Robust and Efficient Algorithms for Separating Latent Overlapped Fingerprints

Jianjiang Feng, *Member, IEEE*, Yuan Shi, and Jie Zhou, *Senior Member, IEEE*

***Abstract*—Overlapped fingerprints are frequently encountered in latent fingerprints lifted from crime scenes. It is necessary to separate such overlapped fingerprints into component fingerprints so that existing fingerprint matchers can recognize them. The most crucial step in separating overlapped fingerprints is estimation of component orientation fields, which is a challenging problem for existing orientation field estimation algorithms. We propose a robust orientation field estimation algorithm (called the basic algorithm) for latent overlapped fingerprints whose core is the constrained relaxation labeling algorithm. We also propose improved versions of the basic algorithm for two special but frequent cases: 1) the mated template fingerprint of one component fingerprint is known and 2) the two component fingerprints are from the same finger. In both cases, further constraints are used to reduce ambiguity in relaxation labeling. Experimental results on both real and simulated overlapped fingerprints show that the proposed algorithm outperforms the state-of-the-art algorithm in both accuracy and efficiency. The two improved versions also perform better than the basic algorithm in respective cases. The latent overlapped fingerprint database collected for this study is made publicly available for performance evaluation.**

***Index Terms*—Overlapped fingerprints, relaxation labeling, ridge extraction, singularity, minutiae.**

I. Introduction

FINGERPRINT is the most widely used trait in biometric recognition. Thanks to its uniqueness and persistence, fingerprint recognition has been successfully deployed in various applications, such as entry control, time and attendance, computer login, forensics, and airport security. Although fingerprint recognition technology has advanced rapidly in the past 40 years [1], there are still some challenging research problems. One challenging problem that has received little attention is the processing and matching of latent fingerprints.

Latent fingerprints are lifted from surfaces of objects that are inadvertently touched or handled by a person. This is achieved through a variety of means ranging from simply photographing the print to more complex dusting or chemical processing [2], [3]. Compared with fingerprints captured using inking or live-scan techniques, automatic feature extraction from latent fingerprints is very difficult due to small finger area, unclear ridge structures, and complex background patterns [4].

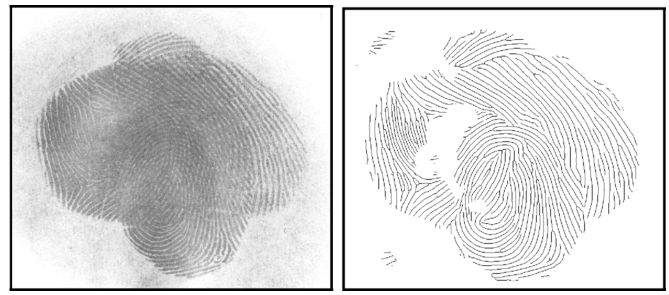

Fig. 1. Latent overlapped fingerprint image and its skeleton image extracted by a well known commercial fingerprint matcher, VeriFinger 6.2 SDK.

One type of latent fingerprint which is very hard to process and match is overlapped fingerprint. Overlapping occurs when the same location of an object is touched by one or more fingers several times. Thus it is very common at crime scenes. Since existing fingerprint feature extraction algorithms are developed under the assumption that fingerprint images contains only one fingerprint, they cannot correctly process overlapped fingerprints. See Fig. 1 for the poor result of applying a well-known commercial fingerprint algorithm, VeriFinger 6.2 SDK, to an overlapped fingerprint image. To identify overlapped fingerprints, fingerprint examiners have to carefully mark the minutiae of each overlapping fingerprint separately. This process is very time-consuming, tedious and prone to error. In fact, fingerprint examiners usually do not collect latent overlapped fingerprints since they are too complicated to process. Thus it is desired to develop an algorithm to separate the overlapped fingerprints into individual fingerprints in order to reduce the labor of fingerprint examiners.

Only a few studies are related to separating overlapped fingerprints [5]–[9]. Among them, only the approaches in [8], [9] contain sufficient details and have been evaluated on public databases. The approach in [9] has a better separating performance at the cost of additional manual markup. The approach in [8], however, only required that the regions of interest (ROI) of two component fingerprints are provided. The separating algorithm in [8] consists of the following steps (see the flowchart in Fig. 2):

1) Region segmentation: The overlapped fingerprint image is divided into background region, overlapped region, nonoverlapped regions of two component fingerprints.
2) Initial orientation field estimation: One dominant orientation is estimated in the nonoverlapped region while two dominant orientations are estimated in the overlapped region.

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The authors are with the Department of Automation, Tsinghua University, Beijing 100084, China (e-mail: jfeng@tsinghua.edu.cn; 20060601@163.com; jzhou@tsinghua.edu.cn).

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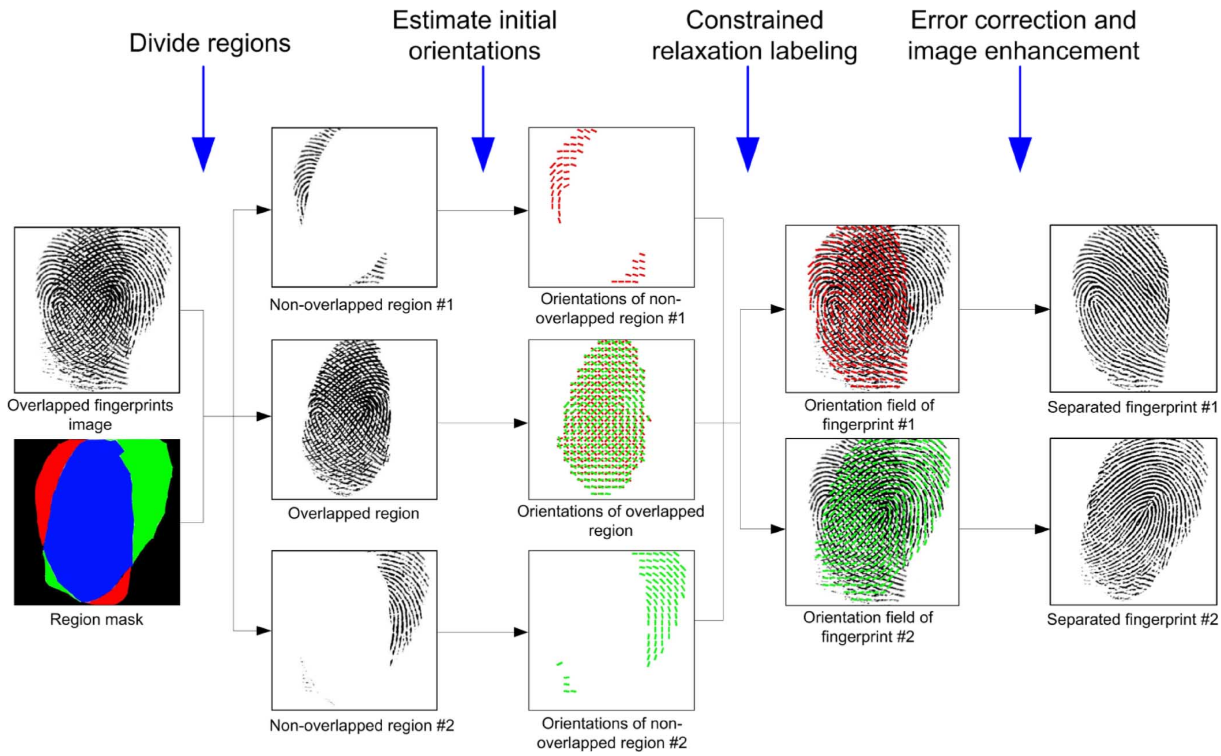


Fig. 2. Flowchart of the proposed separation algorithm.

3) Orientation field separation: The initial orientation field is separated into two component orientation fields.
4) Fingerprint separation: Two component fingerprints are obtained by filtering the overlapped image with Gabor filters tuned to the two component orientation fields respectively.

The most crucial step of this separating method is to separate the mixed orientation field into component orientation fields.

