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Hierarchical palmprint identification via multiple feature extraction

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Abstract

Biometric computing offers an effective approach to identify personal identity by using individual's unique, reliable and stable physical or behavioral characteristics. This paper describes a new method to authenticate individuals based on palmprint identification and verification. Firstly, a comparative study of palmprint feature extraction is presented. The concepts of texture feature and interesting points are introduced to define palmprint features. A texture-based dynamic selection scheme is proposed to facilitate the fast search for the best matching of the sample in the database in a hierarchical fashion. The global texture energy, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination, is used to guide the dynamic selection of a small set of similar candidates from the database at coarse level for further processing. An interesting point based image matching is performed on the selected similar patterns at fine level for the final confirmation. The experimental results demonstrate the effectiveness and accuracy of the proposed method. © 2002 Pattern Recognition Society. Published by Elsevier Science Ltd. All rights reserved.

K : Biometric computing; Palmprint classification; Feature extraction; Texture features; Interesting points; Image matching

1. Introduction

There has been a high demand for personal identification and verification for security reasons. Biometrics is concerned with the unique, reliable and stable personal physiological characteristics such as fingerprints, palmprint, facial features, iris pattern, retina and hand geometry, or some aspect of behavior, like speech and handwriting [1,2]. However, how to develop an automated system for identification and verification of a large collection of image data with accuracy and reliability remains a challenging task. With respect to the given performance specification in terms of cost, speed and accuracy, in general, the design of an automated biometric system involves data acquisition, representation of input data, feature extraction, feature matching and organization of a number of input samples. Research on the issue of fingerprint identification and speech recognition has drawn considerable attention over the last 25 years. Recently, issues on face recognition and iris-based verification have been studied extensively, which results in successful development of biometric systems for commercial applications. However, limited work has been reported on palmprint identification and verification.

Palm is the inner surface of a hand between the wrist and the fingers. Palmprint is referred to principal lines, wrinkles and ridges on the palm. Like fingerprints, palmprint has been used as a powerful means in law

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enforcement for criminal identification because of its stability and uniqueness. The rationale to choose hand features as a base for identity verification is originated by its user friendliness, environment flexibility and discriminating ability. Normally, people do not feel uneasy to have their hand images and prints taken for testing. More importantly, these hand features are stable and uniquely represent each individual's identity. Consequently, it is essential to develop an effective approach to automatic palmprint identification and verification for security reasons.

A key issue is palmprint identification involves the search for the best matching of the test sample from input and the templates in the palmprint database. The selection of features and similarity measures are two fundamental problems to be solved. 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 [3] and have been successfully used for verification. In addition, there are many other features associated with a palmprint [4], such as geometry features, wrinkle features, delta point features and minutiae features.

It is noted that all of these features are concerned with the local attributes based on points or line segments. The lack of global feature representation resulted in the high computation demand for matching which measures the degree of similarity between two sample sets. Although a line feature matching method is reported to be powerful for easy computation, tolerance to noise and high accuracy in palmprint verification by using both line features and datum points [5,6], has the following limitations: (1) for a given test sample, the line matching process was applied to all of the template sets to search for the best matching. For a large collection of templates, the computation burden is high; (2) for an occluded palmprint sample, the principal lines and endpoints might be missing, which would cause the consequent failure of the line matching algorithm. In addition, the traditional exhaustive comparison methods are very time consuming. For a large palmprint database, such a one-by-one comparison method can hardly meet the requirements for real-time on-line identification.

Unlike the existing technique, we propose a dynamic selection scheme to facilitate the coarse-to-fine palmprint pattern matching by combining global and local palmprint features in a hierarchical fashion. The global texture energy (GTE) is introduced to represent the global palmprint feature, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination. Such a global feature is used to guide the dynamic selection of a small set of similar candidates from the database at a coarse level for further matching. Interesting points are used as local feature points and the final identification at fine level is carried out by interesting point based image matching.

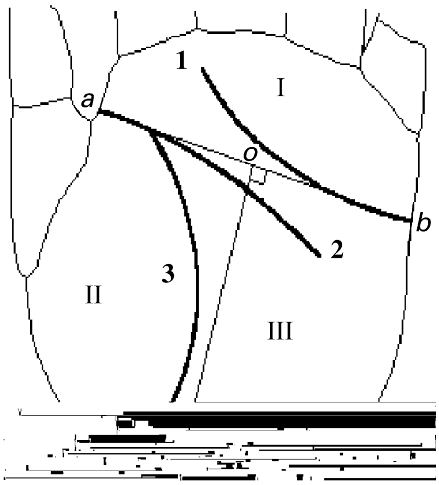


Fig. 1. The layout of a palmprint: regions: I—finger-root region, II—inside region, and III—outside region; principal lines: 1—heart line, 2—head line, and 3—life line; datum points: a, b—endpoints, o—midpoint.

This paper is organized as follows: Section 2 presents an overview of the detection of palmprint features. The texture based dynamic selection scheme is introduced in Section 3 and the interesting point based image matching at fine level is described in Section 4. Section 5 summarizes the experimental results and Section 6 highlights the conclusions.

