Minutiae-Based Template Synthesis and Matching Using Hierarchical Delaunay Triangulations

Tamer Uz, George Bebis, Ali Erol and Salil Prabhakar

Abstract— **Fingerprint-based authentication is a key biometric technology with a wide range of potential applications both in industry and government. However, the presence of intrinsically low quality fingerprints and various distortions introduced during the acquisition process pose challenges in the development of robust and reliable feature extraction and matching algorithms. Our focus in this study is on improving minutiae-based fingerprint matching by effectively combining minutiae information from multiple impressions of the same finger. Specifically, we present a new minutiae template-merging approach based on hierarchical Delaunay triangulations. The key idea is synthesizing a super-template from multiple enrollment templates to increase coverage area, restore missing features, and alleviate spurious minutiae. Each minutia in the super-template is assigned a weight representing its frequency of occurrence, which serves as a minutiae quality measure. During the merging stage, we employ a hierarchical, weight-based, scheme to search for a valid alignment between a given template and the super-template. The same algorithm, with minor modifications, can be used to compare a query template with a super-template. We have performed extensive experiments and comparisons with competing approaches to demonstrate the proposed approach using a challenging public database (FVC2000 Db1).**

I. Introduction

Fingerprint is among the most widely used biometric modalities with a broad range of both government and civilian applications. Developing more sophisticated algorithms that improve accuracy, robustness, and efficiency is a very active research area. In general, getting a perfect match between a query fingerprint and an enrollment fingerprint of the same person is almost impossible due to variations caused by several factors including sensor noise, non-linear geometric distortions due skin elasticity, and inconsistencies in finger contact pressure. These and related issues, along with the fact that many fingerprint sensors have a small sensing area, cause impressions of the same finger to look quite different from each other.

An effective approach to deal with these issues is using multiple enrollment samples to account for within-class variance. In general, multiple enrollment samples can be utilized in two ways. First, the query sample can be compared against each enrollment sample and the results can be fused either at the score level (e.g., taking the maximum score) or at the decision level (e.g. using majority voting). Second, the enrollment samples can be combined into a "super-sample"; then, the query sample is compared against the super-sample only. In general, the first approach has shown to increase accuracy to desired levels, however, its main drawback is that it increases both storage and time requirements. On the other hand, the second approach is less space and time consuming, however, combining the samples properly and voiding registration errors could be challenging.

In this paper, we propose a new, minutiae-based, template synthesis and matching approach based on hierarchical Delaunay triangulations. The proposed approach builds upon our earlier work on fingerprint matching using Delaunay triangulation [1]. Assuming that each user is represented by multiple enrollment minutiae templates, the key idea is combining them into a super-template. First, one of the minutiae templates is selected based on certain criteria as the current super-template. Then, each of the remaining minutiae templates are aligned and merged with the current super-template incrementally.

To compute the alignment transformation, we propose a novel approach based on hierarchical Delaunay triangulations. During this process, each minutia in the super-template is assigned a weight proportional to its frequency of occurrence in the enrollment templates. These weights are very useful in characterize minutiae quality and allow to search for correspondences between an enrollment template and the current super-template in a hierarchical fashion using Delaunay triangulations of minutiae at various levels of quality, making the whole process less sensitive to missing and spurious minutiae. Verification can be performed using the same hierarchical matching algorithm with only minor modifications.

II. Review on Combining Multiple Enrollment Fingerprints

When multiple impressions of the same fingerprint are available, one can in principle expect to make more reliable decisions about the presence or quality of fingerprint features by combining information from the samples in some fashion [2]. Algorithms that combine multiple impressions are based on two main approaches: (i) mosaicking [3]-[4], which combine the data at the image level, and (ii) template synthesis [5][2], which combine the data at the feature level.

In [3], Ratha et al. tiled the image sequence of a rolling fingerprint grabbed by a large area scanner. In [6], Jain and Ross combined multiple enrollment samples both at the image level (i.e., mosaicking) and feature level (i.e, template synthesis) using a modified iterative closest point algorithm. Their experimental results demonstrated that feature-level

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combination performs better than image level combination. In [7], Zhang et al. mosaicked the stream of swipe fingerprint frames. In [8], Choi et al. tried mosaicking different parts of a fingerprint collected by having the subject roll and slide his/her finger on the surface of small area fingerprint scanner. Finally, Shah et al. [4] performed mosaicking by employing thin plane spline as a transformation model to account for nonlinear distortions in fingerprints.

In [5], Toh et al. created a synthesized feature set using multiple enrollment templates. Even though they got significant improvements using the combined feature set compared a single template that included the center of the finger, the reported accuracy rates were much lower than current benchmarks. In [2], Jiang et al. created and updated a super-template as the user provided new samples during verification. Similar to our study, they assigned a weight to each minutia according to its frequency of occurrence. Depending on the weight values, spurious minutiae can fade away over time or missing minutiae can appear at some point in time. In contrast to our approach that utilizes these weights for matching, they simply discarded minutiae having weights less than a threshold. An improvement in accuracy relative to using individual templates was reported; however, a comparison with other fusion approaches was not provided.

