RESEARCH ON OFFLINE PALMPRINT IMAGE ENHANCEMENT

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ABSTRACT

Palmprint identification, a subcategory of biometrics identification, has become a hot research area, and image enhancement is a key problem in offline palmprint identification. Since the physiological characteristics and image quality of palmprints are different from those of fingerprints, existing algorithms on fingerprint image enhancement cannot be directly applied in offline palmprint images. Taking into account the characteristics of palmprint images, an enhancement algorithm specific to offline palmprint images is proposed in this paper. We have performed a series of experiments and provide the enhanced palmprint images in the experiment section. Moreover, we evaluate our algorithm by comparing it with the method only using a low-pass filter to smooth the images under the criteria of GI value. Besides, the running time of each step is given to show the efficiency of the algorithm. The result shows that our algorithm is capable of attaining the objectives of offline palmprint enhancement efficiently.

Index Terms— Offline Palmprint, Orientation Field, Interior Noise, Exterior Noise, Special Area

1. INTRODUCTION

Palmprint, with its unique and abundant characteristics, has become a reliable biological feature. Palmprint identification, including online and offline palmprint images identification, also becomes a hot research topic.

Online palmprint identification, where all palmprint samples are directly obtained by a palmprint scanner, is based on statistical features [1] to recognition. Differently, for offline palmprint identification, the samples are inked on paper and then transmitted into a computer through a digital scanner. With relatively high-resolution (up to 500 dpi) of offline palmprint, a lot of features, such as lines, datum points [2] and minutiae, can be extracted from offline palmprint images. Since the precision of feature extracting highly relies on the image quality, image enhancement has been an indispensable module in offline palmprint system. Although it is recognized that some fingerprint image enhancement techniques can be applied in offline palmprint images, we argue that algorithm specific on offline palmprint image enhancement is greatly demanded due to the following discrepancies between the two.

- Topological Inconsistency: The ridge/valley pattern in fingerprint image has global consistency, while offline palmprint image only has local but not global consistency, which means different areas in the same image have different patterns.
- Image Quality Discrepancy: Offline palmprint images, with the same resolution as fingerprint images, are always of poorer quality.
- Image Size Difference: The size of offline palmprint images is always much bigger than that of fingerprint images, which therefore requires highly efficient enhancement algorithm.

In this paper, we propose an offline palmprint image enhancement algorithm, specifically for the improvement of offline palmprint identification system using minutiae. The paper is organized as follows: Section 2 gives an overview of the algorithm; Section 3 explains the algorithm in detail; Experiments and results are shown in Section 4; and Section 5 concludes the paper.

2. OVERVIEW OF OFFLINE PALMPRINT ENHANCEMENT ALGORITHM

As shown in Fig. 1(a), our offline palmprint identification system uses local ridge characteristics minutiae, including endings and bifurcations [3] for identification. In order to obtain high-quality minutiae, our enhancement algorithm aims at:

- Strengthening genuine minutiae;
- Removing the patterns that produce spurious minutiae;
- And retaining the physiological characteristics of palmprint.

Our enhancement algorithm consists of four steps:

<u>Step 1</u>: Estimate and modify the orientation field.

Concerning that offline palmprint images are much larger and more sensitive to the complexity of an algorithm than fingerprint images，we propose a quick orientation field estimate algorithm based on Methre's algorithm [4] and, an orientation modification algorithm based on the information of *Special Area.*

<u>Step 2</u>: Remove noises in a grey-scale image.

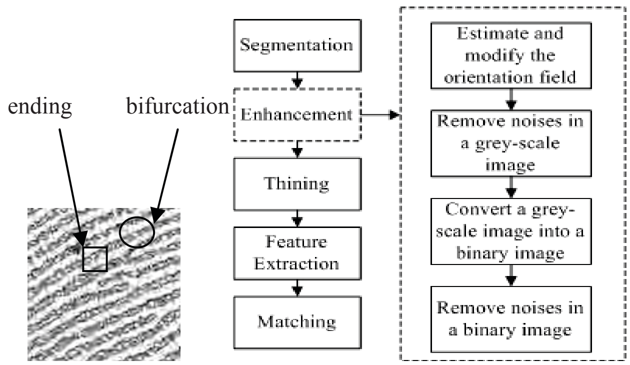
In this paper, we classify noises as interior and exterior noises. In a grey-scale image, interior noises are always represented by lack of grey-scale uniformity in ridges, and exterior noises are denoted by the conglutinations and ruptures between ridges. On the top of techniques provided in [5], we design a group of orientation filters which can filter an image according to its orientation field.

<u>Step 3</u>: Convert a grey-scale image into a binary image

A binarization algorithm based on the local threshold is used to convert grey-scale images into binary images and the local threshold is determined by Otsu threshold selection algorithm [6].