In this paper, based on the same framework as [8], we propose a more robust and efficient orientation field separating algorithm, called constrained relaxation labeling. The proposed algorithm is different from our previous orientation field separating algorithm in [8] in the following three aspects:

1) Formulation of the labeling problem. In this paper an overlapped block is treated as a single object which needs to be labeled in the relaxation labeling procedure, while in [8] each of the two dominant orientations in an overlapped block is treated as a single object. The influence of this change is significant since we can now strictly enforce the mutual exclusion constraint, namely, two dominant orientations in an overlapped block cannot belong to the same fingerprint. In [8], however, this constraint is only loosely used. This change also reduces the number of label probability variables by half and thus speeds up the algorithm.
2) Utilization of nonoverlapped region. In this paper orientation field in the nonoverlapped region is utilized as another important constraint for the relaxation labeling process, while in [8], until the relaxation labeling is finished, nonoverlapped region is then simply combined with the consistent component orientation fields. Using nonoverlapped area as constraints for the labeling process not only leads to better separation results, but also speeds up the convergence of relaxation labeling.
3) Updating algorithm of label probabilities. In this paper label probabilities at overlapped blocks are sequentially updated in an ascending order of the distance from the nonoverlapped region, while in [8], the label probabilities at all overlapped blocks are updated in parallel. Sequential updating is beneficial for both separation performance and efficiency.

A database consisting of 100 latent overlapped fingerprints was collected to evaluate the proposed algorithm[1]. Because of the above differences, the proposed algorithm outperforms the state of art method [8] in both accuracy as well as efficiency.

We also propose two improved versions of the basic algorithm to achieve better separating performance in two special but frequent cases: 1) the mated template fingerprint of one component fingerprint is known, and 2) the two component fingerprints are from the same finger. In both cases, further information on the labels of some overlapped blocks is available. These additional information is used as further constraints in the basic algorithm to reduce ambiguity in relaxation labeling. Experimental results demonstrate that the two improved versions perform better than the basic algorithm in respective cases.

The rest of the paper is organized as follows. In Section II, we give a brief introduction to the whole separating algorithm. In Section III, we describe the proposed orientation field separating algorithm in detail. The improved algorithms for two special cases are described in Section IV. Experimental results

[1]We have made this latent overlapped fingerprint database publicly available (http://ivg.au.tsinghua.edu.cn/) to encourage further research on this important but challenging topic.

TABLE I
NOTATIONS

Symbol	Description
$\mathcal{I}$	Overlapped fingerprint image
R_1	Region of fingerprint #1
R_2	Region of fingerprint #2
R_O	Overlapped region
R_{N1}	Non-overlapped region of fingerprint #1
R_{N2}	Non-overlapped region of fingerprint #2
$\mathbf{x}_i = (x_i, y_i)$	Coordinates of block i
θ_{i1}	First dominant orientations at block i
θ_{i2}	Second dominant orientations at block i
$p_i(1)$	Probability that the label at block i is 1
$p_i(2)$	Probability that the label at block i is 2
$\mathbf{p}_i = (p_i(1), p_i(2))$	Label probability vector at block i

are reported in Section V. Finally we summarize the paper and discuss future work in Section VI.

II. OVERLAPPED FINGERPRINT SEPARATION

A. Region Segmentation

An overlapped fingerprint image is segmented into nonoverlapping blocks of 16×16 pixels. Region mask, orientation field, and frequency map are defined on blocks. In this study, we consider the situation where the overlapped fingerprint image contains only two component fingerprints. The regions of the two component fingerprints are marked manually. Let R_1 and R_2 be the sets of foreground blocks of the two component fingerprints, respectively. Based on R_1 and R_2, an overlapped fingerprint image can be divided into three regions (as shown in Fig. 3):

1) background region, which contains no ridge patterns,
2) overlapped region $R_O = R_1 \cap R_2$, where two fingerprints overlap, and
3) two nonoverlapped regions ($R_{N1} = R_1 - R_2$ and $R_{N2} = R_2 - R_1$), which contains only one fingerprint.

For brevity, we use i to index a block in a region. Let $\mathbf{x}_i = (x_i, y_i)$ be the coordinates of ith block. A block in the overlapped region is called an overlapped block and a block in the nonoverlapped region is called a nonoverlapped block. We will estimate one dominant orientation in each nonoverlapped block and two dominant orientations in each overlapped block. Symbols used in this paper are summarized in Table I

B. Initial Orientation Field Estimation

Since the nonoverlapped region contains only one fingerprint, traditional orientation field estimation approaches, such as gradient-based [10], slit-based [11], [12], or short-time Fourier transform (STFT) [13], can be used to estimate the dominant orientation in each nonoverlapped block. But in the overlapped region, traditional approaches will fail.

Considering the overlapped block as two groups of stripes of different orientations, we use the local Fourier analysis method [14] instead. Discrete Fourier Transform is calculated in the window of 64×64 pixels around an overlapped block. The bright points (i.e., local maximum points) in the frequency spectrum correspond to stripes of different orientations. The two brightest points (i.e., two local maximum points of largest amplitude) correspond to the two orientations in an overlapped block. We only search for the bright points in the area between the two red circles in the frequency domain, which corresponds

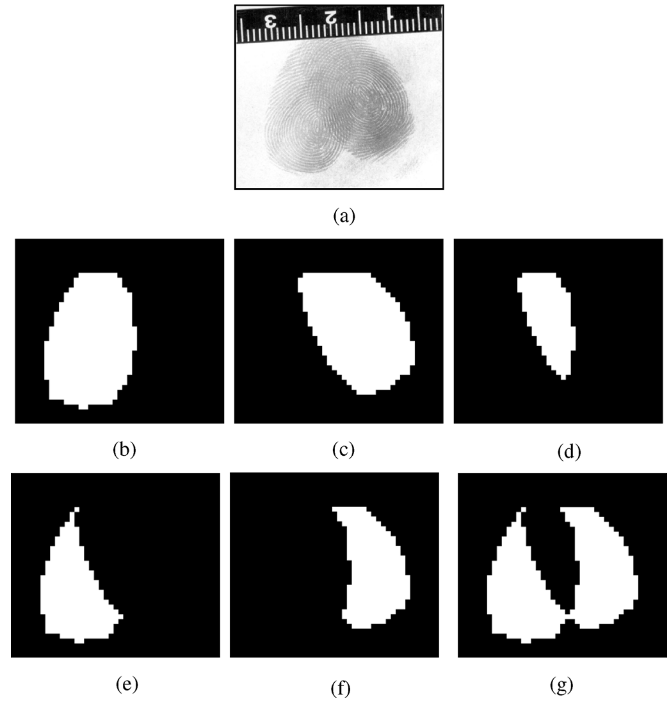


Fig. 3. Different regions of an overlapped fingerprint image. (a) $\mathcal{I}$, (b) R_1, (c) R_2, (d) R_O, (e) R_{N1}, (f) R_{N2}, (g) R_N.

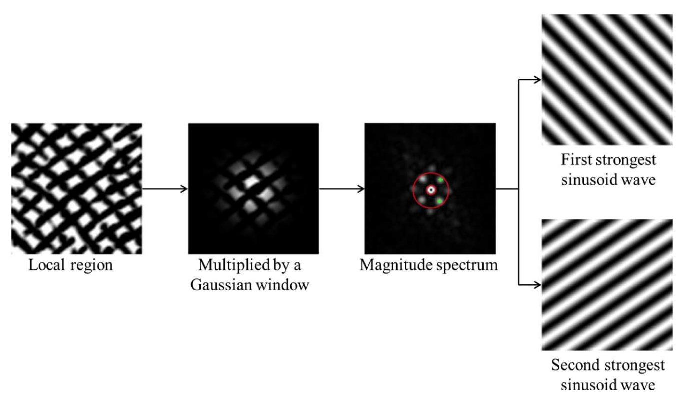


Fig. 4. Estimation of two dominant orientations in an overlapped block.

to valid ridge frequency (See Fig. 4). Although the STFT approach [13] also performs discrete Fourier Transform in the local region, two approaches perform different processing in the frequency domain and our approach is especially suitable for overlapped fingerprints.

This method is used for both overlapped and nonoverlapped blocks. Let θ_{i1} denote the single dominate orientation in a nonoverlapped block i. Let θ_{i1} and θ_{i2} denote the two orientations in an overlapped block i.