III. Fingerprint Matching Using Delaunay Triangulation

Combining multiple enrollment templates into a super-template requires an alignment stage to find the transformation registering two different templates. A common approach to matching pairs of fingerprint templates is by comparing minutiae triangles [9]. The key idea is exploiting the invariance of features computed from minutiae triangles, such as side length and angle under rigid transformations. Local transformations, that align similar triangles, can then be accumulated in a voting space and searched for a global transformation among the ones that received high votes (i.e., hypotheses generation step). Then, the hypotheses are verified using an overlapping minutiae criterion (i.e., hypotheses verification step).

A crucial issue in these algorithms is choosing the minutiae triplets. For a minutiae set, employing all possible triangles is computationally prohibitive (i.e., $O(n^3)$ triangles) but also not expected to produce satisfactory results due to redundancy. To keep the number of minutiae triangles low, Germain et. al. [9] employed a number of heuristics based on the distance between minutiae. Our template synthesis approach builds upon our past work on fingerprint recognition using Delaunay triangulation [1]. The key idea is associating a unique topological structure with the minutiae using Delaunay triangulation in order to reduce the number of triangles considered for matching (i.e., $O(n)$ triangles). To improve accuracy, we have slightly modified our past algorithm here by incorporating minutiae orientation information for matching.

A. Invariant Features

Once the Delaunay triangulation of a set of minutiae has been computed, each triangle is visited and the following features, which is invariant to rigid transformations, are computed:

$$\mathbf{V_t} = [\frac{l_1}{l_3}, \frac{l_2}{l_3}, cos(A)] \tag{1}$$

$$\mathbf{V_m} = [\angle m_1, \angle m_2, \angle m_3] \tag{2}$$

where l_i corresponds to the i-th side of the triangle (i.e., sorted in increasing order $l_1 \leq l_2 \leq l_3$), A is the angle across the largest side, and $\angle m_i$ corresponds to the orientation angle of the i-th minutia in the triangle (i.e., sorted in increasing order $\angle m_1 \leq \angle m_2 \leq \angle m_3$). To avoid skinny triangles, we reject triangles whose largest angle is greater than a threshold (i.e., 168 degrees).

B. Hypotheses Generation

To find matching minutiae triangles between two templates, we check a number of constraints using the invariant features. Let **T** and **Q** correspond to the enrollment and query minutiae templates respectively. Then, each triangle in **T** is compared against each triangle in **Q** using the three criteria shown below. If all three criteria are met, then we assume that the two triangles match.

1) **Similarity Consistency:** If the differences between corresponding pairs of invariants are all below a threshold, then this criterion is met. In our experiments, the thresholds used for the spatial and angular features were 0.3 and 0.5 respectively. The thresholds were chosen relatively high in order to account for nonlinear minutiae dislocations. Many of the false matches are eliminated by the third criterion.
2) **Planarity Consistency:** The purpose of this step is to check whether matching triangles can be brought into alignment using in-plane transformations only.
3) **Minutiae Orientation Consistency**: The purpose of this step is to check whether corresponding minutiae have similar orientations. This is done by estimating the rigid transformation that aligns corresponding triangles and computing the orientation differences of the corresponding minutiae. If the average orientation difference is below a threshold (i.e., 30 degrees), then this criterion is met.

Given a pair of matching triangles, we can compute a rigid transformation (i.e., hypothesis) that can align the two templates. Hypotheses supported by many pairs of triangles are validated in a global sense during the hypotheses verification step. To find transformations that are globally optimum, each matching pair of triangles casts a weighted vote in the transformation space. The weight of the vote is inversely proportional to the average minutiae orientation differences. To compensate for quantization errors in the transformation space, we also cast votes to the immediate neighbors of the estimated transformation using a lower weight.

C. Hypotheses Verification

In this stage, each transformation candidate (i.e., transformations received high number of votes) is first refined (i.e., recomputed) using all pairs of matching triangles that have voted for this transformation. The quality of each hypothesis is then evaluated by aligning the enrollment template with the query template and computing the number of overlapping minutiae between them. The overlap is decided based on the difference between corresponding minutiae locations and orientation angles. The hypothesis giving the maximum number of overlapping minutiae is taken to be the best hypothesis. Finally, the number of overlapping minutiae is normalized to calculate a similarity score between the enrollment and query templates. Let t and q be the number of minutiae in enrollment and query templates respectively, and let m be the number of matching minutiae, then the similarity score s is calculated as follows:

$$s = \frac{2m}{t+q} \times 100 \tag{3}$$

IV. Fingerprint Super-Template Synthesis

The purpose of this step is to synthesize a super-template from multiple enrollment templates to increase finger coverage area, restore missing features, and alleviate spurious minutiae. The super-template is initialized by choosing one of the enrollment templates using certain quality measures. Then, each of the remaining enrollment templates is aligned and merged with the current super-template. Each minutia in the super-template contains additional information corresponding to the number of times that it appears in the enrollment templates. This frequency measure serves as a minutiae quality measure and allows for implementing an efficient scheme for registering two minutiae sets using hierarchical Delaunay triangulations (i.e., at various quality levels). The main advantage of this hierarchical approach is that it reduces the sensitivity of matching due to missing and spurious minutiae.

