

# Latent Palmprint Matching

Anil K. Jain, *Fellow, IEEE*, and Jianjiang Feng

Anil K. Jain and Jianjiang Feng are with Department of Computer Science and Engineering, Michigan State University, East Lansing, MI-48824, U.S.A. [jain](mailto:jain), [jfeng@cse.msu.edu](mailto:jfeng@cse.msu.edu)

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DRAFT

## Abstract

The evidential value of palmprints in forensic applications is clear as about 30% of the latents recovered from crime scenes are from palms. While biometric systems for palmprint-based personal authentication in access control type of applications have been developed, they mostly deal with low resolution (about 100 ppi) palmprints and only perform full-to-full palmprint matching. We propose a latent-to-full palmprint matching system that is needed in forensic applications. Our system deals with palmprints captured at 500 ppi (the current standard in forensic applications) or higher resolution and uses minutiae as features to be compatible with the methodology used by latent experts. Latent palmprint matching is a challenging problem because latent prints lifted at crime scenes are of poor image quality, cover only a small area of the palm and have a complex background. Other difficulties include a large number of minutiae in full prints (about 10 times as many as fingerprints), and the presence of many creases in latents and full prints. A robust algorithm to reliably estimate the local ridge direction and frequency in palmprints is developed. This facilitates the extraction of ridge and minutiae features even in poor quality palmprints. A fixed-length minutia descriptor, MinutiaCode, is utilized to capture distinctive information around each minutia and an alignment-based minutiae matching algorithm is used to match two palmprints. Two sets of partial palmprints (150 live-scan partial palmprints and 100 latent palmprints) are matched to a background database of 10,200 full palmprints to test the proposed system. Despite the inherent difficulty of latent-to-full palmprint matching, rank-1 recognition rates of 78.7% and 69%, respectively, were achieved in searching live-scan partial palmprints and latent palmprints against the background database.

## Index Terms

Palmprint, forensics, latents, minutiae, MinutiaCode, matching, region growing.

## I. INTRODUCTION

Palmprint is a combination of two unique features, namely, the palmar friction ridges and the palmar flexion creases (see Fig. 1). Palmar friction ridges are the corrugated skin patterns with sweat glands but no hair or oil glands [1]. Discontinuities in the epidermal ridge patterns are called the palmar flexion creases. These are the firmer attachment areas to the basal (dermis) skin structure. Flexion creases appear before the formation of friction ridges during the embryonic skin development stage, and both of these features are claimed to be immutable, permanent and unique to an individual [1]. The three major types of flexion creases that are most clearly visible are: distal transverse crease, proximal transverse crease and radial transverse crease. Based on

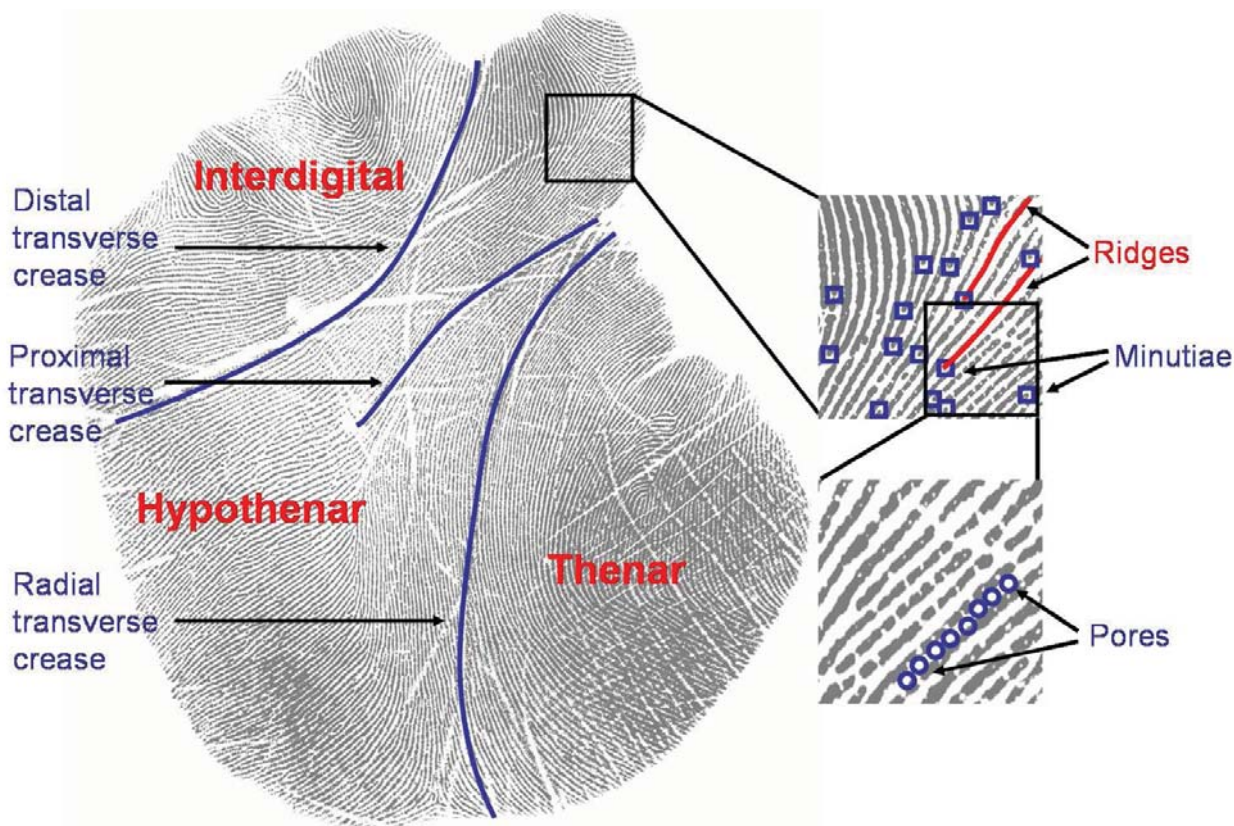


Fig. 1. Regions (interdigital, thenar and hypothenar), major creases (distal transverse crease, proximal transverse crease and radial transverse crease), ridges, minutiae and pores in a palmprint.

these major creases, three palmprint regions are defined: interdigital, thenar and hypothenar (see Fig. 1). Various features in palmprints can be observed at different image resolutions. While major creases can be observed at less than 100 ppi, thin creases, ridges and minutiae can be observed only at  $\sim 400$  ppi, and resolutions greater than 500 ppi are needed to observe pores.

The use of palmprints for person identification traces back to Chinese deeds of sale in the 16th century [2]. Later in 1684, Grew introduced dermatoglyphics, a study of the epidermal ridges and their arrangement on the hand. The first systematic capture of hand, finger and palm images for identification purposes was done by Herschel in 1858 [3]. Galton [4] discussed the basis of contemporary fingerprint science, and introduced palmar ridges and creases. He suggested that the ridges on the finger tips, palms and soles are persistent and unique. Galton defined the peculiarities in the ridges as minutiae and introduced several different minutiae types. He also

divided the palm into three regions and analyzed the correlation between the ridge flow and the major creases in each region. Cummins and Midlo [2] stated that the width of a palmar ridge is 18% larger compared to a finger. They also recognized the significance of the flexion creases, particularly palmar flexion creases, and established the basis of the present flexion crease based identification.

While the use of Automated Fingerprint Identification Systems (AFIS) in the forensic community is pervasive, the development of automated palmprint identification systems has lagged due to the limitations of live-scan technologies for palmprints, large number of creases present in palmprints, and large storage and computing capabilities needed for processing and matching palmprints. The first reported use of palmprints in a criminal case occurred in a British court in 1931. The first automated palmprint identification system became available in the early 1990s [5]. In recent years, with advances in live-scan techniques and increase in computational power, more and more law enforcement agencies are capturing palmprints of suspects and utilizing latent palmprints for suspect and victim identification. Surveys of law enforcement agencies indicate that at least 30% of the prints lifted from crime scenes, called latents, – from knife hilts, gun grips, steering wheels and window panes – are of palms, not fingers [6]. A major component of the FBI's Next Generation Identification (NGI) system is the development of an integrated national palmprint identification system [7].

Palmprint recognition systems have been developed for civilian (mainly access control) applications [8], [9]. But these systems typically utilize low resolution (about 100 ppi) images and only support full-to-full palmprint matching. To facilitate palmprint matching, these systems use pegs to fix hand position and detect gaps between fingers for alignment. Matching is based on texture or crease information in palmprint images. In forensic applications, on the other hand, 500 ppi is the standard resolution and latent-to-full matching must be supported. When latent examiners match latent palmprints, they mainly use minutiae, whose accurate extraction requires a resolution of at least 400 ppi. Therefore, these low resolution palmprint systems are not applicable for forensic applications. Recent work in [10] reports on a prototype image acquisition system to simultaneously acquire multi-spectral fingerprints and palmprints of a hand at 500 ppi. This will enable fusion of fingerprints and palmprints, which is also an objective of the FBI's NGI system in order to improve the matching accuracy.

Latent palmprint recognition shares some common problems with latent fingerprint recog-

