Automatic Segmentation of Latent Fingerprints

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***Abstract*—Latent fingerprints are routinely found at crime scenes due to the inadvertent contact of the criminals' finger tips with various objects. As such, they have been used as crucial evidence for identifying and convicting criminals by law enforcement agencies. However, compared to plain and rolled prints, latent fingerprints usually have poor quality of ridge impressions with small fingerprint area, and contain large overlap between the foreground area (friction ridge pattern) and structured or random noise in the background. Accordingly, latent fingerprint segmentation is a difficult problem. In this paper, we propose a latent fingerprint segmentation algorithm whose goal is to separate the fingerprint region (region of interest) from background. Our algorithm utilizes both ridge orientation and frequency features. The orientation tensor is used to obtain the symmetric patterns of fingerprint ridge orientation, and local Fourier analysis method is used to estimate the local ridge frequency of the latent fingerprint. Candidate fingerprint (foreground) regions are obtained for each feature type; an intersection of regions from orientation and frequency features localizes the true latent fingerprint regions. To verify the viability of the proposed segmentation algorithm, we evaluated the segmentation results in two aspects: a comparison with the ground truth foreground and matching performance based on segmented region.**

I. Introduction

Automated Fingerprint Identification Systems (AFISs) have played a critical role in forensics and law enforcement applications to identify suspects and criminals for more than a century. There are two main types of matching performed in AFIS: (i) tenprint search and (ii) latent search [2]. In tenprint search, the rolled or plain fingerprints of the 10 fingers of a subject are searched against the tenprints in a fingerprint database. Most of the tenprint searches (matchings) can be done effectively in a "lights out mode" (fully-automatic), since rolled and plain fingerprints are typically of good quality with rich ridge information. According to the Fingerprint Vendor Technology Evaluation (FpVTE) report [10], the best performing AFIS had rank-1 identification rate of 99.4% on a database of $10,000$ plain fingerprints (single finger match performance).

The second type of search conducted by AFIS is latent to tenprint match. Latent fingerprints "lifted" from crime scenes are extensively used as forensic evidence in criminal prosecutions. However, latent search is a challenging problem due to poor quality of latents in terms of the clarity of the ridge impressions. Typically, latent fingerprints have significantly poor quality compared to rolled and plain fingerprints and

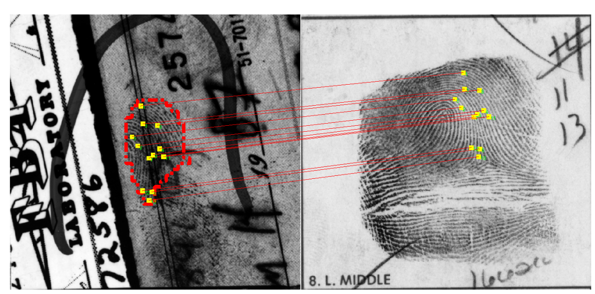
(a) (b) (c)

Fig. 1. Three types of finger impressions. (a) rolled fingerprint (b) plain or slap fingerprint, (c) latent fingerprint. The average number of minutiae in NIST SD27 is 21 for latents versus 106 for the rolled prints [3].

contain only a small area of a finger with unclear ridges and large non-linear skin distortion (see Figure 1).

Due to the above characteristics of latent fingerprints, latent searches are performed in a "semi-lights out mode" (semi-automatic). In other words, manual intervention is necessary in latent feature extraction and verification stages. As an example, latent experts manually mark the region of interest (ROI) in latents. Given this ROI, AFIS is used to filter a large database of reference full prints to a small number of potential mates (typically 50) for manual examination. The manual examination and matching of latent fingerprints are clearly stated in law enforcement protocol, referred to as the ACE-V protocol [1]. Figure 2 shows an example of a latent fingerprint and its mated rolled impression in NIST SD27 [31].

Given the large size of background database containing rolled and plain fingerprints in law enforcement databases



(a) **(b)**

Fig. 2. Example of a latent (a) and its mated rolled fingerprint (b). Manually marked ROI in latent is shown in red and manual markup of corresponding minutiae are shown in yellow [31].

