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Orientation Field Estimation for Latent Fingerprint Enhancement

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Abstract—Identifying latent fingerprints is of vital importance for law enforcement agencies to apprehend criminals and terrorists. Compared to livescan and inked fingerprints, the image quality of latent fingerprints is much lower, with complex image background, unclear ridge structure, and even overlapping patterns. A robust orientation field estimation algorithm is indispensable for enhancing and recognizing poor quality latents. However, conventional orientation field estimation algorithms, which can satisfactorily process most livescan and inked fingerprints, do not provide acceptable results for most latents. We believe that a major limitation of conventional algorithms is that they do not utilize prior knowledge of the ridge structure in fingerprints. Inspired by spelling correction techniques in natural language processing, we propose a novel fingerprint orientation field estimation algorithm based on prior knowledge of fingerprint structure. We represent prior knowledge of fingerprints using a dictionary of reference orientation patches, which is constructed using a set of true orientation fields, and the compatibility constraint between neighboring orientation patches. Orientation field estimation for latents is posed as an energy minimization problem, which is solved by loopy belief propagation. Experimental results on the challenging NIST SD27 latent fingerprint database and an overlapped latent fingerprint database demonstrate the advantages of the proposed orientation field estimation algorithm over conventional algorithms.

Index Terms—Fingerprint matching, fingerprint enhancement, latent fingerprint, orientation field, dictionary, spelling correction.

1 Introduction

Latent fingerprints refer to the impressions unintentionally left on items handled or touched by fingers. Such fingerprints are often not directly visible unless some physical or chemical technique is applied to enhance them [1]. Since the early 20th century, latent fingerprints have served as important evidence for law enforcement agencies to apprehend and convict criminals [2].

Compared to fingerprints captured using inking or livescan techniques (see Fig. 1), the quality of most latent fingerprints is very low, with unclear ridge structure, uneven contrast, and overlapping patterns, such as printed letters, handwriting, or even other fingerprints [3]. Because of the poor image quality, features (such as minutiae) in latents need to be manually marked by latent examiners so that they can be searched against large fingerprint databases by automated fingerprint identification systems (AFIS).

Automatic latent feature extraction is desirable for several reasons.

1) Reducing the time spent by latent examiners in manual markup. A crime scene can contain as many as hundreds of latents. However, only a small portion of them can be processed simply because law enforcement agencies do not have sufficient manpower. It can take twenty minutes or even longer to mark the minutiae in a single latent. Automatic feature extraction can improve the efficiency of processing latents, leading to more identifications quickly [4].
2) Improving the compatibility between minutiae in latent and full fingerprints. In current practice, minutiae in latents are manually marked while minutiae in full fingerprints are automatically extracted. This can cause the compatibility problem. Although this compatibility issue is not a severe problem for full fingerprint matching, this problem cannot be underestimated in the case of latent matching, since in a tiny and smudgy latent, every minutia plays an important role. To address this issue, AFIS vendors usually provide training courses to latent examiners on how to better mark minutiae for their particular AFIS system since different vendors' systems are not very consistent in extracting minutiae. However, it takes time for fingerprint examiners to get familiar with a system. This problem can be alleviated provided features in latents are also extracted by automatic algorithms.
3) Improving repeatability/reproducibility of latent identification. The minutiae in the same latent marked by different latent examiners or even by the same examiner (but at different times) may not be the same. This is one of reasons why different latent examiners or even the same examiner (but at different times) make different matching decisions on the same latent-exemplar pair [5], [6]. The *Daubert* standard, which

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(a) (b) (c)

Fig. 1. Fingerprints obtained using three types of techniques. (a) Inked fingerprint, (b) live-scan fingerprint, and (c) latent fingerprint.

specifies the admissibility of scientific testimony in United States courts, requires that the error rate of latent matching should be known. However, lack of repeatability/reproducibility makes estimating the error rates of latent examiners very difficult [7]. Even if an error rate can be estimated by a "black box" test[1] [5], it cannot apply to a different examiner's decision on a new latent-exemplar pair. The only viable solution appears to be to keep improving automated fingerprint systems' performance so that the role of latent examiners is limited to very difficult latents. Hence, automating latent feature extraction is an indispensable step towards this long-term goal.

To enable reliable feature extraction, a latent fingerprint image, which is often of very poor quality, needs to go through an image enhancement stage, which connects broken ridges, separates joined ridges, and removes overlapping patterns. After the latent is enhanced, conventional minutiae extraction algorithm can be used [8]. Contextual filtering (or directional filtering) is the most widely used fingerprint enhancement technique [9]–[11]. Although different contextual filters differ in details, the intended behavior is the same: (i) performing low-pass filtering along the ridge in order to fill gaps and pores, and (ii) performing bandpass filtering across the ridges in order to separate joined ridges [8].

The contextual filtering techniques require reliable estimation of local ridge orientation, which is not a trivial task for poor quality fingerprints. That is why orientation field estimation and a very related topic, singularity detection, are two of the most active topics in the fingerprint recognition literature [10]–[37]. However, all these algorithms were developed for plain or rolled fingerprints. As shown in Fig. 2, the performance of representative orientation field estimation algorithms on latents is far from satisfactory. Realizing the gap between human and machine's performance in extracting orientation field for latents, a few recent studies have focused on latent orientation field estimation [38], [39]. However these algorithms require manually marked singular points in order to obtain a reasonable performance.

In this paper, a robust orientation field estimation algorithm is proposed to process poor quality fingerprints, especially latents. Given prior knowledge of fingerprint structure, which is represented by a dictionary of reference orientation patches and compatibility constraints between adjacent orientation patches, the proposed algorithm obtains better performance for latents than published algorithms (see Fig. 2). For some latents, the match scores using minutiae automatically extracted from latents enhanced by the proposed algorithm are even higher than the match scores using manually marked minutiae.

The rest of the paper is organized as follows. In section 2, published orientation field estimation algorithms are reviewed. In section 3, the motivation of the proposed algorithm is discussed. The details of the proposed algorithm are presented in section 4. Experimental results are reported and analyzed in section 5. Finally, we conclude the paper and suggest future research directions for this topic.

2 Related Work

In this section, we review published algorithms for orientation field estimation, which are coarsely classified into three categories.

2.1 Local Estimation

Local estimation approaches compute a local ridge orientation at pixel $\mathbf{x} = (x, y)$ using only the neighborhood around $\mathbf{x}$, which is typically 32×32 pixels for 500 ppi fingerprints.

The most well-known local estimation approach is gradient-based [13], [14], [41], [42]. Since gradient operators, such as Prewitt or Sobel operators [43], are sensitive to noise and pores (regularly placed on the ridges), a dominant orientation is computed using the gradients in the local neighborhood.

Slit-based approach is another widely used orientation field estimation method [30]. This approach explicitly utilizes the fact that the variation of intensity is the smallest along the ridge orientation and largest along the orthogonal orientation. By testing such a hypothesis along a number of different orientations, the best orientation is chosen.

Ridge pattern in a local area of a finger can be approximated by a 2D sine wave [44]. Thus the magnitude spectrum of the Fourier transform of a local fingerprint image will contain a pair of peaks whose location corresponds to the parameters of the sine wave. The magnitude spectrum can be mapped to the polar coordinate system. The normalized magnitude spectrum can be viewed as a probability distribution [11]. The best orientation can be estimated as the most probable orientation or the mean.

Orientation fields obtained by local estimation approaches for poor quality fingerprints are usually very noisy. To deal with this problem, two types of algorithms have been adopted to regularize the noisy orientation field, namely, orientation field smoothing and global parametric model fitting. Typically, some constraints or knowledge about the fingerprint orientation field is utilized in the regularization algorithm.

1. In a black box test [5], the latent matching process of examiners is treated as a black box and only the final accuracy in making the decisions is studied.

