Improving Rank-N Identification Rate of Palmprint Identification Using Permutation-Based Indexing

Improving Rank-N Identification Rate of Palmprint Identification Using Permutation-based Indexing

Mizuho Yoshihira[1], Ayumi Serizawa[1], Ryosuke Okudera[1], Yumo Ouchi[1], Yuya Shiomi[1], Naoya Nitta[2], Masataka Nakahara[2], Akira Baba[2], Yutaka Miyake[2], Tetsushi Ohki[1], and Masakatsu Nishigaki[1][0000-0001-6048-3495]

[1] Shizuoka University, Hamamatsu, Shizuoka, Japan
[2] KDDI Research, Inc., Fijimino, Saitama, Japan
nisigaki@inf.shizuoka.ac.jp

Abstract. Biometric information can have high similarity among different people but high variability within the same person. Therefore, it is difficult to identify a person or distinguish between two people based on biometric information. One way to address these issues is to use certain biometric information as pivots to define the feature space of biometric information. However, previous research has not sufficiently examined methods for selecting these pivots. In this study, schemes for pivot selection and robust palmprint identification are proposed that can improve the rank-N identification rate.

Keywords: Biometric Recognition, Palmprint Identification, Permutation-based Indexing.

1 Introduction

Biometric information has advantages over other sources of personally identifiable information as it cannot be forgotten or lost. Further, biometric recognition is convenient because it does not require a password. Therefore biometric recognition has been used not only for smartphone login but also as a means of identity confirmation for purposes such as access control and payment systems. Several different approaches have been proposed with different modalities such as fingerprints, face, and iris [1]. This study is focused on palmprint identification as it is superior in terms of availability, i.e., biometric information can be obtained in a contactless manner via a camera built into a smartphone, social acceptability, i.e., the psychological burden caused by privacy concerns regarding the acquisition of biometric information is lesser than it would be for faces, and convenience, i.e., it can identify a person without the need to enter a user ID.

Fig. 1 shows a pipeline for simple palmprint identification. In the enrollment phase, the users present their biometric information, i.e., their palmprint image, which is then enrolled into the database as a *template*. In the identification phase, the biometric information is obtained as a *query* from the user in the same manner as in the enrollment phase, and the system compares the query with the templates enrolled within the database.

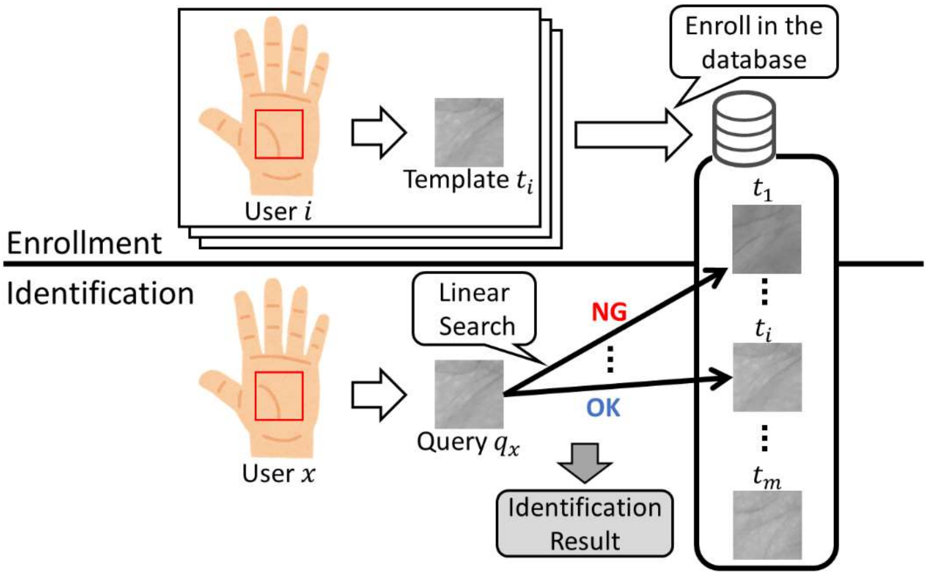


Fig. 1. A scheme for simple palmprint identification.

An issue with biometric recognition is that it can be difficult to distinguish between two people because biometric information generally has *high similarity* among different people and *high variability* within the same person (see Fig. 2). The conventional feature space defined for representing various types of images, such as dogs, bicycles, teacups, etc., cannot be sufficiently capable of distinguishing the differences in the biometric information between users. Furthermore, there is a general issue of the time required for the biometric identification increasing as the number of enrollees (templates) increases.

