Evaluation of Independence between Multiple Fingerprints for Multibiometrics*

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Abstract: Multibiometrics provides high recognition accuracy and population coverage by combining different biometric sources. However, some multibiometrics may obtain smaller-than-expected improvement of recognition accuracy if the combined biometric sources are dependent in terms of a false acceptance by mistakenly perceiving biometric features from two different persons as being from the same person. In this paper, we evaluated whether or not features of multiple fingerprints from a same person are statistically independent. By evaluating false acceptance error using matching scores obtained by Verifinger SDK, we confirmed that these features were dependent and the FAR obtained by a fusion of the multiple fingerprints could be affected by the dependence.

1 Introduction

Biometrics is a technology used to automatically identify individuals using physiological or behavioral features such as fingerprints, faces, veins, irises and hand geometry. In particular, the biometric identification technique (one-to-many matching) is remarkable as a key technology for the further expansion of the use of biometrics. Not only is it useful for users because they can be authenticated without the need for ID cards/license cards, but it can also prove that one person is unique among persons registered on a system. Therefore, in some developing countries where resident card and resident registration systems have not been completed, biometric systems are being introduced in order to manage all residents as identified individuals. In India, progress is currently being made with a unique identification project that provides identification for each resident across the country by collecting facial images, ten fingerprints and two iris images in addition to biographical data consisting of name, address, gender and date of birth [oI14]. Identifications are supplied by proving that a resident is unregistered using one-to-many matching with collected biometric data. In this system, the biometric identification technique is applied in order to find duplicated registrations of individuals and to link records in the same data between

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different systems. Thus, the biometric technology enables those developing countries to link each resident to identification, and then it will contribute to early development of medical services and social infrastructures. In these cases, there is a need for biometric techniques with greater recognition accuracy that can identify from one million to one billion persons for one country.

Multibiometrics integrating evidence from multiple biometric sources is often used in order to obtain high recognition accuracy (low false acceptance rate (FAR)). There are some various sources of information in multibiometric systems: multi-sensor, multi-algorithm, multi-instance, multi-sample and multimodal [ARJ06]. In the first four scenarios, a single biometric trait provides multiple sources of evidence. In the fifth scenario, different biometric traits are used to obtain evidence. The multimodal biometrics and the multi-instance biometrics out of these scenarios are widely applied to the large-scale biometric identification systems as described earlier.

The multimodal biometrics combines the evidence presented by different body traits for establishing identity. For example, the Indian Unique Identification project employs face, fingerprint and iris recognitions [oI14]. Various combinations of existing biometric techniques have been investigated by many researchers [ARJ06]. Physically uncorrelated traits (e.g., fingerprint and iris) are expected to result in better improvement in recognition accuracy than correlated traits (e.g., voice and lip movement). The recognition accuracy can be significantly improved by utilizing an increasing number of traits. However, the cost of deploying these systems is substantially more due to the requirement of more than one sensors and development of appropriate user interfaces. And the size of deploying these systems is also larger than one sensor.

On the other hand, the multi-instance biometrics uses multiple instances of the same body trait. For example, US-VISIT employs ten fingerprints from both hands [oHS14]. Simply, the left and right index fingers, or left and right irises of an individual may be used to verify an individual identity. It can make the capturing devices cost efficient, because multiple biometric sources can be obtained by using only one type of sensor. However, it is said that these biometric sources are correlated. For example, two fingerprints from same person are similar in a width and a pitch of ridge lines. There have been some studies where the dependence between two fingerprints from the same person is investigated by statistical approaches [BUH06], [SYS12]. Because the combined biometric sources are dependent in terms of a false acceptance error, some of multi-instance biometric systems confront various difficulties. Firstly, the combined biometric sources are often assumed to be statistically independent in order to simplify the design of the fusion algorithm. Thus, those systems may obtain smaller-than-expected improvement of recognition accuracy. There have been some studies into the effects on the FAR caused by the dependence of biometric sources [KNJ09], [LKD00], [OKP07]. On the contrary, if the combined biometric sources are independent, the FAR of the fusion of them can be more easily estimated. For example, it is estimated by using a product of the FARs on the AND rule or a summation of them ($FAR_{OR} = 1 - (1 - FAR_1) \times (1 - FAR_2) = FAR_1 + FAR_2$) on the OR rule at the decision level fusion. Especially, we can estimate the FAR in the large-scale identification where it is too difficult to evaluate it experimentally by collecting the real datasets. In terms of the design of the multibiometric systems, it is significant to prove the independence between the combined biometric sources. However, there are few studies about the independence evaluation as described earlier. The evaluation results reported in [BUH06] was in consideration of the FAR as well as the false reject rate. Another research reported in [SYS12] used their original fingerprint matcher for the evaluation results.