C. Fingerprint Separation

After initial orientation field estimation, constrained relaxation labeling will be used to determine the labels of overlapped blocks. Constrained relaxation labeling will be described in detail in the next section. Here we introduce the steps of how to separate the overlapped fingerprints after constrained relaxation labeling.

After constrained relaxation labeling, the orientation fields of the two component fingerprints are obtained. But errors may occur in some area of the orientation field. An error correction algorithm is utilized to smooth the orientation field. The block orientation in each overlapped block is modified as the mean orientation of all block orientations in the 5×5 blockwise square area centered at the block being considered. Although more complicated orientation field regularization algorithms [15]–[17] can be used too, we found this simple approach works well.

After the two component orientation fields are smoothed, the two block-wise frequency maps are calculated using the x-signature approach in [18]. Finally, two component fingerprints are obtained by filtering the overlapped fingerprint image with Gabor filters tuned to the corresponding orientation field and frequency map [18].

III. Constrained Relaxation Labeling

A. Problem Statement

After initial orientation field estimation, we obtain two dominant orientations in each overlapped block and one dominant orientation in each nonoverlapped block. In order to separate the two component fingerprints, we need to know the sources of two dominant orientations in each overlapped block (i.e., which component fingerprint each dominant orientation belongs to). Relaxation labeling (or probabilistic relaxation) was used to identify the sources of overlapped orientations in our previous study [8]. Relaxation labeling refers to a family of iterative algorithms used for function optimization. Originating from the seminar paper of Rosenfeld *et al.* [19], relaxation labeling has been used in many low-level and high-level computer vision problems [20]–[22]. However, the performance of our previous algorithm [8] is not satisfactory in difficult cases due to the following two major limitations: 1) the two orientations in an overlapped block are treated as two objects and the label probability vectors of these two objects are updated independently; 2) orientation fields in the nonoverlapped regions are not utilized in relaxation labeling.

In this paper we propose a new relaxation labeling algorithm, called constrained relaxation labeling. The algorithm is referred to as "constrained" in two senses: 1) an overlapped block is treated as a single object so that the sources of the two orientations in the same overlapped block are mutually exclusive; 2) a nonoverlapped block is treated as an object whose label is deterministic so that nonoverlapped blocks can participate in the relaxation labeling process and influence the labeling of overlapped blocks.

In the language of relaxation labeling, the set of overlapped blocks is the set of objects whose labels are ambiguous and $\Lambda = \{1, 2\}$ is the set of possible labels. Let λ be the label of block i. The relationship between label λ and the sources of the two orientations θ_{i1} and θ_{i2} in block i is as follows.

$$\begin{cases} \text{source}(\theta_{i1}) = \#1, \ \text{source}(\theta_{i2}) = \#2 & \text{if } \lambda = 1 \\ \text{source}(\theta_{i1}) = \#2, \ \text{source}(\theta_{i2}) = \#1 & \text{if } \lambda = 2. \end{cases} \tag{1}$$

Let $p_i(\lambda)$ be the weight of label λ at block i, i.e., the probability that the label λ is the correct label of block i. $p_i(\lambda)$ should satisfy that $0 \leq p_i(\lambda) \leq 1$ and $p_i(1) + p_i(2) = 1$. Let $\mathbf{p}_i = (p_i(1), p_i(2))$ be the label probability vector at block i.

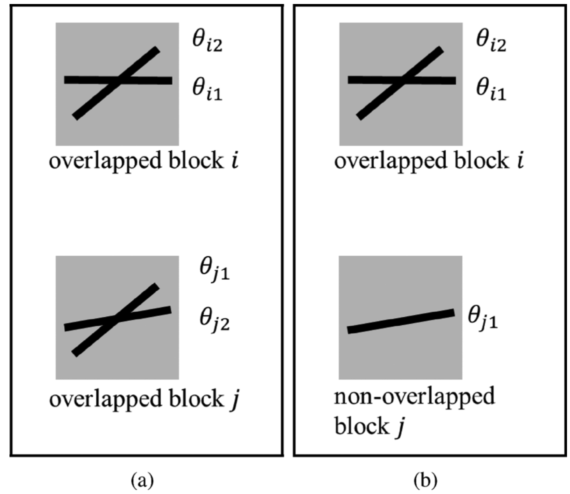


Fig. 5. Two different cases for compatibility function: (a) two overlapped blocks; (b) one overlapped block and one nonoverlapped block.

The labels of nonoverlapped blocks are deterministic. All the foreground blocks in R_{N1} are directly given label 1 and all the foreground blocks in R_{N2} are directly given label 2. Namely, $p_i(n) = 1$ for any nonoverlapped block i of component fingerprint $\#n$. It is the overlapped blocks whose label probability vectors need to be updated by the relaxation labeling process.

B. Compatibility Function

In relaxation labeling, the labels of neighboring blocks affect each other. The compatibility function is used to measure the compatibility between the labels of two blocks. We consider the compatibility functions in two cases shown in Fig. 5.

The first type of compatibility function $R_{ij}(\lambda, \lambda')$ is to measure the compatibility between label λ at overlapped block i and label λ' at overlapped block j.

$$\begin{cases} R_{ij}(1,1) = R_{ij}(2,2) = |\cos(\theta_{i1} - \theta_{j1})| \\ \qquad\qquad\qquad\qquad + |\cos(\theta_{i2} - \theta_{j2})| - 1 \\ R_{ij}(1,2) = R_{ij}(2,1) = |\cos(\theta_{i1} - \theta_{j2})| \\ \qquad\qquad\qquad\qquad + |\cos(\theta_{i2} - \theta_{j1})| - 1. \end{cases} \tag{2}$$

The range of $R_{ij}(\lambda, \lambda')$ is $[-1, 1]$. The compatibility for a pair of labels at two blocks is correlated with the orientation distance (i.e., the angle between two orientations, denoted as $|\cdot|$) between these blocks of the same finger according to the given labels. The larger the orientation distance is, the lower the compatibility is.

The second type of compatibility function is to measure the compatibility between label λ at overlapped block i and label λ' at nonoverlapped block j. Since the label of nonoverlapped block j is known, without loss of generality, we can assume it to be 1.

$$\begin{cases} R_{ij}(1,1) = 2|\cos(\theta_{i1} - \theta_{j1})| - 1 \\ R_{ij}(2,1) = 2|\cos(\theta_{i2} - \theta_{j1})| - 1. \end{cases} \tag{3}$$

The range of the second type of compatibility function is also $[-1, 1]$.

C. Label Probability Updating

Initially, the probabilities of two labels at each overlapped block are set as 0.5, while the probability of the correct label at each nonoverlapped block is set as 1.

Relaxation labeling is an iterative procedure. In each iteration, the label probability vector of block t will be updated by considering the label probability vectors of all neighboring overlapped and nonoverlapped blocks.

The probability updating algorithm should have the following characteristics:

1) The probability $p_i(\lambda)$ of a given label λ for a given block i should be increased if other blocks' labels that have high probabilities are highly compatible with λ at block i.
2) The probability $p_i(\lambda)$ should be decreased if other blocks' labels that have high probabilities are highly incompatible with λ at block i.
3) Labels of other blocks that have low probabilities should have little influence on $p_i(\lambda)$ whether or not they are compatible with each other.

