Separating Overlapped Fingerprints Using Constrained Relaxation Labeling

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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 the separation of mixed orientation fields into component orientation fields. In this paper, a constrained relaxation labeling algorithm is proposed to perform the orientation field separation task. 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.

1. 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 forty years [7], there are still some challenging research problems. One challenging problem that has received little attention is the processing and matching of overlapped fingerprints.

Overlapped fingerprints are frequently encountered in latent fingerprints lifted from crime scenes. Since existing fingerprint feature extraction algorithms are developed under the assumption that fingerprint images contain 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. 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 [4, 3, 10, 2]. Among them, the work by Chen et al. [2] may be viewed as the state of the art. In [2], by applying a relaxation labeling method on the initial/mixed orientation fields obtained by local Fourier analysis, the two component orientation fields are obtained. The two component fingerprints are then separated by filtering the overlapped fingerprint image using Gabor filters tuned to the component orientation fields. In this method, the most crucial step is to separate the mixed orientation field into component orientation fields.

In this paper, we propose an overlapped orientation field separating method based on constrained relaxation labeling. This method differs from the algorithm in [2] in the following aspects:

1. Utilization of non-overlapped area. In this work, non-overlapped area is utilized as important constraints during the relaxation labeling process, while in [2], until the relaxation labeling is finished, non-overlapped area is then simply combined with consistent component orientation fields. Using non-overlapped area as
constraints not only leads to better separation results, but also speeds up the convergence of relaxation labeling.

2. Mutual exclusion constraint. We treat each overlapped block as a single object rather than two ones to strictly enforce the mutual exclusion constraint, namely, two candidate orientations in an overlapped block cannot belong to the same fingerprint. In [2], however, this constraint is only loosely used because the two candidate orientations in an overlapped block are treated as two objects.

3. Order of updating label probabilities. We sequentially update label probabilities in an overlapped block in an ascending order of the distance between itself and non-overlapped area. While in [2], the label probabilities in all overlapped blocks are updated in parallel. Sequential updating is beneficial for both separation performance and computational complexity.

The proposed overlapped fingerprint separation algorithm 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, non-overlapped regions of two component fingerprints.

2. Initial orientation field estimation: One dominant orientation is estimated in the non-overlapped region while two dominant orientations are estimated in the overlapped region.

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.

In section 2, we described the steps 1, 2, and 4. Step 3, which is the most crucial step and also the major contribution of this paper, is described in section 3. Section 4 shows the results of experiments. Finally we present the conclusions and future work in section 5.

2. Overlapped Fingerprint Separation

2.1. Region Segmentation

In this paper, we consider the situation where the overlapped fingerprints image contains only two component fingerprints. The masks of the two component fingerprints are marked manually. An overlapped fingerprint image consists
of three regions: the background region, the overlapped region, and the non-overlapped region of two component fingerprints. The background region does not contain ridge patterns. The overlapped region is the common region of the two masks (i.e. the intersection of the two masks) and it contains the overlapped part of the two fingerprints. The non-overlapped region contains only one fingerprint (i.e. the subtraction of the two masks). Fig. 3 gives the procedure of dividing regions.

An overlapped fingerprint image is segmented into non-overlapping blocks of $16 \times 16$ pixels. The block in the overlapped region is called overlapped block and the block in the non-overlapped region is called non-overlapped block. We estimate one dominant orientation in each non-overlapped block and two dominant orientations in each overlapped block.

### 2.2. Initial Orientation Field Estimation

Since the non-overlapped region contains only one fingerprint, traditional orientation field estimation methods, such as gradient-based [1] or slit-based [8], can be used to estimate the orientation in each non-overlapped block. But in the overlapped region, traditional methods will fail. Considering the overlapped block as two groups of stripes of different directions, we use the local Fourier analysis method [6] instead. Discrete Fourier Transform is calculated in the window of $64 \times 64$ pixels with each overlapped block in its center. The bright points (i.e. local maxima points) in the frequency spectrum correspond to stripes of different directions. The two brightest points (i.e. two local maxima points of largest amplitude) correspond to the two orientations of each overlapped block. We only search the bright points in the area between the two red circles in the frequency domain, which correspond to valid ridge frequency (See Figure 4).

