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Local Correlation-based Fingerprint Matching

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Abstract

Most fingerprint matching systems are based on matching minutia points between two fingerprint images. Each minutia is represented by a fixed number of attributes such as the location, orientation, type and other local information. A hard decision is made on the match between a pair of minutiae based on the similarity of these attributes. In this paper, we present a minutiae matching algorithm that uses spatial correlation of regions around the minutiae to ascertain the quality of each minutia match. The proposed algorithm has two main advantages. Since the gray level values of the pixels around a minutia point retain most of the local information, spatial correlation provides an accurate measure of the similarity between minutia regions. Secondly, no hard decision is made on the correspondence between a minutia pair. Instead the quality of all the minutiae matches are accumulated to arrive at the final matching score between the template and query fingerprint impressions. Experiments on a database of 160 users (4 impressions per finger) indicate that the proposed algorithm serves well to complement the 2D dynamic programming based minutiae matching technique; a combination of these two methods can reduce the false non-match rate by approximately 3.5% at a false match rate of 0.1%.

1. Introduction

Fingerprint matching is a difficult problem due to the large intra-class variations (variations among different impressions of the same finger) and the small inter-class variations (images of different fingers may appear quite similar) [11]. Three fundamental reasons for the large intra-class variations are partial overlap, non-linear distortion, and sensor noise. Due to rotation and displacement of the finger placed on the sensor, there is often only a partial overlap between the template and query fingerprint images. This problem is more severe in the case of small solid-state sensors that are being increasingly deployed. The mapping of a three-dimensional finger into a two-dimensional image results in non-linear distortion. Further, changes in the applied finger pressure and skin conditions (dry skin, sweat, etc.) cause a change in the thickness of the ridges. Noise introduced in the fingerprint sensor in the form of residues left over the sensor surface due to repeated usage also contributes to the intra-class variations. Although it is unlikely that impressions of different fingers are identical in all respects [12], they may be quite similar in terms of their global structure and ridge orientations. This can lead to a number of false matches when the matchers rely on global features alone. The results of the Fingerprint Verification Competition 2004 (FVC2004) [10] show that even the state-of-the-art fingerprint matchers do not achieve extremely high accuracy when the database contains images of poor quality. The best (commercial) fingerprint matcher in FVC2004 had an equal error rate (EER) of 2.07% indicating that fingerprint matching remains a challenging task in the field of pattern recognition and image processing.

The problem of fingerprint matching has been extensively studied and numerous algorithms have been proposed. These algorithms can be classified as correlation-based, minutiae-based, and ridge feature-based approaches. Minutiae-based methods [13],[6],[7] represent minutia points as a feature vector of fixed length. The features representing a minutia point typically consist of its location, orientation, type (e.g., ridge-ending or ridge-bifurcation), and other local information like the ridge count and the quality of the fingerprint region around the minutia point. The matching of two minutiae sets is usually posed as a point pattern matching problem and the similarity between them is proportional to the number of matching minutia pairs. Although the minutiae pattern of each finger is quite unique, noise and distortion during the acquisition of the fingerprint and errors in the minutia extraction process result in a number of missing and spurious minutiae. Since it is difficult to reliably obtain the minutia points from a poor quality fingerprint image, other ridge features like the orientation and the frequency of ridges, ridge shape, and texture information have been proposed for fingerprint matching [8],[17].

However, the ridge feature-based methods suffer from their low discrimination capability. In correlation-based fingerprint matching, the template and query fingerprint images are spatially correlated to estimate the degree of similarity between them. If the rotation and displacement of the query with respect to the template are not known, then the correlation must be computed over all possible rotations and displacements, which is computationally very expensive. Further, the presence of non-linear distortion and noise significantly reduces the global correlation value between two impressions of the same finger. To overcome these problems, correlation is usually done locally only in certain "interesting" regions (regions of high curvature, minutia information regions, etc.) of the fingerprint image.

