Detection and Segmentation of Latent Fingerprints

Xiao Yang[1,2], Jianjiang Feng[2], Jie Zhou[2], and Shutao Xia[1]
1. Graduate School at Shenzhen, Tsinghua University, Shenzhen 518055, China
2. Department of Automation, Tsinghua University, Beijing 100084, China
xiao-yang@sz.tsinghua.edu.cn {jfeng, jzhou}@tsinghua.edu.cn xiast@sz.tsinghua.edu.cn

***Abstract*—Latent fingerprints have been used by law enforcement agencies to identify suspects for a century. However, because of poor image quality and complex background noise, latent fingerprints are routinely identified relying on features manually marked by human experts in practice. A large number of latent fingerprints can not be treated in time due to lacking well trained experts, highlighting the need for "lights out" (fully-automatic) systems. In this paper, we propose a systematic algorithm for latent fingerprint detection, segmentation, and orientation field estimation, without any manual markup. Multiple potential latent fingerprints are detected using a sequential pose estimation algorithm. Then, the full orientation field and confidence map of each detected fingerprint are estimated based on localized dictionaries lookup. Finally, the boundary of each latent fingerprint is delineated by analyzing its confidence map. Experiments on a multi-latent fingerprint database and the challenging NIST SD27 latent fingerprint database show the effectiveness of the proposed algorithm.**

I. Introduction

Law enforcement agencies around the world have been relying on Automated Fingerprint Identification Systems (AFIS) to identify repeat offenders and suspects for decades [1]. To identify the real identity of a suspicious person, ten rolled/plain fingerprints (tenprints) of the person will be matched against the tenprint database of known persons. To identify the suspect of a crime, latent fingerprints found at crime scenes will be matched against the tenprint database of known persons. Given the rich information contained in tenprints, AFIS can perform tenprint identification fully automatically with high accuracy and speed. However, due to poor image quality and strong disturbance of background noise in latent case, AFIS obtain rather lower recognition rate. Therefore, in practical applications AFIS can only perform latent identification semi-automatically, requiring plenty of manual labor in marking minutiae and examining candidate fingerprints found by the AFIS [2].

In recent years, there are increasing needs for fully automatic latent identification to reduce human labor and process more latents with the hope of solving more cases [3]. An ideal fully automatic latent identification system should be able to automatically detect multiple latent fingerprints in an image, extract their features, match them to rolled/plain fingerprints in the gallery, and finally output their identities. With such a system, a crime scene investigator can identify as many latents as possible at the scene in a timely manner. The most critical steps are to detect multiple latents in an image, delineate their boundaries, and extract their orientation fields. These are very challenging problems for conventional fingerprint algorithms. If these steps are successful, conventional minutiae extractors and matchers are able to produce much better results.

The first major challenge is detecting multiple latent fingerprints in a single image. Since most rolled/plain fingerprints are collected under supervision with controlled image quality and clean background, an image usually contains only one upright fingerprint, and detection is not necessary. For latent fingerprint images, however, it is requisite because there are usually multiple latent fingerprints in one image and latent fingerprints are hard to find out against multifarious noise even for human experts. Unfortunately, despite of the practical importance of automatic latent fingerprint detection, this topic has not yet been studied. In current practice, this step is performed by human experts and AFIS systems always assume that the latent image has been cropped.

With the rough position of detected fingerprints, segmentation is conducted to delineate the boundary of each detected fingerprint to avoid extracting false minutiae in background region. Early published fingerprint segmentation algorithms [4]–[7] are developed for rolled/plain fingerprints. Since the ridge and valley pattern of rolled/plain fingerprint is relative clear and image background is clean, segmentation on these fingerprints generally utilizes low-level features. Mehtre and Chatterjee [5] uses local pixel orientation histograms to differentiate ridge pattern from random pattern and gray-scale variance to eliminates flat regions. Average magnitude of the gradient is evaluated by Maio and Maltoni [6]. Bazen and Gerez [7] propose a learning based segmentation method by combining gradient coherence, intensity mean, and intensity variance.

