On Hierarchical Palmprint Coding With Multiple Features for Personal Identification in Large Databases

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***Abstract*—Automatic personal identification is a significant component of security systems with many challenges and practical applications. The advances in biometric technology have led to the very rapid growth in identity authentication. This paper presents a new approach to personal identification using palmprints. To tackle the key issues such as feature extraction, representation, indexing, similarity measurement, and fast search for the best match, we propose a hierarchical multifeature coding scheme to facilitate coarse-to-fine matching for efficient and effective palmprint verification and identification in a large database. In our approach, four-level features are defined: global geometry-based key point distance (Level-1 feature), global texture energy (Level-2 feature), fuzzy "interest " line (Level-3 feature), and local directional texture energy (Level-4 feature). In contrast to the existing systems that employ a fixed mechanism for feature extraction and similarity measurement, we extract multiple features and adopt different matching criteria at different levels to achieve high performance by a coarse-to-fine guided search. The proposed method has been tested in a database with 7752 palmprint images from 386 different palms. The use of Level-1, Level-2, and Level-3 features can remove candidates from the database by 9.6%, 7.8%, and 60.6%, respectively. For a system embedded with an Intel Pentium III processor (500 MHz), the execution time of the simulation of our hierarchical coding scheme for a large database with 10^6 palmprint samples is 2.8 s while the traditional sequential approach requires 6.7 s with 4.5% verification equal error rate. Our experimental results demonstrate the feasibility and effectiveness of the proposed method.**

***Index Terms*—Biometric identification, feature extraction and representation, fuzzy set, guided search, palmprint classification, texture measurement.**

I. Introduction

AUTOMATIC personal identification is playing an important role in security systems. Biometrics, which deals with identification of individuals based on their biological or behavioral characteristics, has been emerging as a new and effective identification technology to achieve accurate and reliable identification results. Although no single biometrics is expected to effectively satisfy the requirements of all identification purposes, the use of such unique, reliable, and stable personal features has invoked increasing interest in the development of biometrics-based identification systems for various civilian, military and forensic applications. Currently, a number of biometrics-based technologies have been commercially available, and many others are being proposed, researched, and evaluated [1]–[3], [14], [16]. It is known that each biometric technology has its strength and limitation in different applications. So far, there are mainly a few different biometrics being utilized, namely face, fingerprint, hand geometry, iris, retinal pattern, signature, voice-print, and facial thermograms. Some other biometrics such as hand vein, keystroke dynamics, odour, DNA, gait, and ear are also currently under investigation.

The general problem of personal identification involves a number of important and difficult research issues such as design, evaluation, integration, and circumvention. For a biometrics-based identification system, the design issue could be related to a pattern recognition system that deals with data acquisition and representation, feature extraction, matching criteria, search methods, database organization, and system scalability. In order to be widely accepted by the public for practical applications, a biometrics-based identification system should be characterized by its easy operation, short response time, and high accuracy. The investigation of fingerprint identification and speech recognition has drawn considerable attention over the last 25 years. Recently, issues on face recognition and iris-based identification have been studied extensively, which has resulted in successful development of biometric systems for commercial applications. Although the use of palmprints for identity authentication has drawn interests from some researchers [5]–[7], [12], the development of an effective and efficient approach to identification and verification of palmprints remains a challenging research topic.

Palmprint refers to principal lines, wrinkles, and ridges on a palm. Like fingerprints, palmprint can be used as a powerful means in law enforcement for criminal identification because of its stability and uniqueness [14]. Table I compares palmprints with both fingerprints and hand geometry in terms of the accuracy and feature complexity for personal identification. The rationale to choose hand features as a base for identity verification is originated by its user friendliness, environment flexibility, and discriminating ability. Thus, it is essential to develop an effective approach to automatic palmprint identification and verification for security systems. Verification refers to the comparison of a claimant's biometrics feature against a person's sample that has been stored in the verification system. In other words, verification is regarded as a one-to-one matching. Identification is concerned with the search for the best match between the input sample and the templates in the database, which is also termed as one-to-many matching. Palmprint verification consists of determining whether two palmprints (test sample from input and the template in the database) are from the same palm. Therefore, a comparison must be made between the template feature set and

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TABLE I
COMPARISON OF PALMPRINT WITH FINGERPRINT AND HAND GEOMETRY

	Public Acceptance	*Accuracy Level*	*Features*
Fingerprint	Medium	High	Minutiae Points
Hand	High	Low	3-D Geometry
Palmprint	High	High	Line & texture

the feature set derived from the hand image at the time of verification. The selection of features and similarity measures are two fundamental issues to be solved. A feature with good discriminating ability should exhibit a large variance between individuals and small variance between samples from the same palm. Thus, the advances in image feature extraction/ representation and similarity measures play an essential role in identification and classification of biometrics patterns.

At a first glance, palmprint and fingerprint patterns appear to resemble each other in some ways. Both consist of a large amount of ridges. Although the minutiae-based matching which utilizes terminations and bifurcations of the ridges is powerful for fingerprint verification and identification, such an approach is not suitable for palmprint patterns due to the change of orientations. Zhang and Shu [4] proposed using datum point invariance and line feature matching for palmprint feature extraction and verification. They introduced a directional projection algorithm to localize the datum points for matching. However, their algorithm is subject to the following limitations.

1) The localization of datum points is based on the detection of distinct principal lines in palmprint patterns. The approach is not suitable for the patterns without clearly dominant principal lines.
2) A set of fixed masks is used to detect feature lines for matching.
3) The link of feature line segments for palmprint line feature representation requires high computation resource and lacks accuracy.

