Texture-Based Palmprint Retrieval Using a Layered Search Scheme for Personal Identification

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***Abstract*—This paper presents a new approach to palmprint retrieval for personal identification. Three key issues in image retrieval are considered—feature extraction, similarity measurement and fast search for the best match of the queried image in an image database. We propose a texture-based approach for palmprint feature representation. The concept of texture energy is introduced to define both global and local features of a palmprint, which are characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination. The searching is carried out in a layered fashion: the global features are first used to guide the fast selection of a small set of similar candidates from the database and then the local features are applied to determine the final output from the selected set of similar candidates. The experimental results illustrate the effectiveness of the proposed approach.**

***Index Terms*—Content-based image retrieval, image matching, palmprint feature extraction, personal identification, similarity measurement, texture features.**

I. Introduction

PERSONAL identification refers to identifying individuals by their unique personal characteristics [1], [2], [9]–[11], [13]. So far-, fingerprint-, speech-, face-, and iris-based personal identification have been studied extensively. However, little has been done on palmprint recognition though it provides rich personal information [2], [6]. A palm is defined as the inner surface of a hand between the wrist and the fingers. A palmprint refers to principle lines, wrinkles, and ridges on a palm. Since the patterns of an individual's palmprint are stable and unique, they can be used as personal features for identity identification. Fig. 1 shows two groups of palmprint images which illustrate the similarity of palmprint patterns from the same hand and the difference of palmprint patterns from different hands. Fig. 1(a), (c), and (d) are from one person while Fig. 1(b), (e), and (f) are from another person.

The problem of palmprint-based personal identification can be described as follows: given an example palmprint, compare it with all of the possible candidates in the database to determine whether the queried example and the candidates are from the same palm. The search for the best matching is crucial for the performance of the system in terms of accuracy and efficiency. The criteria to measure the similarity for search should be accurate and easy to calculate.

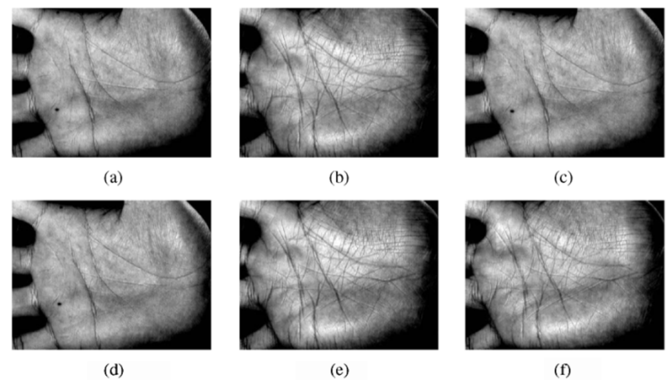

Fig. 1. Palmprint image samples in the testing database.

Like other image retrieval applications [3]–[5], the main tasks in developing a palmprint identification system include: 1) feature extraction; 2) similarity measurement; and 3) database structure and search scheme. Task 1 and Task 2 are to extract a set of features from each palmprint image and measure the degree of similarities between two palmprints by calculating the distance between their feature sets. Task 3 is concerned with the storage structure of images and the searching sequence of the data in a database. When the size of a palmprint database increases, the one-by-one matching becomes too time-consuming to meet the requirement for on-line personal identification. Therefore, it is essential to develop an effective indexing and searching scheme for an image database to facilitate fast retrieval. There are three key issues to be considered: feature extraction, indexing, and matching [7]. In general, in an image database, the extracted features are often associated to the original images as indices. A search for the best matching is conducted in a layered fashion, where one feature is first selected to lead the search by reducing the set of candidates. Then other features are used to reduce the candidate set further. Such a process will be repeated until the final output is determined based on the given matching criteria. The selection of features plays an important role for efficient search. An effective feature selection scheme should be characterized as follows: 1) excludes the most impossible candidates; 2) compare easily; and 3) requires small size of space for storage.

Unlike fingerprints, so far palmprints have not been well studied and defined. To verify whether two palmprints are from the same palm, a line feature extraction method has been

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proposed [6], [12]–[15]. These features are based on points and line segments and represented by binary point or line maps. Though such features can be used to discriminate different palmprints with good accuracy [6], they are not suitable to index palmprint image database of large size due to high computation cost. In this paper, we propose a new texture-based approach to extract both global and local attributes of a palm. These texture-based features are represented in numbers. Therefore, they are compact, comparison effective and suitable for palmprint database indexing. The idea of texture-based feature extraction is to define a small image feature primitive and use it as a mask to convolve with an entire image for feature measurement. The result of convolution is expressed in a numeric number which reflects the correlation between the selected feature primitive and a palmprint image. Therefore, a large value in convolution result indicates a high proportion of the selected feature primitive in a palmprint image sample. In our proposed approach, four primitive masks are used to extract palmprint features along horizontal line, vertical line, 135° angle line and 45° angle line in two layers. At the coarse level, the four primitive masks are convolved with the entire palmprint image and four global features are calculated. At the fine level, the whole palmprint image is divided into many tiles and the corresponding feature representation is calculated by primitive mask convolution within each tile of palmprint image segment. The sequences of numbers out of these small tiles are represented in an array which defines the local texture feature of a palmprit image.