To resolve these issues, the *pivot-based indexing method* has been proposed to define the feature space of the biometric information using certain templates as *pivots*, i.e., representative points for calculating the distance to a template or a query [2][3][4]. Maeda et al. proposed a method of defining biometric features using a set of matching scores referred to as a *matching score vector* between each pivot and templates or query, where the pivots are a subset of the templates randomly selected from the enrolled templates [2]. The matching score vector can aid in finding a more similar template to the query in a step-by-step manner. Using this method, the user (template) that is most similar to the query can be identified in less time than that required for a linear search. Murakami et al. proposed to reduce the time required for the biometric identification by sorting the templates in order of similarity using a similarity search [3][4]. The templates can be quickly sorted in order of similarity using a ranked matching score vector as an index referred to as a *permutation-based index*. The performance of the biometric identification might improve by comparing the query with the templates in order of similarity. and therefore, Murakami et al.'s pivot-based indexing method is known as the *permutation-based indexing method*.

Due to the high similarity of the biometric information, using a feature space with poor discriminability of the biometric information may affect the accuracy and speed of the biometric identification significantly. In the pivot-based indexing method, the pivots are used as the basis for forming the feature space of the biometric information. Therefore, the method of selecting the pivots is crucial to improve the performance of the biometric identification using the pivot-based indexing method. However, in previous studies, the pivots were randomly selected from the templates [2][3] or generated using generative adversarial networks (GANs) [4]. To the best of the authors' knowledge, there are no previous studies that have sufficiently examined the effect of this pivot selection process.

In addition, it is important to address the issue from the perspective of the high variability of the biometric information. The fluctuations in the biometric information affect the pivot-based index generated from the biometric information. Therefore, to improve the accuracy of the biometric identification using the pivot-based indexing method, the pivot-based index must be made robust against the variability that exists within the same person.

Initially, this study was focused on the permutation-based indexing method [3] and two schemes were proposed to improve the performance of the palmprint identification. The performance of the permutation-based indexing method was evaluated using the aspect of the *rank-N identification rate*, the percentage of possibility that the correct template is contained within the top N ranks of the sorted templates. This paper is organized as follows. An account of the previous studies on pivot-based indexing methods is presented in Section 2. The proposed methods that improve the permutation-based indexing method by introducing the two schemes are explained in Section 3. The experimental settings and the experimental results are discussed in Section 4 and 5, respectively. Finally, Section 6 contains the conclusions derived from this study.

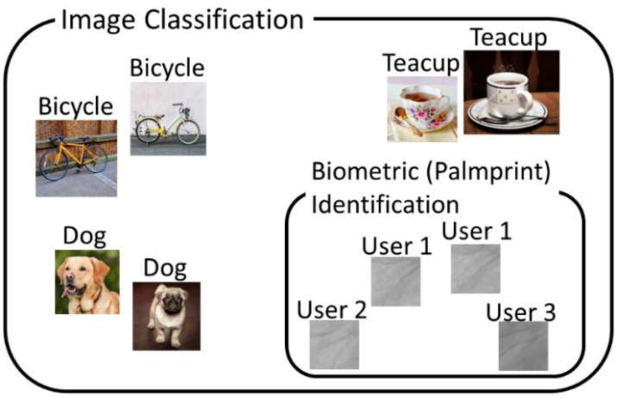


Fig. 2. Image classification and biometric identification.

2 Related Works on Pivot-based Indexing Methods

A naive biometric identification method involves linear search, in which the verification, that is, the one-to-one matching between a query and a template, is performed starting from the top of the database storing all the enrollees' templates. However, with this strategy, the expected number of comparisons increase linearly with the number of enrollees (templates) [1]. Various solutions have been proposed to reduce the number of such comparisons by dividing the templates into several clusters [5][6] or by sorting the templates in order of similarity [2][3]. The former approach has limits in terms of scalability as the number of templates belonging in a cluster could still become large as the number of enrollees increase.

For the latter approach, the sorting accuracy depends on how the feature space of the biometric information is defined. There is no known general method to determine the feature space deductively; however, it has been shown that using certain biometric information as reference points or a basis (referred to as pivots) is effective [2][3]. This is because the biometric information of another person will have a higher matching score, within the range below the threshold, when the similarity between the biometric information is slightly high, and a lower matching score when the similarity is completely low. In this study, these have been referred to as the *pivot-based indexing methods*.

2.1 Matching Score Vector for Biometric Identification

Maeda et al. proposed a method for defining a feature space of biometric information using a randomly selected subset of enrolled templates as pivots [2]. The comparison score set or the matching score vector between the pivots and biometric information was used as the biometric feature. The number of comparisons and the response time of the biometric identification could be greatly reduced compared to a linear search using the matching score vector to select a template with a higher correlation as the next template to be compared, as depicted in Fig. 3. To the best of the authors' knowledge, this study constitutes the first attempt to define biometric features based on comparisons with each pivot.

2.2 Permutation-based Indexing

Murakami et al. proposed a method that uses the templates of certain enrollees as the pivots and characterizes the biometric information according to the order of the magnitude of comparison with each pivot, as shown in Fig. 4 [3]. This method is an example of applying permutation-based indexing, which is known as an efficient similarity search method for images and documents, for biometric identification [3][7][8].

