AUTOMATIC OVERLAPPED FINGERPRINT SEPARATION

R.Reka,
Electronics and Communication Engg,
Coimbatore Institute of Technology,
Coimbatore.

Dr.S.Uma, M.E.,Ph.D,
Associate professor,
Electronics and Communication Engg,
Coimbatore Institute of Technology,
Coimbatore

***Abstract*—Fingerprint images generally contain either a single fingerprint (e.g., rolled images) or a set of non overlapped fingerprints (e.g., slap fingerprints). Overlapped fingerprints constitute a serious challenge to existing fingerprint recognition algorithms. In this paper, relaxation labeling algorithm is proposed to separate overlapped fingerprints into separate fingerprints. We first estimate the orientation field of the given image with overlapped fingerprints using Local Fourier Transform. The relaxation labeling algorithm separate overlapped fingerprints without manual marking and singularity point information. Finally, the two fingerprints are obtained by enhancing the overlapped fingerprint using Gabor filters tuned to these two component separate orientation fields, respectively.**

***Keywords*— Fingerprint matching, fingerprint separation, latent fingerprints, orientation field, overlapped fingerprints, relaxation labeling, singularity.**

I. INTRODUCTION

A fingerprint in its narrow sense is an impression left by the friction ridges of a human finger. In a wider use of the term, fingerprints are the traces of an impression from the friction ridges of any part of a human hand. A print from the foot can also leave an impression of friction ridges. A friction ridge is a raised portion of the epidermis on the fingers and toes, the palm of the hand or the sole of the foot, consisting of one or more connected ridge units of friction ridge skin. These are sometimes known as "epidermal ridges" which are caused by the underlying interface between the dermal papillae of the dermis and the inter papillary pegs of the epidermis. These epidermal ridges serve to amplify vibrations triggered, for example, when fingertips brush across an uneven surface, better transmitting the signals to sensory nerves involved in fine texture perception. These ridges also assist in gripping rough surfaces, as well as smooth wet surfaces.

Fingerprint matchers (manual or automatic) are mainly based on extracting and comparing characteristic points (minutiae) of ridges. As a result, reliable ridge extraction is very important for successful matching. Existing ridge extraction algorithms [4] work very well when ridge structures are well defined or the noise in fingerprint image is not significant. However, there exist many challenging situations, overlapped fingerprints being one of them [see Fig. 1], where state-of-the-art matchers do not perform very well. Overlapped images are mainly encountered in latent fingerprints lifted from crime scenes [5]. When the same surface is touched by two fingers, the developed latent image may contain overlapped fingerprints. Overlapping may also occur in live-scan fingerprint images when the surface of fingerprint sensors contains the residue of fingerprints of previous users.

Fig. 1. Overlapped fingerprint image

In this paper, we present an algorithm to separate overlapped fingerprints and evaluate it using both real overlapped latent fingerprints and simulated overlapped fingerprints. The algorithm is based on the following two assumptions, which are both reasonable and practical:

1) The overlapped fingerprint image consists of at most two fingerprints. An overlapped fingerprint image with more than two component fingerprints is very difficult to separate even for fingerprint experts.

2) There are differences between the orientation fields of the two component fingerprints in the overlapped area. In other words, the components are identifiable.

The proposed algorithm consists of three steps:

1) An initial orientation field of the given overlapped image is estimated using local Fourier analysis [19].

2) A relaxation labeling method [9], [10] is employed to label the initial orientation field into two classes. Based on the labeling result, the initial orientation field is decomposed into two component orientation fields and, each of size.
3) The two component fingerprints are separated by enhancing the overlapped fingerprint image using Gabor filters tuned to these two component orientation fields.

II. ESTIMATING INITIAL ORIENTATION FIELD

A. Obtaining Overlapped Region

Due to complex background and overlapped latent fingerprints in a single fingerprint image, the region masks of two overlapped fingerprints are manually marked. Based on the two region masks, the overlapped region can be easily obtained. Manually marking region mask is a common practice in latent fingerprint community.

B. Estimation of Initial Orientation Field

Ridge orientation is one of the fundamental features of a fingerprint image. Here we take normal overlapped fingerprint and region marked overlapped fingerprint as input. Most existing orientation estimation methods are based on the characteristic of pixel intensity in a block Traditional orientation field estimation algorithms [1], [19], [2], consist of two steps: initial estimation using a gradient-based method, followed by orientation field regularization. Regularization may be done by a simple averaging filter or complicated global model- based methods [19], [2]. But, for overlapped fingerprints, the initial orientation field obtained by gradient-based methods may be a random mix of the orientation fields of the two component fingerprints and this "noise" cannot be removed by existing regularization algorithms.