2. Palmprint feature extraction—an overview

2.1. T

Feature extraction plays an important role in image identification and verification. There are many features exhibited in a palm. There are three principal lines caused by flexing hand and wrist in the palm, which are named as heart line, head line and life line, respectively [3]. Fig. 1 shows the layout of a palm, where a palm is divided into three regions, namely finger-root region I, inside region II and outside region III. The three marked curves, 1, 2 and 3 represent the three principal lines (heart line, head line and life line), respectively. The two endpoints, a and b, are determined by the intersections of life line (curve 3) and heart line (curve 1) on both sides of a palm. Due to the stability of the principal lines, the locations of endpoints and their midpoint o in a palm remain unchanged with respect to rotation of the hand and the change of time. Therefore, these feature lines are regarded as reliable and stable features to distinguish a person from others.

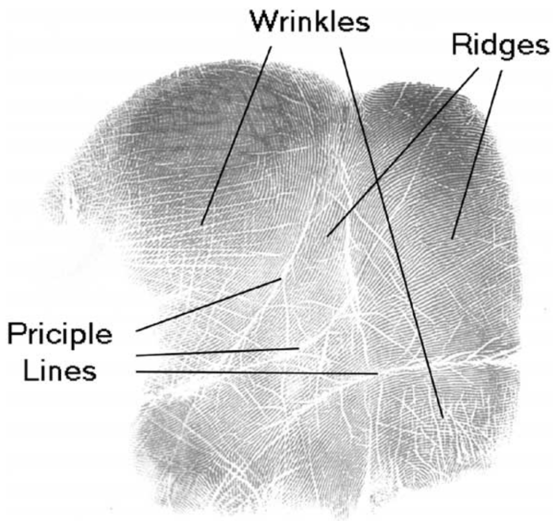


Fig. 2. The line patterns of a palmprint.

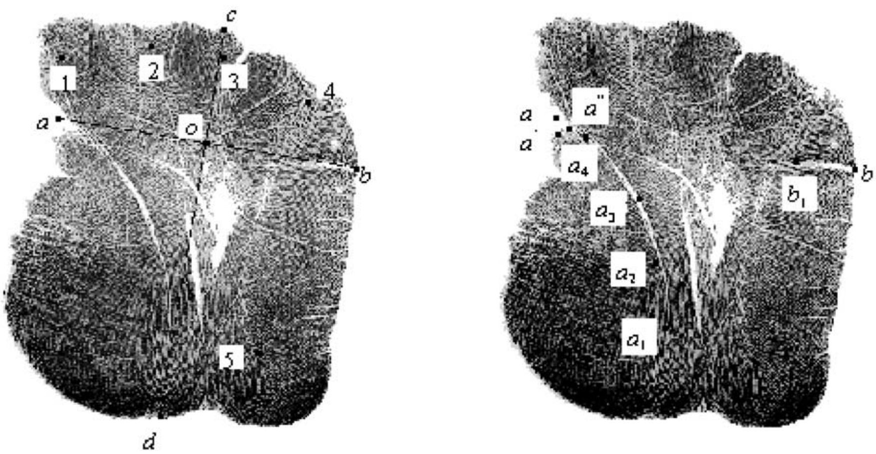
In addition to the principal lines and datum points (two endpoints and a midpoint) as described above, many other features such as wrinkles and ridges are associated with a palmprint. The following lists these features and the relevant line patterns are illustrated in Fig. 2:

- *G*: Width, length and area are the geometry features in accordance to a palm's shape.
- *P*: Very important physiological characteristics to distinguish different individuals because of their stability and uniqueness.
- : Thin and irregular lines and curves different from principal lines.
- *D*: The center of a delta-like region in a palmprint, which is normally located in finger-root region and outside region.
- *M*: Significant feature measurement of ridges existing in a palm.

2.2. *P*

It is essential to locate the endpoints of each principal line for some palmprint identification and verification systems. Some researchers proposed to apply the directional projection algorithm for the detection of principal lines and their endpoints, and the following highlights the major steps of this technique (more details are given in Ref. [6]). Fig. 3 presents the distribution of the relevant feature points and lines. Fig. 3(a) illustrates the geometry features and delta point features of a palmprint, where the line segment *c–d* is the perpendicular bisector of the line segment *a–b* and points 1–5 are delta points. Fig. 3(b) shows the track of datum point determined by the directional projection algorithm.

- *H*: A pixel with suitable offsets to the edges of outside and topside of a palm is considered in a palmprint. All pixels belonging to heart line are located by the horizontal projection algorithm, e.g. point b_1 in Fig. 3.
- *L*: Another subimage close to the wrist is processed by the vertical projection algorithm and point a_1 on the life line is determined.
- *E*: The location of endpoint b can be determined based on the peculiarities of heart line by the horizontal projection algorithm. A pixel which is situated at the outside edge but with the same



(a) (b)

Fig. 3. The distribution of palmprint features; (a) geometry and delta point features, (b) track of datum points.

characteristics of the point set b_1 is considered as the endpoint b.

- *E* : The determination of the endpoint a is more complicated, which is summarized as below:
  - Point a' is defined as the intersection between the inside edge of a palm and the straight line connecting endpoint b and b_1.
  - Pixels a_2 and a_3, which trisect the vertical distance between a_1 and point a', are obtained in a certain order along the life line by the vertical projection algorithm.
  - Pixel a_4 belonging to the life line is determined.
  - Point a'' is detected by the straight line, which flows out from pixel a_4 and intersects the inside edge of a palm at 22.5°.
  - Endpoint a is estimated in the subimage with point a'' by the horizontal projection algorithm.
- *M* : Midpoint o is determined based on the endpoints a and b, which is defined as the center point of the line connections between a and b.