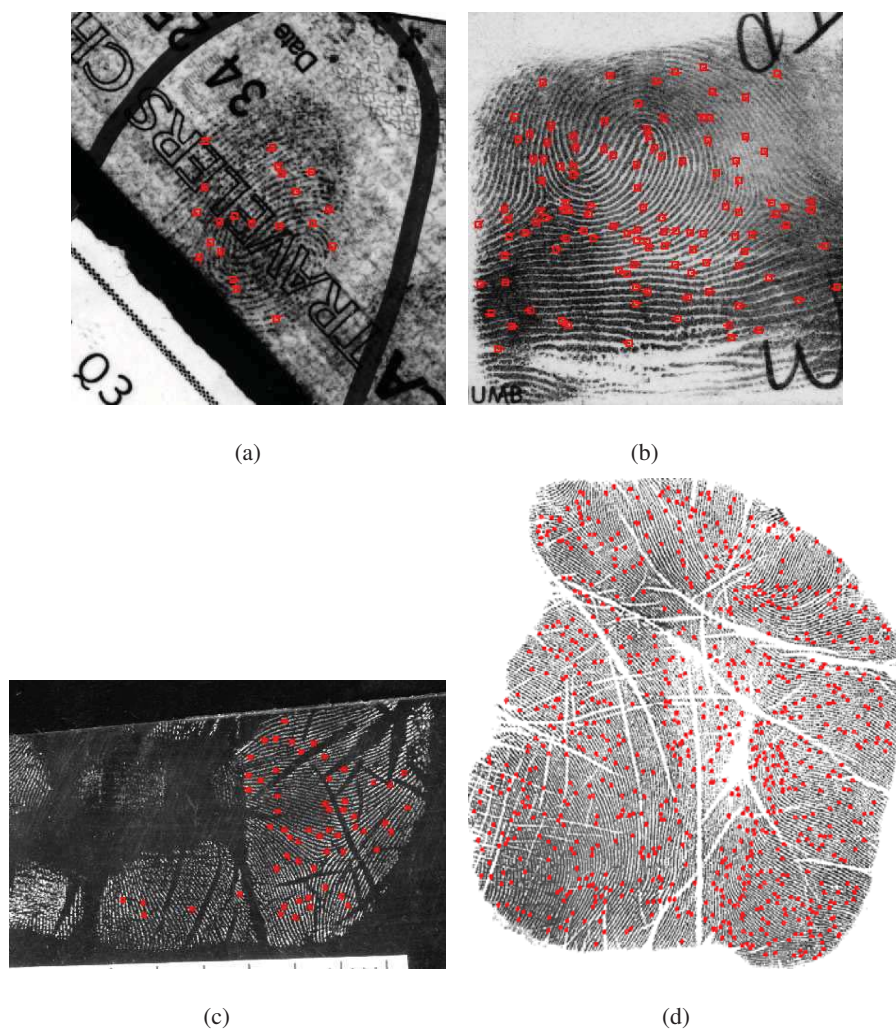


Fig. 2. A comparison of latent fingerprint and latent palmprint problem. (a) Latent fingerprint (from NIST SD27 [11]), (b) mated full fingerprint, (c) latent palmprint and (d) mated full palmprint. The size of these images is  $800 \times 768$ ,  $800 \times 768$ ,  $1164 \times 768$ , and  $1630 \times 1820$  (width  $\times$  height) pixels, respectively. The number of minutiae extracted from these images is 21, 114, 58 and 654, respectively. Minutiae are overlaid on the images.

dition, which has been extensively studied. Some of the common attributes include complex background, poor ridge structures and small image area (see Fig. 2). Although minutiae extraction and matching algorithms designed for fingerprints can be applied to palmprints directly, in order to achieve higher accuracy and faster matching, characteristics of palmprints should be taken into account. The first difference between fingerprints and palmprints is the presence of creases. Although creases are also frequently found in fingerprints, these creases are generally very thin and their number is small. Conventional direction field estimation algorithms [12] can reliably



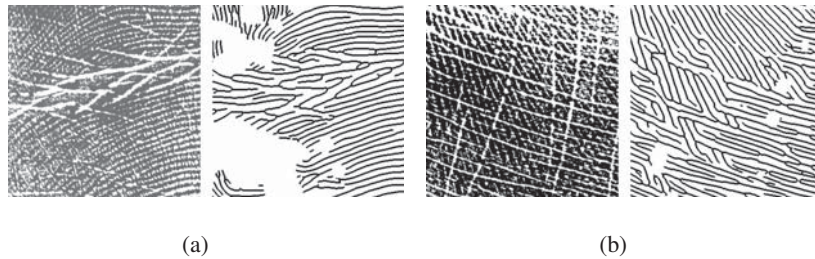


Fig. 3. Creases in palmprints. (a) A palmprint region with a major crease and its ridge skeleton image produced by VeriFinger, (b) a palmprint region with many thin creases and its ridge skeleton image produced by VeriFinger.

estimate the ridge direction in fingerprints, which is then used to remove the creases and recover the ridges. However, palmprints contain very wide creases (major creases) and a large number of thin creases, especially in the thenar area (see Fig. 3(b)). It is not a trivial problem to recover the ridge structure in the presence of a large number of creases. As shown in Fig. 3, VeriFinger 6.0 by Neurotechnology [13], which ranked high according to accuracy in two different fingerprint competitions (FVC2000-2006 [14] and FpVTE 2003 [15]), and was the second best template generator in the MINEX test [16], produces many false ridges around the major crease in a palmprint (Fig. 3(a)), and totally fails in the palmprint area with dense thin creases (Fig. 3(b)). The second difference between fingerprints and palmprints is the image size. A typical full fingerprint image ( $500 \times 500$  pixels) contains about 100 minutiae, while a full palmprint image ( $2000 \times 2000$  pixels) contains about 800 minutiae. Assuming that the time complexity of a minutiae matcher is  $O(n^2)$ , where  $n$  denotes the number of minutiae in a fingerprint or a palmprint, matching palmprints will be about 64 times slower than matching fingerprints. Therefore, the computational efficiency of minutiae matching algorithm is critical for palmprint matching.

A partial-to-full palmprint matching system was proposed in [17] that used both SIFT [18] and minutiae features in matching. The system was evaluated using live-scan partial and full palmprint images. However, this system has the following limitations: (i) SIFT features can not be consistently detected in latents and full prints, (ii) the minutiae extractor and matcher (VeriFinger 4.2) used in [17] are not suitable for latent palmprint matching, and (iii) latent images were not used to evaluate the algorithms.

We propose a minutiae-based latent-to-full palmprint matching system. To deal with creases

in palmprints, a region growing algorithm is proposed to reliably estimate the ridge direction and frequency. To reduce the computational complexity of minutiae matching algorithm, a fixed-length minutia descriptor, MinutiaCode, is proposed, which captures information about the ridges and other minutiae in the neighborhood of a minutia. The proposed system has been evaluated by matching partial<sup>1</sup> palmprints (150 live-scan partial palmprints and 100 latent palmprints) against a background database of 10,200 full palmprints. Rank-1 recognition rates of 78.7% and 69%, respectively, were achieved in searching live-scan partial images and latents against the background database.

## II. MINUTIAE EXTRACTION

The performance of a minutiae extraction algorithm relies heavily on the quality of the input palmprint images. In order to ensure that the minutiae extraction algorithm is robust with respect to the quality of input palmprint images, an enhancement algorithm that improves the clarity of the ridge structures is necessary. Contextual filtering like 2D Gabor filters [19] has been very effective for fingerprint enhancement [20]. Two important parameters of 2D Gabor filters are local ridge direction and frequency. When these parameters are correct, Gabor filtering can connect broken ridges and separate joined ridges. However, when the parameters are incorrect, spurious ridges may be produced after filtering. Hence, reliable ridge direction and frequency estimation is very important for minutiae extraction.

### A. Ridge Direction and Frequency Estimation

As ridge frequency is often estimated based on ridge direction [20], reliable direction estimation is even more important. Most direction field estimation algorithms [12], [21], [22] consist of two steps: initial estimation using a gradient-based method followed by smoothing. The smoothing may be done by a simple weighted averaging filter or more complicated model-based methods [21], [22]. These smoothing algorithms generally make two assumptions either explicitly or implicitly: (i) direction field is smooth except for singular areas, and (ii) noise has a Gaussian distribution. But for palmprints which contain a large number of creases, the initial

<sup>1</sup>In our experiments, two types of partial palmprints, live-scan partial palmprints and latent palmprints, were used. Live-scan partial palmprints were captured using an optical palmprint scanner and latent palmprints were lifted from crime scenes. When we do not distinguish between live-scan partial palmprints and latent palmprints, they are referred to as partial palmprints.

direction field obtained by gradient-based methods significantly deviates from the true direction field and the noise can not be modeled as Gaussian. Hence, it is very difficult for these algorithms to recover the true direction field in palmprints.

Funada et al. [23] proposed a palmprint enhancement approach, which performs image enhancement and local ridge direction and frequency estimation simultaneously. Local image blocks ( $8 \times 8$  pixels) are modeled by sine waves and the six strongest waves (according to amplitude) are found in each block. In the image formed by the first strongest wave in each block, continuous blocks are clustered into regions. Generally, a region contains only ridges (such region is called ridge region) or only creases (such region is called crease region). Based on several properties, these regions are classified as ridge regions or crease regions, and ridge regions are used as a single seed. A region growing algorithm is then used to grow the seed and obtain the enhanced image. The palmprint enhancement algorithm proposed in [23] has two main limitations: (i) crease regions may be incorrectly classified as ridge regions and are grown in the region growing procedure. As a result, the objective of detecting only ridges in palmprints can not be achieved. (ii) The enhanced image is not smooth due to blocking effect and this produces spurious minutiae or leads to inaccurate estimation of the position and direction of minutiae.

We propose a palmprint enhancement approach by modifying the algorithm in [23] in the following ways: (i) regions selected in the seed selection stage are treated as different seeds and are separately grown. Finally, one of the regions is selected as ridge region and the other regions which are compatible with the ridge region are merged with it. By postponing region classification to later stage, our algorithm can reliably remove creases and extract ridges. (ii) To solve the blocking effect problem, we smooth the ridge direction and frequency obtained by the region growing algorithm and use Gabor filters to enhance the palmprint image. These two modifications significantly enhance the robustness of the minutiae extraction algorithm and lead to better recognition accuracy.

We now describe our ridge direction and frequency estimation algorithm, which comprises of four main steps.

1) *Sine Wave Representation*: A palmprint image  $I(x, y)$  is divided into non-overlapping blocks of  $16 \times 16$  pixels. Let  $H$  and  $W$  denote the height and width of the image, and  $N_H$  and  $N_W$  denote the number of blocks in the vertical and horizontal directions, respectively. Since the ridge structure of a block can be approximated by a 2D sine wave, the task of estimating



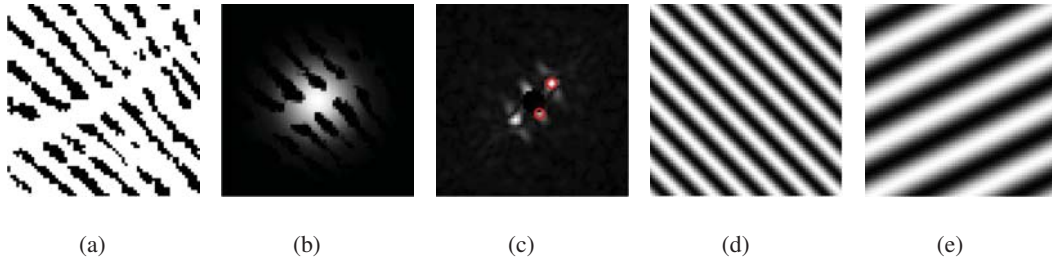


Fig. 4. Sine wave representation. (a) Local gray image ( $64 \times 64$  pixels), (b) local gray image multiplied by Gaussian function, (c) two points with the highest amplitude in the frequency image, (d) the first sine wave, and (e) the second sine wave.