<u>Step 4</u>: Remove noises in a binary image

In a binary image, interior noises exist as white holes in the ridges and exterior noises as small black regions within the valleys. In this paper, a novel algorithm of removing those two kinds of noises is introduced.



(a) (b) (c)

Fig. 1. (a) Minutiae overlaid on a local region of a palmprint image.
(b) The overflow of offline palmprint identification system.
(c) The overflow of offline palmprint enhancement.

Fig. 1 (b) shows the workflow of an offline palmprint identification system using minutiae, and Fig. 1 (c) shows the workflow of the proposed enhancement algorithm.

3. OFFLINE PALMPRINT ENHANCEMENT

In our offline palmprint enhancement algorithm, a palmprint image is divided into several small local area images. For example, if the original image has W×H pixel and each local area has M×M pixel, the set of all local areas can be represented as

$$\{I_{ij} \mid 0 \le i \le W/M - 1, 0 \le j \le H/M - 1\},$$

where I_{ij} represents the ith from the left and jth from the top local area.

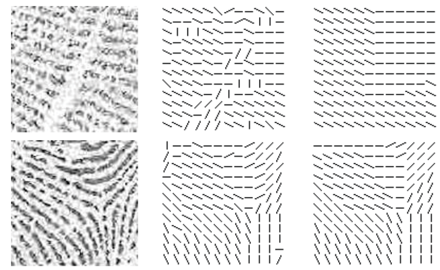
3.1 Orientation field estimation and modification

3.1.1 Orientation field estimation

To improve the efficiency, Methre's method [4] is adopted to estimate orientation field. In addition, observing that orientations are continuous in small local regions, four pixels are considered as a whole when estimating orientation. The estimate steps are:

1) Define N orientations, d=1, 2, …, N , corresponding to the N angles between (0, ∏).
2) Compute the grey variety S_d along each orientation
   $$S_d = \sum_{k=1}^{m} | f_d^*(i,j) - f_d(i_k, j_k) |, \text{ d=1, 2, …, N},$$
   where (i, j) is the coordinate of the current pixel, $f_d^*(i,j)$ is the grey-scale of the pixel (i, j), $f_d\ (i_k, j_k)$ is the grey-scale of the neighbor pixels (i_k, j_k) along orientation d, and m is the number of the neighbor pixels.
3) For each orientation d, sum the S_d of pixel(i, j)'s neighbor pixels that are perpendicular to orientation d.
   $$S_d' = \sum_{k=1}^{m} S_{dk}^*(i,j), \text{ d=1, 2, …, N},$$
   where m is the number of the neighbor pixels.
4) The orientation of pixel(i, j) is the orientation d that has the smallest S_d', where d=1, 2, …, N.

Two examples of palmprint local areas and their orientation fields are shown in Fig. 2 (a) and (b).



(a) (b) (c)

Fig. 2. (a) Local areas of original images.
(b) Orientation fields of local areas in (a).
(c) Modified orientation fields of local areas in

3.1.2 Orientation field modification

Observing Fig. 2 (b), we find that wrinkles and noises in original images may cause errors to orientation estimation, so orientation field modification is an indispensable step. Before our novel orientation modification algorithm is discussed, we will introduce some definitions and then the assumptions of our algorithm.

Definitions:

- *Main Orientation (MO)*

  In a local palmprint area I_{ij}, the Main Orientation of the area I_{ij}, MO (I_{ij}) is defined as the orientation to which the maximum pixels belongs in the local area.

- *Orientation Territory (OT)*

  The Orientation Territory of an orientation *O*, *OT(O)*, is defined as the orientation tuple which consists of the orientation of *O* and its two immediate neighbors' orientations.

  $$OT(O) = \begin{cases} \{(O-1), O, (O+1) \bmod N\} & O != 1 \\ \{(O-1)+N, O, (O+1) \bmod N\} & O = 1 \end{cases},$$

  where O is the orientation between 1~N and N is the number of orientations.

- *Orientation Difference (OD)*

  The Orientation Difference between the two orientations, e.g., O_i and O_j, is defined as *OD* (O_i, O_j) = *N-abs* ($O_i - O_j$), where 1⩽i, j⩽N and N is the number of orientations.

- *Special Area (SA)*

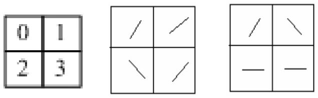
  The local area that includes singular point, either core point or delta point, is defined as Special Area, either Core Area or Delta Area respectively.

- *Non-Special Area (NSA)*

  The local area that is not a Special Area is defined to be Non-Special Area.