In designing a search scheme, the relevant issues such as feature extraction, representation, indexing, and comparison are considered. Since the size of global features is smaller than local features, global features are used to identify all of the possible candidates with similar features at coarse level.

This paper is organized as follows. Section II introduces the basic concepts of texture-based feature measurement for palmprint feature extraction and representation. A coarse-to-fine search scheme is described in Section III and the experimental results are presented in Section IV. Finally, the conclusion is summarized in Section V.

II. Texture-Based Palmprint Feature Extraction

A. Palmprint Features and Texture Pattern Measurement

Feature extraction is one of the key issues in palmprint identification and verification [8]–[15]. A feature with good discriminating ability should exhibit a large variance between individuals and small variance between samples from the same person. Principal lines and datum points are regarded as useful palmprint features and have been successfully used for verification [6]. In addition, there are many other features associated with a palmprint, such as geometry features, wrinkle features, delta point features, and minutiae features [1]. All of these features are concerned with the local attributes based on points or line segments, which require high computation to measure the degree of similarities between two sample sets for matching. This section introduces a texture based palmprint feature measurement.

$$
\underset{\text{(a)}}{\begin{array}{ccccc} -4 & 0 & 8 & 0 & -4 \\ -8 & 0 & 16 & 0 & -8 \\ -16 & 0 & 32 & 0 & -16 \\ -8 & 0 & 0 & 0 & 0 \\ -4 & 0 & -4 & -2 & -1 \end{array}}
\quad
\underset{\text{(b)}}{\begin{array}{ccccc} -8 & -16 & -32 & -16 & -8 \\ 0 & 0 & 0 & 0 & 0 \\ 16 & 32 & 64 & 0 & -4 \\ 0 & 0 & 0 & 0 & 0 \\ -8 & -16 & -32 & -16 & -8 \end{array}}
\quad
\underset{\text{(c)}}{\begin{array}{ccccc} 16 & 0 & -12 & -8 & 0 \\ 0 & 24 & 0 & -16 & -8 \\ -12 & 0 & 32 & 0 & -12 \\ -8 & -16 & 0 & 24 & 0 \\ 0 & -8 & -12 & 0 & 16 \end{array}}
\quad
\underset{\text{(d)}}{\begin{array}{ccccc} 0 & -8 & -12 & 0 & 16 \\ -8 & -16 & 0 & 24 & 0 \\ -12 & 0 & 32 & 0 & -12 \\ 0 & 24 & 0 & -16 & -8 \\ 16 & 0 & -12 & -8 & 0 \end{array}}
$$

Fig. 2. Four masks used to calculate global texture energy.

A palmprint consists of many thin and short line segments represented by wrinkles and ridges. Such a pattern can be well characterized by texture. Thus, we use a texture feature measurement as a powerful technique for palmprint feature extraction, which is termed as "texture energy" (TE). The definition of TE is given as follows. For an image I of size $n \times n$, $\mathrm{TE}_A(I)$ represents its texture energy measurement over a mask, A, of size of $(2a+1) \times (2a+1)$, by

$$
\mathrm{TE}_A(I) = \frac{1}{(n-2a-1) \times (n-2a-1)} \times \sum_{i=a+1}^{n-a} \sum_{j=a+1}^{n-a} F(i,j) \tag{1}
$$

$$
F(i,j) = \left| \sum_{k=-a}^{a} \sum_{l=-a}^{a} \left(I(i+k, j+l) \times A(k,l) \right) \right| \tag{2}
$$

where A is the convolution mask to represent palmprint texture feature. In our proposed approach, four masks are defined in Fig. 2, which are used to extract palmprint features. These masks highlight the distribution of line segments in horizontal, vertical, 45° line and 135° line directions, respectively. Therefore, the TE values associated with the given four masks reflect the directional features in a palmprint image. For example, given a palmprint image, I, using (1)–(2) and the masks shown in Fig. 2, we can obtain each TE value, $TE_i(I) (i = 1, 2, 3, 4)$, where $\mathrm{TE}_1(I)$ indicates the component of horizontal line segments in a palmprint image I and $\mathrm{TE}_2(I)$ shows the component of vertical line segments in an palmprint image I.