Recently, Dute *et al.* investigated the feasibility of matching palmprints based on feature points [5]. Instead of extracting feature lines explicitly as in [4], they applied the following six steps to extract isolated feature points that lie along palm lines: 1) palm image smoothing; 2) image binarization by interactively thresholding the smoothed grey palm image; 3) successive morphological erosions, dilations and subtractions for feature point detection; 4) location adjustment for the feature points; 5) calculation of the orientation of each feature point (the orientation of the palm line which a feature point is associated with); and 6) removal of redundant points. They use their previous point matching technique [5] to determine whether the two sets of feature points/orientations are the same by computing a matching score. Although this approach has the advantages of simplicity and reasonable accuracy, it lacks robustness in the following aspects: 1) the detection of feature points rely on the selection of threshold value for image binarization and the consequent successive morphological operations and 2) the feature point matching is based on the traditional exhaustive comparison method, which is very time consuming and may not meet the real-time requirement for online matching of a large collection of palmprint patterns. Our previous research [6] shows interesting points detected by a Plessey operator are better than edge points to represent feature points in palmprint images. However, it requires a time consuming algorithm for matching the feature points, which is not suitable for searching a palmprint in a large database.

It is known that dynamic feature extraction, guided search, and knowledge-based hierarchical matching will have significant potential in enabling both image identification and image classification to be performed more effectively. However, most of the existing systems and research adopt a fixed scheme for feature extraction and similarity measurement, which are not suitable to search a palmprint image in a large database. To achieve flexibility and multiple feature integration, we propose a hierarchical palmprint coding scheme to facilitate coarse-to-fine matching for efficient and effective identification of a palmprint in large database. More specifically, we extract different palmprint features at different levels: Level-1 feature: global geometry-based key point distance; Level–2 feature: global texture energy; Level–3 feature: fuzzy "interest " line, and Level–4 feature: local directional texture energy vector for fine palmprint matching. We start with a global geometry feature to localize the region of interest (ROI) of the palmprint sample at coarse level and apply a distance measurement of palm boundary to guide the dynamic selection of a small set of similar candidates from the database for further processing. We also use the global texture energy (GTE) for fast search for the best match. Such a mask-based texture feature representation is characterized with a high convergence of inner palm similarities and good dispersion of interpalm discrimination. We then adopt fuzzy set theory to detect "interest" feature lines to guide the search for the best match at fine level. Finally, we apply local texture measurement to establish a feature vector for palmprint matching.

Our hierarchical palmprint identification system consists of four components: palmprint acquisition, preprocessing, feature extraction, and hierarchical matching. We have developed a special CCD-based palmprint scanner to obtain inkless palmprint images, which can support online and real-time personal identification [8]. Preprocessing is used to set up a coordinate system to align different palmprint images. Many preprocessing approaches have been proposed including key point-based and datum point-based approaches [4], [6]–[8]. In this paper, we use key point detection approach to setup the coordinate system to extract the central parts for feature extraction [8]. Feature extraction is to obtain multilevel features for palmprint representation. Hierarchical matching is to determine the similarity of two palmprint images for identity authentication. Fig. 1 illustrates the general structure of our system. Initially, a palmprint image is captured by our palmprint scanner [8]. Then the boundaries between fingers are extracted. Based on the boundaries, the two key points can be determined so as to set up the coordinate system to extract the central parts. The distance of two key points is considered a Level 1-feature. Based on the central parts, global texture energy, fuzzy "interest" line, and local