In this paper, we show 1) our approach of evaluation of statistical independence between multiple fingerprints from the same person, that was based on the approach reported in [SYS12]. We show 2) evaluation results of the independence between multiple fingerprints using matching scores obtained by Verifinger SDK that is licensed for public use. And then, we show 3) evaluation of the false acceptance rate affected by dependence between two different fingerprints from a same person and discussed the reason why the multiple fingerprints are dependent. This point of 3) is a contribution of this paper from the previous version [YS14]. Finally, we confirmed that these features are dependent and the FAR obtained by the fusion of them could be affected by the dependence negatively.

2 Evaluation of Independence between Multiple Fingerprints

2.1 Principle of Evaluation of Independence

This chapter explains our approach to statistically evaluating the independence between two fingerprints from the same person [SYS12]. $P(I_{fp1})$ and $P(I_{fp2})$ are the FAR of one fingerprint and second fingerprint respectively, where these I_{fp1} and I_{fp2} represent false acceptance error based on given thresholds of the fingerprint matching. If the following equation is true, we can confirm that the two fingerprints are independent.

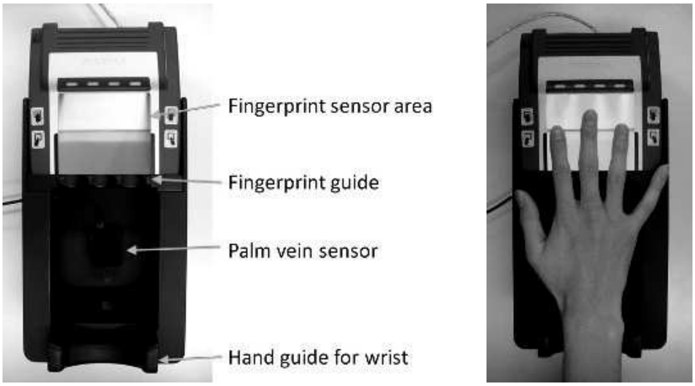
$$P(I_{fp1} \mid I_{fp2}) = P(I_{fp1}) \quad or \quad P(I_{fp2} \mid I_{fp1}) = P(I_{fp2}) \tag{1}$$

The $P(I_{fp1} \mid I_{fp2}) = P(I_{fp1})$ is the probability that the false acceptance of the fingerprint 1 also occurs when the false acceptance of the fingerprint 2 occurs, while the $P(I_{fp2} \mid I_{fp1}) = P(I_{fp2})$ is the probability that the false acceptance of the fingerprint 2 also occurs when the false acceptance of the fingerprint 1 occurs.

In this paper, we confirm whether or not the two fingerprints are statistically independent by evaluating the equation (1) using experimental results of the FARs of the fingerprint matching.

2.2 Fingerprint Database

We have collected the fingerprints images for the evaluation with a capturing device shown in Figure 1. This capturing device was developed in order to simultaneously obtain the palm vein image and the fingerprint image of a single hand [SYS12]. A fingerprint image is acquired using an L Scan Guardian F sensor, which is an optical fingerprint sensor and developed by CROSSMATCH TECHNOLOGIES [TEC14]. The captured fingerprint image has three fingerprint patterns from the index, middle and ring finger. The fingerprint images were acquired from both hands of 1,032 persons that were collected based on the gender and age distribution of Japanese population, and 12 images were acquired per hand.



(a) (b)

Figure 1: The capturing device: (a) structure, (b) example of capturing a hand

2.3 Experimental Results

In order to calculate $P(I_{fp1})$ and $P(I_{fp1} \mid I_{fp2})$ matching scores are obtained by performing the fingerprint matching across all the pairs of two different persons using these images. We used VeriFinger 6.0 Standard SDK developed by NEURO technology that is based on minutiae matching for the fingerprint matching. The matching scores indicate similarity where matching pairs having higher scores are more similar. Four images per finger are used as templates, and the remaining eight images were used for test samples. The number of matching scores is 7,606,451. This number is less than the calculated value because some images with operation mistake were removed by visual checks.