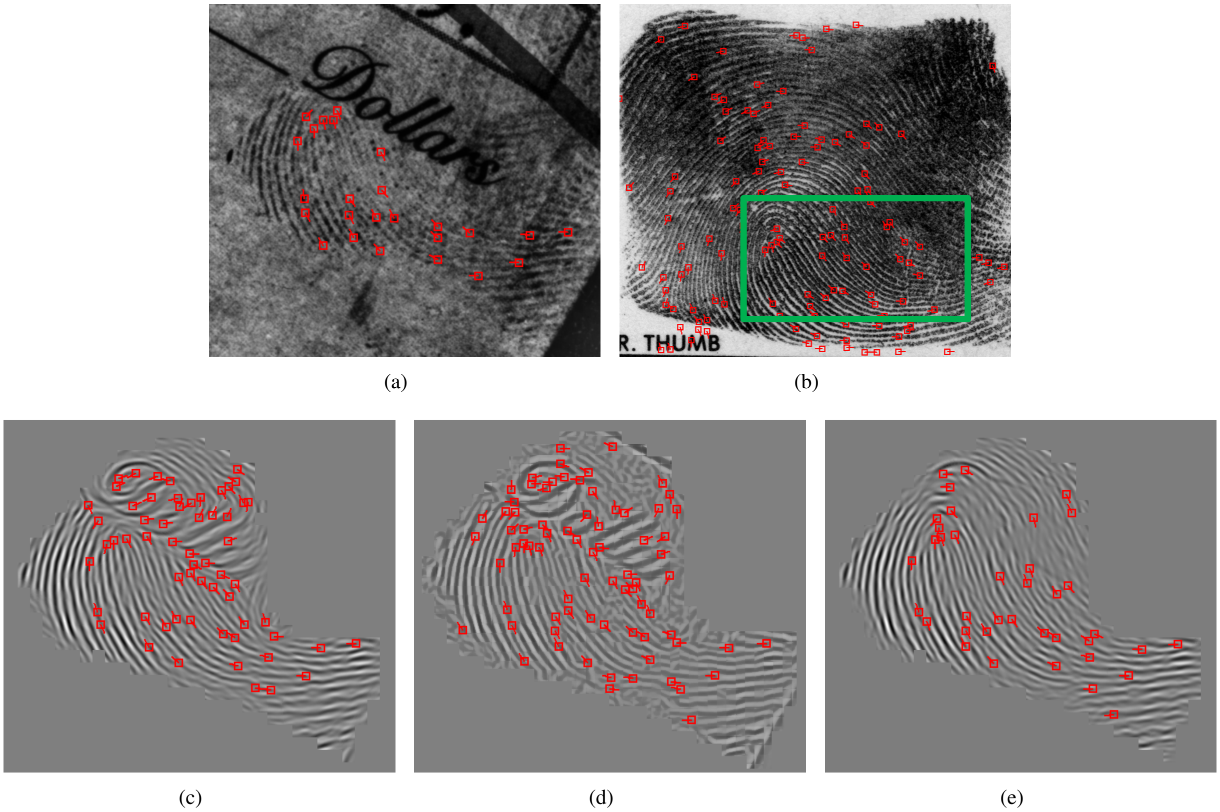


Fig. 2. A latent fingerprint (a), its mated rolled fingerprint (b) with the corresponding region marked by a green box, and its enhanced latents using three different orientation field estimation algorithms: (c) FOMFE [25], (d) STFT [11], (e) proposed. Minutiae in (a) are manually marked by latent examiners, minutiae in (b) are automatically extracted using VeriFinger SDK 6.2 [40], while minutiae in (c, d, e) are automatically extracted from the enhanced images using VeriFinger. The minutiae match scores (computed by VeriFinger) between (a, c, d, e) and the mated rolled fingerprint (b) are 39, 35, 24, and 54, respectively.

2.2 Smoothing

Many orientation field regularization techniques have been proposed to deal with noise present in the fingerprint. The most commonly used smoothing method is based on low-pass filtering [14]. Although the low-pass filtering method is simple and effective, the size of the filtering window is a critical parameter. A large window can suppress the noise better while a small window can preserve the true orientation in high curvature region. Several authors have suggested using multi-resolution orientation fields to address this problem [9], [21], [30], [45]. However, when the noise is severe as in latents, smoothing techniques are not able to recover the true orientation field.

Several researchers have implemented orientation field smoothing by using the Markov random field (MRF) model or energy minimization approach [16], [19], [31]. A well known limitation of these algorithms is that the orientation variable corresponds to a very small image region so that it can be represented by a single dominant orientation. However, a MRF model with small neighborhood or context is able to exploit only limited prior knowledge about fingerprint structure [46], [47] and thus cannot deal with fingerprints of very poor quality.

2.3 Global Parametric Models

Researchers have proposed several mathematical models to represent the whole fingerprint orientation field. Some of the models are quite general, such as polynomials [22] and Fourier series [25], while the others are more specific to fingerprints [12], [20], [29]. Without invoking constraints on the parameters [22], [25], general models tend to have over-fitting (e.g., if the order of the polynomial is high) or under-fitting problems (e.g., if the order of the polynomial is low) especially when the initial orientation field is very noisy. Models which explicitly consider singular points [12], [20], [29] rely on reliable extraction of singular points. However, extracting singular points in latents is a very challenging problem itself. That is why the orientation field estimation approaches in [38], [39] require manually marked singular points as input.

3 Motivation

Although conventional orientation field estimation algorithms can satisfactorily process most live-scan and inked fingerprints, their performance on most of the latents are far from satisfactory (see Fig. 2). We believe that a major limitation of conventional algorithms is that they do not

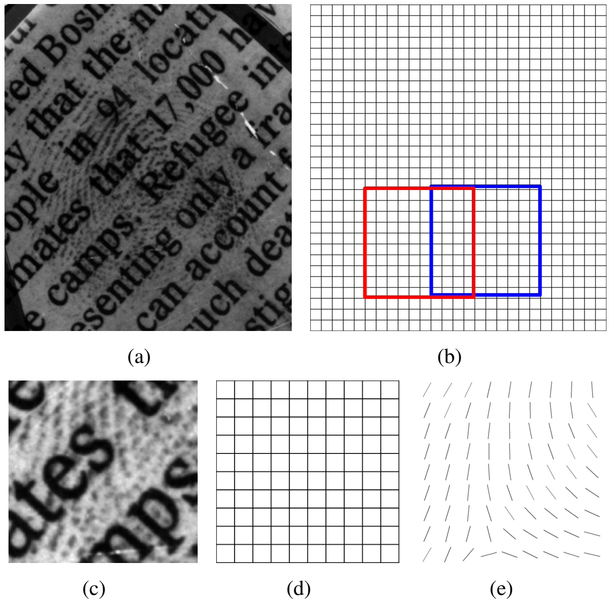


Fig. 3. A fingerprint image in (a) is divided into a number of non-overlapping blocks of 16×16 pixels in (b). A patch contains 10×10 blocks and neighboring patches are overlapped as shown in (b). Given a subimage in (c), the associated blocks and orientation patch is shown in (d) and (e). The orientation element represents the dominant ridge flow in a block.

adequately incorporate prior knowledge of fingerprints. It is now widely recognized that representing and learning prior knowledge is of fundamental importance in many natural language processing and computer vision tasks [47], [48]. However, in the fingerprint recognition area, it has received little attention.

We can draw an analogy between fingerprint orientation field and a sentence in a natural language. A sentence is comprised of words which are further comprised of letters. Similarly, a fingerprint orientation field is comprised of orientation patches which are further comprised of orientation elements. Hence, a fingerprint orientation field can be viewed as a sentence, an orientation patch can be viewed as a word, and an orientation element can be viewed as a letter. These definitions are illustrated in Fig. 3.

Spelling correction [48] in a sentence is possible because not all possible combinations of letters are valid to form words and not all possible combinations of words form a valid sentence. Similarly, error correction in orientation fields is possible because not all possible combinations of orientation elements are valid and not all possible combinations of orientation patches are valid for a fingerprint. For example, Fig. 4 shows 60 orientation patches, which are generated by sampling an independent uniform distribution (namely, each orientation element has the same uniform distribution and the elements are assumed to be statistically independent). None of these orientation patches is likely to appear in real fingerprints.

Spelling correction techniques use dictionary (or lexicon, word list) and context information to detect and correct spelling errors [48]. While dictionary can be used to detect and correct most non-word errors, contextual information is required to resolve ambiguity when there are multiple candidate words. For example, without context, *ater* can be explained as *after*, *later*, *water*, *alter*, or *ate*.

The proposed orientation field estimation algorithm is inspired by the above spelling correction method. We first build a dictionary of reference orientation patches using a set of orientation fields extracted from real fingerprints. Given an input fingerprint, we estimate an initial orientation field using traditional orientation field estimation approaches. For poor quality fingerprints, such as most latents, the initial orientation fields are very noisy. Errors in the initial orientation field need to be corrected using dictionary as well as context information. Specifically, for each initial orientation patch, we find a list of candidates from the dictionary which might be the true orientation patch. Contextual information is then used to determine a single candidate for each patch.

4 Proposed Algorithm

4.1 Overview

The proposed orientation field estimation algorithm consists of an off-line dictionary construction stage and an on-line orientation field estimation stage. In the off-line stage, a set of good quality fingerprints of various pattern types (arch, loop, and whorl) are manually selected and their orientation fields are used to construct a dictionary of orientation patches. In the on-line stage, given a fingerprint image, its orientation field is automatically estimated using the following steps:

1) initial estimation: The initial orientation field is obtained using a local orientation estimation method, such as local Fourier analysis [44].
2) dictionary lookup: The initial orientation field is divided into overlapping patches. For each initial orientation patch, its six nearest neighbors in the dictionary are viewed as candidates for replacing the noisy initial orientation patch.
3) context-based correction: The optimal combination of candidate orientation patches is found by considering the compatibility between neighboring orientation patches.

In the following subsections, we first describe the off-line dictionary construction and then present the three steps in the on-line orientation field estimation algorithm.

4.2 Dictionary Construction

The dictionary consists of a number of orientation patches of the same size. An orientation patch consists of $b \times b$ orientation elements and an orientation element refers to the dominant orientation in a block of size 16×16 pixels.

