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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 evaluate whether or not features of multiple fingerprints are statistically independent. By evaluating false acceptance error using matchign scores obtained by Verifinger SDK, we confirmed that these features are dependent in some degree and have no small effect on the FAR obtained by their fusion.

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 [1]. 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 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 [2]. 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 senarios 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 [1]. Various combinations of existing biometric techniques have been investigated by many researchers [2]. 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. In recent years, there has been an increase in multimodal biometric techniques simultaneously capturing different biometric sources. Multimodal biometrics to integrate the palm vein and the fingerprint recognition was proposed by Fujitsu [3].

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 [4]. Simplely, the left and right index fingers, or left and right irises of an individual may be used to verify an individual ’s 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, and they have same type of patterns, such as arch, loop and whorl. There have been some researches where the dependence between two fingerprints is investigated by statistical approaches [5], [6]. Thus, the combined biometric sources are dependent in terms of a false acceptance error by mistakenly perceiving biometric features from two different persons as being from the same person, and then 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 researches into the effects on the FAR caused by the dependence of biometric sources [7], [8], [9]. On the contrary, if the combined biometric sources are independent, the FAR of their fusion can be more easily estimated. For example, it is estimated by using a product of their FARs on the " AND " rule or a summation of them ($FAR_{OR} = 1-(1-FAR_1)\times(1-FAR_2) \fallingdotseq FAR_1+FAR_2$) on the " OR " rule at the decision level fusion. Especially, we are also able to 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 very significant to prove the independence between the combined biometric sources. However, there are few researches about the independence evaluation as described earlier. The evaluation results reported in [5] was in consideration of the FAR as well as the false reject rate (FRR). Another research reported in [6] used their original fingerprint matching algorithm for their evaluation results.

In this paper, we show 1) our approach of evaluation of statistical independence between multiple fingerprints from same person, that was based on the approach reported in [6]. And then, we show 2) evaluation results of the independence between multiple fingerprins using matching scores obtained by Verifinger SDK that is licenced for public use. Finally, we confirmed that these features are dependent in some degree and affect the FAR obtained by their fusion negatively.

2. Evaluation of Independence between Multiple Fingerprints

This chapter explains our approach to statistically evaluating the independence between two fingerprints. $P(I_{fp1})$ 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 from same person are independent.

$$P(I_{fp1} \cap I_{fp2}) = P(I_{fp1})P(I_{fp2}) \tag{1}$$

The $P(I_{fp1} \cap I_{fp2})$ is a probability that the false acceptance in both two fingerprints occurs concurrently. The equation (1) is rewritten using their conditional probability as follows.

$$P(I_{fp1} \mid I_{fp2}) = P(I_{fp1}) \quad or \quad P(I_{fp2} \mid I_{fp1}) = P(I_{fp2}) \tag{2}$$

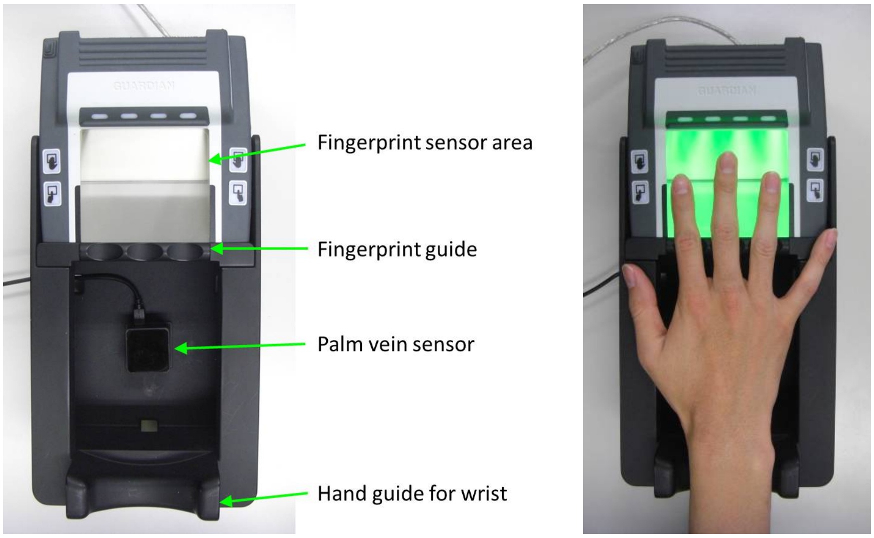
The $P(I_{fp1} \mid I_{fp2}) = P(I_{fp1})$ is the probability that the false acceptance of the fingerprint 1 also occurs when the false acceptance of the fingerprint 2 occurs, while the $P(I_{fp2} \mid I_{fp1}) = P(I_{fp2})$ is the probability that the false acceptance of the fingerprint 2 also occurs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

In this paper, we confirm the independence between the multiple fingerprints by evaluating the equation (2) using experimental results of the FARs of the fingerprint matching.

