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PALMPRINT IDENTIFICATION BY FOURIER TRANSFORM

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Palmprint identification refers to searching in a database for the palmprint template, which is from the same palm as a given palmprint input. The identification process involves preprocessing, feature extraction, feature matching and decision-making. As a key step in the process, in this paper, we propose a new feature extraction method by converting a palmprint image from a spatial domain to a frequency domain using Fourier Transform. The features extracted in the frequency domain are used as indexes to the palmprint templates in the database and the searching process for the best match is conducted by a layered fashion. The experimental results show that palmprint identification based on feature extraction in the frequency domain is effective in terms of accuracy and efficiency.

Keywords: Palmprint; personal identification; biometrics; Fourier transform; feature extraction.

1. Introduction

Computer-based personal identification, also known as biometrics computing began in 1970s. At that time, the first commercial system called *Identimat* was developed, which measured the shape of a hand and focused particularly on finger length. In the meanwhile, fingerprint-based automatic checking systems were widely used in law enforcement. Retina and iris-based systems were introduced in the mid 1980s. Today's speaker identification has its root in the technological achievements of the 1970s; while signature identification and facial recognition are relative newcomers to the industry.[11]

There are now many applications of biometrics being used or considered worldwide. Most of the applications are still at the stage of testing, and are optional for end users. Any situation that allows an interaction between man and machine is capable of incorporating biometrics. Such situations may fall into a range of application areas such as computer desktops, networks, banking, immigration, law enforcement, telecommunication networks, monitoring the time and attendance of

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staff. Fraud is an ever-increasing problem and security is becoming a necessity in many walks of life.[8,10,14]

Though research on the issues of fingerprint identification and speech recognition has drawn considerable attention over the last 25 years[4,9] and recently issues on face recognition and iris-based verification have been studied extensively,[13,16] there are still some limitations to the existing applications. Some people have their fingerprints worn away due to the hand-work and some are born with unclear fingerprints. The existing iris-based identification system has not been proved to be adaptive to eastern people who have quiet different iris patterns from those of western people. Face- and voice-based identification systems are less accurate and easy to be mimicked. Efforts on improving the current personal identification methods are to continue and meanwhile new methods are under investigation.

In this paper, we present our initiative work on palmprint identification, which is a new attempt and necessary complement to the existing biometrics techniques. Not like hand geometry-based system[2] that measures a hand's size and finger length, palmprint is concern with the inner surface of a hand and looks particularly at line patterns and surface shape. A palm is covered with the same kind of skin as finger tips and is larger in size than a finger tip, hence it is quite natural to think of using palmprint to recognize a person, but little has been done to palmprint-based personal identification.[15]

Palmprint identification involves image preprocessing, feature extraction, feature matching and decision making (see Fig. 1). Image preprocessing is to normalize