B. Global Palmprint Texture Feature

Global features describe the overall attributes of a palmprint and local features provide more detailed information of a palmprint. In general, some palmprints are very different and can be discriminated by their global features, but some palmprints are very similar and additional local features are required for recognition. In our proposed approach, the global palmprint texture features are extracted for matching at coarse level. Fig. 3 illustrates the basic steps of the process. The details of operation are summarized as follows:

Step 1: Image Alignment for Feature Extraction: It is important to define a coordinate system to align different palmprint images for feature sampling and matching invariant of orientation. To extract the central part of a palmprint for reliable feature measurements, we use the holes between fingers as reference points to determine a coordinate system. Five major steps are adopted for automatic image alignment (see Fig. 3).

- Step 1: Use a threshold, α, to convert the original gray image $I_{M \times N}$ [Fig. 3(a)] into a binary map $B_{M \times N}$ [see Fig. 3(b)]

$$
B(i,j) = \begin{cases} l, & I(i,j) \geq \alpha \\ 0, & I(i,j) < \alpha \end{cases} \tag{3}
$$

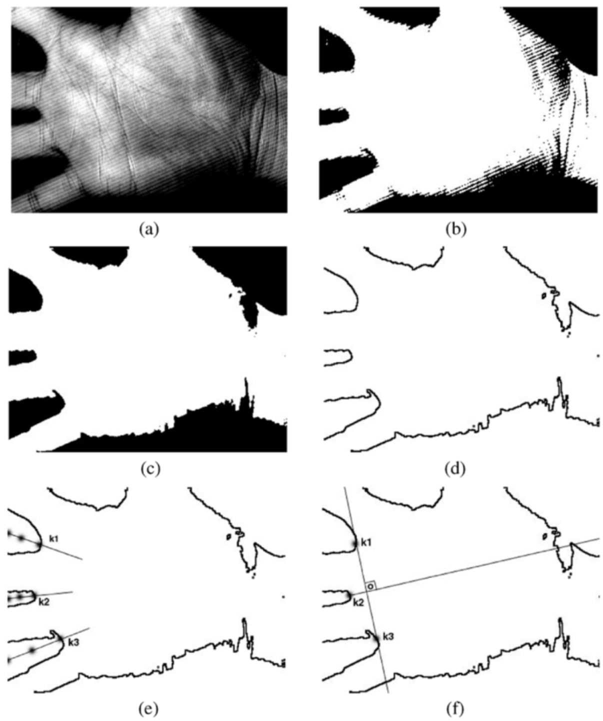


Fig. 3. Major steps of image alignment. (a) Roginal image. (b) Binary map of the original image. (c) Smoothed map of (b) and (d) palmprint boundary. (e) Determination of K1, k2, and K3. (f) Determination of the coordinate system.

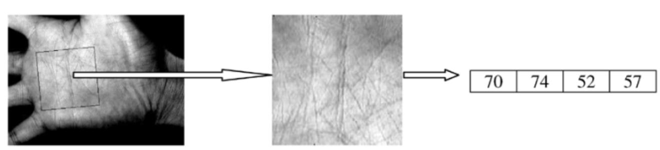


Fig. 4. Process of global feature extraction.

- Step 2: Smooth the binary map by a Gaussian filter in Fig. 3(c)

$$B\prime = B * A \tag{4}$$

  where A is the Gaussian filter.
- Step 3: Trace the boundary of the holes between the fingers as shown in Fig. 3(d).
- Step 4: Calculate the center of gravity of the holes and decide the key points—k1, k2, and k3 [see Fig. 3(e)].
- Step 5: Line up k1 and k3 to get the Y-axis of the palmprint coordinate system and then make a line through k2, perpendicular to the Y-axis to determine the origin of the palmprint coordinate system, as shown in Fig. 3(f)

In our approach, once the coordinate system is established, the central part of each palmprint is used to extract its global feature. After positioning, a subimage is cut from the original image, as shown in Fig. 4. For simplicity, a fixed size of 128×128 is used for feature representation in our experiments. Since the coordinate system is determined with reference to the key points (holes) between fingers, the features extracted from subimages after image alignment are invariant of changes in translation and orientation.

Step 2: Global Texture Energy Computing: Using the four masks listed in Fig. 2 and (1)–(2), four global features are calculated and normalized for each palmprint, which describe an individual palmprint's texture energies in horizontal, vertical, 45° and 135° directions, respectively. These global feature measurements are further represented in a vector, $E_i(i = 1, 2, 3, 4)$, to describe the underlying relationship between a palmprint pattern and its four directional components. This mapping is not one-to-one. Two palmprints may correspond to the same point in the feature space and not all of the points in the space have their corresponding palmprints. Feature points of similar palmprints are close to each other in the feature space and neighbor points in the feature space are also associated with similar palmprints if any. Fig. 5 shows this relationship between palmprints and their global features listed under each palmprint, where Fig. 5(a) is a group of the palmprints from the same palm, Fig. 5(b) shows the similar palmprints from different palms and Fig. 5(c) shows the palmprints with significant difference. In our experiments, the average differences between any two palmprints in Groups (a)-(c) are shown in Table I. Obviously, the difference between samples of the same palm is much smaller than that of significantly different palms, but the difference between samples of similar palms is also small, which requires the use of local palmprint features for further classification.