We construct a dictionary of orientation patches from a set of high quality fingerprints (referred to as reference fingerprints). The orientation fields (defined on blocks of size 16×16 pixels) of these fingerprints are estimated using

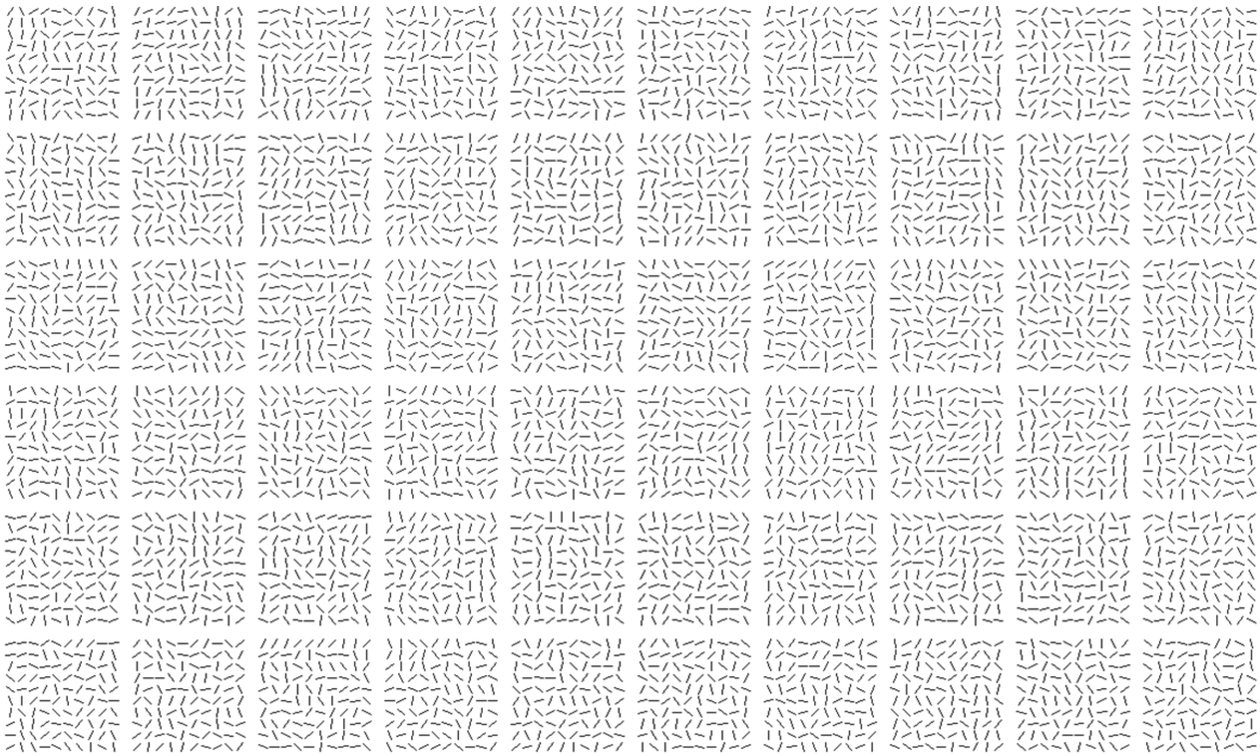


Fig. 4. Orientation patches sampled from a uniform distribution of orientation element. None of these orientation patches is likely to appear in real fingerprints. An orientation patch contains 10×10 orientation elements and an orientation element represents the dominant direction in a block of 16×16 pixels.

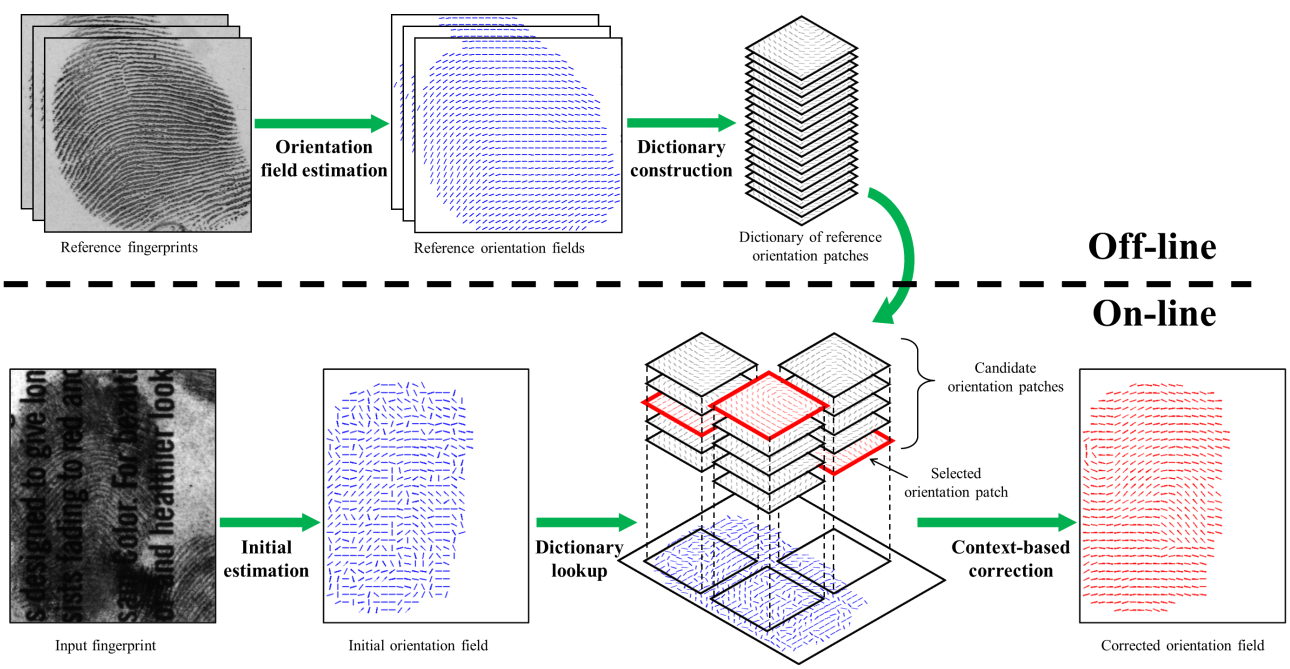


Fig. 5. The proposed system consists of an off-line dictionary construction stage and an on-line orientation field estimation stage.

a state-of-the-art algorithm, VeriFinger 6.2 SDK [40]. High quality fingerprints and the state-of-the-art algorithm are used to ensure that the dictionary does not contain invalid words. A number of orientation patches, whose orientation elements are all available, are obtained by sliding a window (whose size is $b \times b$ blocks) across each reference orientation field and its mirrored version. Considering that the direction of the latent fingerprint is unknown, each orientation patch is rotated by 21 different angles $\{i \cdot 5°, -10 \leq i \leq 10\}$ to generate additional orientation patches.

Given these orientation patches, a greedy algorithm is employed to construct a set of reference orientation patches, which forms the dictionary (see Fig. 6 for a few examples). The greedy algorithm is described below.

1) The first orientation patch is added into the dictionary, which is initially empty.
2) Then we test whether the next orientation patch is sufficiently different from all the orientation patches in the dictionary. If yes, it is also added into the dictionary; otherwise the next orientation patch is tested. Here, the similarity measure between two orientation patches of $b \times b$ blocks is computed as n_s/b^2, where n_s denotes the number of orientation elements whose difference is less than 10 degrees.
3) Repeat step 2 until all orientation patches have been tested.

The number of reference orientation patches in the dictionary depends on the number of reference orientation fields and the size of the patch. When the size of the patch is 10×10 blocks and 50 reference orientation fields are used, the number of reference orientation patches is around 23K.

The size of the orientation patch has a direct impact on the ability of correcting errors in the initial orientation field. However, a large patch also requires a large dictionary which takes more time to search. An example is given in Fig. 7 to demonstrate the impact of patch size on dictionary-based correction performance. If the patch is of size 3×3 or 5×5 blocks, the closest reference orientation patch (similarity measure is described in the next subsection) is incorrect. However, when a 9×9 patch is used, the closest reference orientation patch is very close to the true orientation field. To further demonstrate the impact of patch size, we apply a simple nearest neighbor approach to correct the initial orientation field of two latent fingerprints. Here, the initial orientation patches are directly replaced by the closest reference orientation patches without considering compatibility between neighboring patches. As we can see from Fig. 8, the performance of this approach improves with the increase in patch size. The estimation errors close to the finger boundary are due to border effect (those patches contain very few foreground blocks).

4.3 Initial Orientation Field Estimation

The initial orientation field is obtained using a simple algorithm [44]. Other local estimation algorithms, such as gradient-based and slit-based, should also suffice for this initial step. The dominant orientation in a 16×16 block is computed by detecting the peak in the magnitude spectrum of the local image. Due to the poor quality of latents, the initial orientation field is usually very noisy (see Fig. 9). However, orientation field smoothing should be avoided in this stage since correct orientation elements may even be degraded by strong noise in the neighboring regions. The problem of correcting noisy orientation field is left to the later stages, which utilize prior knowledge of fingerprints.

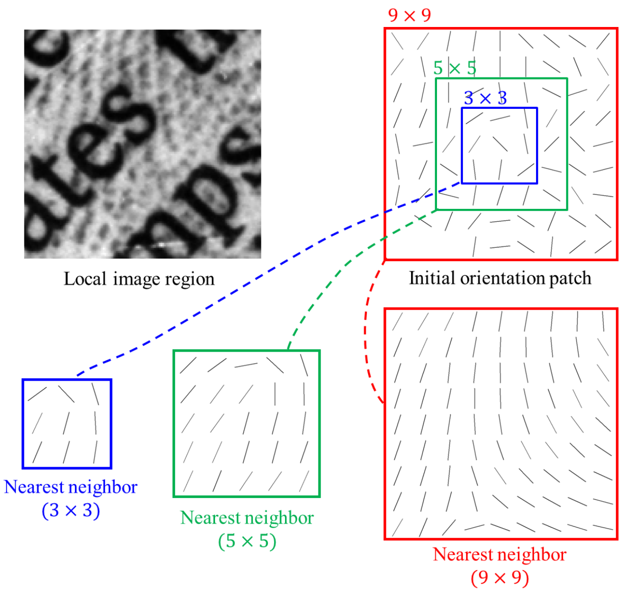


Fig. 7. Nearest neighbors of different patch sizes.

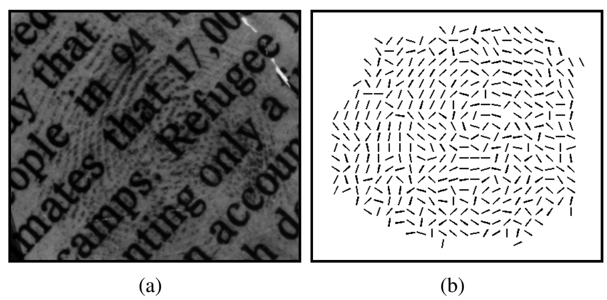


Fig. 9. A latent fingerprint (a) and its initial orientation field (b).