2.3. *L*

Line features include both curves and straight lines. So far there have been many methods proposed to detect lines [7,8]. However, most of these algorithms are not suitable for palmprint images because palmprint consists of lots of ridges and fine wrinkles with various directions, lengths and thicknesses. The method of pyramid edge detection utilized stack filter to detect strip-like line segments in an image and was useful to extract principal lines of palmprint. Unfortunately, such a method failed to detect thin line segments in a palmprint image. Although some non-linear filters can be used to detect thin vertical lines and the extension of these filters can be applied to extract both thick and horizontal lines Ref. [6], these filters were not able to identify other line segments such as wrinkles and ridges with diversity of orientations. As detailed in Ref. [6], an improvement of this approach can be achieved by detecting short line segments at each individual orientation repeatedly and combining them with a post-process algorithm by line linking and thinning at the final stage. The following lists the main steps of the improved algorithm:

- Determine vertical line segments by using five vertical edge detectors given in Ref. [9].
- Apply a post-processing algorithm to thin the detected line segments and remove the segments which are shorter and non-vertical.
- Apply the similar procedure to detect the line segments at other three orientations—horizontal, 45° and −45°.
- Combine all of the line segments in four directions.
- Apply the post-processing algorithm to eliminate the overlapped line segments.

The representation of each line segment is determined by a series of endpoints [10], which is described as below:

For an $M \times N$ palmprint image I, let $I(i,j)$ represent a pixel located in a palmprint image I. The datum points can be derived as (i_a, j_a), (i_b, j_b) and (i_o, j_o), and an only two-dimensional right angle x–y coordinate system is established by them. The mapping between the i–j coordinate system and x–y coordinate system is given by

$$x = \cos(\phi - \theta)\sqrt{(i-i_o)^2 + (j-j_o)^2}, \tag{1}$$

$$y = \sin(\phi - \theta)\sqrt{(i-i_o)^2 + (j-j_o)^2}, \tag{2}$$

where $\phi = \tan^{-1}[(j - j_0)/(i - i_0)]$ and $\theta = \tan^{-1}[(j_a - j_b)/(i_a - i_b)]$. In the x–y two-dimensional right angle coordinate system, the line segments can be described by their endpoints: $(x_1(i), y_1(i))$, $(x_2(i), y_2(i))$, $i = 1, 2, \ldots, N$, where N is the number of line segments. In general, each line segment can be represented by three parameters—slope, intercept and angle of inclination, which can be determined by the following equations:

$$(i) = (y_2(i) - y_1(i))/(x_2(i) - x_1(i)), \tag{3}$$

$$(i) = y_1(i) - x_1(i)\,(i), \tag{4}$$

$$a(i) = \tan^{-1}((i)). \tag{5}$$

3. Coarse-level classification—a texture-based dynamic selection scheme

Palmprint consists of a large amount of thin and short line segments represented in forms of wrinkles and ridges. Such a pattern can be well characterized by texture. This section presents a texture-based dynamic selection scheme for palmprint identification at coarse level. The global texture energy is introduced to define the global palmprint features. The flow chart of the proposed hierarchical approach is shown in Fig. 4.

3.1. *T*

Texture provides a high-order description of the local image content. The analysis of texture requires the identification of those texture attributes which can be used for segmentation, discrimination, recognition, or shape computation. Historically, structural and statistical approaches have been adopted for texture feature extraction [11–13]. The structural approach assumes that the texture is characterized by some primitives following a placement rule. In this view, in order to describe a texture one needs to describe both the primitives and the placement rule. The description should be sufficiently flexible so that a class of equivalent textures can be generated by using similar primitives in similar relationships. Although

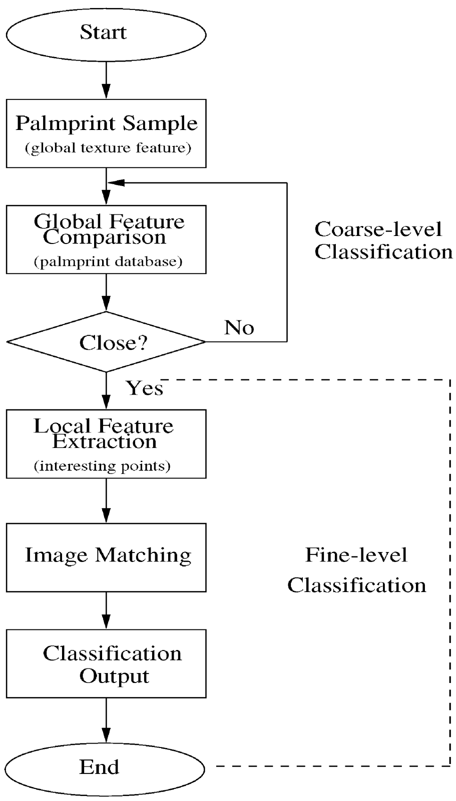


Fig. 4. The flow chart of hierarchical palmprint classification.

there has been reported progress in this area [11], the approach is restricted by the complications encountered in determining the primitives and the placement rules that operate on these primitives. Therefore, textures suitable for structural analysis have been confined to quite regular textures rather than more natural textures in practice.

In the statistical approach, texture is regarded as a sample from a probability distribution on the image space and defined by a stochastic model or characterized by a set of statistical features. The most common features used in practice are based on the tonal properties and the pattern properties [13]. These are measured from first- and second-order statistics and have been used as discriminators between textures. Though these features have been widely used in the classification and segmentation of textured images, they cannot cope with changes in rotation and scale.