C. Local Palmprint Texture Feature

Although global features are powerful to discriminate many palmprints, they cannot separate a palmprint from other samples with similar global features. Thus, it becomes essential to extract local features for further processing. The following lists the major steps.

1) Segmenting a Palmprint Image Into Small Tiles: To extract the local feature of a palmprint, the central part of a palmprint image is divided into 8×8 tiles. These titles are subimages of size of 16×16, which are shown in Fig. 6.

2) Local Texture Energy Computing: Using (1)–(2) to calculate four global texture energies in the subimage and their average value is represented as the tile's attribute.

3) Feature Representation: A sequence of local texture energies of subimages of size of 8×8 is grouped in a one-dimensional (1-D) array to represent the local features of a palmprint. Since the procedure of image alignment is applied prior to feature extraction, the representation is invariant of rotation and translation. Fig. 6 is an example of such a representation to discriminate the similar palmprint patterns from different sources.

III. Similarity Measurement and Layered Search Scheme

Accuracy and efficiency are two major concerns in image retrieval. Accuracy is related to the issue of correctness of search results while efficiency refers to the response time of the system. In general, accuracy is determined by the feature similarity measurement and efficiency depends on both the search strategy and the time required for feature-based matching. In this section, we first define the distance between two palmprint patterns in terms of both global and local features for similarity measurement. A layered search scheme for fast image retrieval is also introduced.

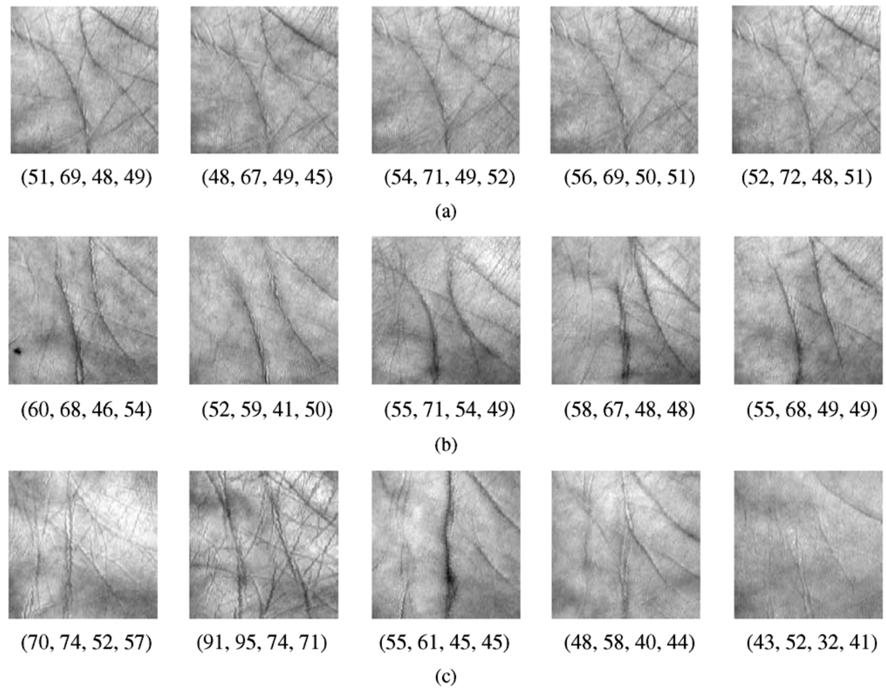


Fig. 5. Relationship between palmprints and their global features. (a) Palmprints from the same palm. (b) Similar palmprints from different palms. (c) Palmprints with significant difference.

TABLE I
COMPARISON OF THE AVERAGE DIFFERENCES, E_i $(i = 1, 2, 3, 4)$, FOR THREE GROUPS DEFINED IN FIG. 5

	Group (a)	*Group (b)*	*Group (c)*
Average difference of E_1 (0-100)	2.24	2.40	15.28
Average difference of E_2 (0-100)	1.52	3.04	13.20
Average difference of E_3 (0-100)	0.64	3.28	11.52
Average difference of E_4 (0-100)	2.08	1.60	9.92

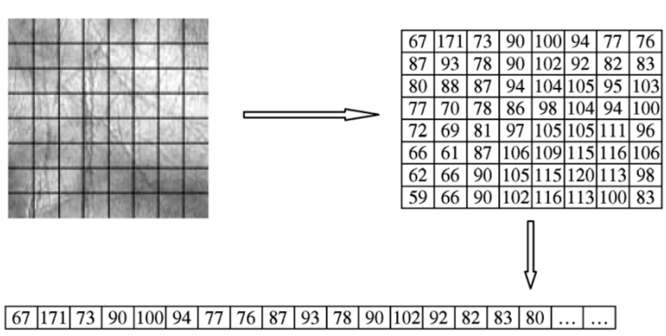


Fig. 6. Process of local feature extraction.