4.4 Dictionary Lookup

Given an initial orientation patch that contains at least one foreground block, we retrieve a list of candidate reference orientation patches from the dictionary, which are sorted according to their similarity with the initial patch. In order to retrieve the correct orientation patches at high rank, proper similarity measure and retrieval strategy need to be designed.

The similarity $S(\mathbf{\Theta}, \mathbf{\Phi})$ between an initial orientation patch $\mathbf{\Theta}$ and a reference orientation patch $\mathbf{\Phi}$ is computed by comparing corresponding orientation elements. Let n_f be the number of orientation elements in the initial orientation patch. Let n_s be the number of orientation elements whose

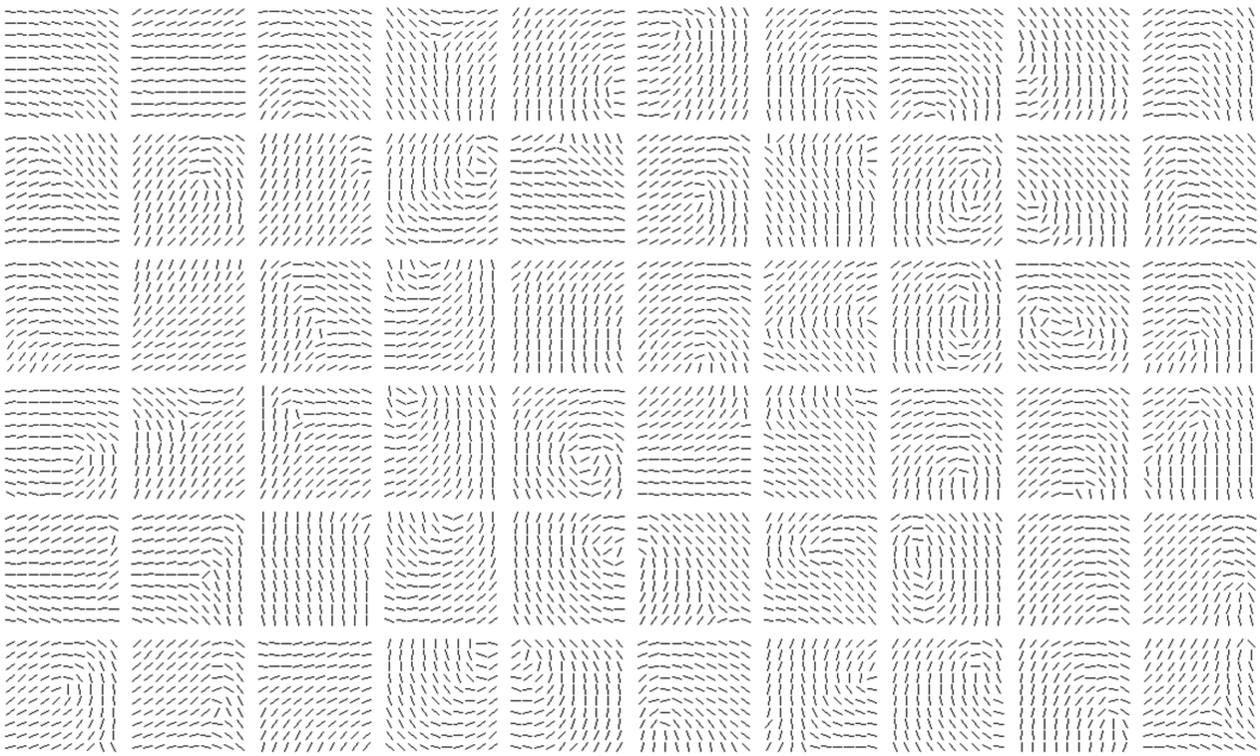


Fig. 6. Examples of reference orientation patches in the dictionary. Recall that an orientation patch contains 10×10 orientation elements and an orientation element corresponds to a block of 16×16 pixels.

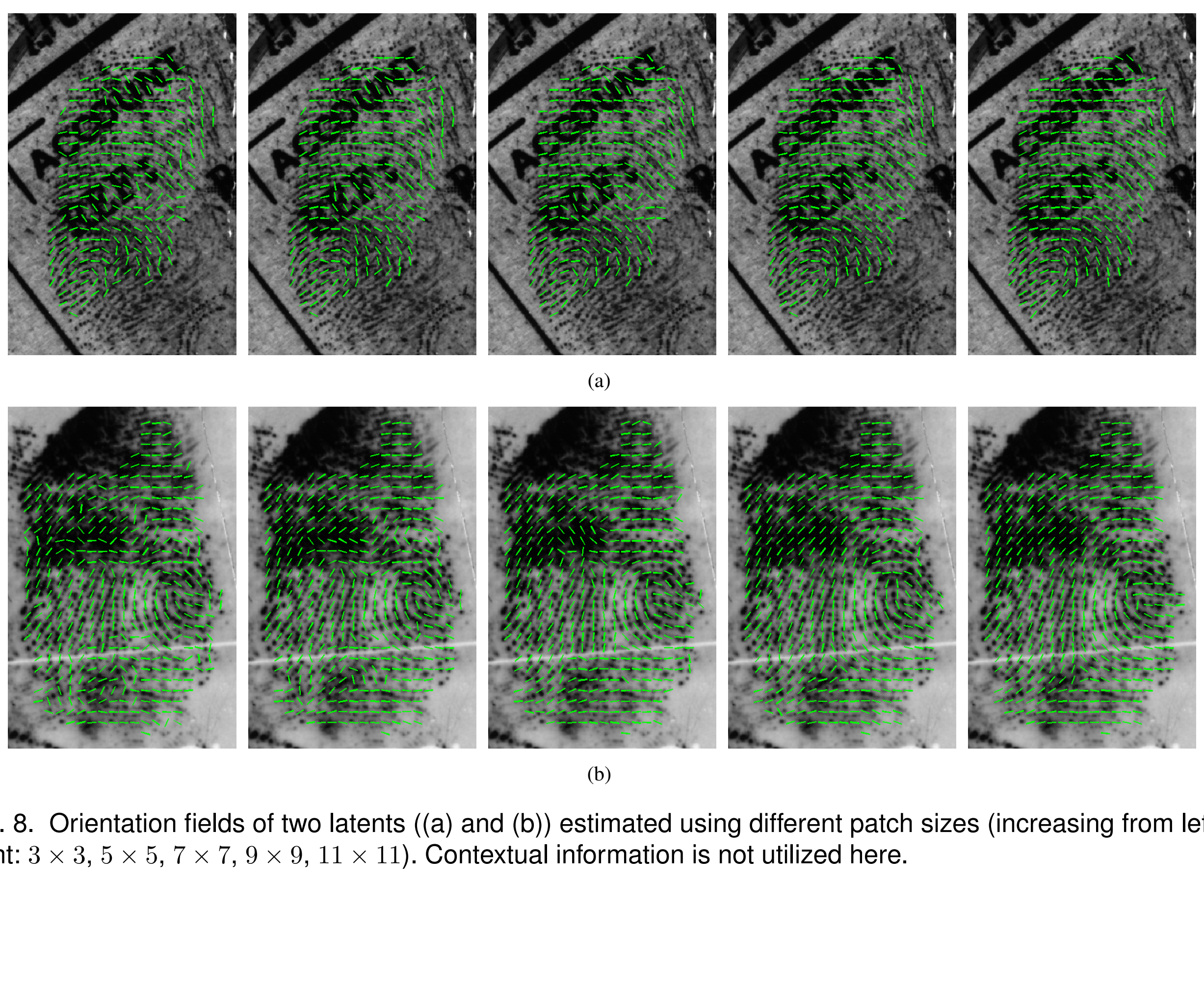
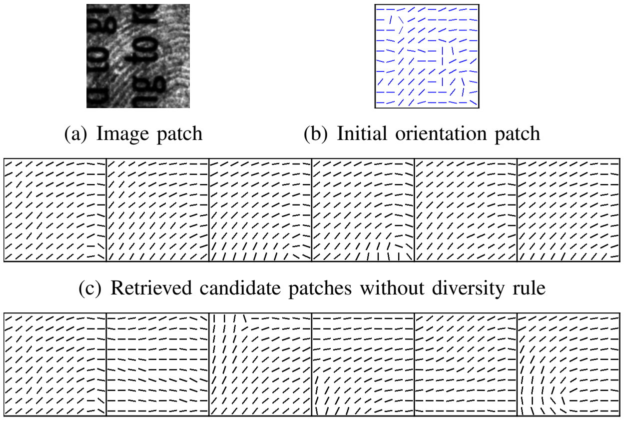


Fig. 8. Orientation fields of two latents ((a) and (b)) estimated using different patch sizes (increasing from left to right: 3×3, 5×5, 7×7, 9×9, 11×11). Contextual information is not utilized here.



(a) Image patch (b) Initial orientation patch

(c) Retrieved candidate patches without diversity rule

(d) Retrieved candidate patches with diversity rule

Fig. 10. Candidate orientation patches obtained without (c) and with (d) diversity rule.

differences are less than a predefined threshold (empirically set as $\pi/12$). The similarity between two patches is defined as

$$S(\mathbf{\Theta}, \mathbf{\Phi}) = n_{\text{s}}/n_{\text{f}}. \tag{1}$$

Orientation field correction is posed as a combinational optimization problem. The total number of possible solutions is ${n_{\text{c}}}^{n_{\text{p}}}$, where n_{c} is the length of candidate list, and n_{p} is the number of patches in the input fingerprint. While a shorter list makes the search more efficient, a longer list will more likely contain the optimal solution.