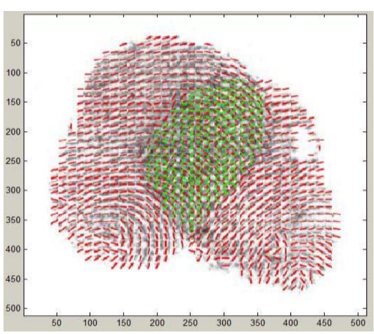

Fig. 2.The initial orientation field.

To extract the orientation fields of two original fingerprints in the overlapped region, we use the local Fourier analysis method [3] to estimate the initial orientation field. An overlapped fingerprint image *I*(*x;y*) is divided into non overlapping blocks of 16 × 16 pixels. Since the ridge structure in a block can be approximated by a 2D sine wave, the task of estimating local ridge orientation is transformed to estimating the parameters of sine wave in each block. Centered at each block, the local image in the 64 × 64 window is multiplied by a bivariate Gaussian function (s = 16). The Discrete Fourier Transform (DFT), *F*(*u;v*), of the resulting image is computed and the amplitude of low frequency components (points within 3 pixels from the center in the frequency domain) is set to 0 [7]. In the frequency domain, one or two (one for the non-overlapped region and two for the overlapped region) local maximum points with the greatest amplitude are found. Each of these points corresponds to a 2D sine wave w(*x;y*) = *a*sin(2p *f* (sin(q)*x*+cos(q)*y*)+F), where *a*, *f* , q , and F represent the amplitude, frequency, orientation, and phase, respectively.

III. SEPARATING OVERLAPPED ORIENTATION FIELD

We now propose a relaxation labeling algorithm to separate it into two different orientation fields which correspond to the two component fingerprints[16],[12].

A. *Relaxation Labeling*

Consider a labeling problem with N objects $O=\{o_1,o_2\ldots 0_N\}$ and M labels $\Lambda=\{1,2\ldots M\}$. A labeling is a function from the set of objects O to the set of labels A. With each object o_i by means of some local measurements we associate a probability vector $p_{i=(}p_{i1},p_{i2,\ldots}p_{iM)}{}^T$ where $O\leq p_{i\lambda}\leq 1$, for i=1,2..N , and λ=1,2…M, $D\lambda p_{i\lambda,}$ for i=1,2,..N. Here, $p_{i\lambda}$ is the probability with which label λ is associated with object o_i. Let $P=(p_1,p_2\ldots..p_{N)}$ denote a label assignment of N objects.

It is assumed that object labels do not occur independently of each other. The domain knowledge relevant to the problem is specified through a set of compatibility functions, $R_{ij}:\Lambda\times\Lambda\rightarrow R$, i=1,2….N, and j=1,2…N. It is a M×M matrix defined as:

$$R_{ij}=\begin{bmatrix} R_{ij}(1,1) & R_{ij}(1,2) & \cdots & R_{ij}(1,M) \\ R_{ij}(2,1) & R_{ij}(2,2) & \cdots & R_{ij}(2,M) \\ \vdots & \vdots & \vdots & \vdots \\ R_{ij}(M,1) & R_{ij}(M,2) & \cdots & R_{ij}(M,M) \end{bmatrix}. \quad (1)$$

$R_{ij}(\lambda,\lambda')$ can be thought of as the degree of compatibility (specified locally) between object–label pairs (o_i,λ) and (o_j,λ') : large values indicate high compatibility and small values indicate incompatibility. The collection of R_{ij}, i=(1,2…N), and j=(1,2….N) constitutes the N×N compatibility block matrix denoted as:

$$R=\begin{bmatrix} R_{11} & R_{12} & \cdots & R_{1N} \\ R_{21} & R_{22} & \cdots & R_{2N} \\ \vdots & \vdots & \vdots & \vdots \\ R_{N1} & R_{N2} & \cdots & R_{NN} \end{bmatrix}. \quad (2)$$

Relaxation labeling computes the label assignment iteratively until it is convergent [16]. At the ţth iteration, a label probability vector $p_i(t)$ is associated with each object o_i, i=1,2…N. The process starts with some initial set of probabilities p(o), obtained through noisy measurements on the objects. The algorithm specifies how the label probabilities are updated at each instant as summarized in Algorithm 1.

