Fingerprint Matching Using Correlation and Thin-Plate Spline Deformation Model

Jiang Li, Sergey Tulyakov, Zhi Zhang and Venu Govindaraju

***Abstract*— One of the difficulties for fingerprint matching lies in the non-linear distortion between fingerprint images originating from same finger. In this paper we present a modification of correlation matching method, which uses Thin-Plate Spline (TPS) as a model for non-linear transformations between two fingerprints. The TPS model is constructed first from the results of a traditional minutia matching algorithm, and by using this model one of the fingerprints is deformed to match the other. After the TPS transformation the correlation scores between the local neighborhood areas of corresponding minutiae pairs and the edges that connect neighboring matched minutiae pairs are calculated and used for final matching score. The FVC2002 DB1 database is used to test the proposed approach. Experimental result shows the improvement when combining TPS deformation model with correlation matching method.**

I. INTRODUCTION

Biometrics is rapidly gaining acceptance as the technology that can meet the ever-increasing need for security in critical applications. Fingerprint has served as one of the mostly used biometrics because of its permanence and individuality. Fingerprint verification is the process of matching a pair (test and enrolled) of finger-skin ridge impressions to determine if the impressions are from the same finger. The non-linear stretching of the finger-skin makes any two instances of impressions of the same finger (quite) different. Other challenges are due to the varying contrast levels (moist fingers tend to give smudged impressions and dry fingers tend to give impressions with broken ridge contours), the rotation of the finger, the pressure applied on the sensor, and the partial nature of most fingerprints captured by commercial sensors.

Fingerprint matching algorithms reported in the literature are of three types based on: (i) minutiae (discontinuities in the ridge contour) (ii) texture, and (iii) image correlation. Minutiae based matching methods consider special points of fingerprint impressions representing ends and bifurcation points of the fingerprint ridge structure. In texture matching, spatial relationship and geometrical attributes of the fingerprint ridges are used. Correlation scores from the intensities of corresponding pixels are used in the third approach. Various matching systems have been developed based on minutiae [1], [2], texture [3], [4], [5] and image correlation [6]. Also, different matching algorithms are combined to seek better performance [7], [8], [9].

Usually, both minutia and correlation based matching algorithms assume the linear transformations between two fingerprint images. The minutia matching algorithm tries to minimize the distance between two sets of minutia over all possible rigid transformations, while the correlation method tries the minimize the correlation scores calculated from local areas of two fingerprints over certain possible rigid transformations. One of the difficulties, these algorithms have, is the existence of the non-linear distortion between fingerprint images of the same finger. Although the distortion is mainly introduced when the 3D fingerprint is mapped to 2D fingerprint image while capturing, it is hard to build such 3D to 2D model. Instead, we want to use Thin-Plate Splines (TPS) as a model for non-linear transformations between two fingerprints within 2D domain. Some previous work has been done using TPS as a deformation model for fingerprint matching [10], [11], [12]. Almansa et al. [10] present a two-step iterative minimization algorithm for elastic matching using TPS modeling. Bazen et al. [11] use several iterations to refine the initial model using the new minutiae correspondences until the model converge to final state. Ross et al. [12] use TPS to estimate an average distortion model for one fingerprint from many prints.

Since the the correlation methods is not effective if compared images are nonlinearly distorted, in this paper, we propose to incorporate the TPS deformation model together with the local correlation matching algorithm to improve the fingerprint matching result. First, a minutia based matching algorithm is used to get the landmark points to generate the TPS deformation model. Then the enrolled fingerprint image is deformed to match the template fingerprint image based on the landmark points. Correlation matching is then applied on the template fingerprint image and the deformed fingerprint image to generate the final matching score. In the following section we will first cover the minutia based matching method that we used to get the matching minutia pairs. Then we introduce the proposed TPS model and the correlation based matching. After that we describe score combination method, followed by the experiment and result section. Finally, conclusion is given in the last section.

II. MINUTUAE BASED FINGERPRINT MATCHING

Since most of the current fingerprint matching systems are based on minutiae extraction and minutiae matching, we use it to get the landmark points for generating the TPS deformation model. A standard minutiae matching system is composed of fingerprint image preprocessing, fingerprint image enhancement, minutiae feature extraction and matching. The preprocessing and enhancement steps reduce image noise and enhance the ridge information, partitioning the

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given image into regions that are composed of the fingerprint ridges and background area. Minutiae can be extracted from binarized fingerprint image or from gray-scale image directly.

