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Review on Identification Using Palm Print

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ABSTRACT

Multibiometrics can provide higher identification accuracy than single biometrics, so it is more suitable for some real-world personal identification applications that need high-standard security. Among various biometrics technologies, palm print identification has received much attention because of its good performance. Biometric based authentication and recognition, the science of using physical or behavioral characteristic for identity verification is becoming a security principal in many areas. Their utilization as an authentication and recognition technology has become widespread from door access to electronic commerce. Security is a very important aspect in the biometric system itself. This paper provides an overview of palm print research, describing in capture devices, preprocessing, verification, palm print -related fusion and measures of security and for protecting users' privacy and palm print system, a sectional explaining the biometric recognition process.
Keywords: Biometrics, Palm Print Identification, Security, Multi-Biometrics, Recognition.

I. INTRODUCTION

Palmprint identification is an important personal identification technology and it has attracted much attention. The palm print contains not only principle curves and wrinkles but also rich texture and miniscule points, so the palm print identification is able to achieve a high accuracy because of available rich information in palm print [1], [8].

No single biometric technique can meet all requirements in circumstances [21]. Unimodal biometric systems are usually more cost efficient than multimodal systems. However, a single physical or behavioural characteristic of an individual can sometimes fail to be sufficient for identification. For this reason, multimodal biometric systems, i.e., systems that integrate two or more different biometric characteristics, are being developed to increase the accuracy of decisions and to decrease the possibility of circumventing the system [4]. In general, multimodal biometric systems require integration schemes to fuse the information obtained from the individual biometric modalities. This fusion process can be performed at four different levels: sensor, feature-generation, matching and decision. Generally, a biometric system can be classified according to the method used for capturing and processing the biometric characteristic, i.e., an *on-line* or an *off-line* system. An on-line system captures the biometric characteristics of a person who is physically present at the point of authentication by means of a sensor that is directly connected to a computer for real-time processing, while an off-line system processes previously captured biometric characteristics and the authentication is not performed in real-time.

To overcome the limitation of the unimodal biometric technique and to improve the performance of the biometric system, multimodal biometric methods are designed by using multiple biometrics or using multiple modals of the same biometric trait, which can be fused at four levels: image (sensor) level, feature level, matching score level and decision level. Various palm print identification methods, such as coding based methods [5], [9] and principle curve methods have been proposed in past decades. In recent years, 2D appearance based methods such as 2D Principal Component Analysis (2DPCA) [15], 2D Linear Discriminant Analysis (2DLDA) [16], and 2D Locality Preserving Projection (2DLPP) [17] have also been used for palm print recognition. Further, the Representation Based Classification (RBC) method also shows good performance in palm print identification [18]. Additionally, the Scale Invariant Feature Transform (SIFT) [19], [20], which transforms image data into scale-invariant coordinates, are successfully introduced for the contactless palm print identification.

II. Palm : Secure Biometric Trait

A comparison of the biometric techniques (biometric traits) based on seven factors [3] is provided in Table1. Table 1 shows the comparison of different biometric traits based on Universality, Distinctiveness, Permanence, Collectability, Performance, Acceptability, and Circumvention as Low, Medium and High.

1) Biometric System Characteristics:
2) Universality: every person should have the characteristic.
3) Uniqueness: capacity of the biometric to distinguish a person from all the others.
4) Permanence: how well a biometric resists aging and others variations over time.
5) Collectability: ease of acquisition for measurement.
6) Performance: measure of the accuracy, speed and robustness of the technology used.
7) User Acceptability: is the term given to the response generated by the biometric characteristic among the subjects who to use the technology. It basically refers to the ease of use for the subject.
8) Circumvention: refers to how easy it is to fool the system.

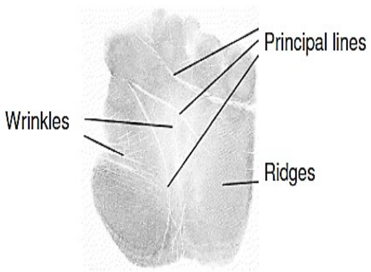


Figure 1. Palm print Features

Palmprint research employs either high resolution or low resolution images. High resolution images are suitable for forensic applications such as criminal detection. Low resolution images are more suitable for commercial and civil application such as access control. Most of the research using palm print verification uses low resolution images [2]. In general the high resolution can be 400 dpi or more and low resolution can be 150 dpi or less.