Thus at iteration k, we update $p_i(\lambda)$ using the following equation proposed in [19]:

$$p_i^{k+1}(\lambda) = \frac{p_i^k(\lambda)\left(1 + q_i^k(\lambda)\right)}{\sum\limits_{\lambda \in \Lambda} p_i^k(\lambda)\left(1 + q_i^k(\lambda)\right)}. \quad (4)$$

Support $q_i^k(\lambda)$ is computed as:

$$q_i^k(\lambda) = \sum_{j \in \mathcal{N}_i} w_{ij} \sum_{\lambda' \in \Lambda} R_{ij}(\lambda, \lambda') p_j^k(\lambda'), \quad (5)$$

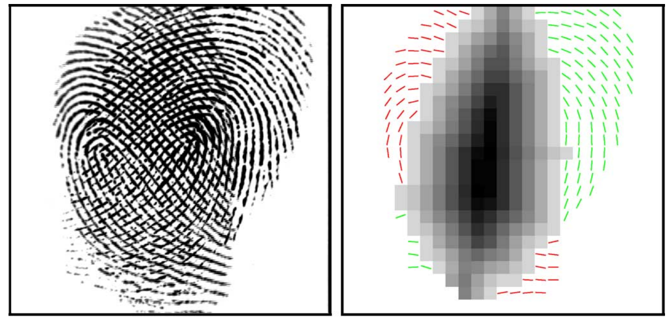
where $\mathcal{N}_i$ denote the set of neighboring blocks of block i, and w_{ij} is the weight used to reflect how strongly block j affects block i. We only take into account the blocks in the square 5×5 block-wise area centered at i. The weight w_{ij} is defined as

$$w_{ij} = \frac{1}{c_i} e^{-\frac{(x_i - x_j)^2 + (y_i - y_j)^2}{2}}, \quad (6)$$

where $c_i = \sum_{j \in \mathcal{N}_i} w_{ij}$ is used to make the sum of weights equal to one.

Generally, we are more confident of the labels at those overlapped blocks which are close to the nonoverlapped blocks. Thus we first update the label probabilities of overlapped blocks adjacent to the nonoverlapped region, then those overlapped blocks (which are not yet updated) adjacent to the updated overlapped blocks, and so on. To implement this idea, we compute the distance transform of the binary image corresponding to nonoverlapped region (shown in Fig. 3(g)). Then the order of overlapped blocks is determined according to the increasing order of the distance. See Fig. 6 for an example. Note that in our previous work [8], the label probabilities are updated in parallel because nonoverlapped blocks are not taken into account in relaxation labeling and the label probabilities of all overlapped blocks are equally uncertain.

We update the probability vectors of all overlapped blocks in one iteration. The iteration is repeated until all $p_i(\lambda)$ converge or the maximum number (empirically set as 50) of iterations is exceeded. The pseudocode of the relaxation labeling algorithm is given in Algorithm 1.



(a) (b)

Fig. 6. (a) Example overlapped fingerprint and (b) the order of updating state probability. State probabilities in overlapped blocks are updated in the increasing order of the distance from nonoverlapped blocks (orientations in the nonoverlapped blocks are shown). In (b), the brighter blocks in the overlapped region are updated earlier than darker blocks.

Initialize label probabilities of all foreground blocks.
Sort overlapped blocks in increasing order of the distance from nearest non-overlapped blocks.
Let N be the number of overlapped blocks.
Set $k = 0$.
while $k < 50$ **do**
  for $i = 1, 2, \cdots, N$ **do**
    for $\lambda = 1, 2$ **do**
      Calculate support $q_i^k(\lambda)$ using Eq. 5.
    end
    for $\lambda = 1, 2$ **do**
      Update probability using Eq. 4.
    end
  end
  if *probability vectors have converged* **then**
    break.
  end
  $k = k + 1$.
end

Algorithm 1. Constrained relaxation labeling algorithm.

D. Orientation Field Separation

After the constrained relaxation labeling process, we obtain the final label probability vector of each overlapped block. The label whose probability is larger is determined as the correct label of an overlapped block. And the sources of two orientations θ_{i1} and θ_{i2} are determined using (1).

We now obtain the orientation fields of the #1 and #2 fingerprints in the overlapped fingerprint image. The orientation field of the #1 fingerprint consists of block orientations whose source is #1 and the #2 orientation field is composed of the block orientations with source #2. After the two component orientation fields are obtained, we use the method described in Section II-C to separate the two component fingerprints.

Fig. 7 shows the separated fingerprints for four latent overlapped fingerprint images via the proposed method and our previous method [8]. The genuine match score (computed by VeriFinger SDK) between the separated component fingerprint and the mated template fingerprint is also shown on each component image. We can observe that the proposed method provides a better separation result. Note that sometimes a better separation result may not produce a higher match score, since the

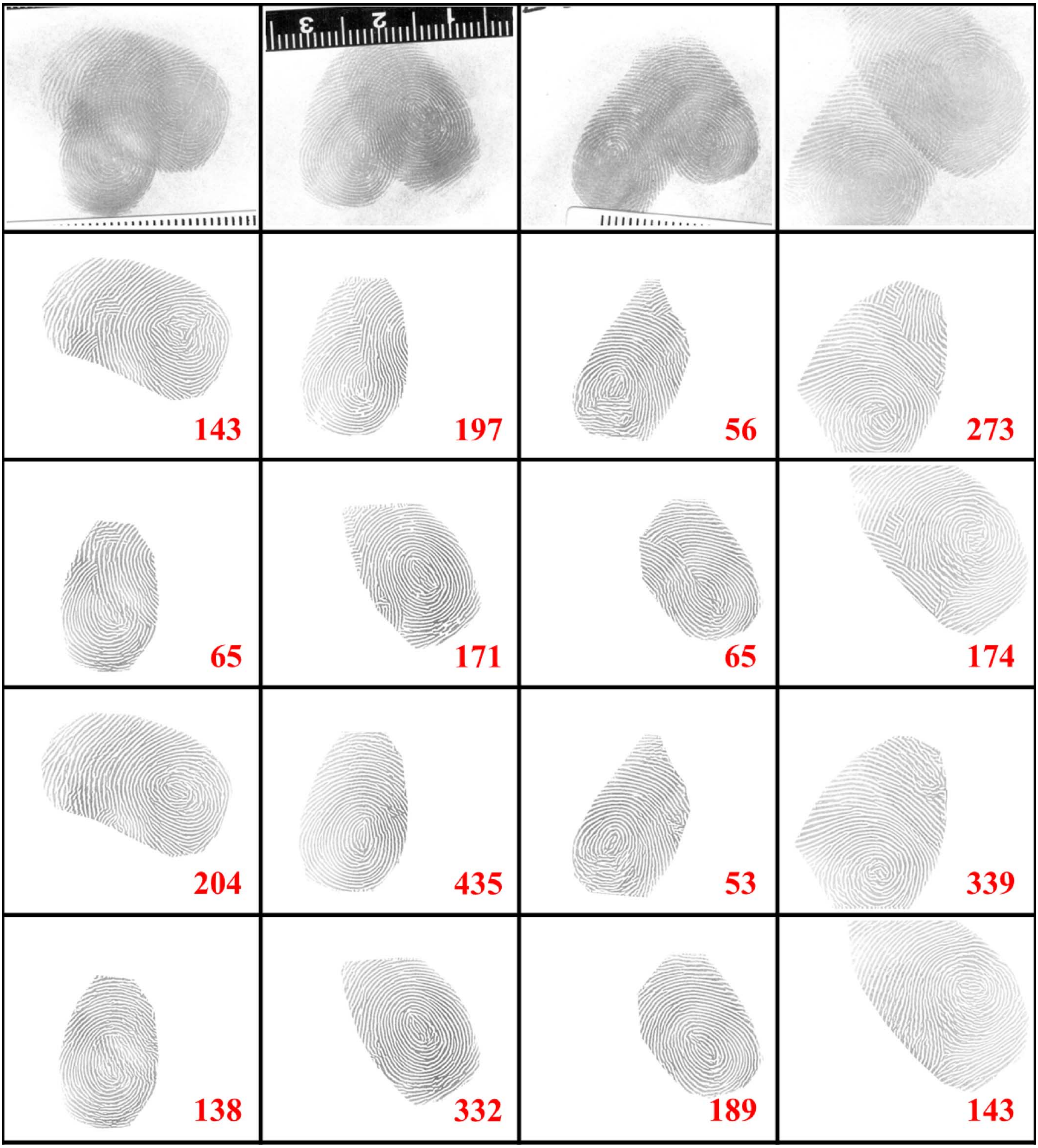


Fig. 7. Four overlapped fingerprints and their separating results by two algorithms. Each column shows one example. In each column, the image on the first row is the latent overlapped fingerprint image; the second and third rows are separated fingerprints by our previous method [8]; the fourth and fifth rows are separated fingerprints by the proposed method. The genuine match score of each component fingerprint is shown on the image.

match score depends on the quality in the common area of two fingerprints and the specific matcher.

