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FINGERPRINT MATCHING USING MINUTIAE AND TEXTURE FEATURES

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ABSTRACT

The advent of solid-state fingerprint sensors presents a fresh challenge to traditional fingerprint matching algorithms. These sensors provide a small contact area ($\approx 0.6" \times 0.6"$) for the fingertip and, therefore, sense only a limited portion of the fingerprint. Thus multiple impressions of the same fingerprint may have only a small region of overlap. Minutiae-based matching algorithms, which consider ridge activity only in the vicinity of minutiae points, are not likely to perform well on these images due to the insufficient number of corresponding points in the input and template images. We present a hybrid matching algorithm that uses both minutiae (point) information and texture (region) information for matching the fingerprints. Results obtained on the MSU_VERIDICOM database shows that a combination of the texture-based and minutiae-based matching scores leads to a substantial improvement in the overall matching performance.

1. INTRODUCTION

Traditionally, passwords (knowledge-based security) and badges (token-based security) have been used to restrict access to secure systems. However, security can be easily breached in these systems when a password is divulged to an unauthorized user or a badge is stolen by an impostor. The emergence of *biometrics* [1] has addressed the problems that plague traditional verification methods. Biometrics refers to the automatic identification (or verification) of an individual (or a claimed identity) by using certain physiological or behavioral traits associated with the person (e.g., fingerprints, hand geometry, iris, retina, face, hand vein, facial thermograms, signature, voiceprint). Biometric indicators have an edge over traditional security methods in that these attributes cannot be easily stolen or shared.

Among all the biometric indicators, fingerprints have one of the highest levels of reliability [2, 3] and have been extensively used by forensic experts in criminal investigations [4]. Traditionaly, fingerprint patterns have been extracted by creating an inked impression of the fingertip on paper. Now compact solid-state sensors provide digital images of these patterns. These sensors can be easily incorporated into a mouse, keyboard or cellular phone making this a very attractive mode of identification. Fingerprint systems are being increasingly incorporated in a wide range of civilian and commercial applications for user-authentication purposes.

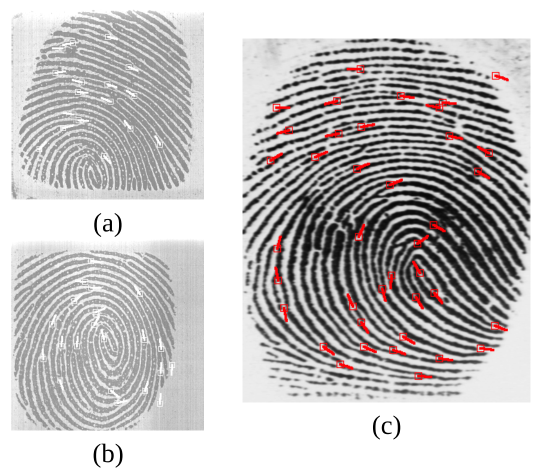
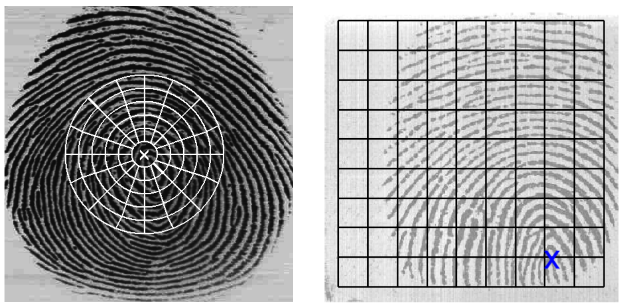


Fig. 1. Fingerprint images acquired using the solid state Veridicom sensor (a,b) and the optical Digital Biometrics sensor (c). The detected minutiae points have been marked in the fingerprint images (17 in (a), 21 in (b), 39 in (c)).