B. Separating Algorithm

1) Problem Modeling: The initial orientation field Oo is an $m \times n \times 2$ matrix. We treat every element Oo(i,j,k), $1 \le i \le m$, $1 \le j \le n$ and $1 \le k \le 2$, as an object $o_{i.n.2+j.2+k}$. Thus the object set is $O=\{o_1,o_2 \ldots o_{m.n.2}\}$, and the label set is $\Lambda=\{1,2\}$. To separate the initial orientation field Oo, we need to label each object of O with exactly one label of Λ.

2) Building Compatibility Coefficients: It is widely known that the performance of relaxation process is greatly affected by the choice of compatibility coefficients. Since relaxation labeling is based on local (contextual) information, an object O(i,j,k) (namely $o_{i.n.2+j.2+k}$; for clarity we use O(i,j,k) instead of $o_{i.n.2+j.2+k}$) is only supported by its neighborhood. The compatibility coefficient matrix $R_{IJ} = R_{(o_{i.n.2+j.2+k})(o_{i'.n.2+j'.2+k'})}$ between two objects O(i,j,k) and O(i',j',k') is defined as :

$$R_{IJ} = \begin{cases} \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, & \text{if } |i-i'| > D \text{ or } |j-j'| > D \\ \begin{bmatrix} s & 1-s \\ 1-s & s \end{bmatrix}, & \text{otherwise} \end{cases} \tag{3}$$

where is the support when objects O(i,j,k) and O(I',j',k') have the same label, and (1-s) is the support for different labels. In other words, s is the support when orientations O(i,j,k) and O(i',j',k') come from the same fingerprint. Obviously, the smaller the difference between O(i,j,k) and O(i',j',k') , the larger the s. Thus s is computed as

$$s = 1 - \frac{\delta\left(|O(i,j,k) - O(i',j',k')|\right)}{\pi/2} \tag{4}$$

Where O(i,j,k) and O(i',j',k') are orientation values normalized to $(-\pi/2,\pi/2)$ and δ(.) is defined as

$$\delta(x) = \begin{cases} x, & \text{if } x \leqslant \frac{\pi}{2} \\ \pi - x, & \text{otherwise.} \end{cases} \tag{5}$$

The purpose of the labeling is to obtain the two component orientation fields. Thus O(i,j,1) and O(i,j,2), $1 \le i \le m$, $1 \le j \le n$ should be set to different labels. Let I = (i.n.2+j.2+1) , and J = i.n.2+j.2+2, then we have $R_{IJ} = R_{JI}$ which are defined as

$$R_{IJ} = R_{JI} = \begin{bmatrix} 0 & 1 \\ 1 & 0 \end{bmatrix}. \tag{6}$$

Equation (6) states that objects O(i,j,1) and O(i,j,2) have support 0 when they have the same label, and 1 for different labels.Up to now, we have not discussed the compatibility coefficient matrix of an object O(i,j,k) itself. Since an object itself has no information to support any label, $R_{II} = R_{(i.n.2+j.2+k)(i.n.2+j.2+k)}$ is set as

$$R_{II} = \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}. \tag{7}$$

To sum up, (3), (6), and (7) give the definition of compatibility coefficients. It should be mentioned that the separation is only performed in the overlapped region due to the following two considerations. First, there is only one orientation in the non overlapped region. Second, processing only the overlapped region can save much computation time.

Algorithm1 : Relaxation Labeling Algorithm

Initialization: set t=0, obtain initial label probabilities:

$P(0)=(p_1(0),p_2(0)\ldots p_N(0))$

while *true* **do**

// *Selection of labels*:

for i=1,2…N do

choose a label at random based on the current label probabilities $p_i(t)$.

end

// *Calculation of responses*:

for i=1,2…N do

Let q be the label selected for o_i in step 1;

Compute the response β_{iq} to o_i as

$\beta_{iq} = (1/N) \sum_j R_{ij}(q, s_j)$

Where s_j is the label selected for object o_j in step 1.

end

// *Updating of label probabilities*:

for i=1,2…N do

Let q be the label selected for o_i in step 1,$p_i(t)$ is updated as

$p_{iq}(t+1)=p_{iq}(t)+\alpha\beta_{iq}(1-p_{iq}(t))$

$p_{ir}(t+1)=p_{ir}(t)+\alpha\beta_{iq}\,p_{ir}(t)$, $r \neq q$

end

// *Iteration*:

if *probability vectors have converged* **then**

break.