Figure 2 shows the evaluation result of independence between the fingerprint of the index and the middle finger from the right hand. These plots indicate $P(I_{fp_{middle,right}})$ and $P(I_{fp_{middle,right}} \mid I_{fp_{index,right}})$. The x axis indicates the threshold of the score that provides FAR, while the y axis indicates $P(I_{fp_{middle,right}})$ and $P(I_{fp_{middle,right}} \mid I_{fp_{index,right}})$ provided by each score threshold. These FARs are shown as relative ratios of each FAR divided by $P(I_{fp_{middle,right}})$ for the sake of simplicity. The $P(I_{fp_{middle,right}} \mid I_{fp_{index,right}})$ are higher than $P(I_{fp_{middle,right}})$ across each threshold. Similar results were also obtained in the evaluation between ring and middle fingers from the right hand as shown in Figure 3 and the evaluation between index and ring fingers from the right hand as shown in Figure 4. Thus, we found that the two fingerprints from the same hand was dependent and confirmed the same results reported in [SYS12].

In addition to the experiment described above, independence of fingerprints between the right and left hands was evaluated in accordance with the same rules as shown in Figure 5. The objective of this experiment is to compare the evaluation results of the two fingerprints from the same hand and from the different hands. The $P(I_{fp_{middle,right}} \mid I_{fp_{middle,left}})$

are higher than $P(I_{fp_{middle,right}})$ across each threshold. The similar results were also obtained in the evaluation of index and middle fingers.

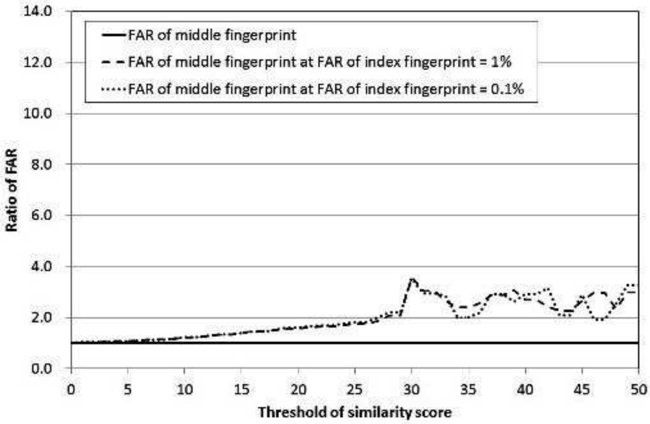


Figure 2: Evaluation results of independence between the fingerprints of index and middle fingers from the right hand.

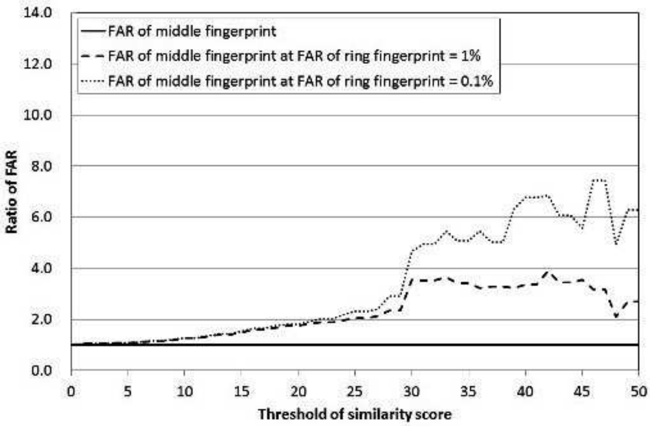


Figure 3: Evaluation results of independence between the fingerprints of ring and middle fingers from the right hand.

3 Evaluation of False Acceptance Rate Affected by Dependence between Two Fingerprints

In this section, we have compared the FAR obtained by the single finger with the FAR obtained by the AND rule of two fingers, in order to evaluate how the FAR was affected by the

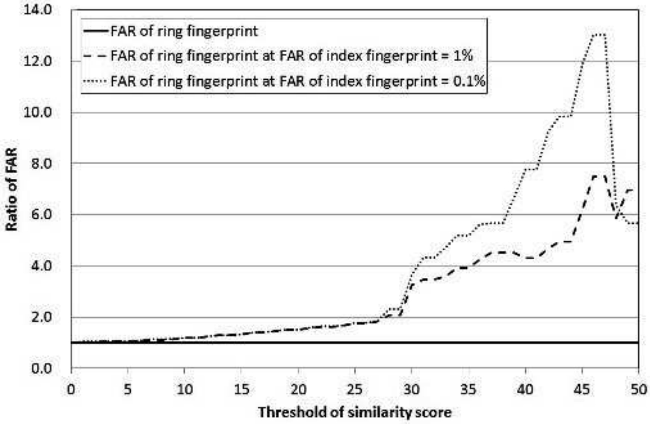


Figure 4: Evaluation results of independence between the fingerprints of index and ring fingers from the right hand.