Recently, researchers have come up with hybrid fingerprint matchers by making use of more than one basic approach to matching. For example, Ross et al. [15] have suggested the use of both minutiae and ridge flow information to represent and match fingerprints. They have shown that the performance of the minutiae-based matcher presented in [6] can be significantly improved by using additional information provided by the FingerCode method [8]. The local correlation-based fingerprint matching algorithm presented in this paper is a similar attempt to improve the performance of a minutiae-based matcher by introducing a correlation step to ascertain the quality of each minutia match. The gray-level information of the pixels around the minutia points contain richer information about the local region than the attributes of the minutia points. Hence, the spatial correlation of regions around corresponding minutia points is a good measure of the degree of similarity between them. The correlation-based fingerprint matcher proposed by Bazen et al. [1] selects certain distinctive regions in the template fingerprint image and searches for those regions in the query image. However, their method is not very robust to rotation. The work of Beleznai et al. [2] attempts to exploit the structural information around minutiae to improve the recognition performance of a minutiae-based matcher. However, the focus of this work is the compression of the region around the minutia points using Principal Component Analysis (PCA) and Discrete Wavelet Transform to achieve a fast verification. Kovacs [9] proposed the use of small windows around the minutia to search for possible correspondences in the query image. Once the possible correspondences were found, the author used triangular matching to match the two fingerprints. Our approach differs from all these methods in the following ways. The query image is aligned to match the template image using the ridges associated with the minutiae. Hence, the search for minutia locations in the query that correspond to the template minutiae is not based on the region around the minutiae. Further, we apply an enhancement algorithm to both the template and the query images before the spatial correlation step, resulting in a better possibility of match between truly corresponding minutia regions. Since the correlation is done locally, the proposed algorithm is relatively tolerant to the problem of non-linear distortion.

The rest of the paper is organized as follows: Section 2 describes the minutia extraction algorithm used in our experiments. The pre-alignment of the template and the query based on the corresponding ridges is presented in section 3. Section 4 describes our proposed minutiae matching algorithm and highlights the advantages of the proposed algorithm. The experimental results are presented in section 5. Finally, section 6 summarizes our work and provides pointers for future work in this direction.

2. Minutiae Extraction

The first stage in our fingerprint verification system is the extraction of minutiae points from a fingerprint image. The algorithm proposed by Jain et al. [6] has been used for this purpose. This method involves five major steps that are shown in Figure 1. The first step is the estimation of the orientation field of the fingerprint image. This is followed by the segmentation of the fingerprint area from the background. Both these steps are achieved by computing block-wise gradients of the input image. The ridges are extracted from the input image by applying two masks that adaptively capture the maximum gray level values along the direction perpendicular to the ridge orientation. Several heuristics are then applied to remove the holes and speckles in the binary ridge map. The extracted ridges are then thinned and minutiae are detected in the thinned image. The location, orientation, and the points on the ridge (sampled at the inter-ridge distance) associated with the minutia are stored for each minutia point. The ridge points are useful in the alignment of the template and the query during the minutiae matching stage.

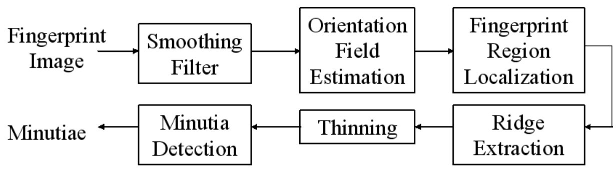

Figure 1. Algorithm for minutiae extraction.

3. Fingerprint Alignment

In the absence of noise and other deformation, the rotation and displacement between two images can be completely determined using two corresponding point pairs. In the ideal scenario, the true alignment can be estimated by testing all possible pairs of minutia for correspondence and then selecting the best correspondence. Since our matcher involves a computationally intensive correlation step, it is not practical to test all possible minutia pairs. Hence, we use the points on the ridge associated with the minutia to reduce the number of possible correspondences. We make use of Procrustes analysis [4] to get a good estimate of the rotation and displacement from a pair of possibly corresponding ridges. Let T represent the set of ridge points in the template and let Q represent the set of points on the corresponding ridge in the query. Let $t = (t_1, \cdots, t_k)$ and $q = (q_1, \cdots, q_k)$ be the centered (mean is subtracted) versions of T and Q, respectively, represented as complex numbers. Here, k is the minimal length of T and Q. Let q^* represent the complex conjugate transpose of q. Let θ be the rotation and τ be the displacement that transforms the points in Q to T. The solution for θ and τ are as follows.

