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A Novel Method of Score Level Fusion Using Multiple Impressions for Fingerprint Verification

Chunxiao Ren, Yilong Yin, Jun Ma, and Gongping Yang
School of Computer Science and Technology
Shandong University
Jinan, China

Abstract—**How to improve the performance of an existing biometric system is always interesting and meaningful. In this paper, we present a novel method of score level fusion using multiple enrolled impressions to achieve higher verification accuracy of existing fingerprint systems. The main idea of the method is to build a representation of the biometric reference as a polyhedron by taking into account the matching results of multiple enrolled impressions. The verification step consists in measuring a distance between the centroid of the polyhedron and the acquired image. This novel method outperforms the traditional uni-matcher based scheme over a wide range of FAR and FRR values. The equal error rate of our method is observed to be 2.25%, while that of the uni-matcher is 5.75%.**

Keywords—**fingerprint, multimodal, multiple enrolled impressions, matching, fusion**

I. INTRODUCTION

Biometric systems are rapidly gaining acceptance as one of the most effective technologies to identify people [1]. There are many commercial biometric systems existing in a wide range of applications: from physical access control to criminal investigation and from inmates managing to corpse identification. The biometric system is widely used nowadays. However, the performance of these systems was not satisfactory in many applications. How to improve the performance of an existing biometric system becomes an interesting and meaningful issue.

Many researchers try to use multi-biometric systems to achieve better performance by consolidating the evidence presented by multiple biometric sources [2]. However, the multi-biometric method means additional spending for affiliated biometric systems. It is usually unacceptable for some customers.

Fingerprint-based recognition is the most popular method in biometric community [3]. Fingerprint recognition technologies can be broadly classified as being single or multimodal fingerprint-based. Many researches have shown that the performance of system based on single fingerprint, single feature or single classifier encounters some drawbacks in some applications, and multimodal fingerprint-based methods, including multiple features [4], multiple matchers [5], multiple fingers [6] and multiple impressions of the same finger [7], have received more and more attention.

Actually, there are usually 2–4 enrolled impressions in real systems taking into account the variations of a same finger, as shown in Figure. 1. The matching method using multiple enrolled impressions is most popular among all the above methods and widely used in real systems.

Figure 1. Multiple enrolled impressions of the same finger

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C. Ren is with the School of Computer Science and Technology, Shandong University, Shunhua Road, Jinan, 250101, China (e-mail: renchunxiao@gmail.com)

Y. Yin is with the School of Computer Science and Technology, Shandong University, Shunhua Road, Jinan, 250101, China (corresponding author to provide phone: 86-531-88391367; fax: 86-531-88391367; e-mail: ylyin@sdu.edu.cn).

J. Ma and G. Yang are with the School of Computer Science and Technology, Shandong University, Shunhua Road, Jinan, 250101, China.

Four different fusion strategies, i.e., sensor level fusion, feature level fusion, decision level fusion and score level fusion, can be utilized to improve the performance of fingerprint system for the matching method using multiple enrolled impressions.

- Sensor level fusion means to mosaic multiple impressions of the same finger into a new fingerprint image [8]. In sensor level fusion, the multiple cues must be compatible and the correspondences between points in the raw data must be either known in advance or reliably estimated [9].
- Feature level fusion refers to the features extracted from multiple enrolled fingerprints are combined [10]. The new augmented feature set has a higher dimensionality or further quantity [11].
- Decision level fusion means to combine multiple unique labels outputted by matching each enrolled impression with the query image to integrate different types of matchers [12]. Since most commercial fingerprint systems provide access to the final decision output by the system, fusion at the decision level is often the viable option [13].
- The fourth strategy, score level fusion, is to fuse multiple matching scores which is a numerical value indicating the probability that the given input belongs to the class to improve performance of systems [14]. Apart from the raw data and feature vectors, the match scores contain the richest information about the input pattern. Consequently, information fusion at the score level is the most commonly used approach in fingerprint systems [15-16].

The methods of multimodal fingerprint fusion are widely used in many applications nowadays. These techniques, however, suffer from the following shortcomings:

- For sensor or feature level fusion, a new fingerprint image or feature vector has to be created and stored, and it will consume much memory and computation. On the other hand, the performance of fusion correlates closely with certain sensor or feature exaction method, therefore, not very robust with the selection of fusion methods.
- For decision or score level fusion, most techniques aim at combining multi-matcher only, and uni-matcher fusion is incompatible to existing techniques.