The solid-state sensors provide only a small contact area ($\approx 0.6" \times 0.6"$) for the fingertip and, therefore, sample only a limited portion of the fingerprint pattern (300×300 pixels at 500 *dpi*). An optical sensor, on the other hand, has a contact area of $1" \times 1"$, resulting in images of size 480×508 pixels at 500 *dpi*. Hence, the number of minutiae points that can be extracted from a fingerprint sample acquired using a solid-state sensor is smaller compared to that acquired using an optical sensor (see Figure 1). Further, multiple impressions of the same finger, acquired at different instances using a solid-state sensor, may overlap only over a small region due to the rotation and translation of subsequent fingerprints (Figures 1(a) and (b)). The minutiae-based matching schemes will not perform well in such situations due to the lack of a sufficient number of common singular points between the two impressions.



(a) (b)

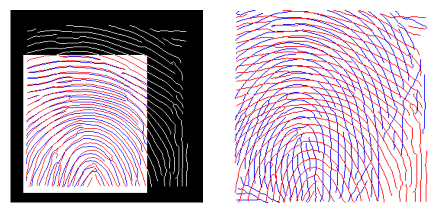
Fig. 2. (a) Circular tesselation (80 sectors) about a core point. (b) Rectangular tessellation (81 cells) of a Veridicom image. Since the core point in (b) is located at the lower right corner of the image, we propose to use a rectangular tesselation.

We describe a hybrid approach to fingerprint matching that combines a minutiae-based representation of the fingerprint with a Gabor-filter (texture-based) representation for matching purposes. The texture-based representation of the fingerprint is a modification of the method described in [5]. The proposed algorithm first aligns the two fingerprints using the minutiae points extracted from both the images, and then uses texture information to perform detailed matching. As a result, more information than minutiae points is being used to match fingerprints. The resultant matching score is combined with that obtained using the minutiae-based matching algorithm. Verification results suggest that the proposed hybrid approach is better suited for images acquired using compact solid-state sensors.

2. BACKGROUND

A fingerprint can be viewed as an oriented texture pattern. Jain *et al.* [5] show that, for sufficiently complex oriented textures such as fingerprints, invariant texture representations can be extracted by combining both global and local discriminatory information in the texture. Given a fingerprint image, they demonstrate that a compact and reliable translation- and rotation-invariant representation can be built based entirely on the inherent properties of the underlying fingerprint texture. They further illustrate that the representation thus derived, is useful for robust discrimination of the fingerprints.

The above scheme for generic representation of oriented texture relies on extracting a core point in the fingerprint. A circular region around the core point is located and tesselated into sectors (or cells) as shown in Figure 2(a). The pixel intensities in each sector are normalized to a constant mean and variance, and filtered using a bank of Gabor filters to produce a set of filtered images. Grayscale variance within a sector quantifies the underlying ridge structures and is used as a feature. A feature vector (640 bytes in length), termed as a FingerCode, is the collection of all the features, computed from all the sectors, in every filtered image. The Fingercode captures the local information, and the ordered enumeration of the tessellation captures the invariant global relationships among the local patterns. The fingerprint matching algorithm is based simply on the Euclidean distance between the two corresponding FingerCodes and hence is extremely fast and scalable.



(a) (b)

Fig. 3. Aligning the input image with the template image. The red thinned image is the template, and the blue thinned image is the input. (a) Alignment of two impressions of the same finger (the non-overlapping regions appear as white on black); (b) Alignment of two impressions of different fingers.

We propose the following improvements in order to adapt this technique for matching images captured by solid-state sensors: (i) Estimate the translation and rotation parameters needed to align the input image with the template using their minutiae points. (ii) Use the foreground segmentation algorithm described in [6] to segment the input and the template images. (iii) Define a rectangular tessellation on the two aligned images. Extract texture features from each rectangular cell (of both images) using Gabor filters. (iv) Match features extracted from all the overlapping foreground cells and weigh the matching distance by the amount of overlap. (v) Combine the confidence scores of the filter-based matcher with the minutiae-based matcher to obtain an improved matching performance. The purpose of using rectangular cells (as opposed to circular sectors) is two-fold: (a) Due to the reduced contact area of the sensor, it may not be possible to detect a core point about which the image can be circularly tesselated. Moreover, even if a core point was detected, it may lie at the image boundary, thereby providing very few valid tesselated sectors. (b) The reduced size of the sensor limits the amount of non-linear deformation of the image. Thus every region in the image is given equal importance while extracting features. This is achieved by having equal-sized cells in a rectangular mesh (Figure 2(b)).

