# TEMPLATE SYNTHESIS AND IMAGE MOSAICKING FOR FINGERPRINT REGISTRATION: AN EXPERIMENTAL STUDY

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## ABSTRACT

Fingerprint registration becomes an important issue for the success of reliable fingerprint verification using small solid state fingerprint sensors. Current major registration techniques include template synthesis and fingerprint image mosaicking. Template synthesis merges the fingerprint features while image mosaicking merges the fingerprint images to generate a composite fingerprint image from features of the images. In this paper, these two techniques were studied and compared under a unique framework to review their characteristics operating under fingerprint images of different sizes. Experiments show that both techniques could have their own merits. In particular, we also present a fingerprint oriented ICP algorithm that aligns the images based on their extracted minutiae.

## 1. INTRODUCTION

Fingerprint verification is the most commonly used biometric authentication method today. Thanks to the advance of sensor technology, a lot of inexpensive and small sized solid-state fingerprint sensors, suitable for mobile applications, are now available. Unfortunately, the small sensing areas of these sensors (e.g. 300x300 pixels in a Veridicom's iTouch sensor) can hinder reliable authentication due to the smaller number of template features, minutiae, that can be located. The smaller number of matching minutiae can introduce higher false rejection rates too. One of the possible solutions to tackle such difficulties is to generate a composite fingerprint template during the enrollment phase when more than one fingerprint images of the same finger are often taken.

In general, there are two common techniques to produce composite fingerprint templates. In 2000-1, Toh and Yau [1] [2] proposed a minutiae-based template synthesis method to combine several minutiae templates for constructing a composite minutiae template. The alignment of two sets of minutiae templates is first computed using an affine transformation. Subsequently, a composition decision is applied to combine the two sets of minutiae together. Their experiment results showed that composite templates could produce a higher accuracy as seen from the ROC curves. On the other hand, in ICASSP 2002 [3], A. K Jain, et al. proposed an image mosaicking technique that combined two fingerprint images from which a composite template could be extracted using traditional minutiae extraction techniques [4] [5]. To align the two images, their minutiae sets were extracted and aligned using a modified ICP algorithm. The image pixels of the two aligned fingerprint images were then directly combined by average weighting their pixels values. Their experiment results implied that image mosaicking was a better solution for fingerprint registration in 300X300 pixels fingerprint images. The purpose of our work here is to study the characteristics of these techniques applied to small fingerprint images and evaluate them using a common testing platform. The details of the implementation for both approaches are discussed in Section II. Experiment results for a relative large fingerprint database testing are presented in Section III. We then show the niches of the two fingerprint registration techniques in Section IV. Finally, we conclude our paper with a discussion of the future direction in fingerprint registration technique in Section V.

## 2. TEMPLATE SYNTHESIS AND IMAGE MOSAICKING

This section conducts a brief overview of the fingerprint template synthesis and fingerprint image mosaicking algorithms.

### 2.1. Template Alignment

In order to perform either template synthesis or image mosaicking, an alignment has to be explored first for matching the corresponding components of the two templates or images. Assume two templates, T1 and T2, represented by two sets of minutiae, M1 and M2 respectively. An alignment f is a transformation, consisting of a translation ($\tau$) and a rotation ($\varphi$), such that f = (τ, φ). The ideal case of transformation is f(M1) = M2. In reality, the ideal transformation does not exist since it is practically impossible places for a user to place exactly the same part of his/her finger on a sensor and exerts the same pressure on the sensor during two different fingerprint capture occasions. Our goal, therefore, aims at the minimization of E(f(M1), M2), where E is an error metric applicable to the two minutia sets [6].

We adopt the Iterative Closet Point (ICP) algorithm [6] [7] for searching the optimal transformation f. ICP is a widely used algorithm for the alignment of 3D geometric models. It iteratively searches the closest point sets and computes the corresponding transformation using covariance matrices until the change in error between the point sets is below a threshold value T.

Our modified ICP algorithm for finding the transformation matrix is summarized below:

1. Apply a minutiae extraction algorithm to extract the minutiae sets from the two fingerprint images. Each minutiae set consists of the (xi, yi, θi), for i= 1,2…N, where xi and yi denote the coordinates of minutia i and θi gives its orientation. The two extracted minutia sets (M1, M2) will be the candidates of the feature point sets for the ICP algorithm.

2. Initialize the initial transformation f by computing the difference of the locations of the reference points in both fingerprint images. An algorithm for extracting the reference point can be found in [8].