Based on the MOs of every four adjacent local areas (Fig. 3(a)), the MOs of two combinations of special areas can be estimated and are shown in Fig. 3(b) and (c). All other scenarios can be obtained through rotating either of the two combinations. Through experiments, we found that Special Areas satisfy the following conditions:

- In four adjacent local areas, at least three have different orientations.
- Among the ODs of each two MOs in four adjacent local areas, at least one is greater than N/2-1.
- Between OD (O_0, O_2) and OD (O_1, O_3), where O_i represents the orientation of area i in the Fig. 3(a), at least one is greater than N/2-2.



(a) (b) (c)

Fig. 3. (a) is the order of four adjacent local areas; (b) is one of MOs compositon of Core Area; (c) is one of MOs compositon of Delta Area.

Assumptions:

- In a Non-Special Area, the local orientation is limited in the OT of MD.
- In a Special Area, orientations of the pixels closed to a singular point vary dramatically; however, those of the pixels far off it vary slowly.

According to the above definitions and assumptions, we propose our orientation modification algorithm as follows:

- In a Non-Special Area, if the orientation of a pixel is in the OT of the MD of the area, nothing needs to be done; otherwise change its orientation to be the MD of the area.
- In a Special Area, the singular point needs to be detected through analyzing the orientation changing rate. Low-pass filter need to be applied on the Special Area except the small area around the singular point to get the modified orientations of the pixels.

Fig. 2(c) shows the modified orientations of pixels in Fig. 2(b).

3.2 Noises removal in a grey-scale image

Noises removal in a grey-scale image mainly has two objectives: to connect the ruptures of a ridge and to break up the conglutination between two ridges. Based on [5], a group of orientation filters are devised to eliminate the noises in a grey-scale image.

-1	-1	-1	-1	-1	-1	-1
5	5	5	5	5	5	5
8	8	8	8	8	8	8
5	5	5	5	5	5	5
-1	-1	-1	-1	-1	-1	-1

Table 1. An Orientation Filter of Orientation 1.

For every pixel, a central line is drawn through the pixel along its orientation. The design principle is that the pixels on the central line have the strongest effect to the current pixel; therefore the corresponding weights of the filter are the biggest. The farther the pixels are off the central line, the less the weights are, which can be formulized as: $A=B-C^D$, where A is the weight of a filter, B and C are two parameters, and D is the distance away the central line. If B=9, C=3, and orientation =1, an orientation filter with a size of 5*7 will be look like what is shown in Table 1. Filters of other orientations are the rotations of this filter.

3.3 Binary Threshold Selection

In order to separate ridges and valleys, grey-scale images have to be converted to binary images first. Since a whole offline palmprint image is usually lack of grey-scale uniformity, the global binary threshold cannot identify ridges and valleys accurately. Therefore, the binary thresholds are selected based on the information of local areas. Otsu threshold selecting algorithm is applied to determine the local threshold when ridges and valleys are regarded as two distinct classes.

However, in the contour local areas of a palmprint, ridge/valley pattern cannot occupy the whole area. Therefore, white background pixels in the contour local areas affect the selection of binary threshold since Otsu threshold selecting algorithm is based on the assumption that all white pixels constitute valleys. So the binary thresholds at contour local areas are relative larger than actual ones, which brings conglutinations of ridges. Thus, the binary threshold of a contour local area can be acquired by the threshold of non-contour local areas in its neighborhood due to the local consistency of an offline palmprint.

3.4 Noises removal in a binary image

The poor quality of offline palmprint images and the quick enhancement algorithm in grey-scale images have some noises left in binary images. Fig. 4 shows that after thinning [7], the noises would cause island structures [8] or spurious endings. So it is necessary to eliminate the noises in binary images. Although the morphological method can solve the problem, it may introduce extra ruptures and conglutinations, the amounts of which are determined by the morphological operators. The proposed method can accurately locate the noises in binary images and then remove them with high efficiency.

3.4.1 Interior noises removal

In binary images, interior noises appear as white holes in ridges which can be divided into two categories according to whether the holes are partially or completely embraced by black pixels, shown in Fig. 5(a) and (b) respectively.

Basically, our approach to interior noises removal consists of two steps. The first step is to detect interior noises. First of all, we classify the pixels in an offline palmprint into three types: the black pixels in original definition, a.k.a. black pixels, the white pixels that have no relation to interior noises, called general white pixels, and the white pixels that are likely to cause interior noises, a.k.a. skeptical white pixels. The objective of the first step is to mark the skeptical white pixels. The main steps are as follows:

- Scan and mark every white pixel in a top-down and left-right manner, with the assumptions that
  - The first scanned white pixel is general white pixel,
  - And a skeptical white pixel is marked if its eight-neighbor pixels are either black pixels or skeptical white pixels.
- For a white pixel P0, we mark the eight neighbors as P1 through P8 in the way shown in Fig. 5(c), if P1~P4 are black pixels or skeptical white pixels, the white pixel is marked as a skeptical white pixel, otherwise, P0 is treated as a general white pixel.
- Scan the mark image in a reverse direction (a bottom-up and right -left manner). For each skeptical white pixel P0, change its mark to general white pixel if at least one pixel among P5 ~P8 is marked as general white pixels.