A. Similarity Measurement Based on Global Features

Let I_i and I_j represent two individual palmprint images and their global features are measured by $E_{\rm ik}$ and $E_{\rm jk}(k = 1, 2, 3, 4)$, respectively. The similarity between I_i and I_j is defined as follows:

$$D(I_i, I_j) = \begin{pmatrix} D_1(I_i, I_j) \\ D_2(I_i, I_j) \\ D_3(I_i, I_j) \\ D_4(I_i, I_j) \end{pmatrix} = \begin{pmatrix} |E_{i1} - E_{j1}| \\ |E_{i2} - E_{j2}| \\ |E_{i3} - E_{j3}| \\ |E_{i4} - E_{j4}| \end{pmatrix}. \quad (5)$$

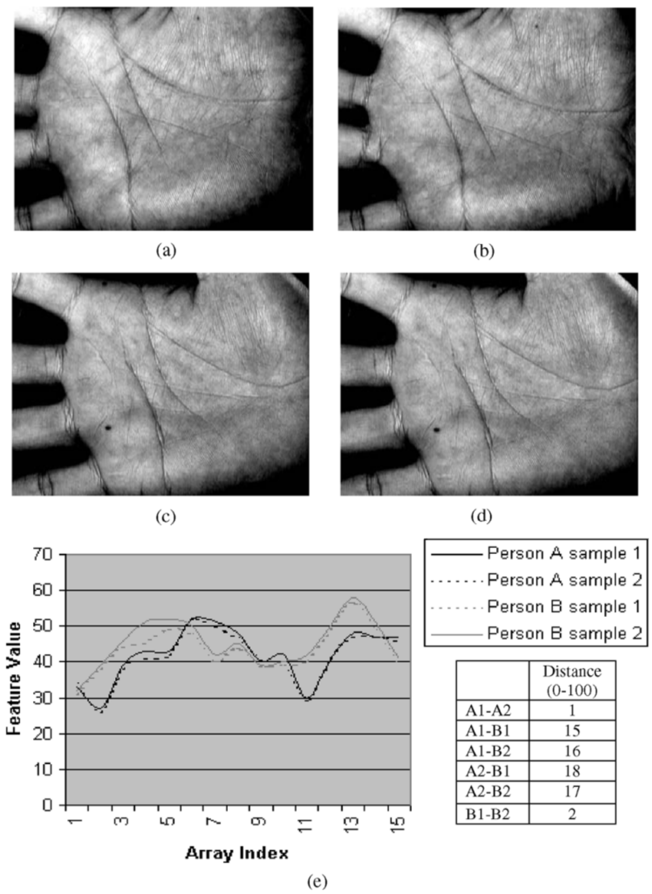
where $D(I_i, I_j)$ reflects the difference between two palmprint samples, which determines whether the given samples are from the same palm. A threshold vector $T_k(k = 1, 2, 3, 4)$ is used to make the decision. The following highlights the selection procedure of thresholding:

If $|E_{\rm ik} - E_{\rm jk}| > T_k(k = 1, 2, 3, 4)$, then I_i and I_j are from different palms; otherwise, they belong to the same palm. $T_k(k = 1, 2, 3, 4)$ is chosen based on a statistical method. If M samples are collected from one palm and the corresponding M global feature vectors $E_{1k}, E_{\ 2k}, \ldots, E_{\rm Mk}(k = 1, 2, 3, 4)$ are obtained, the threshold value $T_k(k = 1, 2, 3, 4)$ can be decided by calculating both the average and largest distance between any two samples in the group, i.e.,

$$T_k = \left(\left(\frac{1}{2M} \sum_{i=1}^{M} \sum_{j=1}^{M} |E_{\rm ik} - E_{\rm jk}| \right) \right. \\ \left. + \operatorname{Max}_{i=1}^{M} \operatorname{Max}_{j=1}^{M} |E_{\rm ik} - E_{\rm jk}| \right) \Big/ 2 \quad (k = 1, 2, 3, 4). \quad (6)$$

B. Similarity Measurement Based on Local Features

Similarity measurement based on local features is used to discriminate the similar palmprints from different palm sources. As described in Section II-C, the local palmprint texture features are represented in a 1-D array as shown in Fig. 6. The idea of local feature matching is to calculate the linear relation coefficients. Fig. 7 illustrates the process of local feature-matching algorithm, where Fig. 7(a)–(b) shows two samples from person A, and Fig. 7(c)–(d) from person B. Their features are given in the left part of Fig. 7(e). A table in Fig. 7(e) lists the distances



	Distance (0-100)
A1-A2	1
A1-B1	15
A1-B2	16
A2-B1	18
A2-B2	17
B1-B2	2

Fig. 7. Similarity measurement to similar palmprints based on local features.

between each sample pair. It is obvious that the distance between two samples from the same person (A or B) is less than 3; however, the distance between two samples from different person is larger than 14. Therefore, a threshold can be set to determine whether two samples are from the same palm.