The special interest of our proposed method for palmprint identification is to determine a feature, the texture energy computed using Laws' convolution masks [14] to directly function as a classifier. Such a statistical approach pioneered by Laws is notable for its computational simplicity. He introduced the notion of a single parameter, the local "texture energy" (E) evaluated at each pixel location (i,j) in the convolved image over a

1	-4	6	-4	1		-1	0	2	0	-1
-4	16	-24	16	-4		-2	0	4	0	-2
6	-24	36	-24	6		0	0	0	0	0
-4	16	-24	16	-4		2	0	-4	0	2
1	-4	6	-4	1		1	0	-2	0	1
		R5R5						E5S5		
-1	0	2	0	-1		-1	-4	-6	-4	-1
-4	0	8	0	-4		-2	-8	-12	-8	-2
-6	0	12	0	-6		0	0	0	0	0
-4	0	8	0	-4		2	8	12	8	2
-1	0	2	0	-1		1	4	6	4	1
		L5S5						E5L5		

Fig. 5. Laws' four most powerful masks.

large window size 15×15 as the measure of texture features in the spatial domain. Basically, his approach to texture characterization consists of two steps. The first step involves convolving the whole image by a zero-sum mask. The 2D convolution of the image $I(i,j)$ and mask $A(i,j)$ with size $2a+1$ by $2a+1$ is given by the relation

$$F(i,j)=A(i,j)*I(i,j) \tag{6}$$

$$=\sum_{k=-a}^{a}\sum_{l=-a}^{a}A(k,l)I(i+k,j+l) \tag{7}$$

for $i=0,1,\ldots,N-1$ and $j=0,1,\ldots,N-1$, where $*$ denotes 2D convolution. After convolving, the (signed) image $F(i,j)$ has mean zero over a significantly large region of uniform texture. In most cases, the size of the mask $A(i,j)$ is 5×5. The convolution masks are intended to be sensitive to visual structure such as edges, ripples and spots. Fig. 5 shows four Laws' most powerful masks with the best discrimination in his test.

The second step involves determining the difference between the convolved image $F(i,j)$ and the real image $I(i,j)$. For a zero-sum mask, the local texture measures are determined as statistical variances of the filtered image by computing the squared signal values in the filtered image. From the computational efficiency point of view, the sample mean deviation of the filtered image, called *ABSAVE*, is introduced as the most useful statistics by Laws. The *ABSAVE* $E(i,j)$ is defined as the mean deviation within a $2n+1$ by $2n+1$ window at point (i,j) and is given by

$$E(i,j)=\frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n}|F(k,l)-M(i,j)|, \tag{8}$$

where the mean $M(i,j)$ is given by

$$M(i,j)=\frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n}F(k,l). \tag{9}$$

The mean is zero over a large window, therefore, the *ABSAVE* $E(i,j)$ becomes

$$E(i,j)=\frac{1}{(2n+1)^2}\sum_{k=i-n}^{i+n}\sum_{l=j-n}^{j+n}|F(k,l)|, \tag{10}$$

which Laws called the texture energy measure, which is used in his test as the texture feature.

Although individually Laws' masks can be used in isolation as a texture classifier, they are subject to a number of limitations due to the lack of robustness with respect to the fixed masks. One feasible approach to improve the performance is to replace the fixed masks with adaptive masks "tuned" to be robust to the classification tasks. This process involves the determination of texture class 'tuned' mask which when applied to a textured image smooth out regions of common texture so that the variance of the convolved image, typically over a 15×15 local window, is (a) reasonably constant over all locations within a region of uniform texture, so that such a region is essentially converted into a region of uniform grayscale, and (b) markedly different in value between regions of different textures. The approach reported here is an extension of the work of the Benke et al. [15] and our previous work [16], Although Benke–Skinner introduced and applied the adaptive mask concept [15], in our previous work, we have further revised this methodology which leads to a satisfactory segmentation of 15 distinct textures using a single mask [16]. For the purpose of fast selection of a small set of similar palmprint patterns from the database, we modify this approach by the use of 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. Fig. 6 lists four of our modified 'tuned' masks. In our approach the local variance after convolution is well approximated as the sum of squared values of convolved image within the test window, which is expressed as below:

$$TE(i,j)=\frac{\sum_{W_x}\sum_{W_y}(I*A)^2_{rs}}{P^2W_xW_y}, \tag{11}$$

where rs is the sum over all pixels within a square window W of size W_x*W_y centered on the pixel at i, j, A 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:

- insensitive to noise,
- insensitive to shift changes,

-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

Horizontal Line

-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

Vertical Line

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

45^0 Line

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

-45^0 Line

Fig. 6. The four 'tuned' masks for global palmprint texture feature extraction.

- easy to compute,
- high convergence within the group and good dispersion between groups.

