Pores and Ridges: Fingerprint Matching Using Level 3 Features

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Abstract

Fingerprint friction ridge details are generally described in a hierarchical order at three levels, namely, Level 1 (pattern), Level 2 (minutiae points) and Level 3 (pores and ridge shape). Although high resolution sensors (∼1000dpi) have become commercially available and have made it possible to reliably extract Level 3 features, most Automated Fingerprint Identification Systems (AFIS) employ only Level 1 and Level 2 features. As a result, increasing the scan resolution does not provide any matching performance improvement [1]. We develop a matcher that utilizes Level 3 features, including pores and ridge contours, for 1000dpi fingerprint matching. Level 3 features are automatically extracted using wavelet transform and Gabor filters and are locally matched using the ICP algorithm. Our experiments on a median-sized database show that Level 3 features carry significant discriminatory information. EER values are reduced (relatively ∼20%) when Level 3 features are employed in combination with Level 1 and 2 features.

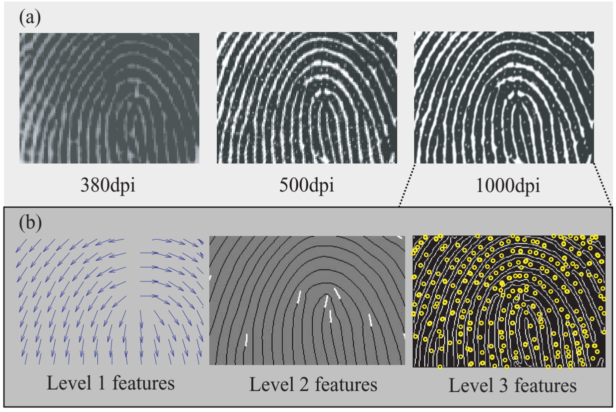


Figure 1: Fingerprint Features. (a) A partial fingerprint image captured at various resolutions (380dpi, 500dpi, and 1000dpi) using Identix 200DFR and CrossMatch ID1000 sensors. (b) Features extracted at different levels from the 1000dpi fingerprint in (a).

1 Introduction

The history of scientifically establishing distinctive fingerprint features traces back to 1872, when Galton first quantified the uniqueness of fingerprints by conducting a probabilistic analysis of minutiae pattern [3]. In 1912, Locard studied the use of pores for identification (or poroscopy), and showed that 20 to 40 pores should be sufficient to establish human identity [3]. From then on, fingerprint identification information is generally divided into three levels. Level 1 (pattern) is macro detail such as ridge flow and pattern type. Level 2 (points) is the Galton characteristics, or minutiae points, such as bifurcations and endings. Level 3 (shape) includes all dimensional attributes of a ridge, such as ridge path deviation, width, shape, pores, edge contour, incipient ridges, breaks, creases, scars, and other permanent details (Figure 1).

Statistical analysis has shown that Level 1 features, or fingerprint pattern, though not unique, are useful for classification purpose, while Level 2 features, or points, have sufficient discriminating power to establish the individuality of fingerprints [5, 6]. FBI has set the standard for fingerprint resolution to be 500dpi for forensic applications in order to reliably extract Level 2 features. However, human examiners perform not only quantitative (Level 2) but also qualitative (Level 3) examination since Level 3 features are also permanent, immutable and unique [3, 4]. As stated by latent print examiner Ashbaugh, "It is *not* the points, but what's in between the points that matters" [3]. With the availability of high resolution sensors ($\geq$ 1000dpi), richer features can be extracted (Figure 1(a)). Hence, it is desirable to investigate performance improvement by introducing Level 3 features in fingerprint matching.

Use of Level 3 features in fingerprint matching was studied by Roddy and Stoz [6] and Kryszczuk [8]. They focused on pore-based Level 3 matching using fingerprint fragments, but the alignment of the template and query fragments is either manually determined or predefined. Unlike these studies, our system uses the entire fingerprint for matching. Both pores and ridge contours are automatically extracted and aligned using the ICP algorithm [12]. In addition, we demonstrate the performance of our system on fingerprint images (1000dpi) captured using a commercial CrossMatch 1000ID sensor, rather than custom built devices ($\geq$ 2000dpi).