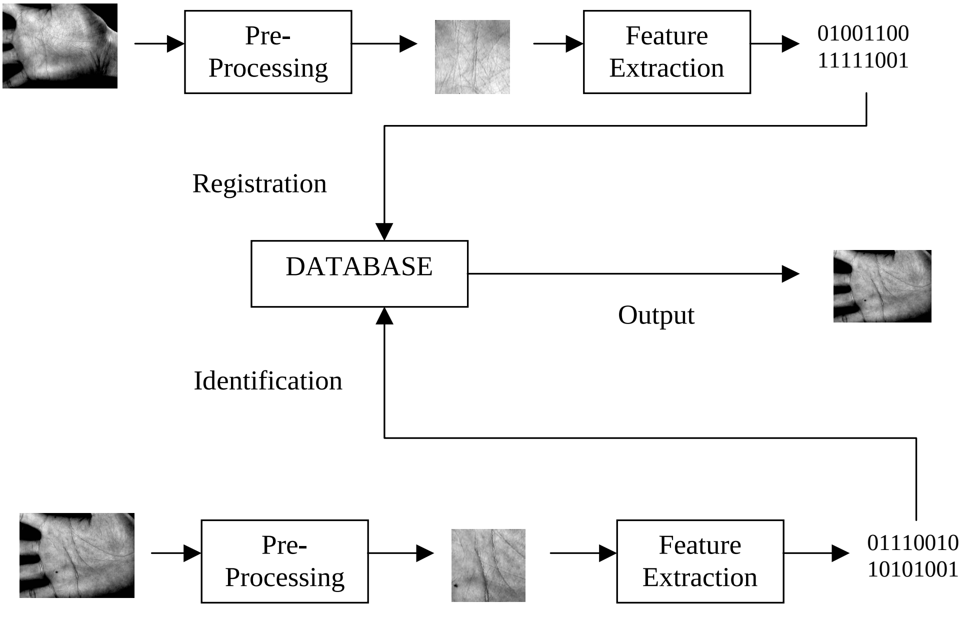


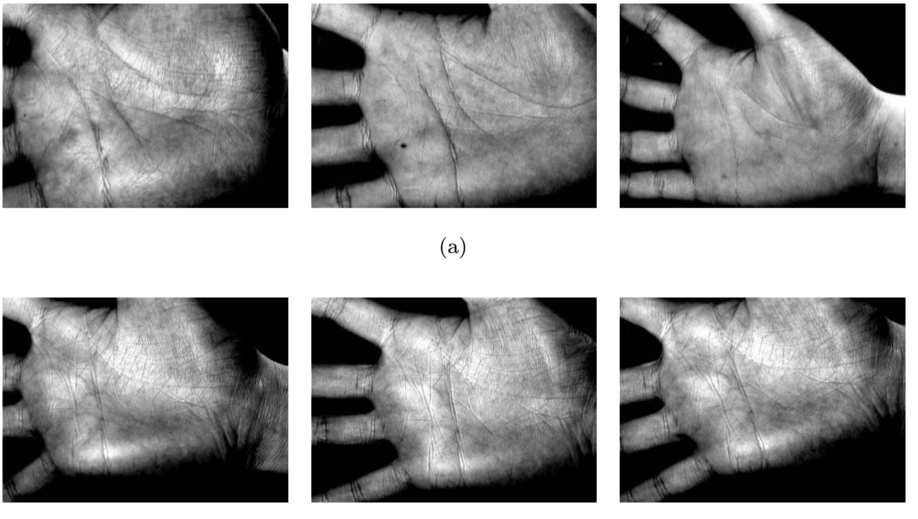
Fig. 1. The general process of palmprint identification.

the original palmprint images. Because the captured palmprint may have some rotations and shifts and the sizes of different palms are not the same, the original images should be processed before feature extraction. Figure 2 shows a group of original palmprint samples, where (a) the different palmprints with various sizes and (b) the same palm's samples with some rotation and shift. After the preprocessing the rotation and shift are corrected and a fixed size subimage is extracted so that the different palmprints are converted into the same size images for extracting the features. During the feature extraction, a palmprint image is first transformed into the frequency domain image and then feature extraction is conducted in this new image. Feature matching is to compare the feature sets so that a decision is made to tell whether two palmprints are from the same palm.

The rest of this paper is organized as follows: Section 2 presents the preprocessing process for rotation and shift correction to extract a subimage with the fixed size. The proposed feature extraction method using Fourier Transform is introduced in Sec. 3. Section 4 develops our feature matching and palmprint identification method. Sections 5 and 6 summarize the experimental results and highlights the conclusions, respectively.

2. Palmprint Preprocessing

When capturing a palmprint image, its position, direction and stretching degree may vary from time to time, even on the same palm (see Fig. 2). It is necessary to align all the palmprints and normalize their sizes for further feature extraction and matching.



(a)

(b)

Fig. 2. Palmprint samples with some rotation, shift and different sizes. (a) Palmprint samples with different sizes. (b) Palmprint samples from the same palm with some rotation and shift.

In order to align the palmprints, we define a right-angle coordination system, which is based on three key points between fingers. The basic steps of palmprint alignment are defined as follows:

(1) Use a threshold, α, to convert an original gray image into a binary map, i.e.

$$I_{\mathrm{BinaryMap}}(i,j) = \begin{cases} 1 & I_{\mathrm{GrayMap}}(i,j) \geq \alpha \\ 0 & I_{\mathrm{GrayMap}}(i,j) < \alpha \end{cases} . \tag{1}$$

(2) Smooth the binary map by a Gaussian filter,

$$I_{\mathrm{SmoothedMap}} = I_{\mathrm{BinaryMap}} * A\,, \tag{2}$$

where A is the Gaussian filter.