In the enrollment phase, the indexes are created from the templates using the pivot, and they are enrolled in the database. In the identification phase, a permutation-based index of a query is first calculated, and then the templates with the highest similarity are retrieved from the database and matched in order of similarity.

The similarity between the two indexes π_a and π_b is calculated using the Spearman Rho correlation coefficient, as shown in Equation 1. m is the number of elements of each pivot, and $\pi(i)$ denotes the ith element in the permutation-based index π.

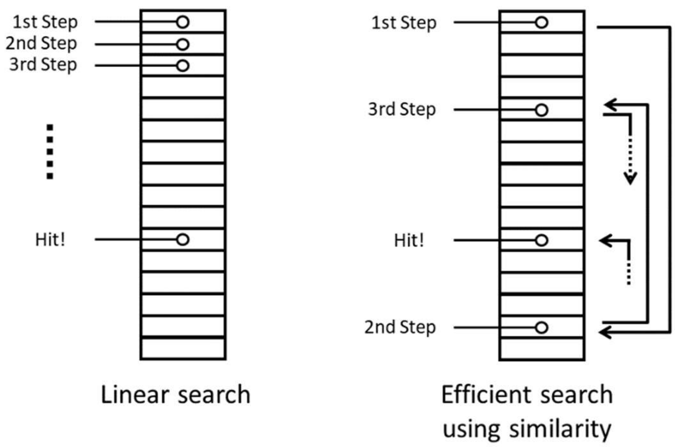


Fig. 3. Linear search and efficient search using similarity. (Quoted from [2], with certain modifications.)

$$s(\pi_a, \pi_b) = \sum_{i=1}^{m} |\pi_a(i) - \pi_b(i)|^2 \quad (1)$$

In Reference [3], the identification algorithm is multiplexed by combining the permutation-based indexing with the score level fusion technique in the Bayes decision rule to achieve efficient multimodal biometric identification. Moreover, instead of randomly selecting the pivots from the templates, a method for generating them using generative adversarial networks (GANs) has been proposed [4]. However, as the purpose of the current method is to prevent privacy leakage from templates used as pivots, the generation of pivots that improve identification accuracy has not been considered.

3 Proposed Methods

3.1 Challenges Identified within Previous Studies with Approaches for Improvement

In the existing pivot-based indexing methods [2][3][4] described in Sections 2.1 and 2.2, the method of selecting the pivots which are the basis for forming the feature space of the biometric information has a significant impact on the identification accuracy and speed. However, in all the existing methods, the pivots are selected randomly, and the pivot selection method is put down as a future concern. To be precise, in reference [2] the number of pivots is analyzed theoretically; however, the selection of the pivots is based on the most accurate from the combinations chosen at random. In

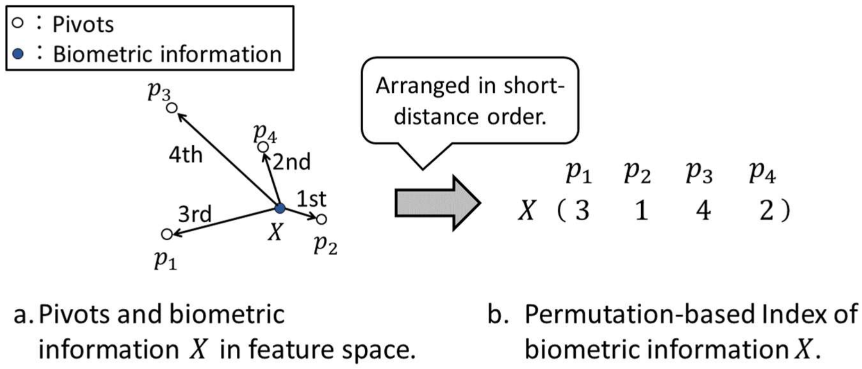


Fig. 4. A scheme for creating a permutation-based index from a template and pivots.

addition, the existing methods do not emphasize on the robustness of the pivot-based index against the variability of the biometric information within the same person.

In this study, two schemes are proposed for constructing pivots with efficient properties in terms of spatial separability of the pivots (Section 3.2) and robustness of the permutation-based index (Section 3.3). The nature of the biometric information, which is both (i) highly similar between different people and (ii) highly variable within the same person, renders biometric identification difficult. The former scheme aims to move the biometric features of different people away from each other, which contributes to improving the pivot-based indexing method from the viewpoint of nature (i). The latter scheme aims to absorb the variations within the biometric features of the same person, which contributes to improving the pivot-based indexing method from the viewpoint of nature (ii).

The aim of this study is to improve the rank-N identification rate of palmprint identification using permutation-based indexing. The pipeline for the improved palmprint identification is shown in Fig. 5.

3.2 PCA-based Pivot Orthogonalization

To improve the spatial separability of the pivots, pivot orthogonalization based on principal component analysis (PCA) is proposed, to efficiently select the pivots that improve the rank-N identification rate of palmprint identification. Specifically, the templates (palmprint images of the enrollment phase) of all enrollees are subjected to two-dimensional PCA to generate a sequence of the principal component images, and the first p members of the sequence are used as pivots. In this study, p=30 was set throughout the preliminary experiments. This scheme has been referred to as *PCA-based pivot orthogonalization*.