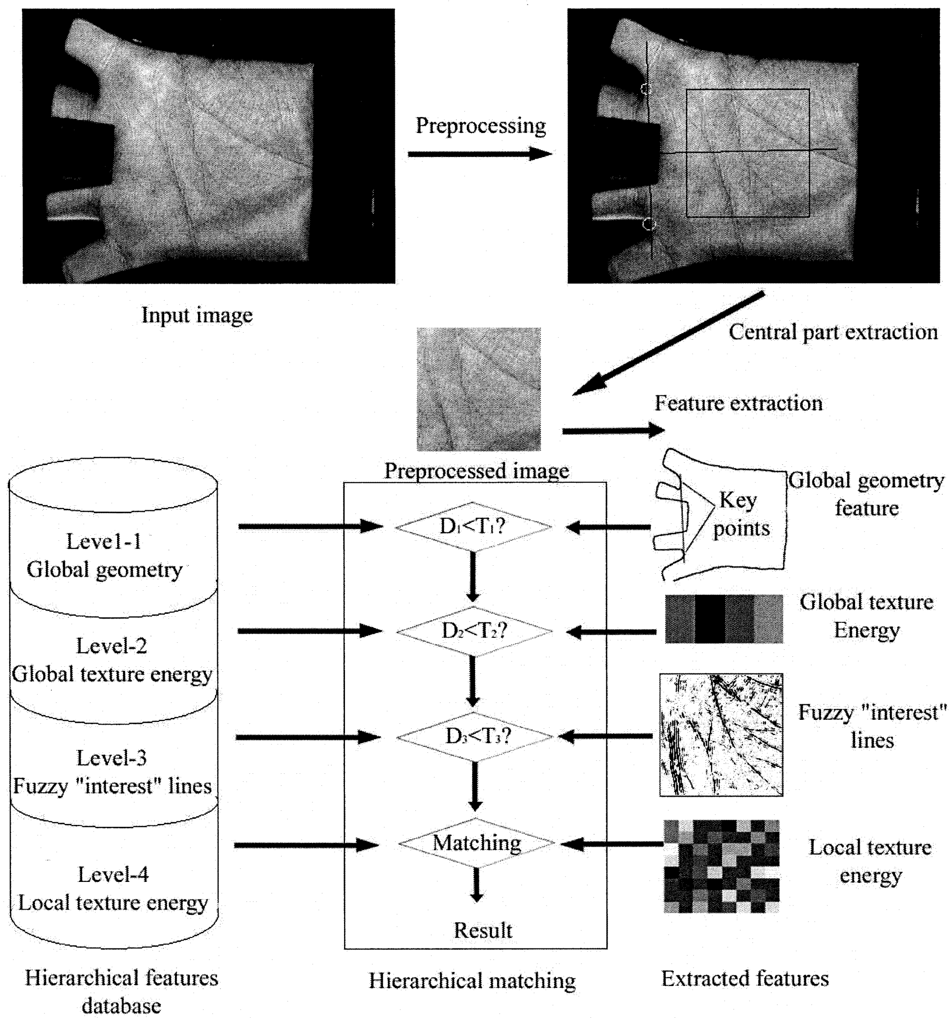


Fig. 1. System diagram of our hierarchical palmprint system.

directional texture energy are extracted. The features in the hierarchical feature database are retrieved and compared with input features, in a multilevel fashion.

This paper is organized as follows. Section II introduces a hierarchical palmprint coding scheme which embraces global geometry boundary segments, global texture energy, fuzzy "interest" lines, and local directional texture energy. The use of multilevel features for matching measurement is described in Section III and a guided search for the best match is summarized in Section IV. Section V reports the experimental results and Section VI highlights the conclusions.

II. Hierarchical Palmprint Coding

Feature extraction is a key issue for pattern recognition and palmprint consists of very complicated patterns. It is very difficult, if not impossible, to use one feature model for palmprint matching with high performance in terms of accuracy, efficiency, and robustness. Although the research reported in [5] resulted in a more reliable approach to palmprint feature point detection than the line matching algorithm detailed in [4], the issues of efficiency and robustness remain untackled. The technique detailed in [5] involves one-to-one feature point-based image matching, which requires a high computation resource for a large palmprint database. In addition, the matching lacks flexibility because only one similarity measurement is applied. To speed up the search process for the best match with reliable features and flexible matching criteria, we adopt multilevel feature extraction and flexible similarity measurement. Instead of using a fixed feature extraction mechanism and a single matching criterion as in [4] and [5], we apply a hierarchical coding scheme to extract multiple palmprint features at both the global and local levels. This section summarizes our proposed algorithms for multiple feature extraction.

A. Level-1 Global Geometry Feature: Key Point Distance

The key point distance is measured based on boundary segments between fingers. To obtain a stable palmprint image for reliable feature extraction, six pegs on the platform of the palmprint scanner are installed to serve as control points for the placement of the user's hands. In addition, a coordinate system is defined to align different palmprint images for feature measurement. Fig. 1 illustrates the global geometry feature of fingers. Such boundary segments can be obtained by a boundary tracking algorithm with the following major steps.

(a)

-1	-2	-4	-2	-1
0	0	0	0	0
2	4	8	4	2
0	0	0	0	0
-1	-2	-4	-2	-1

(b)

-1	0	2	0	-1
-2	0	4	0	-2
-4	0	8	0	-4
-2	0	4	0	-2
-1	0	2	0	-1

(c)

0	-1	-4	0	2
-1	-6	0	8	0
-4	0	12	0	-4
0	8	0	-6	-1
2	0	-4	-1	0

(d)

2	0	-4	-1	0
0	8	0	-6	-1
-4	0	12	0	-4
-1	-6	0	8	0
0	-1	-4	0	2

Fig. 2. Four kinds of "tuned masks" for global palmprint texture extraction. (a) Horizontal line. (b) Vertical line. (c) 45° line. (d) $-45°$ line.

Step 1) Convert an original palmprint image to a binary image by convolving a lowpass filter with the original image and thresholding.

Step 2) Apply boundary tracing to obtain the boundaries between fingers.

Step 3) Compute the tangent of line segments.

Step 4) Identify the two key points and calculate their distance as the global geometry feature.

B. Level-2 Global Texture Feature: "Tuned" Mask Based Texture Energy

For the purpose of fast selection of a small set of similar palmprint patterns from the database, previously we applied four "tuned" masks to capture the global palmprint texture features which are more sensitive to horizontal lines, vertical lines, 45° lines and $-45°$ lines, respectively [9], [13], [15]. In our approach, the local variance after convolution is well approximated by the sum of squared values of convolved images within the test window, which is expressed as

$$TE(i,j) = \frac{\sum\limits_{W_x}\sum\limits_{W_y}(I^*A_k)^2_{rs}}{P^2W_xW_y} \tag{1}$$

where the rs sum is over all pixels within a window W of size $W_x \times W_y$ centered on the pixel at i, j, A_k is a zero sum "tuned" 5×5 convolution mask, and P is the parameter normalizer $P^2 = \sum_{i,j}(A_{i,j})^2$. Such a texture energy measurement for global palmprint feature extraction has the following characteristics: 1) insensitive to noise; 2) insensitive to shift changes; 3) easy to compute; and 4) high convergence within the group and good dispersion between groups. In this paper, we apply this approach to extract the global texture feature for Level-2 feature representation. Fig. 2 lists the four "tuned" masks. The horizontal global texture energy is the mean of all the texture energy term (TE) obtained from the given horizontal "turned" masks, similarly for the vertical, 45° and $-45°$ global texture energy. The four directional global texture energies constitute global texture energy.