Considering the widespread deployment of fingerprint systems, especially the use of existing systems, it is necessary to carefully investigate to improving the performance of uni-matcher system. In particular, it is important to understand whether such a fingerprint system can be improved through a simple modification.

This work introduces a novel method of score level fusion using multiple enrolled impressions, which is a wrapper method of a traditional fingerprint system to improve performance of the system with minimum modification. The proposed method is consists of a sequence of steps: starting from the multiple enrolled impressions, attempt to convert them to points in multidimensional space via analyzing one-on-one matching results; then a matching step is achieved by calculating the distance between query image and the centroid of multiple enrolled impressions in multidimensional space. This method can be easily integrated with existing fingerprint system. The efficacy of the proposed approach has been assessed by comparing the performances of the fusion system with that of original one.

The remainder of the paper is organized as follows. Section 2 presents score level fusion method. Section 3 describes experiment procedures and presents some experimental results. Section 4 gives conclusions and some discussions about this presented method.

II. Score Level Fusion Method

To multiple impressions of the same finger, we usually try to fusion the information themselves. In fact, from other viewpoint, the matching score is a measure of similarity between two fingerprint images [17]. In this work, we regard the impression as a point in a multidimensional space, and the matching score as a distance between two points. So we can use the relationship of impressions in the multidimensional space to enhance the accuracy of matching. Traditionally, when matching scores outputted by different fingerprint matchers are consolidated in order to achieve a final decision, fusion is said to be done at the score level.

Our score level fusion method involves two stages: enrollment and verification. During enrollment, multiple enrolled impressions of the same user's finger are acquired and stored as templates, and these relativities in multidimensional space are extracted through matching them between every pair of impressions. During verification, a new impression is acquired and compared to the stored templates to verify the user's claimed identity by computing a distance from the query fingerprint to the centroid of templates in multidimensional space. The scheme of our method can be illustrated by Figure. 2.

Given a polyhedron with vertices and a set of edges, we would like to measure the centroid of all of the vertices. We argue that the centroid of vertices is the most representative point of "real" fingerprint in multidimensional space. Centroid computation provides a principled method to combine the "comparability" of a vertex with those of polyhedron in matching. For example, other factors being equal, a vertex closer to the centroid of polyhedron should match more than others. The idea of refining results to improve accuracy of system can also be find in information retrieval community [18].

Contrast with other techniques, this scheme has following advantages.

- No new fingerprint image or feature vector need to be established. The modification to original system is slight.
- No certain algorithm of feature extraction or matching is bound with this wrapper method. It means the