local ridge direction and frequency is transformed to estimating the parameters of sine wave in each block. Centered at each block, the local image in the  $64 \times 64$  window is multiplied by a Gaussian function ( $\sigma = 16$ ). The larger window ( $64 \times 64$  pixels) has the following two advantages over the smaller window ( $16 \times 16$  pixels): (i) it is more robust to noise and (ii) the resolution in the frequency domain is higher. 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. In the frequency domain, six points with the maximum amplitude are found. Each of these points corresponds to a 2D sine wave  $w(x, y) = a * \sin(2\pi f(\cos(\theta)x + \sin(\theta)y + \phi))$ , where  $a$ ,  $f$ ,  $\theta$ , and  $\phi$  represent the amplitude, frequency, direction and phase, respectively. These waves are sorted in the decreasing order of amplitude and are referred to as the first wave, the second wave, ..., and the sixth wave. The above steps are shown in Fig. 4. The parameters of the sine wave at position  $(u, v)$  are computed as:

$$a = |F(u, v)|, \quad (1)$$

$$f = \frac{\sqrt{u^2 + v^2}}{64}, \quad (2)$$

$$\theta = \arctan\left(\frac{u}{v}\right), \text{ and} \quad (3)$$

$$\phi = \arctan\left(\frac{\text{Im}(F(u, v))}{\text{Re}(F(u, v))}\right). \quad (4)$$

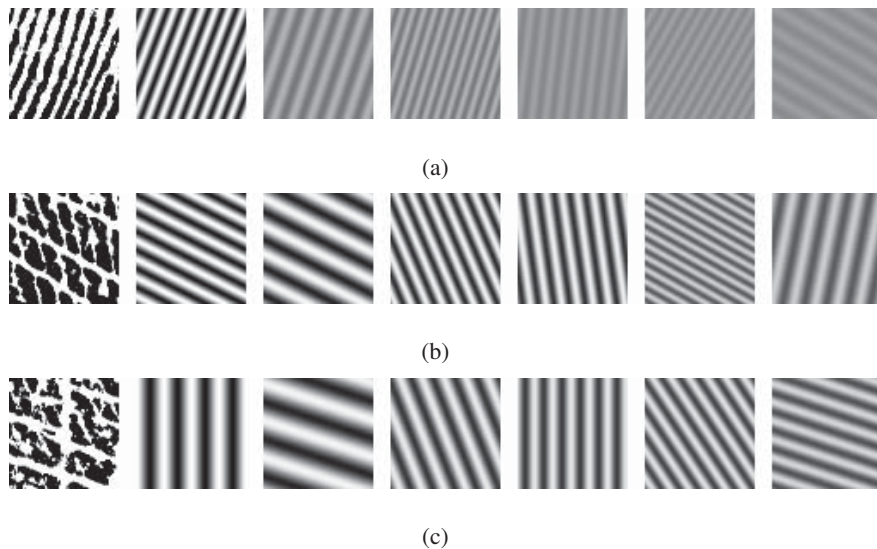


Fig. 5. Six strongest sine waves corresponding to three types of local regions ( $64 \times 64$  pixels) in a palmprint: (a) no crease, (b) creases with one direction, and (c) creases with two directions. In these three local regions, the sine wave corresponding to ridges is the first, the third, and the third one of the six waves, respectively.

When a local image contains only ridges, the DFT has a single strong peak which corresponds to the ridges. When the local image contains both ridges and creases, the DFT has multiple strong peaks. Fig. 5 shows the six strongest waves of three types of local palmprint images: (i) no crease, (ii) creases with one direction, and (iii) creases with two directions. As shown in Fig. 5, it is not easy to reliably determine which wave corresponds to ridges based on the local information alone, namely the amplitude. The basic idea of the proposed algorithm is to utilize the fact that waves corresponding to ridges form continuous clusters.

Two adjacent waves (namely, waves in adjacent blocks)  $w_1$  and  $w_2$  are said to be continuous if the following three conditions are satisfied:

$$\text{Angle}(\theta_1, \theta_2) \leq \pi/6, \quad (5)$$

$$\left| \frac{1}{f_1} - \frac{1}{f_2} \right| \leq 3, \text{ and} \quad (6)$$

$$\frac{1}{16} \sum_{(x,y) \in L} \left| \frac{w_1(x,y)}{a_1} - \frac{w_2(x,y)}{a_2} \right| \leq 0.8, \quad (7)$$



Fig. 6. Continuity of adjacent waves. (a) Two waves are continuous, (b) the direction of two waves is discontinuous, (c) the frequency of two waves is discontinuous, and (d) the normalized grayscale values of two waves are discontinuous.

where  $Angle(\theta_1, \theta_2)$  computes the angle  $\Delta\theta$  ( $0 \leq \Delta\theta \leq \pi/2$ ) between two directions  $\theta_1$  and  $\theta_2$ , and  $L$  denotes the 16 pixels on the border of two adjacent blocks. The above three conditions measure the continuity of direction, frequency and normalized grayscale values between two adjacent waves, respectively. A pair of continuous adjacent waves, which satisfies the above three conditions, and three pairs of discontinuous adjacent waves, which dissatisfy one of the three conditions above, are shown in Fig. 6.

2) *Seed Selection*: The reliability of the first wave of a block is computed as  $a_1/(a_1 + a_2)$ , where  $a_i$  denotes the amplitude of the  $i$ th wave. The first wave of a block is deemed as reliable if its reliability is greater than a threshold (0.67). A reliable first wave is represented by a node in a graph. The adjacent nodes (waves) that are continuous are connected by edges. All connected components with more than 20 nodes in the graph are used as seeds and the seeds are sorted in the decreasing order of size (the number of blocks). An auxiliary image of  $N_H \times N_W$  pixels,  $I_S(m, n)$ , is created to record the seed index of each block.  $I_S(m, n)$  is 0 for the blocks that do not belong to any seed. Seeds selected in this step may include both ridge regions and crease regions. For instance, one of the six seeds in Fig. 7(c) is a crease region.

3) *Region Growing*: Each seed is grown in turn by a region growing algorithm (see pseudocode RegionGrow). The three inputs to this algorithm are  $s_k$ ,  $I_S$ , and  $I_W$ .  $s_k$  denotes the index of the current seed.  $I_S$  is an image of  $N_H \times N_W$  pixels that is used to record the seed index of all blocks.  $I_W$  is an image of  $N_H \times N_W$  pixels that is used to represent the current region.  $I_W(m, n) = i, i = 1, 2, \dots, 6$  indicates the  $i$ th wave is selected in block  $(m, n)$ .  $I_W(m, n) = 0$  indicates no wave is selected in block  $(m, n)$ . Initially, the current region consists of only the current seed, namely,  $I_W(m, n) = 1$  for blocks belonging to the current seed and 0 for the remaining blocks. The region growing algorithm iteratively selects waves in new blocks that are

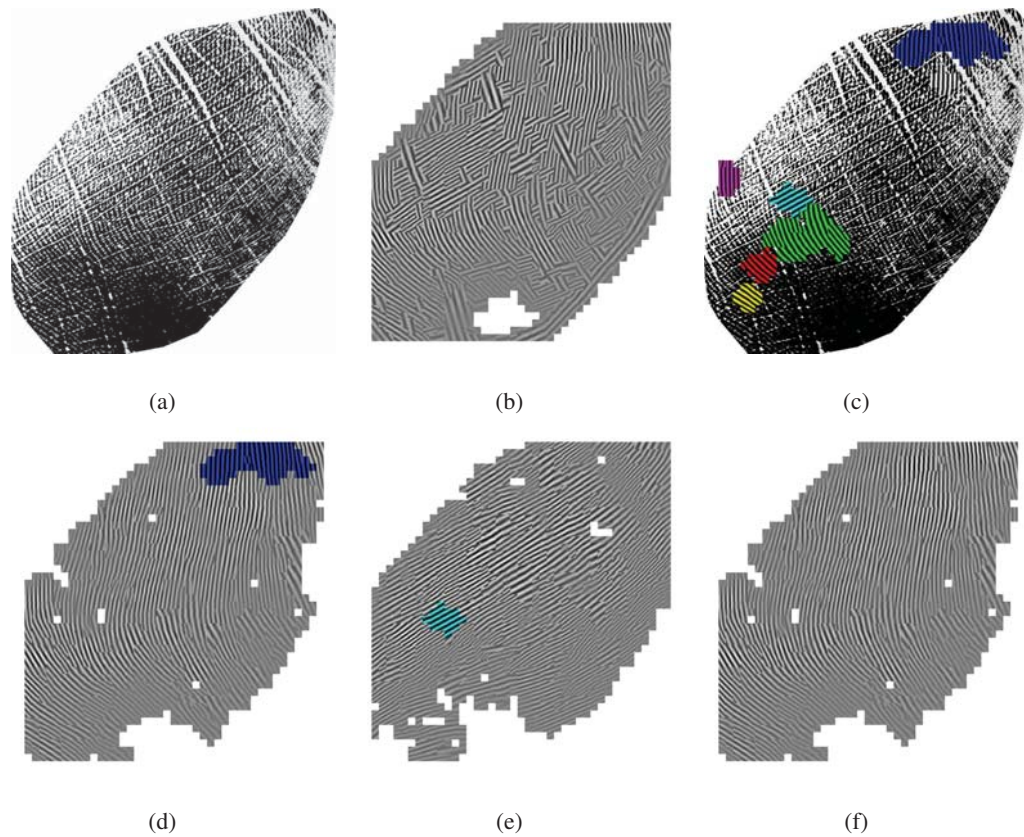


Fig. 7. Stages in the region growing algorithm: (a) a live-scan partial print (height: 765 pixels, width: 717 pixels) from the thenar region, (b) first wave image, (c) six seeds overlaid on the gray image, (d) region grown from one seed which is a ridge region, (e) region grown from another seed which is a crease region, and (f) final region.

continuous with the current region, and adds them to the current region, until no more waves can be added.

The region growing algorithm starts by finding candidate waves (see pseudocode FindCandidateWaves). For each block  $(m, n)$  of the current region, candidate waves are found in its 4-connected neighbors which do not belong to the current region. In a neighboring block,  $(m', n')$ , each of the six waves is checked in the decreasing order of amplitude if it is continuous with the wave of block  $(m, n)$ . If the  $i$ th wave in block  $(m', n')$  is continuous with the wave of block  $(m, n)$ , it is referred to as a candidate wave. A record about this candidate wave,  $w_c = (m', n', i)$ , is added to a priority queue,  $Q$ , where  $i$  is the priority value and the first wave has the highest priority.