Segmentation of latent fingerprints is much harder since many different kinds of background noise exist in latent fingerprint images, and the intensity of noise may be much stronger than fingerprint ridges. Therefore, latent fingerprint segmentation algorithms take more information into account and use more complex models [8]–[13]. Karimi and Kuo [8] exploit a projection based method along with a brute-force orientation searching strategy, and analyze accumulated intensities on all the orientations to find out a best ridge like pattern. Short *et al.* [9] generate a set of ideal ridge templates to check if local image blocks fit ideal ones by cross-correlation. However, due to rather poor image quality of most latents it is hard to fit to ridges of latent fingerprints. Choi *et al.* [10] combine orientation feature calculated by decomposing the orientation tensor response and frequency feature generated from the smoothed local wave amplitudes to check if local

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image block resembles a fingerprint ridge. Zhang *et al.* [11] directly decompose the image into texture component and cartoon component by their adaptive directional total-variation model, in which texture component contains texture whose wavelength is similar with real fingerprints and orientation satisfies an initial orientation field extracted by gradient methods, and cartoon component consists of the smooth parts. Cao *et al.* [12] learn a fingerprint image block dictionary and uses this dictionary to compute the ridge quality of texture component of latent fingerprint decomposed by local total variation model, then perform segmentation based on the quality map. Xu *et al.* [13] directly learn "ridge-valley" atoms from the target image and then segment the ROI by sparse coding. These methods mainly utilize the characteristic that local fingerprint ridge/valley pattern can be modeled as 2-D sinusoidal waves whose frequencies are within a small range, and smoothness between adjacent regions. Hence, these algorithms cannot deal with the images with very strong noise and the cases with multiple latent fingerprints.

The third step is to estimate the orientation field of the segmented fingerprint. Since this step is critical for fingerprint enhancement and orientation field is very costly for manual marking, it is the most active research direction for fingerprint feature extraction recently [12], [14]–[16]. Due to the presence of strong noise in most latents, the methods incorporating prior knowledge of fingerprints usually achieved better performance. Since it is not the main contribution of this paper, only the closely related localized dictionaries based method [16] is briefly reviewed. For a more comprehensive and detailed review of published orientation field estimation algorithms, readers can refer to [1], [17].

The localized dictionaries based algorithm [16] takes advantage of location related prior knowledge of fingerprints. Defined by fingerprint center and direction, poses of a set of real training fingerprints are manually marked. The training fingerprints are registered into a unified coordinate system rely on the poses and their orientation fields are manually marked. Real orientation patches along with corresponding positions are extracted and then two models are learned for further processing. The first one is a set of prototype orientation patches and corresponding spatial probability distributions. The second one is a set of localized orientation patch dictionaries containing real orientation patches at respective position. For an unknown fingerprint, its pose can be estimated by selecting the maximum in the Hough images accumulating the prediction for fingerprint pose contributed by all the initial orientation patches. Then in the unified coordinate system, candidate real patches are selected by dictionary lookup at each position respectively and finally optimized along with adjacent compatibility. Although this algorithm achieved the state-of-the-art performance in orientation field estimation for latent fingerprints, it requires manually marked region mask as input, which is inconvenient. If an image contains multiple latent fingerprints and all these latents need to be processed, the region masks of all of them are required, which is even more inconvenient.

In this paper, we propose a systematic latent fingerprint processing algorithm which can detect multiple fingerprints from an image with complex background noise, and for each detected fingerprint, delineate its boundary, and estimate its orientation field. This algorithm consists of two major extensions of our previous algorithm in [16] which requires manual segmentation as input and cannot detect multiple latent fingerprints, namely sequential multi-fingerprint detection and localized dictionaries based fingerprint segmentation.

The sequential multi-fingerprint segmentation algorithm is an extension of the pose estimation algorithm in [16]. It is an iterative algorithm. In each iteration, the pose voting process is performed on the initial orientation field and the maximum response indicating the most possible fingerprint pose is located. If the maximum response is larger than a predefined threshold value, a new fingerprint is detected, and the initial orientation field is modified by removing orientation elements that cast votes for this fingerprint, and next iteration begins. Otherwise the iteration procedure ends.