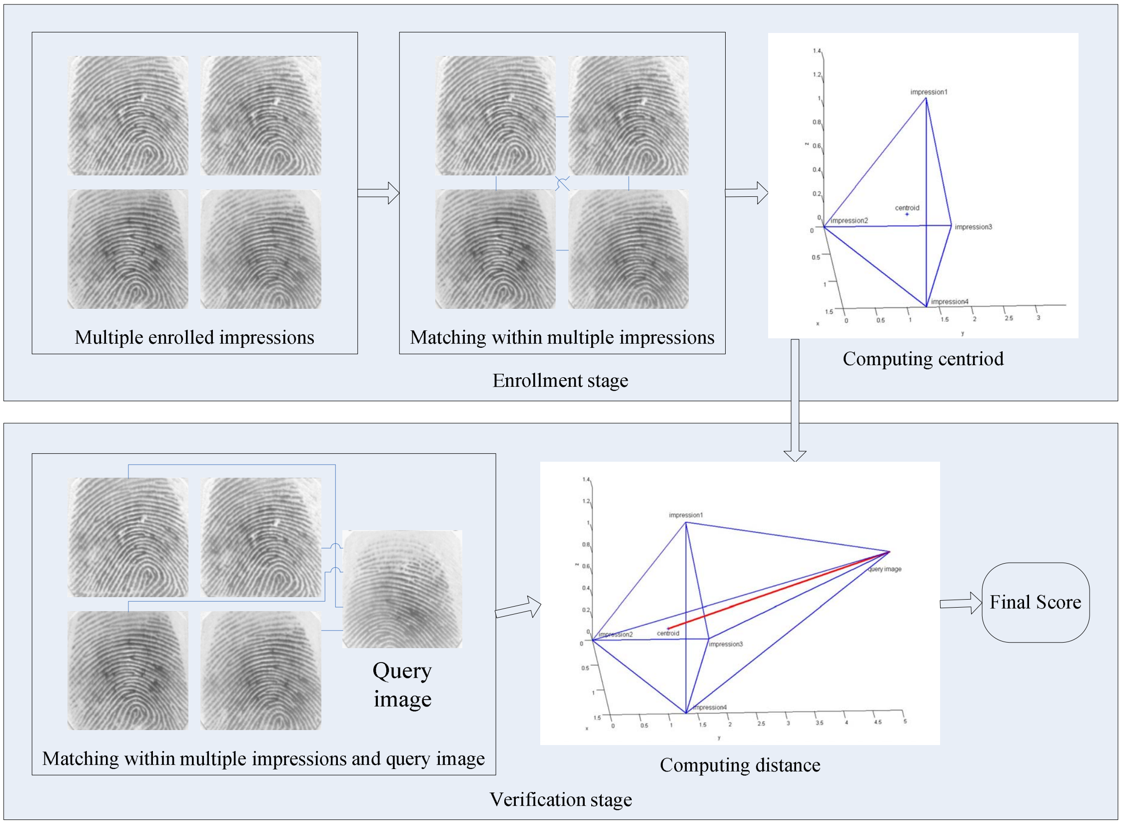

Figure 2. The scheme of our method

performance of system will be improved no matter what the matcher is used in the system.

- Both uni-matcher and multi-matcher methods can be applied in this method.

A. Enrollment Stage

Suppose the set of enrolled impressions of the same finger is represented as

$$E = \left\{ F^i \mid i = 1,2,\ldots,m \right\} \tag{1}$$

where m is the number of the enrolled impressions and F^i is the ith impression. In the enrollment stage, we calculate the similarity $S(F^i, F^j)$ between two enrolled impressions F^i and F^j by matching them. The set of similarities within enrolled impressions is represented as

$$I = \left\{ S(F^i, F^j) \mid F^i, F^j \in E \right\} \tag{2}$$

There are n elements in I, and

$$n = C_m^2 = m(m-1)/2 \tag{3}$$

Because these computations are not online, it is a background process and hardly consumes much memory and computation. The running time of the stage is *O(1)*.

In the verification stage, a set of match scores can be calculated between query image and every enrolled impression.

$$V = \left\{ S(F^i, Q) \mid F^i \in E \right\} \tag{3}$$

There are m elements in I. This stage requires *O(m)* time.

Suppose every impression F^i is a point r_i in an *m-1* dimensional space, it can be represented as

$$r_i\left(x_{i1}, x_{i2}, \ldots, x_{i(m-1)}\right) \tag{4}$$

Considering the distance between F^i and F^j in an *m-1* dimensional space,

$$l_{ij} = \left\| r_i r_j \right\| = \sqrt{\sum_{k=1}^{m-1} \left(x_{ik} - x_{jk} \right)^2} \tag{5}$$

Because the centroid of regular polyhedron is its geometrical center [19], the centroid of E in an *m-1* dimensional space is

$$r_c\left(\frac{1}{m}\sum_{i=1}^{m} x_{i1}, \frac{1}{m}\sum_{i=1}^{m} x_{i2}, \ldots, \frac{1}{m}\sum_{i=1}^{m} x_{i(m-1)} \right) \tag{6}$$

B. Verification Stage

When a query image is presented, the matching proceeds as follows:

- The query image and each impressions of the same finger stored in database are matched to generate matching scores;
- Computing the distance from query image to the centroid, and output the distance as score level fusion result.