$$\theta = angle\left(\frac{q^*t}{q^*q}\right), \tag{1}$$

$$\tau = \bar{T} - e^{i\theta}\bar{Q}, \tag{2}$$

where $\bar{T}$ and $\bar{Q}$ are the mean of the points in T and Q, respectively, represented as complex numbers. The Procrustes analysis can also be used to find the scaling factor. However, in our experiments all the fingerprint images were obtained using the same sensor and hence, the scale factor is set to 1. Let $\hat{T}$ be the value of T predicted using Q, θ and τ. If T and Q are truly related by a rigid transformation, then the difference between $\hat{T}$ and T must be very small. Let d be the sum of the squared error between $\hat{T}$ and T. A minutia pair is considered as a possible correspondence only if $d \leq c$, where c is a fixed threshold (set to 5 in our experiments). Further, if the estimated translation in the horizontal (vertical) direction is greater than half the width (height) of the image or if the absolute value of the estimated rotation is greater than 30°, then the minutia pair is not considered as a possible correspondence. These two heuristics are based on the assumption that the rotation and displacement cannot be larger than the selected thresholds and applying these heuristics reduces the number of possible minutia correspondences significantly. Since the minutiae matcher evaluates all possible correspondences and selects the one that maximizes the correlation value, the requirement is that there should at least be one reasonably accurate estimate of the rotation and displacement in the selected set to obtain a high matching score for a genuine match. In our experiments, it was observed that when the template and query images were of reasonable quality, the selected correspondences had at least one good estimate of the rigid transformation parameters.

4. Local Correlation-based Matching

Our algorithm for fingerprint matching is shown in Figure 2. The minutiae extraction algorithm is applied to the template and the query fingerprint images and the minutia points and the associated ridge points are extracted. The query image is rotated using the estimated rotation. The template and the rotated query images are enhanced using a modified version of the Gabor filter-based enhancement technique proposed by Hong [5]. Hong proposed a method for the reliable estimation of the orientation field using coarse ridge maps. However, in our implementation, this orientation field estimation procedure is replaced by the algorithm proposed by Dass [3]. This algorithm is based on a Markov random field model and generates a smooth orientation field in blocks of size $b \times b$ pixels. There is a trade-off in the selection of an appropriate value of b. If b is small, the orientation estimation is more accurate, but is more susceptible to noise. When b is large, the estimation of the orientation field in the regions of high curvature is not very accurate. An optimum value of b must be chosen according to the nature of the fingerprint images in the database. The value of b is set to 5 in our experiments. Since the enhancement of the query image is accomplished after the rotation, the distortion resulting from the rotation process is suppressed. The application of a bank of Gabor filters of different orientations during the enhancement stage also allows us to segment the foreground regions in a fingerprint image. If the variation of the filtered values across the different orientations is small in the entire block, it indicates that the particular block is not oriented along any specific direction. This can occur if the block comes from the background region or is too noisy and hence, unrecoverable. Therefore, such blocks are marked as background.

The size of the fingerprint images in our database is 300×300 pixels. Windows of size 42×42 pixels are chosen around the minutia locations in the template image. Regions of size 32×32 are selected around the corresponding locations in the query image. *The size of the template window is selected to be slightly greater than that of the query window in order to make the correlation values tolerant to small errors in computing the location of the minutia point.* Note that after the pre-alignment stage, the minutiae locations in the query are not used and the selected query window may or may not contain a minutia point. Problems like spurious or missing minutiae in the query, do not affect the matching as long as there is at least one good estimate of the rotation and displacement. Typically, the template image is obtained under human supervision in a controlled manner. Hence, the template can be expected to be of good quality and has a smaller probability of producing false or spurious minutiae (no special care was taken during the acquisition of the template images in our database;