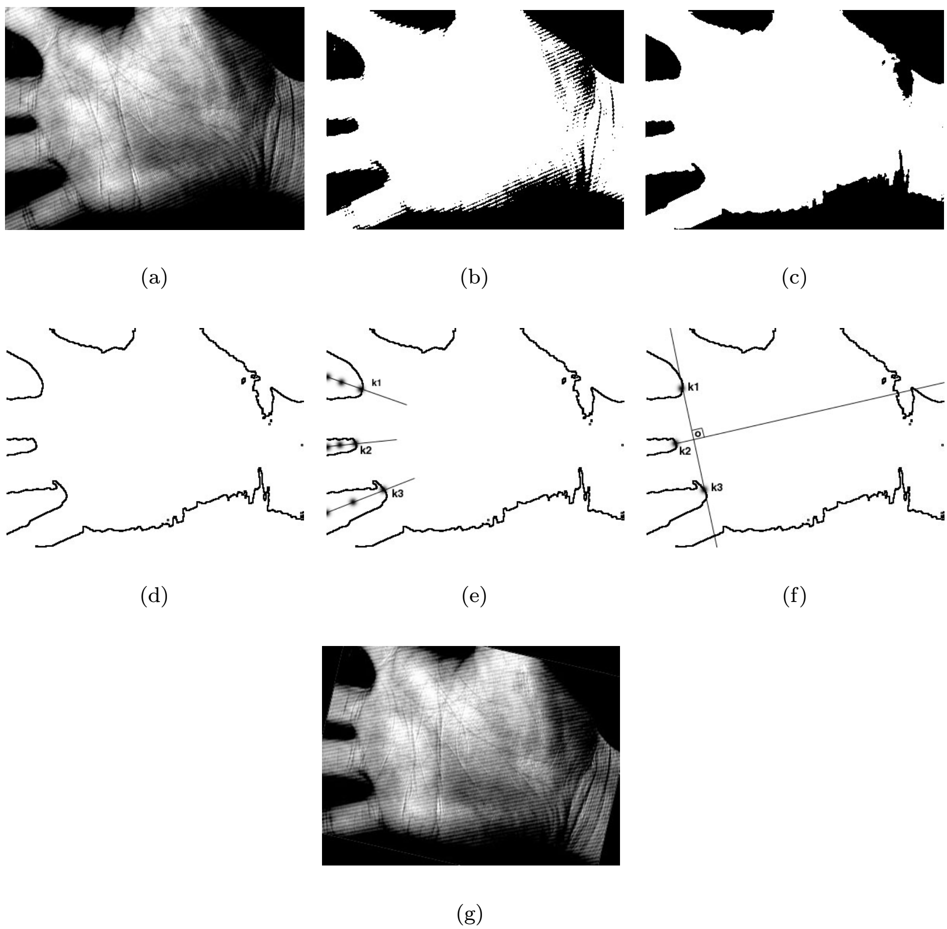
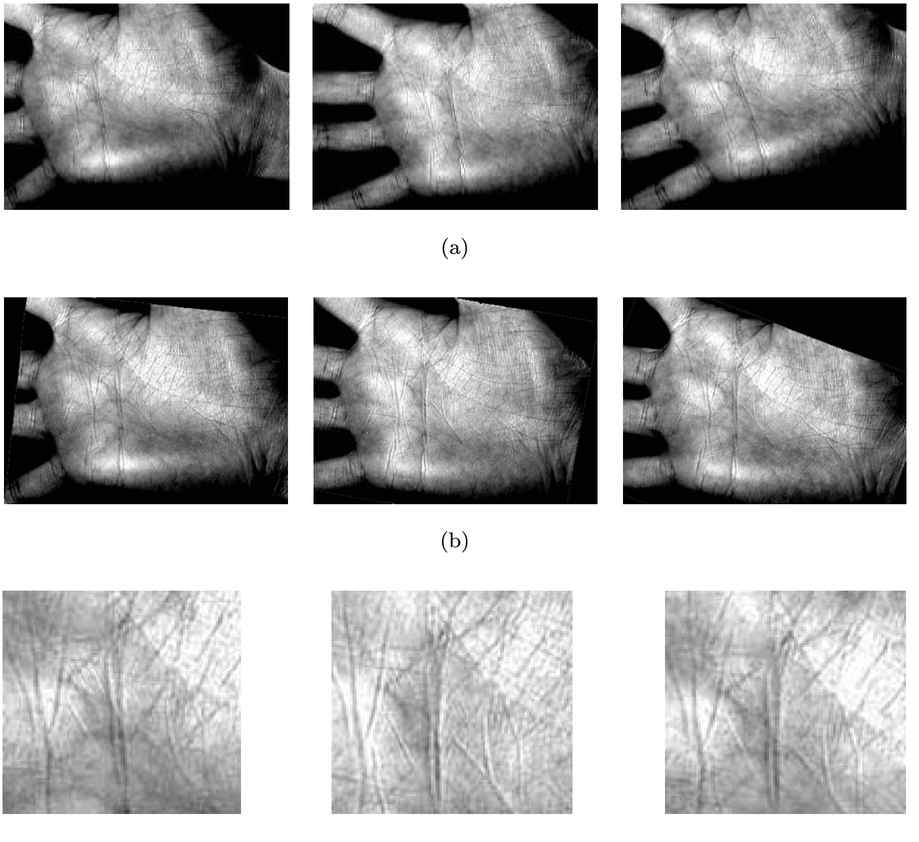


Fig. 3. The process of palmprint alignment. (a) Original image. (b) Binary image. (c) Smoothed binary image. (d) Boundary tracing. (e) Key points determination. (f) Coordination system. (g) Rotated image.

(3) Trace the boundary of the holes between fingers.
(4) Calculate the center of gravity of the holes and decide the key points — k1, k2, and k3.
(5) Line up k1 and k3 to get the Y-axis of the palmprint coordination system and then make a line through k2 and perpendicular to Y-axis to determine the origin of the palmprint coordination system.
(6) Rotate the image to make the Y-axis on the vertical direction.

The procedure mentioned above is described in Figs. 3(a)–3(g), respectively. It is very natural that each palm is not of the same size, so this results in the difficulty of feature extraction and matching. In order to solve this problem, only a subarea of a palmprint image is used in feature extraction. All the palmprints are cut off into subimages with a fixed size and from the same location. The principle to decide the



(a)

(b)

(c)

Fig. 4. Contrast to palmprints before and after alignment and their extracted subimages. (a) Three samples from the same palm with different directions and locations. (b) Alignment results. (c) The extracted subimages.

size and the location of the subimage is to make sure that most palmprint features are still within this area and all the palmprints have that piece of the subimage. Figure 4 shows the results of palmprint alignment and subimage extraction, where there are three samples from the same palm with different directions and locations in Fig. 4(a). Their alignment results and the extracted subimages are shown in Figs. 4(b) and 4(c), respectively.