(e.g., FBI's IAFIS contains fingerprint records of about 70 million subjects), latent search in a lights out mode is very desirable. In fact, this is one of the major goals of the FBI's Next Generation Identification (NGI) system [12]. Such a process should automatically identify the region of interest (separate the foreground from background), extract features from latent fingerprints and match them with a database of known prints (rolled and plain) to obtain a set of possible mates (with high confidence) with no or little manual intervention. For high-profile and "cold" cases[1], a fast and accurate response to latent queries would permit latent examiners to spend more time to visually verify the returned fingerprint matches. To benchmark and analyze the state of the art in latent search, National Institute of Standards and Technology (NIST) initiated a project on Evaluation of Latent Fingerprint Technologies (ELFT). In ELFT Phase I [30], the rank-1 accuracy of the best system was 80% in identifying 100 latents against $10,000$ rolled prints. In ELFT Phase II [24], the best rank-1 accuracy of 97.2% was reported on good quality latent fingerprints when matched with a background database of $100,000$ rolled fingerprints. In a recent report on "ELFT: Extended Feature Sets (EFS)" [25], NIST evaluated the state of the art in latent feature-based matching, by comparing the performance of using images alone against using different feature sets. The best matcher achieved a 66.7% rank-1 accuracy while matching $1,114$ latents with a background of $100,000$ full prints. While the inclusion of extended feature set (EFS) provided an improvement in accuracy, the latent fingerprint image itself was shown to be the single most effective search component for improving accuracy in current AFIS.

To achieve efficient automatic latent identification, it is important to minimize human intervention while, at the same time, maintaining the same matching accuracy as obtained by trained latent experts. Based on above consideration, there is an urgent need to develop an accurate automatic latent segmentation method that separates foreground from background as an initial step towards lights out latent identification. The rest of the paper is organized as follows. Section II presents a summary of previous approaches to fingerprint segmentation. Section III presents the proposed method based on ridge orientation and frequency information. Section IV presents experimental results. Conclusions and future work are addressed in Section V.

II. Related work

One of the first processing steps in AFIS is segmentation of fingerprint images. Fingerprint images usually consist of two components: foreground and the background. The foreground is the friction ridge impression from the fingertip whereas the background contains the noisy area or any non-friction ridge pattern which is irrelevant to fingerprint matching. The aim of the segmentation is to decompose the input fingerprint image into foreground and background regions. Accurate segmentation is especially important for reliable feature extraction (e.g., minutiae), since most feature extraction methods extract a number of false minutiae in the background region (see Figure 3).

Several approaches are available in the literature for the segmentation of rolled and plain fingerprints. These methods typically extract features for every element, which can be a pixel or a block of pixels, say $N \times N$, in the fingerprint image. Each element is then classified as a foreground or background based on a threshold. Mehtre et al. [9] proposed a segmentation method based on directional image features. The ridge direction is selected by using the value of total fluctuations of the gray values among the 8 possible directions and the blockwise histogram of ridge direction is used to find the foreground. In [8], a composite method was proposed using both gray value variance and directional image. Ratha et al. [28] measured the variance of the ridge projection signal on different directions to find the foreground. Foreground blocks have a large variance in a direction orthogonal to the ridges whereas background blocks have small variance along all directions. Hong et al. [22] proposed a method to classify the fingerprint image into non-ridge-and-valley (unrecoverable) and ridge-and-valley (recoverable) regions based on the amplitude, frequency and variance features obtained from projected ridge signals. Bazen and Gerez [5] proposed a segmentation method based on pixel-wise coherence to handle the noisy background. Bazen and Gerez [6] further improved their segmentation method based on three pixel-based features (coherence, mean and variance). An optimal linear classifier was used for the classification. Yin et al. [36] developed a quadric surface formula based on coherence, mean and variance features to overcome the limitations of a linear classifier. Wang et al. [23] proposed an algorithm based on Gaussian-Hermite Moments (GHM) for non-uniform background removal. Bernard et al. [32] proposed a multiscale Gabor wavelet filter bank based approach to segment the fingerprint images. The phase component of Gabor wavelet was used to determine ridges and valleys. Some segmentation methods were especially designed for segmenting low quality fingerprint images. These methods rely on gradient-based features [18], intensity-based features [13], [37] and structure-based features [21].

While rolled and plain fingerprint segmentation solutions

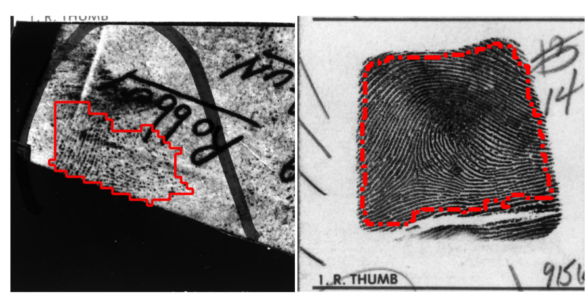
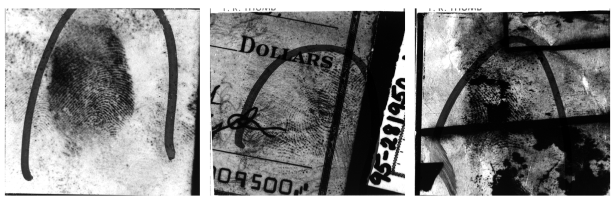


Fig. 3. Desired segmentation results for a latent and a full print. Latent segmentation is a more difficult task compared to full print segmentation.