The localized dictionaries based fingerprint segmentation algorithm is closely coupled with the localized dictionaries based orientation field estimation algorithm in [16]. A full orientation field covering a sufficiently large region is first estimated using the algorithm in [16]. Then a confidence map is computed by comparing initial orientation patches with the corresponding orientation patches retrieved from the localized dictionaries. Finally the fingerprint region is obtained by analyzing the confidence map.

Extensive experiments have been conducted to evaluate the proposed algorithm in terms of accuracies of latent fingerprint segmentation and matching respectively. In order to evaluate the performance of latent fingerprint detection which is a new topic, a multi-latent fingerprint database has been collected and tested. In latent segmentation experiments, the proposed approach achieved a better trade-off curve between Missed Detection Rate (MDR) and False Detection Rate (FDR) than previous approaches. In latent matching experiments, without any manual markup, the proposed method achieved a performance comparable to the state-of-the-art approach [16], which needs manual segmentation.

The rest of this paper is organized as follows. The proposed algorithm is detailed in section II. Then experiments are shown in section III and finally the proposed work is summarized and future work is discussed in section IV.

II. Proposed Algorithm

The proposed algorithm consists of initial orientation field estimation, fingerprint detection, full orientation field estimation, and fingerprint segmentation. Fig. 1 shows the flowchart of the proposed algorithm.

A. Initial orientation field estimation

The following fingerprint detection, segmentation and final orientation field estimation are based on only initial orientation field. Firstly the initial orientation field is estimated by local Fourier analysis. Since the signal-to-noise ratio (SNR) of

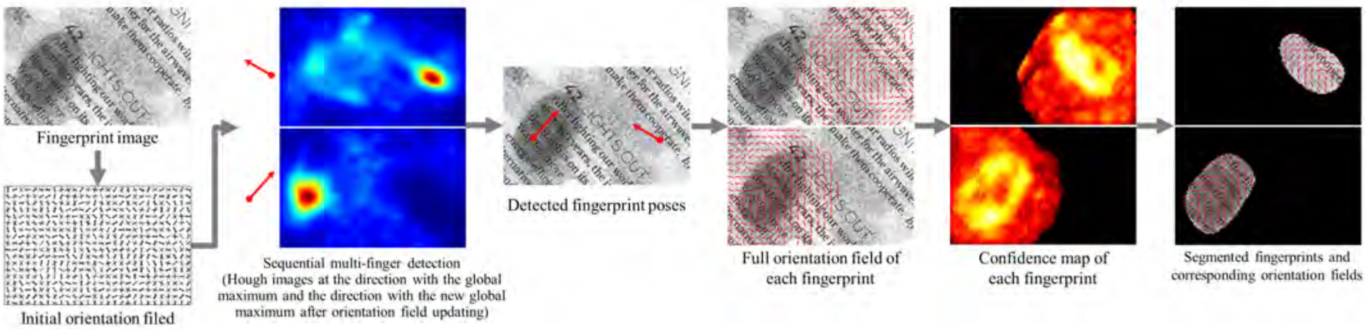


Fig. 1: Flowchart of the proposed latent fingerprint processing algorithm. Initial orientation field is first estimated, and then potential fingerprints are detected. Full orientation field and confidence map of each detected fingerprint are then estimated and finally region mask of each fingerprint is estimated by analyzing the confidence map.

the latent fingerprint ridge may be very low, the strongest response in frequency domain may be noise rather than ridge. Therefore, top 2 orientation elements with highest magnitudes are estimated for each 8×8 image block (for visualization purpose, all the orientation fields drawn in figures are down-sampled to fit bigger image blocks).