3. Palmprint Feature Extraction Using Fourier Transform

3.1. *Fourier transform*

Fourier Transform is one of the most popular and useful transforms in image processing applications.[1,3,5,6,12] The major applications involve image enhancement and feature extraction. Fourier Transform includes feed-forward Transform and inverse Transform. The former converts an image from the spatial domain into the frequency domain and the latter changes it back from the frequency domain. Two-dimensional discrete Fourier Transform is defined as:

$$F(u,v) = \frac{1}{MN} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} f(m,n) \exp\left[-j2\pi\left(\frac{mu}{M} + \frac{nv}{N}\right)\right], \tag{3}$$

where $f(m,n)$ is an image with $M \times N$, $j = \sqrt{-1}$, $u = 0, 1, \ldots, M-1$; $v = 0, 1, \ldots, N-1$. The inverse Transform is defined as:

$$f(x,y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} F(u,v) \exp\left[j2\pi\left(\frac{mx}{M} + \frac{ny}{N}\right)\right]. \tag{4}$$

In Ref. 7, the calculation on Fourier Transform is described in detail.

It is natural to use Fourier Transform to do the image enhancement, where a high pass filter is supposed to the edge lines and a low pass filter is used to smooth the image. Figures 5(c)–5(e) and 5(f)–5(h) show the results of both high pass and low pass filters to the palmprint image, respectively. It is obvious that they do not provide more values to the palmprint feature extraction except the frequency domain image as shown in Fig. 5(b).

3.2. *Palmprint features exhibited in the frequency domain*

In our palmprint identification, Fourier Transform can be used in feature extraction. This is because there exist some correspondences between palmprint features on a spatial domain image and those on a frequency domain image. In general, the stronger the creases are on a spatial domain image, the less compact the information is on a frequency domain image. And if a palmprint image in the spatial domain has a strong line, in the frequency domain there will be more information in the line's perpendicular direction. As a result, Fig. 6 shows three typical palmprints and their correspondence frequency domain images, where (a) is a palmprint without strong creases and its frequency domain image shows that the information is centralized at

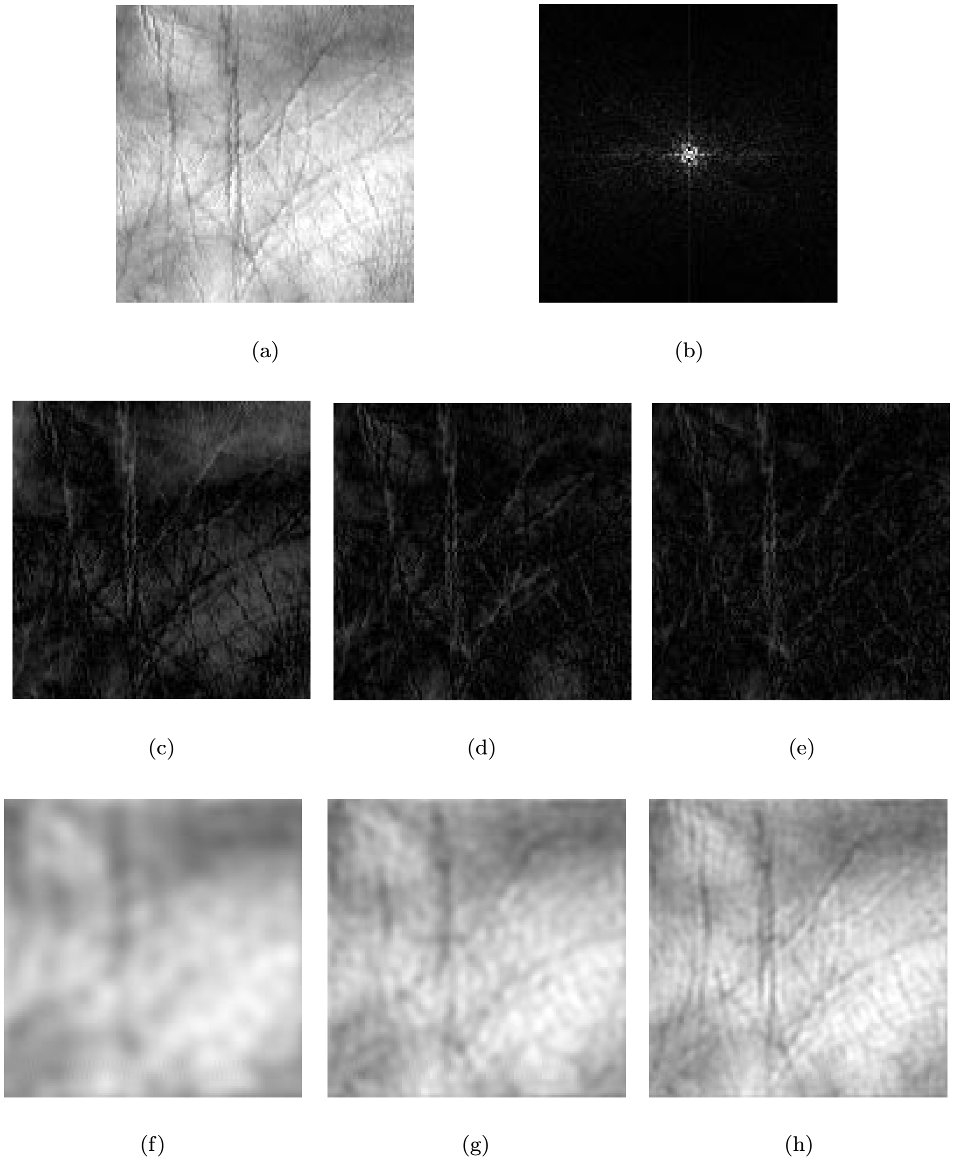
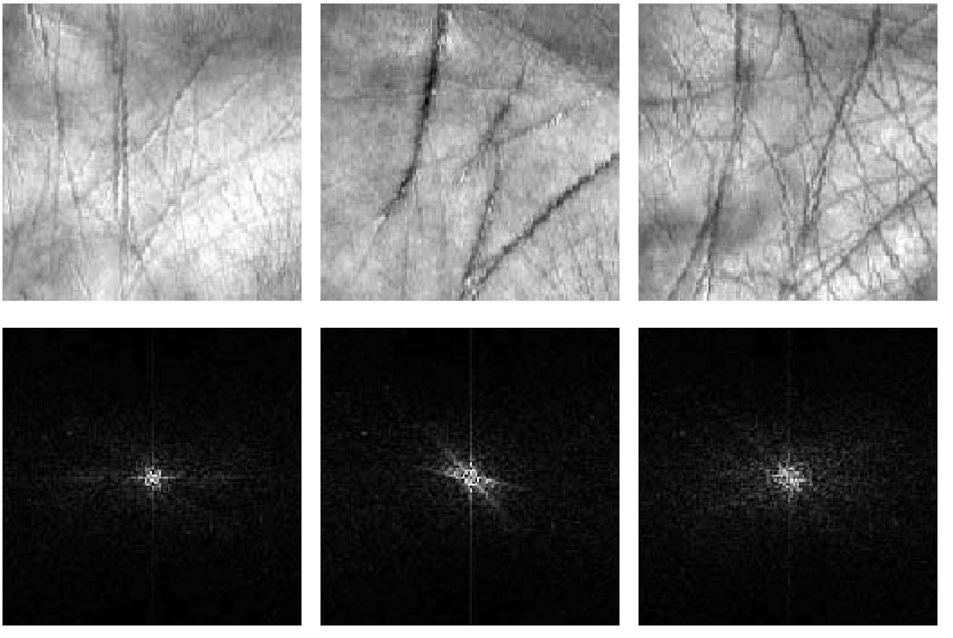