Jea et al.[13] proposed a multi-path matching system based on the secondary features, which are the five element tuples extracted from each minutiae and its two nearest neighbors. Heuristic rules are used to get the matching score for final decision. Based on this work, we will introduce thin-plate spline as a deformation model for fingerprint images, implement the correlation methods in next section, and show the improvement made in result section when it is combined with this minutia matching system.

III. THINE-PLATE SPLINE DEFORMATION MODEL

After we get the landmark points from minutia matching algorithm introduced in previous section, we can build our TPS model. Thin-Plate Splines (TPS) [11] refers to a physical analogy involving the bending of a thin sheet of metal. In the physical setting, the deflection is in the z direction, orthogonal to the plane. In order to apply this idea to the problem of coordinate transformation, one interprets the lifting of the plate as a displacement of the x or y coordinates within the plane. In 2D cases, given a set of K corresponding points, the TPS warp is described by 2(K + 3) parameters which include 6 global affine motion parameters and 2K coefficients for correspondences of the control points. These parameters are computed by solving a linear system, in other words, TPS has close-form solution.

The resulting function $f(x,y)$ is defined as follow:

$$f(x,y) = a_1 + a_x x + a_y y + \sum_{i=1}^{n} w_i U(|P_i - (x,y)|) \quad (1)$$

where $U(r) = r^2 log(r)$, $r = (x^2+y^2)^{1/2}$ and we define $U(0) = 0$. The first 3 terms describes global affine transform and the rest term describes the non-linear deformation.

Using the TPS model,the enrolled fingerprint image is deformed to match the template fingerprint image based on the landmark points that are extracted through the minutia matching algorithm. Fig 1 shows an example of such transform. After this transformation, the warped fingerprint image and the template fingerprint image are ready for the correlation matching method introduced in next section.

IV. CORRELATION MATCHING BASED ON THE DEFORMATION MODEL

The idea of correlation method is, when minutiae based matching method fails to provide a convincing measure of how well the two fingerprint match, we will retrieve the local gray-scale information around the matched minutiae pairs from the original fingerprint images, and use the similarity of the gray-scale regions as the measure of how well the two minutiae matched with each other. By statistically examining the matching scores over all matched minutiae between the two fingerprint images, we can get a better understanding of how well the two fingerprint match with each other, and thus reduce the heuristic effects in the decision stage using the measure of minutiae based matching result alone.

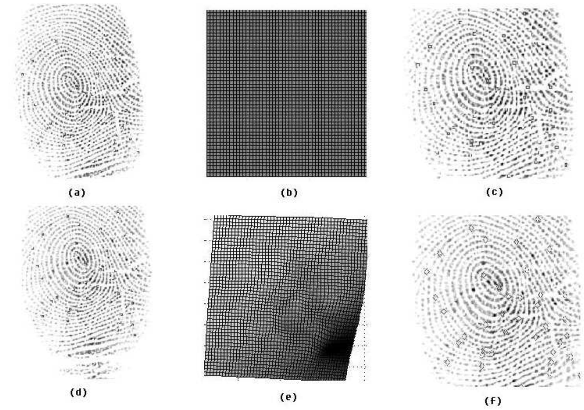

Fig. 1. TPS deformation model. (a) Template fi ngerprint image (b) Original Thin Plate (c) Template fi ngerprint image (d) Enrolled fi ngerprint image (e) Warped Thin Plate (f) Warped fi ngerprint image

After the TPS deformation model is implemented on the enrolled fingerprint image, we will use local gray-scale information for correlation based method in two different levels.

A. Local neighborhood similarity

First, the neighborhood correlation is used to measure the local similarity between the matched pair of minutiae of the two fingerprint images. We select a neighborhood of 21*21 region around the minutiae, compute the two-dimensional correlation coefficient between the two regions using Eq. 2 and get a neighborhood correlation score for each pair of matched minutiae:

$$cor(1,2) = \frac{\sum_{i,j=1}^{21}(p_{ij}^1 - M^1)(p_{ij}^2 - M^2)}{(\sum_{i,j=1}^{21}(p_{ij}^1 - M^1))^{1/2}(\sum_{i,j=1}^{21}(p_{ij}^2 - M^2))^{1/2}} \quad (2)$$

In this equation M^k denotes the mean value of pixel intensities p_{ij}^k in considered $21 * 21$ minutia neighborhood of fingerprint k.