The algorithm iteratively pops up a candidate wave  $w_c = (m, n, i)$  from  $Q$  and processes it

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**Function** RegionGrow( $s_k, I_S, I_W$ )
 

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 $Q \leftarrow \emptyset;$ 
for each pixel  $(m, n)$  in image  $I_W$  do
  if  $I_W(m, n) > 0$  then FindCandidateWaves( $I_W, m, n$ );
end
while  $Q \neq \emptyset$  do
  Pop up a candidate wave  $w_c = (m, n, i)$  from  $Q$ ;
  if  $I_W(m, n) > 0$  then continue;
   $I_W(m, n) = i$ ;
  FindCandidateWaves( $I_W, m, n$ );
  if  $i = 1$  &  $I_S(m, n) > s_k$  then
    Merge seed  $I_S(m, n)$  with the current region;
  end
end

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until  $Q$  is empty. If the wave of block  $(m, n)$  has been selected, pop up and process the next candidate wave in  $Q$ ; otherwise, the  $i$ th wave is selected for block  $(m, n)$  and we find candidate waves in its 4-connected neighbors. In addition, we check whether  $i = 1$  and  $s_l = I_S(m, n) > s_k$ . If yes, this wave also belongs to another seed  $s_l$  and we merge seed  $s_l$  with the current region by performing the following steps: (i) all pixels of  $I_W$  corresponding to seed  $s_l$  are set as 1, (ii) seed  $s_l$  is made invalid by setting all pixels in  $I_S$  corresponding to seed  $s_l$  to 0, and (iii) candidate waves are found based on the blocks of seed  $s_l$ .

4) *Region Merging*: After region growing is performed for each seed, a set of regions is obtained. These regions are merged into a final region by first sorting in the decreasing order of the number of reliable first waves. The first region is deemed as a ridge region and copied to the final region. Then the other regions are checked in turn to see if they have different waves in the overlapped blocks with the final region. If waves are not different, this region is deemed as compatible with the final region and is copied to the final region; otherwise next region is checked.

Fig. 7 shows different stages of the proposed region growing algorithm. Fig. 8 and Fig. 9 compare the ridges extracted by VeriFinger 6.0 [13], the algorithm in [23], and the proposed



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**Function** FindCandidateWaves ( $I_W, m, n$ )

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for each 4-connected block  $(m', n')$  of block  $(m, n)$  do
  if  $I_W(m', n') > 0$  then continue;
  for  $i \leftarrow 1$  to 6 do
    if the  $i$ th wave is continuous with the wave in block  $(m, n)$  then
      // Assume  $Q$  can be accessed in this function
      Add candidate wave  $w_c = (m', n', i)$  to priority queue  $Q$ ;
      break;
    end
  end
end
end

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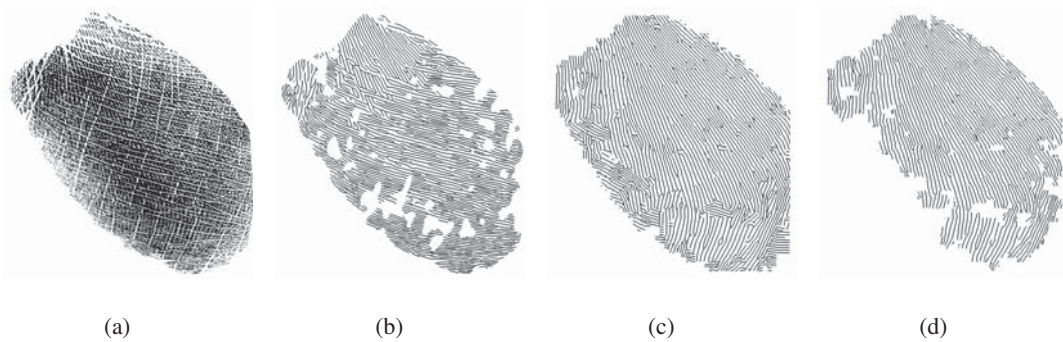


Fig. 8. Comparison of VeriFinger 6.0, the algorithm in [23] and the proposed algorithm for ridge detection. (a) A live-scan partial print (height: 973 pixels, width: 893 pixels) from the thenar region, (b) skeleton image of (a) by VeriFinger, (c) skeleton image of (a) by the algorithm in [23], (d) skeleton image of (a) by the proposed algorithm.



Fig. 9. Comparison of VeriFinger 6.0, the algorithm in [23] and the proposed algorithm for ridge detection. (a) A latent print (height: 523 pixels, width: 886 pixels), (b) skeleton image of (a) by VeriFinger, (c) skeleton image of (a) by the algorithm in [23], and (d) skeleton image of (a) by the proposed algorithm.

algorithm for a live-scan partial print from the thenar region and a latent print, respectively. This comparison shows that two region growing based algorithms (the algorithm in [23] and the proposed algorithm) are more robust than VefiFinger 6.0 for ridge direction estimation in the presence of creases. The algorithm in [23] failed to remove some creases which the proposed algorithm successfully removed (see Fig. 8) and produced more spurs than the proposed algorithm (see Fig. 9).

### B. Minutiae Extraction

Given local ridge direction and frequency, a sequence of image processing steps is performed to extract the minutiae: enhancement, binarization, thinning, and ridge and minutia extraction. The extracted minutiae include many spurious minutiae due to image noise, which are removed in the following way. The ridge validation procedure in [24] is used to classify ridges as reliable or unreliable and the minutiae associated with unreliable ridges are removed. The remaining minutiae are further classified as reliable or unreliable minutiae. A minutia is deemed as unreliable if it forms an opposite pair with other minutia in the neighborhood; otherwise, it is deemed as reliable. An opposite pair is a pair of minutiae that are close to each other but have opposite directions. Both reliable and unreliable minutiae are used in the proposed matching algorithm, but treated differently. The results of different steps in minutiae extraction are shown in Fig. 10. It should be noted that due to complex background and multiple overlapping latent prints in a single latent image, the region of interest (ROI) is manually marked for latent palmprints. This is a common practice in forensics. But for other images (full palmprints and live-scan partial palmprints), no manual intervention is needed.

## III. MINUTIAE MATCHING

Given the minutiae features of two palmprints, the matching algorithm consists of (i) local minutiae matching - the similarity between each minutia of a partial print and each minutia of a full print is computed, (ii) global minutiae matching - using each of the five most similar minutia pairs in step (i) as an initial set, a greedy matching algorithm is used to find additional matching minutia pairs, and (iii) matching score computation - a matching score is computed for each set of matching minutia pairs and the maximum score is used as the matching score between two palmprints.

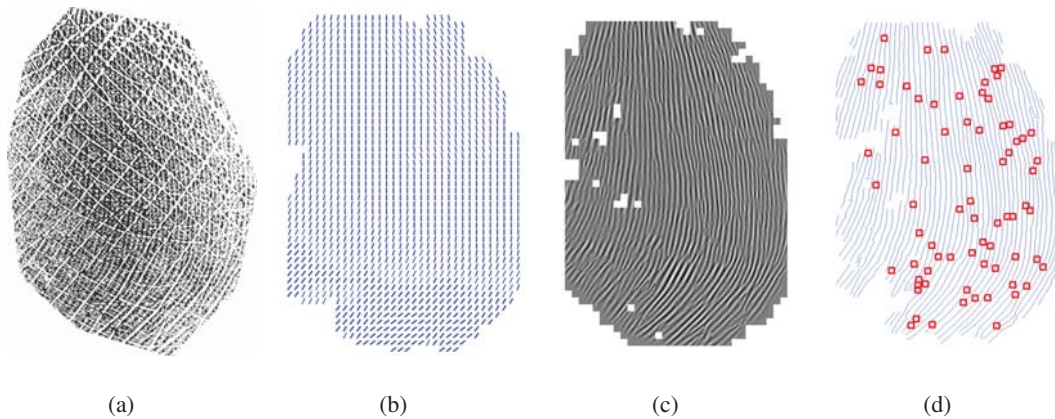


Fig. 10. Minutiae extraction. (a) A live-scan partial print (height: 636 pixels, width: 578 pixels) from the thenar region, (b) direction field, (c) enhanced image, and (d) extracted ridge and minutiae.

### A. Local Minutiae Matching

A minutia is generally tagged with the following features: location, direction, type (ending or bifurcation) and quality (reliable or unreliable) [24]. Since the relative transformation between the two palmprints to be matched is not known a priori, and considering the large size of palmprint images, the minutiae correspondence problem is very challenging. To reduce the ambiguity in matching, we attach additional distinguishing information to a minutia in the form of a minutia descriptor. In the fingerprint recognition literature, four types of information have been widely used as minutia descriptors, namely image intensity [25], texture [26], ridge information [27] and neighboring minutiae [28], [29]. Among these four types of descriptors, texture-based and minutiae-based descriptors are known to provide good performance and a combination of texture and neighboring minutiae information can achieve higher accuracy [30]. However, the length of the neighboring minutiae-based descriptor in [30] is variable, depending on the number of neighboring minutiae. Computing the similarity between two variable-length minutiae descriptors is not very efficient. Therefore, a fixed-length minutia descriptor, called MinutiaCode, that captures neighboring texture and minutiae information is proposed here.

The MinutiaCode of a minutia (referred to as central minutia) is constructed as follows. The circular region around a central minutia is divided into  $(R-1) \times K$  sectors by  $R = 5$  concentric circles and  $K = 8$  lines as illustrated in Fig. 11. The radius of the  $r$ th circle,  $1 \leq r \leq R$ , is  $20 * r$  pixels. The direction of the  $k$ th line,  $1 \leq k \leq K$ , is  $\theta + (k-1) \cdot \pi/K$ , where  $\theta$  denotes

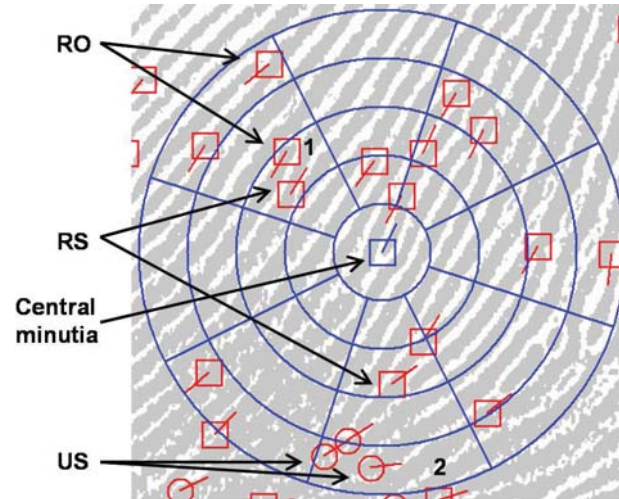


Fig. 11. The configuration of a MinutiaCode. The numbers of four types of neighboring minutiae, RS, US, RO and UO, in sectors 1 and 2 are [1 0 1 0] and [0 2 0 0], respectively. Square indicates reliable minutiae and circle indicates unreliable minutiae.

the direction of the central minutia. For each sector, a set of features is computed, including the quality (1: foreground, 0: background), mean ridge direction, mean ridge period, and the numbers of four types of neighboring minutiae. These four types of neighboring minutiae are defined as: (i) reliable and with the same direction as the central minutia (RS), (ii) unreliable and with the same direction as the central minutia (US), (iii) reliable and with the opposite direction to the central minutia (RO), and (iv) unreliable and with the opposite direction to the central minutia (UO). Whether a neighboring minutia has the same or opposite direction to the central minutia is determined by the angle between the direction of the neighboring minutia and the direction of the central minutia. If the angle is less than  $\pi/2$ , the neighboring minutia has the same direction to the central minutia; otherwise, it has opposite direction to the central minutia. See Fig. 11 for the numbers of four types of neighboring minutiae in two of the 32 sectors (excluding the central part).