After observing the top candidate orientation patches of many initial orientation patches, we determined that the top candidates of the same initial orientation patch are quite similar to each other (see Fig. 10(c)). However, to increase the probability of including the correct patches in a short candidate list, it is better to have a diverse set of candidates. Hence, a diverse set of n_{c} (empirically set as 6) candidates is selected from the top $10n_{\text{c}}$ initial candidates using the following greedy strategy:

1) Choose the first initial candidate.
2) The next initial candidate is compared to each of the chosen candidates. If its similarity to all the chosen candidates is below a predefined threshold (empirically set as 0.8 in our experiment), it is chosen. Note that similarity is measured using only the foreground blocks in the initial orientation patch.
3) Repeat step 2 for all the initial candidates until n_{c} candidates have been chosen or all initial candidates have been checked.

Figure 10 compares the candidates obtained without and with this diversity rule. With the diversity rule, the candidates contain more variations. As a result, when the initial orientation patch is very noisy or incomplete, the possibility that correct orientation patches appear in the candidate list is larger.

4.5 Context-based Orientation Field Correction

After dictionary lookup, we obtain a list of c_i $(1 \leq c_i \leq n_{\text{c}})$ candidate orientation patches, $\mathbf{\Phi}_i = \{\mathbf{\Phi}_{i,1}, \mathbf{\Phi}_{i,2}, ..., \mathbf{\Phi}_{i,c_i}\}$, for an initial orientation patch $\mathbf{\Theta}_i$. To resolve the ambiguity, i.e., determine a single candidate for each patch, contextual information needs to be utilized.

We address this problem by searching for a set of candidates, $\mathbf{r}^*$, which minimizes an energy function $E(\mathbf{r})$. Let r_i denote the index of the selected candidate for patch i, and $\mathbf{r} = \{r_1, r_2, ..., r_{n_{\text{p}}}\}$ be the vector of the indices of the selected candidates for all n_{p} foreground patches. The solution space for $\mathbf{r}$ is all possible combinations of candidate indices, which is very large. Choice of a proper energy function is crucial for the success of this method. We consider two factors in designing the energy function: (i) the similarity between the reference orientation patches and the corresponding initial orientation patches, and (ii) the compatibility between neighboring reference orientation patches.

The energy function is defined as

$$E(\mathbf{r}) = E_{\text{s}}(\mathbf{r}) + w_{\text{c}} E_{\text{c}}(\mathbf{r}), \tag{2}$$

where $E_{\text{s}}(\mathbf{r})$ denotes the similarity term, $E_{\text{c}}(\mathbf{r})$ denotes the compatibility term, and w_{c} (empirically set to 1) is the weight of compatibility term. The similarity term is defined as

$$E_{\text{s}}(\mathbf{r}) = \sum_{i \in \mathcal{V}} \Big(1 - S(\mathbf{\Theta}_i, \mathbf{\Phi}_{i,r_i})\Big), \tag{3}$$

where $\mathcal{V}$ denotes the set of foreground patches and $S(\cdot)$ is defined in Eq. (1). The compatibility term is defined as

$$E_{\text{c}}(\mathbf{r}) = \sum_{(i,j) \in \mathcal{N}} \Big(1 - C(\mathbf{\Phi}_{i,r_i}, \mathbf{\Phi}_{j,r_j})\Big), \tag{4}$$

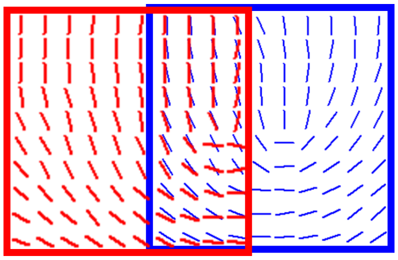
where $\mathcal{N}$ denotes the set of adjacent foreground patches which are four-connected neighbors.

The compatibility between two neighboring orientation patches $\mathbf{\Phi}_{i,r_i}$ and $\mathbf{\Phi}_{j,r_j}$ is measured by the similarity of orientations in the overlapping blocks. Let $\{\alpha_n\}_{n=1}^{N_{\text{o}}}$ and $\{\beta_n\}_{n=1}^{N_{\text{o}}}$ be the set of orientations in the N_{o} overlapping blocks of two orientation patches. The compatibility is computed as

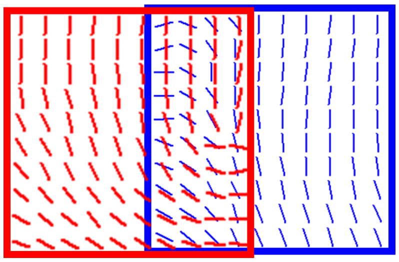
$$C(\mathbf{\Phi}_{i,r_i}, \mathbf{\Phi}_{j,r_j}) = \frac{1}{N_{\text{o}}} \sum_{n=1}^{N_{\text{o}}} |\cos(\alpha_n - \beta_n)|. \tag{5}$$

Two examples are given in Fig. 11 to illustrate the compatibility between two neighboring patches. The two reference orientation patches in Fig. 11(a) are compatible, while the two reference orientation patches in Fig. 11(b) are not compatible. Fig. 12 shows the compatibility matrix between two neighboring patches. Due to the fact that relatively large size orientation patches are treated as a whole and adjacent patches contain an overlapping region, the compatibility constraint holds in both low curvature regions as well as high curvature regions (such as core and delta). However, in previous work [16], [19], [31], compatibility constraint did not hold in high curvature regions.

To minimize the energy function in Eq. (2), a number of optimization algorithms can be employed. Since this is not the focus of this study, we adopt the well-known



(a)



(b)

Fig. 11. Compatibility between neighboring orientation patches. (a) A pair of orientation patches (one shown in blue and the other in red) with high compatibility value (0.92), (b) a pair of orientation patches with low compatibility value (0.69).

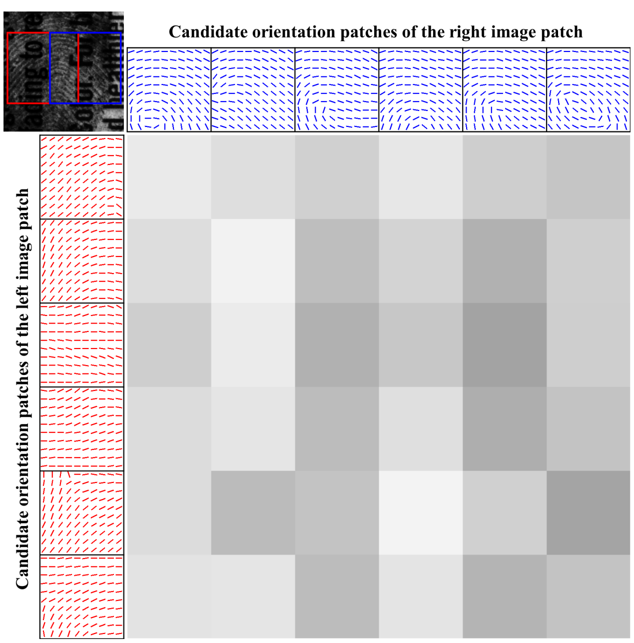


Fig. 12. Compatibility matrix between the candidate orientation patches for two neighboring patches. The compatibility value between two candidates is depicted by the brightness of the corresponding square.

loopy belief propagation algorithm [47]. It was originally proposed to perform exact inference on trees (e.g., graphs without closed loops) [49]. But many empirical studies have shown that it also yields good approximate results on graphs with closed loops, such as Markov random field [47].

5 Experiments

In this section, we first describe the databases used in this study. We report the orientation field estimation performance and the resulting matching performances on the NIST SD27 latent fingerprint database and an overlapped fingerprint database. Finally, we discuss the impact of reference fingerprints on orientation field estimation.

5.1 Databases

To construct a dictionary of reference orientation patches, we used a set of 50 good quality fingerprints in the NIST SD4 database[2]. All five major pattern types (plain arch, tented arch, left loop, right loop, and whorl) are covered by these 50 fingerprints. The distribution of different pattern types in this sample is not necessarily similar to the distribution in large population or the NIST SD27 database.

The latent orientation field estimation and subsequent matching experiments are conducted on the public domain latent fingerprint database, NIST SD27, which contains 258 latent fingerprints and their corresponding rolled fingerprints. Each latent image in this database was assigned one of three (subjective) quality levels - “good”, “bad”, and “ugly” - by latent examiners. The numbers of “good”, “bad” and “ugly” latents are 88, 85 and 85, respectively.

We also tested this algorithm on the Tsinghua OLF database[3] which consists of 100 overlapped latent fingerprints. These overlapped latent fingerprints were obtained using the following procedure: 1) press two fingers at roughly the same location on a white paper, 2) enhance the latent prints using black powder and brush, and 3) convert the enhanced prints into electronic version using a general purpose scanner. For each of the twelve different fingers used to form the latents, one flat fingerprint obtained using an optical fingerprint scanner was used as the template fingerprint.

To make the latent matching problem more realistic and challenging, 27,000 rolled fingerprints (file fingerprints) in the NIST SD14 database were used as the background database. Details of databases used in this study are summarized in Table 1.

5.2 Performance Evaluation

The direct goal of an orientation field estimation algorithm is to obtain an accurate estimation of fingerprint orientation field, while its final goal is to improve the fingerprint matching accuracy. Thus, we conducted experiments to

2. The filename list of these fingerprints is available as supplemental material.

3. Available at http://ivg.au.tsinghua.edu.cn.

TABLE 1
Fingerprint databases used in this study.