IV. Improved Algorithms for Two Cases

Quite often there is additional information available which can be utilized to obtain better separation performance. Here we describe how to modify the basic separation algorithm described in the preceding section for the following two special but frequent cases:

1) The mated template fingerprint of one component fingerprint is known. For example, this component fingerprint may be left by the victim or his/her family member, or by

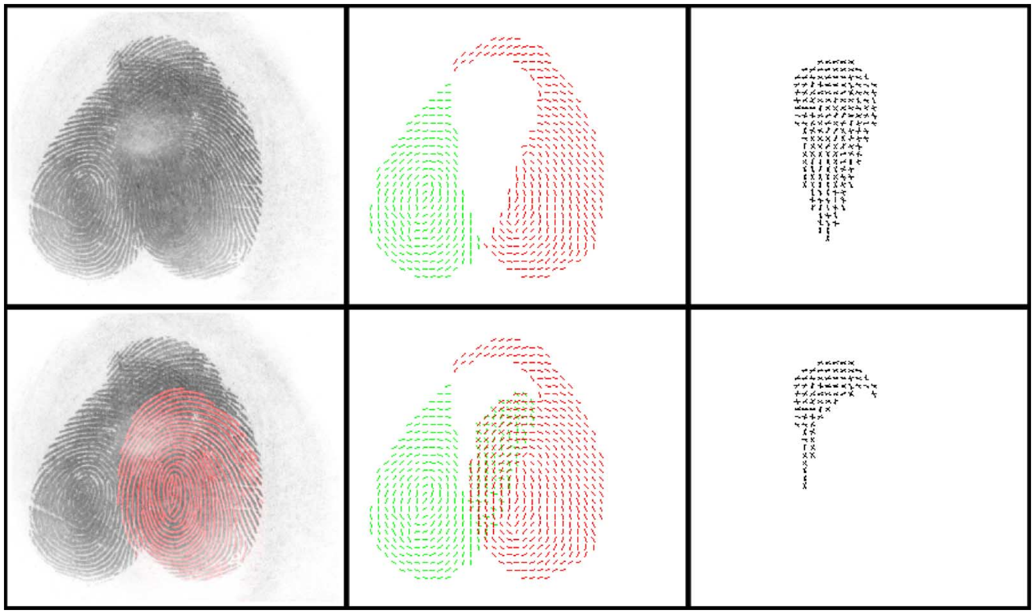


Fig. 8. Top row shows the overlapped fingerprint image, orientation elements whose sources are known, and orientation elements whose sources are unknown. Bottom row shows the overlapped fingerprint image with template fingerprint overlaid, orientation elements whose sources are known and orientation elements whose sources are unknown with guidance of template fingerprint.

a police officer who is investigating the crime scene. Thus the list of candidate fingerprints is short and it is relatively easy to link this component fingerprint to its template fingerprint. This component fingerprint may also be identified from a fingerprint database because its separation result is good. In both situations, we wish to improve the separation performance of the other component fingerprint so that it can be identified too.

2) The two component fingerprints are from the same finger. This type of overlapping occurs when the same location of an object is touched by the same finger several times. Such overlapped fingerprints are common in weapons used by criminals, doorknobs, bottles, etc. Experienced fingerprint examiners can easily tell whether two component fingerprints are from the same finger or not from their overall ridge flow (orientation field).

A. Case I

In this case, we have an overlapped fingerprint image and a template fingerprint which is known to be mated to one of the two component fingerprints, and we know the spatial transformation between the template fingerprint and the mated component fingerprint. Without loss of generality, we assume that the component fingerprint #1 is mated to the template fingerprint. The spatial transformation between the template fingerprint and the mated component fingerprint can be automatically estimated using minutiae matcher or manually specified.

Let T be the spatial transformation from the component fingerprint #1 to the template fingerprint. The transformed coordinate of an overlapped block i is computed as $\mathbf{x}_i' = T(\mathbf{x}_i)$. If $\mathbf{x}_i'$ is in the foreground region of the template fingerprint, the ridge orientation (referred to as guiding orientation) at $\mathbf{x}_i'$ of the template fingerprint can be used to guide the labeling of block i and the sources of the two orientations in block i are clear before the relaxation labeling procedure. Otherwise, if $\mathbf{x}_i'$ is in the background region of the template fingerprint, the sources of the two orientations in block i are unclear before the relaxation labeling procedure.

To utilize the template fingerprint, we make two changes to the basic separating algorithm described in Section III:

1) Estimation of initial orientation field. For each overlapped block i which is mapped to the foreground region of the template fingerprint, we check whether the two orientations in block i are close to the guiding orientation. If neither of them is close, the initial orientation estimate is not correct. Thus we adjust the two candidate orientations as follows. The second candidate orientation is discarded. The first candidate is set as the second, and the guiding orientation is set as the first one.
2) Initialization of label probabilities. For each overlapped blocks i which is mapped to the foreground region of the template fingerprint, the source of the orientation which is closer to the guiding orientation is determined as #1. The probability of the corresponding label at block i is initialized as 1. For other overlapped blocks, the probabilities of both labels are initialized as 0.5.

An example is given in Fig. 8 to illustrate the idea of this improved algorithm. According to the basic separation algorithm, the labels of all overlapped blocks are unknown and all overlapped blocks need to be labeled. But with the guidance of the template fingerprint, the labels of some overlapped blocks become known and fewer overlapped blocks need to be labeled.

Four examples of case I are shown in Fig. 9 to compare the separating results with/without guidance of the template fingerprint of one component fingerprint. As we can see, guidance of the template is very helpful, especially around the singularity region, where orientation field is discontinuous.

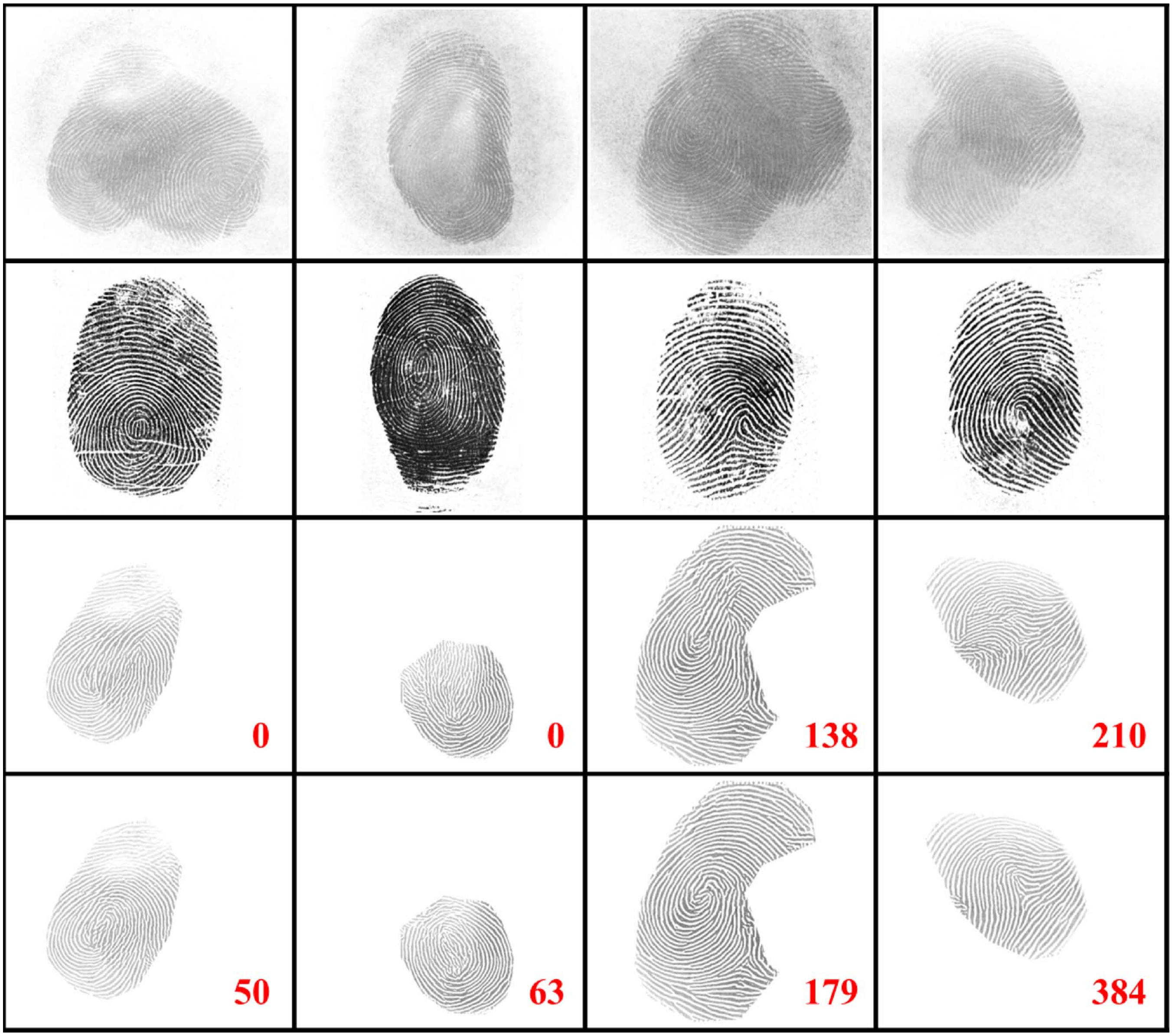
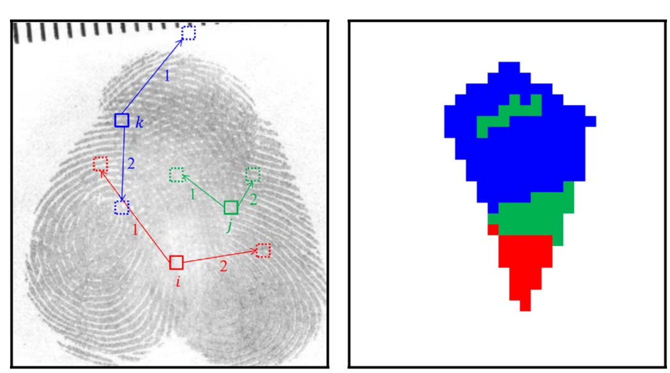