3.2. S

It is very important to group similar palmprint patterns from the given palmprint database for further identification and verification. This grouping task can be viewed as a decision-making process which allocates an input palmprint sample to those categories with similar measurements in the database. In traditional classification problems, various ad hoc means are used to derive feature sets, and this process is clearly demarcated as the feature stage [17]. What is involved in the general classification stage is the abstraction of features of the classes of entities being considered. For the classification to be useful, it must be reliable and computationally attractive. This means the choice of the textural features or the models must be as compact as possible, and yet as discriminating as possible [16]. In other words, the texture energy measurements of palmprint samples with distinct texture primitives should exhibit large variances while the measurements of the similar patterns should possess very small diversity. Therefore, such a global feature is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination. Fig. 7 shows four palmprint samples from four different individuals with distinctive texture features and Fig. 8 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

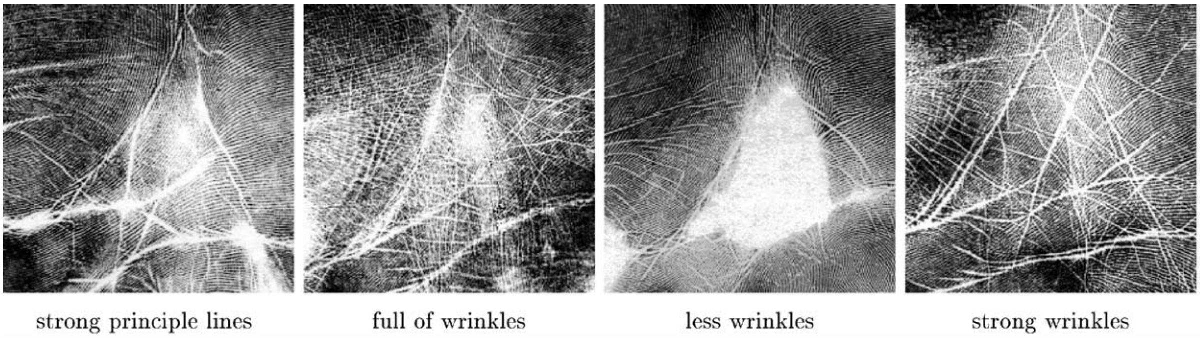


Fig. 7. Samples of different palmprint patterns with distinctive texture features.

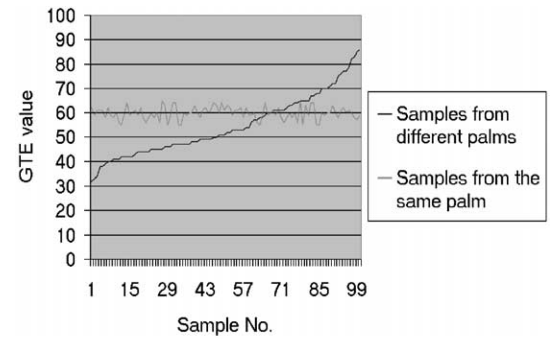


Fig. 8. The comparison of palmprint GTE distribution: inter-palm dispersion vs. inner-palm convergence.

very difficult, if not impossible, to classify them based on the global texture features only. Fig. 9 shows the samples of similar palmprint patterns from different groups. To tackle such a problem, we propose a dynamic selection scheme to group a small set of the most similar candidates in the database for further identification by image matching at fine level. The idea behind this is to eliminate those candidates with large GTE differences and generate a list of very similar candidates with very close GTEs. The following summarizes the main steps for implementation:

S 1: Convolve the sample palmprint image I_{sample} with four tuned masks A_i, $i=1,2,3,4$ and obtain the corresponding global texture energy $GTE_{sample}(i)$, $i=1,2,3,4$.

S 2: Compare the sample with the candidate in the database in terms of GTE and calculate their difference d, where d is given by

$$d=\sum_{i=1}^{4}|GTE_{sample}(i)-GTE_{candidate}(i)|, \quad i=1,2,3,4. \tag{12}$$

S 3: If d is smaller than the pre-defined threshold value, this candidate is added to the list for further matching.

S 4: Go to Step 2 and repeat the same procedure until all of the candidates are considered.

S 5: Provide the final list of candidates to guide the search for the best matching at fine level.

4. Fine-level identification by image matching

A guided image matching scheme is developed to determine the degree of similarities between the template pattern and every possible sample pattern selected throughout the texture classification procedure which is detailed in Section 3. Unlike the traditional image matching methods which are based on the detection of edge points, we proposed to detect interesting points in textured images to achieve high performance. To avoid the blind searching for the best fit between the given samples, a guided search strategy is essential to reduce computation burden. We applied a dynamic selection of interesting points to search for the best matching in a hierarchical structure.

4.1. *F*

Most matching algorithms are based on binary images to identify the interested object(s). Therefore, the original image, either grayscale or color images, should be converted into a binary image. Traditional methods that convert an original image into a binary image rely on edge detection. Despite edge detection being successfully used for many years mostly due to its simplicity, it has some problems which prevent it from being applied on a real-time image matching scheme, such as the following:

- It is susceptible to noise in the image.
- Feature points may not be well distributed.