2 Level 3 Feature Extraction

It must be noted that Level 1, 2 and 3 features are not independent within the domain of fingerprint authentication [8]. For example, the distribution of pores is not random, but naturally follows the ridge structure. Therefore, in order to reliably extract Level 3 features, namely, pores and ridge contours, we propose the following feature extraction algorithm by combining wavelet transform and Gabor filter enhancement.

2.1 Pore Detection

Based on the position on the ridges, pores are often divided into two categories: open and closed. A closed pore is entirely enclosed by a ridge, while an open pore intersects with the valley lying between two ridges (Figure 2(a)). A method to extract pores using skeletonized image was proposed for 2000dpi fingerprint images [6, 8]. Generally, if a point has 1 (or 3) neighbors in the skeletonized image, it is determined as an open (or close) pore. However, this method is very sensitive to noise and fails to work in cases when images are of poor quality or of lower resolution (1000dpi).

Pore positions often give high negative frequency response as intensity values change abruptly from white to black. In order to capture this sudden change, we apply the Mexican hat wavelet transform to the original image $f(x, y) \in R^2$ to obtain the frequency response w:

$$w(s, a, b) = \frac{1}{\sqrt{s}} \int\int_{R^2} f(x, y)\phi(\frac{x-a}{s}, \frac{y-b}{s})dxdy, \tag{1}$$

where s is the scale factor $(= 1.32)$ and (a, b) is the shifting parameter. Essentially, This wavelet is a band pass filter with scale s. After normalizing the filter response (0-255) using min-max rule, pore regions that typically have high negative frequency response are represented by small blobs with low intensities (Figure 2(b)).

Since pores are naturally distributed along the ridge, it is important to also identify the ridges such that no points in the valley are misclassified as pores. We apply the Gabor filter enhancement proposed in [9] to separate ridges from valleys (Figure 2(c)). By simply adding the wavelet response to the Gabor enhanced image, we obtain "optimal" enhancement of pores on the ridges (Figure 2(d)). This procedure also removes the difference between open and closed pores and, therefore, simplifies the pore extraction process. Finally, an empirically determined threshold (=58) is applied to extract pores with blob size less than 40 pixels (Figure 2(e)).

2.2 Ridge Contour Extraction

Since the wavelet response of an image emphasizes the regions with high intensity variation, we further exploit it for

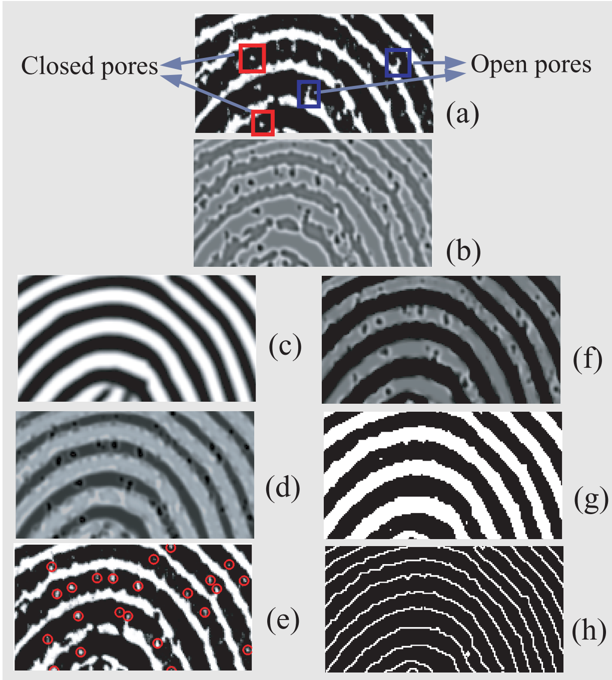


Figure 2: Level 3 feature extraction. (a) A partial fingerprint image at 1000dpi. (b) Wavelet response (s=1.32) of the image in (a). (c) Ridge enhancement of image in (a) using Gabor filters. (d) Pore enhancement using a linear addition of (b) and (c). (e) Extracted pores (red circles) after thresholding on (d). (f) Ridge enhancement using a linear subtraction of wavelet response (s=1.74) and (c). (g) Identified ridges after binarization on (f). (h) Extracted ridge contours after applying filters on (g).

the extraction of ridge contours. First, the scale s (Eq. 1) is increased (=1.74) to accommodate smoother ridge contours. Then we subtract the wavelet response from the enhanced image to identify the ridges (Figure 2(f)). The resulting image is further binarized using an empirically defined threshold δ (=10) (Figure 2(g)). Finally, ridge contours can be extracted by convolving the binarized image $f(x, y)_b$ with a filter H (Figure 2(h)):

$$r(x, y) = \Sigma_{n,m} f(x, y)_b H(x - n, y - m), \tag{2}$$

where filter $H = (0, 1, 0; 1, 0, 1; 0, 1, 0)$ counts the number of neighborhood edge points for each pixel. A point (x, y) is classified as a ridge contour point if $r(x, y) = 1$ or 2.

