Latent Fingerprint Matching: Fusion of Manually Marked and Derived Minutiae

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***Abstract*—Matching unknown latent fingerprints lifted from crime scenes to full (rolled or plain) fingerprints in law enforcement databases is of critical importance for combating crime and fighting terrorism. Compared to good quality full fingerprints acquired using live-scan or inking methods during enrollment, latent fingerprints are often smudgy and blurred, capture only a small finger area, and have large nonlinear distortion. For this reason, features (minutiae and singular points) in latents are typically manually marked by trained latent examiners. However, this introduces an undesired interoperability problem between latent examiners and automatic fingerprint identification systems (AFIS); the features marked by examiners are not always compatible with those automatically extracted by AFIS, resulting in reduced matching accuracy. While the use of automatically extracted minutiae from latents can avoid interoperability problem, such minutiae tend to be very unreliable, because of the poor quality of latents. In this paper, we improve latent to full fingerprint matching accuracy by combining manually marked (ground truth) minutiae with automatically extracted minutiae. Experimental results on a public domain database, NIST SD27, demonstrate the effectiveness of the proposed algorithm.**

***Keywords*-latent fingerprint; fingerprint matching; rolled fingerprint; enhancement; minutiae extraction; interoperability**

I. Introduction

Fingerprints have been routinely used as a method for person identification for more than a century. One of the irreplaceable functionality of fingerprint recognition is its capability to link partial prints found at crime scenes to suspects who are enrolled in a large fingerprint database. These partial prints, called latent fingerprints or simply latents, are lifted from surfaces of objects that are inadvertently touched or handled by a person. Lifting of latents may involve a complicated process, and it can range from simply photographing the print to more complex dusting or chemical processing. Compared to rolled or plain fingerprints, which are captured by inking methods or livescan devices in an attended mode, latent fingerprints are smudgy and blurred, capture only a small finger area, and have large nonlinear distortion due to pressure variations (see Fig. 1). Due to their poor quality and small area, latents have a significantly smaller number of minutiae compared to rolled or plain prints (the average number of minutiae in NIST Special Database 27 (NIST SD27) [1] images is 21 for latents versus 106 for the corresponding rolled prints).

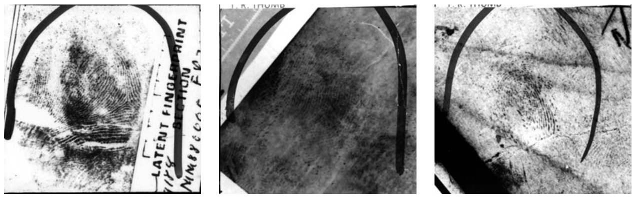
(a) (b) (c)

Figure 1. Fingerprints obtained by different acquisition methods. (a) Rolled ink (NIST SD27), (b) live-scan (FVC2002), and (c) latent (NIST SD27).

Before the introduction of Automatic Fingerprint Identification Systems (AFIS), fingerprint matching (both full to full and latent to full) was performed by fingerprint examiners. Latent print matching requires substantial human intervention through a procedure referred to as ACE-V, namely, analysis, comparison, evaluation and verification. Unlike full print to full print matching, which is somewhat facilitated by fingerprint pattern type, manually matching a latent print against a large gallery (database) is not feasible. Generally, latents are only matched against full prints of a small number of suspects who are identified based on other evidential means (e.g. gender, ethnicity, age, etc.).

The emergence of AFIS makes searching large fingerprint databases for mates of a latent print feasible. A typical latent matching procedure consists of following stages: (i) manually mark the features, (ii) launch an AFIS search, and (iii) visually verify each of the candidate fingerprints returned by AFIS. However, compared to full print matching, existing latent matching techniques are not satisfactory in terms of accuracy and speed. To overcome these limitations, there are two extreme strategies: one consists of developing a fully automatic latent feature extraction and matching system, so-called “Lights-Out” system, which does not require any input from latent examiners; the other one consists of requiring latent examiners to provide as many manually marked features in latents as possible to improve the matching accuracy.