The neighborhood correlation score helps to identify if the two minutiae are well matched as far as local gray-scale information is considered. When an appropriate size of neighborhood is selected, high correlation score can still be obtained from a pair of impostor matched minutiae, as long as their neighborhood have certain extent of similarity, while low correlation score may be obtained from the genuine pair of matched minutiae due to the local noises from the pressure and skin condition or deformations. Thus, we need another measure of similarity to compensate such situations.

B. Local edge similarity

Edge correlation is used to measure the similarity of the local gray scale edges between two pairs of matched minutiae. Edge is defined as a line segment between two minutiae points. For each pair of matched minutiae points, we choose two edges that connect them to the two nearest matched minutiae points in both fingerprints. We calculate the correlation scores for both edges, excluding the insides of 21*21 minutia neighborhood regions, and take the average value as the edge correlation score for the pair of matched minutiae points. The formula for each edge correlation score is:

$$cor(1,2) = \frac{\sum_{i=1}^{N}(p_i^1 - M^1)(p_i^2 - M^2)}{(\sum_{i=1}^{N}(p_i^1 - M^1))^{1/2}(\sum_{i=1}^{N}(p_i^2 - M^2))^{1/2}} \quad (3)$$

where p_i^k represents an interpolated intensity value on the ith subinterval of the considered edge of fingerprint k, M^k are the corresponding mean values of these intensities. N coincides with the number of pixels in one edge.

Edge correlation gives the similarity measure of areas that are in between the two corresponding minutiae pairs. It can also be seen as a replacement of matching methods utilizing the ridge intersection numbers between two minutiae. The correlation score is rather more reliable since there is no need to find exact ridge information. Moreover, it contains more useful information - two line segments may have same ridge intersection number but different intersection distribution.

The edge correlation helps to distinguish genuine matched minutiae and impostor matched minutiae. Two mismatched minutiae may have a relatively high neighborhood correlation score if certain local neighborhood similarity exists, but edge correlation score that take a more extended directional area into consideration can help to find the mismatch. On the other hand, two genuine matched minutiae may have a relatively low neighborhood correlation score if there are local noise and deformation exists, it may generate a high edge correlation score.

Given a pair of fingerprint images , for each of the matched minutia pair, we can get a neighborhood correlation score and an edge correlation score, the median value of both of the scores are used as neighborhood matching score and edge matching score.

V. Score Combinations

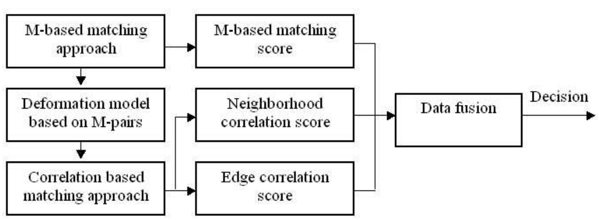

Fig. 2. Flowchart of the whole fingerprint matching system using neighborhood and edge correlations.

When both deformation and local similarity are considered, together with the original minutiae based matching result, we can have a better evaluation of how well two fingerprints match with each other. There are various rules for combining scores, in this paper we use the simple product rule to combine the three scores.

As mentioned before, minutia based matching considers the match of global minutia distribution, neighborhood correlation score gives a measure of how well the match is in the local level, and edge correlation score measures the semi-local semi-global, similarity between two fingerprints. The correlation scores that are used to measure the similarity between two fingerprint images are more representative since the TPS model is applied first. When the number of matched minutiae pairs (minutiae score) is multiplied with neighborhood correlation score, it gives the simple sum of correlations of matching minutiae pairs, this sum represents a composite of evidences collected for all matching minutiae pairs. The combination of minutiae score with edge correlation score represents same measure but in a more extended way.

VI. Experiments and Results

Fig. 3. Samples of used fingerprint images from FVC2002 DB1.

FVC2002 DB1 is used as experimental set for the algorithm we proposed.The database contains 8 impressions is 110 fingers(880 fingerprints in all). For genuine match tests, each sample is matched against the remaining samples of the same finger to compute the false rejection rate - FRR. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. The total number of genuine tests (in case no enrollment rejections occur) is: ((8*7) /2) * 100 = 2,800. For impostor match tests, the first sample of each finger is matched against the first sample of the remaining fingers to compute the false acceptance rate - FAR. If the matching g against h is performed, the symmetric one (i.e., h against g) is not executed to avoid correlation. The total number of false acceptance tests (in case no enrollment rejections occur) is: ((100*99) /2) = 4,950.