The similarity  $s$  between two MinutiaCodes is defined as the weighted average value of the similarities of all valid sectors. A pair of corresponding sectors is deemed valid if both sectors are in the foreground. If the number of the valid sectors is less than 16,  $s$  is set to 0; otherwise

$s$  is computed by:

$$s = \frac{1}{\sum_{i=1}^{32} w_i} \sum_{i=1}^{32} w_i s_i, \quad (8)$$

where  $s_i$  denotes the similarity of the  $i$ th sector and  $w_i$  denotes the weight of the  $i$ th pair of corresponding sectors. To assign a larger weight to sectors containing more reliable minutiae,  $w_i$  is defined as  $(\max(n_1, n_2) + w_0)$ , where  $n_1$  and  $n_2$  are the number of reliable minutiae in the two corresponding sectors and  $w_0$  is a weight for sectors without reliable minutiae (set to 0.2 in our experiments).

The similarity  $s_i$  between two corresponding sectors is computed as follows. If the difference between ridge directions or the difference between ridge periods is greater than the corresponding threshold ( $\pi/6$  and 3 pixels),  $s_i$  is set to 0; otherwise,  $s_i$  is computed using the following formulas:

$$s_i = \frac{n_M}{n_S}, \quad (9)$$

$$n_M = n_{MS} + n_{MO}, \quad (10)$$

$$n_S = n_{SS} + n_{SO}, \quad (11)$$

$$n_{MS} = \min(n_{RS1} + n_{US1}, n_{RS2} + n_{US2}), \quad (12)$$

$$n_{MO} = \min(n_{RO1} + n_{UO1}, n_{RO2} + n_{UO2}), \quad (13)$$

$$n_{SS} = \max(n_{RS1}, n_{RS2}, n_{MS}), \text{ and} \quad (14)$$

$$n_{SO} = \max(n_{RO1}, n_{RO2}, n_{MO}), \quad (15)$$

where the description of the symbols is given in Table I. The range of  $s_i$  is  $[0, 1]$ . If  $n_M$  is equal to  $n_S$ ,  $s_i$  is maximum (1). If  $n_M = 0$  and  $n_S > 0$ ,  $s_i$  is minimum (0). If  $n_M = 0$  and  $n_S = 0$  (namely, there is no minutiae which should be matched in the two sectors),  $s_i$  is set to 1.

### B. Global Minutiae Matching

Given the similarity of all minutia pairs, the one-to-one correspondence between minutiae is established in this stage. All minutia pairs are sorted in the decreasing order of normalized similarity defined in [24] and each of the top-5 minutia pairs is used to align the two sets of minutiae. Minutiae are examined in turn and minutiae that are close in both location and direction, and have not been matched to other minutiae are deemed as matching minutiae. After all the minutia pairs have been examined, a set of matching minutiae is obtained.



TABLE I  
SYMBOLS USED IN THE COMPUTATION OF THE SIMILARITY BETWEEN TWO MINUTIA CODES

Symbol	Description
$s_i$	Similarity between the $i$ th pair of corresponding sectors
$n_M$	Number of the matched minutiae
$n_S$	Number of the minutiae that should be matched
$n_{MS}$	Number of the matched minutiae of type RS and US
$n_{MO}$	Number of the matched minutiae of type RO and UO
$n_{SS}$	Number of the minutiae of type RS and US that should be matched
$n_{SO}$	Number of the minutiae of type RO and UO that should be matched
$n_{RSj}$	Number of the minutiae of type RS in partial ( $j = 1$ ) or full ( $j = 2$ ) palmprint
$n_{USj}$	Number of the minutiae of type US in partial ( $j = 1$ ) or full ( $j = 2$ ) palmprint
$n_{ROj}$	Number of the minutiae of type RO in partial ( $j = 1$ ) or full ( $j = 2$ ) palmprint
$n_{UOj}$	Number of the minutiae of type UO in partial ( $j = 1$ ) or full ( $j = 2$ ) palmprint

### C. Matching Score Computation

The matching score  $S$  between two palmprints is computed as

$$S = W_m * S_m + (1 - W_m) * S_d, \quad (16)$$

where  $S_m$  and  $S_d$  denote the minutiae-based matching score and the direction field based matching score, respectively; the weight  $W_m$  is empirically set to 0.8.

The minutiae-based matching score  $S_m$  is the product of a quantitative score  $S_{mn}$  and a qualitative score  $S_{mq}$ . The quantitative score measures the quantity of evidence and the qualitative score measures the consistency in the common region between two palmprints. The quantitative score  $S_{mn}$  is computed as  $M/(M + 20)$ , where  $M$  denotes the number of matched minutiae. The qualitative score is computed as

$$S_{mq} = S_D \times \frac{M}{M + N_L} \times \frac{M}{M + N_F}, \quad (17)$$

where  $S_D$  is the average similarity of descriptors for all the matching minutiae, and  $N_L$  and  $N_F$ , respectively, denote the number of unmatched minutiae in latent and full prints that are reliable and belong to the common region of the two palmprints.

The direction field based matching score  $S_d$  is the product of a quantitative score  $S_{dn}$  and a qualitative score  $S_{dq}$ . The quantitative score  $S_{dn}$  is computed as  $N_b/(N_b + 900)$ , where  $N_b$  is the number of blocks where the difference of direction between latent and full print is less than  $\pi/8$ . The qualitative score  $S_{dq}$  is computed as  $(1 - 2 * D_d/\pi)$ , where  $D_d$  is the mean of the difference of direction values of all the blocks.

## IV. EXPERIMENTS

### A. Palmprint Database

There is no public domain latent and mated full palmprint database available. Further, to our knowledge, while there have been several large-scale performance evaluations organized by NIST for fingerprint (FpVTE [15] and ELFT [31]), face (FRVT [32]) and iris (ICE [33]), such performance evaluation of latent/partial palmprint matching algorithms has not yet been conducted. The announcement of the FBI's NGI program has created a substantial interest in palmprint matching and it is likely that a similar evaluation for palmprint recognition will be conducted in the near future. In our experiments, we used two sets of latent palmprints provided to us by Noblis [34] and the Forensic Science Division of Michigan State Police (MSP). The Noblis latent database consists of 46 latent palmprints which correspond to eight different palms. The MSP latent database consists of 54 latent palmprints which correspond to 22 of the 36 different palms. The latents from Noblis and MSP have been merged to form a database of 100 latents. Michigan State Police also provided us with 10,040 full palmprints that are used to form a background database for latent matching. Due to the limited number of latent palmprints available to us, we also collected live-scan partial palmprints and their mated full palmprints using a CrossMatch L SCAN 1000P optical scanner in our laboratory. Live-scan partial images were collected from 50 unique palms (25 subjects who provided images of both left and right palms) with three impressions per palm, one impression each from the thenar, hypothenar and interdigital regions. Full prints of these 50 palms and other 66 palms were also scanned. The live-scan partial images and the latent images were not merged, since they are quite different, both in size and quality. The 116 live-scan full palmprints, 44 (8 from Noblis and 36 from MSP) mated full palmprints of latents, and 10,040 full palmprints from the Michigan Forensic Laboratory were merged to form a background database of 10,200 full palmprints. In our databases, most images (the 10,040 full prints from the Michigan Forensic Laboratory) are at 500 ppi; remaining

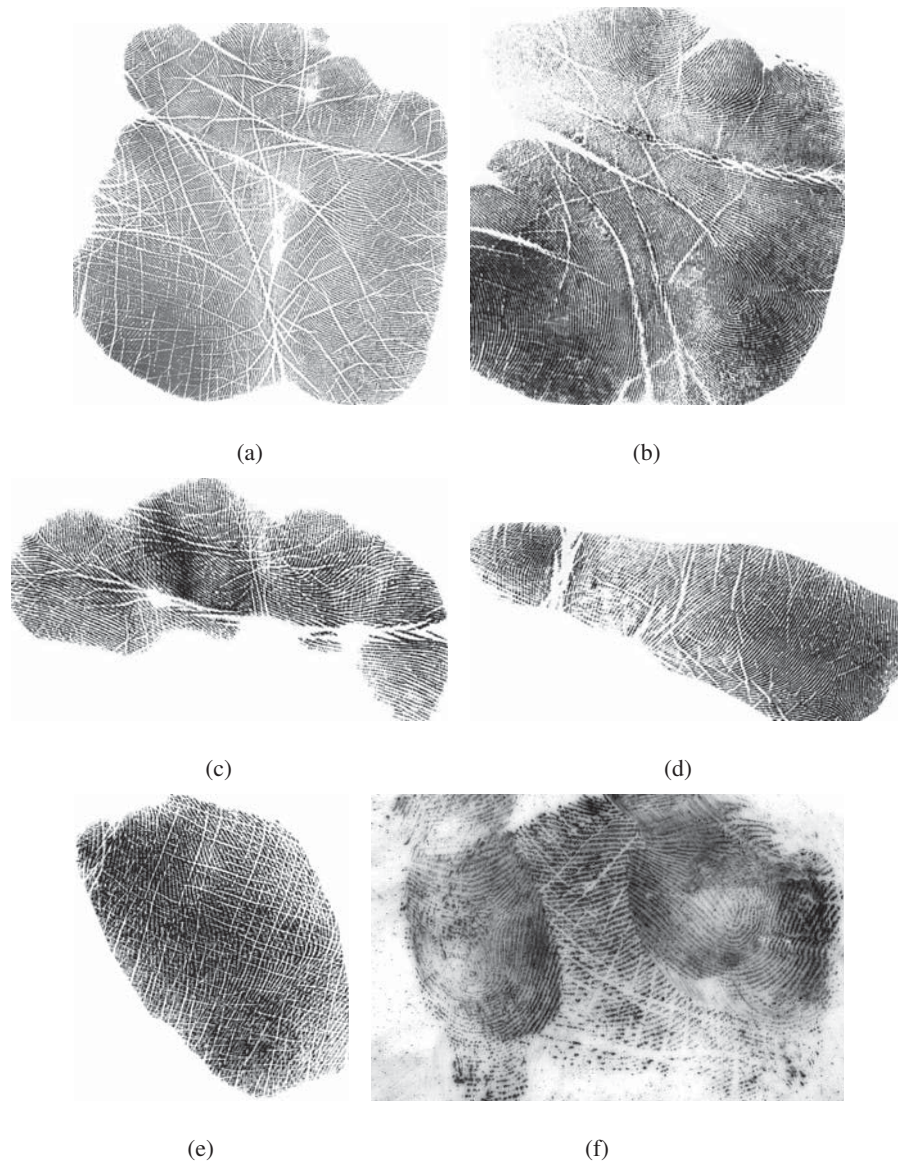


Fig. 12. Examples of different types of palmprint images. (a) Live-scan full print (height: 1,753 pixels, width: 1,710 pixels), (b) inked full print (height: 1,649 pixels, width: 1,575 pixels), (c) live-scan partial print (height: 581 pixels, width: 1,319 pixels) from the interdigital region, (d) live-scan partial print (height: 549 pixels, width: 1,425 pixels) from the hypothenar region, (e) live-scan partial print (height: 837 pixels, width: 748 pixels) from the thenar region, and (f) latent print (height: 649 pixels, width: 998 pixels).