The definition of the distance d_{xy} between two feature sets $(x_1, x_2, \ldots, x_n)$ and $(y_1, y_2, \ldots, y_n)$ is given as follows:

$$d_{\mathrm{xy}} = 1 - r_{\mathrm{xy}} \tag{7}$$

where

$$r_{\mathrm{xy}} = \frac{l_{\mathrm{xy}} l_{\mathrm{xy}}}{l_{\mathrm{xx}} l_{\mathrm{yy}}} \tag{8}$$

and

$$l_{\mathrm{xx}} = \sum_{i=1}^{n} (x_i - \bar{x})^2,\ l_{\mathrm{xy}} = \sum_{i=1}^{n} (x_i - \bar{x})(y_i - \bar{y}) \tag{9}$$

$$\bar{x} = \frac{1}{n}\sum_{i=1}^{n} x_i, \quad \bar{y} = \frac{1}{n}\sum_{i=1}^{n} y_i. \tag{10}$$

If the distance d_{xy} is smaller than a given threshold value T, the two palmprints are from the same palm; otherwise, they belong to different palm sources. If $x = y$, the two feature sets refer to the same sample and their distance is zero. T is determined by using a statistical method which is similar to what is described in Section III-A.

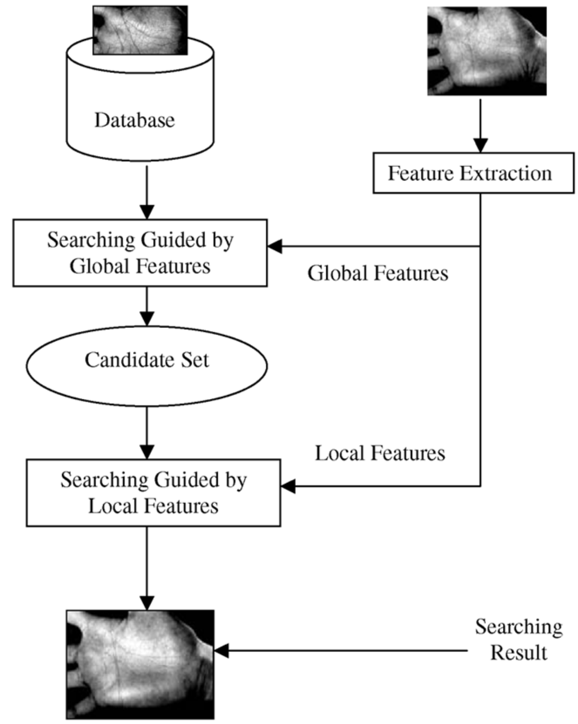


Fig. 8. Process of layered search scheme.

C. A Layered Search Scheme

The search process of texture-based palmprint retrieval is carried out in a layered fashion. Global features are applied to search for the most similar candidates at coarse level. Only the candidates in the database which are close to the queried palmprint sample with small distance in global feature measurement given by (5) are selected for further classification. Local features are then applied to determine the final output at fine level. Within the selected candidate set obtained at coarse level, the search for the best matching is performed using local feature similarity measurement given in (5) (see Fig. 8).

In our experiments, a large database of 5000 palmprint images is created for testing. All of the image samples in the database are sorted by their global features. On the average, only less than 20% of palmprint samples in the database will remain for further processing after the coarse-level search. During fine-level search, all of the palmprint images in the candidate set are compared with the queried sample in terms of their local features. The final output may include zero (none of the matched sample), one, or more than one similar samples which are matched to the queried template. Since the global feature-based matching is much faster than the local feature-based matching, the proposed layered search scheme speeds up the retrieval of the queried palmprint sample in a given database.

IV. Experimental Results

A series of experiments have been conducted to test the accuracy and efficiency of our palmprint image retrieval system. The testing includes the setup of a palmprint database, accuracy assessment, and efficiency evaluation. Our experiments are conducted on a Pentium III (CPU 450 MHz and RAM 128M).

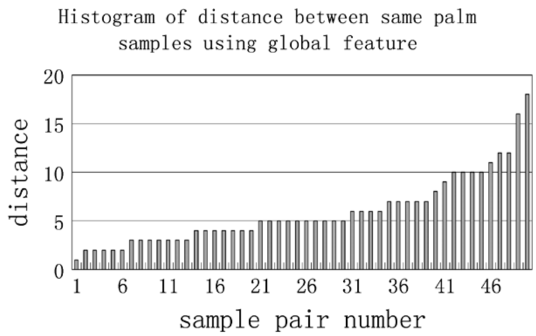


Fig. 9. Distribution of global feature distance for the same palm.

