Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

Fast Palmprint Retrieval Using Principal Lines

Wei Jia, Yi-Hai Zhu, Ling-Feng Liu, De-Shuang Huang
Hefei Institute of Intelligent Machines, CAS, Hefei, China
Department of Automation, University of Science and Technology of China
icg.jiawei@gmail.com

***Abstract*— In this paper, we propose a novel palmprint retrieval scheme based on principal lines. In the proposed scheme, the principal lines are firstly extracted by the modified finite radon transform. And then, a lot of key points located in three principal lines i.e. heart line, life line and head line are detected. Finally, the palmprints are retrieved by several key points' position and direction. The results of experiments conducted on PolyU palmprint database show that the proposed scheme is feasible and has high accurate retrieval rate with fast speed.**

***Keywords*—biometric, palmprint, principal lines, retrieval**

I. Introduction

In information and network society, there are many occasions in which the personal authentication is required, e.g., access control to a building, information security in a computer or mobile-phone, visitor management, and electronic payment etc. There is no doubt that biometric is one of the most important and effective solutions for this task. Generally, biometric is a field of technology that uses automated methods for identifying or verifying a person based on a physiological or behavioral trait. And the traits that are commonly measured in different systems are the face, fingerprints, hand vein, hand geometry, palmprint, handwriting, iris, retinal, and voice etc. Among them, palmprint based biometric systems, as a new biometric technology, has drawn wide attention from researchers [1].

So far, there have been many approaches proposed for palmprint recognition. Kong et al. made a survey for this technique and divided the approaches into several different categories [2]. For texture based approaches, Wavelet transform, Discrete cosine transform, Local binary pattern and some statistical method are often used for texture feature extraction [2]. There are also some line based approaches since lines including principal lines and wrinkles are essential and basic features of palmprint [3]. Coding approaches are deemed to have the best performance on both accurate recognition rate and matching speed. The representative coding methods are PalmCode, FusionCode, Competitive Code, Ordinal Code, and Robust Line Orientation Code [4, 5, 6]. In addition, some representative appearance based approaches were also applied to palmprint recognition [7, 8, 9]. Recently, correlation methods such as optimal tradeoff synthetic discriminant function (OTSDF) filter have been adopted for palmprint recognition, and low Equal Error Rates (EERs) were reported [10].

From the definition of biometric aforementioned, we can know that there are two different recognition models in a biometric system i.e. verification and identification. Verification is a one-to-one comparison in which the biometric system attempts to verify an individual's identity, and answers the question of 'whether the person is whom he claims to be'. Identification is one-to-many comparison in which the system attempts to find out who the sample belongs to, by comparing the sample with all templates in whole database. Generally, compared with verification, identification is a more difficult task since it requires very fast matching speed when conducting the comparisons on a large database for real-time application. As we know, there are two ways that have been investigated for fast identification in palmprint recognition field. The first way is to use classification methods in which all palmprints was divided into several different classes. For example, Wu et al. proposed a palmprint classification approach based on principal lines' number and points of intersection [11]. However, the error rate of Wu's classification method is high, and the processing of feature extraction is rather complex. In particular, the classification results of Wu's method are unbalanced. Due to these drawbacks, Wu's classification method can not be practically used. Even Li et al. proposed a method to further divide the unbalance class, the problem of high classification error rate has not been well solved yet [12]. The second way is to exploit hierarchical approaches in which the system firstly retrieves a sub-set of whole database according to several simple features, and then the fine comparisons are made for final decision. Li et al. proposed a layered search scheme according to global and local texture features [13]. You et al. proposed a four-level based method in which global geometry feature, global texture energy, line feature, and local texture energy are exploited, respectively [14]. Han et al. proposed a coarse-to-fine strategy for fast identification [15]. However, the error rates of Li's and You' methods are very high, and Han's method requires to capture hand shape feature. Thus, these approaches can not be widely adopted for real application due to their limitations.

In this paper, we propose a fast palmprint retrieval scheme exploiting principal lines, which belongs to hierarchical approaches. That is to say, we firstly retrieve a sub-set of whole database according the information of principal lines, and then other fine recognition methods can be performed on this sub-set for final decision. In our opinion, there are several strong reasons to carefully study this issue. Firstly, the principal lines are very stable in a palmprint which is not easily masked by bad illumination condition, compression and noise. Secondly, the retrieval scheme based on principal lines can be used for searching some palmprints with similar principal lines. Thirdly, the principal lines contain rich information such as positions and directions, which is sufficient for fast and accurate retrieval. As a result, the proposed scheme might achieve satisfying retrieval results. Finally, the principal lines can be extracted on ROI image. That is, the proposed scheme does not need to extract features on whole hand image.