In the long run, “Lights-Out” latent identification capability is desirable. Consider the following two scenarios: (i) a



(a) (b) (c)

Figure 2. Latent fingerprints of three different quality levels in NIST SD27. (a) Good, (b) Bad, and (c) Ugly.

patrol officer wants to check fingerprints of a suspect against latent fingerprints from unsolved cases; (ii) a crime scene specialist hopes to identify latents lifted at a crime scene in the field. In both these cases, it would be desirable to get a quick (real time) response to the query. To understand and advance the state of the art in automatic latent feature extraction and matching, NIST has been conducting a multi-phase project on Evaluation of Latent Fingerprint Technologies (ELFT)[2]. The rank-1 accuracy of the most accurate system in ELFT Phase I was 80% in matching 100 latents against $10,000$ rolled prints. Much higher accuracies were reported in ELFT Phase II organized shortly after Phase I. The rank-1 accuracy of the most accurate system in Phase II was 97.2% in matching 835 latents against a gallery of $100,000$ rolled prints. Unfortunately, Phase I and Phase II accuracies cannot be compared because different databases were used in the two evaluations. Further, the Phase II accuracy does not reflect the performance in field applications, since the latents used in Phase II are of very good quality. Fig. 2 shows three latents of different qualities in NIST SD27.

For latent matching, current AFIS mainly use minutiae and singular points. In recognizing that latent examiners routinely use additional features during manual latent matching, fingerprint community has recently started to investigate the value of extended features. A committee, CDEFFS, was established to define a set of standards for extended features in fingerprints. In [3], extended features, including ridge flow map, ridge wavelength map, ridge quality map, and ridge skeleton, were combined with minutiae to improve the matching accuracy. However, all the features in latents were manually marked in this study, which requires extensive manual labor. NIST has recently launched the ELFT-EFS Evaluation 1 to evaluate the extended feature matching techniques of major fingerprint vendors.

It is our opinion that research efforts in latent fingerprint identification should be focused on improving the matching accuracy based on existing mark-ups by latent experts, rather than on completely eliminating manual input, or asking examiners for too much input. This opinion is supported by the following facts: (i) latent matching accuracy is still the major concern of law enforcement agencies, (ii) manually marking extended features is very labor extensive, and (iii) state of the art "Lights-Out" latent identification systems cannot yet offer satisfactory accuracy for most latents of casework quality.

In the current practice, latent examiners are required to mark minutiae and optionally mark singular points (core/delta). In this paper, we assume that the manually marked features include the Region of Interest (ROI), singular points, and minutiae. Orientation field can usually be reliably estimated from the image in the case of rolled or plain fingerprints of good quality. In latent fingerprint images, this estimation is not very reliable because of their poor quality. Manually marked orientation field, although reliable, is not easy to obtain; it requires a lot of manual effort. Therefore, we reconstruct the orientation field based on manually marked features (minutiae and singular points). Gabor filters are used to enhance latent images, which are automatically matched to the rolled print database. We show that the performance of manually marked minutiae matching can be improved by combining scores from both manually marked minutiae matching and automatically extracted minutiae from enhanced latent matching. The performance of fully automated minutiae extraction and matching based on the input image is very poor. The experiments were conducted on a public domain fingerprint database, NIST SD27, consisting of 258 latents along with their rolled mates. To make the conclusion more reliable, the gallery size was increased by including $27,000$ rolled images from NIST SD14 [4]. The softwares used for minutiae extraction and matching was VeriFinger SDK [5].

II. Orientation Field Estimation

The value of an orientation field at a given pixel is the angle that the fingerprint ridges form with the horizontal axis in a small neighborhood around that pixel. The simplest and the most natural approach for computing orientation field is based on the gradient values. Because of the computational effort and the presence of noise, the orientation field is usually computed in a small neighborhood instead of at each pixel [6].

Another approach to compute the orientation field that differs from this image-based approach is the model-based approach (e.g. zero-pole model [7], [8], [9]), which uses the location of singular points to estimate the orientation field based on a model.

In the latent fingerprint case, since the images are usually of poor quality, it is very difficult to estimate the orientation field based only on the image itself. Also, in many cases, the region of the latent fingerprint is small and does not contain singular points, which makes the model-based orientation field unreliable. A combination of image-based and model-based approaches can be very useful for latents. In [10], such a combination was used to enhance the latent fingerprint images and it was shown to improve the matching performance compared to the performance based on latent image alone.

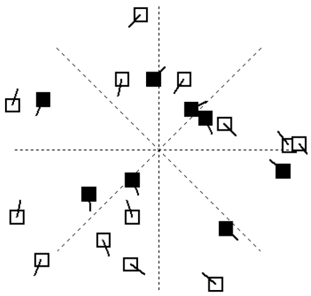


Figure 3. Local ridge orientation estimation based on the nearest minutiae in each sector.