C. Level-3 Fuzzy"Interest" Lines

The so-called "interest" lines refer to the dominant feature lines such as principal lines or wrinkles in palmprint. The major steps of extracting dominant lines are listed below.

Step 1) Convert the preprocessed images into the feature image as described in [10].

Step 2) Apply the fuzzy rule to extract the "interest" lines. Let I_T be a feature image. The fuzzy output is given by the following piecewise linear membership function:

$$S(l) = \begin{cases} 0, & \text{if } l < a \\ \frac{(l-a)}{(b-a)} & \text{if } a \le l \le b \\ 1, & \text{if } l > b. \end{cases} \tag{2}$$

The parameters a and b depend on the feature images. We set $a = \mu$ and $b = \mu + \sigma$, where μ and σ are the sample mean and standard deviation of $I_T(x,y)$, respectively. A sample of fuzzy interest lines is shown in Fig. 3.

Step 3) Take the mean of the fuzzy output in a small window to represent the local interest lines such as

$$v(I_T) = \frac{1}{MN}\sum_x\sum_y S(I_T(x,y)) \tag{3}$$

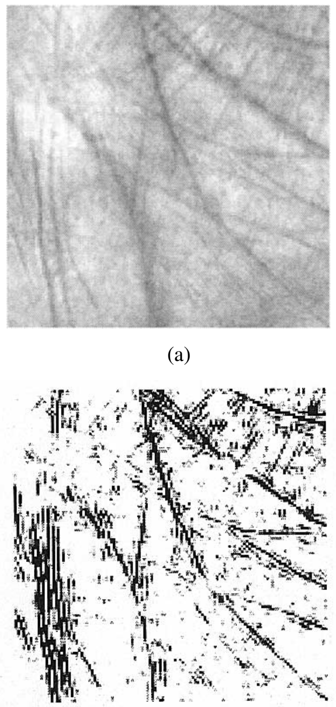
where the size of the local block is M by N. In our experiments, both M and N are set to 20. Thus, the "interest" lines can be represented by a 64-dimension feature vector obtained from 64 overlapped blocks.

D. Level-4 Local Directional Texture Energy

This level is the last level to make a final decision so a high accuracy is expected. To achieve this goal, we generate a long feature vector from local directional texture energy to facilitate more information. The local directional texture energy can be obtained by the following equation:

$$u_i = \frac{1}{XY}\sum_x\sum_y\left|\sum_{W_X}\sum_{W_Y}(I^*A_i)_{rs}\right| \tag{4}$$

where X by Y is the size of the local block for computing the local directional texture energy. We set $X = 20$ and $Y = 20$, which balances the size of the feature vector and the accuracy of the system. Therefore, each block is overlapped with the adjacent blocks.



(a)

(b)

Fig. 3. Detection of "interest" lines based on fuzzy theory. (a) Original image and (b) its "Interest line."

III. Multiple-Similarity Measurement

Feature extraction is a key issue for pattern recognition, and a palmprint consists of very complicated patterns. It is very difficult, if not impossible, to use one feature model for palmprint matching with high performance in terms of accuracy, efficiency, and robustness. Although the research reported in [4] resulted in a more reliable approach to palmprint feature point detection than the line-matching algorithm detailed in [5], the issues of efficiency and robustness remain untackled. The technique detailed in [4] involves one-to-one feature point-based image matching, which requires a high computational resource for a large palmprint database. In addition, the matching lacks flexibility because only one similarity measurement is applied. Instead of using a fixed feature extraction mechanism and a single matching criterion as in [4] and [5], we adopt a multiple-similarity measurement in terms of different features. We use global geometry features and texture energy to identify a small set of the most relevant candidates at the coarse level. The local line-based matching and feature vector comparison are performed at the fine level. Unlike the matching scheme described in [4], our fine matching is conducted in a hierarchical manner based on different features. This section briefly describes multiple-similarity measurement.

A. Minimum Distance for Global Feature Matching

We have defined two global features: 1) geometry distance of key points and 2) global texture energy. Our goal is to search a palmprint in large database; as a result, the searching speed is one of the main concerns. Simple and effective distance measures are expected. The distance measure for the geometry feature vectors is

$$D_1 = |d_i - d_j| \tag{5}$$

where i and j represent two palmprint images and $d_i(d_j)$ is the distance between key points of the $i(j)$ palmprint images.

The global texture energy can be measured by the similar distance measure. Let the global texture energy vector of the ith palmprint image be $[v_{0i}, v_{1i}, v_{2i}, v_{3i}]$, similarly for the jth palmprint image. Their similarity can be measured by

$$D_2 = \sum_{k=0}^{3} |v_{ki} - v_{kj}|. \tag{6}$$

B. Minimum Distance for Local Feature Matching

In addition to the two global features, we also design two local features in our coding scheme: "interest" lines and local directional texture energy. The "interest" lines are represented by a 64-dimension feature vector. At this level, we use an angular distance to evaluate the difference between two feature vectors. Let X and Y be two "interest" lines. The angular distance is defined as