B. Fingerprint detection

Though noise in latent fingerprint images are severe and diversified, their combinations in a large area are not like real fingerprints in most situations. Thus, the pose estimation algorithm in [16] can be conducted on the whole initial orientation field to predict the poses of potential fingerprints, since the contribution of background orientation elements are messy and poses of fingerprints will usually receive the highest voting. In latent fingerprint detection, however, there may be more than one latent fingerprint in an image, thus a multi-finger detecting algorithm should be exploited. Simply running the pose voting algorithm in [16] and detecting multiple peaks in the Hough space is not robust. Since each orientation patch casts votes in the whole Hough space, the votes received by some false poses may be higher than some small real ones. We hope one orientation element casts vote only for one pose. To achieve this goal, the following sequential multi-finger detection algorithm is proposed:

1) Denote the initial orientation field as O_1, and let $k = 1$.
2) Based on O_k, the possibilities of kth fingerprint pose on all the positions and quantized directions are predicted by the probabilistic pose voting algorithm in [16].
3) The global maximum of Hough image is located and corresponding parameter (location and direction) is set as the pose of the kth latent fingerprint. If the maximum is smaller than a predefined threshold (empirically set as 1.0), the pose will be set as invalid and the procedure is terminated, and finally poses of $k-1$ latent fingerprints are returned. Otherwise go to the next step.
4) An assumption is used here that each orientation element can only be a part of one fingerprint. Thus to prevent orientation elements belonging to the kth latent fingerprint from casting votes in the following iterations, these orientation elements are removed. One orientation element is said to belong to the kth latent fingerprint if it casts a big enough vote for the kth pose (the threshold is empirically set as 0.001).
5) After removing all the orientation elements belonging to the kth latent fingerprint, we get a new initial orientation field O_{k+1}, and go to step 2.

Obviously, if the above algorithm runs just for one iteration, it degenerates into the pose estimation algorithm in [16].

C. Full orientation field estimation and segmentation

For each pose predicted in the preceding section, a subimage is obtained by cropping the whole image with a fixed sized window centered at the finger center and aligned with respect to the finger direction. Since the foreground mask of this subimage is still unknown, every block where localized orientation patch dictionary is available is regarded as foreground. Then, a full orientation field is computed by the localized dictionaries based method [16]. The similarity between an initial orientation patch and corresponding selected real patch after MRF optimization indicates the possibility (namely, confidence) of this initial orientation patch being a real part of this fingerprint, which is illustrated in Fig. 2. Finally, segmentation can be conducted by binarizing the confidence map.

Detailed steps of the proposed segmentation algorithm are described as follows:

1) Localized dictionary lookup and optimization of MRF are executed as introduced in [16]. As a result, a full orientation field is obtained and at each foreground position an optimized real orientation patch is selected.
2) At each position a confidence is computed by

$$C\left(\boldsymbol{o}_{\mathrm{i}}, \boldsymbol{o}_{\mathrm{r}}\right) = n_{\mathrm{s}}/n_{\mathrm{a}}, \tag{1}$$

between the initial orientation patch $\boldsymbol{o}_{\mathrm{i}}$ and corresponding real orientation patch $\boldsymbol{o}_{\mathrm{r}}$, where n_{s} is the number of orientations whose differences (the closer one is chosen if two initial orientations are available in a block) are less