Fig. 5. High pass and low pass filters to the palmprint images. (a) The original palmprint image. (b) The frequency domain image. (c)–(e) High pass filters ($r > 0, 1, 2$). (f)–(h) Low pass filters ($r < 10, 20, 30$).

the center, which is the high frequency area; (b) is a palmprint with two clear and strong creases. Note that its frequency domain image indicates that there exists rich information on the direction perpendicular to the creases; and (c) is a palmprint full of strong creases, where its frequency domain image illustrates that the information is not as centralized as that in Fig. 6(a).



(a) (b) (c)

Fig. 6. Different palmprints and their corresponding frequency domain images. (a) Palmprint without strong creases. (b) Palmprint with two clear and strong creases. (c) Palmprint full of strong creases.

In our palmprint identification, if feature extraction is conducted in the frequency domain, it is important that similar palmprints resemble each other when converted into frequency images. As an illustration, Fig. 7 shows these three groups of palmprints and their correspondening frequency images, which are from the same palm, similar palms and different appearance palms.

3.3. *Palmprint feature representation*

Palmprint feature representation is to describe the features in a concise and easy for comparison. If we use a polar coordination system, (r, θ), to represent the frequency domain images, the energy change tendency along r shows the intensity of a palmprint's creases and that along θ shows the directions of a palmprint's creases. Therefore, we may use a statistical method to represent palmprint's features.

The image can be converted from a right-angle coordination system into a polar coordination system by

$$I'(r,\theta) = I(64 + r\cos\theta, 64 + r\sin\theta)\,, \quad (0 \le r \le 64,\ 0 \le \theta \le \pi) \tag{5}$$

where I is the image under right-angle coordination system and I' is the image under polar coordination system.