Fig. 9. Four overlapped fingerprint images in case I and their separating results by the proposed basic separating algorithm and the modified version for such cases. Each column corresponds to one example. Rows 1–4 correspond to the overlapped image, the mated template fingerprint of one component fingerprint, the other component fingerprint separated by the basic separating algorithm, and the other component fingerprint separated by the modified version.

B. Case II

In this case, we have an overlapped fingerprint image in which the two component fingerprints are from the same finger, and we know the spatial transformation between the two component fingerprints. The spatial transformation is estimated based on a few matching points which are manually marked by examining the whole orientation fields of the two component fingerprints.

Let T be the spatial transformation from the component fingerprint #1 to the component fingerprint #2 and T^{-1} the inverse transformation of T, namely, the spatial transformation from the component fingerprint #2 to the component fingerprint #1. For each overlapped block i, we compute its transformed coordinate $\mathbf{x}_i^1 = T^{-1}(\mathbf{x}_i)$ in component fingerprint #1 and transformed coordinate $\mathbf{x}_i^2 = T(\mathbf{x}_i)$ in component fingerprint #2. Fig. 10(a) shows three overlapped blocks (i, j, and k) and their



(a) (b)

Fig. 10. Three types of overlapped blocks in an overlapped fingerprint image where the two component fingerprints are from the same finger. (a) Three overlapped blocks of different types and their transformed locations; (b) Type map of overlapped blocks. Three types are shown in three different colors (red, green, and blue).

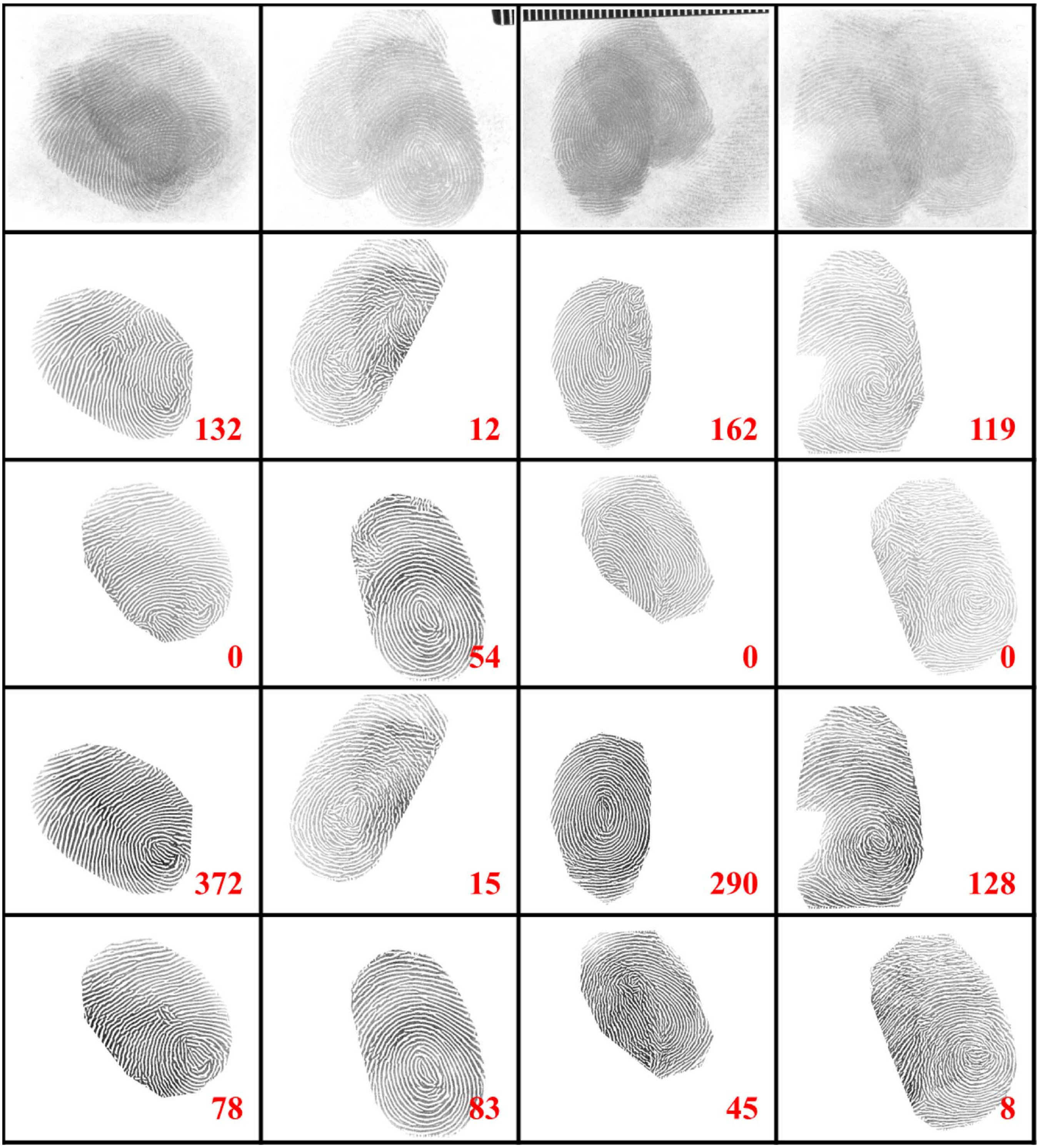


Fig. 11. Four overlapped fingerprint images in case II and their separating results by the proposed basic separating algorithm and the modified version for such cases. Each column corresponds to one example. Rows 1–5 correspond to the overlapped image, two component fingerprints separated by the basic separating algorithm, and two component fingerprints separated by the modified version.

transformed coordinates (shown as rectangles of dashed edges) in two component fingerprints.