In [11], the authors proposed a method to reconstruct the orientation field assuming (i) only the minutiae information (location and direction) is given, and (ii) both minutiae and singular point are given. The advantages of this approach over the previously mentioned ones are: it can be used in cases where no singular points are available (small area latents) and it uses minutiae information that is reliable. Our experiments show that when this reconstructed orientation field is used for latent enhancement, the matching performance of the enhanced image is comparable to the matching performance of images enhanced by manually marked orientation field. Therefore, we adopt this approach which is described in detail below.

A. Minutiae based Orientation Field Reconstruction

In this section, we describe the method proposed in [11] to reconstruct the orientation field based on minutiae and singular points, if available. Here we assume that a latent expert has marked the minutiae and singular points. Also, in cases in which an odd number of singular points were marked in the region of interest, paired singular points outside of the region of interest are guessed (referred to as virtual singular points [10]) to satisfy the constraints of singularity number, which states the total number of singular points is even, and the numbers of cores and deltas are the same.

Because of the reasons mentioned in Section II, the orientation field is also computed in non-overlapping blocks of a predefined size (e.g. 8×8 or 16×16). Now, consider lines passing through the non-overlapping blocks, that divides the image into 8 equally spaced sectors as shown in Fig. 3. Then, a local orientation field estimate is obtained for each block based on the direction of the nearest minutia in each of the 8 sectors.

Let $\{x_n, y_n, \alpha_n\}$, $1 \leq n \leq N$, be a set of N fingerprint minutiae marked by a latent expert, where (x_n, y_n) is the location and α_n is the direction of the n^{th} minutia. Then, by doubling the minutia direction α_k, which means taking $2\alpha_k$ instead of α_k as the minutia direction, it becomes equivalent to $\alpha_k + \pi$ (this is necessary since fingerprint ridges are not oriented). For the K minutiae selected in eight sectors, cosine and sine components can be computed and summed as follows:

$$u = \sum_{k=1}^{K} cos(2\alpha_k) w_k, \tag{1}$$

$$v = \sum_{k=1}^{K} sin(2\alpha_k) w_k, \tag{2}$$

where w_k is a weighting function based on the Euclidean distance between the block center and the k^{th} minutia that makes the closest minutia direction dominates the ridge orientation of neighboring blocks.

The orientation at block (m, n) is then computed as:

$$D(m,n) = \frac{1}{2} \arctan \frac{v}{u}. \tag{3}$$

We also consider that singular points have been marked in some of the latent fingerprints. In those cases, the direction field of N_s singular points is given by the Zero-Pole model [7], [8]:

$$D_s(m,n) = \sum_{i=1}^{N_s} t_{s_i} \arctan \frac{n - n_{s_i}}{m - m_{s_i}}, \tag{4}$$

where m_{s_i}, n_{s_i}, and t_{s_i} (core: 1, delta: -1) are the location and type of the i^{th} singular point.

Orientation field is first estimated using minutiae whose direction is subtracted by D_s. The reconstructed orientation field is then given by

$$O(m,n) = \frac{2D(m,n) + D_s(m,n)}{2}. \tag{5}$$

If there are no marked singular points, the orientation field is reconstructed simply as $D(m, n)$.

Fig. 4 shows some examples of reconstructed orientation field. The first column shows the original latent image, the second column shows the orientation field estimated directly from the gray scale image, the third column shows the reconstructed orientation field and the fourth column shows manually marked orientation field. We can observe that it is not easy to estimate the orientation field from the latent image. But, the reconstructed orientation field from minutiae and singular points is quite reliable, although it is not as smooth as manually marked orientation field.

III. Fingerprint Image Enhancement

Automatic and reliable extraction of minutiae from poor quality images is a very difficult problem. Image enhancement is one way of improving the matching performance, as shown in [12], where a method based on the estimated local ridge orientation and frequency is proposed to improve the clarity of ridges and valleys. For latent images, it is very difficult to obtain a reliable orientation field based on the image itself. Also, the ridge frequency estimated from the