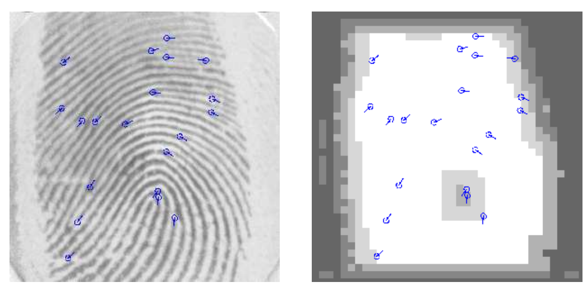
In the rest of the paper, the enrollment template used to initialize the super-template is referred to as the ”prime” template since its selection can affect the performance of the algorithm. The order in which the remaining enrollment templates are merged with the super-template is determined by their similarity to the current super-template. Specifically, given a set of enrollment templates and quality measures for each of them, the super-template is built as follows:

1) Set $t = 1$, choose the highest quality enrollment template as the prime template T_p and initialize the super-template $S_1 = T_p$. Set the minutiae frequencies in the initial super-template to one.
2) Compute the similarity of each of the remaining enrollment templates with the current super-template and select the one having the highest similarity as the next template T_n to be merged with the super-template.
3) Update the super-template: $S_{t+1} = S_t \cup T_n$
4) If there are still enrollment templates to be merged, then set $t = t + 1$ and go to 2, otherwise exit

A. Prime Selection and Order of Merging

The selection of the prime template to initialize the super-template has a profound impact on the performance of the algorithm. For example, selecting a low-quality template initially would cause subsequent registration operations to fail. We have experimented with two different approaches for selecting the prime template. The first approach compares all possible pairs of enrollment templates and picks the one having the highest average similarity score with the enrollment templates. This method is analogous to the one provided in [10]. However, we did not find this methodology very effective since it does not take into consideration the quality of the fingerprint image.

The second approach uses a global quality measure to select the prime template. In this case, we associate a quality measure with the minutiae and select the template having the highest quality overall. To obtain a global quality measure, we used NIST's fingerprint processing software [11] to compute a quality map for a given fingerprint image. This software computes a block-wise (i.e., 8x8 blocks) quality index map where the quality index is an integer in the range [0-4] (i.e., 0 represents the lowest quality level). To compute a global quality measure for the image, we extracted its minutiae and assigned a quality index to each of them by overlaying them on the quality map (see Figure 1) and taking the average over all minutiae quality indices.



(a) (b)

Fig. 1. Associating a quality measure with a minutiae set: (a) extracted minutiae, (b) minutiae overlayed onto the quality map. Lighter areas correspond to higher quality regions. The quality measure corresponds to the average of the minutiae quality indices.

Once the prime template has been selected, the next question is which enrollment template to select and merge with the current super-template. Although it is possible to go on with the same idea, we found experimentally that using similarity measures (i.e., first approach) yields better results. This is because once the prime template has been selected properly, then the reliability of the registration and matching operations using similarity rather than quality measures increases. Therefore, the enrollment template having the highest similarity score with the current super-template is selected to update the super-template.

It should be emphasized that the presence of very low quality enrollment templates could hamper the construction of the super-templates. The reason is that the minutiae templates corresponding to low quality images can not be aligned correctly with the super-template, resulting in an increase of false minutiae. To deal with this issue, we used similarity scores to filter out low quality minutiae templates. In other words, our system does not force every enrollment template to be merged with the current super-template. In contrast, it updates the super-template only if certain matching criteria are met.

We used a hysteresis-based decision making approach to implement this idea. Specifically, if an enrollment template has a similarity score (i.e., Equation 3) higher than a threshold s_1, the merging can take place. If its similarity score is less then s_2 (i.e., $s_2 < s_1$), then it is rejected. However, if it its similarity score is between s_2 and s_1, then we examine the similarity scores of this template with the super-templates at previous iterations. If the similarity of the template with one of the previous super-templates was more than s_1, then we merge it with the current super-template; otherwise, it is rejected. The values of s_1 and s_2 were experimentally set to 20 and 10 respectively.