In the experiment, we randomly choose 1000 genuine matches and 1000 impostor matches from above test set from each database. Note, that the TPS deformation model and the correlation scores are computed only for hypothesized matched and aligned minutia and neighboring matched minutia pairs.

We tested few different combination methods, and the product rule achieved best performance. The ROC curves for both correlation measures using product combination rule are showed in Figures 4 and 5. The figures show that, when the TPS deformation model is implemented, either the combination of the minutiae matching score and the neighborhood correlation score, or the combination of the minutia matching score and the edge correlation score, both gives improvements for the final matching decisions. This implies that the TPS deformation model affects both type of the correlation scores for the matching decision in a positive way.

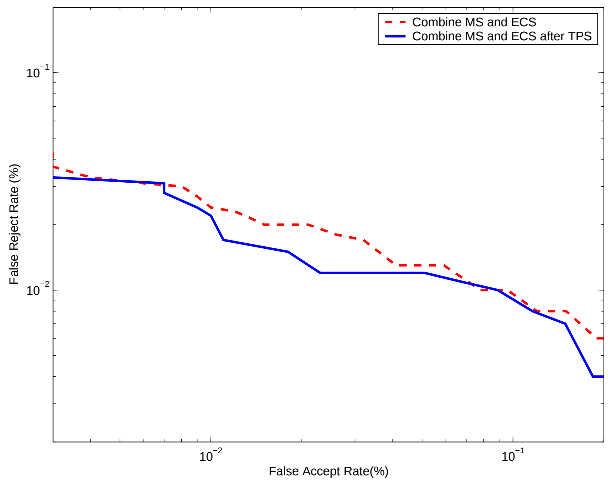

Fig. 4. ROC curves of different score combinations of DB1 data set. MS: Minutiae score. ECS: Edge correlation score. TPS: Thin-Plate Spline. Combining rule: product rule.

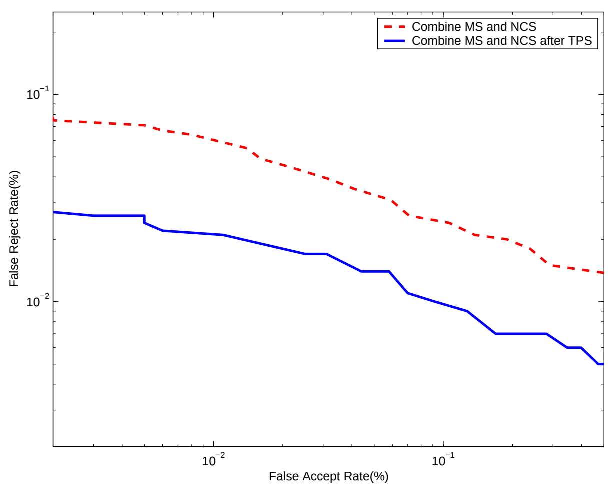

Fig. 5. ROC curves of different score combinations of DB1 data set. MS: Minutiae score. NCS: Neighborhood correlation score. TPS: Thin-Plate Spline. Combining rule: product rule.

Since the landmark points that have been extracted from the minutia matching are not necessarily always correct considering the corresponding minutia locations, or may not be genuine matches, due to the error propagation from minutia extraction and matching algorithm. The correlation score we get after TPS model is implemented may not necessarily higher than the original correlation score. However, since the final correlation score considers overall similarity between two fingerprints, the deformation that is introduced by impostor minutia points will effect less on genuine matches than on impostor matches. Thus, it improves the overall matching results.

Also, from the result we can see that the edge correlation score is not improving the result as much as the neighborhood correlation score, this implies that the edge correlation is not as sensitive to the deformation as neighborhood correlation.

VII. CONCLUSION

This paper proposed a fingerprint matching algorithm that combines TPS deformation model with correlation based matching method. It improves the matching result for both correlation measures. The main contribution of this paper is the usage of the TPS deformation model on the fingerprint images to improve the correlation matching results. It seems possible to explore other deformation models at both global and local level to improve the result of fingerprint matching algorithms in general.

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