[1]The definition of a "cold" case varies from one law enforcement agency to other agency. The National Institute of Justice currently defines a cold case as any case whose probative investigative leads have been exhausted [29].

Method	Approach	Database	Performance evaluation	Matcher	Limitation
Karimi et al. [34]	Ridge frequency computation	2 latents from NIST SD27	N/A	N/A	No performance evaluation
Short et al. [26]	Correlation with ideal ridge templates	NIST SD27	EER of 33.8%	Not reported	Did not use a state of the art matcher
Zhang et al. [20]	Adaptive Total Variation model	3 latents from NIST SD27	N/A	N/A	No performance evaluation
Proposed approach	Ridge orientation and frequency computation	NIST SD27 WVU DB	Rank-1 identification accuracy of 16.28%, 35.19% in NIST SD27 and WVU DB	COTS matcher	Need a robust confidence[2] measure for segmentation output

TABLE I
A COMPARISON OF PUBLISHED AND THE PROPOSED LATENT FINGERPRINT SEGMENTATION METHODS.



(a) (b) (c)

Fig. 4. Latent fingerprints of three different quality levels in NIST SD27 [31]. (a) Good, (b) Bad, and (c) Ugly.

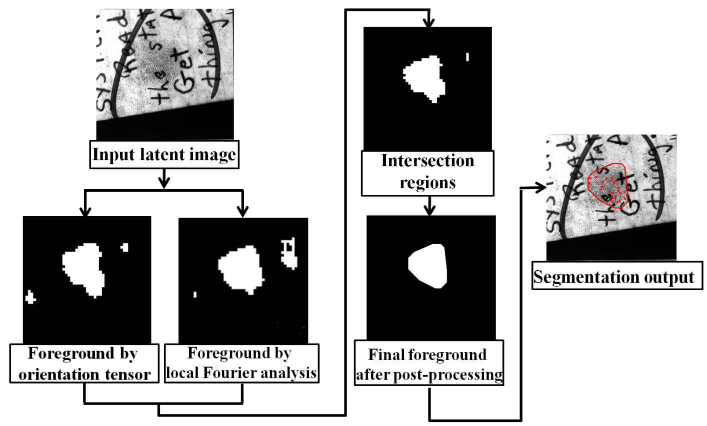


Fig. 5. A flowchart of the proposed latent fingerprint segmentation algorithm.

are available, latent fingerprint segmentation still poses a challenge. The segmentation methods designed for rolled/plain fingerprints do not work properly on latents due to their poor quality in terms of the clarity of the ridge impressions. Further, latent images contain severe background noise (such as speckle, stain, line, and text), which makes the latent segmentation problem significantly more challenging (see Figure 4).

There have been a few recent studies on latent fingerprint segmentation [34], [20], [26]. In [34], local frequency of the ridge/valley pattern was estimated based on ridge projection with varying orientations (5 degree resolution). The variance of frequency and amplitude of the ridge signal was used as features for the segmentation algorithm. However, segmentation results for only two latent images were reported without any evaluation. Short et al. [26] proposed ridge template correlation method for latent segmentation. An ideal ridge template was generated and then cross-correlation values were computed to define the local fingerprint quality. Authors manually selected 6 different threshold values to assign a quality value to each fingerprint block. Unfortunately, the information regarding the ideal ridge template (size and number) was not reported and evaluation criteria was not clearly described. Zhang et al. [20] proposed an adaptive total variation (TV) model for latent segmentation. The weight assigned to the fidelity term in the model is adaptively determined according to the background noise level. This was used to remove various kinds of background noise in the latent fingerprint images. However, the effectiveness of the segmentation results in latent fingerprint matching was not reported. Table I summarizes published methods to segment latent fingerprint images.