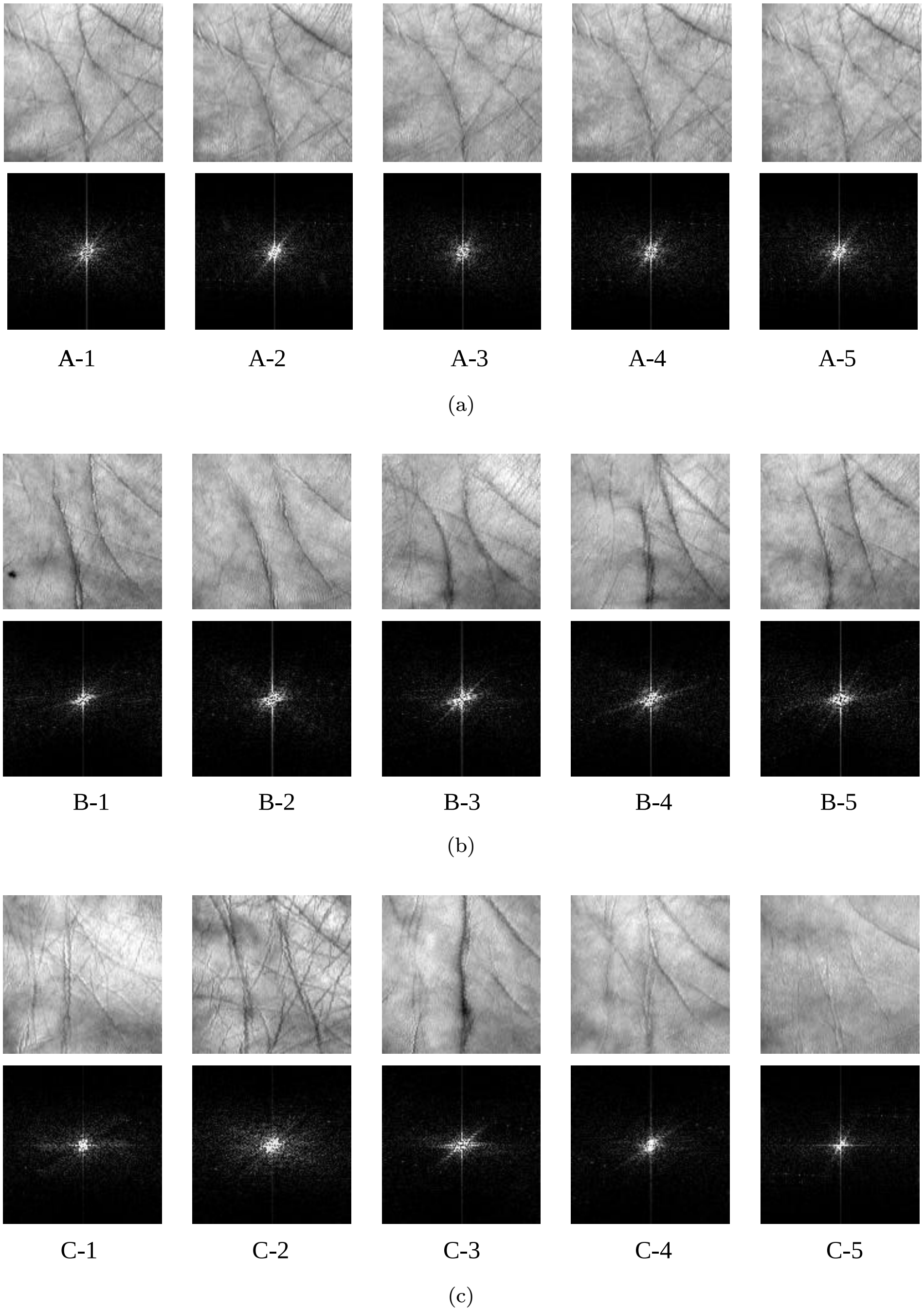
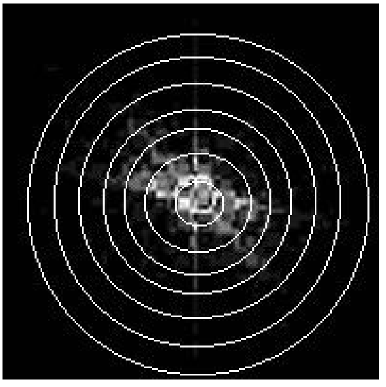
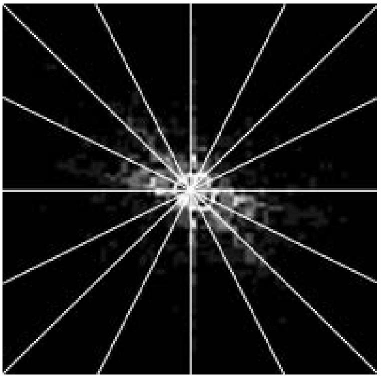


Fig. 7. Comparison of various frequency domain images. (a) Samples from the same palm. (b) Samples from similar palms. (c) Samples from different appearance palms.



(a)



(b)

Fig. 8. Palmprint feature representation: (a) R feature and (b) θ feature.

In order to represent a palmprint's crease intensity, the frequency domain image is divided into some small parts by a series of circles that have the same center, as shown in Fig. 8(a). The energy in each ring-like area is defined as

$$R_i = \sum_{\theta=0}^{\pi} \sum_{r=8(i-1)}^{8i} I'(r,\theta)\,, \quad (i = 1, 2, \ldots, 8) \tag{6}$$

where I' is the subimage under a polar coordination system, and $R_i(i = 1, 2, \ldots, 8)$ is called R feature.

In order to represent a palmprint's crease direction, the frequency domain image is divided by a series of lines that go through the center of the image, as shown in Fig. 8(b). The energy in each fan-like part is defined as

$$\theta_i = \sum_{\theta=(i-1)}^{i} \sum_{r=0}^{64} I'(r, \theta\pi/8)\,, \quad (i = 1, 2, \ldots, 8) \tag{7}$$

where $\theta_i(i = 1, 2, \ldots, 8)$ is defined as θ feature.

4. Feature Matching and Palmprint Identification

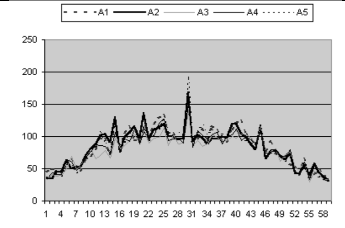
4.1. *Feature matching by R and θ*

Feature matching is to obtain the distance between two palmprint feature sets. Because a palmprint is represented by both R and θ features, their matching calculates the distance between R features and θ features.