B. Registration and Matching

The registration algorithm employed here builds upon the algorithm described in Section III and detailed in [1], with a major extension to account for missing and spurious minutiae. Specifically, a key problem with employing Delaunay triangulation for matching is that missing/spurious minutiae can introduce or remove important triangles from the triangulation. As a result, the quality of the match can be degraded significantly, especially when the overlap between two fingerprints is poor. To address the issue of missing/spurious minutiae, we associate a quality measure with the minutiae and perform the matching operations hierarchically, by applying Delaunay triangulations considering minutiae of various quality levels, from the highest to the lowest. At each level, the alignment transformation can be further refined on an iterative fashion using affine transformations in the spirit of [1].

1) Hierarchical Delaunay Triangulations: Missing and/or spurious minutiae as well as nonlinear distortions can severely affect the Delaunay triangulation as illustrated in Figure 2. Specifically, Figures 2(a) and (b) show two pairs of corresponding triangles (i.e., yellow and white). However, the yellow triangle in Figure 2(b) can not actually be formed since there exist a minutia inside the yellow triangle which is missing in Figure 2(a) due to smudging. As a result, the two triangulations look entirely different in this local region. Figures 2 (a) and (b) contain no missing minutiae; however, the nonlinear dislocation due to the elasticity of the skin has altered the topology of the triangles too.

Minutiae quality comes handy at this point, allowing us to match a template against a super-template by representing the minutiae in the super-template hierarchically, based on their quality. As mentioned in Section IV, each minutia in the super-template is associated with a quality measure which corresponds to its frequency of occurrence in the enrollment templates. Minutiae quality is inversely proportional to the probability that the minutiae might be missing or spurious.

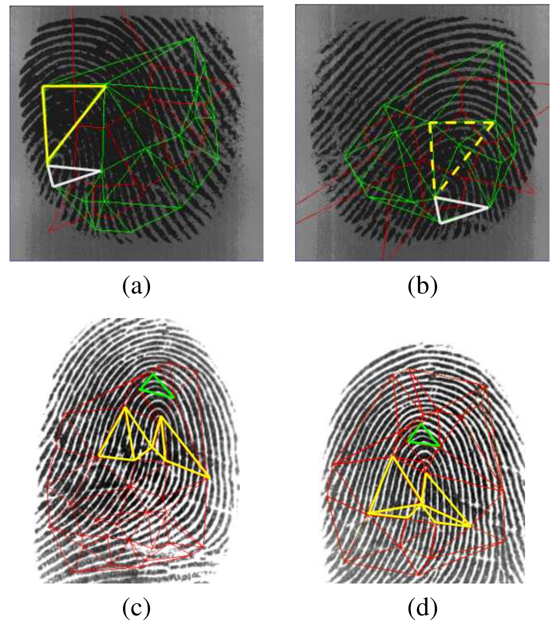


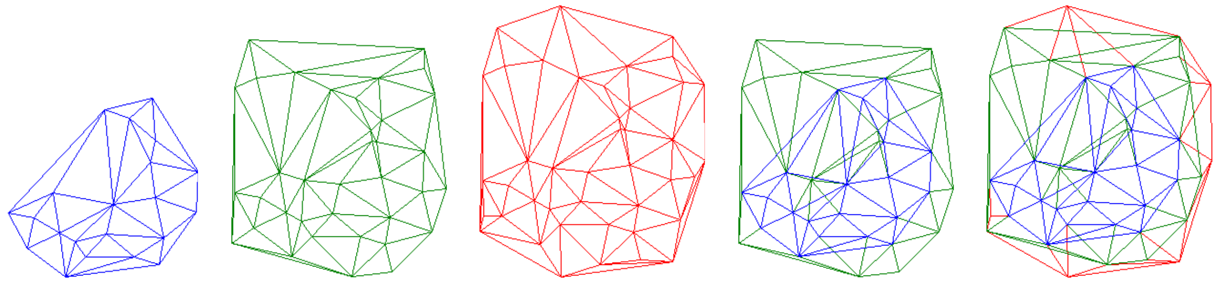
Fig. 2. Problems associated with the Delaunay triangulation of minutiae: (a),(b): effect of missing/spurious minutiae, (c),(d): effect of nonlinear distortions.

This implies that minutiae with large weights would be more likely to show up in most impressions compared to those having lower weights. Based on this observation, we group the super-template minutiae based on their quality and perform the matching hierarchically based on different quality groups.

Assuming that the minutiae weights orange from 1 to k, then there would be k minutiae groups. The group at the top of the hierarchy would contain only minutiae having a weight equal to k. The group at some level i, where $1 \leq i \leq k$, would contain those minutiae having a weight equal to i but also all those minutiae having weights greater than i (i.e., minutiae having better quality). As we traverse the hierarchy in a top-down fashion, this is equivalent to adding less likely minutiae to a given group of minutiae in order to compensate for missing minutiae. Finally, the group at the bottom level of the hierarchy (i.e., level 1) would contain all possible minutiae, independently of their quality.