3 Level 3 Feature Matching

In latent print comparison, when Level 1 or Level 2 features are similar between the template and the query, a forensic expert often investigates Level 3 details. To be compatible with current AFIS systems, our matching using Level 2 and

Level 3 features is done separately, except using the Level 2 information (minutiae) for initial alignment for Level 3 matching. Then a score-level fusion of both the matching stages is performed using the sum rule and min-max normalization [11].

We employed two different matchers, namely minutiae-based [10] and correlation-based matcher [10] for matching at Level 2. For the matching at Level 3, we implemented a modified Iterative Closest Point algorithm (ICP) [12]. Due to non-linear deformation and degradation of image quality (caused by varying skin condition), the Level 3 features, especially the pores, can not always be extracted consistently. So the numbers of Level 3 features extracted from the template and the query, in practice, are different. ICP algorithm is an ideal solution for this problem because it aims to minimize the distances between points in one image to geometric entities (as opposed to points) in the other without requiring 1:1 correspondence. When applied locally, ICP also provides alignment correction to compensate for non-linear deformation [13], assuming that the initial estimate of the transformation is reasonable.

To initialize ICP, we first align template and query using minutiae. This alignment is usually available from Level 2 matching. Then we segment local regions around corresponding minutiae pairs for Level 3 feature examination. In order to achieve a balance between large fingerprint area and high matching speed, we obtain a convex hull of the minutiae and use only those minutiae that are on the boundary (polygon) of the convex hull (Figures 3(a-b)). Let $(x_i, y_i), i = 1, 2, ..., n$ be the n minutiae on the polygon and (x_m, y_m) be their mean. The window size for Level 3 examination is 60×120, centered at the middle point between the mean location and each of the n minutiae (Figures 3(c-d)). This ensures that only foreground fingerprint regions are included and are sampled as widely as possible.

Let T_p and Q_q denote the Level 3 feature sets from the template and query, respectively (Figures 3(e-f)). Each feature set includes triplets $(x_i, y_i, w_i), i = 1, 2, ...,$ where (x_i, y_i) represents the location of feature points (pores or ridge contour points) and w_i is the weight. In our experiment, we assign higher wights to pores to take advantage of their sparse and more unique distribution compared to ridge contours. The ICP algorithm minimizes the distance E, given by

$$E(T_p, Q_q) = \Sigma_k d_s^2(T_{p_i}^k, q_j^k), \tag{3}$$

where d_s is the distance between a triplet in the template $p_i = (x_i, y_i, w_i)$ and its closest point in the query $q_j^k = (x_j^k, y_j^k, w_j^k)$ at the k-th iteration. Given an initial alignment, the closest points are automatically established between the template and query and a transformation matrix $T^k (k = 1)$ based on these corresponding points is obtained. This matrix is then applied to the template before a new set of closest points in the query is obtained for the template. An iterative procedure is adopted to ultimately minimize E (Figure 3(g)). Rapid convergence to the global minimum is usually assured because the initial alignment based on minutiae is generally good.

If there are n minutiae pairs on the convex hull between the template and the query, we will obtain n match distances from the ICP algorithm. Considering the noise and possible false alignments, we keep the first four minimum distances and use their mean as the distance measure for Level 3 matching. Pairs that have less than four minutiae correspondences result in a predefined large distance value.

