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Orientation Field Estimation for Latent Fingerprint Using Region Segmentation

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ABSTRACT:Latent fingerprint matching has played a critical role in identifying suspects and criminals. However, compared torolled and plain fingerprint matching, latent fingerprint identification accuracy is much lower due to complex background noise,poor ridge quality and overlapping structured noise in latent images. Accordingly, manual markup of various features (e.g.,region of interest, singular points and minutiae) is typically necessary to extract reliable features from latents. To reduce thismarkup cost and to improve the consistency in feature markup, fully automatic and highly accurate latentmatching algorithms are needed. In this paper, we propose an automatic region segmentation algorithm whose goal is to separate the fingerprint region (region of interest) from background. It 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 region segmentation algorithm, we evaluated the segmentation results in two aspects: a comparison with the ground truth foreground and matching performance based on segmented region.

KEYWORDS:Latent Fingerprint, Decomposition, segmentation, ridge frequency, minutiae, orientation feature

I. INTRODUCTION

Latent fingerprints (or simply latents) refer to fingerprints lifted from the surfaces of objects inadvertently touched or handledby a person typically at crime scenes. Comparedto rolled and plain fingerprints, latents are typically of poor quality in terms of ridgestructure,containing background noise and non-lineardistortion (see Fig. 1). Due to these factors, the latent identification (i.e., latent to exemplar matching)accuracy is much lower than that of exemplar fingerprints (exemplar to exemplar matching).One of the challenging problems in latent identification is how to automatically extract reliable featuresin latents, especially latents with poor quality. Giventhe difficulty of automatic feature extraction, a manual markup of various features in latents, such as regionof interest (ROI), singular points and minutiae, is thecurrent practice. However, this human factor issue inlatent examination has raised some concerns relatedto repeatability and reliability [3],[4]. For example,markup of a specific feature type (e.g., minutiae)by different latent examiners or even by the sameexaminer at different times may not give the sameresults. A study conducted by NIST showed that theaccuracy of a latent matcher is highly affected by theprecision of latent examiner markup, especially whenthe latent image itself is not available to the matched. One of the factors that affect human markupperformance is that latent examiners often work under extreme time pressure due to heavy case work.Studies have shown that when the comparison timeis limited, latent examiners are more likely to make aninconclusive matching decision between a latent andits mated rolled print [5].

One of the priorities of FBI's Next Generation Identification (NGI) is to support the development of a lights-out1 capability for latent identification [9]. An essential component of this lights-out capability is to develop a fully automatic latent feature extraction module. This is highly desirable to (i) increase the throughput of latent matching systems, (ii) improve repeatability of latent feature extraction and, (iii) increase the compatibility between features extracted in the latents and features extracted in the reference prints by an AFIS [10].

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Figure 1: Three types of finger impressions. (a) Rolled fingerprint (b) plain fingerprint, (c) latent fingerprint

Feng et al. [22] were the first to propose the use of dictionary for fingerprint orientation field estimation. However, their dictionary was based on orientation patches and they ignored the ridge structure information. This is the main reason their method in [22] was not very successful for segmentation and frequency field estimation.

For high profile and "cold" cases, a fast and accurate response tolatent queries would permit latent examiners to spend moretime to visually verify the returned fingerprint matches. Tobenchmark and analyze the state of the art in latent search, National Institute of Standards and Technology (NIST) initiateda project on Evaluation of Latent Fingerprint Technologies (ELFT). In ELFT Phase I [7], the rank-1 accuracy of thebest system was 80% in identifying 100 latents against 10,000rolled prints. In ELFT Phase II [8], the best rank-1 accuracyof 97.2% was reported on good quality latent fingerprintswhen matched with a background database of 100,000 rolledfingerprints. In a recent report on "ELFT: Extended Feature Sets (EFS)" [9], NIST evaluated the state of the art inlatent feature-based matching, by comparing the performanceof using images alone against using different feature sets.The best matcher achieved a 66.7% rank-1 accuracy whilematching 1,114 latents with a background of 100,000 fullprints. While the inclusion of extended feature set (EFS)provided an improvement in accuracy, the latent fingerprintimage itself was shown to be the single most effective searchcomponent for improving accuracy in current AFIS.

To achieve efficient automatic latent identification, it isimportant to minimize human intervention while, at the sametime, maintaining the same matching accuracy as obtained by trained latent experts. Based on above consideration, thereis an urgent need to develop an accurate automatic latentsegmentation 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 2 presents summary of previous approaches to fingerprint segmentation. Section 3 presents the proposed method basedon ridge orientation and frequency information. Section 4 presents experimental results and Section 5 presents conclusions and future work.

II. RELATED WORK

Fingerprint images usually consist of twocomponents: foreground and the background. The foregroundis the friction ridge impression from the fingertip whereas thebackground contains the noisy area or any non-friction ridgepattern which is irrelevant to fingerprint matching. The aim ofthe segmentation is to decompose the input fingerprint imageinto foreground and background regions. Accurate segmentation is especially important for reliable feature extraction(e.g., minutiae), since most feature extraction methods extracta number of false minutiae in the background region (seeFigure 2).