   Compute the closest point pairs P between the two minutiae templates by estimating the Euclidean distance between the minutiae coordinates. Here closeness between two points and is simply their Euclidean distance. Some false pairs (p, q) are then removed if the Euclidean distance of the difference of coordinates or orientation is larger than a threshold value.

3. Find out the registration (new alignment) required for M1 by using the computed covariance matrix of the point sets.

4. Calculate the error metric between the newly transformed M1 and the original M2. The error metric used in our implementation is the mean squared error of the matched feature points, that is, error where is the set of matched point pairs.

5. Repeat the procedure until the mean square error is less than a pre-defined threshold.

In our implementation, the above ICP algorithm converges to the global optimal quickly, usually in less than 3 iterations, assuming an accurate estimation of the initial approximate transformation is used. In our experience, we have already achieved 97.3% accuracy in locating the initial reference point extraction [8].

### 2.2. Template Synthesis

Having obtained the pre-computed transformation from ICP, we can start a template synthesis to merge two templates together. First, we apply the bounding box [8] method to pair up the minutiae from the two templates. For each pair of minutiae $(p_1, p_2)$, found in both templates, a new minutia $p_{new}$ is generated by averaging the minutiae attributes of $(p_1, p_2)$, i.e.

$$p_{new}.x = (p_1.x + p_2.x)/2$$
$$p_{new}.y = (p_1.y + p_2.y)/2$$
$$p_{new}.\vartheta = (p_1.\vartheta + p_2.\vartheta)/2$$

Minutiae that are not paired up are considered to be supplementary of the counterpart, and will be directly copied to the merged template. Hence, the number of minutiae in the combined template is always greater than or equal to the maximum of the number of minutiae in its parent templates. Figure 1 illustrates the template synthesis process.

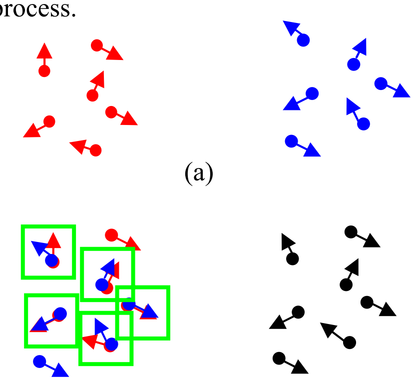


Figure 1. Template synthesis process. (a) Two sets of minutiae template. (b). The minutiae template after using the bounding box (green) for pairing. (c) The resultant composite template

### 2.3. Image Mosaicking

In image mosaicking, all the pixels in a component image will be transformed using a pre-calculated alignment. Then a segmentation algorithm [10] [11] is applied to compute the segmentation map Seg that segments a region of interests (ROI) from the background. At the same time, a coherence map Coh of the fingerprint image blocks is also computed. The composite fingerprint image is created by integrating the gray level intensities of the two original images, based on their coherence values. For the region common to the two images, the region with the higher coherence value will be copied to the resultant composite image. For the other regions, the ROIs will be copied to the final image. We found that this approach works better to reduce the image blurring effect due to inconsistent integration of the fingerprint ridges pixels originated from the elastic deformation of the fingerprint images. In the conventional weighted average approach mentioned in [3], the resultant pixel values in the overlapping area of the two merging images are set to the weighted sums of the corresponding pixel values of the two merging images. If the image regions do not coincide due to the elastic distortion, the final image could be blurred.

After a new fingerprint image is formed, minutia extraction can be carried out to extract the new set of minutiae template. An example of image mosaicking is depicted in Figure 2.

Figure 2. Fingerprint mosaicking of two small fingerprint images.

## 3. EXPERIMENTS

For a population of 383 individuals, each individual enrolled his or her same finger 3 times to build up a database of 1149 fingerprint images. In our experiments, 256 x 256 fingerprint images were acquired using a fingerprint sensor with 450 dpi resolution. In order to mimic the small fingerprint images captured from solid state sensors, as well as to investigate the effect of image size on template synthesis and image mosaicking, the fingerprint images were cut into sizes of 208x208, 192x192 and 176x176. The frame of image cut is chosen arbitrarily. As a result, there are 4 sets of databases of different sizes; each has 1149 fingerprint images.