TABLE II

PARTIAL PALMPRINT DATABASES. THE SUM OF THE LATENTS FROM THE THREE REGIONS (INTERDIGITAL, THENAR AND HYPOTHENAR) MAY BE GREATER THAN THE TOTAL NUMBER OF THE LATENTS, AS SOME LATENTS CONTAIN DATA FROM MORE THAN ONE REGION.

	Noblis latent database	MSP latent database	MSU live-scan partial database
Resolution (ppi)	1000	400	1000
No. of partial prints	46	54	150
No. of palms	8	36	50
Interdigital region	23	24	50
Thenar region	3	14	50
Hypothenar region	21	22	50

TABLE III

FULL PALMPRINT DATABASES.

	Noblis mated full database	MSP mated full database	MSP full database	MSU live-scan full database
Resolution (ppi)	1000	400	500	1000
No. of palms	8	36	10,040	116

images were either downsampled or upsampled to 500 ppi using bicubic interpolation. Our partial and full palmprint databases are summarized in Table II and Table III, respectively. Examples of different types of palmprint images are shown in Fig. 12.

### *B. Matching Performance on Full Background Database*

Due to the differences in the nature and quality of live-scan partial and latent palmprints, we separately searched them against the full background database. Since a large number of full prints are not oriented properly, no rotation constraint is used in the minutiae matching algorithm. Hand type information (left hand or right hand) is utilized if this information can be reliably estimated from partial palmprints. 55 latents among all 100 latents have hand type

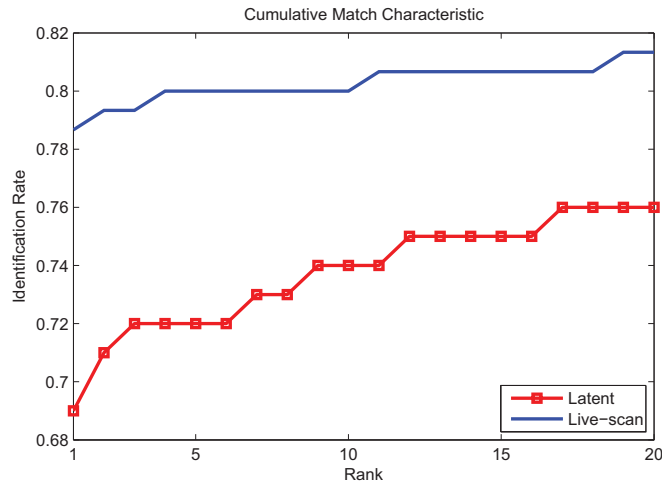


Fig. 13. CMC curves for latent and live-scan partial palmprint identification with a background database of 10,200 full prints. The number of latents is 100 and the number of live-scan partial palmprints is 150. The curves are not smooth due to the small number of partial images.

information and all 150 live-scan partial images have hand type information. The hand type information for all the full prints was already available with the images. The number of left and right hands in the background database is roughly equal. The CMC curves for searching 100 latents and 150 live-scan partial images against 10,200 full prints are shown in Fig. 13. The rank-1 recognition rates of 78.7% and 69%, respectively, were achieved for live-scan partial and latent palmprints. As expected, the performance for live-scan partial images is much better than that for latents due to better image quality and larger image size of the former. There are two things that should be noted. In forensic applications, latent experts generally manually correct minutiae extracted by algorithms. With intervention of latent experts, the matching accuracy can be significantly improved. In practice, latent experts generally examine top 20 candidates provided by the automated system, and in high profile cases such as murder, latent experts may examine as many as 100 candidates. As shown in Fig. 13, the rank-20 recognition rates of 81.3% and 76%, respectively, were achieved for live-scan partial and latent palmprints.

### C. Comparison to Other Algorithms

The proposed palmprint enhancement algorithm has two main improvements over the original algorithm of Funada et al. [23], namely, more robust direction field estimation and elimination



of blocking effect, which have been qualitatively shown in Fig. 8 and Fig. 9. To evaluate the proposed improvements quantitatively, we combined the two enhancement algorithms with the same minutiae extraction and matching algorithms proposed in this paper. An experiment was conducted by searching 100 latents and 150 live-scan partial palmprints against a background database of 160 full prints which consists of the 44 mated full prints of latents and 116 live-scan full prints. Hand type information was not used in matching. The CMC curves of the two enhancement algorithms for two types of partial images are given in Fig. 14. This figure indicates that the improved algorithm provides higher palmprint matching accuracy than the original algorithm in [23].

Since to our knowledge, there is no partial-to-full palmprint matching algorithm available in the open literature, we compared our matching algorithm to a commercial fingerprint SDK, Neurotechnology VeriFinger. However, VeriFinger can not be directly used for palmprint matching, because it has a limit on the number of minutiae that can be dealt with in feature extraction and matching and this limit is smaller than the number of minutiae observed in full palmprints. In [17], full palmprints are split into five sectors and minutiae are extracted separately for each sector using VeriFinger. No minutiae are extracted from the central part of the palms, as this part is less frequently found in latents. Major creases are extracted and minutiae around the major creases are removed. After these steps, VeriFinger matcher can be used for partial-to-full palmprint matching. A rank-1 recognition rate of 67.5% was reported in [17] when matching 240 live-scan partial (which are from 20 palms of all the 50 palms in the MSU live-scan partial database) against 100 live-scan full prints (which is a subset of the MSU live-scan full database). The rank-1 rate (67.5%) of VeriFinger on a small background database (100 full prints) is much lower than the rank-1 rate (78.7%) of the proposed algorithm on a much larger background database (10,200 full prints).

#### *D. Utilization of Ancillary Information*

Given a latent palmprint, proficient latent examiners can often reliably estimate (depending on the quality of the latent image) the hand (left or right) that made the latent, the part of the palm that the latent was from, and the orientation of the latent [35]. To determine the matching performance gain in the presence of such information, an experiment was conducted by searching 100 latents against a small background database of 160 full prints which consists

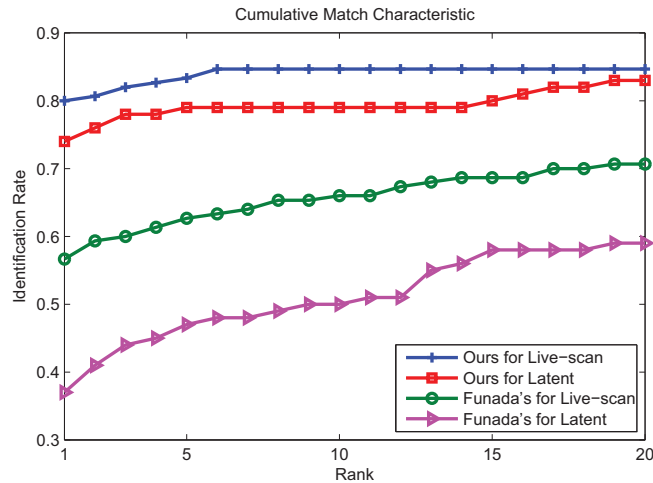


Fig. 14. CMC curves of using two different palmprint enhancement algorithms (Funada's [23] and ours) in searching 100 latents and 150 live-scan partial palmprints against a background database of 160 full prints.

of the 44 mated full prints of latents and 116 live-scan full prints. A small background database is selected, as it is not a trivial task to automatically extract ancillary information for the full background database where a large number of palmprints are of poor quality and not in upright position. For the 160 full prints, region map and palm orientation were manually marked by the authors. The region map of a full palmprint is shown in Fig. 15. The region map is a 3-bit-depth image of the same size as the palmprint image, where one of the three bits of each pixel is used to record which of the three palmprint regions it belongs to. The different regions are allowed to overlap somewhat in order to account for errors in marking the region map for latents. For the 100 latents, hand type, region map and orientation are estimated by the authors using the methods described in [35]. Due to the poor quality of latents, hand type can not be estimated for 45 latents and palm orientation can not be estimated for 27 latents. Fig. 16 shows one example for each of the following three situations: (i) the ancillary information can be reliably estimated, (ii) no ancillary information can be reliably estimated, and (iii) partial ancillary information can be reliably estimated. The ancillary information is utilized in the minutiae matcher in the following way: (i) the similarity between palmprints of different hand types (left vs. right) is 0; (ii) the similarity between two minutiae of different palm regions (e.g., interdigital region vs. thenar region) is 0; (iii) the similarity between two minutiae whose direction (with respect

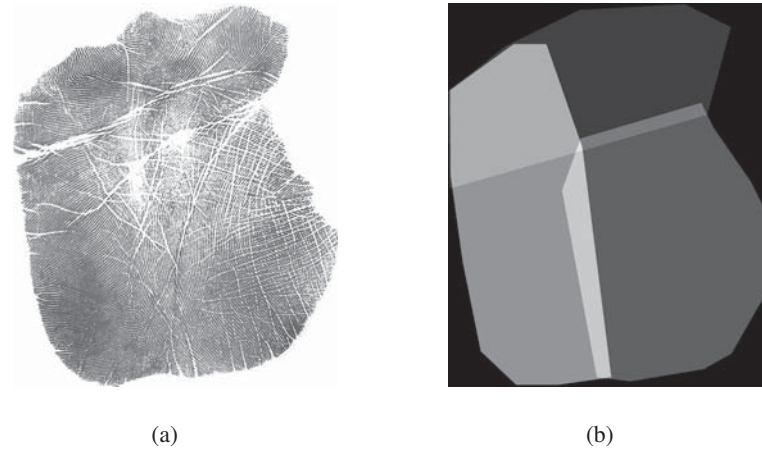


Fig. 15. Region map. (a) A full palmprint and (b) its region map.