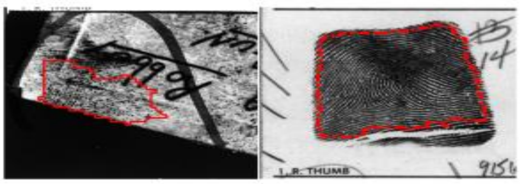

Figure 2: Desired segmentation results for a latent and a full print

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Several approaches are available in the literature for thesegmentation of rolled and plain fingerprints. These methodstypically extract features for every element, which can be apixel or a block of pixels, say N ×N, in the fingerprint image.Each element is then classified as a foreground or backgroundbased on a threshold. Mehte et al. [10] proposed a segmentationmethod based on directional image features. The ridge direction is selected by using the value of total variations of thegray values among the 8 possible directions and the block wisehistogram of ridge direction is used to find the foreground. In[23], a composite method was proposed using both gray valuevariance and directional image. Ratha et al. [24] measured thevariance of the ridge projection signal on different directions tofind the foreground. Foreground blocks have a large variancein a direction orthogonal to the ridges whereas backgroundblocks have small variance along all directions. Hong et al.[13] proposed a method to classify the fingerprint imageinto non-ridge-and-valley (unrecoverable) and ridge-and-valley(recoverable) regions based on the amplitude, frequency andvariance features obtained from projected ridge signals. Gabor wavelet was used to determine ridges and valleys.Some segmentation methods were especially designed forsegmenting low quality fingerprint images. These methods rely on gradient-based features [14], intensity-based features [15],[16] and structure-based features [17].

While rolled and plain fingerprint segmentation solutionsare available, latent fingerprint segmentation still poses achallenge. The segmentation methods designed for rolled/plainfingerprints do not work properly on latents due to theirpoor quality in terms of the clarity of the ridge impressions.Further, latent images contain severe background noise (suchas speckle, stain, line, and text), which makes the latent segmentation problem significantly more challenging (see Figure3).

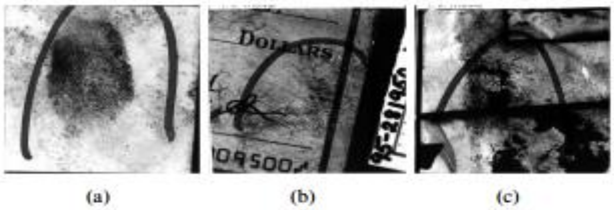

Figure 3: Latent fingerprints of three different quality levels in NIST SD27(a) Good, (b) Bad, and (c) Ugly

III. PROPOSED METHOD

A. Background

The main 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), in this paper, we utilize both fingerprint orientation and frequency information to segment latents. The major problem in latent fingerprint segmentation is the presence of structured noise (e.g., arch, line, character and speckle) (see Fig. 4).

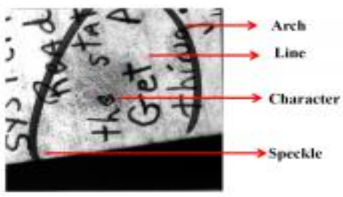

Figure 4: Various types of structured noise in a latent fingerprint image

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

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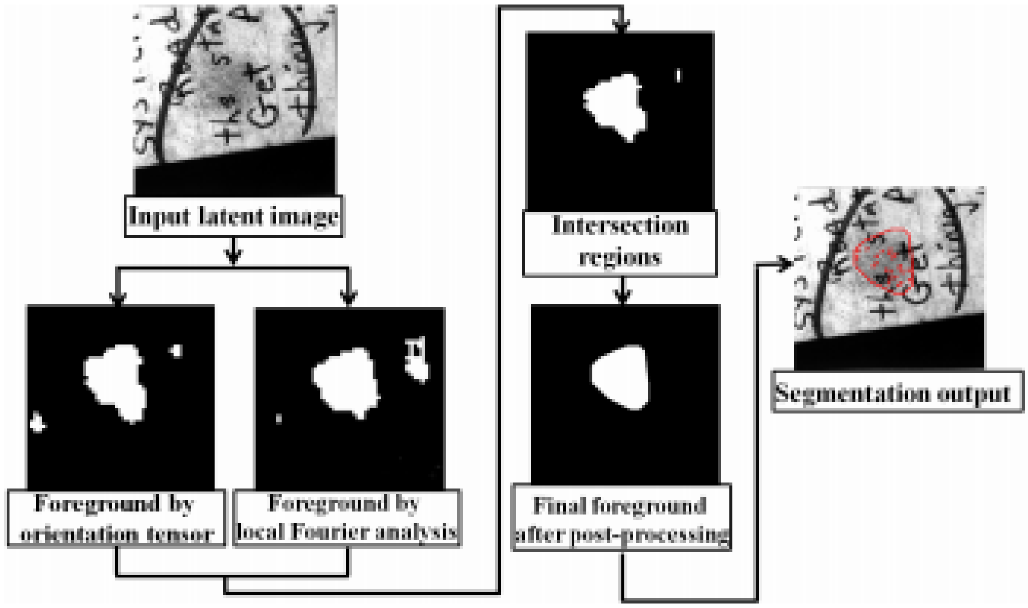

Figure 5: A flowchart of the proposed latent fingerprint segmentation algorithm

B. Orientation Feature:

In our paper symmetry features based on orientation tensor are exploited, since orientation tensor contains edge and texture information in an image [18], [19]. Compared to rolled and plain fingerprint images, the structured noise such as arch, line, character and speckle is frequently present and mixed with friction ridge pattern in latent images (see Figure 4). 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.