PCA is a popular technique used to find an optimal representation of data. However, it has not yet been applied to pivot selection for palmprint identification using permutation-based indexing method. The orthogonalization of the pivots, that is, the basis that forms the feature space of the biometric information, is expected to increase the discriminability of the biometric information. Thus, improvements in the feature space property can be achieved using PCA-based pivot orthogonalization.

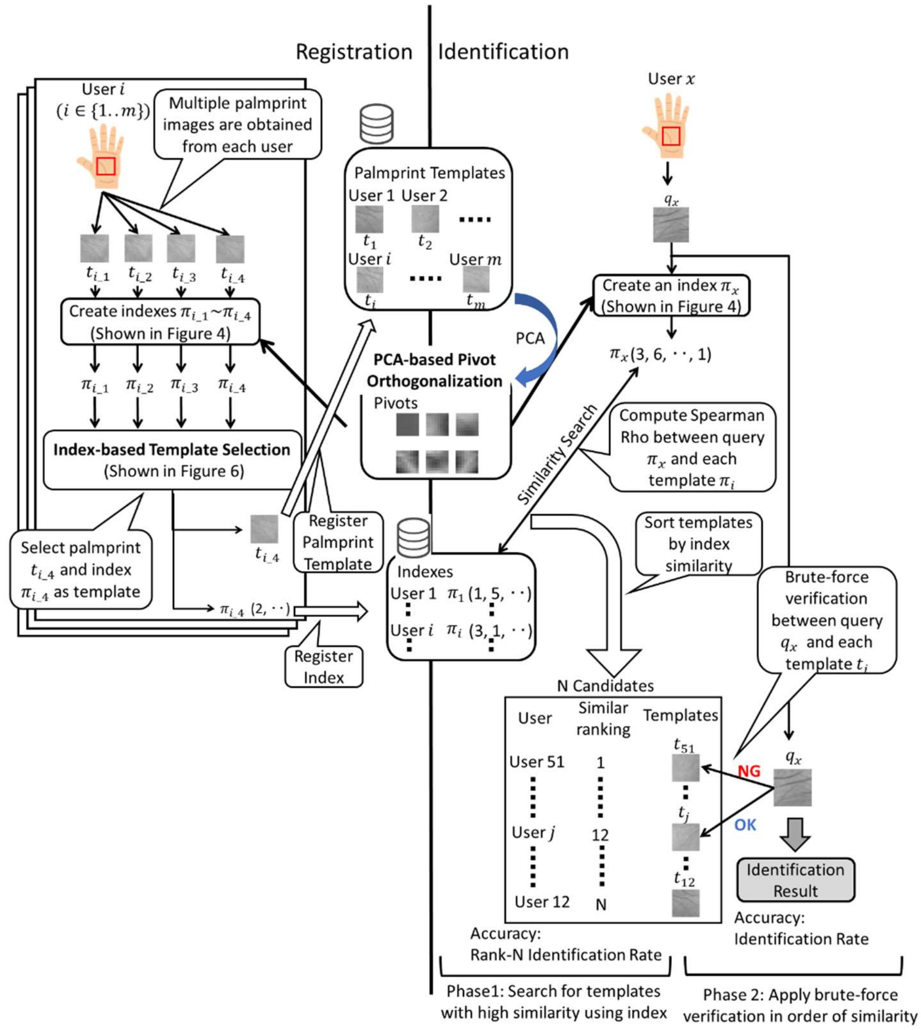


Fig. 5. Pipeline of palmprint identification using permutation-based indexing.