Suppose the query image F^* is r_* in an *m-1* dimensional space, it can be represented as

$$r_*\left(x_{*1}, x_{*2}, \ldots, x_{*(m-1)}\right) \tag{7}$$

The distance from F^i to F^* will be

$$d_{*i} = \|r_* r_i\| = \sqrt{\sum_{k=1}^{m-1}\left(x_{*k} - x_{ik}\right)^2} \tag{8}$$

The distance from F^* to the centroid will be

$$d_{*c} = \|r_* r_c\| = \sqrt{\sum_{k=1}^{m-1}\left(x_{*k} - \frac{1}{m}\sum_{i=1}^{m} x_{ik}\right)^2} \tag{9}$$

and,

$$\begin{aligned}
d_{*c}{}^2 &= \sum_{k=1}^{m-1}\left(\frac{1}{m}\left(m x_{*k} - \sum_{i=1}^{m} x_{ik}\right)\right)^2 \\
&= \frac{1}{m^2}\sum_{k=1}^{m-1}\left(\left(x_{*k} - x_{1k}\right) + \left(x_{*k} - x_{2k}\right) + \ldots + \left(x_{*k} - x_{mk}\right)\right)^2 \\
&= \frac{1}{m^2}\sum_{k=1}^{m-1}\begin{pmatrix}\left(x_{*k} - x_{1k}\right)^2 + \left(x_{*k} - x_{2k}\right)^2 + \ldots + \left(x_{*k} - x_{mk}\right)^2 \\ +2\sum_{i=j+1}^{m}\sum_{j=1}^{m-1}\left(x_{*k} - x_{ik}\right)\left(x_{*k} - x_{jk}\right)\end{pmatrix} \\
&= \frac{1}{m^2}\left(\sum_{k=1}^{m} d_{*k}{}^2 + \sum_{k=1}^{m-1}\sum_{i=j+1}^{m}\sum_{j=1}^{m-1}\begin{pmatrix}\left(x_{*k} - x_{ik}\right)^2 + \left(x_{*k} - x_{jk}\right)^2 \\ -\left(x_{ik} - x_{jk}\right)^2\end{pmatrix}\right) \\
&= \frac{1}{m^2}\left(\sum_{i=1}^{m} d_{*i}{}^2 + \sum_{i=j+1}^{m}\sum_{j=1}^{m-1}\left(d_{*i}{}^2 + d_{*j}{}^2 - l_{ij}{}^2\right)\right) \\
&= \frac{1}{m^2}\left(m\sum_{i=1}^{m} d_{*i}{}^2 - \sum_{i=j+1}^{m}\sum_{j=1}^{m-1} l_{ij}{}^2\right)
\end{aligned}$$

So,

$$d_{*c} = \frac{1}{m}\sqrt{m\sum_{i=1}^{m} d_{*i}{}^2 - \sum_{i=j+1}^{m}\sum_{j=1}^{m-1} l_{ij}{}^2} \tag{10}$$

Because m is const in an instance,

$$\text{the fusion result} \propto \; m\sum_{i=1}^{m} d_{*i}{}^2 - \sum_{i=j+1}^{m}\sum_{j=1}^{m-1} l_{ij}{}^2 \tag{11}$$

The final matching result will be given if we decide the distance expression. For example, the inverse of similarity $S(F^i, F^j)$ is a naïve choice of distance expression. In this work, we use three distance expressions (1/S, 1-S and $\frac{1-S}{1+S}$) to compute the final matching result, respectively.

III. Experiments

The fingerprint databases used in our experiments are FVC2000 DB1, DB2 [20] and FVC2002 DB2, DB3 [21]. FVC DB consists of fingerprint impressions obtained from 100 non-habituated, cooperative subjects. Every subject was asked to provide 8 impressions of the same finger. We select 1st to 4th impressions of every subject as "in-database" and 5th to 8th impressions as "out-database". So there are 400 images in training set while 400 images in each testing set.

In these experiments, a minutiae-based matching method is used as an original matcher for completing one-on-one matching. The performance of a fingerprint verification system is mainly described by two values, i.e., False Acceptance Rate (FAR) and False Rejection Rate (FRR). FAR and FRR are defined as

$$FAR = P(D_1 \mid \omega_2) \tag{12}$$

and

$$FRR = P(D_2 \mid \omega_1) \tag{13}$$

where w_1 and w_2 represent the classes of true genuine matches and impostor matches, respectively, D_1 and D_2 denote the decisions of genuine matches and impostor matches, respectively. The Equal Error Rate (EER) is computed as the point where FAR(t)=FRR(t), usually we use EER to evaluate the biometric system [22].