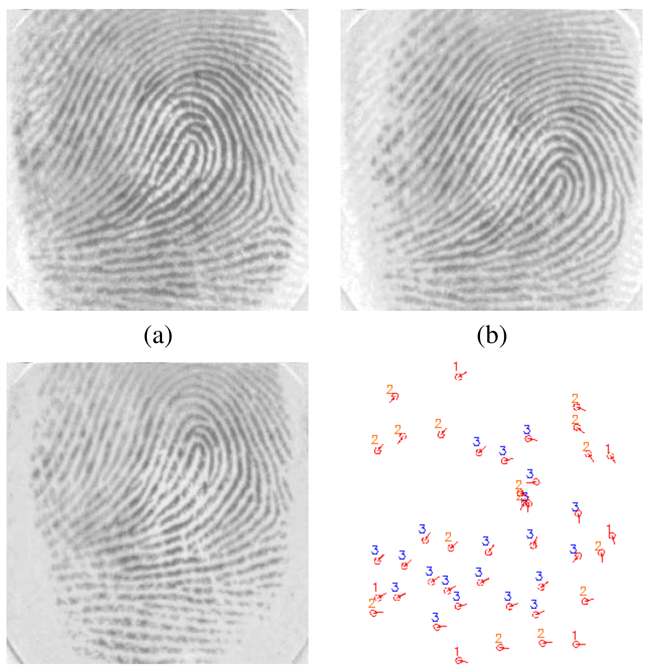
When comparing a template against a super-template, matching works hierarchically, starting with minutiae at the highest level of the hierarchy (i.e., best quality), which do not contain spurious minutiae, and ending with minutiae at the lowest level of the hierarchy. At each level, matching is performed as previously by applying Delaunay triangulation at each level separately. An important observation at this point is that the Delaunay triangles computed at level $i+1$ are not necessarily a subset of the Delaunay triangles produced at the lower level i. To improve matching by getting stronger support in the transformation space, our algorithm considers not only the Delanuay triangles computed at level i but also the Delaunay triangles computed at higher levels which were successfully matched with the input template.

The hierarchical matching process is illustrated in Figures



(a) (b) (c) (d) (e)

Fig. 4. Hierarchical Delaunay triangulation of the super-template formed in Figure 3: (a) triangulation formed by the minutiae having weight 3; (b) triangulation formed by the minutiae having weights 3 and 2; (c) triangulation formed by the minutiae having weights 3, 2, and 1; (d) combination of the triangulations from (a) and (b); (e) combination of the triangulations from (a), (b), and (c)



(a) (b) (c) (d)

Fig. 3. Illustration of the synthesis using three templates. The numbers associated with the minutiae are the number of times each appeared in the three templates (i.e., frequencies).

3 and 4. Figure 3 illustrates the synthesis results assuming 3 templates and Figure 4 shows the hierarchical triangulation. Figure 4(a) shows the Delaunay triangulation using minutiae having weight 3 only. The triangulation shown in Figure 4(b) contains minutiae having weights 3 and 2. In Figure 4(c), the triangulation was formed using all possible minutiae. In Figure 4(d), we have combined the triangulations of Figure 4(a) and (b). Finally, in Figure 4(e), we have combined the triangulations of Figures 4(a), (b), and (c). When a new enrollment template needs to be combined with the current super-template, all 5 triangulation shown are used to calculate an alignment between the super-template and the new template. The triangulation that produces the best alignment is used to merge the new template with the super-template.

2) Affine Refinement: Due to non-linear distortions present in fingerprints, using rigid transformations to register two sets of minutiae at any level of the hierarchy might not yield a good alignment. As it is important to align the enrollment templates with the super-template as good as possible in order to merge them more accurately, we have adopted the approach in [1] where affine transformations were applied on an iterative fashion to refine the initial alignment based on rigid transformations. The idea is finding more and more minutiae correspondences iteratively and recompute a more accurate alignment. More details can be found in [1].

C. Super-template Updating

When an enrollment template is merged with the current super-template, then all minutiae in the super-template that correspond to some minutiae in the enrollment template have their weights increased by one. However, minutiae in the enrollment template that do not have correspondences with the super-template are just added to the super-template and their weights are initialized to one. Figure 5 illustrates the updating process. Figure 5(a) shows the prime template used to initialize the super-template, and Figures 5(b)-(d) show the updating process. As new templates are merged with the super-template, the super-template grows in terms of area, addressing the small area problem. The weights of the minutiae also increase, reflecting the frequency of their occurrence in the enrollment templates, addressing the spurious minutiae problem.

V. Verification

When matching a query template to a super-template for verification purposes, the same hierarchical matching scheme can be used with minor modifications. First of all, the super-templates are not updated during verification although one can envision schemes where the super-templates are continuously updated over time. Second, although affine refinements were found to be very useful when merging together a number of templates that are known to come from the same finger, their use during verification has a tendency to increase imposter scores. Therefore, we do not apply affine refinements during verification. Another issue was choosing more conservative thresholds and other parameters in the case of verification. Using exactly the same values as in the case of building the super-templates had a negative effect on imposter scores again.