III. PROPOSED METHOD

A. Algorithm overview

The most evident structural characteristic of a fingerprint is a pattern of interleaved ridges and valleys. Thus, by considering a fingerprint as a texture pattern (oriented line pattern within a certain valid range of frequency), we utilize both fingerprint orientation and frequency information to segment latents. The main difficulty in latent fingerprint segmentation is the presence of structured noise (e.g., arch, line, character and speckle). This motivates the use of orientation tensor approach to extract the symmetric patterns of a fingerprint as well as to remove the structured noise in background. Local Fourier analysis method is used to estimate the local frequency in the latent fingerprint image and locate fingerprint region by considering valid frequency regions. Candidate fingerprint (foreground) regions are obtained for each feature (orientation and frequency) and then an intersection of these regions is used to localize the latent fingerprint region. A flowchart of the proposed method is shown in Figure 5.

[2]Confidence is an indicator of the reliability of the segmentation output. If the confidence of the segmentation output is high, it suggests no manual intervention is necessary.

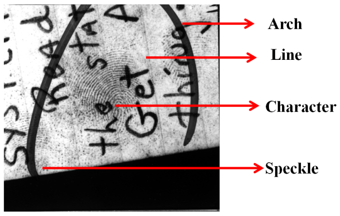


Fig. 6. Various types of structured noise in a latent fingerprint image.

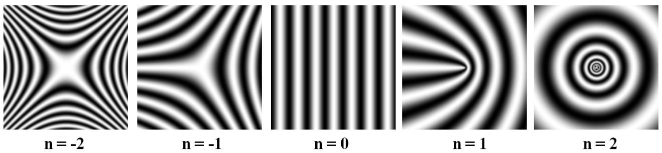


Fig. 7. Examples of the symmetry patterns of order n. Linear, parabolic and circular symmetry for $n = 0$, $n = \pm1$ and $n = \pm2$, respectively. Method in [7] is used to generate the patterns.

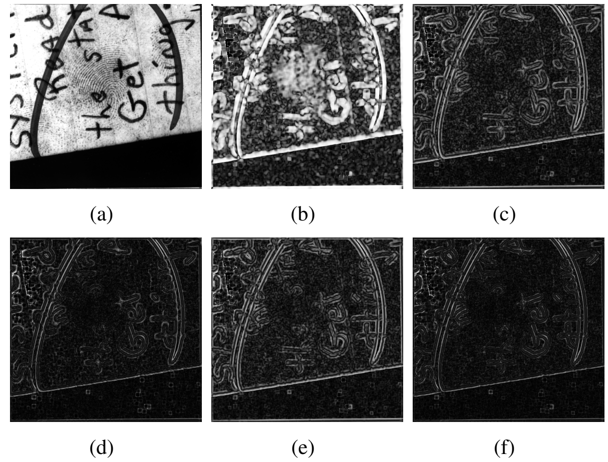


Fig. 8. Latent fingerprint image decomposition by orientation tensor. (a) Original latent image, (b) s_0 response, (c) s_1 response, (d) s_2 response, (e) s_{-1} response, and (f) s_{-2} response.

B. Orientation feature

In our method symmetry features based on orientation tensor are exploited, since orientation tensor contains edge and texture information in an image [16], [14]. Compared to rolled and plain fingerprint images, the structured noise such as arch, line, character and speckle is frequently present and intermingled with friction ridge pattern in latent images (see Figure 6). Orientation tensor is appropriate for the representation of various kinds of symmetry type and can distinguish ridge and valley pattern from background noise in latent images. Figure 7 illustrates the patterns with simple orientation description $z = exp(in\phi)$. The linear symmetry type ($n = 0$) corresponds to the typical ridge-valley flow whereas parabolic symmetry types ($n = \pm1$) correspond to the singular points of a fingerprint as well as the structured noise.

We decompose the orientation tensor of the latent image into several symmetry representations. The orientation tensor is computed as

$$z = (D_x f + iD_y f)^2, \tag{1}$$

where $D_x f$ and $D_y f$ denote the gradients of the latent image $f(x, y)$ with respect to the x and y axes [14]. Then, the orientation tensor is decomposed into symmetry features of order n by applying filters, h_n, which can model these symmetry descriptions. Filters are defined as

$$h_n = (x + iy)^n.g, \quad for\ n \geq 0,$$
$$h_n = (x - iy)^{|n|}.g, \quad for\ n < 0, \tag{2}$$

where g denotes a 2D Gaussian function (23×23 Gaussian kernel with $\sigma = 8$). To detect the nth order symmetry property in an image, normalized filter responses are obtained by calculating

$$s_n = \frac{< z, h_n >}{< |z|, |h_n| >}, \tag{3}$$

where $<\cdot, \cdot>$ denotes the 2D complex valued scalar product. The filter response of the nth order s_n is a complex value, where high magnitude regions in the image indicate a probable nth order symmetry. Thus, normalized filter responses, $\{s_n\}_{n \in N}$, describes the various symmetry properties of an image. The filter responses are normalized in the [0, 1] interval. Figure 8 shows decomposition of a latent fingerprint image into 5 symmetries ($n = 0, \pm1, \pm2$).