The operating system is Windows' 98 and the programming language is JDK1.2. Oracle database is used to store both the images and their features.

A. Palmprint Image Acquisition

The data collection process involves the following major steps: 1) select various persons of different ages, sexes and occupations; 2) capture palmprints from the individual's right hand to form a testing data set; and 3) obtain additional palmprint samples from each person as templates stored in the database. The resolution of the palmprint images used is 320×240 with 100 dpi.

B. Palmprint Feature Clustering

To assess the capabilities of the proposed approach to reject imposters and achieve low rate of false reject for individuals in the database, a sequence of testing is performed to demonstrate the distributions of the distance difference in both intra-class and inter-class cases.

- *Global feature convergence for palmprints from the same palm*
  The distance of global features between two samples from the same palm is calculated by

$$d_{\mathrm{xy}} = |x_{S1} - y_{S1}| + |x_{S2} - y_{S2}| + |x_{S3} - y_{S3}| + |x_{S4} - y_{S4}| \quad (11)$$

  where S1, S2, S3, and S4 denote the values of the sample's global feature measurements with respect to the given four masks specified in Section II-B. The corresponding histogram for 100 samples of 50 pairs is shown in Fig. 9. In Fig. 9, most palmprint pairs have distance less than 5.
- *Global feature dispersion for palmprints from different palms*
  The distance of global palmprint feature measurement for different palms varies. For some palms with distinctive palmprint patterns, their global distance is large. However, some palms possess very similar palmprint patterns and their global distance is very close. Fig. 10 illustrates the distance distribution of three cases—the best, the worst, and the average cases. By using global features, the elimination rate for the best case is 100%, while 68% is achieved for the worst case. Fig. 10(a) shows the best case, Fig. 10(b) is the average case, and Fig. 10(c) is the worst case.

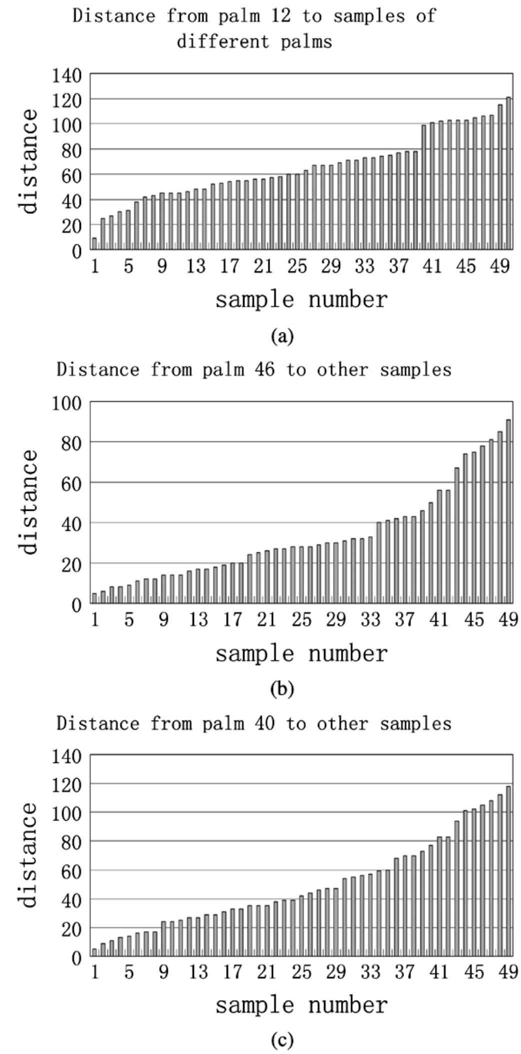


Fig. 10. Global feature dispersion for different palms. (a) Best case. (b) Worst case. (c) Average case.

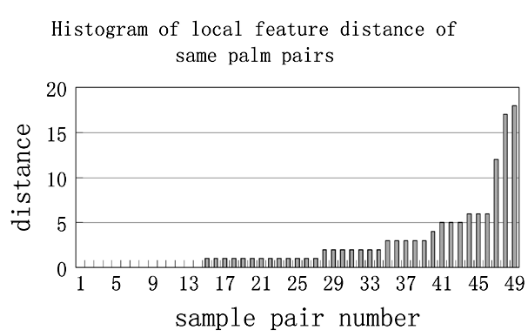


Fig. 11. Distribution of local feature distance.

- *Local feature distribution for the same palm*
  The histogram of distance between the same palm pairs with local feature measurement is shown in Fig. 11. It is noted that the local features of the same palm are clustered quite well and can be used to discriminate the queried sample at fine level.