Table 1: Comparison of Biometric Traits

Biometric identifier	Universality	ess	Permanence	Collectability	Performance	Acceptability	n
DNA	H	H	H	L	H	L	L
Ear	M	M	H	M	M	H	M
Face	H	L	M	H	L	H	H
Fingerprint	M	H	H	M	H	M	M
Gait	M	L	L	H	L	H	M
Hand geometry	M	M	M	H	M	M	M
Iris	H	H	H	M	H	L	L
Keystroke	L	L	L	M	L	M	M
Palm print	M	H	H	M	H	M	M
Signature	L	L	L	H	L	H	H
Voice	M	L	L	M	L	H	H

III. Image Acquisition & Preprocessing

To capture palm print image, various types of scanner devices are used. Few of the examples are CCD-based scanners, digital scanners, video camera and tripod to collect palm print images.

Pre-processing is used to align different palm print images and to segment the centre for feature extraction. Most of the preprocessing algorithms employ the key points between fingers to set up a coordinate system. Preprocessing involves five common steps:

(1) Binarizing the palm images
(2) Extracting the contour of hand and/or fingers
(3) Detecting the key points
(4) Establishing a coordination system
(5) Extracting the central parts.

Step 1: Binarization of Image

The hand images of 256 gray levels are acquired from a platform scanner as shown in Fig. 2. The image thresholding operation is to binarize the gray images to obtain the binary hand shape images. In this step, the histograms of gray images are analyzed to determine a threshold value. This value is automatically set at the local minimal value between 50 and 100.

Step 2: Border Tracing

After the image thresholding step, the binary images are traced to obtain the contours of hand shape by making use of the border tracing algorithm [8]. The main purpose of this step is to find the boundary of a hand image and then locate the positions of five fingers for the determination of region of interest (ROI).

At the beginning, the first point of hand shape is set at the upper-left point of a hand shape image. The contour of hand shape is then traced in counterclockwise direction. The coordinates of each traced pixel should be kept to represent the shape of hand.

Step 3: Detecting the key points

The first and second steps in all the preprocessing algorithms are similar. However, the third step has several different implementations including tangent, bisector and finger-based to detect the key points between fingers. The tangent-based approach considers the two boundaries—one from point finger and middle finger and the other from ring finger and last finger—as two convex curves and computes the tangent of these two curves. The two intersections are considered as two key points for establishing the coordinate system. Tangent-based approaches have several advantages. They depend on a very short boundary around the bottom of fingers. Therefore, it is robust to incomplete and the presence of rings. Bisector-based approach constructs a line using two points, the center of gravity of a finger boundary and the midpoint of its start and end points.

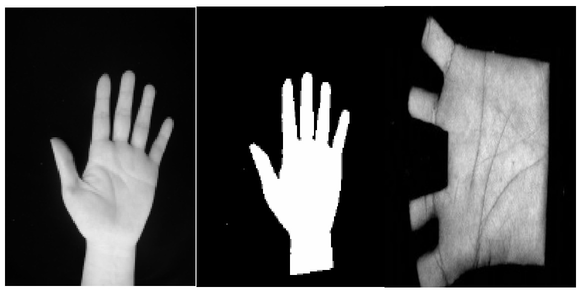
Step 4: Establishing a coordination system

Tangent-based approaches have several advantages. They depend on a very short boundary around the bottom of fingers. Therefore, it is robust to incomplete and the presence of rings. Bisector-based approach constructs a line using two points, the center of gravity of a finger boundary and the midpoint of its start and end points. The intersection of the line and the finger boundary is considered a key point. Han and his team propose two approaches to establish the coordinate system, one based on the middle finger and the other based on the point, middle and ring fingers. The middle finger approach uses a wavelet to detect the fingertip and the middle point in the finger bottom and construct a line passing through these two points. The multiple finger approach uses a wavelet and a set of predefined boundary points on the three fingers to construct three lines in the middle of the three fingers. The two lines from point and ring fingers are used to set the orientation of the coordinate system and the line from the middle finger is used to set its position. These approaches use only the information on the boundaries of fingers.

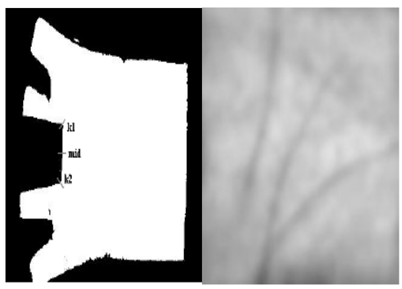
Step 5: Extracting the central parts

After obtaining the coordinate systems, the central parts of Palm prints are segmented. Most of the preprocessing algorithms segment square regions for feature extraction but some of them segment circular and half elliptical regions.

The square region is easier for handling translation variation, while the circular and half elliptical regions may be easier for handling rotation variation.