As shown in Figure 8, the response of order 0, s_0, is high not only in fingerprint regions but also in the background containing structured noise. However, for the other responses, only structured noisy background regions have high responses. Based on this observation, we eliminate background to segment the fingerprint region. Segmentation based on orientation tensor is summerized as follows:

1) Compute the normalized filtered responses, $\{s_n\}_{n \in N}$, where
   - s_0 has high response in fingerprint regions (straight lines);
   - $\{s_k\}_{k \in \{-2,-1,1,2\}}$ has high response in noisy regions (non-fingerprint patterns representing structured background);
2) Obtain orientation response in the image by calculating
$$s_{OT} = s_0 \cdot \prod_k (1 - s_k), k \in \{-2, -1, 1, 2\}. \tag{4}$$
3) Divide the orientation response image, s_{OT}, into non-overlapping blocks of size 16×16 pixels and calculate the mean value of each block. A 5×5 block median filter is applied to smooth the response.
4) If the mean value of a block is larger than a threshold, the block is considered as a foreground (value 1), otherwise it is set to background (value 0). In here, the threshold value is automatically obtained by Otsu's method [27] (see Figure 9).
5) Remove individual foreground blocks that are surrounded by background blocks.

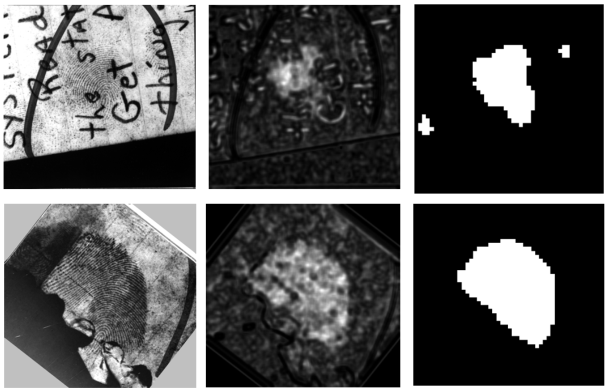


Fig. 9. Examples of latent fingerprints and their orientation feature maps (second column) and obtained foregrounds by adaptive thresholding (third column). High response (bright) regions in the image indicate a probable ridge-valley flow.

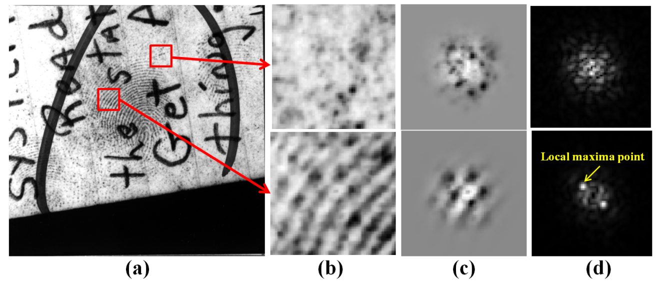


Fig. 10. Estimation of ridge frequency by local Fourier analysis. (a) Original latent image, (b) local image blocks (64×64), (c) local image multiplied by Gaussian function, (d) local maximum points with the highest amplitude in the frequency image.

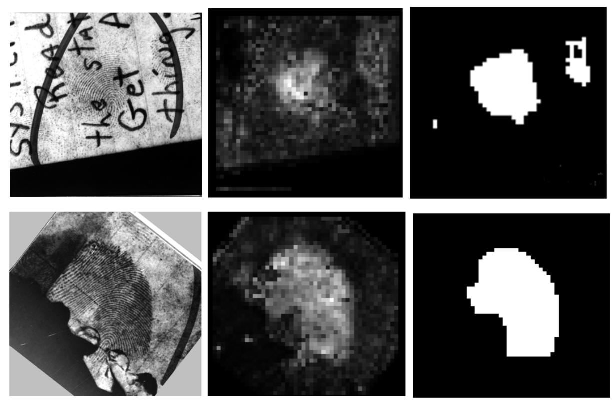
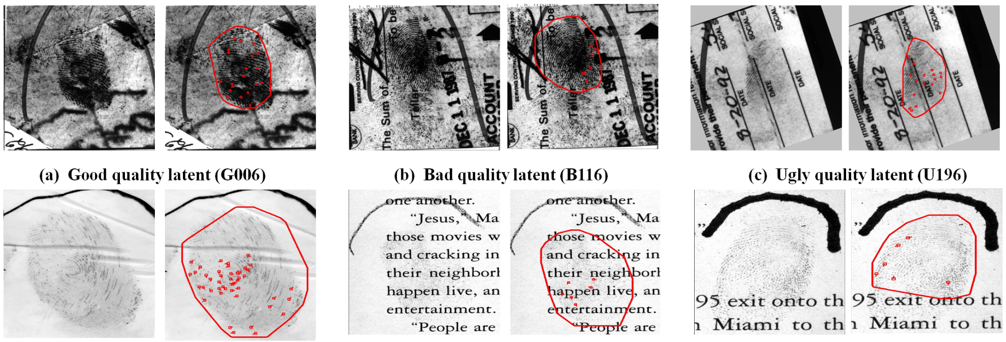