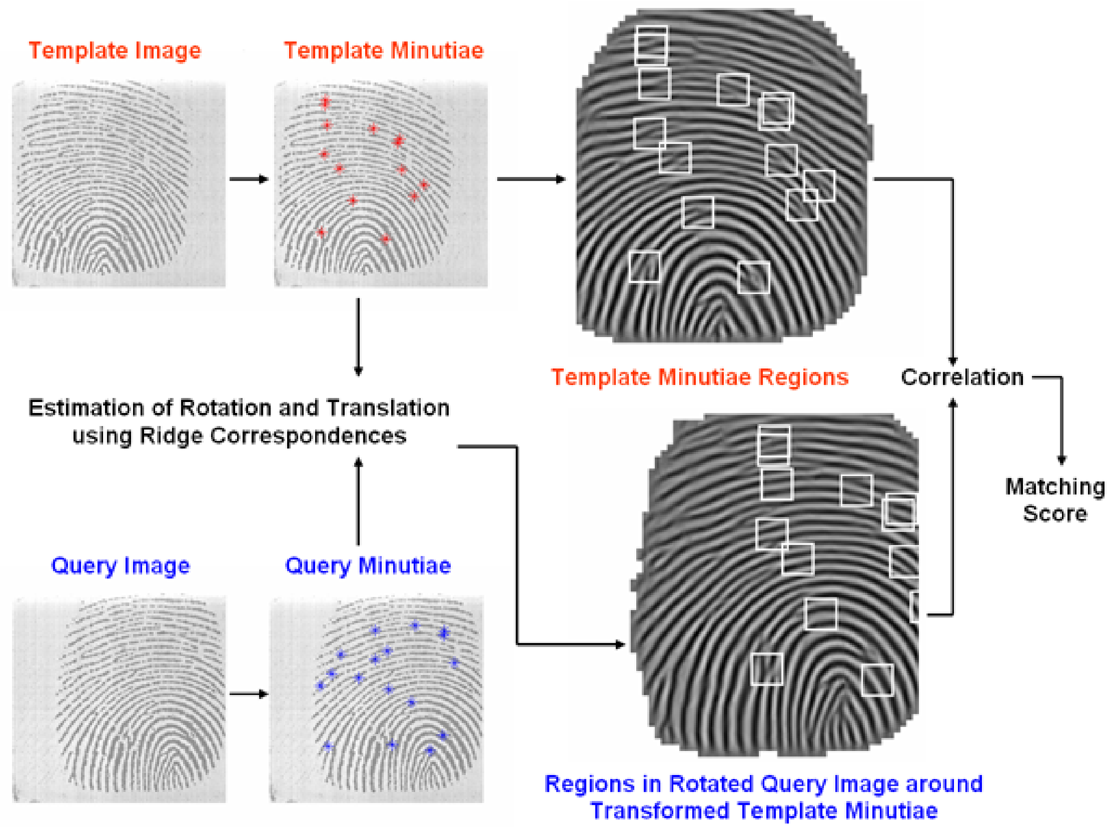

Figure 2. Algorithm for local correlation-based fingerprint matching.

so it does contain some poor quality images). The normalized cross-correlation between the query window and the template window is computed and the peak is detected. If the estimation of rotation and displacement is accurate and there is no non-linear distortion, the peak would occur at the center of the correlation matrix. In practice, the peak should be close to the center. We allow a deviation of ± 10 pixels from the center. If the peak lies outside this tolerance region, the correlation is set to zero. Otherwise, the absolute value of correlation at the location of the peak is considered as the correlation between the query and template windows. When the overlap between the template and query fingerprint images is partial, some of the template minutiae may fall outside the fingerprint region of the query. Those minutiae are not considered for correlation. The local correlation of all the template windows with the corresponding regions in the query are computed and the mean correlation value is found. All possible correspondences from the alignment stage are tested and the maximum correlation value over all the correspondences is taken as the matching score between the template and the query.

5. Experimental Results

Our database consists of fingerprint impressions of 160 users obtained using a Veridicom sensor. Each user provided four impressions of each of the four fingers, namely, the left index finger, the left middle finger, the right index finger, and the right middle finger. The results reported in this paper are based only on the four impressions of the left index finger. The fingerprint verification performance of the local correlation-based matcher is compared with that of the 2D dynamic programming based matcher proposed in [7]. The equal error rates (EER) and the genuine accept rates (GAR) of the two matchers at two values of false accept rate (FAR) are shown in Table 1.