It is worth noting that the directions of the two stripes may be the same. To handle this case, we compute the ratio of the amplitude of the first brightest point to the amplitude of the second brightest point. If the ratio is larger than a threshold (i.e. the second brightest point is spurious), the orientations of the two stripes are deemed as the same and the first brightest point corresponds to the two stripes.

### 2.3. Fingerprint Separation

After orientation estimation, constrained relaxation labeling will be used to determine the labels of orientations 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 some 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 $5 \times 5$ block-wise square area centered at the block being considered.

After the two component orientation fields are smoothed, the two block-wise frequency images are calculated using the x-signature method in [5]. Finally, two component fingerprints are obtained by filtering the overlapped fingerprint image with Gabor filters tuned to the corresponding orientation field and frequency image [5].

### 3. Constrained Relaxation Labeling

#### 3.1. Problem Statement

After initial orientation estimation, we obtain two orientations in each overlapped block. But we do not know their labels (i.e. which orientation belongs to which fingerprint). Relaxation labeling [9] is used to identify the labels of the two orientations in [2]. But their result is not satisfactory because the authors only use the orientations in each overlapped block and do not take the inherent constraints of them into account. In this paper we propose the con-
strained relaxation labeling algorithm to identify the labels. Not only the orientations in overlapped blocks but also the orientations in non-overlapped blocks are taken into consideration.

We introduce a two dimension vector to denote the two orientations of each overlapped block. Suppose there are $N$ blocks in overlapped region and the vector $a_i = (a_{i1}, a_{i2})^T$ is the orientation-vector of the $i$th overlapped block ($a_{i1}$ and $a_{i2}$ are the two orientations). So $A = \{a_1, a_2, \ldots, a_N\}$ is the set of $N$ orientation-vector objects to be labeled. We use the set $L = \{1, 2\}$ to describe the labels of the orientations. Since $a_i$ is two dimension vector, we introduce a state set $S = \{1, 2\}$ to describe the state of labels of $a_{i1}$ and $a_{i2}$:

$$s_{a_i} = \begin{cases} 
1 & \text{if } \text{label}(a_{i1}) = 1, \text{label}(a_{i2}) = 2 \\
2 & \text{if } \text{label}(a_{i1}) = 2, \text{label}(a_{i2}) = 1.
\end{cases} \quad (1)$$

The orientations of the non-overlapped region #1 are given label 1 and the orientations of the non-overlapped region #2 are given label 2. Suppose there are $M$ blocks in the two non-overlapped regions and $b_j$ is the orientation of the $j$th non-overlapped block. So $B = \{b_1, b_2, \ldots, b_M\}$ is the set of $M$ orientations whose labels are known. To keep correspondence with $A$, we also introduce the state set $S = \{1, 2\}$ to describe the label of $b_j$:

$$s_{b_j} = \begin{cases} 
1 & \text{if } \text{label}(b_j) = 1 \\
2 & \text{if } \text{label}(b_j) = 2.
\end{cases} \quad (2)$$

Now $A \cup B = \{a_1, a_2, \ldots, a_N, b_1, b_2, \ldots, b_M\}$ is the set of the orientations of blocks in overlapped region and non-overlapped region.

Let $p_{a_i}(s_{a_i})$ be the probability that the state $s_{a_i}$ is the correct state of and satisfy: $0 \leq p_{a_i}(s_{a_i}) \leq 1$ and $p_{a_i}(1) + p_{a_i}(2) = 1$. Let $p_{b_j}(s_{b_j})$ be the probability that the state $s_{b_j}$ is the correct state of $b_j$ and satisfy: $0 \leq p_{b_j}(s_{b_j}) \leq 1$ and $p_{b_j}(1) + p_{b_j}(2) = 1$. Because the states of all non-overlapped blocks are known, we find that the state probability of $b_j$ is $p_{b_j}(1) = 1, p_{b_j}(2) = 0$ if $b_j$ belongs to the first non-overlapped region and $p_{b_j}(1) = 0, p_{b_j}(2) = 1$, if $b_j$ belongs to the second non-overlapped region.

3.2. Compatibility Function

In relaxation labeling, the labels of objects affect each other. The compatibility function is used to measure the correlation between the labels of two objects. In this paper, the states of two objects in $A \cup B$ affect each other. We consider two types of compatibility functions: one for two objects in A, and another one for one object in A and one object in B.