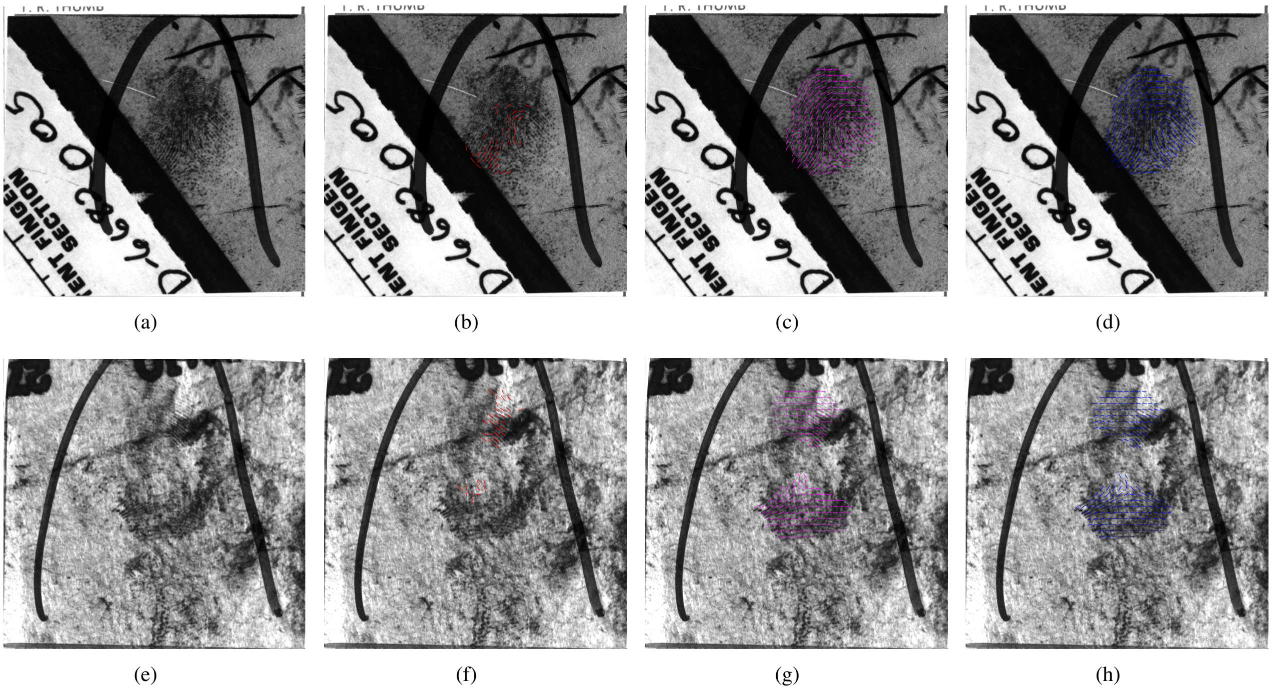


Figure 4. Comparison of orientation field estimation methods: (a) and (e) Original latent fingerprint images, (b) and (f) orientation fields estimated directly from the given images, (c) and (g) orientation fields estimated from minutiae and singular points, and (d) and (h) manually marked orientation fields.

latent image is not reliable. Therefore, we applied the enhancement process proposed in [12] using the reconstructed orientation field described in Section II-A and the median ridge frequency estimated in small image blocks. Fig. 5 shows some examples of enhanced latent images, along with their skeletons, the corresponding enhanced images and their enhanced image skeletons. It can be noted from the figure that the clarity of the ridges improves and the noise is greatly reduced.

IV. Fusion

Another approach that is often used to improve the matching accuracy consists of combining different sources of information. A combination can be implemented at a variety of levels, such as feature level, score level, and rank level. Feature level fusion in our context would involve both manually marked minutiae and automatically extracted minutiae for matching. In early experiments, this fusion level did not show promising results, so we focus at the other two fusion levels, rank and score.

A. Rank-level Fusion

For rank-level fusion, we considered two techniques: Borda count [13] and the highest rank method.

Borda count is a generalization of the majority vote. In our case where we have two different “classifiers” (one matching manually marked latent to rolled and the other matching enhanced latent image to rolled), the Borda count for a given finger will be the sum of the number of fingers that are ranked below the true finger by each classifier. Then, the ranking is performed by sorting the fingers in descending order based on their Borda count. The magnitude of the Borda count for each finger in the database measures how much the different classifiers agree on whether the input comes from the same finger as the latent.

In the highest rank approach, each finger in the database is assigned the highest rank as computed by different “classifiers” [14]. If there are any ties, the fingers are sorted by their lower rank. If both higher and lower ranks are the same, the tie is broken randomly.

Our experiments show that Borda count does not improve the matching performance of manually marked minutiae. The highest rank shows some improvement. These results will be discussed in Section V-B.