II. EXTRACTING PRINCIPAL LINES

In our scheme, the first step is to extract principal lines. We have proposed a modified finite radon transform (MFRAT) to extract principal lines in [3], and in this paper the MFRAT will also be adopted to detect some key points of principal lines for fast retrieval. Here, the definition of MFRAT is given as follows:

Denoting $Z_p=\{0,1,\ldots,p-1\}$, where p is a positive integer, the MFRAT of real function $f[x,y]$ on the finite grid Z^2_p is defined as:

$$r[L_k] = MFRAT_f(k) = \frac{1}{S}\sum_{(i,j)\in L_k} f[i,j] \tag{1}$$

where S is a scalar to control the scale of $r[L_k]$, and L_k denotes the set of points that make up a line on the lattice Z^2_p, which means:

$$L_k = \{(i,j): j = k(i-i_0)+j_0, i\in Z_p\} \tag{2}$$

where (i_0,j_0) denotes the center point of the lattice Z^2_p, and k means the corresponding slope of L_k. In our paper, L_k has another expression i.e. $L(\theta_k)$, where θ_k is the angle corresponding to different index k.

In the MFRAT, the direction θ_k and the energy e of center point $f(i_0, j_0)$ of the lattice Z^2_p are calculated by following formula:

$$\theta_{k_{(i_0,j_0)}} = \arg(\min_k(r[L_k])) \quad k=1,2,\cdots N \tag{3}$$

$$e_{(i_0,j_0)} = \left|\min(r[L_k])\right| \quad k=1,2,\cdots N \tag{4}$$

where $|\cdot|$ means the absolute operation. In this way, the directions and energies of all pixels can be calculated if the center of lattice Z^2_p moves over an image pixel by pixel. And then, two new images i.e. Direction_image and Energy_image (see our previous paper [3]), will be created, which can be used for subsequent extraction of principal lines.

In this paper, when extracting principal lines, we make three minor changes compared with our previous work [3]. The first change is that the size of MFRAT is set to 35, the width is set to 1 pixel, and the number of k is 23. That is to say, θ_k is defined by the following formula:

$$\theta_k = \frac{\pi\times k}{24}, \quad k=1,2,\ldots,23. \tag{5}$$

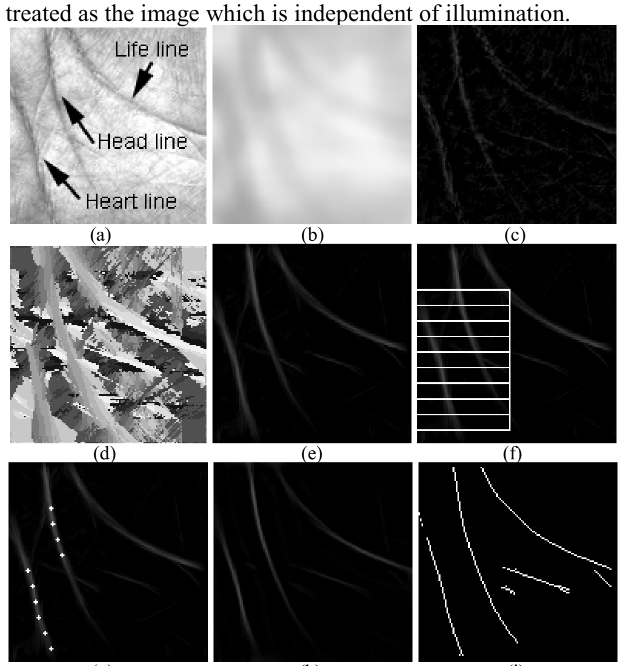
It should be noted that lines at the direction of π is not adopted. The second change is that after obtaining the first Energy_image, we extract the second Energy_image by applying 35×35 MFRAT to the first Energy_image again. The advantage of this operation is that the extracted principal lines contain less noisy lines and are more beautiful. The third change is that we design a new simple criterion to judge that a palmprint image was captured from which palm, left or right. This new criterion will be presented in the later part of this section.