Fig. 11. Examples of latent fingerprints and their frequency feature maps (second column) and obtained foregrounds by adaptive thresholding (third column). Brighter regions in the image indicate higher energy in valid ridge and valley frequency regions.

C. Frequency feature

Even though the orientation tensor based approach can estimate the foreground region well, it still contains some background regions which have linear symmetry patterns. Therefore, based on the fact that ridge frequency is an intrinsic feature of a fingerprint, we utilize it to segment the foreground region more accurately. Ridge frequency or ridge density is a measure of the number of ridges per unit area. According to [22], the range of valid ridge frequency is $[1/3, 1/25]$ for a 500dpi fingerprint image. Methods for measuring the ridge frequency can be roughly classified into two categories: spatial-domain methods [22], [19], [35], [11], and frequency-domain methods [33], [4]. The methods in [22], [19], [35] assumed that the gray levels along ridges and valleys can be modeled as a 1D sinusoidal-shaped wave along a direction normal to the local ridge orientation. Peaks of the wave (called x-signature) are used to measure the ridge frequency. In [11], this assumption was extended to 2D spatial domain and the variation and the average amplitude of a 2D ridge pattern were estimated to measure the local ridge frequency. However, due to the relatively poor quality of latent fingerprint images, this assumption may not be correct and it is difficult to reliably detect the peaks of the wave. Further, an accurate estimation of local ridge orientation is a critical limitation. Therefore, we adopt the local Fourier analysis method [4] to classify a latent fingerprint image into valid and non-valid frequency regions since the method can easily localize the valid frequency regions with suitable amplitude and frequency parameters. In a valid frequency region, a corresponding frequency image has energy concentration in corresponding ridge and valley frequency. However, in a non-valid frequency region, a corresponding frequency image has more diffused energy distribution with relatively low amplitude. The approach used for the segmentation based on local Fourier analysis is as follows:

1) Divide the image into nonoverlapping blocks of size 16×16 pixels.
2) Centered at each block, the local image in the 64×64 window is normalized using the norm of the block (to handle the intensity variation of each block) and multiplied by a Gaussian function ($\sigma = 16$). See Figure 10 (c).
3) The Discrete Fourier Transform (DFT), $F(u, v)$, of the local image $I(x, y)$ is calculated.
4) The largest local amplitude value is found within the valid frequency range which corresponds to a ridge period in the range (5.3, 12.8) pixels. (see Figure 10 (d)).
5) The amplitude value is obtained in each block which are normalized in [0, 1]. A 5×5 block median filter is applied to smooth the values.
6) If the normalized value of the block is below a threshold, the block is considered as background (value 0), otherwise it is set as foreground (value 1). In here, the threshold value is automatically obtained by Otsu's method [27] (see Figure 11).
7) Remove individual foreground blocks that are surrounded by background blocks.



(a) Good quality latent (G006) (b) Bad quality latent (B116) (c) Ugly quality latent (U196)

(d) WVU latent (W034F01) (e) WVU latent (W055F01) (f) WVU latent (W484F06)

Fig. 12. Examples of segmentation results on NIST SD27 (first row) and WVU database (second row). Foreground regions and manually marked minutiae are indicated by polygons and dots, respectively.

D. Post-processing

Candidate fingerprint (foreground) regions are obtained for each of the two fingerprint features (orientation and frequency). Common regions between them are used to localize the foreground region. To obtain final segmentation results, morphological operations (dilation and opening) are applied to remove small foreground blocks as well as to fill holes inside the foreground. The convex hull of a set of foreground blocks is computed to determine the final segmentation result.

