Verifying Fingerprint Match by Local Correlation Methods

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***Abstract*— Most fingerprint matching algorithms are based on finding correspondences between minutiae in two fingerprints. In this paper we present a modification of minutiae matching method, which utilizes correlation scores between the local neighborhood areas of corresponding minutiae pairs and the edges that connect neighboring matched minutiae pairs. Minutiae based matching approach considers the overall minutiae distribution pattern between the two fingerprints. Neighborhood correlation score represents the local similarity between the matched pair of minutiae. Edge correlation score gives the resemblance of areas that in between the two corresponding minutiae pairs. Thus, both the global minutiae distribution structure and the local matching similarity between the two fingerprints are considered for final decision. The described matching approach has been tested on FVC2002's DB1 and DB3 database. The experimental results confirm the effectiveness of combining matching scores of different origin - minutia matching score and local correlation matching scores.**

I. INTRODUCTION

Because of its permanence and individuality, fingerprint is one of the most used biometric currently used for individual identification in applications such as access control. Fingerprint verification is the process of comparing test and enrolled skin ridge impressions from fingers to determine if the impressions are from the same finger. The flexibility of the fingerprint ridge skin means that no two fingerprints are ever exactly alike, even if two impressions are recorded immediately after each other. Some factors that make fingerprint matching very difficult are the varying darkness level caused by the changing finger pressure and skin condition, the non-linear distortion caused by the elasticity of the skin, the rotation and partial overlap caused by the enrollment etc. Many fingerprint matching algorithms have been developed for the purpose of identification and recognition during past years.

We can distinguish three main fingerprint matching techniques. The first technique is a minutiae based matching. Minutiae are defined as the discontinuities of the ridges of the fingerprint. Given a fingerprint image, after appropriate image pre-processing, enhancement, segmentation, minutiae points can be extracted through different minutiae detection algorithm. Usually, minutiae are represented by a tuple of values including its coordinates, the ridge direction and the type of endings. Through approaches of point pattern matching, minutia based matching can be implemented. Various minutiae based matching systems have been developed. Prabhakar et al. [1] perform a minutiae verification and classification through a feedback path for the feature extraction stage, followed by a feature refinement stage for improving the matching performance. Xifeng et al. [2] propose a fingerprint feature named complex minutiae vector (CMV) for fingerprint minutiae matching, which consists of a ridge rotation angle associated with a minutia and four ridge counts between the minutia and the four corresponding adjacent points. Xuefeng and Asano [3] define minutia polygon that describes not only the minutia type and orientation but also the minutia shape, which has a higher ability to tolerate distortion. An improved distortion model is used for the proposed matching method. Tico and Kousmanen [4] present a fingerprint matching algorithm based on a representation scheme that relies on describing the orientation field of the fingerprint pattern with respect to each minutia detail.

The second fingerprint matching technique is based on texture matching. Spatial relationship and geometrical attributes of the ridge of fingerprints are used to check if the global ridge structure of the two fingerprints match. Ross et al. [5] present a method that uses ridge feature maps to represent, align and match fingerprint images. Marana and Jain [6] present a fingerprint matching technique based on fingerprint ridge features. Jain et al. [7] extract a compact fixed length FingerCode by using a bank of Gabor filters, then perform the fingerprint matching based on the Euclidean distance between the two corresponding FingerCodes. Ross et al. [8] present a method to estimate the nonlinear distortion in fingerprint pairs based on ridge curve correspondences.

The third technique relies on correlation matching. Bazen et al. [9] first choose appropriate templates from the primary fingerprint, then template matching are used to locate those templates on the input fingerprint, by comparing the positions of these templates one can decide if the two fingerprints match or not. This matching is based on the correlation scores from the intensities of corresponding pixels of template and input fingerprint.

There are some matching techniques been proposed under frequency domain. Jianxin et al. [10] first use Fourier-Mellin transform (FMT) to align two fingerprints, then use the Band-Limited phase-only correlation (BLPOC) method to match two aligned images.

Recently matching techniques are developed by combining different matching algorithms. Jain et al. [11] present a hybrid matching algorithm that uses both minutiae information and texture information for matching the fingerprints. Nandakumar and Jain [12] combine minutiae based matching with correlation based method. Ito et al. [13] propose an efficient fingerprint recognition algorithm combining phase-based image matching and feature-based matching.