Let $RX_i(i = 1, 2, \ldots, 8)$ and $RY_i(i = 1, 2, \ldots, 8)$ represent two R feature sets. The distance, DR_{xy}, between RX_i and RY_i is defined as:

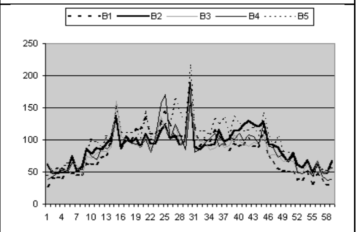
$$DR_{xy} = \frac{1}{8} \sum_{i=1}^{8} |RX_i - RY_i|\,. \tag{8}$$

	R Feature (Average Distance = 3.7)								θ Feature
A-1	57	48	63	59	56	62	56	60	
A-2	56	53	62	59	58	58	48	57	
A-3	52	50	57	54	52	57	53	60	
A-4	56	43	57	56	58	62	57	56	
A-5	59	47	59	58	67	59	57	61	



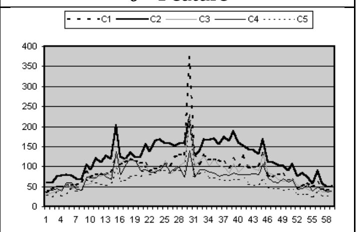
(a)

	R Feature (Average Distance = 9.4)								θ Feature
B-1	43	39	45	55	53	63	62	74	
B-2	45	54	56	60	67	72	67	67	
B-3	63	49	56	58	52	58	53	51	
B-4	65	39	54	49	52	68	57	69	
B-5	55	49	61	56	66	81	76	80	



(b)

	R Feature (Average Distance = 20.0)								θ Feature
C-1	48	46	56	68	69	64	62	64	
C-2	66	77	91	89	87	87	77	80	
C-3	63	46	55	47	54	62	61	61	
C-4	50	36	48	47	49	54	49	51	
C-5	33	30	37	40	43	44	43	49	



(c)

Fig. 9. Comparison of both R and θ feature values of the palmprint samples in Fig. 7. (a) Distance between R and θ feature values from samples of the same palm. (b) Distance between R and θ feature values from samples of similar palms. (c) Distance between R and θ feature values from samples of different appearance palms.

Also let $\theta X_i (i = 1, 2, \ldots, 8)$ and $\theta Y_i (i = 1, 2, \ldots, 8)$ represent two θ feature sets. Their distance, $D\theta_{xy}$, is defined as:

$$D\theta_{xy} = \left(1 - \frac{l_{xy} l_{xy}}{l_{xx} l_{yy}}\right) \times 100\,, \tag{9}$$

where

$$l_{xx} = \sum_{i=1}^{8} \left(\theta X_i - \frac{1}{8}\sum_{i=1}^{8} \theta X_i\right)^2\,, \tag{10}$$

$$l_{yy} = \sum_{i=1}^{8} \left(\theta Y_i - \frac{1}{8} \sum_{i=1}^{8} \theta Y_i \right)^2 , \tag{11}$$

and

$$l_{xy} = \sum_{i=1}^{8} \left(\theta X_i - \frac{1}{8} \sum_{i=1}^{8} \theta X_i \right) \left(\theta Y_i - \frac{1}{8} \sum_{i=1}^{8} \theta Y_i \right) . \tag{12}$$

The scope of $D\theta_{xy}$ is between 0 and 100, where the smallest distance is 0 and the largest distance is 100. Figure 9 shows both values of R and θ features from the given palmprints shown in Fig. 7. For Group A, which includes the samples from the same palm, the average distance of R features is 3.7 and the θ features are very close to each other. Group B includes the samples from similar palms, where the average distance of R features is 9.4 and the θ features are close to each other. For Group C, which covers the samples from palms with different appearances, the average distance of R features is 20.0 and the θ features are far from each other. Both R and θ features are used in feature matching and palmprint identification.

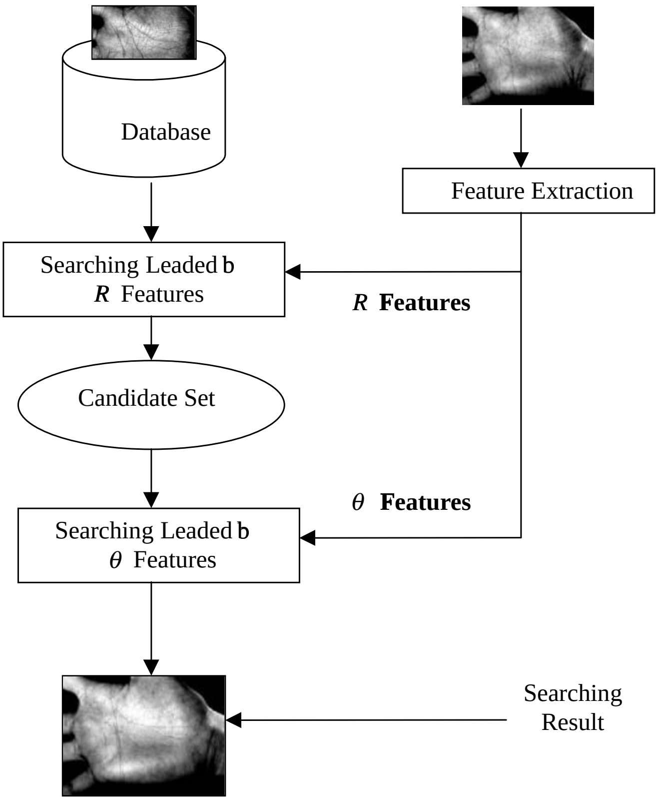


Fig. 10. The process of palmprint identification using R and θ features.