IV. Experimental results

Our experiments were conducted on two latent databases: NIST SD27 database [31] and West Virginia University latent database (WVU DB) [15]. NIST SD27 and the WVU DB, respectively, contain 258 and 449 latent fingerprints with their corresponding rolled prints. NIST SD27 contains latents and mated full prints from operational settings whereas WVU DB was collected in a laboratory setting at West Virginia University. The characteristics of these two databases are quite different with NIST SD27 being a better representative of type of images processed by AFIS. Figure 12 shows examples of segmentation results on NIST SD27 and WVU databases. The proposed method provides satisfactory results as far as visual inspection is concerned. However, to determine the performance of the proposed segmentation method quantitatively, we evaluated the segmentation results in two aspects: segmentation accuracy as compared to ground truth and matching performance.

A. Comparison with manual segmentation

The aim of this evaluation is to analyze the segmentation accuracy by comparing the segmentation results to manual markup (ground truth). The segmentation accuracy was evaluated based on two error measurements: Missed Detection Rate (MDR) and False Detection Rate (FDR). MDR refers to the frequency of a ground truth foreground pixel being classified as background and FDR refers to the frequency of a ground truth background pixel being classified as foreground. MDR and FDR are computed as follows:

TABLE II
SEGMENTATION ACCURACY OF THE PROPOSED METHOD.

Database	Segmentation error (%)	
	MDR	FDR
NIST SD27	14.78	47.99
WVU DB	40.88	5.63

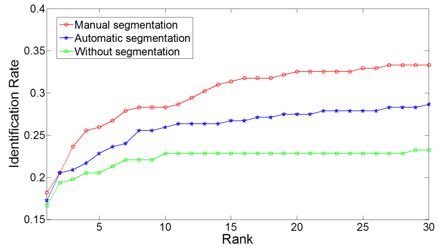
$$MDR = \frac{N_{MD}}{N_{GF}},$$
$$FDR = \frac{N_{FD}}{N_{SF}}, \tag{5}$$

where N_{GF} and N_{SF} denote the number of pixels in the ground truth foreground and foreground obtained by the proposed method, respectively, and N_{MD} and N_{FD} denote the number of pixels misclassified as background and foreground by the proposed method, respectively. As shown in Table II, the FDR value is higher than the MDR value for NIST SD27 since the images in NIST SD27 have complex background with high feature responses. However, for the WVU DB, even though the background is relatively simple, the MDR value is relatively higher than NIST SD27 due to the poor ridge contrast and relatively large foreground size. This further confirms the very different characteristics of the two latent databases.

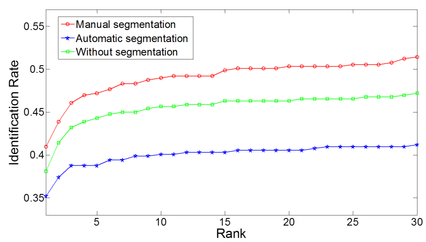
B. Matching performance evaluation

The accuracy of the proposed latent fingerprint segmentation algorithm was also evaluated by measuring the latent matching performance using a commercial off the shelf (COTS) matcher[3]. The range of match scores given by this matcher is $[0, 16783]$. To make the latent matching problem more realistic, the background database was extended to 31,997 fingerprints by including 258, 27,000 and 4,739 rolled prints in NIST SD27, NIST SD14 and WVU databases, respectively. We report our results on the following three scenarios on NIST SD27 and WVU DB.

[3] Since we were unable to obtain any SDK for latent to full print matcher, we used a state of the art SDK for full print to full print comparison.



(a)



(b)

Fig. 13. CMC curves for three different scenarios on (a) NIST SD27 and (b) WVU DB.

- Manual segmentation: Input to the matcher is the segmented image by manual segmentation.
- Automatic segmentation: Input to the matcher is the output of the proposed segmentation algorithm.
- Without segmentation: Input to the matcher is the original latent image.

The Cumulative Match Characteristic (CMC) curves of the three scenarios are shown in Figure 13. As expected, the performance with manually marked ROI provides the upper bound. The matching performance is higher when automatically segmented images are used as input to the COTS matcher compared to the case without segmentation for NIST SD27. However, for the WVU DB, the matching performance is degraded since our segmentation algorithm fails to detect some low contrast latents that are prevalent in this database.