The first type of compatibility function is to measure the affection from $a_i$ in $A$ to $a_j$ in $A$. We can denote this type of compatibility function in the form of conditional probability: $C_{ij}^{aa}(s_{a_i}, s_{a_j}) = p_{a_i, a_j}(s_{a_i}, s_{a_j})$. Because of symmetry we can find that:

$$\begin{align*}
C_{ij}^{aa}(1, 1) &= C_{ij}^{aa}(2, 2) = \beta \\
C_{ij}^{aa}(1, 2) &= C_{ij}^{aa}(2, 1) = 1 - \beta, \\
\end{align*} \quad (3)$$

where

$$\beta = \frac{\text{dis}_{ij}^{a_1} + \text{dis}_{ij}^{a_2}}{\text{dis}_{ij}^{a_1} + \text{dis}_{ij}^{a_2}}$$

$$\text{dis}_{ij}^{a_1} = |a_{i1} - a_{j1}| + |a_{i2} - a_{j2}|$$

$$\text{dis}_{ij}^{a_2} = |a_{i1} - a_{j2}| + |a_{i2} - a_{j1}|.$$  

The compatibility is measured according to the 1-norm distances of different states of $a_i$ and $a_j$. The larger the distance is, the lower the compatibility is.

The second type of compatibility function is to measure the affection from $b_k$ in $B$ to $a_j$ in $A$. We can define this type of compatibility function like this: $C_{kj}^{ba}(s_{b_k}, s_{a_j}) = p_{b_k, a_j}(s_{b_k}, s_{a_j})$. Because of symmetry we can find that:

$$\begin{align*}
C_{kj}^{ba}(1, 1) &= C_{kj}^{ba}(2, 2) = \lambda \\
C_{kj}^{ba}(1, 2) &= C_{kj}^{ba}(2, 1) = 1 - \lambda, \\
\end{align*} \quad (4)$$

where

$$\lambda = \frac{\text{dis}_{ij}^{b_1} + \text{dis}_{ij}^{b_2}}{\text{dis}_{ij}^{b_1} + \text{dis}_{ij}^{b_2}}$$

$$\text{dis}_{ij}^{b_1} = |b_{k1} - a_{j1}|$$

$$\text{dis}_{ij}^{b_2} = |b_{k2} - a_{j2}|.$$  

The second type of compatibility is also measured according to the distances of different states of $b_k$ and $a_j$. The distance here has a special form.

Since the state of arbitrary $b_k$ is known, we do not need to define the compatibility function from arbitrary $b_k$ in $B$ to $b_j$ in $B$ or from arbitrary $a_i$ in $A$ to $b_j$ in $B$.

3.3. State Probability Updating

Relaxation labeling is an iterative procedure. In each iteration, the state probability of $a_j$ will be updated by considering all the state probability of any neighboring object $a_i$ and $b_k$ (if $a_i$’s block is the neighbor of $a_j$’s block, we call $a_i$ the neighbor of $a_j$; so is $b_k$).

We can calculate the probability increment like this:

$$\Delta p_{a_j}(s_{a_j}) = \sum_{a_i \in A, i \neq j} w_{ij}^{aa} \sum_{s_{a_i} \in S} p_{a_i}(s_{a_i}) C_{ij}^{aa}(s_{a_i}, s_{a_j}) + \sum_{b_k \in B} \sum_{s_{b_k} \in S} p_{b_k}(s_{b_k}) C_{kj}^{ba}(s_{b_k}, s_{a_j}), \quad (5)$$

where $w_{ij}^{aa}$ is the weight used to measure how strongly $a_j$ affects $a_i$ and $w_{kj}^{ba}$ is the weight used to measure how strongly $b_k$ affects $a_j$. We only take into account the blocks in the square $5 \times 5$ block-wise area whose center is $a_j$’s block.
3.4. Orientation Field Separation

After the constrained relaxation labeling process, we obtain the final state probability $p_{a_j}(s_{a_i})$. The state whose probability is larger is determined as the right state of $a_j$. And the labels of two orientations $a_{j1}$ and $a_{j2}$ are determined:

$$\begin{align*}
\text{label}(a_{j1}) = 1, \text{label}(a_{j2}) = 2 & \quad \text{if } p_{a_j}(1) \geq p_{a_j}(2) \\
\text{label}(a_{j1}) = 2, \text{label}(a_{j2}) = 1 & \quad \text{if } p_{a_j}(1) < p_{a_j}(2).
\end{align*}$$

Because the label of any $b_k$ is known and fixed, 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 label is 1 and the #2 orientation field is composed of the block orientations with label 2. After the two component orientation fields are obtained, we use the method described in section 2.3 to separate the two component fingerprints.