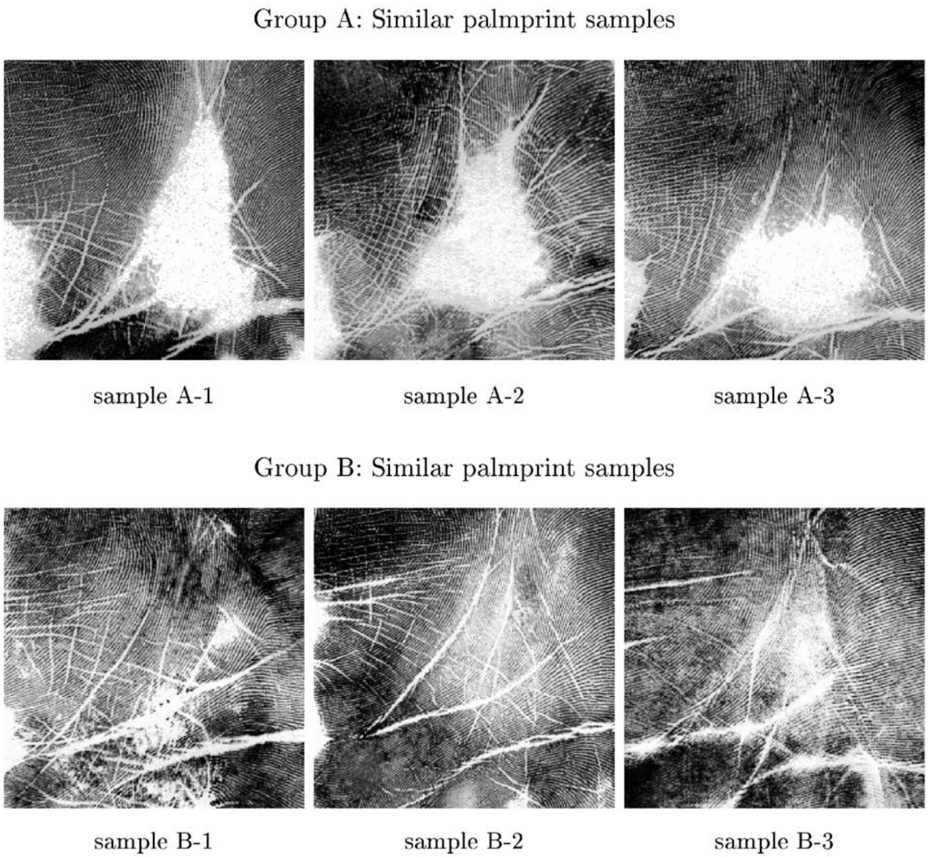


Fig. 9. Samples of similar palmprint patterns from different groups.

- It produces a large number of feature points for an image, many of the points however are redundant.

The redundant information limits the possible speed up in subsequent operations, since the time consumption of a matching algorithm, such as Borgefors' hierarchical chamfer matching [18], and the Hausdorff distance [19], is directly related to the number of feature points used in matching. The more the number of points are, the more the time is required. Therefore, it is desirable to use an algorithm which only extracts those feature points that

- Are representative and distinctive, such as corners, and without redundancy.
- Are robust to "noise".

This has prompted the research in Ref. [23] to use interesting point detectors rather than edge detectors to extract feature points from a given image for matching. According to Haralick and Shapiro [20], ideally, the interesting, points should satisfy the conditions of (1) distinctness, (2) invariance, (3) stability, (4) uniqueness, and (5) interpretability. A number of interesting point operators have been developed (see Ref. [20] for a survey)—these include, e.g. Plessey operator [22] and Moravec operator [21]. The detection of interesting points is based on the measure of how interesting a point is. *I* here has its own special meanings depending on different applications. In order to reduce the number of points during matching while still retaining the feature of the original image, such an interesting point should be distinguishable from immediate neighbors, which exclude points sitting on the same edge. In general, the operation of the existing interesting point operators can be summarized as a three-step procedure which is clearly highlighted in Ref. [20].

- *S*: The selection is based on the average gradient magnitude within a window of pre-specified size. Search for local maxima, while suppressing windows on edges, guarantees (local) distinctness. The measure used is also invariant with respect to rotation.
- *C* -: The classification distinguishes between types of singular points such as corners, rings,

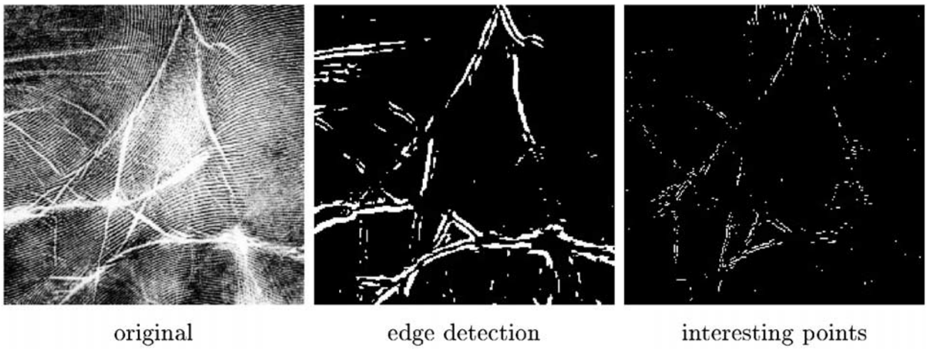


Fig. 10. The comparison of palmprint feature point detection: edge points vs. interesting points.

spirals, and even isotropic texture based on a statistical test.

- *E* : The estimation is precise for corners and for the centers of circular symmetric features or spirals.

Our previous research [23] indicates that the Plessey operator is superior to the Moravec operator according to the criteria set above. Hence, the Plessey operator is chosen as the interesting point detector in this work. Fig. 10 shows the comparison of edge points and interesting points in representing the original image. Fig. 10(a) is a histogram equalized image of size 232 × 232 ranging from 0 to 255 in grayscale, Fig. 10(b) shows edge points detected by Prewitt operator and Fig. 10(c) shows interesting points detected by Plessey operator.

