A TWO-STAGE FUSION SCHEME USING MULTIPLE FINGERPRINT IMPRESSIONS

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ABSTRACT

In this paper, we propose a two-stage fusion scheme that takes full advantage of the complementary information among multiple fingerprint impressions. While comparing the query fingerprint with a template impression, all the other impressions are also transformed using the 2D warping model to register with the query fingerprint so that the additive matched minutiae pairs can be detected to improve the matching result with a subset combination scheme. Then a matching score level fusion or decision level fusion is performed to integrate the improved matching results corresponding to different impressions. Experiments conducted on FVC2002 show that the proposed method produces a much better performance for fingerprint matching.

***Index Terms*—** Fingerprint Matching, 2D Warping, Subset Combination

1. INTRODUCTION

Fingerprints are graphical flow-like ridges present on human fingers [1]. They are used as one of the most popular biometrics due to their uniqueness and invariance with age. A number of automatic fingerprint matching techniques [2][3][4][5][6][7][8][9] have been proposed in the literature. Most of them are based on minutiae matching according to the common hypothesis that the individuality of fingerprints can be faithfully captured by minutiae and their spatial distributions [10].

Nowadays, live-scan fingerprint sensors can be easily embedded into a variety of devices for user authentication. Since the sensors provide a small contact area for the finger and capture only a partial portion of the fingerprint, the acquired fingerprint images may not contain sufficient information and every two impressions of the same finger may share only a small overlapping region, as shown in Figure 1. In such cases, the minutiae-based fingerprint matching systems using a single impression cannot meet the low false acceptance rate (FAR) and false rejection rate (FRR) requirements of high-level security applications, because the minutiae-based techniques may not perform well if no sufficient number of common minutiae points exist in the query and template fingerprints. We believe that an efficient and effective method to improve the matching performance is to combine multiple impressions, multiple fingers, or multiple matchers. Combining multiple fingers or multiple matchers may not make remarkable sense because of the small overlapping region between fingerprints, so we aim at constructing an optimal model for the fusion of multiple impressions.

(a) (b)

Fig. 1. Two impressions of the same finger acquired by a live-scan fingerprint sensor.

The multiple-impression models have been previously constructed at three levels: (i) feature extraction level [11], (ii) matching score level [12], and (iii) decision level [13]. By extracting a composite minutiae set from the minutiae sets of all the impressions or from the composite image mosaicked by all the impressions, the feature extraction level fusion utilizes the rich information available in multiple impressions, and therefore is considered to be able to greatly improve the matching performance. However, it is difficult to perfectly obtain the composite minutiae set because of the missing of genuine minutiae and the existence of spurious minutiae due to noise, distortion, feature extraction error, and especially the registration error. The matching score level fusion combines the matching score of the query and every template impression to calculate the probability of matching or non-matching, while the decision level fusion evaluates the likelihood ratio to make the final decision after estimating the joint density of all the scores corresponding to different impressions. They both attempt to achieve an optimal matching probability of the matching scores or their distributions, but they ignore most of the complementary information among multiple impressions.

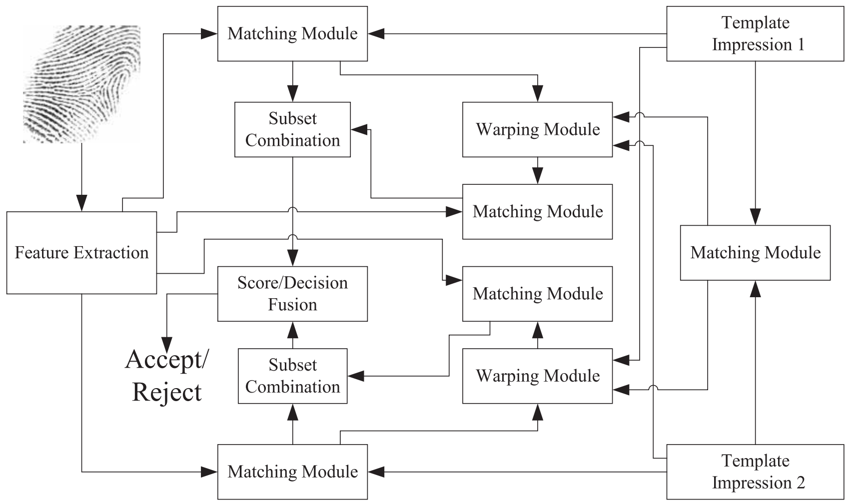


Fig. 2. Flowchart of the proposed fusion scheme with two template impressions.

To achieve the optimal trade-off between information utilization and error reduction, in this paper we propose a two-stage fusion scheme using multiple fingerprint impressions. While comparing the query fingerprint with a template impression, all the other impressions are also transformed using the 2D warping model [14] to register with the query fingerprint so that the additive matched minutiae pairs can be detected to improve the matching result based on subset combination. After that, a matching score level fusion or decision level fusion is utilized to integrate the improved matching results corresponding to different impressions.