C. Confidence in segmentation

It is necessary to provide a confidence (reliability) value to the latent segmentation output. If the confidence of the segmentation output is high, it means no manual intervention is necessary and the segmentation output can be directly used for further processing. Our scheme for estimating the confidence is based on the separability of the feature responses (F) (in here, orientation and frequency features) between segmented foreground and background regions. If the ridge structure in fingerprint is clear and background is simple, the feature response values between foreground and background will be highly separable. However, if the quality of fingerprint is poor, the separability of feature values will be relatively low and the segmentation output may not be as reliable. To calculate the separability of the given feature response (S_F), we modified

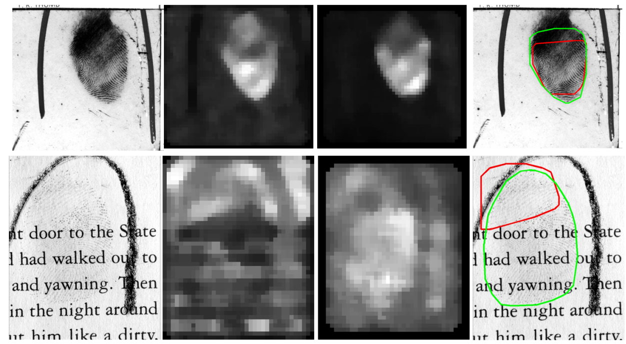
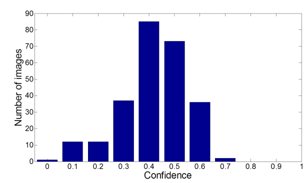
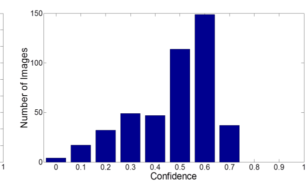


Fig. 14. Two latents with their feature maps (orientation (second column) and frequency (third column)) and segmentation output. Manually marked ROI (green) and ROI by the proposed method (red) are shown. The confidence value of the segmentation is 0.72 (top) and 0.29 (bottom).



(a)



(b)

Fig. 15. Histograms of the confidence values for latent databases. (a) NIST SD27, (b) WVU DB.

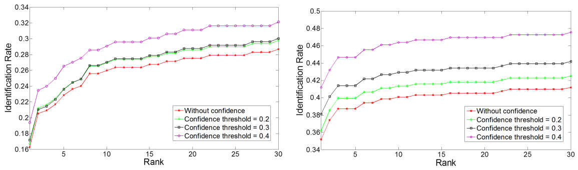
the d' measure [17] as follows:

$$S_F = \frac{mean(FF) - mean(BF)}{1 + \sqrt{\frac{1}{2}(var(FF) + var(BF)}} \times \frac{1}{mean(FF)}, \quad (6)$$

where FF and BF are, respectively, the feature response values in the segmented foreground and background. Note that the feature response values were normalized to [0, 1]. Then the separability values for each feature response (orientation (S_{OT}) and frequency (S_{FR})) were obtained based on equation 6. Finally, the confidence value is calculated as follows:

$$Confidence = \frac{(S_{OT} + S_{FR})}{2} \times \frac{1}{N_{FG}}, \quad (7)$$

where N_{FG} is the number of foreground regions obtained by the proposed method. Figure 14 shows two latent segmentation examples with their respective confidence values. Figure 15 shows the histograms of confidence values for segmentations obtained for NIST SD27 and WVU DB. To validate the usability of our confidence measure, we also analyzed the identification rate for various thresholds on the confidence measure. In here, threshold values of 0.2, 0.3, and 0.4 were used. We accept a latent for automatic processing if the confidence value of segmentation output exceeds the threshold. The identification rates monotonically increase as we reject more latents with low confidence (higher threshold). As shown in Figure 16, for the NIST SD27 and WVU DB, at a rejection threshold of 0.4 on segmentation confidence, the rank-20 identification accuracy increased by about 4% and 5%, respectively.



(a) (b)

Fig. 16. Identification rate for different confidence threshold values. (a) NIST SD27, (b) WVU DB.

V. Conclusions and Future Work

We have proposed a new latent fingerprint segmentation algorithm that identifies the region of interest, namely the friction ridge pattern, and suppresses the background. The segmentation algorithm utilizes both ridge orientation and frequency features. Experimental results on two latent print databases were provided. The matching performance of a commercial matcher is improved by utilizing the segmented latent fingerprints compared to the case of using original latent image without segmentation on NIST SD27. However, for poor quality latent fingerprint images, the automatic segmentation remains a challenging problem. Our ongoing work consists of (i) improving the segmentation accuracy by incorporating additional features (such as orientation and frequency continuity) and fingerprint models, and (ii) developing more accurate confidence measures for the segmentation results.

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