Database	Description	Purpose
NIST SD4	2,000 pairs of rolled fingerprints; http://www.nist.gov/srd/nistsd4.cfm	dictionary construction
NIST SD14	27,000 pairs of rolled fingerprints; http://www.nist.gov/srd/nistsd14.cfm	background database
NIST SD27	258 pairs of latent fingerprints and mated rolled fingerprints; http://www.nist.gov/srd/nistsd27.cfm	algorithm evaluation
Tsinghua OLF	100 overlapped latent fingerprints and 12 mated plain fingerprints; http://ivg.au.tsinghua.edu.cn	algorithm evaluation

TABLE 2
Average estimation error (in degrees) of the proposed and two published orientation estimation algorithms on the NIST SD27 database.

Algorithm	All	Good	Bad	Ugly
Proposed	18.44	14.40	19.18	21.88
FOMFE [25]	28.12	22.83	29.09	32.63
STFT [11]	32.51	27.27	34.10	36.36

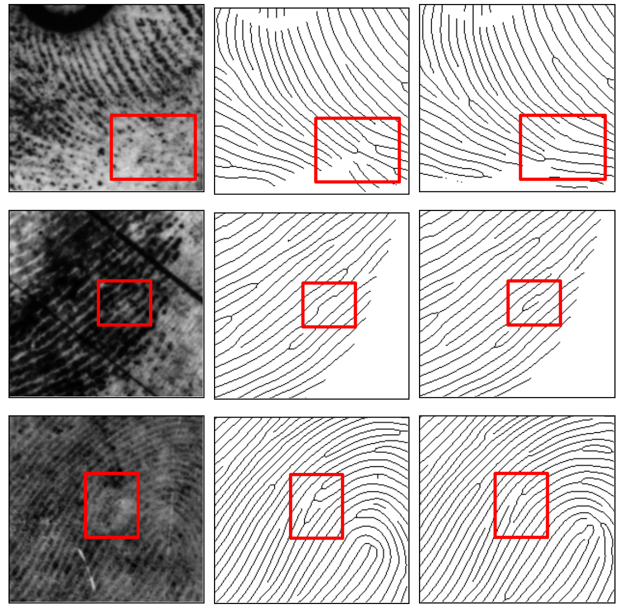
evaluate the accuracy of orientation field estimation and the accuracy of fingerprint matching, respectively.

In addition to the proposed orientation field estimation algorithm, two other approaches were included:

1) combination of gradient-based local estimation and FOMFE-based global model [25], and
2) combination of STFT-based local estimation and low-pass filtering [11].

The accuracy of orientation field estimation algorithm is measured using the average Root Mean Square Deviation (RMSD) from the ground truth suggested in [37]. The ground truth was established based on the manual marking of the orientation field by one of the authors. Average RMSD of the proposed algorithm and FOMFE and STFT are computed on all the 258 latents in the NIST SD27 database and also on the subsets of NIST SD27 belonging to three quality levels (Good, Bad and Ugly). As shown in Table 2, the proposed algorithm outperforms the other two algorithms on latents of all three quality levels. To facilitate comparison by other interested researchers, the manually marked orientation fields and the orientation fields estimated by the three algorithms are available as supplemental material.

To evaluate the matching accuracy, we need to integrate an orientation field estimation approach with the other modules in the matching system, namely fingerprint enhancement, feature extraction, and matching. Latent fingerprints are enhanced using a Gabor filter whose frequency parameter is fixed at $1/9$ cycles per pixel, standard deviations of the Gaussian envelope are fixed as 4, and orientation parameter is tuned to the estimated orientation field [10]. VeriFinger SDK 6.2 [40] is used to extract features from enhanced latents and original full fingerprints. The same SDK is then used to compute the match scores between



(a) Local image region (b) Manual (c) Proposed

Fig. 16. Three latent examples where the proposed orientation field estimation algorithm performs slightly better than manual approach. Regions showing the difference in orientation field estimation are marked with red boxes.

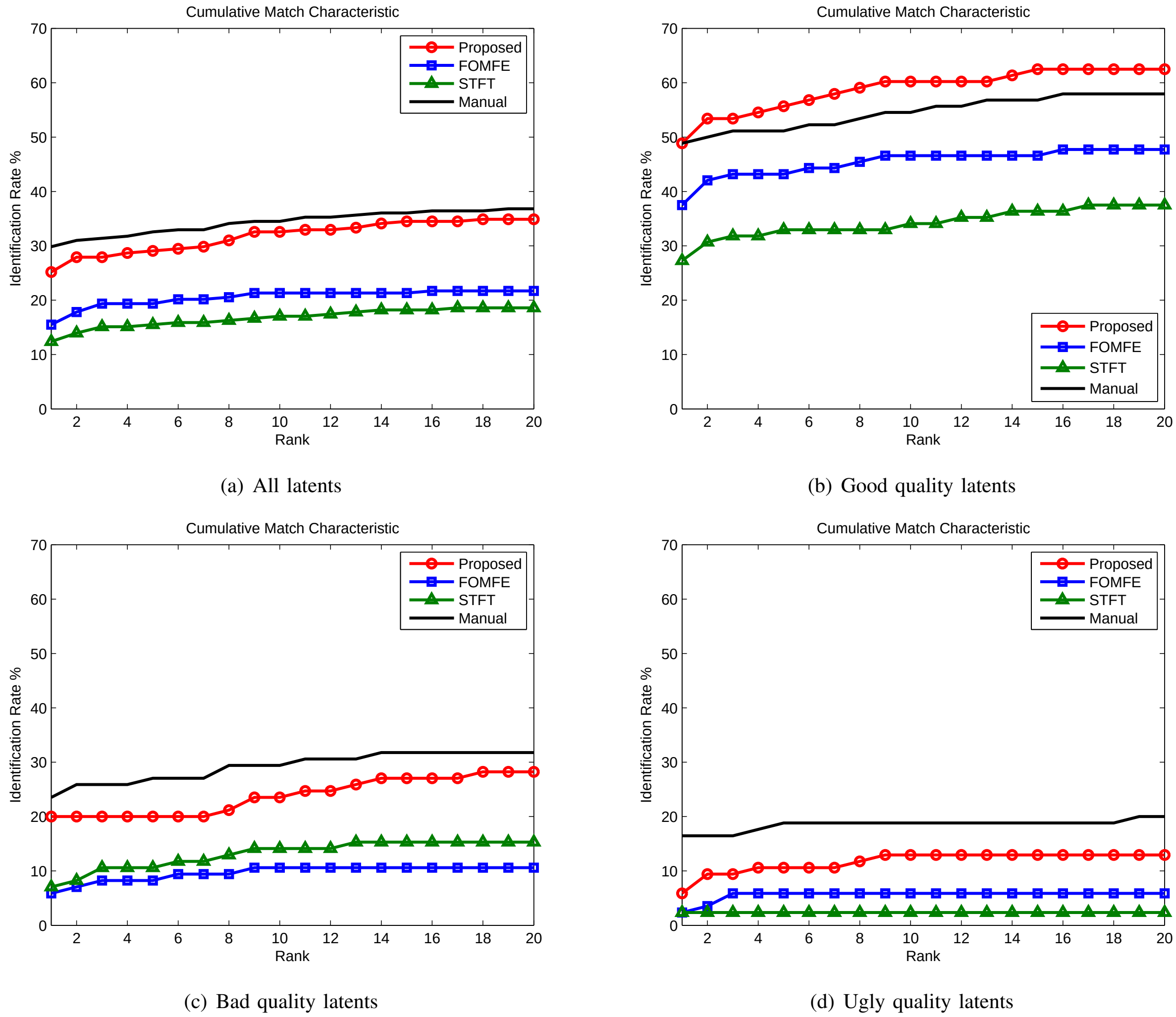
latents and full fingerprints.

The Cumulative Match Characteristic (CMC) curves on the NIST SD27 latent database corresponding to the three algorithms and the manual markup are shown in Fig. 13. The proposed algorithm consistently outperforms the two published algorithms on latents of all three quality levels. Three examples are given in Fig. 14 to compare the enhanced latents using the orientation fields obtained by the three algorithms (proposed, FOMFE and STFT). Orientation fields estimated for twelve additional latents of various qualities by the proposed algorithm are given in Fig. 15.

For many latents of good quality, the proposed algorithm even outperforms the manual ground truth (see Fig. 13(b)). Our analysis of these examples (see Fig. 16) shows that the propose algorithm has smaller deviation from true ridge orientation for good quality latents. It is difficult and time-consuming for a fingerprint expert to accurately mark the complete orientation field in a latent. However, fingerprint experts still perform better than the proposed algorithm in estimating orientation field of poor quality latents, but the proposed algorithm has narrowed the performance gap.

5.3 Overlapped Latent Fingerprints

Some latents may contain overlapped texture with regular direction and high contrast (see Fig. 17). For such latents, the initial orientation field can be completely wrong, making it difficult to recover the true orientation field. Although several specific orientation field estimation algorithms have been developed for overlapped fingerprints [50]–[52], we



(a) All latents

(b) Good quality latents

(c) Bad quality latents

(d) Ugly quality latents

Fig. 13. CMC curves comparing three orientation field estimation algorithms and the manual approach on the NIST SD27 latent database: (a) all (258 latents), (b) good quality (88 latents), (c) bad quality (85 latents), and (d) ugly quality (85 latents).