The main steps of extracting principal lines are described as follows and some main images appearing in this stage are depicted in Figure 1.

Step 1: Given an original image O (see Fig. 1(a)), we can obtain its filtered image O_f (see Fig. 1(b)) by applying a mean filter whose size is about 15×15 to O. And then, a difference image D (see Fig. 1(c)) can be created by the following formula:

$$D = |O_f - O| \tag{6}$$

where $|\cdot|$ means the absolute operation. Obviously, D can be treated as the image which is independent of illumination.



(a) (b) (c) (d) (e) (f) (g) (h) (i)

Figure 1. (a) original image O, (b) filtered image O_f, (c) image D, (d) Direction_image, (e) the first Energy_image, (f) rectangle area "RA" in (e), (g) piexles with largest energy in each row within RA, (h) the second Energy_image, (i) the extracted principal lines.

Step 2: Extracting Direction_image (see Fig. 1(d)) and Energy_image (see Fig. 1(e)) from image D using 35×35 MFRAT with 23 directions [3].

Step 3: Judging a palmprint image was captured from left or right palm. The judging operations will be conducted on a rectangle area 'RA' of the first Energy_image. In this paper, the RA is set to Energy_image(20:120, 1:60) (in matlab format), which is shown in Fig. 1(f). In RA, we select 10 rows with an interval of 10 rows. Of course, the number of selected rows and the interval can be adjusted. In Fig. 1(f), the selected rows are those white segments. For each selected row(i), we search the pixel $P_i(x_k,y_k)$ which has largest energy in this row (see Fig. 1(g)). Suppose that the energy of $P_i(x_k,y_k)$ is $e(P_i(x_k,y_k))$ and the direction of $P_i(x_k,y_k)$ is $\theta(P_i(x_k,y_k))$, the left energy $E_{left}(O)$ and right energy $E_{right}(O)$ of image O can be calculated by the following two formulas:

$$E_{left}(O) = \sum_{i=1}^{10} e(P_i(x_k,y_k)) \;\; if \;\; \theta(P_i(x_k,y_k)) < \pi/2 \tag{7}$$

$$E_{right}(O) = \sum_{i=1}^{10} e(P_i(x_k,y_k)) \;\; if \;\; \theta(P_i(x_k,y_k)) > \pi/2 \tag{8}$$

At last, the judging can be implemented by comparing $E_{left}(O)$ with $E_{right}(O)$. The corresponding program code is written as follows:

IF E_{left}(O) > E_{right}(O)
    THEN The directions of principal lines ≤ π/2
    ELSE The directions of principal lines ≥π/2
END IF

Step 4. Applying a mean filter whose size is 3×3 to smooth the first Energy_image, and treating the first Energy_image as a new original O_{new}. Repeating the Step 1 and Step 2 again on O_{new} to calculate the second Energy_image (see Fig. 1(h)). It should be noted that if O_{new} come from left palm, only those lines in MFRAT, whose directions belong to $(0°,\ldots,\pi/2]$, will be used. Similarly, the lines in MFRAT, whose directions belong to $[\pi/2,\ldots,\pi)$, will be used to extract principal lines from those palmprint, which come from right palm.

Step 5. Selecting the N^{th} largest pixel value of the second Energy_image as an adaptive threshold T to generate the Lines_image [3]. After thinning Lines_image, the final principal lines can be obtained (see Fig. 1(i)).

III. DETECTING KEY POINTS OF PRINCIPAL LINES

Generally, most palmprints have three principal lines: heart line, head line, and life line, which are longest, strongest, and widest lines in palmprint image, and have stable line initials, directions and positions as shown in Fig. 1(a). Thus, it is possible to retrieve palmprints according to the directions and positions of principal lines. Obviously, it is not necessary to exploit all points of principal lines for retrieval. In this section, we design a method to detect some key points for fast retrieval.

Fig. 2 depicts the framework of proposed scheme. It can be seen that the primary retrieval is to judge a palmprint image was captured from left or right palm. This work has been done during extracting principal lines. If a test palmprint was captured from a left palm, it will only be compared with all templates in whole database that are also captured from left palms.