In this paper, we introduce a new matching algorithm

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combining minutia based matching and correlation based matching. In contrast to [12] we not only consider correlation of the local neighborhood regions around minutiae, but also the correlation between edges of neighboring minutiae. Though the correlation methods might not be effective if compared images are nonlinearly distorted, our experiments show that intervals between neighboring minutia still deliver useful correlation scores. When used along with minutia matching score such correlation scores reduce the ambiguity between matched minutia pairs in genuine and impostor fingerprint matches. In our approach, the product rule is used to combine the minutia matching and two level of correlation based matching results.

In the following section we will first cover the minutia based matching methods we used to get the matching minutia pairs and fingerprints alignment. Then we present the proposed correlation based methods of two different levels. After that we describe score combination method, followed by the experiment and result section. Finally, conclusion is given in the last section.

II. MINUTIAE BASED MATCHING

Most of the current fingerprint matching systems are based on minutiae extraction and minutiae matching; Huvanandana et al. [14] present a basic structure for such systems. Fig 1 shows a standard minutiae matching system. It is composed of fingerprint image preprocessing, fingerprint image enhancement, minutiae feature extraction and matching.

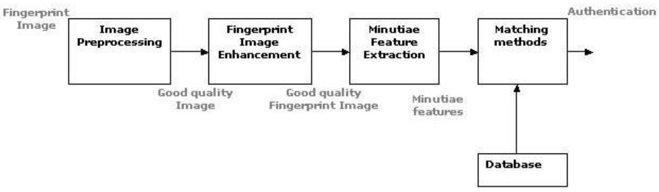

Fig. 1. Standard minutiae based matching system.

The preprocessing and enhancement steps reduce image noise and enhance the ridge information, partitioning the 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.[15] 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 our correlation methods in next section, and show the improvement made in result section when it is combined with this minutia matching system.

III. CORRELATION METHODS

Generally speaking, the minutiae based matching method is highly relied on how well the ground truth minutiae points may be extracted. In cases when bad quality fingerprint image or partial fingerprint image is provided, there may be many fake minutiae or only few genuine ones extracted. With error propagation, it will affect the matching result and final decision greatly. 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.

From the minutia based matching algorithm which is introduced in the previous section, we have all the alignment parameters that are needed for further correlation based methods, including the image alignment angle, the list of matched minutia pairs from the two fingerprint images etc. After the two fingerprints been aligned based on the result from the minutiae matching algorithm, we will use local gray-scale information for correlation based method in two different levels. Because the correlation is not sensitive to the local image quality, we do not use any enhancement method, but calculate the correlation values directly. However, we do expect to take possible local deformation into account in later works, which might improve the precision of the correlation values. The computational cost of current method depends on the size of the areas being correlated, but since the minutiae are already pre-matched, the increase in matching time is not significant. Additionally, we spend time on the search for best local shifts, which were necessitated by the errors in locating precise minutia positions. A better minutia extraction algorithm will make such searchers unnecessary.

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. 1 and get a neighborhood correlation score for each pair of matched minutiae:

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

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 minutiae extraction methods usually will not give the exact location of the minutiae at pixel level due to different extraction techniques been used, and thus the exact alignment between two matched minutia at pixel level will not always hold. In order to achieve a more reliable correlation score we calculate correlation scores for close hypothesized alternative locations of minutia points. A best matching correlation score is used to find the best match between the two regions as showed in figure 2. The found best match and corresponding alternative minutia location is used subsequently in the calculation of edge correlation scores. For each pair of matched minutiae, we get described neighborhood region matching score and the median of these scores is taken as a final minutia neighborhood correlation score.

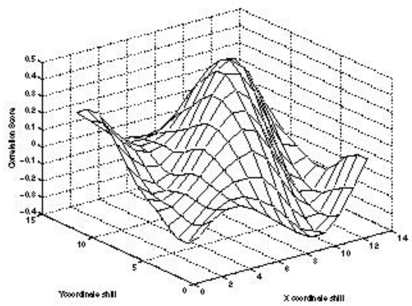

Fig. 2. Local maximum correlation searching for neighborhood alignment.