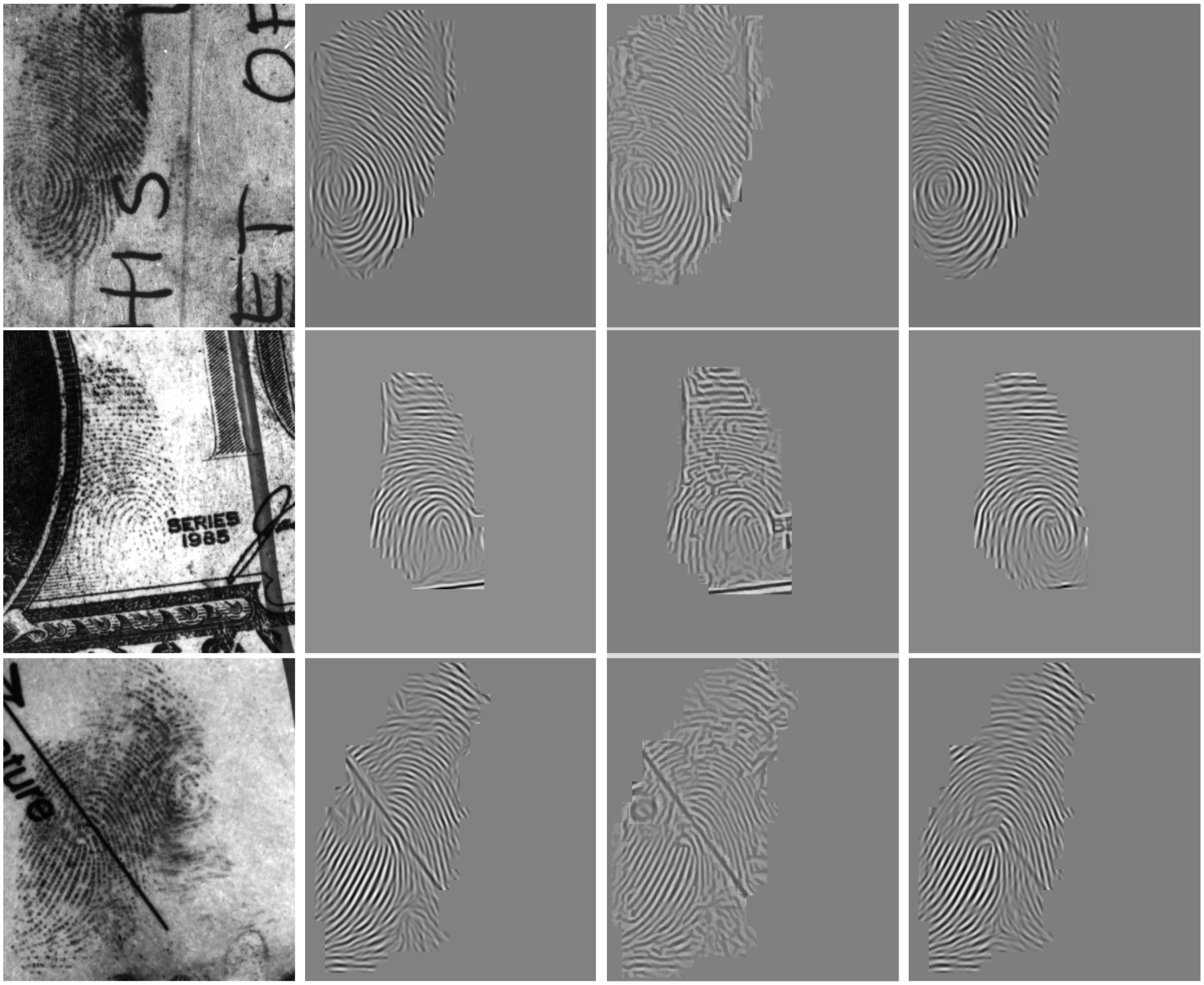
will show that, with a minor modification, the proposed algorithm can also deal with overlapped latent fingerprints. Given a region mask for the fingerprint of interest and the region mask for the overlapped pattern, following changes are needed in initial orientation field estimation and similarity computation.

1) The initial orientation field estimation algorithm detects one dominant orientation element in the non-overlapped fingerprint region and two dominant orientation elements in the overlapped region. This is under the assumption that the true ridge pattern is the first or the second strongest component in the overlapped image.
2) While the similarity between an initial orientation patch and a reference orientation patch is still computed using Eq. (1), in counting the number n_s of similar blocks between two orientation patches, a block with at least one similar orientation element is viewed as a similar block.

Fig. 17 shows that the modified algorithm can correctly estimate orientation fields of fingerprints with overlapped texture. To perform a systematic comparison between the proposed algorithm and the constrained relaxation labeling algorithm in [52], which was specially designed for separating overlapped fingerprints, a matching experiment was conducted using 100 overlapped latents in the Tsinghua OLF database. All 27,000 rolled fingerprints in the NIST SD14 database are used as the background database. The CMC curves in Fig. 18 show that the proposed algorithm performs as well as the specially designed overlapped fingerprint separating algorithm.

5.4 Impact of Reference Fingerprints

A proper choice of corpus is very important in natural language processing. Since reference fingerprints used to construct the dictionary serve a similar role in our problem, we conducted two experiments to study the impact of reference fingerprints.



(a) Latent fingerprint (b) FOMFE (c) STFT (d) Proposed

Fig. 14. Enhanced images of three latent fingerprints in (a) using orientation fields estimated by three algorithms (FOMFE, STFT, and the proposed algorithm).

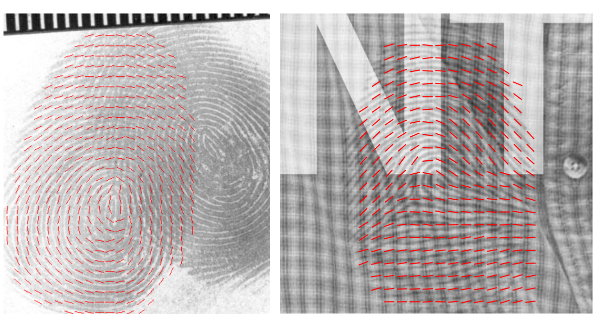


Fig. 17. Estimated orientation fields for two fingerprint images with overlapping textures using the proposed method.

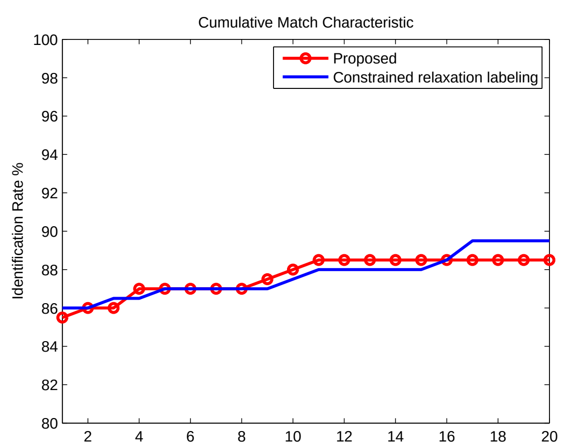


Fig. 18. CMC curves of the proposed algorithm and the constrained relaxation labeling algorithm [52] on the Tsinghua overlapped latent fingerprint database.

First, we examine whether orientation field estimation performance is related to the type of the latent fingerprints (e.g., arch, whorl, loop) and the reference fingerprints used for constructing the dictionary. Two reference fingerprints

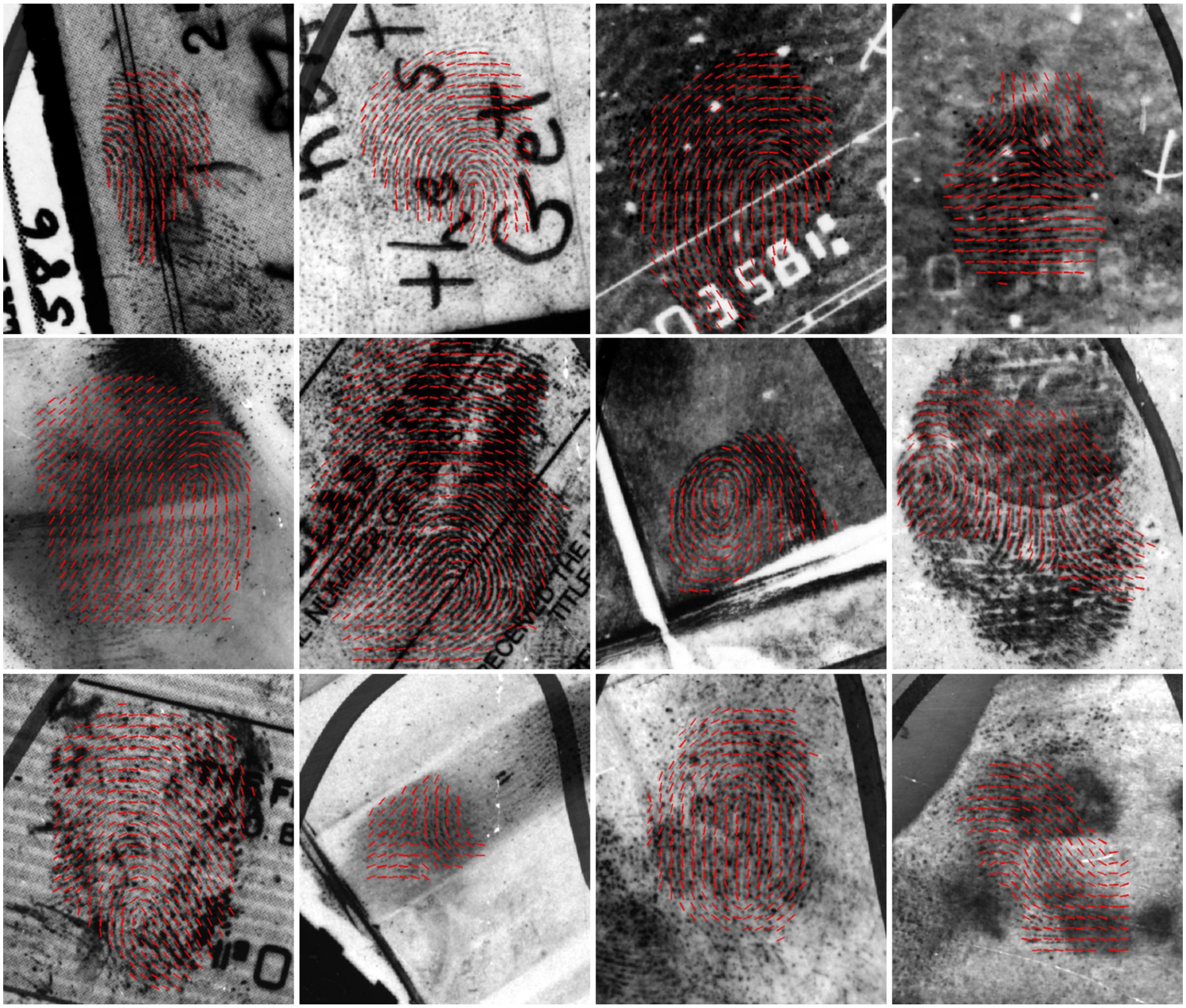


Fig. 15. Orientation fields estimated by the proposed algorithm for twelve latent fingerprints in the NIST SD27 database.