B. Score-level Fusion

Min, max, product and weighted sum rules are well-known score-level fusion rules. Let s_1 and s_2 be two matching scores obtained for the same (latent, rolled) fingerprint pair by using two different sources 1 and 2. Then, for the score pair s_1 and s_2 we can compute fused scores based on each one of the score level fusion rules mentioned above by:

$$\begin{aligned} S_{min} &= \min(s_1, s_2) \\ S_{max} &= \max(s_1, s_2) \\ S_{prod} &= s_1 s_2 \\ S_{wsum} &= w_1 s_1 + w_2 s_2 \end{aligned} \tag{6}$$

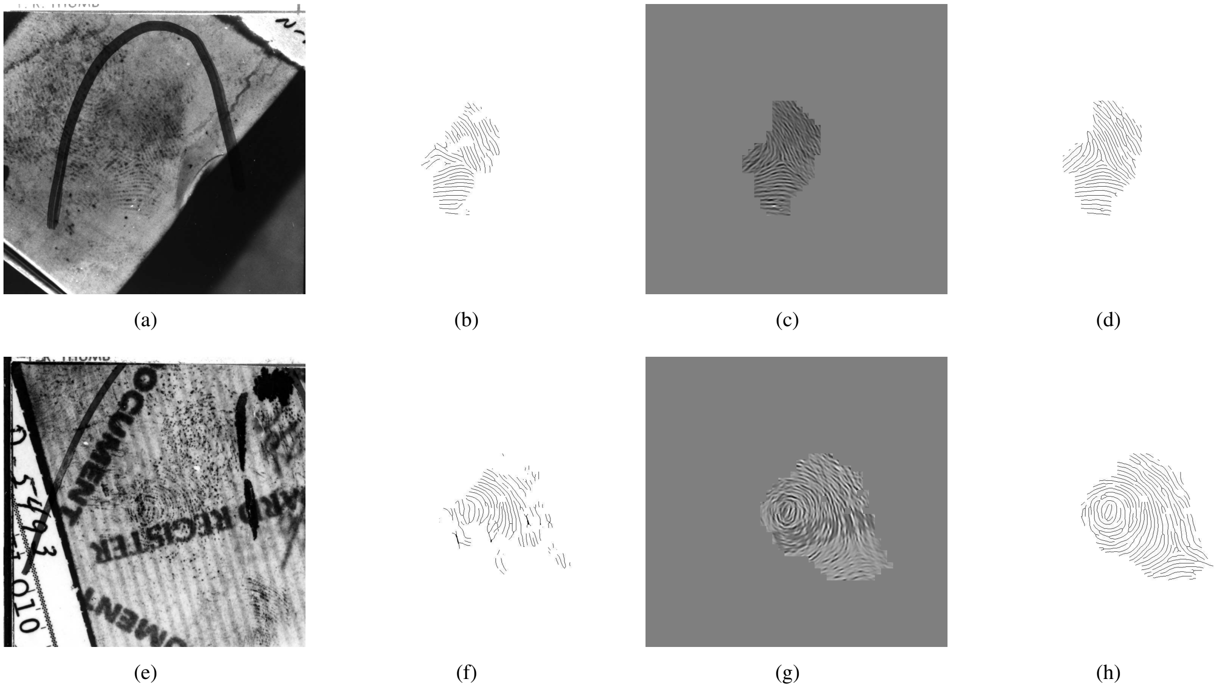


Figure 5. Examples of enhanced latent images. (a) and (e) are original latent images, (b) and (f) are the skeletons of the original latent images extracted by VeriFinger, (c) and (g) are enhanced images using reconstructed orientation field, and (d) and (h) are the skeletons of the enhanced images extracted by VeriFinger.

We propose to combine the two matching scores by applying a slight modification of the boosted max fusion approach proposed in [15]. The main purpose of boosted max is to boost the scores of genuine matches. It relies on the assumption that the spatial transformations among latent, enhanced and rolled fingerprints are consistent for genuine matches and inconsistent for impostor matches.