We match every image in training set with 1st impression of the same subject, and 5th impression of every subject with 4 images from other subject which are random selected. So there are 400 genuine matches and 400 impostor matches.

Table 1 summarizes the comparison results. As the choice of distance expression is changed the accuracy of system is affected. In all the tests that were conducted, the score level fusion method outperforms the original system.

TABLE I. THE EXPERIMENT RESULTS

EER	**FVC2000 DB1**	**FVC2000 DB2**	**FVC2002 DB1**	**FVC2002 DB2**	**Average Results**
Original	8.50%	3.75%	1.75%	9.00%	5.75%
Fusion **d=1/S**	4.25%	1.75%	1.25%	5.50%	3.19%
Fusion **d=1-S**	4.00%	1.75%	1.25%	4.00%	2.75%
Fusion **d=** $\frac{1-S}{1+S}$	3.00%	1.50%	1.00%	3.50%	2.25%

Some more specific detail could be illustrated as an example. The database is FVC2000 DB1. The original result is EER=8.50%, FMR100=16.75%, and FMR1000=24.00%. The ROC (Receiver Operating Characteristic) curve depicting the performances of the single fingerprint-based matching method is shown in Figure 3.

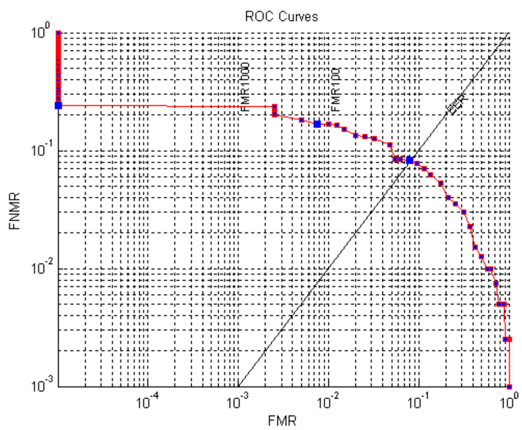

Figure 3. The ROC curves of single fingerprint-based matching method

The result of our method, using the distance expression d=1-S, is EER=4.00%, FMR100=9.00%, FMR1000=15.50%, as shown in Figure 4.

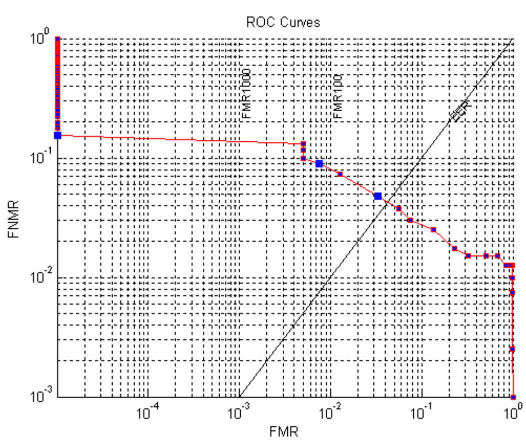

Figure 4. The ROC curves of our method

From experimental results we can find that our method has much smaller equal error rate (EER) than those of traditional matching method. The fusion method outperforms the single fingerprint-based scheme over a wide range of FAR values. It is evident that the fusion method of score level implements this by preventing uncertain errors using centrality.

IV. Summary and Future Work

In this work, we experimented with the idea that uni-matcher fingerprint system can be improved by introducing a method of score level fusion. For the purpose of facilitating system configuration, we have developed a wrapper method to achieve higher recognition accuracy.

The novel method we proposed is consists of a sequence of steps: starting from the multiple enrolled impressions, attempt to convert them to points in multidimensional space via analyzing one-on-one matching results; then a matching step is finally achieved by calculating the distance between query image and the centroid of multiple enrolled impressions in multidimensional space. We formulate this task as a distance computation in multidimensional space task, and propose the method to solve this problem. Experiments indicate that the method performs much better than a uni-matcher based system.

Because the increased performance is originated from the sufficient utilization of multiple impressions, we argue that our method has the same effect with any other fusion method in nature, such as fingerprint mosaicking or template synthesis. But our method is more facilitating because it is a wrapper method.

Currently, the minutiae-based matching method is used to match the query and the template images. We are working on correlation-based matching method that makes use of orientation field and ridge map information to match image pairs. To find a better distance expression will be the focus of our future work as well.

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