4.2. *D*

Given two images, a matching algorithm determines the location of the template image on the target image and places a value on their similarity at this point. The value determines the degree of similarity. Based on the Huttenlocker et al. work [19], we are able to use Hausdorff distance algorithm to search for portions, or partial hidden objects. This feature also allows us to partition the target image into a number of subimages, and then carry out the matching process simultaneously on these subimages in order to accelerate the process. Instead of using edge points, we use interesting points as a basis for computing the Hausdorff distance. It aims to reduce the computation required for a reliable match. Also, by using a matching scheme such as the Hausdorff distance we are able to find partially hidden objects while keeping the amount of computation minimal.

The hierarchical guided matching scheme was first introduced by Borgefors [18] in order to reduce the computation cost required to match two images. We extended it by using interesting points rather than edge points in a similar fashion, i.e., an interesting point pyramid is created and the matching starts from the lowest resolution and the results of this match guides the search on the possible area of higher resolutions. We further extend it by using the Hausdorff distance as a measure of similarity instead of Chamfer matching. The advantage of using Hausdorff distance in a matching process relies on the capability of searching for portions of images, which allows us to partition the target image into a number of subimages and simultaneously match the template image on these subimages.

The Hausdorff distance is a non-linear operator which measures the mismatch of the two sets. In other words, such a distance determines the degree of the mismatch between a model and an object by measuring the distance of the point of a model that is farthest from any point of an object and vice versa. Therefore, it can be used for object recognition by comparing two images which are superimposed on one another. The key points regarding this technique are summarized as below.

Given two finite point sets $A=\{a_1,\ldots,a_m\}$ and $B=\{b_1,\ldots,b_n\}$, the Hausdorff distance D_H between these two sets is defined as

$$D_H = \max(d_{AB}, d_{BA}), \tag{13}$$

where d_{AB} is the distance from set A to set B expressed as

$$d_{AB} = \max_{a_i \in A}(d_{a_iB}), \tag{14}$$

while d_{a_iB} is the distance from point a_i to set B given by

$$d_{a_iB} = \min_{b_j \in B}(d_{a_ib_j}). \tag{15}$$

Obviously, the Hausdorff distance D_H is the maximum of d_{AB} and d_{BA} which measures the degree of mismatch between two sets A and B.

In general, image data are derived from a master device and represented by grid points as pixels. For a feature detected image, the characteristic function of sets A and B can be represented by a binary array $A[i,j]$ and $B[i,j]$, respectively, where the (i,j)th entry in the array is non-zero for the corresponding feature pixel in the given image. Therefore, distance arrays $D[i,j]$ and $D'[i,j]$ are used to specify for each pixel location (i,j) the distance to the nearest non-zero pixel of A or B, respectively, where $D[i,j]$ denotes the distance transform of A and $D'[i,j]$ denotes the distance transform of B. Consequently, the Hausdorff distance as a function of translation can be determined by computing the pointwise maximum of all the translated D and D' array in the form of

$$F[i,j] = \max\left(\max_a, \max_b\right), \tag{16}$$

where

$$\max_a = \max_a D[a_i - i, a_j - j], \tag{17}$$

$$\max_b = \max_b D'[b_i + i, b_j + j]. \tag{18}$$

4.3. A ...

The hierarchical image matching scheme was first proposed by Borgefors [18] in order to reduce the computation required to match two images. The section details our extension of this scheme by introducing a guided search strategy to avoid the blind searching for the best fit between the given patterns. In order to avoid the blind searching for the best fit between the given patterns, a guided search strategy is essential to reduce computation burden. Our extension of the hierarchical image matching scheme (HIMS) was based on a guided searching algorithm that searches first at the low level, coarse grained images, to the high level, fine grained images. To do this we needed to obtain a Hausdorff distance approximation for each possible window combination of the template and target image at the lowest resolution. Those that returned Hausdorff distance approximation equal to the lowest Hausdorff distance for those images were investigated at the higher resolution. The following summarizes the key steps involved in a HIMS algorithm:

```
create image pyramid
for all combinations of windows
at lowest level
        get value of match for this combination
        if low value add to lowest list
end-for

for each remaining level
        remove area from lowest list
        get match value for this area
        if low value add to lowest list
end-for
```

5. Experimental results

The palmprint image samples used for testing are 232×232 size with the resolution of 125 dpi and 256 grayscales. In our palmprint image database, a total of 200 images from 100 individuals are stored. These palmprint samples are collected from both female and male adults with the age range from 18 to 50. Although there are some electronic sensors available to get digitized palmprint images on-line, such devices are more application dependent and sensitive to noise and unexpected disturbance such as the movement of hands, lighting, settings, etc. In our tests reported in this paper, the palmprints are printed on paper by coloring palms with washable ink, which is done in the similar way as is described in Ref. [24]. The palmprint images marked on paper are digitized by using a scanner at 125 dpi with 256 grayscales. Samples of such palmprint images are shown in Fig. 7. A series of experiments have been carried out to verify the high performance of the proposed algorithms.

Laws' texture energy concept is extended by the use of four 'turned' masks to extract the global palmprint texture features sensitive to the horizontal lines, vertical lines, 45° lines and -45° lines. Such a global texture energy measurement is used to guide the fast selection of the small set of the most similar palmprint patterns for fine matching. The effectiveness of this proposed hierarchical search guided by global palmprint texture feature selection scheme is summarized in Table 1, which is further demonstrated in Fig. 11. For a given test palmprint sample, on the average, 91% of the candidates in the database are classified as distinctive from the input data and filtered out at the coarse classification stage. In the worst case, the elimination rate of the candidates is 72% and only 28% of the samples remained fro further identification at fine level by image matching.