4 Experimental Results

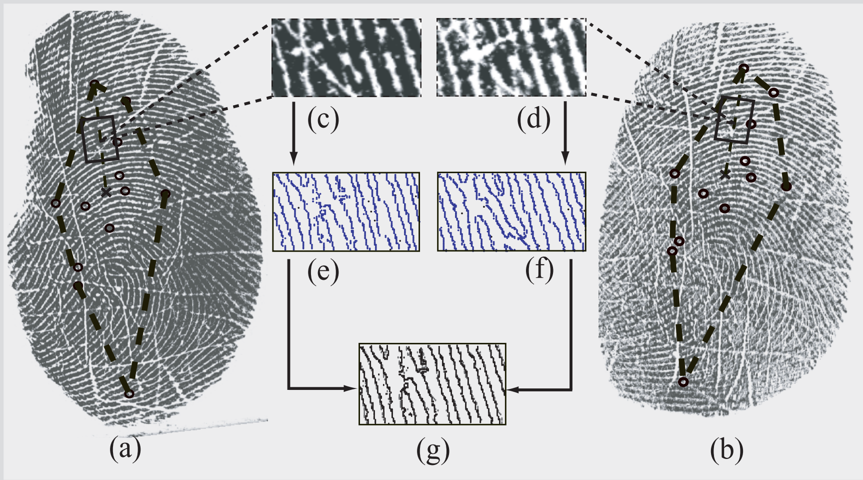
To our knowledge, there is no 1000dpi resolution fingerprint database available in the public domain. So, we collected 1000dpi (slap) fingerprint impressions of 410 different fingers (41 subjects $\times$ 10 fingers per subject) using a Cross-Match 1000ID sensor Each user provided four impressions (2 impressions $\times$ 2 sessions with an interval of three days). Two different matchers, namely, a minutiae-based Level 2 matchers and our proposed Level 3 matcher are applied to this database. ROC curves for each individual matcher and the fusion algorithm are shown in Figure 4. The number of genuine and imposter matches, respectively, are $2,460$ (410×6) and $83,845$ ($\frac{410 \times 409}{2}$).

It is observed that matching results based on Level 3 features alone is very comparable to that of Level 2 features. Significant performance improvement (20%) is observed when the proposed Level 3 matcher is combined with Level 2 matchers using score-level fusion [11], as shown in Figure 4. This suggests that Level 3 features provide some discriminative information and should be used in combination with lower level features.

It must be noted that the performance of both Level 2 and Level 3 matchers can be further improved if the images are captured in a more controlled environment. Currently, the high resolution optical sensor used in our experiment requires movement of the finger over a glass panel, resulting in partial distortion and smudginess in the captured images. In addition, the sensor is sensitive to skin condition and there is a large variance in image quality due to dryness or moisture (Figures 3(a-b)).

5 Summary and Conclusions

We have presented a fingerprint matcher that utilizes Level 3 features, including pores and ridge contours, extracted from 1000dpi fingerprint images. We introduced two separate methods using wavelet transform and Gabor filters to extract pores and ridge contours and a modified ICP algorithm for the matching. It is observed that matching results based on Level 3 features alone is very comparable to that of



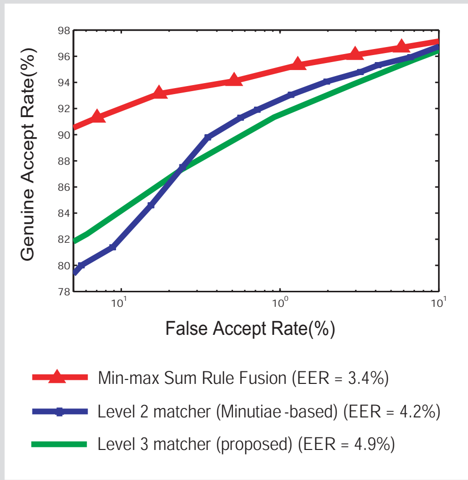


Figure 3

Figure 4

Figure 3: Level 3 feature matching. (a-b) The template and query images with corresponding minutiae overlaid. Minutiae on the convex hull are used to extract segments for Level 3 examination. (c-d) Windows segmented from the template and query. (e-f) Extracted Level 3 features from the segmented windows from the template and query. (g) Level 3 matching using the modified ICP algorithm.

Figure 4: ROC curves for Level 2 and Level 3 matchers and the fusion algorithm based on using sum-rule and min-max normalization.

Level 2 features. Integrating Level 2 and Level 3 matchers at the score level results in significant improvement (relatively ~20% in EER). To further improve the performance, integrating Level 2 and Level 3 features at the feature level is being conducted on a larger 1000dpi fingerprint database.

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