C. Performance Evaluation

The performance testing is carried out as follows: 1) take 500 samples from 500 persons as the database templates; 2) take 2

TABLE II
FRR AND FAR FOR DIFFERENT THRESHOLDING VALUES USING GLOBAL FEATURES

Threshold(0-100)	*FRR (%)*	*FAR(%)*
6.5	32	.94
7.5	22	1.27
8.5	20	2.90
9.5	18	4.12
10.5	10	5.27
11.5	8	6.65
12.5	4	8.08
13.5	4	9.63
14.5	4	11.84
15.5	4	13.31
16.5	2	14.49
17.5	2	15.55
18.5	0	17.43

TABLE III
FRR AND FAR FOR DIFFERENT THRESHOLDING VALUES USING LOCAL FEATURES

Threshold(0-100)	*FRR (%)*	*FAR(%)*
6.5	8	0
7.5	8	.08
8.5	8	.16
9.5	8	.24
10.5	8	.65
11.5	8	.90
12.5	6	1.59
13.5	6	2.24
14.5	6	3.59
15.5	6	4.73
16.5	6	5.88
17.5	4	7.47
18.5	2	9.43

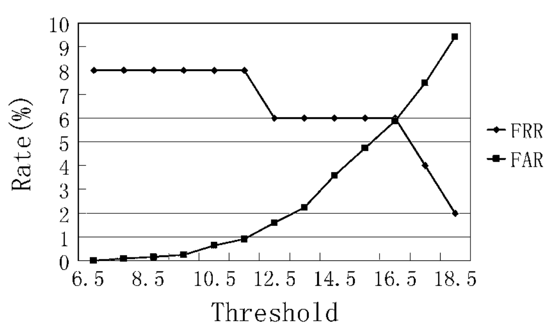


Fig. 12. ROC map for different thresholding values using global features.

500 samples (each person five samples) as the testing set; 3) for each sample in the testing set, the system provides all of the templates which belong to the same palm; 4) count the number of times that the system responds with the correct answer; and 5) record the response time for each attempt. The testing result shows that the system responds 2385 times correctly for 2500 queries. Therefore, the identification rate of our approach is 94.5%. The classification accuracy of the proposed layered search scheme based on global and local features is presented in Tables II and III, respectively. The corresponding ROC mapping curves of FAR and FRR are illustrated in Figs. 12 and 13. The system efficiency is further demonstrated by its response time, as shown in Fig. 14. Of 2500 trials, the best response time is within 0.3 second and the worst response time is around 3.7 s to generate the final result. On the average, it takes about 2 s to process each query.

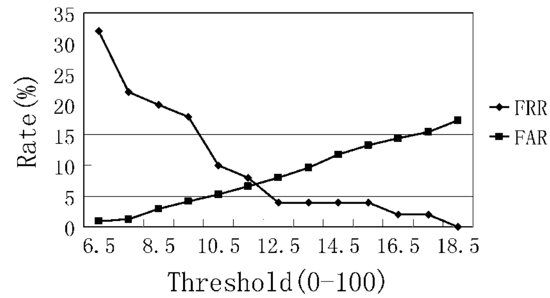


Fig. 13. ROC map for different thresholding values using local features.

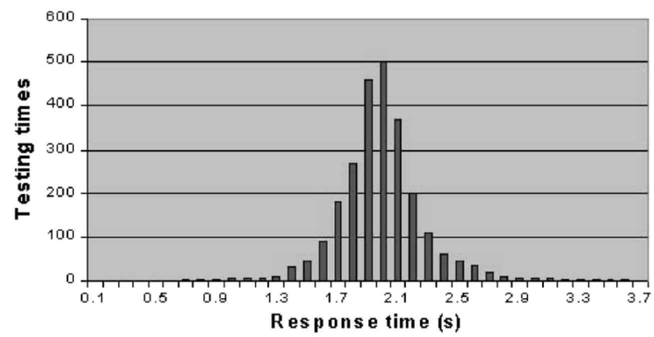


Fig. 14. Result of system efficiency testing: response time.

V. CONCLUSION

The palmprint is regarded as one of the most unique, reliable, and stable personal characteristics and personal identification by palmprint retrieval provides a powerful means to authenticate individuals for many security systems. In contrast to the traditional method based on local line and point feature extraction, we propose a new approach using texture energy and develop a dynamic selection scheme to guide the search for the best matching. Our extensive study of palmprint feature extraction shows that palmprint patterns can be well described by textures since the texture energy measurement possesses a large variance between different classes while remaining high compactness within the class. A layered selection scheme based on both the global and local features offers a simple approach to speed up query processing by eliminating irrelevant samples from the database. The experimental results provide the basis for further development of a fully automatic palmprint-based personal identification system with high performance in terms of effectiveness, accuracy, robustness and efficiency.

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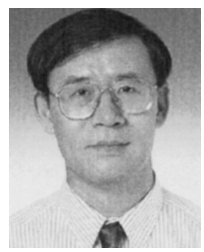

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