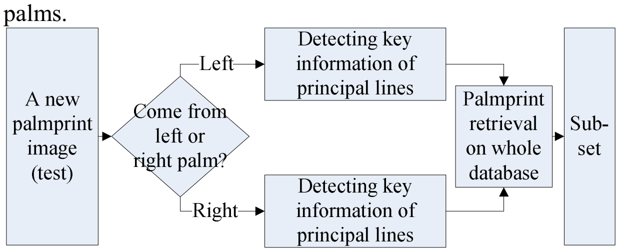


Figure 2. The framework of proposed retrieval scheme

In section 2, we used MFRAT with 23 directions for the principal lines' extraction. That is, the span of each direction is π/24. However, this span is too coarse to perceive small changes between two palmprints with similar structures. Thus, we design a new MFRAT with more directions for feature extraction.

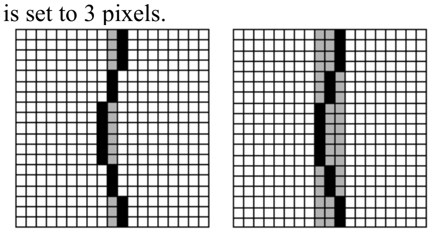
A. *The designed MFRAT*

For designing the new MFRAT, the first thing is to determine the number of directions. According to our observation, the span of π/60 for a direction is reasonable. Of course, the span of π/180 is also feasible. However, adopting small span requires more computational cost. On the other hand, there might be a little rotation between the palmprints which come from a same palm. The span of π/180 might be very sensitive to this slight rotation. In our opinion, the span of π/60 might be the best choice. Thus, in designed MFRAT, θ_k is defined by the following formula:

$$\theta_k = \frac{\pi \times k}{60}, \quad k = 1,2,\ldots,59. \tag{9}$$

Then, the second thing is to determine the size (or the scale) of MFRAT. Since there are many long principal lines, which are longer than 60 pixels, we set the size of new MFRAT is 65.

When extracting principal lines, the width of 35×35 MFRAT is 1 pixel. However, for 65×65 MFRAT, the width of 1 pixel might be not suitable for detecting the long lines with small curvature. Fig. 3(a) depicts an example, in which a curve is composed of some black lattices, and gray lattices represent the line of MFRAT with 1 pixel wide and at the direction of π/2. Obviously, the MFRAT with 1 pixel wide can not detect lines with small curvature very well. If the width of line is set to 3 pixels, this line can cover the black curve well (see Fig. 3(b)). Based on the above analysis, the line width of 65×65 MFRAT is set to 3 pixels.



(a) (b)

Figure 3. Detecting a curve by MFRATs with different widths. (a) MFRAT with 1 pixel wide, (b) MFRAT with 3 pixel wide.

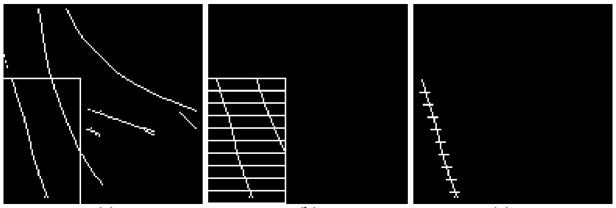
B. *Detecting key points of heart line*

Although the structures of principal lines extracted from different palms might change obviously, the distribution of three principal lines in different palms are always stable. For example, if a palmprint like Fig. 1(a) come from a right palm, the heart line may always locate in the left lower part, the life line may always locate in the right upper part, and the head line may always locate in the middle part of the ROI image. This distribution can be treated as the prior knowledge, which can be used to effectively distinguish heart line, life line and head line.

In our scheme, we will firstly use heart line for retrieval task. The size of ROI image R in our paper is 128×128, the heart line will locate in the rectangle area R(48:128,1:50) (in matlab format) named as Heart_R. Fig. 4(a) shows Heart_R of Fig. 1(i). As we have discussed, only several key points of heart line will be used for palmprint retrieval. Here, the main steps of detecting these key points are given as follows:

Step 1: In Heart_R, we select 10 rows with an interval of eight rows (see Fig. 4(b)). In these 10 rows, if there are points belonging principal lines, the designed 65×65 MFRAT will be used to detect their directions and energy.