Let T_{MR}, T_{ER}, and T_{ME} be the best transformation between manually marked minutiae and rolled fingerprints, enhanced latent images to rolled fingerprints, and manually marked minutiae to enhanced latent images, respectively. Given T_{ER} and T_{ME}, we can compute $T_{MER} = T_{ER} * T_{ME}$, which denotes the spatial transformation of the manually marked latent to the enhanced, which is then matched to the rolled fingerprint image. The transformations T_{MR} and T_{MER} should be similar for genuine pairs and different for impostor pairs. The similarity between the two transformation matrices is measured in terms of the rotation angle and the Euclidean distance between the translations in x and y directions of each transformation. If the difference between the two rotation angles in the two matrices T_{MR} and T_{MER} is less than some threshold and the Euclidean distance between the two translations in those same matrices is less than another threshold, then the pair is considered consistent. In our study, the rotation and translation thresholds were set to 30 degrees and 140 pixels, respectively. The boosted max score for a given pair of scores s_1 and s_2 is

$$S_b = \begin{cases} w_1 \max(s_1, s_2) + w_2 \min(s_1, s_2), & if\, consistent \\ \max(s_1, s_2), & otherwise. \end{cases} \quad (7)$$

In the next section, we discuss the results obtained by using enhanced images and different fusion schemes.

V. Experimental Results

Matching experiments were conducted on the NIST Special Database 27, which consists of 258 latent fingerprint images and 258 mated rolled fingerprint images. NIST SD27 contains images of three different qualities, termed “good”, “bad”, and “ugly”. Some examples of these images were shown in Fig. 2. The manually marked features in the latents in this database are region of interest (ROI), minutiae, visible singular points (inside the ROI) and “virtual” singular points (outside the ROI). To make the matching problem more challenging and realistic, the background database (gallery) was increased from 258 mated rolled fingerprints to $27,258$ total rolled fingerprints by adding $27,000$ fingerprint images from the database NIST SD14. For the rolled fingerprint images, only minutiae were needed for matching and they were automatically extracted using Verifinger [5]. For boosted max, the transformations were computed based on the matched minutiae output by Verifinger for each pair of fingerprints being matched.

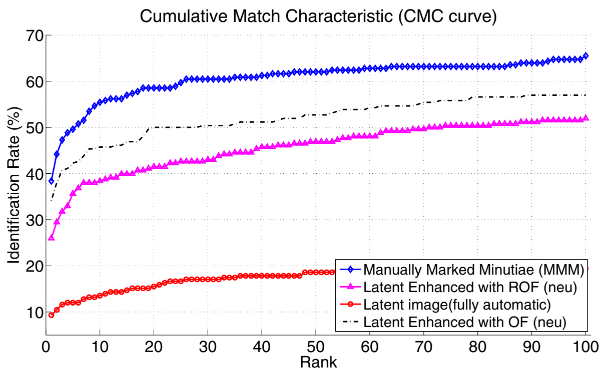


Figure 6. CMC curves for manually marked minutiae, enhanced image using reconstructed orientation field, automatically extracted minutiae from latent image and enhanced image using manually marked orientation field.

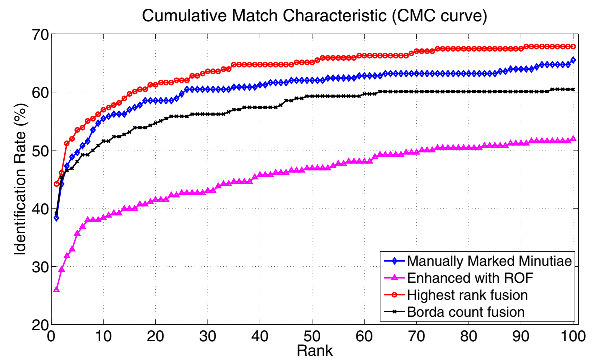


Figure 7. CMC curves for manually marked minutiae, enhanced image using reconstructed orientation field, highest score rank-level fusion and Borda count fusion.

A. Latent enhancement

The latent images from NIST SD27 were enhanced using the approach described in [12]. In addition, since latent images are usually of poor quality, ridge frequency values were estimated for each image block, and the median of those values was chosen as the frequency for the entire image. We also tested a constant frequency value for all the images, and different frequency values in each block of the image, but the median frequency value provided the best performance and therefore the results shown here are based on it.

The matching performance of enhanced latent images using reconstructed orientation field against rolled fingerprints is much better than the matching performance using minutiae automatically extracted from the original latent image. The matching performance of enhanced images is worse than the performance of manually marked minutiae. However, this performance is comparable to the matching performance of enhanced images using manually marked orientation field, which requires significantly more manual labor. Fig. 6 shows the Cumulative Matching Characteristic curves on NIST SD 27 for manually marked minutiae, enhanced images using reconstructed orientation field, automatically extracted minutiae from latent image, and enhanced images using manually marked orientation filed.