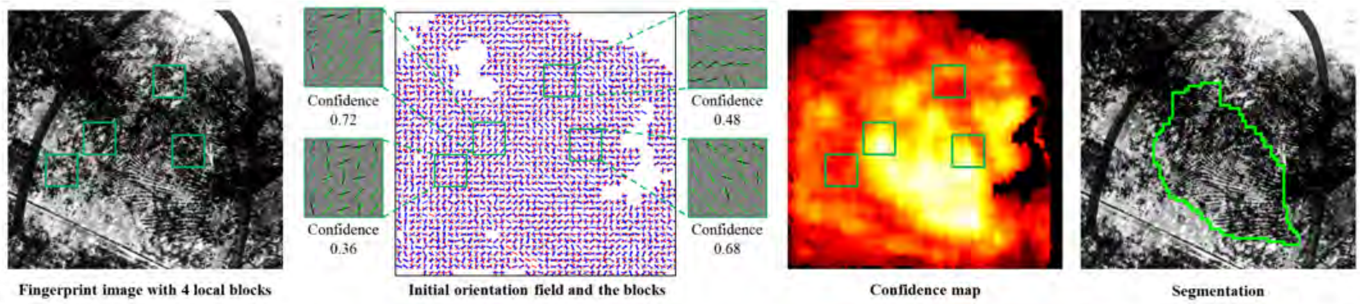


Fig. 2: Example of calculating confidence and segmentation. Four blocks are marked in latent fingerprint image, initial orientation field, and confidence map. In the four orientation blocks, green orientation elements are best real orientation elements optimized by the dictionary lookup process and black orientation elements are closer ones selected in the top 2 orientation elements. Corresponding confidences are placed below the orientation blocks respectively. In this example, the two blocks in the fingerprint region have higher confidences than the other two blocks in the background.

than a predefined threshold (empirically set as $\pi/18$), and n_{a} is the number of valid blocks of $\boldsymbol{o}_{\mathrm{i}}$.

3) The confidence map is smoothed by a 5×5 median filter.
4) A threshold is obtained by Otsu's method based on the smoothed confidence map, then the blocks with confidence higher than the threshold are set as foreground while others are set as background.
5) Morphological operations (eroding and dilating) are conducted on the segmentation image to fill the holes and eliminate small isolated blocks to generate the final foreground mask.
6) The final orientation field is obtained by setting the orientation elements outside of the foreground mask as invalid.

To classify a local image block as foreground or background, traditional fingerprint segmentation methods mainly check if the local image resembles ridge patterns. However, the combination of a set of local images which resemble ridge patterns may not constitute a valid fingerprint. In the proposed method, with the help of finger coordinate system and localized dictionaries, we can consider much more information in the segmentation task: 1) the local image should resemble to real ridge patterns, 2) the local orientation pattern should resemble real orientation patterns at the current location, and 3) the local orientation pattern should be consistent with adjacent orientation patterns. With the above rich information, the proposed method can make more accurate classification between foreground and background in the case of poor quality latent fingerprint images.

III. Experimental results

The proposed algorithm is evaluated in terms of latent fingerprint detection, and accuracies of latent fingerprint segmentation and matching.

A. Detection result

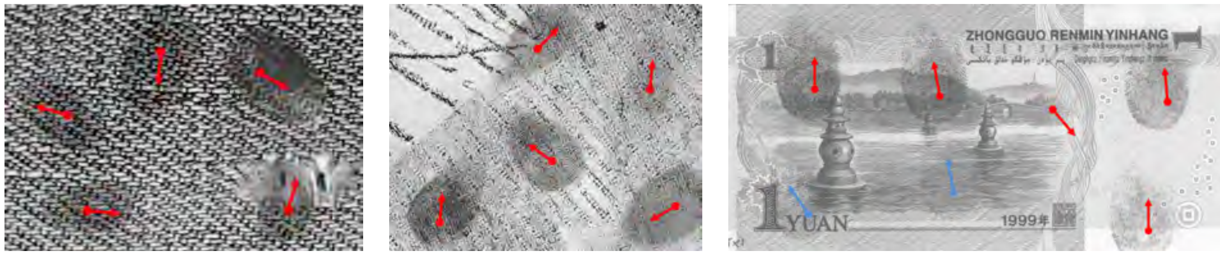
Latent fingerprint databases used in previous studies [10]–[12], [14]–[16], such as NIST SD27 and West Virginia University latent database, are manually cropped images which usually contain a single latent in the center. Since these databases are not suitable for evaluating multi-latent fingerprint detection algorithms, we collected a multi-latent fingerprint database for the evaluation. This database is composed of 11 latent images which contain 5 to 8 latent fingerprints in each of them. Latents in four of these images were collected by pressing inked fingers on paper with complex patterns, another four of them were collected by pressing fingers on paper with complex patterns and then brushing magnetic powder to make them visible, and the rest three were collected by pressing fingers on banknotes and then fumigating by ninhydrin steam for visualizing. Three examples and corresponding detection results by the proposed algorithm are shown in Fig. 3.

B. Segmentation accuracy

For evaluation of latent segmentation algorithms, the most widely used public domain latent fingerprint databases are NIST SD27 and NIST SD27A, which are composed of 258 latent fingerprints and mated rolled ones with resolution of 500 ppi and 1000 ppi respectively. Some segmented results of our algorithm on NIST SD27 are shown in Fig. 4.