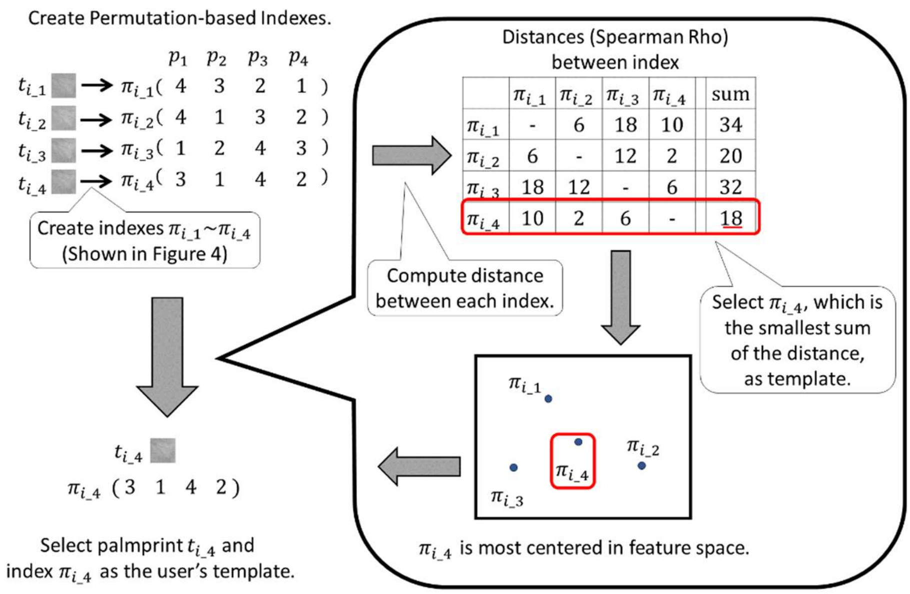
3.3 Index-based Template Selection

To improve the robustness of the permutation-based index generated based on the biometric information, a scheme was adopted in which multiple palmprint images were obtained from each user at the time of enrollment, and the palmprint image with the most stable permutation-based index was selected as the template of the user. This scheme is referred to as the *index-based template selection*.

The specific procedure for the index-based template selection is as follows. First, t palmprint images (templates) $T_{u,1}, \cdots, T_{u,t}$ are obtained from any user u for enrollment and the permutation-based index $\pi_{T_{u,i}}$ is created for each palmprint image $T_{u,i}$. Next, using equation (2), the permutation-based index $\pi_{T_{u,s}}$ is chosen from $\{\pi_{T_{u,1}}, \cdots, \pi_{T_{u,t}}\}$ which minimizes the sum of the distances between the permutation-based indexes. The index $\pi_{T_{u,s}}$ and the corresponding palmprint image $T_{u,s}$ are registered as user u's template.

$$\pi_{T_s} = \underset{\pi_{T_j} \in \{\pi_{T_1}, \cdots, \pi_{T_t}\}}{\arg\min} \sum_{\substack{i=1 \\ i \neq j}}^{t} S(\pi_i, \pi_j) \tag{2}$$

Equation (2) selects the palmprint image closest to the center (on the distance scale of Equation (1)) from t palmprint images of candidate within the same person. This contributes to creating a template that is robust against the high variability within the same person introduced with each palmprint image acquisition. Thus, improvement of the rank-N identification rate can be achieved by the index-based template selection. Fig. 6 shows a schematic of the index-based template selection.



	π_{i_1}	π_{i_2}	π_{i_3}	π_{i_4}	sum
π_{i_1}	-	6	18	10	34
π_{i_2}	6	-	12	2	20
π_{i_3}	18	12	-	6	32
π_{i_4}	10	2	6	-	18

Fig. 6. A scheme of the index-based template selection.

4 Experiments

4.1 Experimental Patterns

To evaluate the effectiveness of the PCA-based pivot orthogonalization and index-based template selection proposed herein, the rank-N identification rate is compared with the five evaluation patterns, A through E, as shown in Table 1.

When a query (a palmprint image for identification) is entered into the palmprint identification system, the templates of all enrolled users (all palmprint images enrolled in the palmprint identification system) are sorted in order of similarity to the query. Pattern A is sorted using the existing permutation-based indexing method as described in Section 2.2. Patterns B and C modify pattern A by applying PCA-based pivot orthogonalization scheme and index-based template selection, respectively. Pattern D is the proposed method, in which both schemes are applied together to pattern A.

Pattern E is the control group, and band-limited phase-only correlation (BLPOC) [9] in low resolution is used to sort the templates of all the enrollees in order of similarity to the query. More specifically, the center region 128×128 [px] of the palmprint image was cropped and the matching score calculated using the BLPOC algorithm for palmprint recognition proposed in [10] with only the center k×k of the frequency domain. Through preliminary experiments, k=32 was empirically adopted for speed and accuracy (hereafter referred to as "32-BLPOC"). The matching score is used as the similarity.

Table 1. Evaluation patterns.

	Template Sorting Method	Apply	
		PCA-based Pivots Orthogonalization	Index-based Template Selection
A	Permutation-based Indexing		
B		✓	
C			✓
D		✓	✓
E	BLPOC in low resolution		

4.2 Experimental Steps

As explained in Section 3.1, the pipeline from enrollment to identification in the proposed method (pattern D) is shown in Fig. 5. The pipelines for pattern C, B, and A differ from that for pattern D only by the difference between having or not having the PCA-based pivot orthogonalization, index-based template selection, and both together, respectively. The pipeline for pattern E includes a procedure for sorting the templates with a low-resolution BLPOC in a brute-force manner, instead of using the pivots and indexes.

These pipelines are composed of two stages: template sorting and exact matching. The performances of patterns A to E were evaluated for each stage. In the first stage, the rank-N identification rate for patterns A to E was calculated by applying the sorting method for each pattern and evaluating whether the template for the query user x is included within the top N positions of the resulting sorted templates. In the second stage, the identification accuracy of patterns A to E was calculated by repeatedly performing a one-to-one comparison (known as *verification* in biometric recognition) of the query and template, starting from the top of the sorted templates, and evaluating whether the identified user is determined to be user x. For this comparison in the proposed experiment, the BLPOC algorithm was used for palmprint recognition [10]. Further, the time required to sort the templates and for the one-to-one comparison after sorting were compared.