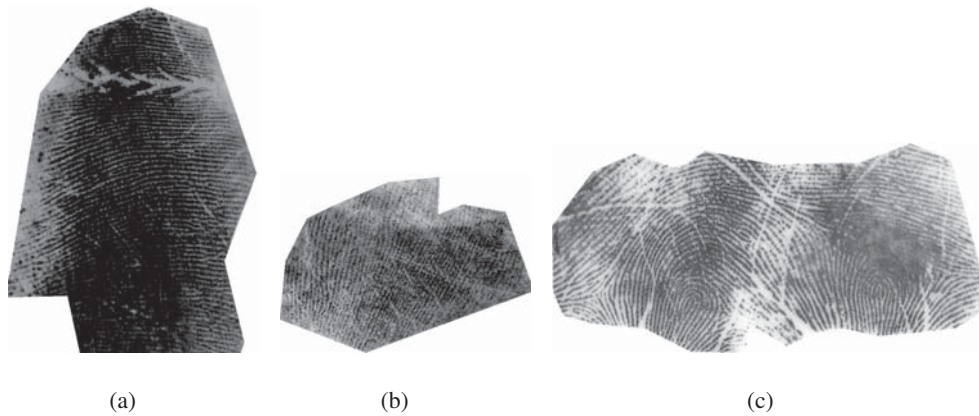


Fig. 16. Estimating latent palmprint ancillary information. (a) Ancillary information can be reliably estimated (left hand, hypothenar region, 90 degree), (b) no ancillary information can be reliably estimated, and (c) partial ancillary information can be reliably estimated (unknown hand, interdigital region, -90 degree).

to palm orientation) difference is greater than a threshold ( $\pi/3$ ) is 0. Fig. 17 shows the CMC curves demonstrating the performance improvement in the presence of ancillary information. The improvement of rank-1 identification rate due to the use of ancillary information indicates that such information is quite useful. The matching speed with ancillary information is also about 2.5 times faster than without such information. The rank-20 identification rates with and without ancillary information in Fig. 17 are the same due to the small size of the background database.

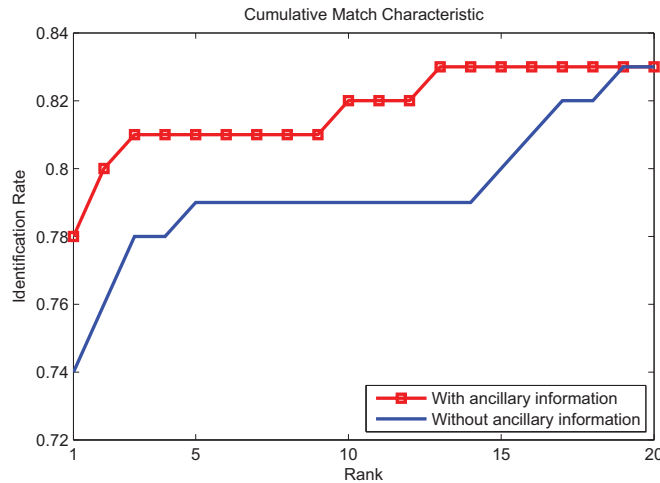


Fig. 17. CMC curves for latent palmprint matching (100 latents) with and without ancillary information against a background database of 160 full prints.

### E. Different Palm Regions

To examine the identification performance of different palm regions, we computed three separate CMC curves (see Fig. 18) for matching images from the three palm regions in the 150 live-scan partial images against the background database of 10,200 full prints. The thenar region was found to be the most challenging palmprint region with a rank-1 recognition accuracy of only 52%, which is much lower than the accuracy of the interdigital region (98%) and the hypothenar region (86%). The low accuracy for the thenar region is due to the presence of a large number of creases in the thenar region and the smaller size of the images from the thenar region. During our collection of live-scan partial palmprints, we intended to capture each of the three regions exclusively. However, it is not easy to scan the thenar region alone without interference of the other two regions due to the structure of the thenar region. Therefore, only a part of the thenar region, which is characterized by a large number of creases, is scanned. As a result, the size of the images from the thenar region is smaller than that of the images from the other two regions. The superior performance of the interdigital to the hypothenar is due to: (i) the direction field in the interdigital region is more distinctive than that in the hypothenar region), and (ii) some of the hypothenar images in our database contain the edge of the palm where the ridge pattern is not present. Since just using partial palmprints from the interdigital region can

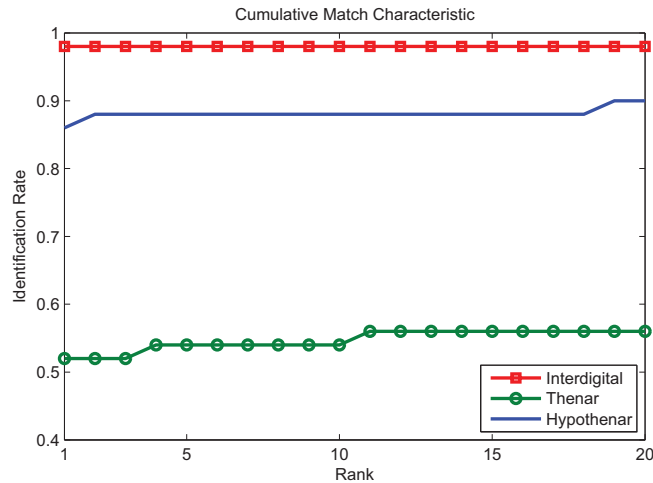


Fig. 18. CMC curves for matching live-scan partial images from three different palm regions against the background database of 10,200 full prints. The numbers of the partial images from the three palm regions are the same (50).

achieve a rank-1 recognition rate of 98%, we can predict that the rank-1 recognition accuracy of full-to-full palmprint matching (searching the full prints of the live-scan partial palmprints against the full background database) using the proposed algorithm should be greater than or equal to 98%.

#### F. Quality of Latents

We manually classified the 100 latent palmprints into three different quality levels: good (45 latents), bad (34 latents) and ugly (21 latents). This terminology for latent palmprint quality is adapted from NIST SD27 [11] where latent fingerprints were assigned the same labels. The average number of reliable minutiae extracted in good, bad, and ugly latents is 77, 56, and 45, respectively. An example image with each quality level is shown in Fig. 19. Fig. 20 shows the CMC curves for matching latents with these three quality levels against the background database of 10,200 full prints. As expected, the matching performance of latents with different quality levels is dramatically different. These results indicate that, while the proposed system can deal with latents of good quality satisfactorily, the intervention of latent experts is still necessary in the case of latents with bad and ugly quality.

The three latents (same as those in Fig. 19) and their mated full prints, which were all

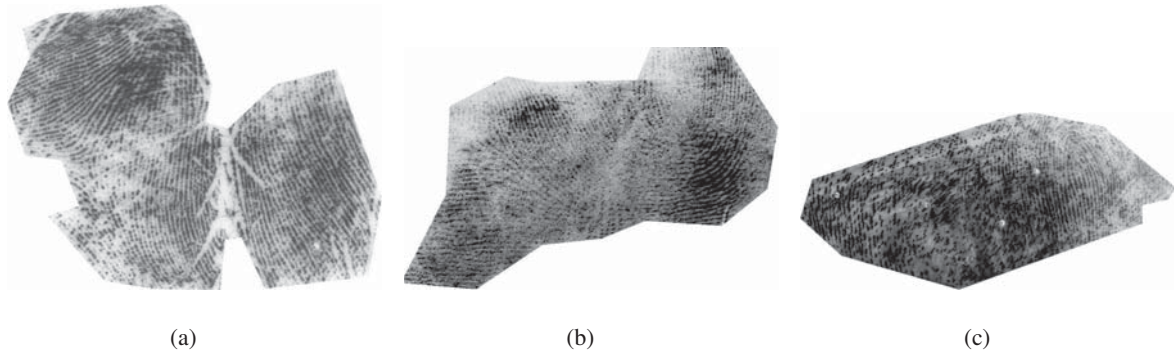


Fig. 19. Latents with three different quality levels. (a) Good (height: 552 pixels, width: 726 pixels), (b) bad (height: 511 pixels, width: 905 pixels), and (c) ugly (height: 473 pixels, width: 999 pixels).

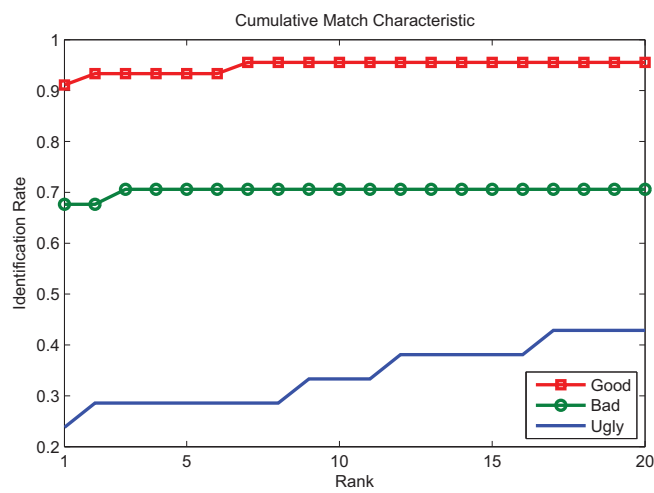


Fig. 20. CMC curves for matching latents with three different quality levels: good (45 latents), bad (34 latents) and ugly (21 latents) against the background database of 10,200 full prints.

correctly identified at rank 1 by the proposed algorithm, are shown in Fig. 21. The latents have been aligned with the mated full prints. An example of unsuccessful match is shown in Fig. 22, where the poor quality of both the latent and full print is the reason for the matching failure.