end

else

*t=t+*1

end

end

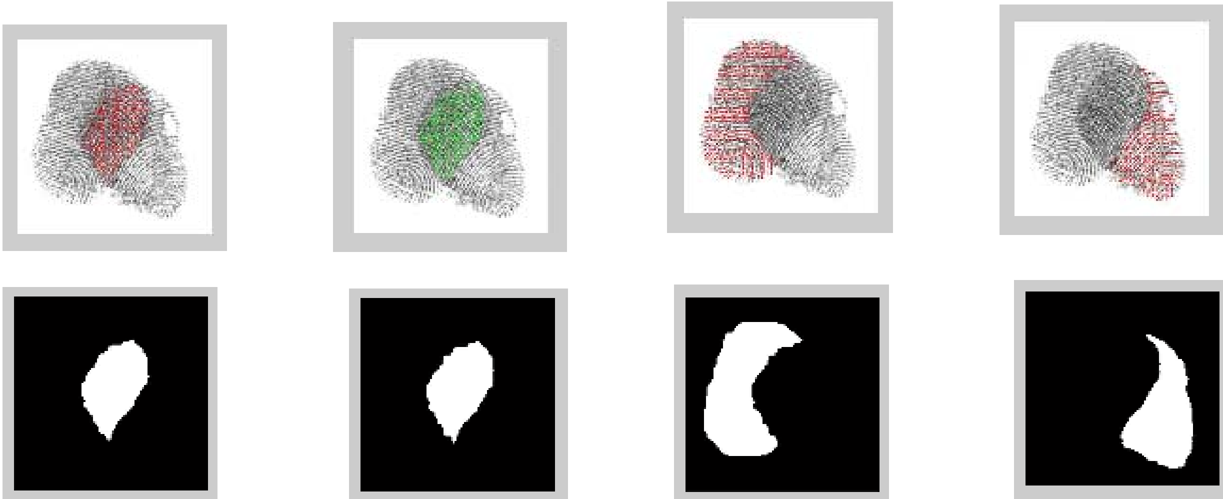

Fig. 3. Orientation fields in the overlapping and non overlapping regions.

Using relaxation labeling, the initial orientation field in the overlapped area is correctly separated into two component orientation fields [Figs. 3]

3) Merging Orientation Fields: The two separated orientation fields in the overlapped area should be merged with the two orientation fields in the non overlapped area to finalize the orientation field separation process.

Now we try to find which one of the two possible combinations should be chosen to merge the orientation fields. The two possible combinations are: (i) $O_{0,1}$ with $O_{n,1}$ and $O_{0,2}$ with $O_{n,2}$, and (ii) $O_{0,1}$ with $O_{n,2}$ and $O_{0,2}$ with $O_{n,1}$, as shown in Fig. 8. For each combination, we compute the compatibility defined as

$$c_2 = \frac{1}{2}\left(\frac{1}{N_1}\sum_x\sum_y \delta\left(\left|O'_{o,2}(x,y) - O_{n,1}(x,y)\right|\right)\cdot B_1(x,y) + \frac{1}{N_2}\sum_x\sum_y \delta\left(\left|O'_{o,1}(x,y) - O_{n,2}(x,y)\right|\right)\cdot B_2(x,y)\right) \quad (10)$$

Where $O'_{0,1}$ and $O'_{0,2}$ are dilated [24] from $O_{0,1}$ and $O_{0,2}$, respectively, $\delta(.)$ is defined in (5), and N_1 and N_2 are defined as

$$N_1 = \sum_x\sum_y B_1(x,y) \quad (11)$$

and

$$N_2 = \sum_x\sum_y B_2(x,y). \quad (12)$$

If $c_1 < c_2$, we choose the first combination; otherwise, choose the second combination. After obtaining the two component orientation fields, an averaging filter is used to remove noise in each of the two orientation fields, and the resulting component orientation fields. The above algorithm does not perform very well when the singularity region of component fingerprints is overlapped. The underlying cause of this problem is that the relaxation labeling algorithm is solely based on local continuity of orientation field.