Step 2: There might have several noisy lines in Heart_R. In this step, these noisy lines should be removed. In order to do this task, all lines in binary image Heart_R are treated as connected components. And the lengths of them can be calculated. Meanwhile, we can also know each key point belongs to which connected components. At last, those connected components which are longest and have the key points with strongest energy will be selected as the genuine heart line (see Fig. 4(c)).



(a) (b) (c)

Figure 4. Detecting key points of heart line. (a) rectangle area Heart_R, (b) selected 10 rows with an interval of eight rows, (c) heart line and several key points marked by short segments.

Step 3: Storing those key points' position, directions, and energies by a matrix whose size is 3×10. Table I shows the stored key points detected in Fig. 4(c). The first row of Table I is the index of key points. For a key point $P(x,y)$, where (x,y) means P's coordinate. Obviously, we can easily know the value of y corresponding to the index of P. Thus, the second row of Table I records the value of x_0 for each key points. The third row of Table I records the direction of each key point, where the corresponding value is k described in formula (9). The fourth row records the energy of each key point. In addition, if there are no points in selected ten rows, the values of position, direction, and energy in matrix will be set to 0. We can denote this matrix by $M_{heart}(i,x,k,e)$, where i is the index of 10 key points i.e., i=1,2,...,10; x is the corresponding position, k means the direction, and e denotes the energy of point i.

TABLE I. STORRING 10 KEY POINTS IN HEART LINE BY A MATRIX

i	1	2	3	4	5	6	7	8	9	10
x	8	11	13	15	18	20	22	25	27	0
k	36	35	35	35	35	35	35	36	36	0
e	41	49	57	65	65	59	51	44	37	0

C. Detecting key points of life line

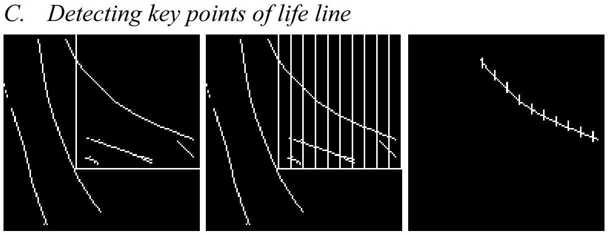
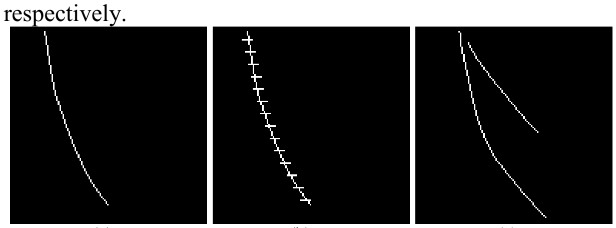


Figure 5. Detecting key points of life line. (a) rectangle area Life_R, (b) selected 10 columns with an interval of eight columns, (c) life line and several key points marked by short segments.

After detecting key points of heart line, we can use similar strategy to detect key points of life line. Generally, the life line locates in the rectangle area R(1:88,48:128) (in matlab format) named as Life_R. In Life_R, we select 10 columns with an interval of eight columns. In these 10 columns, if there are some points belonging to principal lines, the designed 65×65 MFRAT will be used to detect their directions and energies. After removing noisy lines, key points' position, directions, and energies can also be stored by a matrix whose size is 3×10. It should be noted that, for life line the key point's position is y.

D. Detecting key points of head line

After detecting heart line and head line, detecting key points of head line will be conducted on whole image R. We select 16 rows with an interval of 8 rows in R, and if there are points belonging to principal lines, the designed 65×65 MFRAT will be used to detect their directions and energies (see Fig. 6(b)). As we know, after removing heart line and life line, there might have one or two very long wrinkles (longer than 50 pixels) besides head line, which are also very useful for retrieval (see Fig. 6(b)). Thus, the head line and long wrinkles will be stored by different matrixes whose size is 3×16, respectively.



(a) (b) (c)

Figure 6. Detecting key points of head line. (a) the head line of Fig. 1(i), (b) head line and its key points marked by short segments, (c) head line and one long wrinkle after removing heart line and life line.

IV. PALMPRINT RETRIEVAL USING KEY POINTS

In our scheme, firstly, we exploit the key points of heart line for retrieval. Fig. 7 shows six heart lines extracted from six different palms. Obviously, the positions and directions of these heart lines are very different. Thus, it is feasible to use the values of x and k of key points in $M_{heart}(i,x,k,e)$ for retrieval.