3. Experimental results

3.1. 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 [6]. A fingerprint image is acquired using an L Scan Guardian F sensor, which is an optical fingerprint sensor and developed by CROSSMATCH TECHNOLOGIES [10]. It is most widely used at the borders around the world. 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 of the device, (b) example of capturing a hand

3.2. Evaluation of independence between two fingerprints

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 scatter plot of matching scores from the fingerprints of the middle finger and the index finger. The x axis indicates the fingerprint matching score of the middle finger, and the y axis indicates the fingerprint matching score of the index finger. Both of the two matching scores are mostly distributed in lower score areas. There are some plots having either higher score of the index or middle finger, while there are very few plots having both higher scores. Figure 2 shows that the dependence of two fingerprints is mostly low.

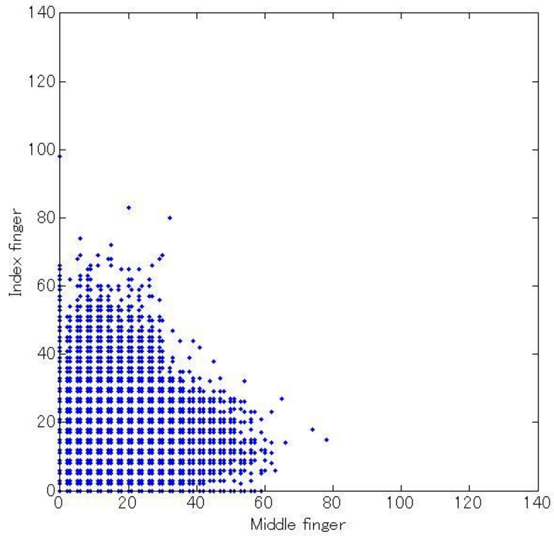


Figure 2: Scatter plot of matching scores from the fingerprint of index finger and middle finger. These matching scores are obtained by matching between two different persons.

Figure 3 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. From Figure 3, 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 4 and the evaluation between index and ring fingers from the right hand as shown in Figure 5. Thus, we found

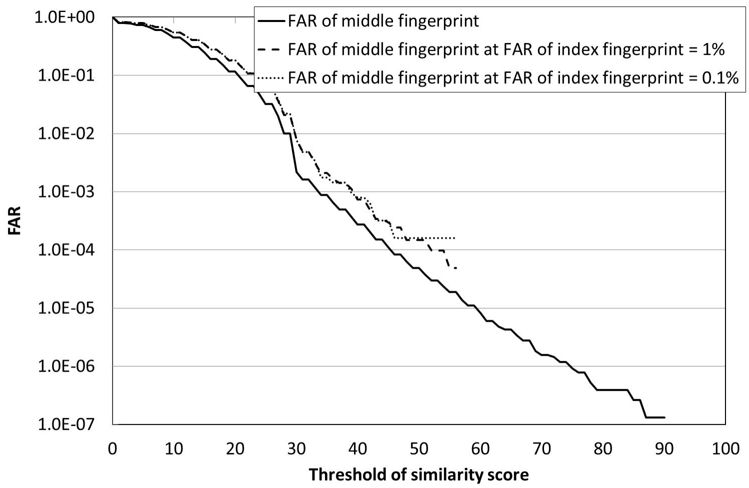


Figure 3: Evaluation results of independence between the fingerprints of index and middle fingers from the right hand.

that the pair of fingerprints from the same hand was dependent in some degrees and confirmed the same results reported in [6].

In addition to the experiment described above, independence of fingerprints between the right and left hands was evaluated in accordance with the same rules. In general, it is said that a pair of fingerprints from the same hand are dependent. So, the objective of this experiment is to confirm whether or not a pair of fingerprints from the different hands (right, left hand) is also dependent. This evaluation result is shown in Figure 6. The $P(I_{fp_{middle,right}} \mid I_{fp_{middle,left}})$ are higher than $P(I_{fp_{middle,right}})$ across each threshold. So, similar results were also obtained in the evaluation of index and middle fingers.

4. Conclusions

We have evaluated their independence between multiple fingerprints. 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 some degree. In addition, the similar results were also obtained in the features of two fingers from the different hands (right and left hands). Thus, we confirmed that the features of multiple fingerprints are dependent in some degree and have no small effect on the FAR obtained by their fusion.

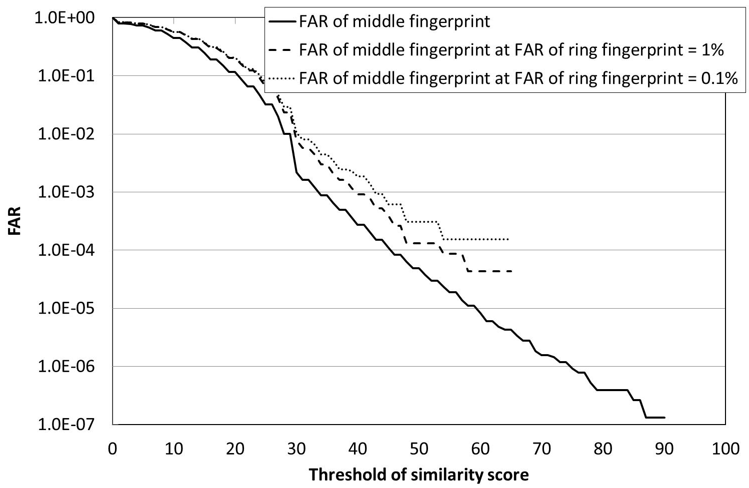


Figure 4: Evaluation results of independence between the fingerprints of ring and middle fingers from the right hand.