### G. Fusion of Latent Palmprints

At crime scenes, multiple latent palmprints from the same palm can be frequently found. Based on image and non-image information (such as the position of the latents), latent experts can often reliably determine whether two latents are from the same palm. To determine the



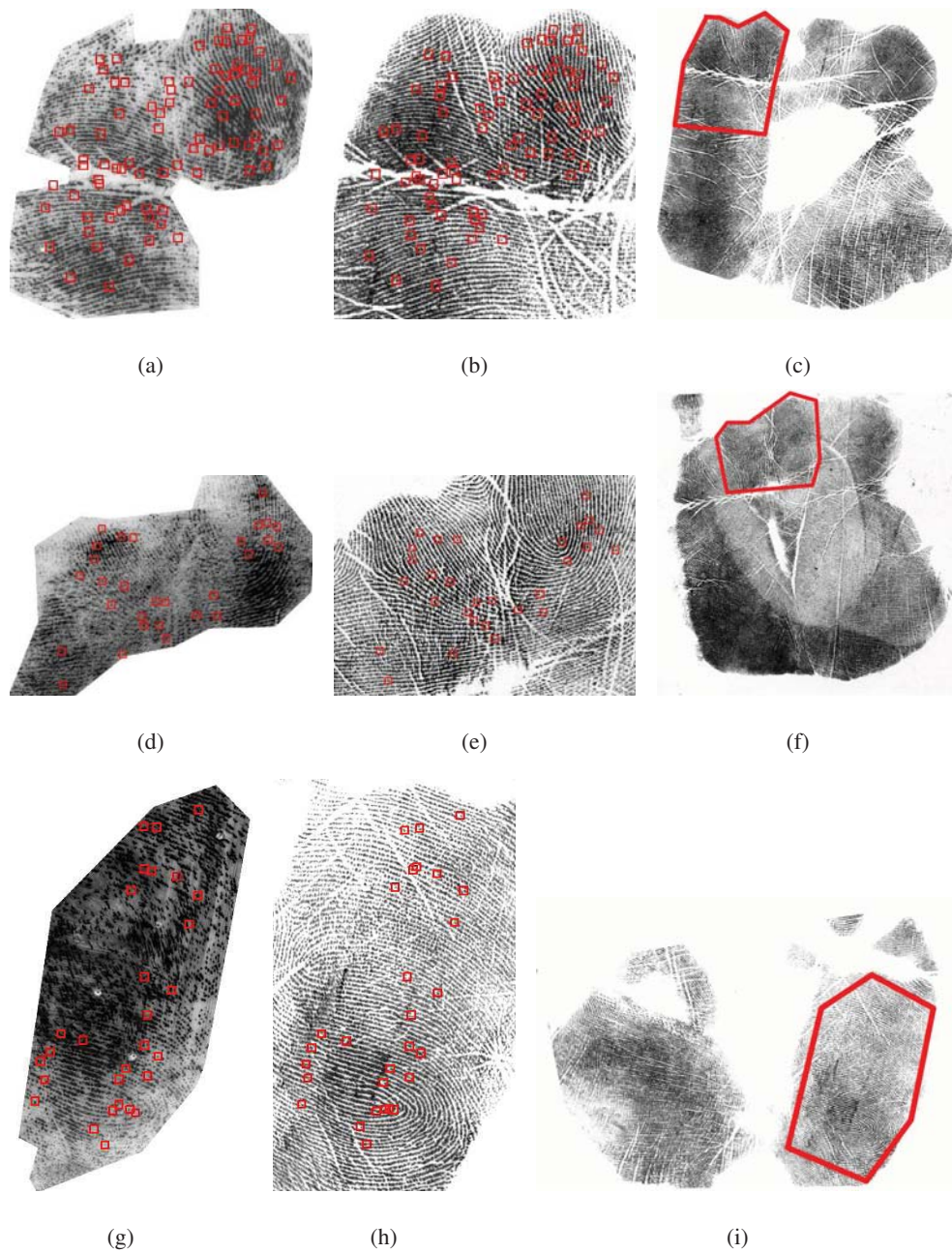


Fig. 21. Examples of successful latent match. (a) Latent of good quality, (b) corresponding region in the mated full print of (a), (c) the mated full print of (a), (d) Latent of bad quality, (e) corresponding region in the mated full print of (d), (f) the mated full print of (d), (g) Latent of ugly quality, (h) corresponding region in the mated full print of (g), and (i) the mated full print of (g). The matching minutiae are overlaid on the images. The corresponding region are marked on the full prints.

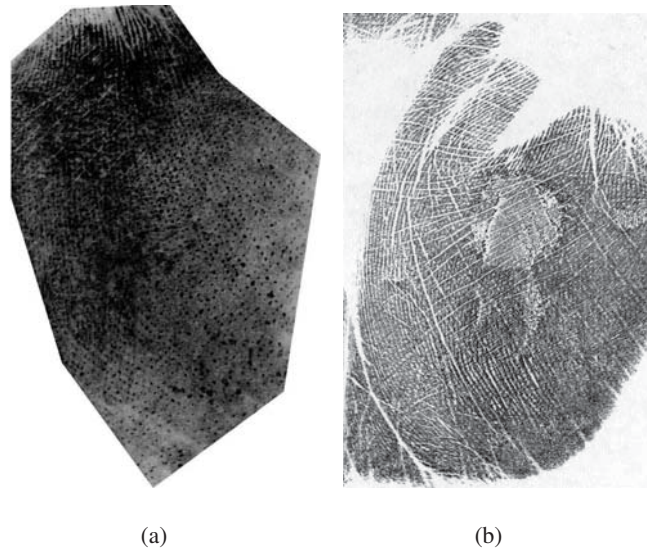


Fig. 22. Example of an unsuccessful latent match. (a) Latent and (b) its mated full print which ranks 2108 in matching against the background database of 10,200 full prints (only the corresponding part is shown).

performance gain of fusing multiple latent palmprints, the following experiment was conducted. The 100 latents in our database were merged into 30 groups, each of which consists of multiple latents from the same palm. If any latent of a group leads to a successful match (identified at rank-1), this group is deemed as a successful match. This ‘OR’ rule is consistent with the practice in forensics. Based on this rule, the rank-1 recognition rate of searching 30 groups against the full background database is 90%, which is much higher than the rank-1 rate (69%) without fusion. A latent group with two latents from the same palm is shown in Fig. 23, where one latent has much better quality than the other and it was correctly identified at rank-1. All 3 (10%) latent groups that failed to identify contain only one latent that is of poor quality and can not be improved by fusion.

#### *H. Computational Requirements*

The computational requirements of different modules of the proposed system on a PC with Intel 3GHz CPU and Windows XP operating system are as follows. The average feature extraction time is 7 seconds for partial palmprints and 22 seconds for full palmprints. The DFT and Gabor filtering are the most computationally demanding parts of the feature extraction algorithm. The average matching time between a partial palmprint and a full palmprint is 0.34 seconds.

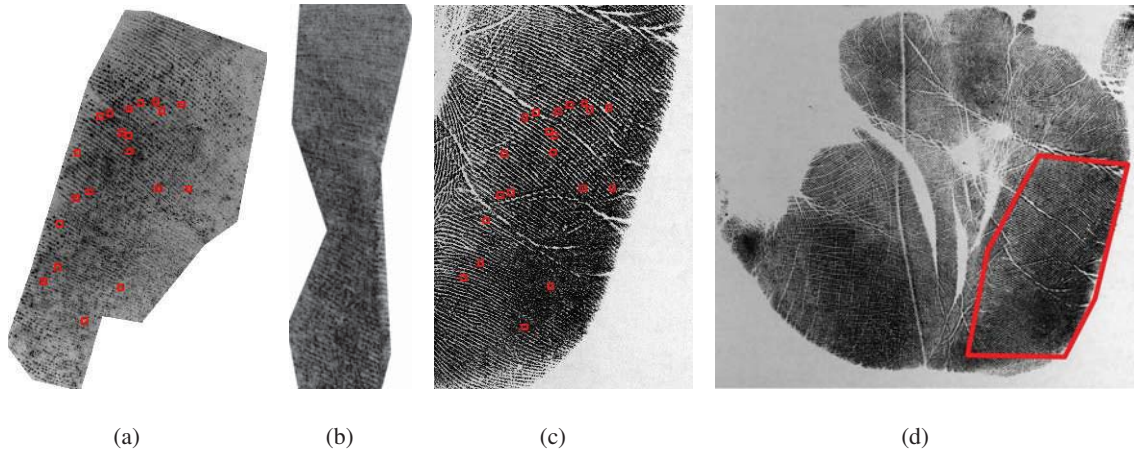


Fig. 23. A latent group consisting of two latent palmprints from the same palm. (a) A good latent (height: 1,324 pixels, width: 630 pixels) which was correctly identified at rank-1 in searching against the full background database, (b) an ugly latent (height: 999 pixels, width: 318 pixels) which was not identified, (c) the corresponding region (with matching minutiae marked) in the mated full print of (a), and (d) the mated full print (height: 2,146 pixels, width: 2,341 pixels) of (a) and (b).

Considering that a typical full palmprint has about 800 minutiae and a typical partial palmprint in our database has about 150 minutiae, and no pre-alignment stage has been used prior to minutiae matching, this matching speed is reasonable. We have also tested the descriptor in [30] on a subset of palmprint images; its matching speed was found to be more than 10 times slower than MinutiaCode proposed here.

## V. CONCLUSION AND FUTURE WORK

We have developed a prototype latent-to-full palmprint matching system. A region growing algorithm was developed to robustly estimate the local ridge direction and frequency even in the presence of overwhelming amounts of noise. Our minutiae matching algorithm is based on a new fixed-length minutia descriptor which captures texture and neighboring minutiae information. The proposed system achieves rank-1 recognition rates of 78.7% and 69%, respectively, in searching 150 live-scan partial palmprints and 100 latent palmprints against a background database of 10,200 full palmprints. Partial palmprints from the thenar region are most difficult to match among the three palm regions. Quality of latents has a significant effect on the matching accuracy. Ancillary information in the form of hand type, palm region and palm orientation can significantly improve both the matching accuracy and matching speed. A simple ‘OR’ rank level fusion of

multiple latents from the same palm can improve the matching accuracy from 69% to 90%.

Designing a robust latent palmprint segmentation algorithm is our ongoing work. While the proposed region growing algorithm can recover a flat direction field even when the noise is overwhelming, it needs to be improved to deal with noisy high curvature areas of palmprints. For high resolution (1000 ppi) palmprints that are becoming available, we are exploring how to reliably extract and utilize various types of extended features [36], especially creases, as palmprints often contain a large number of stable creases. Utilizing creases in latent palmprint matching is more likely to improve the matching accuracy for latents from the thenar region. For efficient search on a large background database (of the order of millions), our matching algorithm needs to be made more efficient. One approach is to use an indexing technique based on minutia triplets [37]. Another approach is to utilize hand type, palm region and palm orientation, since we have shown that such information can improve both the matching accuracy and matching speed. We plan to develop an algorithm to estimate the ancillary information from latent palmprints. Besides the interdigital, the thenar and the hypothenar regions, the writer's palm (the edge of palm opposite the thumb) is also frequently found at crime scenes. As the joint part of the palm and the back of the hand, the writer's palm generally contains very few minutiae. We plan to collect images of writer's palm and design a matcher which takes into account the characteristics of the writer's palm. It is generally believed that fusion at feature level can lead to better accuracy than fusion at score/rank level. We plan to explore how to merge multiple fragmental latents from the same palm into a single latent palmprint with larger image size and better quality [38]. To automatically determine whether two latents are from the same palm, we need to develop a latent-to-latent palmprint matching algorithm.

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