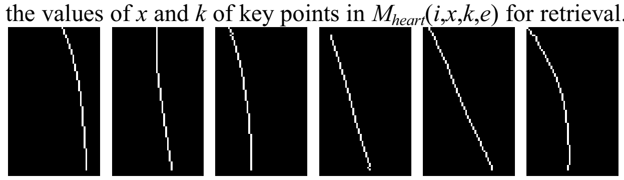


Figure 7. Six heart lines extracted from six different palms

Suppose that we only use x of key point i in $M_{heart}(i,x,k,e)$ to retrieve palmprints, and suppose that there C classes in training set and each class contains C_p training sample, the operations is summarized as follows:

Step 1: Calculating the mean ($\bar{x}$) of x^1, x^2, … , x^{Cp} of key point i for C_p training images in a class, where $\bar{x} = (x^1 + x^2 + \ldots + x^{Cp})/C_p$.

Step 2: Generate a retrieval table as shown in Table II. The first row of this table is the possible value of $\bar{x}$, whose range is [1,2,…,50] in this paper. The second row contains the class labels associated with $\bar{x}$. For example, if $\bar{x}$ values of class 3, 45, 77 and 95 in point i are all 22, we can associate these classes' labels with position 22.

Step 3: Given a test image, detecting the values of 10 key points in heart line including the position x_T for key point i.

Step 4: Retrieving palmprints in retrieval table according to a radius r. The possible class labels (PCL) we want to get are those class labels where $\bar{x}$ belongs to the range [x_T-r, x_T-r+1, … , x_T+r]. We define the PCL as $PCL_{heart}(i,x)$ which means the possible class labels retrieved by x of key point i in heart line.

TABLE II. RETRIEVAL TABLE FOR $\bar{x}$ OF KEY POINTS OF HEART LINE

Possible position of $\bar{x}$	1	…	22	…	50
Associated Class label	. . .	. . .	(3) (45) (77) (95)	. . .	. . .

In the similar way, we also can obtain $\text{PCL}_{heart}(i,k)$ which means the possible class labels retrieved by direction k of key point i in heart line. Further, we can obtain a smaller set

Since there are 10 key points in heart line, we can establish 20 tables (10 tables for poison x and 10 tables for direction k) for retrieval. However, it is unnecessary to use all of them. In experimental section, we will select one or two key points for fast retrieval.

In our scheme, the operations using life line and head line for retrieval are nearly same to the operations using heart line, so we will not give the details here due to space limitation of this paper. Fig. 7 shows four life lines extracted from four different palms. And Fig. 8 shows three life lines extracted from three different palms. Here, it should be noted that if there two long lines in head line map, these two lines will be added to retrieval table simultaneously. That is, the class label may associate with two positions (or two directions).

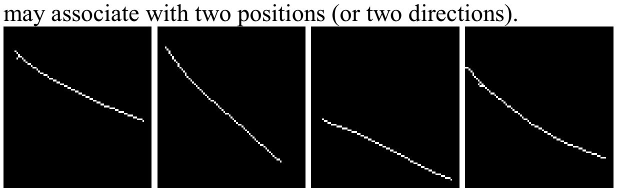


Figure 8. Four life lines extracted from four different palms

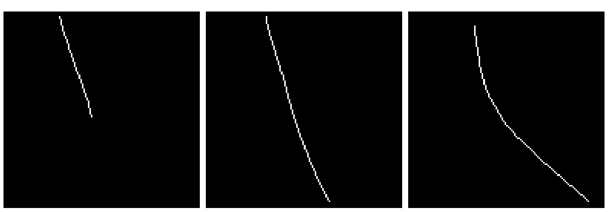


Figure 9. Three head lines extracted from three different palms

V. EXPERIMENTS

The proposed approach in this paper was tested on the Hong Kong Polytechnic University (PolyU) Palmprint Database I. Database I contains 600 grayscale images in BMP image format, corresponding to 100 different palms (50 left palms and 50 right palms), in which 6 samples from each of these palms were collected in two sessions, where 3 samples were captured in the first session and the second session, respectively. In our paper, by using the similar preprocessing approach described in literature [1], palmprint is orientated and the ROI, whose size is 128×128, is cropped. In this Database, those images captured in the first session are selected as training images, and those images captured in the second session and come from right palms are selected as test images. Thus, the numbers of training images and test images are 300 and 150, respectively. The experiments were conducted on a personal computer with an Intel Duo T7500 processor (2.20GHz) and 2.0G RAM configured with Microsoft Vista and Matlab 7.0.