(one left loop and one whorl) were used to construct a dictionary, respectively. For a subset of 26 latents in the NIST SD27 database, two orientation fields were estimated using these two dictionaries and then used to enhance the latent. Fig. 19 shows that the enhancement result is better when the pattern types of reference and latent fingerprints are the same. This indicates that reference fingerprints should include fingerprints of all five major pattern types that are most commonly observed in practice.

We also tested different combinations of patch size (ranging from 4×4 to 12×12 blocks) and the number of reference fingerprints (ranging from 5 to 50). When more than 10 reference fingerprints (containing all five pattern types) were used, we did not observe any significant difference in the orientation field estimation performance. But the speed of the proposed orientation field estimation algorithm is clearly related to patch size and dictionary size, which depends on the number of reference fingerprints. On a PC with 2.93 GHz CPU, the average time for processing a latent by the proposed orientation field estimation algorithm (implemented in MATLAB) ranges from 4 seconds (for patch size 8×8) to 50 seconds (for patch size 4×4).

The implementation using smaller patch size is slow because the number of patches is large and the clustering-based diversifying algorithm for each patch is computationally intensive. For large patch size (12×12), dictionary lookup is slow because of the large size of the dictionary. The implementation based on medium patch size (ranging from 7×7 to 10×10 blocks) is better in terms of both matching accuracy and efficiency. The CMC curves in Fig. 13 are obtained using 8×8 patches. However, considering the small number of latents in the NIST SD27 database, this experiment is just a qualitative study on the parameters of the algorithm. In order to make quantitative and more reliable conclusions about the impact of various parameters (including patch size, the number of reference fingerprint, parameters of energy function, parameters of similarity measure, etc.) on accuracy and efficiency, we need to utilize

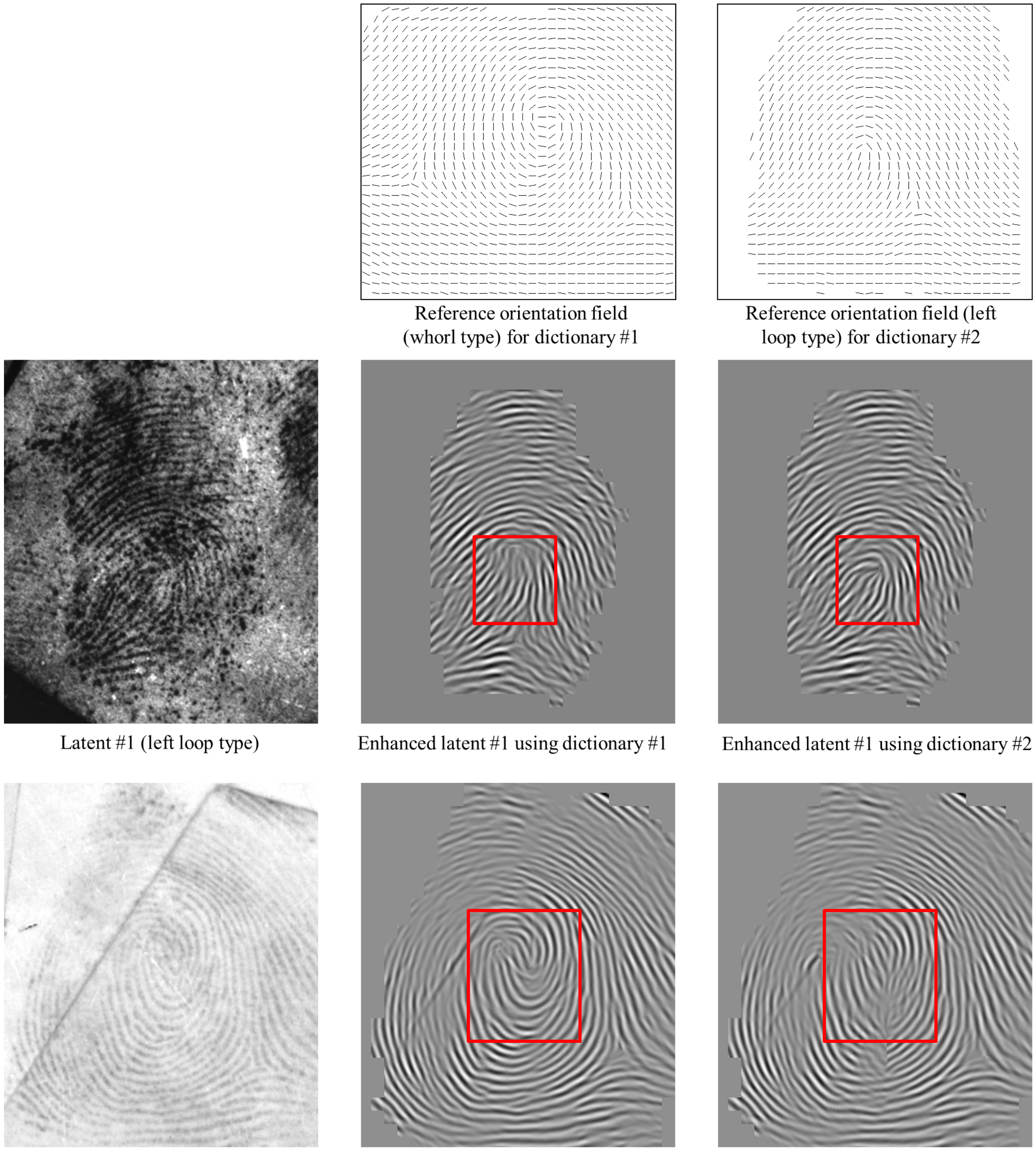


Fig. 19. Enhancement results using the dictionary constructed from reference orientation fields of the same pattern type is better than the results from different pattern types. Major differences are marked by red boxes.

a much larger latent database.

6 Summary and Future Work

Although automatic fingerprint recognition technology has evolved over the past forty years, fingerprint matching is far from a fully solved problem. There is a consensus in the fingerprint community that the capability of state-of-the-art fingerprint recognition systems is still not comparable to the ability of fingerprint examiners. This is particularly true for low quality latent fingerprint matching. For this reason, manual markup of various features (such as minutiae) in latents is a common practice in forensics.

There has been a growing interest in improving automatic latent fingerprint encoding and matching capabilities [4]. Law enforcement agencies have shown a great interest in supporting the development of "lights-out" latent identification techniques [53]. Government sponsored performance evaluations have been organized by NIST to evaluate automatic latent feature extraction and matching algorithms [54].

To significantly improve the performance of automatic systems, it is necessary to examine which specific capability of fingerprint examiners is lacking in the systems. We believe that, at the fundamental level, it is the prior knowledge of fingerprints acquired through observing a large number of fingerprints that gives fingerprint examiners an edge over automatic algorithms in accurately identifying features (e.g., marking minutiae) in latent prints of poor quality. However, there have been only a few attempts in the literature to incorporate such prior knowledge into fingerprint recognition algorithms.

Inspired by spelling correction techniques in natural language processing, we have proposed a robust orientation field estimation algorithm for latent fingerprint enhancement. A simple local estimation approach is used to obtain an initial orientation field of the latent fingerprint. For each patch in the initial orientation field, candidate patches are found in an orientation patch dictionary learnt from a set of true fingerprint orientation fields. The final orientation field for the latent is obtained by finding the combination of candidates that minimizes an energy function. The experimental results on the challenging NIST SD27 latent fingerprint database showed that the proposed algorithm outperformed two well-known orientation field estimation algorithms. With a minor modification, the proposed algorithm can also estimate the orientation field of overlapped latent fingerprints and its performance is comparable to the state-of-art special purpose algorithm.

However, the proposed algorithm is still inferior to manual marking especially on low quality latents and its speed is slow. The following aspects should be considered to improve the current algorithm:

1) developing an indexing algorithm for fast retrieval of candidate orientation patches from a large dictionary,
2) using a multi-resolution approach to construct orientation patch dictionaries for both small and large fingerprint regions,
3) developing an automatic region segmentation algorithm, and
4) conducting a comprehensive study of various algorithmic parameters using large latent fingerprint databases.

Acknowledgments

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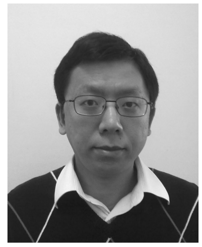

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