3. THE HYBRID MATCHING APPROACH

The matching technique described here is referred to as the "hybrid" technique because it combines minutiae information available in a fingerprint with the underlying texture information in local regions to perform the matching.

3.1. Image Alignment

Minutiae points from both the input and template images are extracted using the algorithm described in [6]. The algorithm provides the following two outputs: (a) A set of minutiae points, each characterized by its spatial position and orientation in the fingerprint image. (b) Local ridge information in the vicinity of each minutiae point. The two sets of minutiae points are then matched using a point matching algorithm. The algorithm first selects a reference minutiae pair (one from each image) and then determines the number of corresponding minutiae pairs using the remaining set of points. The reference pair that results in the maximum number of corresponding pairs determines the best alignment.

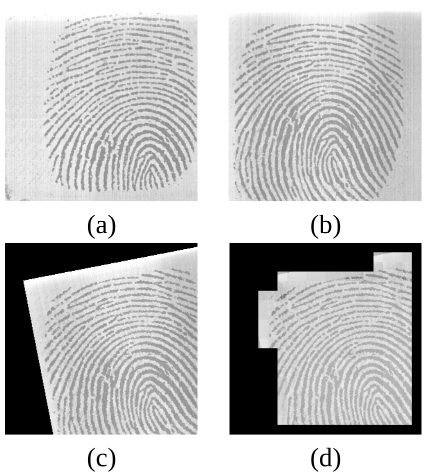


Fig. 4. Masking out background regions: (a) Template image, (b) Input image, (c) Input image after translation and rotation, (d) Masked input image.

An exhaustive evaluation of all point correspondences is avoided due to the availability of local ridge information at every minutiae point. Once the minutiae points are aligned by this method, the rotation and translation parameters are computed. The estimated rotation parameter is the average of the individual rotation values of all corresponding minutiae pairs. The translation parameters are computed using the spatial coordinates of the reference minutiae pair that resulted in the best alignment. The results of the alignment of two impressions of the same finger and two impressions of different fingers are shown in Figure 3. For the purpose of visualization, the thinned ridge map of each impression has been shown.

3.2. Image Tesselation

Background regions of the input fingerprint image are not used in the feature extraction and matching stages of the algorithm (Figure 4). The input and template images are normalized by constructing equal-sized non-overlapping windows over them and normalizing the pixel intensities within each window to a constant mean and variance. Each normalized image is tessellated into equal-sized non-overlapping rectangular cells of predefined dimensions (30×30). The dimensions of the cell were chosen after observing that two neghbouring ridges span over approximately 30 pixels. For a 300×300 image, this results in 81 tessellated cells.

3.3. Feature Extraction

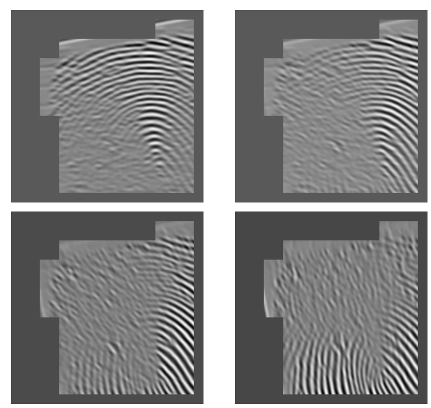


Fig. 5. Result of applying Gabor filters to Fig 4(d). Filtered images for orientations 0^o, 22.5^o, 45^o, and 67.5^o are shown.