4.3 Experimental Environment

The execution environment used for the experiment is shown in Table 2.

Table 2. Execution environment.

CPU	Intel Core i7-11375H 3.3 GHz
RAM	LPDDR4X-4266 16 GB
OS	Ubuntu 20.04 LTS
Container engine	Docker 20.10.5
Language	Python 3.6.9

4.4 Dataset and Preprocessing

Ten palm images from both hands of 523 users (523 users × 2 hands = 1,046 enrollees) were acquired. Each of the ten palm images was divided into two groups in order of acquisition; five images were prepared as templates for registration and five images as queries for identification.

The palmprint images were created by performing the following preprocessing on all the palm images. Fig. 7 shows examples of the palm and palmprint images used in this study.

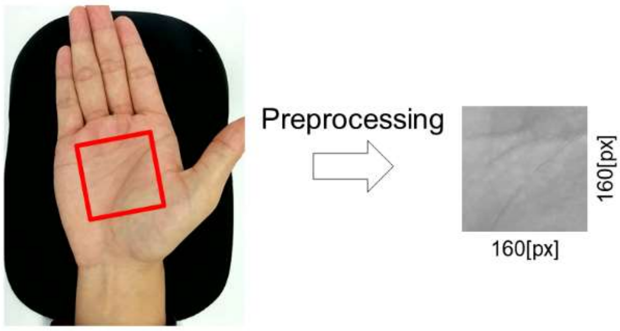


Fig. 7. Examples of palmprint images used in the evaluation experiments.

1. Apply the procedures used in [11] for cutting out the palmprint region of interest (ROI) in the palm image.
2. Resize the ROI of the palmprint to 160×160 [px].
3. Convert RGB color space to YUV color space and create a 160×160 [px] gray-scale image with only Y values as a palmprint image.

4.5 Matching Score-based Template/Query Selection

As described in Section 4.4, in this experiment, five palmprint images were provided per user for enrollment and five for identification.

In the enrollment phase, for each user, the image closest to the center (in terms of the distance measure of the verification algorithm) was selected from the five enrollment images using Equation (3), and this image was enrolled in the identification system database as the template for the user. This operation is referred to as *matching score-based template selection*.

$$q_s = \underset{q_j \in \{q_1, \cdots, q_v\}}{\arg\max} \sum_{\substack{i=1 \\ i \neq j}}^{v} M(q_i, q_j) \tag{3}$$

Here, $q_1, \cdots, q_v$ is the biometric information, and M is the verification algorithm. In this experiment, $v=5$ was used and M is 32-BLPOC.

Owing to the use of matching score-based template selection, the palmprint images selected as templates are robust against the high variability within the same person. In other words, matching score-based template selection has a purpose similar to index-based template selection as described in section 3.3, in that it increases the robustness of the biometric information. However, the difference is that index-based template selection contributes to a more stable permutation-based index, whereas the matching score-based template/query selection contributes to a more stable extraction of the palmprint images. Notably, the verification (one-to-one matching between a query and a template) is performed in the second stage of all the patterns A through E. In other words, it is necessary for all patterns A to E to choose a robust palmprint image in the enrollment phase. Hence, index-based template selection is applied to only patterns C and D, whereas matching score-based template selection is applied to all the patterns A through E.

This type of palmprint image selection can be applied in the identification phase, too. This operation is referred to as *matching score-based query selection*.

4.6 PCA-based Pivot Orthogonalization

For patterns B and D, the PCA-based pivot orthogonalization was applied. In this study, based on the results of the preliminary experiments, it was decided that PCA-based pivot orthogonalization would be performed as follows. For each of the 5,230 palmprint images for enrollment (1,046 enrollees × 5 images), cut out the center 128×128 [px] from the 160×160 [px] palmprint image and reduce the image to 8×8 [px] to create an intermediate image. The results of the PCA for all the intermediate images are 64 basis images (8×8 [px]). The 30 basis images from the 1st to the 30th principal components were used as the pivots, as depicted in Fig. 8.

To calculate the matching score between a palmprint image (160×160 [px]) and each pivot (8×8 [px] base image), firstly, an intermediate image of the palmprint image was created in the same manner by cutting out the center 128×128 [px] and reducing the image to 8×8 [px]. Secondly, the normalized cross correlation (NCC) between this intermediate image and the basis image was calculated, and the NCC score was used as the matching score between the palmprint image and the base image.