An overlapped block i can be classified into one of the following three types:

1) both $\mathbf{x}_i^1$ and $\mathbf{x}_i^2$ are in the foreground region of the corresponding component fingerprint (e.g., block i in Fig. 10(a)), thus there are two guiding orientations for block i and the component fingerprints containing the transformed blocks are referred to as the guiding component fingerprints;
2) either $\mathbf{x}_i^1$ or $\mathbf{x}_i^2$ is in the foreground region of the corresponding component fingerprint (e.g., block j in Fig. 10(a)) and thus there is one guiding orientation for block i;

Fig. 12. Query fingerprints of four groups of matching experiments. (a) Overlapped fingerprints (i.e., no separation); (b) overlapped fingerprints separated by mask images; (c) component fingerprints separated by our previous method [8]; (d) component fingerprints separated by the proposed method.

3) both $\mathbf{x}_i^1$ and $\mathbf{x}_i^2$ are in the background region of the corresponding component fingerprint (e.g., block k in Fig. 10(a)), and thus there is no guiding orientation for block i.

Fig. 10(b) shows the types of all overlapped blocks of an overlapped fingerprint image.

To utilize the guiding orientations, we make two changes to the basic separating algorithm described in Section III:

1) Estimation of initial orientation field. For each overlapped block i of the first type, we directly set the ridge orientations (namely, the guiding orientations) at the two transformed locations as the two orientations in block i, since the transformed locations are in the nonoverlapped region and thus more reliable in general. For each overlapped block of the second type, we check whether the two orientations in this block are close to the guiding orientation. If neither of them is close, the initial orientation estimate is not correct. Thus we adjust the two candidate orientations as follows. The second candidate orientation is discarded. The first candidate is set as the second, and the guiding orientation is set as the first one.
2) Initialization of label probabilities. For each overlapped block of the first type, the sources of the two orientations are assigned to the guiding component fingerprints with dissimilar guiding orientations, respectively. For each overlapped block of the second type, the source of the orientation which is dissimilar to the guiding orientation is determined as the guiding component fingerprint and the source of the other orientation is assigned to the other component fingerprint. For each overlapped block of the first or second type, the probability of the correct label is initialized as 1. For overlapped blocks of the third type, the probabilities of both labels are initialized as 0.5.

Four overlapped fingerprint images from the same finger are shown in Fig. 11 to compare the separating results of the basic separating algorithm and the modified version for such cases. The modified version perform better than the basic separating algorithm for all four examples. The recognition accuracy for this type of overlapping can be further improved by fusing the two component fingerprints into a single fingerprint with larger size and/or higher image quality using the fingerprint mosaicking technique described in [23]. But this topic is out of the scope of this paper.

V. Experimental Results

The final goal of separating overlapped fingerprint images is to successfully match the separated fingerprint (query fingerprint) to the corresponding template fingerprint. Thus matching experiments on two overlapped fingerprint databases were conducted to evaluate the proposed algorithm. Both two databases (including region masks) are publicly available (http://ivg.au.tsinghua.edu.cn/).

The first database is the simulated overlapped fingerprint database used in our previous study [8]. The images of overlapped fingerprints are synthesized by the no. 3 impressions and no. 4 impressions of ten fingers in FVC2002 DB1_B [24]. Each no. 3 impression will be overlapped with no. 4 impressions of all the ten fingers. So there are $10 \times 10 = 100$ images of overlapped fingerprints. No. 1 impressions of the ten fingers are utilized as template fingerprints.

We also collected a new database which consists of 100 latent overlapped fingerprints (see Fig. 7 for some examples). These latent overlapped 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

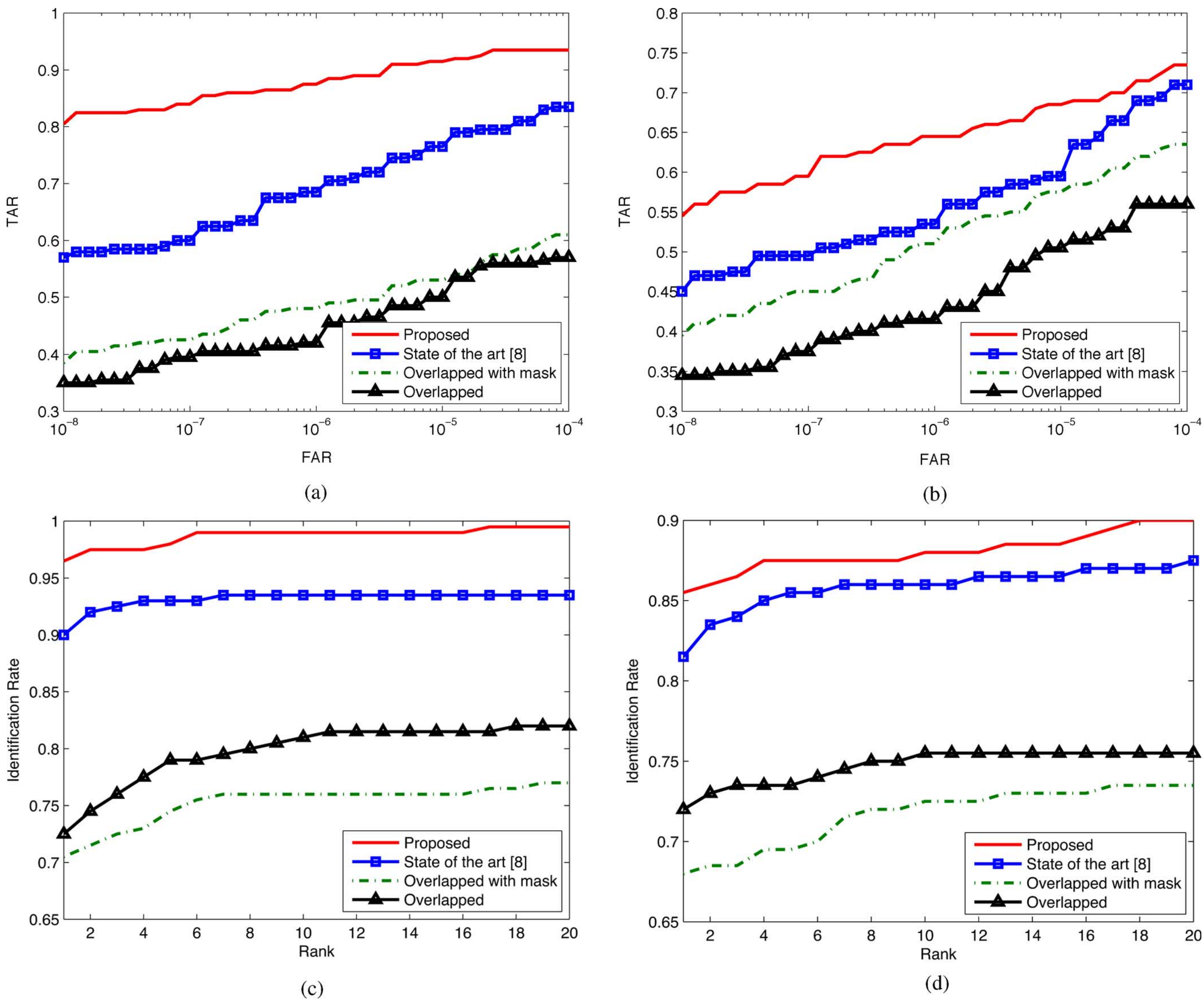


Fig. 13. ROC and CMC curves on two overlapped fingerprint databases. Four curves correspond to the four types of query images shown in Fig. 12. (a) ROC on simulated database; (b) ROC on latent database; (c) CMC on simulated database; (d) CMC on latent database.

brush, and 3) convert the enhanced prints into electronic version using a general purpose HP scanner. For each of the twelve different fingers participating this experiment, one flat fingerprint is obtained using an optical fingerprint scanner. These are used as template fingerprints. The resolution of the fingerprints in both databases is 500 ppi.

A commercial fingerprint matcher, VeriFinger 6.2 SDK, is used to match the separated fingerprints with the corresponding template fingerprints. To plot the Receiver Operating Characteristic (ROC) curve, only genuine matches are executed because the output scores of the VeriFinger matcher are linked to the False Accept Rate (FAR). To plot the Cumulative Match Characteristic (CMC) curve, 2 000 rolled fingerprints in NIST SD4 are used as the background database.