Before conducting experiments, two performance criterions of retrieval will be defined here. Given a test image, we retrieval it in training set. If its genuine class label is within the returned PLC, we can define this retrieval as an "accurate retrieval" (AR), otherwise as an "error retrieval" (ER). So the "AR rate" (ARR) can be given as:

$$ARR = \frac{(number\ of\ AR) \times 100}{total\ number\ of\ test\ images}\% \qquad (10)$$

For one time retrieval, if the returned class number of PLC is N_p, the retrieval efficiency (RE) of this retrieval can be defined as:

$$RE = \frac{N_p \times 100}{total\ number\ of\ classes\ in\ training\ set}\% \qquad (11)$$

Actually, we are more interesting in average RE (ARE), which is the mean of RE for all test images.

Sometimes, a life line (or heart line, or head line) can not be extracted in a palmprint image due to some reasons such as bad illumination etc, which is defined as "fail to detection" (FD). Thus, the FD rate (FDR) can be defined as:

$$FDR = \frac{(number\ of\ FD) \times 100}{total\ number\ of\ test\ images}\% \qquad (12)$$

In the stage of extracting principal lines, we can judge the samples come from which palm, left or right, with 100% accurate judging rate.

A. Experiment 1

In the first experiment, we use the key points of heart line for retrieval. When we use point i to do retrieval task, position x will combine with direction k to find PCL, that is:

$$\text{PCL}_{heart}(i) = \text{PCL}_{heart}(i,x) \cap \text{PCL}_{heart}(i,k)$$

In addition, the radius r for x is set to 8 pixels and for k is set to 2. The *FDR* of heart line is zero. Table III shows the ARR and ARE using key points for retrieval. It can be seen, the ARR of 100% can be obtained using key points 5, 6, 7, and 8. Further, if we do the retrieval combing points 5 and 8, we can obtain an ARE of 19.78%.

TABLE III. ARR AND ARE USING 10 KEY POINTS OF HEART LINE FOR RETRIEVAL

Point (i)	ARR %	ARE %
1	76.00	14.13
2	86.67	17.77
3	94.00	19.61
4	98.00	21.86
5	100	24.28
6	100	25.1
7	100	23.42
8	100	23.97
9	99.33	22.92
10	97.33	22.7

B. Experiment 2

In the second experiment, we use the key points of heart line for retrieval with the similar strategy of experiment 1. The radius r for y is set to 10 pixels and for k is set to 3. The *FDR* of life line is 7.3%. Table IV shows the related ARR and ARE. It can be seen that the ARR of 100% can be obtained using key points 4, 5, 6, 7, and 8. If we combine points 4 and 8 for retrieval, an ARE of 15.75% can be obtained. Additionally, if we combine points 5 and 8 of life line, and points 4 and 8 of heart lines, we can obtain an ARE of 9.3%.

TABLE IV. ARR AND ARE USING 10 KEY POINTS OF LIFE LINE FOR RETRIEVAL

Point (i)	ARR%	ARE%
1	16.5	30.48
2	88.48	18.46
3	98.56	19.27
4	100	20.65
5	100	20.64
6	100	20.48
7	100	19.98
8	100	19.98
9	90.64	19.97
10	85.61	17.83

C. Experiment 3

In first experiment, we use the key points of head line for retrieval. Since head lines may be very long, and upper, middle and lower part of head lines are all important, we select three points from three parts for retrieval according to energy criterion as shown in Fig. 10. That is, the point with maximum energy will be selected in three parts. Furthermore, if there is a short head line depicted in the first image of Fig. 9, we will select one or two points for retrieval. Additionally, if there are two long lines in head line map as shown in Fig. 6(c), we only select those points with maximum energy within two lines in three parts.