$$D_4 = \frac{X^T Y}{\|X\| \, \|Y\|}. \tag{7}$$

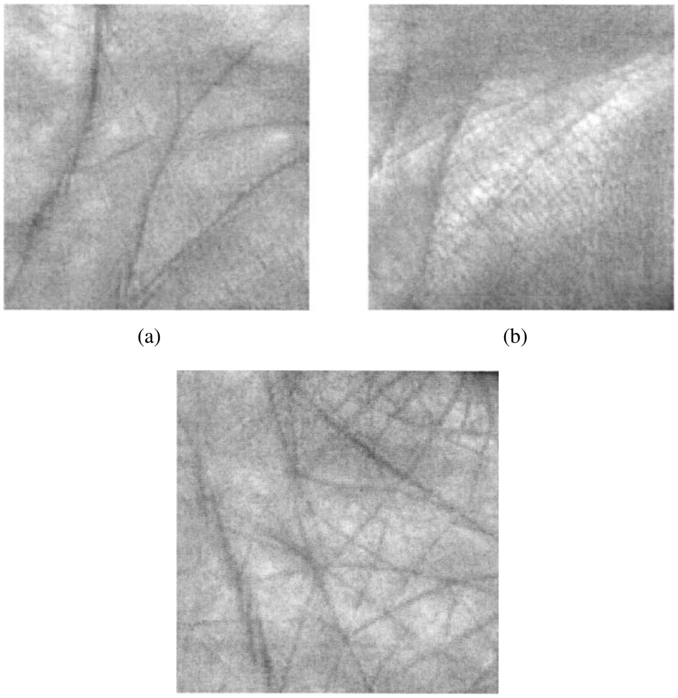
In the local directional texture energy, we use a local angular distance to evaluate the difference between two feature vectors. For simplicity, let the local directional texture energy vector of the ith palmprint image be $[y_{0i}, y_{1i}, y_{2i}, y_{3i} \ldots y_{64i}]$, where $y_{ki} = [u_0, u_1, u_2, u_3]$ where u_k is defined in (4). The local angular distance is defined as

$$D_4 = \frac{1}{64} \sum_{k=1}^{64} \frac{y_{ki} y_{kj}^T}{\|y_{ki}\| \, \|y_{kj}\|}. \tag{8}$$

IV. Hierarchical Palmprint Matching

To avoid the blind search for the best fit between the template pattern and all of the sample patterns stored in an image database, a guided search strategy is essential to reduce the computational burden. We propose here to consider multiple palmprint features and adopt different similarity measures in a hierarchical manner to facilitate a coarse-to-fine palmprint-matching scheme for personal identification. As stated in Section II, four palmprint features are extracted—Level-1 global geometry feature, Level-2 global texture energy, Level-3 "interest" lines, and Level-4 local directional texture energy.

We begin an initial search for the best similar palmprint matching subset with a Level-1 global geometry feature. Our similarity measurement method is based on the comparison of a key point distance with respect to its length of different samples. The candidates with small distance difference such as $D_1 < T_1$ will be considered for further coarse-level selection by global texture energy. The selected candidates will be subject to fine matching based on "interest" line and a comparison of local directional texture energy.



(a) (b) (c)

Fig. 4. Samples of different palmprint patterns with distinctive texture features. (a) Strong principal lines. (b) Less wrinkle. (c) Strong wrinkles.

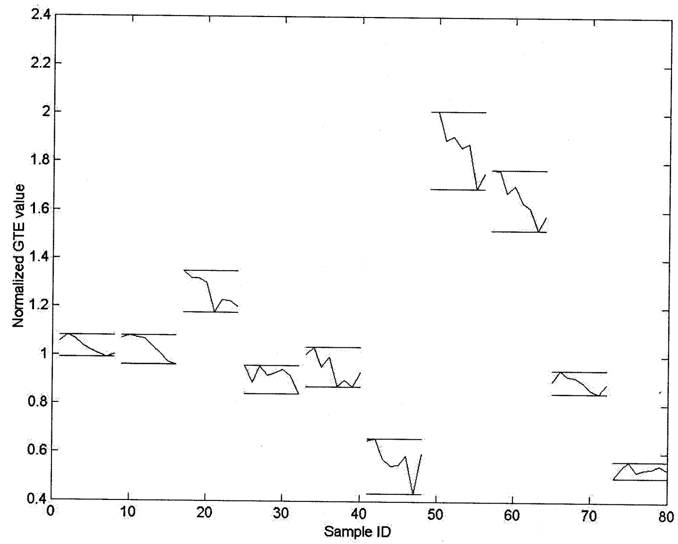
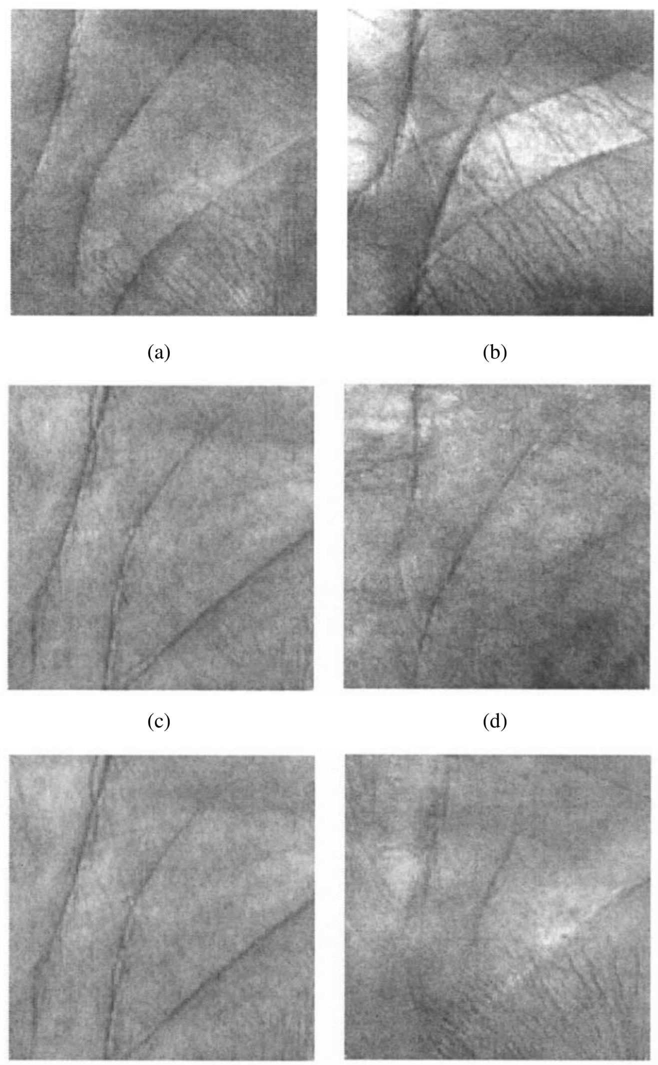