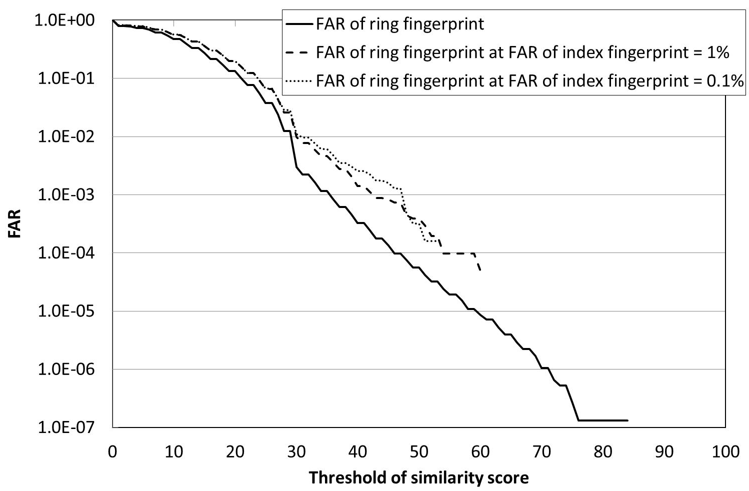


Figure 5: Evaluation results of independence between the fingerprints of index and ring fingers from the right hand.

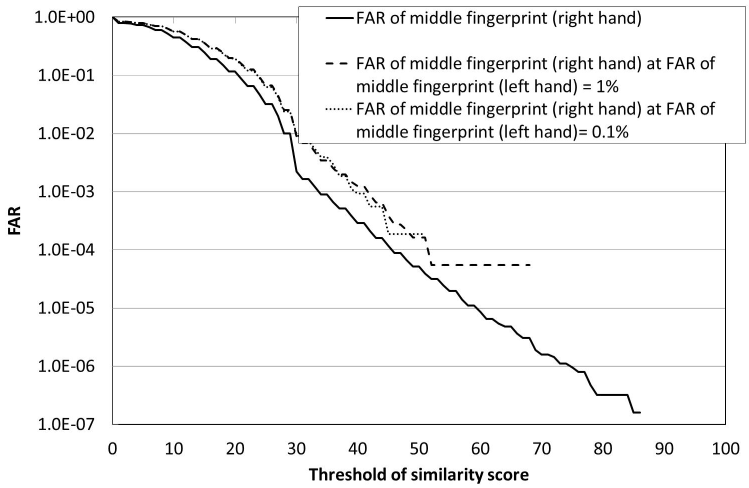


Figure 6: Evaluation results of independence between middle fingerprints from right and left hands.

References

[1] Unique Identification Authority of India: http://www.uidai.gov.in/, last accessed on March. 04, 2014.

[2] Ross, A.; Nandakumar, K.; Jain, A.K.: Handbook of Multibiometrics, Springer, 2006.

[3] Fujitsu Laboratories Ltd.: http://www.fujitsu.com/global/news/pr/archives/month/2011/20110601-01.html, last accessed on March. 04, 2014.

[4] U.S. Department of Homeland Security: https://www.dhs.gov/xlibrary/assets/usvisit/usvisit_edu_10-fingerprint_consumer_friendly_content_1400_words.pdf, last accessed on March. 04, 2014.

[5] Ulery, B.; Hicklin, A.; Watson, C.; Fellner, W.; Hallinan, P.: Studies in Biometric Fusion : NISTIR 7346. September 2006.

[6] Yamada, S.; Endoh, S.; Shinzaki, T.: Evaluation of independence between palm vein and fingerprint for multimodal biometrics: IEEE International Conference of the Biometrics Special Interest Group (BIOSIG 2012), Darmstadt, Germany, 2012.

[7] Nandakumar, K.; Ross, A.; Jain, A.K.: Biometric Fusion: Does Modeling Correlation Really Matter?: Proceedings of IEEE 3rd International Conference on Biometrics: Theory and, Applications and Systems (BTAS09), Washington DC, pp. 1-6, Sept. 2009.

[8] Kuncheva, L.I.; Whitaker, C.J.; Shipp, C.A.; Duin, R.P.W.: Is Independence Good For Combining Classifiers?: Proceedings of International Conference on Pattern Recognition (ICPR), vol. 2, Barcelona, Spain, pp. 168-171, 2000.

[9] Koval, O.; Voloshynovskiy, S.; Pun, T.: Analysis of multimodal binary detection systems based on dependent/independent modalities: Proceedings of Workshop on Multimedia Signal Processing (MMSP), Crete, Greece, pp. 70-73, 2007.

[10] CROSSMATCH TECHNOLOGIES, http://www.crossmatch.com/l-scan-guardian.php, last accessed on March. 04, 2014.

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