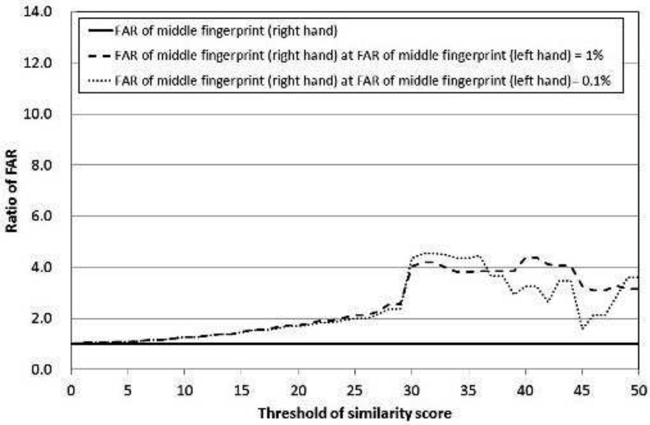


Figure 5: Evaluation results of independence between middle fingerprints from right and left hands.

dependence between two fingerprints. The FARs of the single fingerprint were based on the threshold of 36 defined by Verifinger SDK as FAR=0.1%. Table 1 shows the evaluation results of the FAR using fingers from the right hand. The $FAR_{setting}$ indicates the FAR based on the setting threshold, while the $FAR_{experimental}$ indicates the FAR experimentally obtained by comparing all the matching scores with the threshold. The $FAR_{estimated}$ indicates the FAR obtained by calculating the product of the $FAR_{experimental}$ of each finger on the AND rule. These $FAR_{experimental}$ using two fingers became two to eight times as large as the $FAR_{estimated}$. The evaluation results of the left hand were almost the same results as Table 1. Therefore, we confirmed that the dependences between two fingerprints from the same person could affect the FAR obtained by combining the two fingerprints.

Although the fingerprint minutiae utilized in the Verifinger SDK indicates not a global structure but a local structure (ridge ending and ridge bifurcation) in the fingerprint pattern, there are the dependences between two fingerprints from same person in terms of the false acceptance error. In order to clarify the reason why the fingerprint minutiae are dependent between two fingerprints from same person, we investigated all pairs of fingerprint images falsely accepted on the AND rule. Most of the pairs have same types of the fingerprint pattern. In addition, the fingerprints from same person also have almost same type. The types of the fingerprint pattern are related to a distribution of fingerprint minutiae, and they can be reconstructed from the minutiae points [FJ11] [FJ09] [ARJ05]. Therefore, the two different fingerprints from same person are dependent in terms of the false acceptance error regardless of using the minutiae based matching.

Table 1: Evaluations of the FAR on AND rule using two fingers from the right hand

Finger type	$FAR_{setting}$	$FAR_{experimental}$	$FAR_{estimated}$
$P(I_{fp_{index,right}})$	0.10000%	0.08214%	-
$P(I_{fp_{middle,right}})$	0.10000%	0.06501%	-
$P(I_{fp_{ring,right}})$	0.10000%	0.06204%	-
$P(I_{fp_{index,right}} \cap I_{fp_{middle,right}})$	0.00010%	**0.00012%**	0.00005%
$P(I_{fp_{index,right}} \cap I_{fp_{ring,right}})$	0.00010%	**0.00039%**	0.00005%
$P(I_{fp_{middle,right}} \cap I_{fp_{ring,right}})$	0.00010%	**0.00030%**	0.00004%

4 Conclusions

We have evaluated the independence between multiple fingerprints from the same person. By evaluating the false acceptance error obtained by matching all the pairs of two different persons using the fingerprint images, we were able to confirm that the features of the fingerprints from the same hand were dependent. In addition, the similar results were also obtained in the features of two fingers from the different hands (right and left hands). We have evaluated how the false acceptance rate became larger than the estimated values on the AND rule due to dependence between two fingerprints from a same person and discussed the reason why they are dependent with using the minutiae matching. Thus, we confirmed that the features of multiple fingerprints were dependent and the FAR obtained by the fusion of them could be affected by the dependence.

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