Fig. 5. Comparison of palmprint GTE distribution: interpalm dispersion versus inner palm convergence. This figure shows the distribution of GTE from 80 palmprint images from 10 palms.



(a) (b) (c) (d) (e) (f)

Fig. 6. Two sets of the similar palmprint patterns. (a), (c), (e) One set. (b), (d), (f) The second set.

A. Coarse-Level Similar Palmprint Pattern Classification

This classification task can be viewed as a decision- making process that allocates an input palmprint sample to those palmprint images with the similar measurements in the database. It is very important to select suitable features that can discriminate different palmprint categories. Therefore, the choice of the palmprint features must be as compact as possible and yet as discriminating as possible [11]. In other words, the feature measurements of palmprint samples with distinct texture primitives should exhibit large variances while the measurements of the similar patterns should possess very small diversity. Thus, such a global feature is characterized with a high convergence of inner palm similarities and good dispersion of interpalm discrimination. Fig. 4 shows three palmprint samples from the different individuals with distinctive texture features and Fig. 5 demonstrates the distribution of global palmprint texture energy measurements.

Although different individuals have different palmprint patterns, some of these patterns are so similar that it is very difficult, if not impossible, to classify them based on the global texture features only. Fig. 6 shows the samples of two sets of similar palmprint patterns. To tackle such a problem, we propose a dynamic selection scheme to obtain a small set of the most similar candidates in the database for further identification by image matching at a fine level. The idea behind this is to eliminate those candidates with a large difference in Level-1 global geometry features and generate a list of the very similar candidates with very small difference between their key point distances. The candidates in the list will undergo further selection in terms of Level-2 GTE. Only those samples that remain very close GTEs will be considered for fine-level matching.