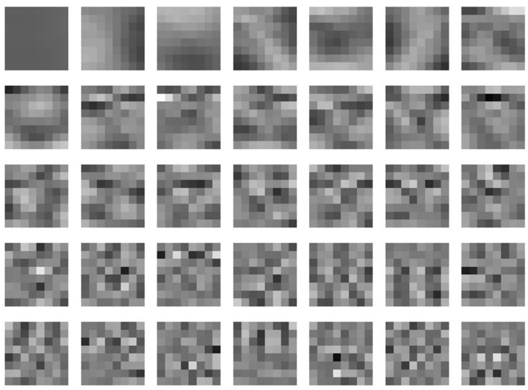


Fig. 8. Image obtained through the principal component analysis of a template. (Image size 8×8[px], from the 1st to the 30th principal components)

4.7 Index-based Template Selection

For patterns C and D, index-based template selection was applied. In this case, five palmprint images were prepared for the enrollment of all users, therefore, $t = 5$ in Equation (2) of Section 3.3.

In the case of a server-client identification system, the palmprint images captured by the client was sent to the server, and a palmprint identification was executed in the server. By capturing a series of images for the sequence of actions when the user presents his palm, the client device could capture multiple palmprint images. Therefore, the client device can always perform matching score-based template/query selection and send only the most stable palmprint image to the server. As matching score-based template/query selection is an operation that is completed within the client device, it can be used for both the enrollment and identification phases. Conversely, to perform the index-based template selection, the matching score with each pivot must be calculated. As the pivots are stored on the server, the client alone cannot perform the index-based template selection. Although it is possible to execute an index-based template selection on the server side by sending all the palmprint images captured by the client device to the server in the enrollment phase, the intention is to minimize the communication between the client and server during every identification transaction. Therefore, the index-based template selection is applied only during the enrollment phase.

5 Results

5.1 Experiments on Rank-N Identification Rate

Fig. 9 compares the rank-N identification rate of patterns A to E using cumulative match characteristic (CMC) curves. The nearer the CMC curve is located to the top, the more accurate the performance. The rank-1 / 5 / 20 identification rates for each pattern are shown in Table 3. Here, pattern E is a brute force comparison of the query to all the templates using a low-resolution BLPOC, involving sorting templates in a time-consuming and foolproof manner. In other words, pattern E is possibly the most accurate, and the question is in what manner the accuracy of patterns A through D approaches that of pattern E.

Fig. 9 and Table 3 show that the PCA-based pivot orthogonalization and the index-based template selection proposed in this paper contribute to the improvement of the rank-N identification rate of palmprint identification using permutation-based indexing. The effect of the PCA-based pivot orthogonalization (pattern B) is greater than that of the index-based template selection (pattern C), and the combined use of the PCA-based pivot orthogonalization and index-based template selection (pattern D) achieves an accuracy that greatly surpasses that of pattern A.

Table 3. Comparison rank-1/5/20 identification rate for each pattern.

Pattern	Rank-1 identification rate [%]	Rank-5 [%]	Rank-20 [%]
A	26.77	45.32	62.43
B	67.11	79.64	87.09
C	29.06	48.66	67.21
D	71.89	84.23	91.20
E	97.99	98.95	99.52

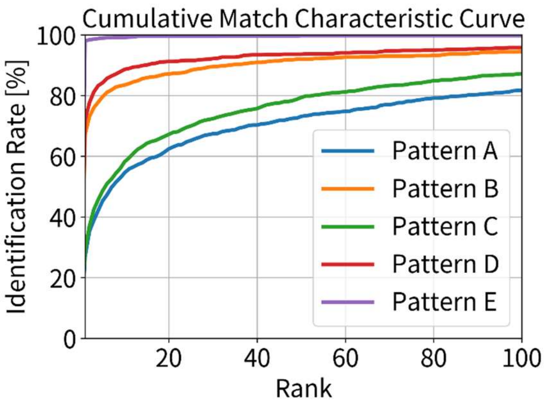


Fig. 9. Comparison of the rank-N identification rate for each pattern with the CMC curves.

5.2 Experiments on the Identification Accuracy and Required Time

The identification accuracy and time required for patterns A to E were evaluated in terms of speed and the number of comparisons. For the evaluation, the number of times the verification (one-to-one matching) was terminated was fixed to ensure that the success rate of identification for all the patterns would be 98%. Table 4 shows the results of the number of times the verification was repeated to find the identified person (average number of verifications) and the time required to find the identified person (average time required and maximum time required).

The average number of verifications in Table 4 further confirms that the efficiency of the palmprint identification improved in order of the index-based template selection (Pattern C), PCA-based pivot orthogonalization (Pattern B), and the combination of both methods (Pattern D), which was consistent with the results of Fig. 9 and Table 4. The average processing time in Table 4 shows that patterns A through D outperform the control group (pattern E) in terms of processing speed.

For a more precise comparison of the processing speed, the breakdown of the average time required for patterns D and E is shown in Fig. 10. Pattern E is a brute force comparison of the query to all the templates using a low-resolution BLPOC. As shown in Table 4, the average number of verifications in pattern E can be suppressed by sorting the templates over time to ensure high quality sorting. With the improvement in the permutation-based indexing in this study, Pattern D succeeded in significantly reducing the time required to sort the templates; however, the quality of sorting was not at par with that of pattern E, which is the reason for the average number of verifications in pattern D being greater. However, the reduction in the processing time required for sorting was overwhelming, therefore, pattern D consumed approximately 1/6th of the time required for the entire identification process.