2. MULTIPLE-IMPRESSION FUSION STRATEGY

As illustrated in Figure 2, taking a query fingerprint as the input, our multiple-impression fusion scheme is composed of the following two stages,

- Compare the query fingerprint with each template impression and then perform a feature level fusion based on subset combination to take full advantage of the complementary information available in multiple impressions.
- Perform a matching score level or decision level fusion to compute the final matching score or matching probability.

When comparing the query fingerprint with the template impression, we adopt the minutiae-based fingerprint matching algorithm described in [15][16]. It consists of four steps: (a) minutiae alignment, (b) minutiae matching, (c) ridge count matching, and (d) distortion removal. Since we focus on the performance of subset-combination-based feature level fusion, the matching score level fusion is performed by calculating the mean value of the matching scores corresponding to different impressions, and the decision level fusion is carried out by the product rule.

Let I^Q denotes the query fingerprint, I_i^T $(i = 1, 2, \ldots, l)$ denotes one of the l template impressions, $\mathbf{F}^Q$ and $\mathbf{F}_i^T$ $(i = 1, 2, \ldots, l)$ denote the corresponding minutiae set of I^Q and I_i^T. The subset combination algorithm (see Figure 3) includes the following steps,

1. Compare each template impression I_i^T with the query fingerprint I^Q and all the other impressions $I_{j\neq i}^T$ to obtain the matched minutiae sets $\mathbf{S}_i^Q$ and $\mathbf{S}_{ij}^T$.
2. Estimate the transformations g_i^Q and g_{ij}^T by the 2D warping model [14] according to the minutiae correspondences $\mathbf{S}_i^Q$ and $\mathbf{S}_{ij}^T$, where g_i^Q is the transformation function from I^Q to I_i^T, and g_{ij}^T is the transformation function from $I_{j\neq i}^T$ to I_i^T. In practice, g_{ij}^T can be estimated during the enrollment and saved in the template.
3. Use the above transformation functions to convert $\mathbf{F}^Q$ to $\widetilde{\mathbf{F}}^Q$ and $\mathbf{F}_{j\neq i}^T$ to $\widetilde{\mathbf{F}}_j^T$, which can be registered with $\mathbf{F}_i^T$ more optimally.
4. Compare $\widetilde{\mathbf{F}}^Q$ with $\widetilde{\mathbf{F}}_j^T$ to obtain the corresponding matched minutiae set, and remove those minutiae pairs that are close to the previously detected matched minutiae pairs or any non-matched minutiae in I_i^T. The remaining subset of matched minutiae pairs (denoted by $\widetilde{\mathbf{S}}_{ij}^T$) will be integrated with $\mathbf{S}_i^Q$ to form a new set $\mathbf{S}_i^{Q_2}$, and the corresponding matched minutiae from $I_{j\neq i}^T$ are combined with $\mathbf{F}_i^T$ to form another set $\mathbf{F}_i^{T_2}$.

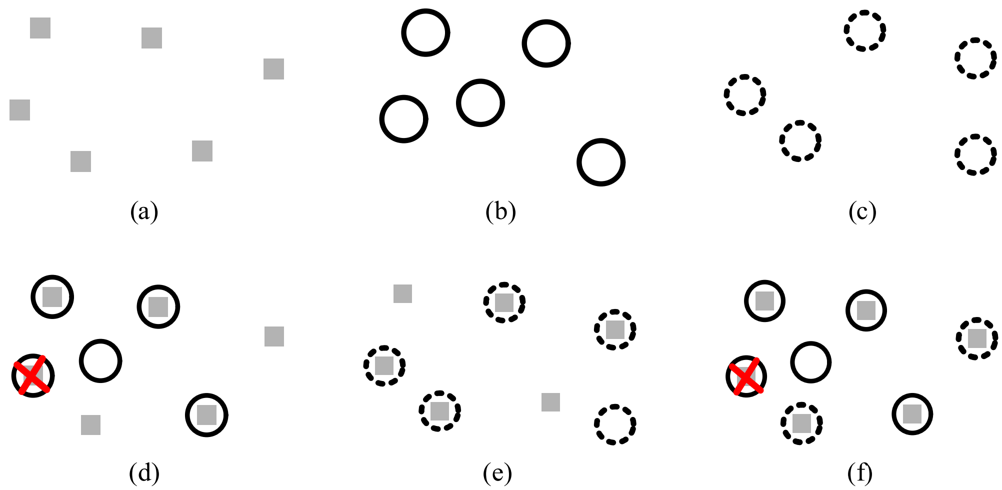


Fig. 3. A feature level fusion example based on subset combination. (a) query minutiae set, (b) primary template minutiae set, (c) complementary template minutiae set, (d) matching result of (a) and (b), (e) matching result of (a) and (c), (f) final matching result. (The red 'x' represents the non-matched minutiae pairs.)