B. Fusion methods

We performed experiments using different fusion levels and methods. These fusion scenarios always used manually marked minutiae-based information and enhanced images using reconstructed orientation field-based information (scores, ranks, etc). We found Borda count (rank-level) could not improve the matching performance of manually marked minutiae. This might be because Borda count method assumes all the matchers perform equally well, which is not true in our case. However, the highest rank fusion improved the matching performance most of the time, as can be seen in Fig. 7. The highest rank fusion explores the strength of each matcher more effectively, since being assigned a high rank from only one of the matchers increases the likelihood of receiving a high rank after the second sorting.

Min and product fusion rules do not improve the matching performance while the Max rule provides very minor improvement. The best results were obtained using weighted sum rule and boosted max (Fig. 8(a)). At rank 1, the improvement due to boosted max is approximately 10% over all image quality levels as well as for each quality level separately. This means boosted max was able to correctly rank 25 additional latents than using manually marked minutiae alone. In the case of latent search, since the AFIS accuracy is not sufficiently high, the output is a list of N candidates for comparison by a latent examiner.

For good quality images, although the boosted max performed better than manually marked minutiae in the top few ranks, its performance dropped for some ranks (Fig. 8(b)). This might indicate that the best approach for good quality latents is the simple sum rule. For bad quality images, the boosted max outperformed manually marked minutiae by an average of 10% at all ranks (Fig. 8(c)). In the bad quality images, boosted max shows consistent improvement at all ranks compared to manually marked minutiae, and performs better for the first 30 ranks compared to the sum rule (Fig. 8(d)).

As discussed in Section IV-B, we modified the boosted max approach to include a second weight. Therefore, two different parameters (weights w_1 and w_2) must be specified in order to apply the boosted max. These two weights do not need to sum to one because the purpose is to boost the scores of image pairs that are found to be consistent. The computation of the transformation matrices used to decide the consistency between a pair of fingerprints in boosted max approach is based on the matched minutiae output by VeriFinger. Ideally, T_{ME} should be the Identity matrix because the two sets of minutiae are extracted from the same image, in practice manually markings and automatically extracted minutiae differ in their positions, which leads to a transformation matrix near to the Identity matrix, but not exactly the same.

We observed that in almost all cases, if the mated rolled finger was ranked first in one of the matching experiments (manually marked minutiae or enhanced images), it was also ranked first in the boosted max approach. Fig. 9(a) shows an example of this case where the latent was ranked 1 by manually marked minutiae, ranked $2,403$ by enhanced image, and ranked 1 by boosted max.

Boosted max ranked true mated rolled fingerprints at a lower rank in only two cases that were ranked first by manually marked minutiae (two good quality images). It also corrected the rank in eleven cases (4 good quality, 3 bad and 4 ugly quality latents). This means the mated rolled was not ranked first in neither manually marked minutiae nor enhanced images, but it was ranked first after boosted max fusion. Fig. 9(b) shows an example of a latent that was ranked as 268 by manually marked minutiae, ranked 2 by enhanced image, and ranked 1 by boosted max.

VI. Conclusions

Latent matching is a very difficult problem due to their poor quality and small area. A fully automatic system is desired, but given the difficulty of the problem and the poor performance of available AFIS, manual input is still needed.

We have shown that the performance of manually marked minutiae in latents can be improved by utilizing automatically extracted minutiae from enhanced latent images. This framework consists of the following steps: (i) reconstruct the orientation field based on manually marked minutiae and singular points; (ii) enhance the latent using median ridge frequency computed in small image blocks and the reconstructed orientation field; (iii) match enhanced latents and rolled fingerprints; (iv) combine the scores from two matchers using boosted max. This framework improved the latent matching performance irrespective of their quality. To make the matching problem more challenging, realistic and the conclusions more reliable, the background database (gallery) was increased from 258 mated rolled fingerprints to $27,258$ total rolled fingerprints by adding $27,000$ fingerprint images from the database NIST SD14.

Although the reconstructed orientation field is comparable to ground truth orientation field, it is not completely accurate. During image enhancement, if the estimated orientation field in a block is not reliable, spurious minutiae can be created. Therefore, improving the orientation field reconstruction is necessary for better performance. We used manually marked ROI to reconstruct the orientation field and enhance the image only inside that region. Our ongoing work reconstructs a larger part of the latent image to use in the matching process.