An interesting point based image matching is performed for the final confirmation at fine level by the proposed hierarchical structure. The average accuracy rate is 95%. Since the majority samples have been filtered out by the coarse classification, the execution speed of fine identification has been increased significantly.

Comparing 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 1
The performance summary of the selected scheme: elimination rate and candidate percentage

	Best (%)	Worst (%)	Average (%)
Elimination	99	72	91
Candidate	1	28	9

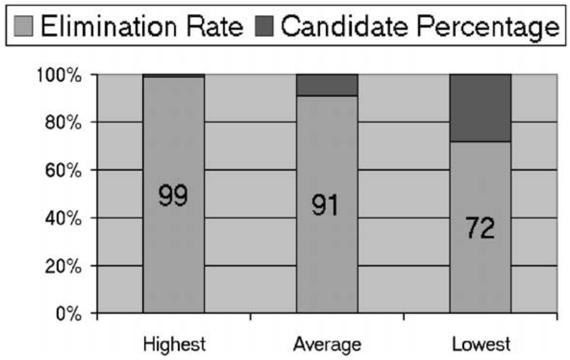


Fig. 11. The performance of the selection scheme: elimination rate vs. candidate percentage.

Table 2 summarizes the major features of our method and the other techniques [4,6] with respect to database size, feature selection, matching criteria, search scheme and accuracy. It should be pointed out that no numerical estimations are presented because such data is not available in the papers reviewed.

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.

6. Conclusions

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 proposed a dynamic selection scheme by introducing global texture feature measurement and the detection of local interesting points. Our comparative study of palmprint feature extraction shows that palmprint patterns can be well described by textures, and the texture energy measurement possesses a large variance between different classes while retaining high compactness within the class. The coarse-level classification by global texture features is effective and essential to reduce the number of samples for further processing at fine level. The guided searching for the best matching based on interesting points improves the system efficiency further. The use of Hausdorff distance as the matching criterion can handle the partial occluded palmprint patterns, which makes our system more robust. The experimental results provide the basis for the further development of a fully automated palmprint-based security system with a high performance in terms of effectiveness, accuracy, robustness and efficiency.

7. Summary

There has been a high demand for personal identification and verification for security reasons. Biometric computing offers an effective approach to identify personal identity by using individual's unique, reliable and stable physical or behavioral characteristics such as fingerprints, palmprint, facial features, iris pattern, retina, hand geometry, speech and handwriting. Research on the issue of fingerprint identification and speech recognition has drawn considerable attention over the last 25 years. Recently, issues on face recognition and iris-based verification have been studied extensively, which results in successful development of biometric systems for commercial applications. However, how to develop an effective authentication system for a large collection of

Table 2
Comparison of different palmprint matching methods

	Feature point based matching [4]	Line based matching [6]	Hierarchical matching (proposed approach)
Database size	100 samples	200 samples	200 samples
Feature extraction	Feature points (single feature extraction)	Lines (single feature)	Texture and feature points (multiple features)
Matching criteria	Euclidian distance (fixed measurement)	Euclidian distance (fixed measurement)	Energy difference and Hausdorff distance (flexible measurement)
Search method	One-to-one comparison (sequential)	One-to-one comparison (sequential)	Guided search (hierarchical)
Accuracy	Limited	Limited	Good

personal data with accuracy and reliability remains a challenging task. With respect to the given performance specification in terms of cost, speed and accuracy, in general, the design of an automated biometric system involves data acquisition, representation of input data, feature extraction, feature matching and organization of a number of input samples.

This paper describes a new approach to palmprint identification and verification for automatic authentication. Like fingerprints, palmprint has been used as a powerful means in law enforcement for criminal identification because of its stability and uniqueness. A key issue in palmprint identification involves the search for the best matching of the test sample from input and the templates in the palmprint database. The selection of features and similarity measures are two fundamental problems to be solved. A feature with good discriminating ability should exhibit a large variance between individuals and small variance between samples from the same person. Although principal lines, datum points, and other features such as geometry features, wrinkle features, delta point features and minutiae features are regarded as useful palmprint features, they are concerned with the local attributes based on points or line segments and require high computation for matching which measures the degree of similarity between two sample sets.

Unlike the existing techniques, we propose a dynamic selection scheme to facilitate the coarse-to-fine palmprint pattern matching by combining global and local palmprint features in a hierarchical fashion. The global texture energy (GTE) is introduced to represent the global palmprint feature, which is characterized with high convergence of inner-palm similarities and good dispersion of inter-palm discrimination. Such a global feature is used to guide the dynamic selection of a small set of similar candidates from the database at coarse level for further matching. Interesting points are used as local feature points and the final identification at fine level is carried out by an interesting point based image matching.

Our comparative study of palmprint feature extraction shows that palmprint patterns can be well described by textures, and the texture energy measurement possesses a large variance between different classes while retaining high compactness within the class. The coarse-level classification by global texture features is effective and essential to reduce the number of samples for further processing at fine level. The guided searching for the best matching based on interesting points improves the system efficiency further. The use of Hausdorff distance as the matching criterion can handle the partial occluded palmprint patterns, which makes our system more robust. 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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