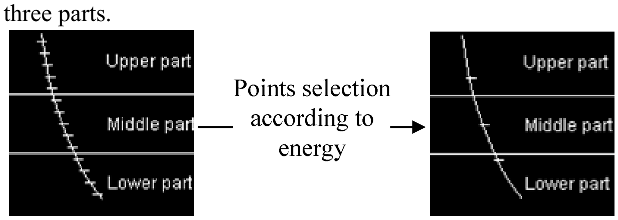


Figure 10. Points selection in head line according to enery criterion

In this experiment, the radius r for x is set to 11 pixels and for k is set to 3. The *FDR* of head line is 3.9%. For remaining test images, we can obtain 100% ARR with an ARE of 17.36%. Particularly, if we combine points 5, 8 of heart line, points 4, 8 of life lines, and head line, we can obtain 100% ARR with an ARE of 4.83%, which is an encouraging retrieval result.

Since we only use several key points for retrieval in our scheme, the retrieval speed is very fast. The executing time of one retrieval (search 1 test image from 300 training images) is about 0.5ms.

VI. CONCLUSION

In this paper, we propose a novel palmprint retrieval scheme based on principal lines. A lot of key points located in three principal lines i.e. heart line, life line and head line are detected, and adopted for retrieval. The results of experiments conducted on PolyU palmprint database show that the proposed scheme can achieve 100% ARR with an ARE of 4.83%. Meanwhile, the proposed scheme has fast retrieval speed. In the future work, we will optimize it, and test it on a large database.

ACKNOWLEDGMENT

This work is supported by the grants of the National Science Foundation of China, No.60705007 & 60805021; the grant of Postdoc Foundation of China, No. 200801231.

REFERENCES

[1] D. Zhang, A. Kong, J. You, and M. Wong, “Online palmprint identification,” IEEE Trans. Pattern. Anal. Mach. Intell, vol. 25 (9), pp. 1041–1050, 2003.

[2] A. Kong, D. Zhang, and M. Kamel, “A survey of pamprint recognition,” Pattern Recognition., 42(7), pp. 1408-1418, 2009.

[3] D.S. Huang, W. Jia, and D. Zhang, “Palmprint verification based on principal lines,” Pattern Recognition, vol. 41(4), pp. 1316-1328, 2008.

[4] W. Jia, D.S. Huang, and D. Zhang, “Palmprint verification based on robust line orientation code,” Pattern Recognition, vol. 41(5), pp. 1504-1513, 2008

[5] F. Yue, W.M. Zuo, and D. Zhang, “FCM-based orientation selection for competitive code-based palmprint recogniton,” Pattern Recognition, in press.

[6] W. Jia, D.S. Huang, D. Tao, and D. Zhang, “Palmprint identification based on directional represention,” IEEE International Conference on SMC 2008, pp. 1562-1567, 2008

[7] D. Tao, X. Li, X. Wu, and S. Maybank, “General tensor discriminant analysis and gabor features for gait recognition,” IEEE. Trans. Pattern Analysis and Machine Intelligence, vol. 29(10), pp. 1700-1715, 2007.

[8] D. Tao, X. Li, X. Wu, and S. Maybank, “Geometric mean for subspace selection,” IEEE. Trans. Pattern Analysis and Machine Intelligence, vol. 31(2), pp. 260-274, 2007.

[9] T. Zhang, D. Tao, et al., “ Patch alignment for dimension reduction,” IEEE. Trans. Knowledge and Data Engineering, in press

[10] P. Hennings-Yeomans, et al, “Palmprint classification using multiple advanced correlation filters and palm-specific segmentation,” IEEE Trans. on Information Forensics and Security, 2(3), pp. 613-622, 2007

[11] X. Wu, D. Zhang, K. Wang, and B. Huang, “Palmprint classification using principal lines”, Pattern Recognition, 37(10), pp. 1987-1998, 2004

[12] F. Li, et al., “Palmprint classification”, IEEE International Conference on SMC 2006, pp. 2965-2969, 2006

[13] W.X. Li, J. You, and D. Zhang, “Texture-based palmprint retrieval using a layered search scheme for personal identification,” IEEE Trans. on Multimedia, 7(5), pp. 891-898, 2005

[14] J. You, A. Kong, D. Zhang, and K.H. Cheung, “On hierarchical palmprint coding with multiple features for personal identification in large databases,” IEEE Trans. on Circuits and Systems for Video Technology, 14(2), pp. 234-243, 2004

[15] C. C. Han, “A hand-based personal authentication using a coarse-to-fine strategy,” Image and Vision Computing, 22, pp.909-918, 2004