It should be mentioned that associating quality measures (i.e. frequency of occurrence) with the super-template minutiae is critical to the success of the proposed matching algorithm since many times, low-weight minutiae are spurious. One possible way to deal with false minutiae is by removing all minutiae having a small weight. This would actually enable any minutiae-based matching algorithm to use the super-templates built by our methodology verification. In our experiments, however, we found that keeping even minutiae with small weights improves performance, however, we had to design a more specialized matching algorithm based on hierarchical Delaunay triangulations.

VI. EXPERIMENTS

In our experiments we aimed at analyzing the accuracy fingerprint verification system utilizing our super-template synthesis algorithm and other methods of fusion. To extract the minutiae from fingerprints, we used the Verifinger library [12]. The output of Verifinger provides both the coordinates and orientation of the detected minutiae.

A. Database

In our experiments, we used the publicly available database Db1_a of FVC 2000 [13], which was acquired using a low cost small area optical scanner ("Secure Desktop Scanner" by KeyTronic). It contains a total of 800 300x300 images composed of 8 different impressions of 100 different fingers. It corresponds to a typical, small area, low-quality database. The images were taken from untrained people in two different sessions and no efforts have been made to assure a minimum acquisition quality. The presence of cores and deltas is not guaranteed since no attention was paid on checking the correct finger centering. The sensor platens were not systematically cleaned.

B. Description of the Experiments

In our experiments, we tested three different schemes: (i) Score Level Fusion (SLF), (ii) Template Selection (T_SEL), and (iii) Template Synthesis (T_SEL). In the case of SLF, multiple enrollment templates are stored in the database for each user. To verify a query template, we match it to all enrollment templates of a user and take the maximum matching score. In the case of T_SEL, only one of the enrollment templates is chosen to represent each user. We used the prime selection method described in Section IV-A to select the enrollment template for this approach.

For experimentation, the database was randomly partitioned into two parts, keeping N of the 8 impressions of the 100 fingers in the first part and the rest impressions in the second part. We used the first partition to create the enrollment database and the second partition for testing. To show the effect of choosing different numbers of enrollment impressions, we conducted experiments using N = 2,3,4 and 5. Since randomness is involved in the selection of the enrollment and test impressions, we repeated each experiment 30 times and report average performance. For error rate estimation, we randomly picked one sample from each finger in the test set and compared it against all the other fingers in the outside of the test set, yielding a total of 9900 imposter scores. The number of genuine scores depended on the number of enrollment impressions. Using 2, 3, 4, and 5 impressions for enrollment, the number of genuine scores used were 600, 500, 400 and 300 respectively.

C. Results

Figure 6, shows the ROC curves for each approach separately as the number of enrollment templates increases from 2 to 5 (please note that the graphs have been logarithmically scaled). Clearly, more enrollment templates increase the performance of SLF and T_SYN, however, it does not have any effect on the performance of T_SEL. Figure 7 compares each method side-to-side using different number of templates. As this is a very low quality (high noise, small area) database, it can be clearly observed that using multiple enrollment templates does make a difference in terms of accuracy and consistency. Overall, T_SEL performed much worst compared to SLF and T_SYN, especially when the number of enrollment templates increased.

Comparing SLF with T_SYN, we found that SLF performed slightly better than T_SYN which was surprising for us as we expected T_SYN to outperform SLF overall. By carefully analyzing our results, we concluded that the main reason that T_SYN did not outperform SLF is due to inaccuracies in the merging (i.e., registration) of the enrollment templates with the super-template. Employing a more powerful registration model, instead of using rigid transformations followed by affine refinements, would allow us to estimate the locations of the minutiae in the super-template more accurately and boost the performance of the proposed method. Nevertheless, although SLF performed slightly better than T_SYN, this was at the expense of higher storage and time requirements. In these experiments, the average storage requirements of SLF, T_SEL and T_SYN were 1540, 385 and 729 bytes respectively per user (N=4). In terms of time, T_SEL was the fastest, requiring 0.56 seconds on the average (N=4). T_SYN was faster on the average than SLF, taking 1.84 seconds versus 2.24 seconds (N=4).

TABLE I

SUPER-TEMPLATE MINUTIAE AND WEIGHT STATISTICS

	Number of Templates				
	1	2	3	4	5
Avg. # of minutiae	32.64	41.11	48.13	54.03	59.23
weight 5	N/A	N/A	N/A	N/A	10.40
weight 4	N/A	N/A	N/A	11.79	7.37
weight 3	N/A	N/A	13.54	9.65	7.86
weight 2	N/A	19.92	12.30	10.95	10.40
weight 1	32.64	22.29	21.19	21.64	23.20

Finally, Table I provides some statistics on the minutiae counts in the super-templates, and the distribution of weights.