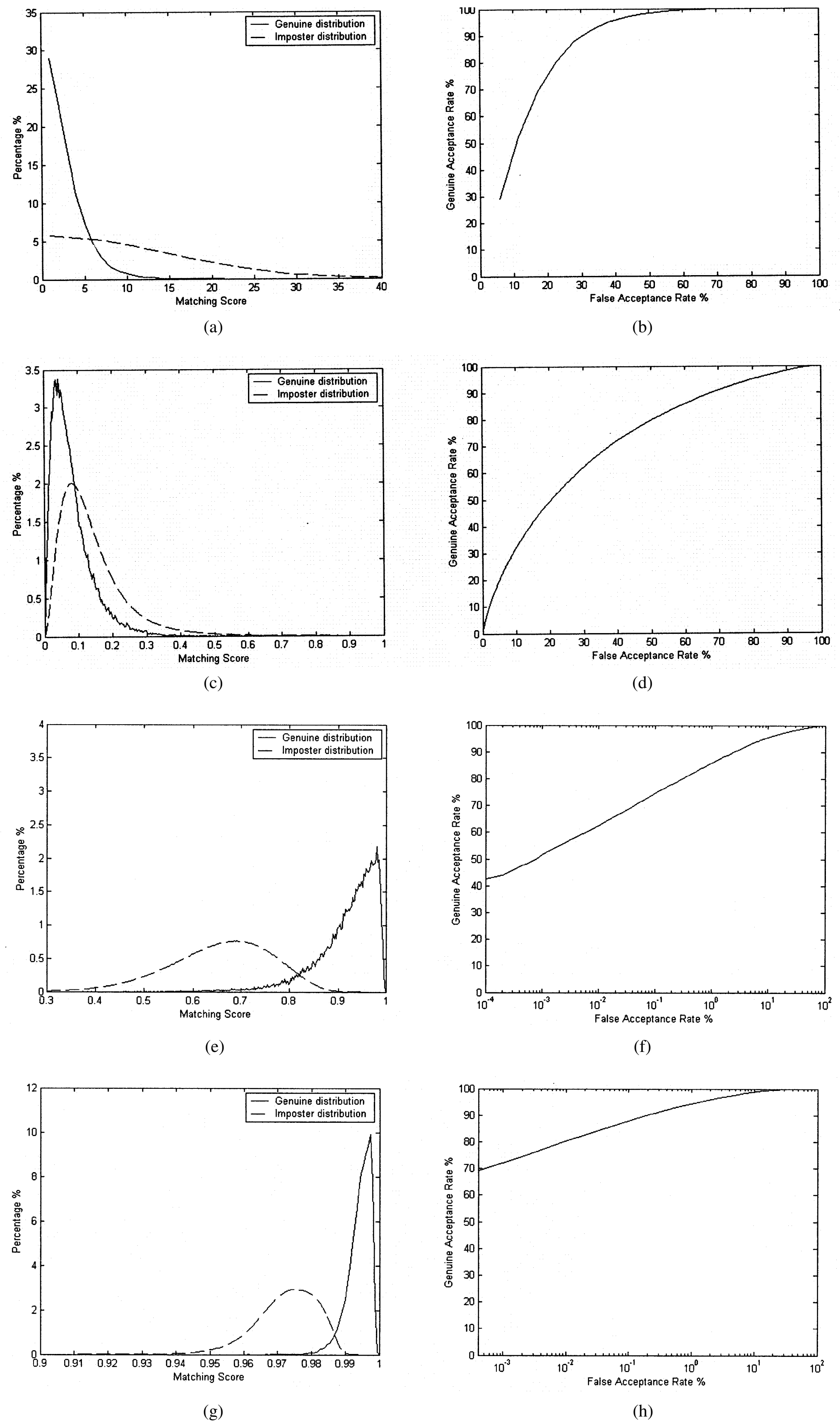


Fig. 7. Performance analysis for different multilevel features. (a), (c), (e), (g) Imposter and genuine distributions from Level-1 to Level-4 features, respectively. (b) (d), (f), (h) Their ROC curves.

B. Fine-Level Multistep Image Matching

The proposed fine matching algorithm starts with a simple distance measure for the "interest" line. If the matching score D_3 is larger than the threshold T_3, controlling the false acceptance and false rejection rates at this level, the palmprint images will go through the final fine matching in terms of their local directional texture energy. The final matching is based on the comparison of local feature vectors in terms of their local angular distance. The best match is the candidate with the least distance.

V. Experimental Results

The palmprint image samples used for the testing are 384×284 in size with a resolution of 75 dpi and 256-level grayscale. In our palmprint image database, 7752 palmprint images from 386 different palms are stored. The images are collected on the two occasions with an average time interval 69 days. The palmprint samples are collected from both female and male adults with an age range of 18–50. Some image samples are automatically removed during the preprocessing due to the inappropriate placement of a palm for data acquisition. The total number of images for testing is 5437 images. A special electronic sensor was used to obtain digitized images. Samples of such palmprint images are shown in Figs. 4 and 6. A series of experiments have been carried out to verify the high performance of the proposed algorithms.

The dynamic selection of image features is demonstrated by multilevel palmprint feature extraction for personal identification and verification (see our work on palmprint verification [6]). The experiment is carried out in two stages. In stage one, the global palmprint features are extracted at the coarse level and candidate samples are selected for further processing. In stage two, the regional palmprint features are detected and a hierarchical image matching is performed for the final retrieval.

The verification accuracies at different levels are shown in Fig. 7. Fig. 7(a), (c), (e), and (g) presents the probability distributions of genuine and impostor sampels at different feature levels. The corresponding receiver operating characteristic (ROC) curves, being a plot of genuine acceptance rate against false acceptance rate for all possible operating points are demonstrated in Fig. 7(b), (d), (f), and (h). Based on the ROC curves, we conclude that Level-4 local texture is the most effective feature. The Level-3 fuzzy "interest" lines are better than Level-2 global texture energy. The Level-1 geometry information only provides limited classification power. To evaluate the verification accuracy of our hierarchical palmprint system, we use three parameters, T_1, T_2, and T_3, which control the false acceptance and false rejection rates of the first three levels. Three sets of parameters, T_a, T_b, and T_c are tested. Table I lists these parameters and the corresponding ROC curves are illustrated in Fig. 8 for comparison. It is shown that Level-4 local texture feature performs better than our hierarchical palmprint approach when the false acceptance rate is large, such as 5%. However, a biometric system always operates under the condition of a low false acceptance rate. Apparently, our hierarchical palmprint approach and fine-texture method yield a similar performance when they keep low false acceptance rates. The false rejection and correct rejection rates of the first three levels are given in Table II.

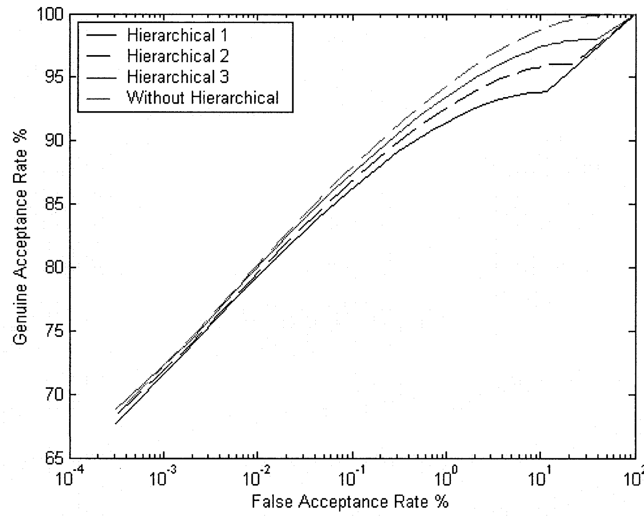


Fig. 8. ROC curves of our hierarchical approach with different parameters.