The manual segmentations used in [14], [16] are used as the ground truth (available at http://ivg.au.tsinghua.edu.cn/). Since the coordinate systems of latent fingerprints of NIST SD27A are different from the ones of NIST SD27, our ground truth segmentations for SD27 are transformed into the coordinate systems of SD27A manually.

To evaluate the performance of latent segmentation, published literatures compute two numbers: Missed Detection Rate (MDR) and False Detection Rate (FDR) [10]. MDR is defined as the ratio of foreground pixels misclassified as background in all ground truth foreground pixels, while FDR is defined as the ratio of background pixels misclassified as foreground in all automatically segmented foreground pixels. However, it is difficult to compare the performances reported in previous studies [10], [11] because these two numbers can be trade-off and previous studies reported only a single point.



(a) Obtained with ink (b) Obtained with magnetic powder (c) Obtained with ninhydrin

Fig. 3: Examples of three multi-latent fingerprint images. Fingerprints detected by the proposed algorithm is drawn too, in which the red arrows indicate the detected poses (fingerprint centers and directions). In (a) and (b), all detected poses are correct and there is no false detection or missed detection. In (c), however, there is a false one and meanwhile, two latent fingerprints marked by blue arrows are missed.

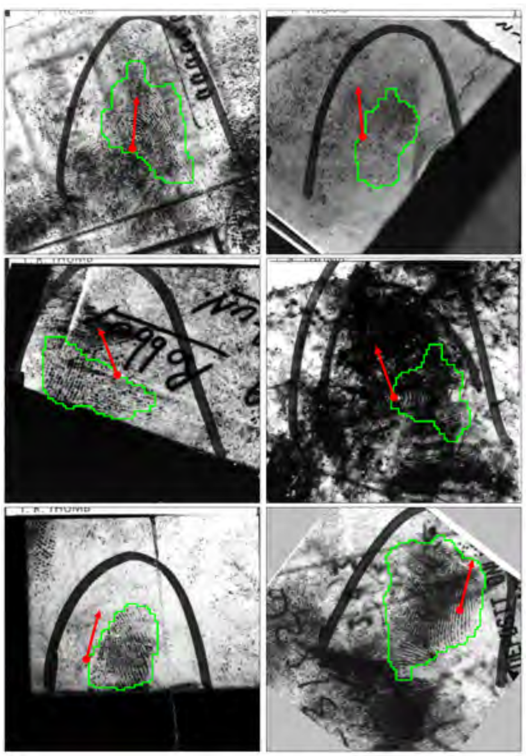
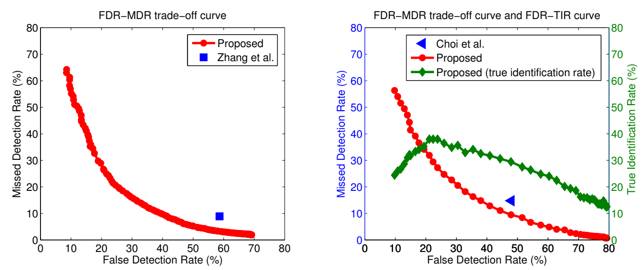


Fig. 4: Experimental results of detection and segmentation on six latent fingerprint images. Note that the proposed algorithm can predict the finger center even when the finger center is not visible.



(a) Compared with Zhang *et al.* [11] on NIST SD27A (b) Compared with Choi *et al.* [10] on NIST SD27

Fig. 5: Segmentation performances of the proposed algorithm and two other algorithms. (a) FDR-MDR trade-off curve on NIST SD27A. (b) FDR-MDR trade-off curve and FDR-TIR curve on NIST SD27. The relationship between FDR and TIR is illustrated by the green curve.

In order to give a complete evaluate of segmentation accuracy, we plot FDR-MDR trade-off curve.