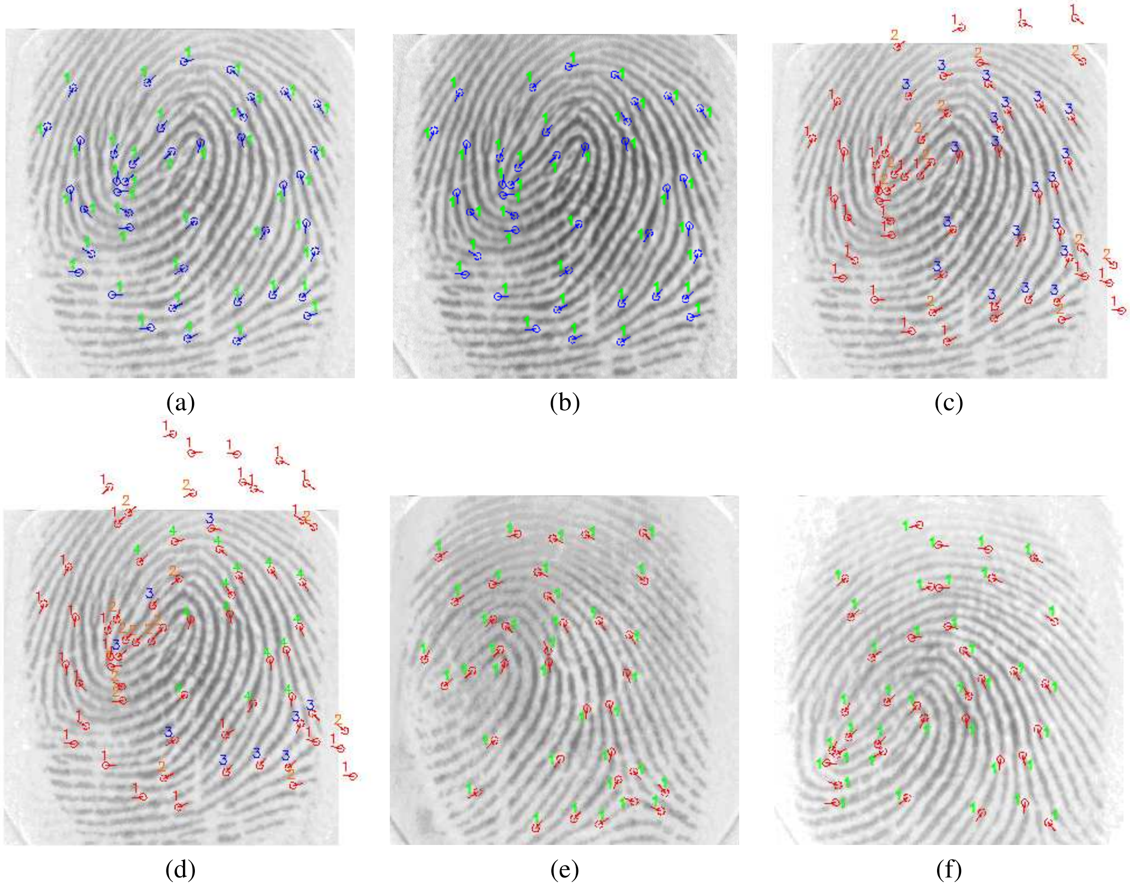


Fig. 5. Super-template updating: (a) prime template used to initialize the super-template; (b)-(d) updating the super-template as more enrollment templates ate merged with it; (e),(f): the enrollment templates used to update the super-template in the last two iterations.