. We assume that the singular points (core and delta) have been marked manually for each component fingerprint in the input overlapped area. Manual marking of singular points is a common practice in latent fingerprint community [5]. As proposed in [18], a fingerprint orientation field can be decomposed into singular orientation field and continuous orientation field

$$O_o = O_s + O_c \quad (13)$$

The singular orientation field O_s is defined by the Zero-Pole model proposed by Sherlock and Monro [13] as

$$O_s = \frac{1}{2}\arg\left(\frac{\prod_i^K (z - z_{c_i})}{\prod_j^L (z - z_{d_j})}\right) \quad (14)$$

where $z_{c1}.....z_{ck}$, $z_{d1}.....z_{dl}$ are the K core and L delta points in the fingerprint. The continuous orientation field is defined by

$$O_c = O_o - O_s \quad (15)$$

Note that the continuous orientation field is smooth everywhere. This suggests that we should use the continuous orientation field rather than the original orientation field for relaxation labeling. Singular points are incorporated into the relaxation labeling algorithm by modifying the compatibility coefficient matrix in (3). Suppose the singular orientation fields of two component fingerprints are denoted by $O_s(1)$ and $O_s(2)$. Then we have four possible continuous orientation fields $O_c\{k,l\}$ (k=1,2 l=1,2), as follows:

$$O_c\{k,l\} = O_0(:,:,k) - O_s(l). \quad (16)$$

The compatibility coefficient matrix of (3) is changed to

$$R_{IJ} = \begin{cases} \begin{bmatrix} 0 & 0 \\ 0 & 0 \end{bmatrix}, & \text{if } |i-i'| > D \text{ or } \\ & |j-j'| > D \\ \begin{bmatrix} s_s(1,1) & s_s(1,2) \\ s_s(2,1) & s_s(2,2) \end{bmatrix}, & \text{otherwise} \end{cases} \quad (17)$$

Where $s_s(l,l')$ (l=1,2, l'=1,2) is defined as,

$$s_s(l,l') = 1 - \frac{\delta\left(|O_c\{k,l\}(i,j) - O_c\{k',l'\}(i',j')|\right)}{\pi/2} \quad (18)$$

Where δ( ) is defined in (5). $O_c\{k,l\}(i,j)$ and $O_c\{k',l'\}(i',j')$ are continuous orientation values normalized to $(-\pi/2, \pi/2)$.

Fig. 4. Separating overlapped fingerprints of Fig. 1(a) (using singular points input)

The relaxation labeling algorithm now has better performance and provides better component fingerprints.

IV. WITHOUT SINGULAR POINTS INPUT

The singular points - cores and deltas - are the most important topological features of a fingerprint. The singular point area is defined as a region where the ridge curvature is higher than normal and where the direction of the ridge changes rapidly. These singular points not only represent the characteristics of local ridge patterns but also determine the topological structure.

Here we use the region marked overlapped fingerprint as input. We take only the overlapped region for singular points information. We set the minimum threshold value and check it for every ridge values. We perform the process up to 256 levels. For each pixel we perform the operation based on neighbor pixels. The previous work requires singular points as input. In that, while separating the overlapped fingerprints, we have to give the singular point information as input. So processing time will be increased. In this paper, we separate the overlapped fingerprints without any singular point input. While performing the separation no need to give the singular point information. It reduce the complexity and processing time of the separation. The output of these two method will be same (see fig 4 & 5). But when compared to previous work, this paper reduce the processing time and user complexity.

Fig. 5. Separating overlapped fingerprints of Fig. 1(a) (without using singular points input)

V. CONCLUSION AND FUTURE WORK

(i) CONCLUSION :

We have proposed a novel algorithm for separating overlapped fingerprints. By applying a relaxation labeling method on the initial orientation field obtained by local Fourier analysis, we extract the two component orientation fields. The two component fingerprints are separated by filtering the overlapped fingerprint image using Gabor filters tuned to the component orientation fields.

The previous work requires singular points as input. In that, while separating the overlapped fingerprints, we have to give the singular point information as input. So processing time will be increased. In this paper, we separate the overlapped fingerprints without any singular point input. While performing the separation no need to give the singular point information. It reduce the complexity and processing time of the separation. The output of these two method will be same. But when compared to previous work, this paper reduce the processing time and user complexity. Satisfactory results were obtained on latent overlapped fingerprints.

(ii) FUTURE WORK:

This study can be extended along the following directions: (i) The proposed algorithm assumes that the component orientation fields should be different or completely separable in the overlapped region. This may not always be the case. The algorithm needs to be improved to handle the more general case. (ii) The current algorithm requires manually marked region masks as input. We plan to develop a separating algorithm without any manual marking.

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