Another limitation of the previous evaluation method in [10], [11] is that they did not consider the relationship between segmentation performance and matching performance. Since the final goal of segmentation is matching, we wish to learn what region of FDR and MDR is better for matching performance. We use VeriFinger SDK 6.2 for computing matching scores between segmented and enhanced latent fingerprints and mated rolled fingerprints. A genuine match score higher than or equal to 30 is viewed as a true identification and true identification rate (TIR) is computed over all latent fingerprints in NIST SD27. Our experience with VeriFinger SDK shows that this definition of TIR is very related with rank 1 identification rate, but takes much less time in running experiments. The FDR-TIR curve illustrates the relationship between segmentation and matching performance, and indicates what is a good segmentation in terms of matching accuracy.

Firstly, we compare our algorithm with the state-of-the-art segmentation algorithm Zhang *et al.* [11], whose segmentation results are available online. However, it is unclear what ground truth was used in [11] and hence we evaluate both their segmentation results and ours on SD27A using our ground truth. The result is shown in Fig. 5a. Note that probably due to the difference of the ground truth, the performance of Zhang *et al.* [11] evaluated according to our ground truth is different from their published performance.

Another state-of-the-art segmentation algorithm Choi *et al.* [10] was evaluated on NIST SD27. Since their algorithm and segmentation results are not publicly available, we directly

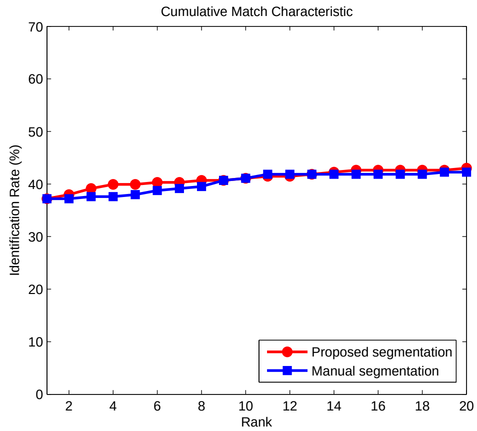


Fig. 6: CMC curves of two segmentation methods (proposed automatic and manual) combined with the LocalDict orientation field estimation algorithm [16].

draw their published performance along with our curve in Fig. 5b. Note that due to the differences in image region and contrast, the segmentation results of the proposed approach conducted on NIST SD27 and NIST SD27A are slightly different. Besides the FDR-MDR trade-off curve, the FDR-TIR curve is also shown in Fig. 5b. The FDR-TIR curve indicates that the best identification performance is obtained at a low FDR (22%). A lower FDR is important for matching because minutiae matchers are usually more sensitive to spurious minutiae than missing minutiae. Zhang *et al.* [11] and Choi *et al.* [10] produce very high FDRs (59% and 48%), which means that more than half of the segmented foreground region is in fact background region. This will produce many spurious minutiae, which is very harmful to minutiae matching.

C. Matching accuracy

Since the final goal of feature extraction is to improve matching accuracy, matching experiment is conducted on NIST SD27 to evaluate the proposed algorithm. To make the evaluation more realistic and challenging, 27,000 fingerprints in NIST SD14 is used as the background database. The LocalDict algorithm [16] with manually marked foreground is used for comparison. With the estimated orientation fields by above algorithms respectively, all the fingerprints are enhanced with the same enhancement strategy [4] in [16]. Then VeriFinger SDK 6.2 is used to extract minutiae from enhanced fingerprints and compute the match scores between latents and rolled fingerprints. Finally, the Cumulative Match Characteristic (CMC) curve is used to evaluate the matching performance, as shown in Fig. 6. As we can see from the figure, the two methods produce similar performances.

IV. Conclusion and Future Work

In this paper, we proposed an automatic latent fingerprint processing algorithm, which addressed a major limitation of our localized dictionaries based orientation field estimation algorithm [16], i.e., automatic fingerprint detection and segmentation. The proposed approach achieved a good recall-precision trade-off performance on a multi-latent fingerprint database and a better trade-off curve between MDR and FDR than previous segmentation approaches. In latent matching experiments, with identical condition in all other aspects, the proposed automatic segmentation achieved a comparable performance with manual segmentation.

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