For each database, we merged every pair of fingerprint images of the same finger. As there are 3 combinations for the 3 images of the same finger, 1149 possible syntheses exist. In reality, the number is smaller due to ICP failures. Nevertheless, the ICP algorithm requires at least 3 pairs of minutia to be matched; otherwise the covariance matrix cannot operate. Moreover, we also require the final distance between two templates should be bounded (10 pixels in our implementation) after ICP alignment. ICP is said to fail when either of the two requirements cannot be met. We found that as the size of image diminishes the failure rate of ICP increases. This is because there are fewer minutiae in the small images, and hence it is less likely that correspondence between two templates can be found. The following table illustrates the relationship between the number of minutia and ICP failure.

| Image Size | 256 | 208 | 192 | 176 |
|---|---|---|---|---|
| Ave. Number of minutia | 18 | 17 | 15 | 13 |
| ICP Failure Rate (%) | 11 | 16 | 26 | 40 |

After template synthesis or image mosaicking is done, the new templates will be compared with all original templates to investigate the false accept rate (FAR) and genuine accept rate (GAR). Three ROC curves are then plotted for each database. They correspond to the accuracy of fingerprint verification with (1) template synthesis, (2) image mosaicking and (3) no synthesis. Figures 4 and 5 illustrate the results. We found that both template synthesis and image mosaicking improves the accuracy, and the improvement becomes more significant in smaller images. When the image size diminishes, image mosaicking outperforms template synthesis. This is because the false minutiae generated in template synthesis can become dominating errors when the total number of minutiae decreases in small images. On the contrary, template synthesis regains its disadvantages against image mosaicking in large images. This is because image mosaicking could suffer more from plastic deformations when the images are large. Figure 3 illustrates the scenario. When the two fingerprint images suffer non-uniform elastic distortion in different directions, it is often difficult to merge these fingerprints without defects, especially in regions near the merging boundary.

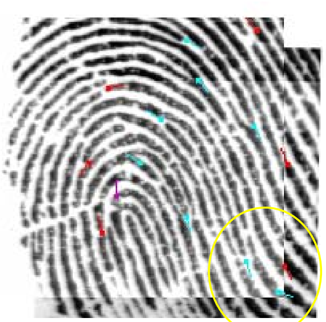

Figure 3. Elastic distortion in image mosaicking

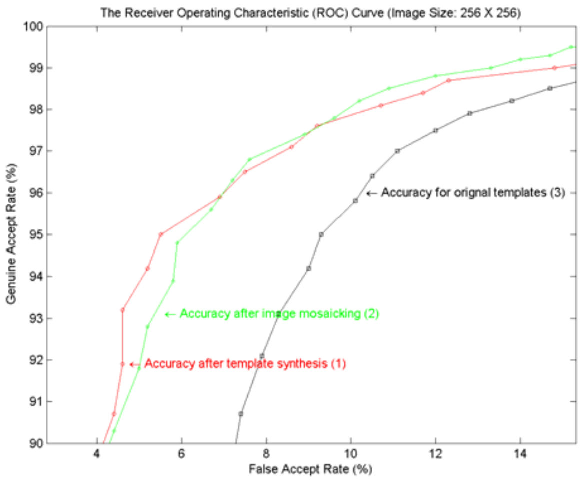


Figure 4. The ROC curves for image size 256 X 256

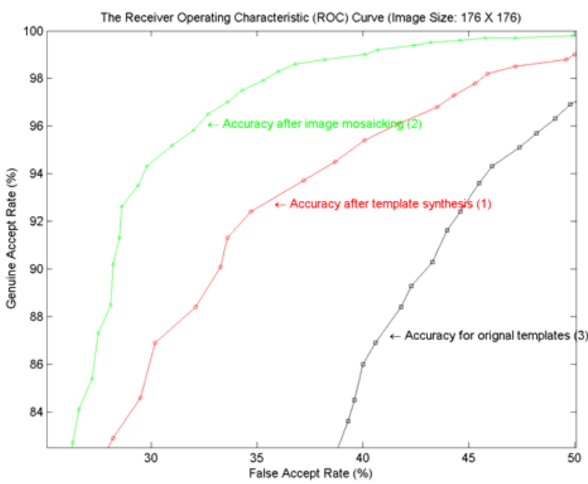


Figure 5. The ROC curves for image size 176 X 176

## 4. CONCLUSION AND FUTURE WORK

In this paper, we propose a modified ICP algorithm for searching the optimal transformation when merging the minutiae from two fingerprint images. We have also compared the performance of two important techniques for merging the fingerprint templates: template synthesis and image mosaicking under a common platform. Our findings suggest that both fingerprint registrations can improve the fingerprint verification accuracy. Experiments show that image size becomes a critical factor when deciding the particular merging approach to be used during fingerprint registration. Template synthesis, which is faster and less affected by elastic deformation, is suitable for larger images. Image mosaicking, on the other hand, should be chosen when accurate performance for small images is wanted.

## 5. REFERENCES

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