TABLE II
SELECTION OF PARAMETERS T_1, T_2, T_3 AND $T_a T_b, T_c$

	T_a	T_b	T_c
T_1	20	23	25
T_2	0.0194	0.0216	0.0250
T_3	0.764	0.73	0.68

TABLE III
COMPARISON OF SYSTEM PERFORMANCE

	False Rejection Rate	*Correct Rejection Rate*
T_a	6.13%	88.23%
T_b	3.89%	78.19%
T_c	1.98%	60.51%

The proposed system is implemented by using Visual C++ 6.0 on an embedded Intel Pentium III processor (500 MHz) PC. The execution time for the preprocessing, feature extraction, and matchings are shown in Table III. The total execution time is about 0.7 s, which is fast enough for real-time verification. Based on the computing time in Table III, we can estimate the computing time for searching a palmprint in a large database. Let P_1, P_2, and P_3 be the percentages of the total number of palmprint samples in the database removed by Level-1, Level-2, and Level-3 features, respectively. They depend on the thresholds T_1, T_2, and T_3. Also, let the size of the database be $\boldsymbol{D}$ and the computation time for preprocessing, feature extraction, Level-1 matching, Level-2 matching, Level-3 matching, and Level-4 matching be S_p, S_f, S_1, S_2, S_3, and S_4, respectively. Based on these variables, we obtain the following formulas for searching a palmprint image in a database with $\boldsymbol{D}$ images by sequential and hierarchical approaches.

Sequential approaches:

$$T_S = S_p + S_f + D \times S_4. \tag{9}$$

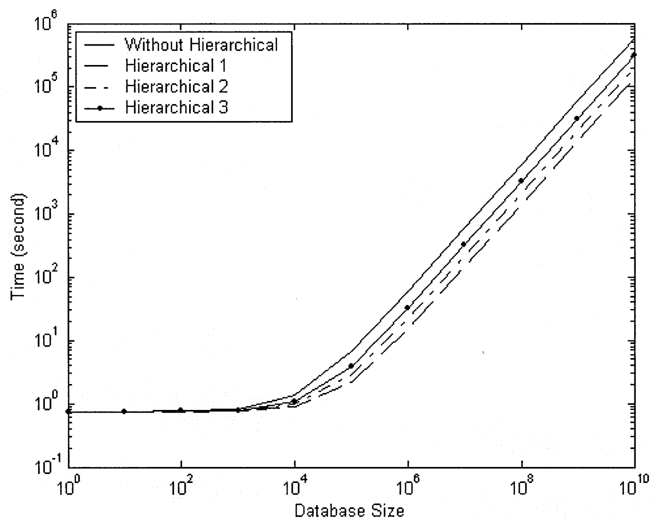


Fig. 9. Computation time for a large database.

TABLE IV
SYSTEM EXECUTION TIME

Operations	*Times (ms)*
Preprocessing	538
Feature Extraction	215
Level 1 matching	$4.7*10^{-5}$
Level 2 matching	$3.4*10^{-4}$
Level 3 matching	0.009
Level 4 matching	0.059

Hierarchical approaches:

$$T_H = S_p + S_f + D \times S_1 + D \times (1-P_1) \times S_2 + D \times (1-P_1-P_2) \times S_3 + D \times (1-P_1-P_2-P_3) \times S_4. \quad (10)$$

Based on these two equations and the computation time listed in Table IV, we can estimate the computation time for searching a palmprint in a large database with $\boldsymbol{D}$ images by sequential and hierarchical approaches when P_1, P_2, and P_3 are known. We use T_a, T_b, and T_c to obtain their corresponding P_1, P_2, and P_3 for Fig. 9, plotting the database size $\boldsymbol{D}$ against the computation time. According to Fig. 9, the execution time of our hierarchical coding scheme which includes preprocessing, feature extraction, and matching for a simulated large database with 10^5 palmprint samples is 2.8 s while the traditional sequential approach requires 6.7 s with an equal error rate of 4.5%. It is obvious that our hierarchical approach is much more effective than the sequential method when the database is large.

Compared with the current existing techniques for palmprint classification and identification, our approach integrates multiple palmprint features and adopts a flexible matching criterion for hierarchical matching. Table V summarizes the major features of our method with those of the other techniques [4] and [5] with respect to their testing database size, feature selection, matching criteria, search scheme, and accuracy. The experimental results presented above demonstrate the improvement and advantages of our approach. For future work, a dynamic indexing will be developed to handle the expansion of the palmprint database with robustness and flexibility.

TABLE V
COMPARISON OF DIFFERENT PALMPRINT MATCHING METHODS

	Feature Point Based Matching [5]	*Line Based Matching [4]*	*Hierarchical Matching (Proposed Approach)*
Database Size	30 samples	200 samples	7,752
Feature Extraction	Feature points (single feature)	Lines (single feature)	Texture, geometry, lines (multiple features)
Matching Criteria	Distance measurement (fixed measurement)	Euclidian distance (fixed measurement)	Energy difference, angular difference (flexible measurement)
Search Method	One-to-one comparison (sequential)	One-to-one comparison (sequential)	Guided search (hierarchical)
Accuracy	good	limited	good

VI. CONCLUSION

The palmprint is regarded as one of the most unique, reliable, and stable personal characteristics, and palmprint verification provides a powerful means to authenticate individuals for many security systems. Palmprint feature extraction and matching are two key issues in palmprint identification and verification. In contrast to the traditional techniques, we propose a hierarchical palmprint coding scheme to integrate multiple palmprint features for guided palmprint matching. The combination of four levels of features, including Level-1 global geometry feature, Level-2 global texture energy, Level-3 fuzzy "interest" line, and Level-4 local texture feature possesses a large variance between different classes while maintaining a high compactness within the class. The coarse-level classification by Level-1, Level-2, and Level-3 features is effective and essential to reduce the number of samples significantly for further processing at the fine level. The Level-4 local texture leads to a fast search for the best match. The experimental results provide the basis for the further development of a fully automated palmprint-based security system with high performance in terms of effectiveness, accuracy, robustness, and efficiency.

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