Fig. 6 shows the separated fingerprints from four latent overlapped fingerprint images via the proposed method and the method in [2]. We can observe that the proposed method provides a better separation result than the method in [2].

4. Experimental Results

The final goal of separating overlapped fingerprint images is to successfully match the component fingerprint to the corresponding template fingerprint. We utilize the same data set which was used in [2] to test the performance of our separating method. As recited in [2], the images of overlapped fingerprints are synthesized by the no. 3 impressions and no. 4 impressions of ten fingers in FVC2002 DB1_B. 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, 2, 5, 6, 7 and 8 impressions of the ten fingers are utilized as template fingerprints which are matched with the separated fingerprints by using VeriFinger matcher. Only genuine matches (i.e. match the testing fingerprint image and template fingerprint images belonging to the same finger) are executed because the output scores of the VeriFinger matcher are linked to the False Accept Rate (FAR).

In order to compare the two algorithms, four groups of matching experiments are conducted. In the first group (called ideal separation), no. 3 and 4 impressions are matched with the template fingerprints, which gives the upper bound of the matching accuracy. In the second group (called no separation), the overlapped fingerprint images (segmented using the two region masks) are directly matched with the template fingerprints, which gives the lower bound of the matching accuracy. In the third and fourth groups, our method and Chen et al.’s method (using singularity information) are used to separate the overlapped images respectively, and the separated fingerprints are matched with the template fingerprints. The left four columns in Fig. 7 show the input images of four groups of matching experiments for an overlapped image. The Receiver Operating Characteristic (ROC) curves are given in Fig. 8. We observed that at the same FAR, our method’s
True Accept Rate (TAR) is at least 10 percent higher than the TAR of the method in [2].

There is still room for improvement in our method. In the experiments, we find that the estimation error of the initial orientations in the overlapped blocks greatly impact the separation results. The smaller the estimation error is, the better the quality of the separated fingerprints will be, and the matching accuracy will be higher. In order to demonstrate this, we conduct two groups of contrast experiments. In the first group of experiments, we use the ideal 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 values (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 input images for these two experiments are given in the fifth and sixth columns in Fig. 7. The ROC curves of these two groups of matching experiments and the ROC curves of ideal separation and the proposed separation algorithm are shown in Fig. 9. As can be observed from this figure, the performance of our method using ideal initial orientation field is almost the same as the performance of directly using the ideal orientation fields.

Figure 6. Some examples of the separated fingerprints from latent overlapped fingerprints. Each row shows a group of separating results. In each group, the image in first column (from left to right) is the latent overlapped fingerprint image; the second and third columns are separated fingerprints by the proposed method; the fourth and fifth columns are separated fingerprints by Chen et al.’s method.
This indicates that the proposed constrained relaxation labeling algorithm is satisfactory, while the initial orientation field estimation may need large improvement.

The proposed method is much faster than Chen et al.’s method. The average time of the proposed constrained relaxation labeling algorithm is about 3 seconds, while it is 36 seconds for Chen et al.’s method. The other parts of the two separation algorithms are very similar in speed. It is worth noting that the proposed method achieves higher accuracy without using the information of singular points, while manually marked singular points are used in Chen et al.’s method. The Matlab implementation of the proposed algorithm has been made available for comparison purpose at http://ivg.au.tsinghua.edu.cn/people/~JianjiangFeng/software.html.

5. Conclusions and Future Work

Separating overlapped fingerprints into component fingerprints is very useful in latent fingerprint recognition.
We proposed an algorithm for separating overlapped fingerprints, which outperforms the state of the art method in both accuracy and efficiency. In addition, our method does not require the information of singular points, and thus costs less human labor.

There is still limitations in our method. Initial orientations in the overlapped blocks have a large influence on the separation performance. As a future work, we will explore how to estimate the initial orientation more accurately. The current separation algorithm is not yet fully automatic. The region masks of the two components fingerprints must be marked manually. As another future work, we plan to develop a fully automatic separating algorithm which can estimate the region masks of component fingerprints automatically.

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References