4.2. *Palmprint identification in a layered fashion*

Palmprint identification is to search in the database in order to find the palmprint that is from the same palm as the input one. Two key issues involved in the searching are accuracy and efficiency. Accuracy depends at what rate the searching result is correct and how efficiently and fast the final output can be given. Now that a palmprint is represented by R and θ features, these features are used as indexes to the palmprint database. The searching is carried out in a layered fashion, R feature is used to lead the first round searching and a candidate set is obtained, then θ feature is applied to lead the second round searching and a final output is given after the second round searching. Using R feature to lead the first round searching is due to its relatively short comparing time. Figure 10 shows our whole identification process.

5. Experimental Results and Analysis

The following experiments are achieved for testing the accuracy and efficiency of the proposed method. The data collection process involves four steps: (1) Find 500 people of different ages, sexes and occupations; (2) capture six palmprint samples from each person; (3) randomly pick up one from the six samples to set up the database, which has 500 templates; and (4) use the left 2 500 samples (five each) as the testing set. All the palmprints are from the right hands and are captured by a palmprint input device, which can set a limit on a palmprint's rotation and shift by using the two holders between fingers. However, we still allow the palmprint samples from the same palm to have some rotations (± 30 degrees) and shifts (± 50 pixels). The size of all the palmprint images is 320×240.

The testing process is for each sample in the testing set, find out the template in the database, which is captured from the same palm. The output for a query may be correct or not correct and we count the number of correct answers to evaluate the proposed method's accuracy. Also the response time is recorded to evaluate the efficiency of the proposed method. Table 1 shows the testing results on our database with 500 templates, where the identification accuracy is 95.48%, the shortest response time is about 1.2 seconds, the longest one about 3.7 seconds and the average about 2 seconds in the layered fashion searching. Figure 11 shows an identification example using our method, where (a) is an input sample and (b)–(f)

Table 1. The results of the palmprint performance testing.

Templates in the database	500
Attempts in testing	2500
Correct answers	2387
Identification rate	95.48%
Average response time (s)	2

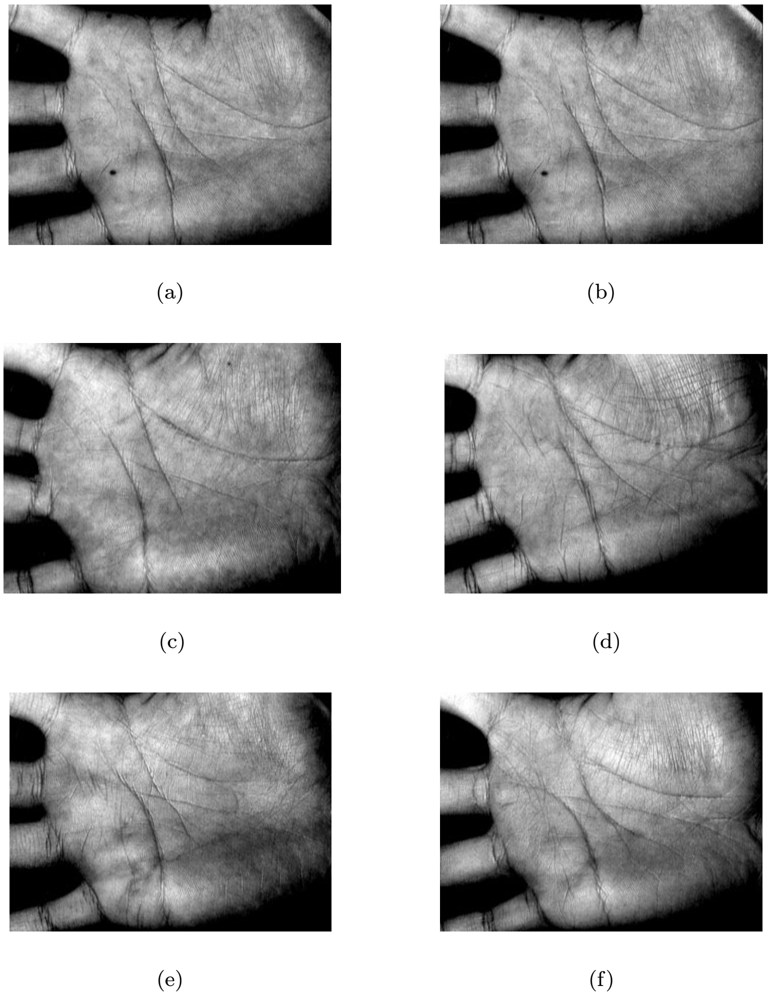


Fig. 11. An example of palmprint identification. (a) The input palmprint. (b)–(f) Palmprints of the shortest distances with (a) in the ascending order.

are the templates selected by the first round searching and (b) is the final output decided by the second round searching.

6. Conclusions

Palmprint identification provides a new way for authentication identity. In this paper, we introduce a Fourier Transform-based feature extraction and representation method for palmprint identification. A palmprint is first converted into the frequency domain image and two kinds of features are extracted there. These different features are used to lead a layered fashion searching for the best matching with the templates in the database. Experiments are carried out to measure the performance of the proposed method, which can obtain 95.48% identification accuracy on our database while the response time is acceptable.

Acknowledgments

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