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

$$z = (D_x f + iD_y f)^2 \qquad (1)$$

where$D_x f$ and $D_y f$represents the gradients of the latent image f(x, y) with respect to the x and y axes [20]. Then, the orientation tensor is decomposed into symmetry featuresof order n by applying filters, h_n, which can model these symmetry descriptions.

Filters are defined as

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

where g denotes a 2D Gaussian function (23 × 23 Gaussian kernel with σ = 8). To detect the n^{th} order symmetry property in an image, normalized filter responses are obtained by calculating

$$s_n = \frac{<z,hn>}{<|z|,|hn|>} \qquad (3)$$

where<· , · > denotes the 2D complex valued scalar product.

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The filter response of the n^{th} order s_n is a complex value, where high magnitude regions in the image indicate a probable n^{th} 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 ($n = 0, \pm1, \pm2$). 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). Here, the threshold value is automatically obtained by Otsu's method [21].

5) Remove individual foreground blocks that are surrounded by background blocks.

C. Frequency feature

The orientation tensor based approach canestimate the foreground region, but, it still contains somebackground regions which have linear symmetry patterns.Therefore, based on the fact that ridge frequency is an intrinsicfeature of a fingerprint, we utilize it to segment the foregroundregion more accurately. Ridge frequency or ridge density isa measure of the number of ridges per unit area. We adopt the local Fourier analysis method [4] toclassify a latent fingerprint image into valid and non-validfrequency regions since the method can easily localize thevalid frequency regions with suitable amplitude and frequencyparameters. In a valid frequency region, a correspondingfrequency image has energy concentration in correspondingridge and valley frequency. However, in a non-valid frequencyregion, a corresponding frequency image has more diffused energy distribution with relatively low amplitude. The approachused for the segmentation based on local Fourier analysis isas follows:

- Divide the image into non-overlapping blocks of size 16 × 16 pixels.
- 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 ($\sigma = 16$).
- The Discrete Fourier Transform (DFT), F(u, v), of the local image I(x, y) is calculated.
- 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.
- 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.
- 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.
- Remove individual foreground blocks that are surrounded by background blocks.

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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 and West Virginia University (WVU). NIST SD27 and the WVU DB, respectively, contain 258 and 192 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. The characteristics of these two databases are quite different with NIST SD27 being a better representative of type of images processed by AFIS. The proposed method provides satisfactory results as far as visual inspection is concerned.

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 d 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:

$$MDR = N_{MD} / N_{GF},$$
$$F\,DR = N_{FD} / N_{SF},$$

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 mis-classified as background and foreground by the proposed method, respectively.

As shown in Table I, 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 DBDB, 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.

Database	Segmentation Error (%)	
	MDR	FDR
NIST SD27	12.22	42.64
WVU DB	36.42	7.39

Table 1: Segmentation accuracy of the proposed method.

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) matcher3. 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.

a) **Manual segmentation:** Input to the matcher is the segmented image by manual segmentation.

b) **Automatic segmentation**: Input to the matcher is the output of the proposed segmentation algorithm.

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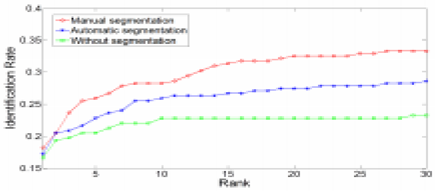
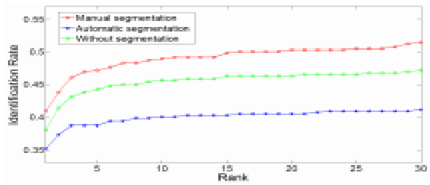
c) **Without segmentation:** Input to the matcher is the original latent image.



(a)



(b)

Figure 6: CMC curves for three different scenarios on (a) NIST SD27 and (b) FVC2002

The Cumulative Match Characteristic (CMC) curves of the three scenarios are shown in Figure 6. 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.

V. CONCLUSIONS AND FUTURE WORK

We have proposed a new latent fingerprint segmentationalgorithm that identifies the region of interest, namely thefriction ridge pattern, and suppresses the background. Thesegmentation algorithm utilizes both ridge orientation andfrequency features. Experimental results on two latent printdatabases were provided. The matching performance of acommercial matcher is improved by utilizing the segmentedlatent fingerprints compared to the case of using originallatent image without segmentation on NIST SD27. However,for poor quality latent fingerprint images, the automatic segmentation remains a challenging problem. The following aspects should be considered to improve the current algorithm.

(i) The segmentation accuracy by incorporating additional features (such as orientation and frequency continuity) and fingerprint models.
(ii) Developing more accurate confidence measures for the segmentation results.

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