A bank of 8 Gabor filters is applied to each of the tessellated cell. All the 8 Gabor filters used for feature extraction have the same frequency, 0.1 pix^{-1}, but different orientations (0^o to 157.5^o in steps of 22.5^o). This frequency is chosen based on the average inter-ridge distance in the fingerprints (which is $\sim$ 10 pixels). This particular filtering results in a set of 8 filtered images for *each* cell. Four of the filtered images are show in Figure 5. The absolute average deviation of intensity in each filtered cell is treated as a feature value (Figure 6). Thus there are 8 feature values for each cell in the tessalation. The feature values from all the cells are concatenated to form a 648-dimensional (81×8) feature vector. Feature values that reside in the masked regions of the input image are not used in the matching stage of the process, and are marked as missing values in the feature vector.

3.4. Matching

Matching an input image with a stored template involves computing the sum of the squared differences between the two feature vectors after discarding missing values. This distance is normalized by the number of valid feature values used to compute the distance. The matching score is combined with that obtained from the minutiae-based method, using the sum rule of combination. If the matching score is less than a predefined threshold, the input image is said to have successfully matched with the template.

4. EXPERIMENTAL RESULTS

Our database consists of fingerprint impressions obtained from 160 users using the Veridicom sensor. Each user was asked to provide 4 different impressions of each of 4 different fingers - the left index finger, the left middle finger, the right index finger and the right middle finger. A set of $2,560$ $(160 \times 4 \times 4)$ images were collected. An automatic quality checker was used to reject poor quality images.

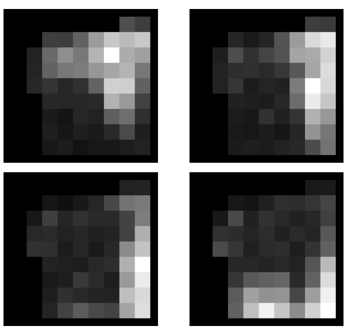


Fig. 6. Feature values derived from the filtered images of Fig 5. For purposes of visualization, the feature values have been scaled to the 0 - 255 range.

The performance of a biometric system can be shown as a Receiver Operating Characteristic (ROC) curve that plots the Genuine Accept Rate against the False Accept Rate (FAR) at different thresholds on the matching score. Figure 7 shows the performance of the hybrid approach presented here. We compare this performance with a minutiae-based approach [6] that does not utilize texture information for representing the fingerprint. As can be seen in the graph, the hybrid approach outperforms the minutiae-based approach over a wide range of FAR values. For example, at a 1% FAR, the hybrid matcher gives a Genuine Accept Rate of 92% while the minutiae-based matcher gives a Genuine Accept Rate of 72%.

The computational requirement of the hybrid matcher is dictated by the convolution operation associated with the eight Gabor filters. The entire matching algorithm, that includes feature extraction from the input image, and the subsequent matching process, takes around 8 seconds of CPU time in an Ultra 10 SPARC machine. However, it is possible to enhance the speed of this algorithm by implementing the convolution operation via a dedicated DSP chip.

5. CONCLUSIONS

We have presented a novel fingerprint matching scheme that utilizes both the minutiae and texture information available in the fingerprint. A bank of Gabor filters is used to extract features from the tessellated cells of the template and input images. Although non-linear deformations present in the fingerprint images have not been accounted for by this method, our contention is that the small size of the contact area alleviates the effects of such deformations on the estimation of the rotational and translational parameters.

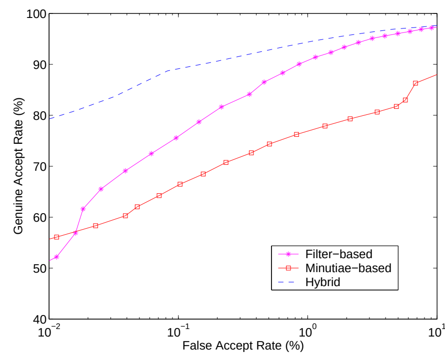


Fig. 7. The ROC curve comparing the performance of the proposed hybrid approach with the minutiae based approach.

6. REFERENCES

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