The neighborhood correlation score helps to identify if the two minutiae are well matched as far as local gray-scale information is considered. The correlation score is very sensitive to the local alignment or deformation. The size of the neighborhood should be large enough to capture the similarity of the local areas of the two matched minutiae, but should not be so large that the correlation score will always be low due to the non-linear deformation in the relatively larger local area. 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:

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

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.

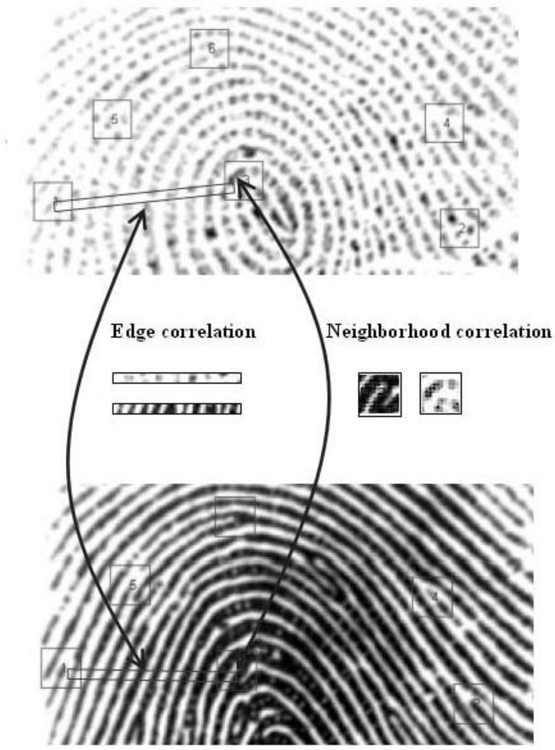

Fig. 3. Proposed minutia neighborhood and edge correlations.

Figure 3 illustrates the presented algorithms for calculating neighborhood and edge correlation scores. 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.

IV. SCORE COMBINATIONS

When both local neighborhood similarity and edge similarity are considered, together with the original minutiae

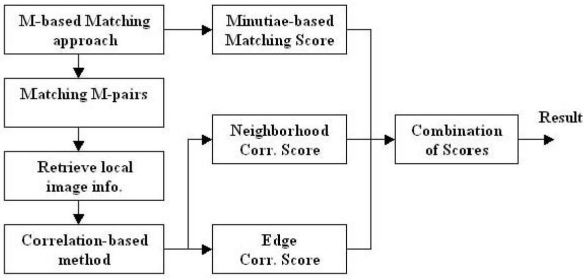

Fig. 4. Flowchart of the whole fingerprint matching system using neighborhood and edge correlations.

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. 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. When all three scores are combined, it gives a measure that represents a total sum of matching areas in two fingerprints.

V. EXPERIMENTS AND RESULTS

Fig. 5. Samples of used fingerprint images from FVC2002 DB1 (upper row) and DB3 (low row).

FVC2002 DB1 and DB3 are used as experimental set for the algorithm we proposed. Fig. 5 shows the samples of fingerprint images from DB1 and DB3, the general image qualities are quite different.

Each 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.

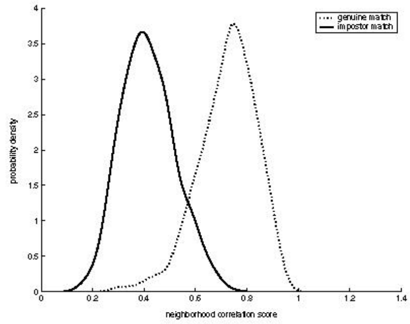

Fig. 6. Histograms of neighborhood correlation scores of DB1.

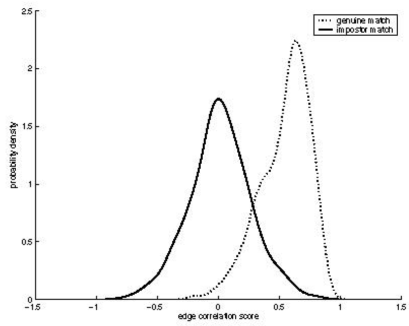

Fig. 7. Histograms of edge correlation scores of DB1.

In the experiment, we randomly choose 1000 genuine matches and 1000 impostor matches from above test set from each database. Histograms of neighborhood correlation scores and edge correlation scores for genuine and impostor fingerprint pairs are shown in Fig. 6 and Fig. 7 respectively. Note, that the scores are computed only for hypothesized matched and aligned minutia and neighboring matched minutia pairs. From these graphs it is clear that both correlation methods have good discrimination between genuine fingerprint matches and impostor fingerprint matches.