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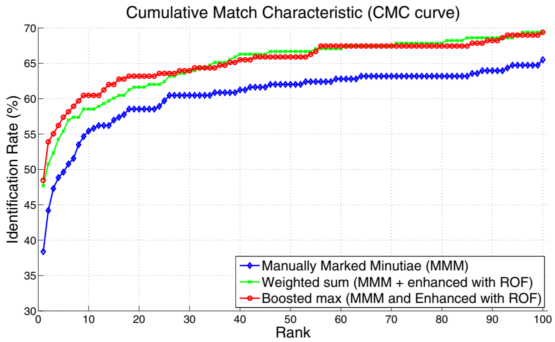
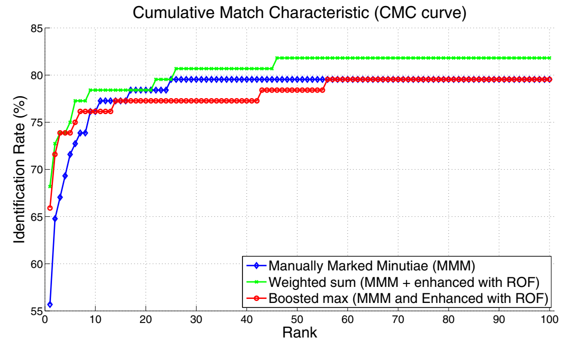
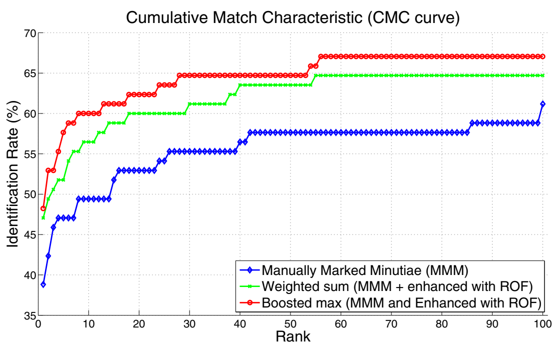


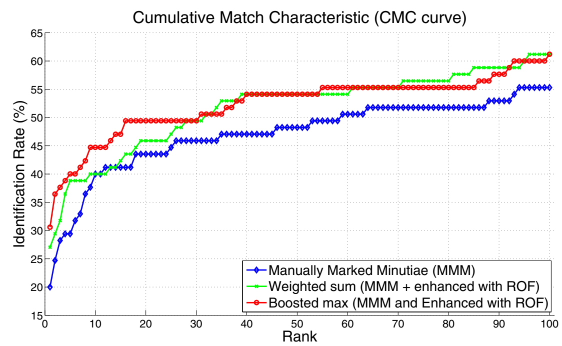
(a) All quality images



(b) Good quality images

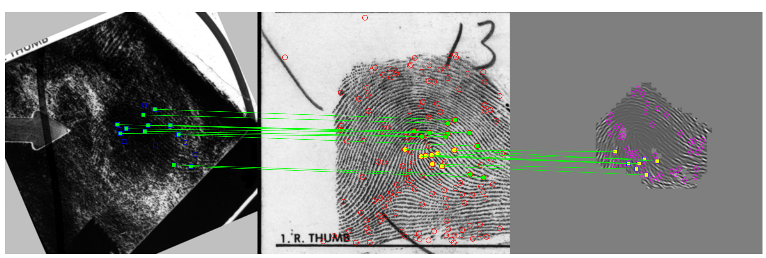


(c) Bad quality images

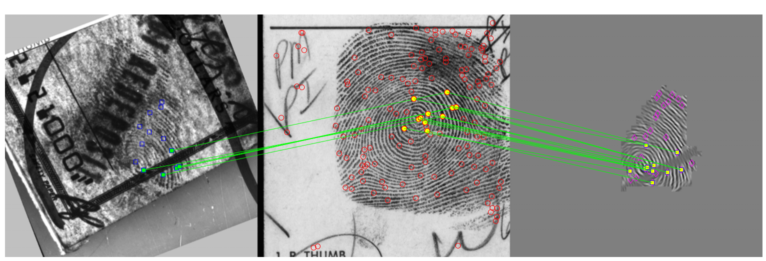


(d) Ugly quality images

Figure 8. CMC curves for score level fusion separated by quality.



(a)



(b)

Figure 9. Matched minutiae shown for manually marked, rolled and enhanced latent images. (a) Boosted max ranked this latent first even though one of the ranks (enhanced image) was $2,403$ and (b) the rank for this latent is first after boosted max was applied even though neither manually marked minutiae or enhanced image ranked it first.