Table 4. Performance comparison when the identification success rate was set to 98%.

Pattern	A	B	C	D	E
Number of times to terminate verifications	724	705	525	508	4
Average number of verifications	70.64	30.45	48.35	21.01	1.068
Standard deviation of the number of verifications	147.25	113.44	102.32	81.26	0.4333
Average processing time [s]	0.2764	0.1307	0.1932	0.09371	0.6405
Standard deviation of the average processing time [s]	0.5375	0.4201	0.3692	0.2931	0.02961
Maximum processing time [s]	2.6613	2.6590	1.8980	1.8529	0.9067

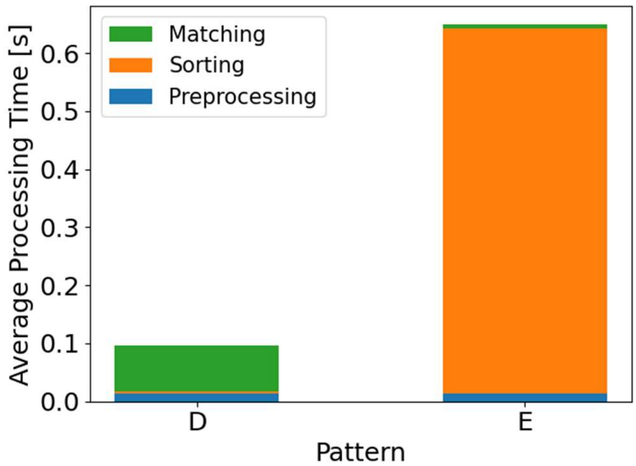


Fig. 10. Comparison of average processing time between patterns D and E.

6 Conclusion

In this study, a method to improve the accuracy of template retrieval by applying PCA-based pivot orthogonalization to palmprint identification using permutation-based indexing to improve the spatial separability of pivots was proposed. Furthermore, the application of index-based template selection to multiple permutation-based indexes obtained from multiple biometric records was suggested to improve the robustness of permutation-based index. The results confirmed that the proposed methods improved the rank-N identification rate and reduced the time required for palmprint identification.

References

1. Bolle, R.M., Connell, J.H., Pankanti, S., Ratha, N.K., Senior, A.W.: Guide to Biometrics. Springer (2003).
2. Maeda, T., Matsushita, M., Sasakawa, K.: Identification Algorithm Using a Matching Score Matrix. IEICE Transactions on Information and Systems E84-D(7), 819-824 (2001).
3. Murakami, T., Takahashi, K.: Fast and Accurate Biometric Identification Using Score Level Indexing and Fusion. In: The IEEE/IAPR International Joint Conference on Biometrics, Washington, D.C., pp. 1-8 (2011).
4. Murakami, T., Fujita, R., Ohki, T., Kaga, Y., Fujio, M., Takahashi, K.: Cancelable Permutation-based Indexing for Secure and Efficient Biometric Identification. IEEE Access, Vol.7, pp.45563-45582 (2019).
5. Kamei, T., Mizoguchi, M.: Fingerprint preselection using eigenfeatures, In: IEEE Computer Society Conference on Computer Vision and Pattern Recognition, Santa Barbara, California, pp. 918-923 (1998).
6. Germain, R.S., Califano, A., Colville, S.: Fingerprint matching using transformation parameter clustering, IEEE Computational Science and Engineering, 4(4), 42-49, (1997).
7. Chávez, E., Figueroa, K., Navarro, G.: Effective proximity retrieval by ordering permutations, IEEE Transactions on Pattern Analysis and Machine Intelligence, 30(9), 1647-1658 (2008).
8. Amato, G., Savino, P.: Approximate similarity search in metric spaces using inverted files, In: The 3rd International Conference on Scalable Information Systems (InfoScale '08), Brussels, Belgium, pp. 1-10 (2008).
9. Ito, K., Nakajima, H., Kobayashi, K., Aoki, T., Higuchi, T.: A fingerprint matching algorithm using phase-only correlation, IEICE Transactions on Fundamentals of Electronics, Communications and Computer Sciences, E87-A(3), 682-691 (2004).
10. Ito, K., Iitsuka, S., Aoki, T.: A palmprint recognition algorithm using phase-based correspondence matching, In: 16th IEEE International Conference on Image Processing (ICIP), Cairo, Egypt, pp. 1977-1980 (2009).
11. Nitta, N., Nakahara, M., Baba, A., Miyake, Y.: A Method for Estimating Palmprint Regions using Skeletal Information in Palmprint Authentication, In: Symposium on Cryptography and Information Security (SCIS 2021), 3F3-2, pp.1-6 (2021). (in Japanese)