For each of the two overlapped fingerprint databases, four groups of matching experiments (where query fingerprints are processed by different methods) are conducted. In the first group, the overlapped fingerprint images are directly matched with the template fingerprints. In the second group, the overlapped fingerprint images segmented using the two region masks are matched with the template fingerprints. In the third and fourth groups, our previous method and current method are used to separate the overlapped images respectively, and the separated fingerprints are matched with the template fingerprints. Fig. 12 shows the query images of four groups of matching experiments for an overlapped image. The ROC and CMC curves on two databases are given in Fig. 13. From these figures, we observed that:

1) The proposed separating method outperforms the rest three methods on both simulated and real overlapped fingerprint databases.
2) Both our previous and current methods outperform the rest two methods.
3) The latent overlapped fingerprint database is more difficult than the simulated database.

The area of overlapped and nonoverlapped regions may impact the relative performances of different separating approaches. According to the ratio of overlapped region to the whole fingerprint region, overlapped latent fingerprints are classified into three categories of equal size: small, medium,

TABLE II
RANK-1 IDENTIFICATION RATES OF FOUR SEPARATING APPROACHES FOR DIFFERENT OVERLAPPING RATIOS

	Proposed	State of the art [8]	Overlapped with mask	Overlapped
Small	0.8209	0.8507	0.7313	0.7612
Medium	0.8955	0.8507	0.6716	0.7313
Large	0.8485	0.7424	0.6364	0.6667

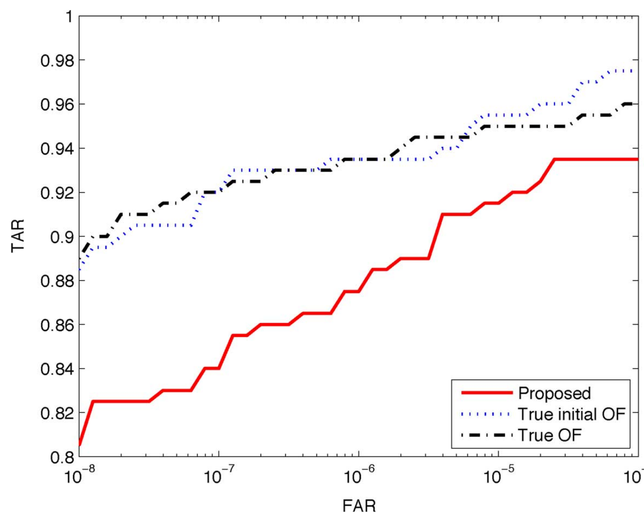


Fig. 14. ROC curves of three groups of matching experiments using different query images: (1) component fingerprints separated by using true orientation fields, (2) component fingerprints separated by the proposed separation method using true initial orientation field, and (3) component fingerprints separated by the proposed separation method.

and large. The rank-1 identification rates of the four separating approaches for three categories are given in Table II. As we expected, the accuracy gain due to the relaxation-based separating algorithms is significant when the overlapped area is large. We also noted that the matching accuracy of the proposed separating algorithm for the small category is not the highest. This is because image quality also has a large impact on the matching accuracy.

In the experiments, we found that the estimation error of the initial orientations in the overlapped blocks greatly impact the separation results. In order to demonstrate this, we conducted two groups of contrast experiments using the simulated overlapped fingerprint database. In the first group of experiments, we use the true orientation fields (we obtain this information from the original fingerprint image) of the two component fingerprints to separate the overlapped fingerprints. In the second experiment, we use the true values of the two orientations in the overlapped blocks as the two estimated value (i.e., the initial orientation field is ideal), but their labels are not known and we use the proposed relaxation labeling algorithm to determine them. The other parts of the separation algorithm are the same in all experiments. The ROC curves of these two groups of matching experiments and the ROC curve of the proposed separation algorithm are shown in Fig. 14. As can be observed from this figure, the performance of our method using true initial orientation field is almost the same as the performance of directly using the true orientation fields. This indicates that the initial orientation field estimation is the bottleneck of the whole separating algorithm.

The proposed method is much faster than our previous method. The average time of the proposed algorithm (implemented in MATLAB) is about 10 seconds on a PC with 2.93 GHz CPU, while it is around 2 minutes for our previous method.

VI. CONCLUSIONS AND FUTURE WORK

Separating overlapped fingerprints into component fingerprints is very useful in latent fingerprint recognition. Although a few preliminary studies on this topic have been published, these algorithms are not robust for realistic latent overlapped fingerprints. We proposed a robust and efficient relaxation labeling algorithm to estimate the component orientation fields of latent overlapped fingerprints. With component orientation field correctly estimated, obtaining component fingerprints becomes a straightforward task. We also proposed two improved versions of the basic algorithm to better handle two special cases of overlapping: 1) the mated template fingerprint of one component fingerprint is known and 2) the two component fingerprints are from the same finger. Experiments on both simulated and real overlapped fingerprint databases demonstrated that the basic algorithm outperforms the state of the art method in both accuracy and efficiency. The two improved versions also perform better than the basic algorithm in respective cases. To encourage further research on this important and challenging topic, we have made both the real and simulated overlapped fingerprint databases publicly available.

There are still some limitations in our method. Initial orientation estimation has a large influence on the separation performance of the current algorithm. However, it is very hard for local operator (such as local Fourier analysis) to correctly estimate initial orientation from poor quality latent fingerprints. The current algorithm cannot deal with latent images with more than two overlapped fingerprints or latent images with two overlapped fingerprints and structured noise. As a future work, we plan to study global fingerprint orientation field model and develop more robust separating algorithms.

The current algorithm also does not perform very well if the overlapped region contains singular points. It is mainly because the assumption that the two overlapped orientations should be different does not hold around overlapped singular points. A possible solution is to detect overlapped singular points using a robust singular point detector and then explicitly consider the impact of singular points.

Another limitation of the current separation algorithm is that it is not yet fully automatic. The region masks of the two component fingerprints must be marked manually. Our long term goal is to develop a fully automatic separating algorithm which requires no input from human. But because the quality of latent fingerprints varies significantly, it is impractical to develop a single separating algorithm that works for all latent overlapped fingerprints. Thus as a short term goal, we will also explore more efficient human interaction.

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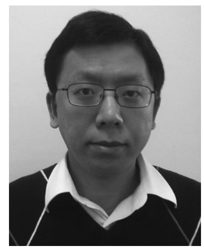

Jianjiang Feng (M'10) is an assistant professor in the Department of Automation at Tsinghua University, Beijing. He received the B.S. and Ph.D. degrees from the School of Telecommunication Engineering, Beijing University of Posts and Telecommunications, China, in 2000 and 2007, respectively. From 2008 to 2009, he was a Postdoctoral researcher in the Pattern Recognition and Image Processing Laboratory at Michigan State University. His research interests include image processing and pattern recognition.

Yuan Shi received the B.S. and M.S. degrees from the Department of Automation, Tsinghua University, Beijing, China, in 2007 and 2011. His research interests are in pattern recognition, image processing, and ranking of web pages.

Jie Zhou (M'01–SM'04) received the B.S. and M.S. degrees from the Department of Mathematics, Nankai University, Tianjin, China, in 1990 and 1992, respectively, and the Ph.D. degree from the Institute of Pattern Recognition and Artificial Intelligence, Huazhong University of Science and Technology (HUST), Wuhan, China, in 1995.

From 1995 to 1997, he was a postdoctoral fellow with the Department of Automation, Tsinghua University, Beijing, China. Currently, he is a full professor with the Department of Automation, Tsinghua University. His research area includes pattern recognition, computer vision, and data mining. In recent years, he has authored more than 100 papers in peer-reviewed international journals and conferences.

He received the Best Doctoral Thesis Award from HUST in 1995, First Class Science and Technology Progress Award from Ministry of Education (MOE) in 1998, Excellent Teaching Award from Tsinghua University in 2003, and Best Advisor Awards from Tsinghua University in 2004 and 2005, respectively. He was selected as one of outstanding scholars of MOE in 2005. He is an associate editor for the *International Journal of Robotics and Automation* and *Acta Automatica Sinica*.