The Receiver Operating Characteristic (ROC) curves for the correlation-based and 2D dynamic programming based matchers are shown in Figure 3. It can be seen that the GAR of the two matchers are comparable at higher FAR values. At lower values of FAR, the dynamic programming based matcher outperforms correlation-based matcher by approximately 10%. The presence of some poor quality images in the database reduces the GAR of the correlation-based matcher at low FAR values, while the performance

Table 1. Error rates of the three matchers

Matcher	Equal Error Rate	GAR at 1% FAR	GAR at 0.1% FAR
2D dynamic programming based	5.6%	91.2%	86.1%
Correlation-based	5.1%	87.3%	76.7%
Combined	4.5%	94.7%	89.7%

of the dynamic programming based matcher is unaffected. Figure 4 shows two examples of poor quality images in the database that were not handled appropriately by the correlation-based matcher. The image in figure 4(a) contains very little ridge information. In the image shown in figure 4(b), the ridge thickness near the singular points is large and these regions were marked as unrecoverable by the enhancement algorithm. This shows that the local correlation-based matcher is not robust with respect to image quality and hence more work needs to be done to enable it to handle poor quality images.

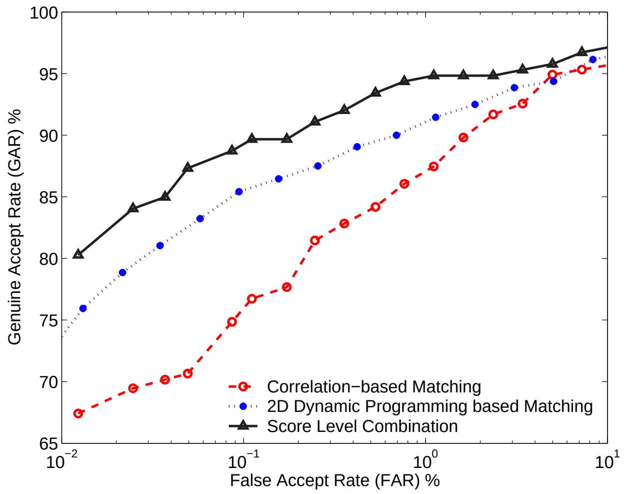

Figure 3. ROC curves for the three matchers.

A score-level combination of the two matchers using the sum rule [14] and min-max normalization [16] results in a significant improvement (about 3.5% increase in GAR at 0.1% FAR) in the matching performance. Figure 5(a) shows two impressions of an user that were assigned a low matching score by the 2D dynamic programming based matcher (due to the presence of a number of spurious minutiae in the query image); the same pair was assigned a high matching score by the correlation-based matcher. On the other hand, the pair of impressions in Figure 5(b) was assigned a low matching score only by the correlation-based matcher (due to the failure in finding the correct alignment). In both these cases, the combined score of the two matchers was sufficiently high. This indicates that combining the hard minutiae correspondences found by the 2D dynamic programming based matcher with the correlation in the local minutiae regions can lead to a more accurate matcher.

6. Summary and Future Work

We have presented a correlation-based fingerprint matcher that utilizes local correlation of regions around the minutiae to determine the degree of match between two fingerprint images. This method uses a well-known algorithm for minutiae extraction and uses Procrustes analysis of corresponding ridge curves to align the query with the template. The two images are enhanced using Gabor filter-banks and the normalized cross-correlation is used as the quality of the minutiae match. The performance of our algorithm is slightly inferior to that of the 2D dynamic programming based minutiae matcher, mainly due to the inability to handle fingerprint images of very low quality. However, integrating the proposed algorithm with the 2D dynamic programming based matching yields a better matcher. The enhancement and correlation tasks are computationally intensive and hence, a fast implementation of our algorithm needs to be developed for real-time applications.

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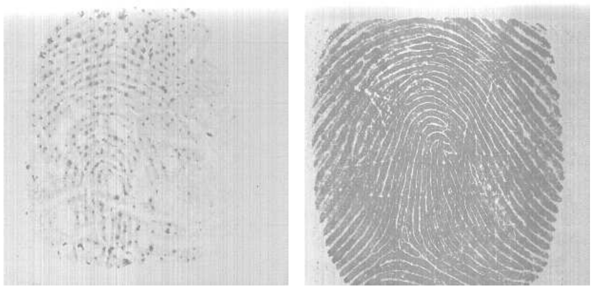

(a) (b)

Figure 4. Examples of poor quality fingerprint images.

Template Query Template Query

(a) (b)

Figure 5. Examples of matching failures (a) in dynamic programming based matcher (b) in correlation-based matcher.

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