5. Compute the matching score M_{si} according to $\mathbf{S}_i^{Q_2}$, $\mathbf{F}_i^{T_2}$, and $\mathbf{F}^Q$ using the following formula,

$$M_{si} = \frac{N_m + C_{pair} - \not{C}_{pair}}{\max(N_Q, N_i) + C_{pair} + \not{C}_{pair}}, \qquad (1)$$

   where N_m denotes the number of final matched minutiae pairs, N_Q denotes the number of minutiae in I^{Q_2}, N_i denotes the total number of minutiae in $I_i^{T_2}$ and matched minutiae pairs in $\widetilde{\mathbf{S}}_{ij}^T$, C_{pair} and $\not{C}_{pair}$ denote the number of matched ridge count pairs and non-matched ridge count pairs [15], respectively.

With this scheme, the features of each impression can be effectively enriched, thus makes the corresponding matching result more reliable. Although partial information is ignored in the feature level fusion stage, it will be compensated in the later matching score level or decision level fusion stage.

3. EXPERIMENTS

Experiments are conducted on FVC2002 DB1, a database for fingerprint verification competition. It is composed of 880 fingerprint images (388×374, 500dpi) from 110 individuals. Each finger has eight impressions.

To evaluate the performance of the proposed multiple-impression fusion scheme, we also implement the fingerprint mosaicking algorithm [11], the matching score level fusion algorithm [12] with the mean value, and the decision level fusion algorithm [13] with the product rule. For simplicity, we only use two template impressions per individual. The overall matching performance is measured by the receiver operating characteristic (ROC) curve, which plots the genuine acceptance rate (GAR) against the false acceptance rate (FAR) at different operating points (matching score thresholds).

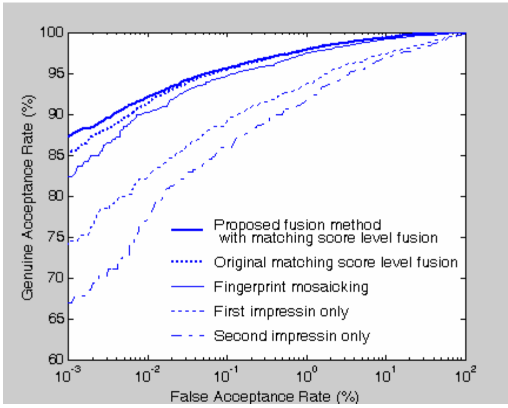
Figure 4 illustrates the ROC curves of our multiple-impression fusion scheme in comparison with the fingerprint mosaicking scheme and the original matching score/decision level fusion scheme. As shown by the results, the proposed two-stage fusion scheme outperforms the other methods, especially at low FAR values. Its matching performance is much better than that of using a single impression only, which indicates that the features of each impression can be effectively enriched by the feature level fusion scheme based on subset combination. In addition, the first impression produces a higher accuracy than the second one due to its larger fingerprint area. It is expected to achieve a better performance if we purposely enroll multiple impressions that cover different fingertip areas with a large overlapping region between each other.

4. CONCLUSION

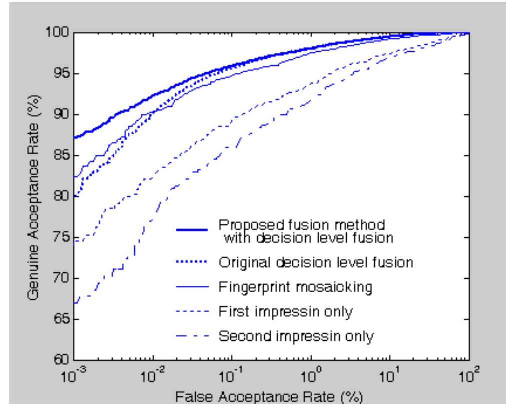
In this paper, we have developed a multiple-impression fusion scheme for fingerprint matching. The features of each impression can be effectively enriched by the feature level fusion scheme based on subset combination, taking full advantage of the complementary information contained in multiple impressions. Experimental results clearly demonstrate the superiority of our method.

5. ACKNOWLEDGMENT

The work described in this paper was fully supported by grants from the Research Grants Council of the Hong Kong Special



(a) Matching score level fusion with mean value



(b) Decision level fusion with product rule

Fig. 4. The ROC curves of the proposed two-stage fusion scheme, the fingerprint mosaicking scheme, and the original matching score/decision level fusion scheme.

Administrative Region. The work was done while all the authors are with the Chinese University of Hong Kong.

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