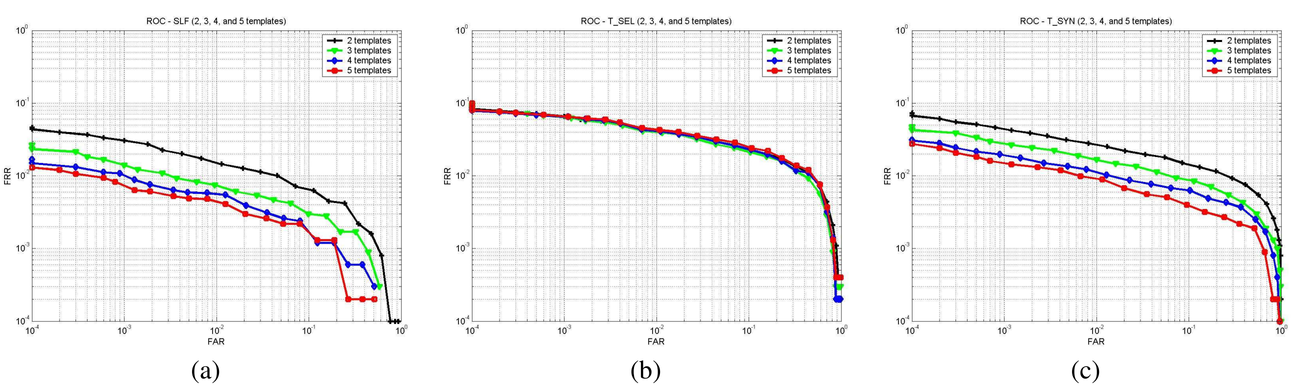
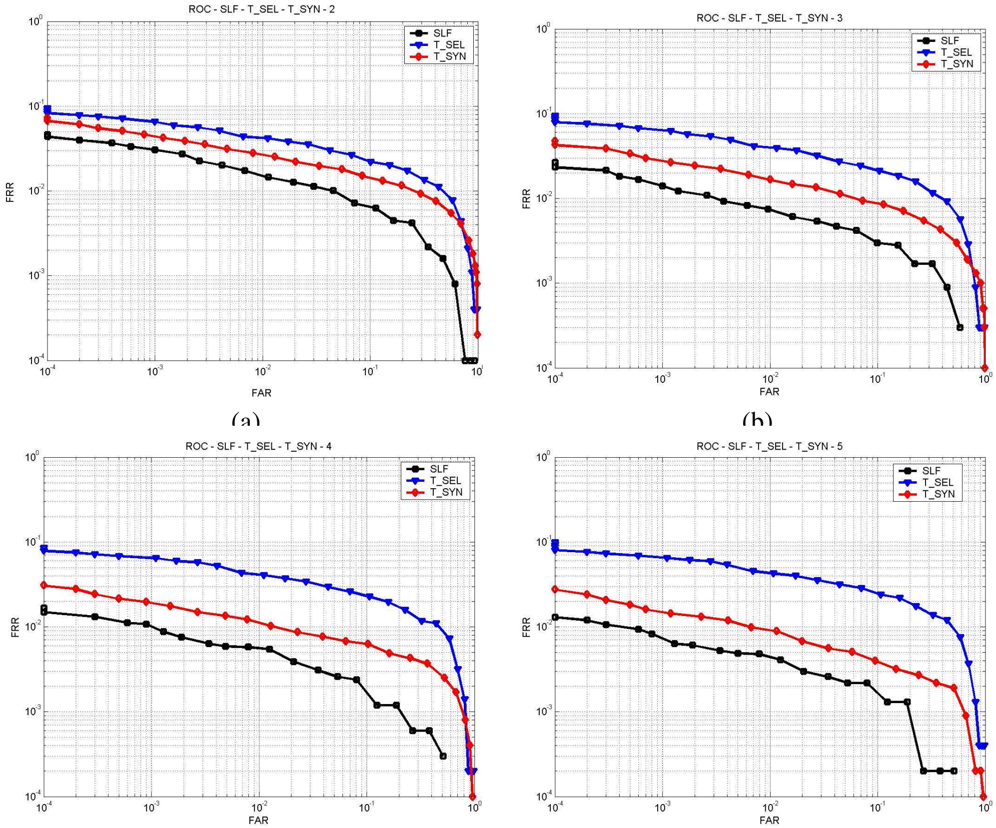


Fig. 6. ROC curves of each fusion method. (a) SLF, (b) T_SEL, (c) T_SYN

Compared to an individual template, the number of minutiae increased by 25.95%, 47.46%, 65.53% and 81.46% when creating super-templates using 2, 3, 4, and 5 impressions respectively. When using 2 impressions, the percentage of minutiae having weight more than 1 was 48.46% of the total number of minutiae in the super-template. The corresponding percentages for 3, 4, and 5 impressions were 55.97%, 59.95% and 60.83%. This observation suggests that when a sufficient number of templates is used to synthesize the super-templates, the minutiae having weight more than 1 will constitute the entire true minutiae set and the unaccounted minutiae (those that have much smaller weights) could be safely discarded.

VII. Conclusion and Future Work

In this study, we presented a super-template synthesis and matching algorithm based on hierarchical Delaunay triangulations. Problems related to small area and missing minutiae were addressed by combining the individual enrollment



(c) (d)

Fig. 7. ROC curves for diffrent number of enrollment templates. (a), (b), (c) and (d) show the ROC curces for 2, 3, 4 and 5 templates respectively.

templates, while problems related to spurious minutiae were addressed by assigning weights (i.e., quality measures) to the minutiae in the super-template based on the frequency of their occurrence in the enrollment templates. We performed extensive experiments to demonstrate the proposed approach using a very challenging database containing low quality fingerprints. Our experimental results showed that T_SYN performed slightly worst than SLF in terms of accuracy, however, it had lower space and time requirements. For future work, we plan to improve the proposed method in several ways. First of all, we plan to use a more powerful registration model to merge the enrollment templates into the super-template. Second, we plan to incorporate additional features with the minutiae (e.g., ridge count information) to reduce the probability of false alignments in the merging process. Finally, we plan to test the proposed approach on more databases.

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