0000194 |

Table 2: The total processing time of an identification and the error rate of the linear search and MSM.

| | Processing Time (sec) | Error Rate (%) |
|---|---|---|
| Linear Search | 16.6 | 20.9 |
| MSM | 5.83 | 9.41 |

the nearest vector takes $O(N)$. Reducing the time of the process is one of our future work.

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