Note, that the impostor correlation scores for neighborhood correlations in Fig. 6 are centered near .4. This is explained by our additional search for better minutia neighborhood re-alignment. For edge calculations, we do not perform such search, but use already pre-aligned minutia neighborhoods, so the correlations scores are close to 0.

We tested few different combination methods, and the product rule achieved best performance. The ROC curves for both DB1 and DB3 and for product combination rule are showed in Figures 8 and 9. The figures show that, when two of the scores are combined, either the combination of the

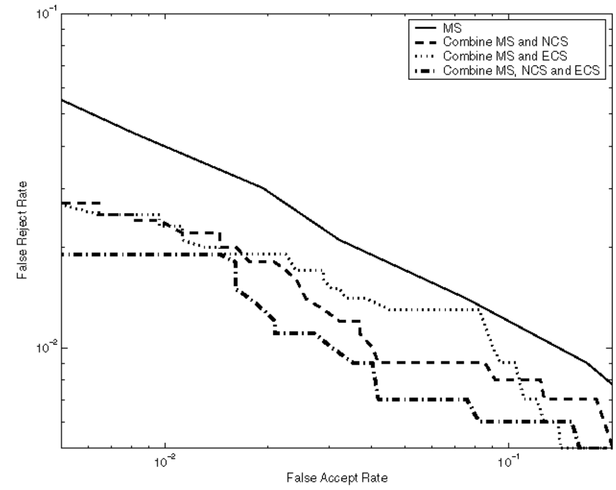

Fig. 8. ROC curves of different score combinations of DB1 data set. MS: Minutiae score. NCS: Neighborhood correlation score. ECS: Edge correlation score. Combining rule: product rule.

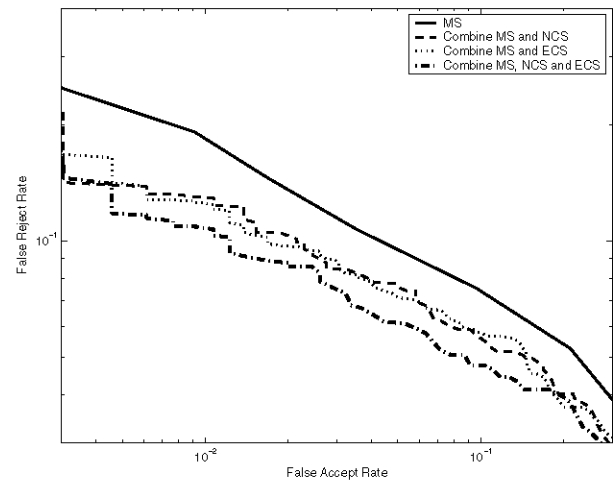

Fig. 9. ROC curves of different score combinations of DB3 data set. MS: Minutiae score. NCS: Neighborhood correlation score. ECS: Edge correlation score. Combining rule: product rule.

minutiae matching score and the neighborhood correlation score, or the combination of the minutia matching score and the edge correlation score, both gives similar improvements for the final matching decisions. This implies that both type of the correlation scores affects the matching decision in a positive way. When the three scores are combined, the ROC curves show that it gives another boosting from the combination of the two scores, which implies the two types of correlation scores helps independently on the improvement for the final matching decision.

Also, Fig. 9 shows the results of different score combinations for DB3. From the two ROC curve figures of DB1 and DB3, it is clear that more improvement is made on DB3 when the scores from the minutia based method and the correlation based method are combined. DB3 has bad quality images comparing to that of DB1, this implies the correlation based method works better when low quality of fingerprints are presented, comparing with minutiae based method.

VI. CONCLUSION

This paper proposed a fingerprint matching algorithm that combines minutia based matching method with correlation based matching method. The main contribution of this paper is the usage of the correlation scores between edges connecting neighboring minutia points. This correlation method improves minutia matching results to the same extent as previously presented local minutia neighborhood correlation methods, and both methods have cumulative positive effect on final results. It seems possible to extend this technique to other inter-minutia structures as opposed to the previous research efforts utilizing correlation scores of only local minutia neighborhoods.

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