The second step involves removing interior noises with the information provided by skeptical white pixels. Firstly the size of connected region of skeptical white pixels is calculated.

```
if (size < threshold t1) the region is filled with black pixels
else if (threshold t1 < size < threshold t2)
        if (the region is completely embraced by black pixels)
                the region is filled with black pixels
        else nothing is done.
else nothing is done.
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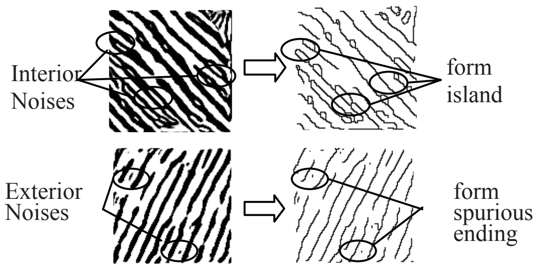


Fig. 4. Interior noises and Exterior noises bring troubles to feature extraction module.

(a) (b) (c)

Fig. 5. (a) Interior noises completely combraced by black pixels.
(b) Interior noises partially combraced by black pixels.
(c) Eight neighbors of a pixel P0.

3.4.2 Exterior noises removal

Exterior noises appear as small black regions within the valleys in binary offline palmprint images. We assume that if the size of a black region is smaller than threshold t_3, it is an exterior noise. Similar to the approach of removing interior noises, the size of connected region of black pixels is computed. In this process, we stop computing and mark the scanned black pixels if the size of connected region is greater than t_3. The termination of computation on a black connected region means that the region is an exterior noise, and it will be filled with white pixels.

4. EXPERIMENT RESULT

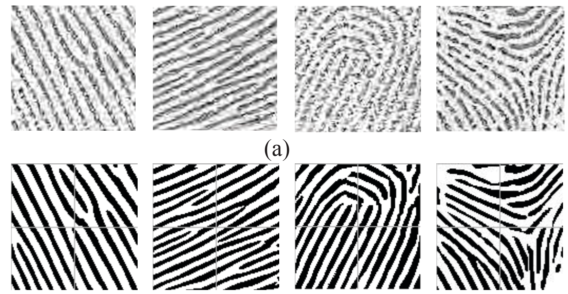
The offline palmprint image samples used for evaluating our enhancement algorithm are 2400×2400 in size with the resolution of 500 dpi and 256 grayscales. A total of 131 images from 89 individuals are tested. The size of a local area is 60×60. The threshold t_1 is set to 30, t_2 to 50 and t_3 to 20. A group of enhanced binary local areas of offline palmprints are shown in Fig. 6.

In order to quantitatively evaluate the performance of the proposed enhancement, we compare it to the method of only using a low-pass filter to smooth the images and let GI value be the criteria [3]. Standard minutiae are given by human experts and detected minutiae are extracted automatically after the two enhancements are done respectively. Table 2 shows the GI values of eight randomly selected samples and the average value of all 131 samples, which proves that our enhancement approach makes the image delivers fewer spurious minutiae and more genuine minutiae than the method of simply smoothing the images does.

Moreover, we show the average time of our algorithm running on the whole palmprint images in Table 3, where average time for each stage and the average total time are shown.

5. CONCLUSIONS

We have introduced a new offline palmprint enhancement algorithm. The experiment results show that our algorithm is capable of attaining the objectives of offline palmprint enhancement. The efficiency also meets the demands of database with millions of offline palmprints in practical use.



(a)

(b)

Fig. 6. (a) A group of local areas in original palmprint images. (b) Enhanced binary local areas of group (a).

Image No.	GI value	
	The proposed algorithm	Low-pass filter
1	0.31	-3.87
2	0.19	-6.06
3	0.27	-4.79
4	0.11	-3.81
5	0.07	-3.45
6	0.06	-6.14
7	0.05	-9.96
8	0.04	-5.80
average	0.14	-6.25

Table 2. GI values of 8 random selected samples and the average value of total 131 samples in our palmprint database.

Step1(s)	Step2(s)	Step3(s)	Step4(s)	Total(s)
1.720	0.813	0.094	0.75	3.377

Table 3. Running time of the algorithm on a Pentium 2.66GHz PC.

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