(a) **(b)** **(c)**



(d) **(e)**

Figure 2. (a) Original Image (b)Counter of Hand (c) Key Points (d) Co-Ordinate System (e) Central Part i.e. ROI

IV. VERIFICATION

Once the central part is segmented, features can be extracted for matching. There are two types of recognition verification and identification. Verification algorithms must be accurate. Identification algorithms must be accurate and fast (matching speed). This section concentrates on verification algorithms and identification algorithm. Verification algorithms are line, subspace and statistic based.

A. *Feature Extraction*

Feature extraction is a step to extract the meaningful features from the segmented ROI for the later modeling or verification process.

1. Coding Based Method

Coding based methods are the most influential palm print identification methods [5], [9]. Representative coding based methods include the competitive code method, ordinal Code method, palm code method and Binary Orientation Co-occurrence Vector (BOCV) method [14], and so on. The competitive code method [6] uses six Gabor filters with six different directions to extract orientation features from the palm print as follows. Six directional Gabor templates are convoluted with the palm print image respectively. The dominant direction is defined as the direction with the greatest response, the index of which is indicated as the competitive code.

Differing from the competitive code method, the palm code method [5] uses only one optimized 2D Gabor filter with direction of $\pi/4$ to extract palm print texture features. Then it uses a feature vector to represent image data that consists of a real part feature and an imaginary part feature. Finally it employs a normalized Hamming distance to calculate the matching score of two palm print feature vectors. In the ordinal code method [8], three integrated filters, each of which is composed of two perpendicular 2D Gaussian filters, are employed to convolute a palm print image and three bit ordinal codes are obtained based on the sign of filtering results. Then the Hamming distance is used to calculate the matching score of two palm print ordinal codes. In the fusion code method [9] multiple elliptical Gabor filters with four different directions are convoluted with palm print images, and then the direction and phase information of the responses are encoded into a pair of binary codes, which are exploited to calculate the normalized Hamming distance for palm print verification. In the BOCV method, the same six filters as the competitive code method are convoluted with the palm print image, respectively. All six orientation features are encoded as six binary codes successively, which are joined to calculate the Hamming distance between the query palm print and the gallery palm print.

The Sparse Multiscale Competitive Code (SMCC) method [7] adopts a bank of Derivatives of Gaussians (dog) filters with different scales and orientations to obtain the multiscale orientation features by using the $l1-norm$ sparse coding algorithm. The same coding rule as the competitive code method is adopted to integrate the feature with the dominant orientation into the SMCC code and finally the angular distance is calculated for the gallery SMCC code and the query SMCC code in the matching stage.

2. *Subspace Based Methods*

Subspace based methods include the PCA, LDA, and ICA etc. The key idea behind PCA is to find an orthogonal subspace that preserves the maximum variance of the original data. The PCA method tries to find the best set of projection directions in the sample space that will maximize the total scatter across all samples.

LDA tries to find an optimal projection matrix W and transforms the original space to a lower-dimensional feature space. In the low dimensional space, LDA not only maximizes the Euclidean distance of samples from different classes but also minimizes the distance of samples from the same classes.

3. Representation Based Method

The representation based method uses training samples to represent the test sample, and selects a candidate class with the maximum contribution to the test sample. The Collaborative Representation based Classification (CRC) method, Sparse Representation-Based Classification (SRC) method and Two- Phase Test Sample Sparse Representation (TPTSSR) method are two representative representation based methods [15], [16]. Almost all representation based methods can be easily applied to perform palm print identification. The CRC method uses all training samples to represent the test sample.

4. SIFT Based Method

SIFT was originally proposed in [19] for object classification applications, which are introduced for contactless palm print identification in recent years [20], [18]. Because the contactless palms print images have severe variations in poses.

The SIFT based method firstly searches over all scales and image locations by using a difference-of-Gaussian function to identify potential interest points. Then an elaborated model is used to determine finer location and scale at each candidate location and key points are selected based on the stability.

Then one or more orientations are assigned to each key point location based on local image gradient directions. Finally, the local image gradients are evaluated at the selected scale in the region around each key point [19]. In the identification stage, the Euclidean distance can be employed to determine the identity of the query image. A smaller Euclidean distance means a higher similarity between the query image and the training image.

5. Line-Based Method

To extract palm lines, Wu et al. [2006b] used the second order derivatives of a Gaussian to represent the line magnitude, and the first-order derivatives of a Gaussian to detect the location of the line. The final result is obtained by combining all directional line detection results and then encoded using the chain code. To simultaneously extract the location and width information of palm lines, Liu et al. [2007] proposed a wide line detector using an isotropic nonlinear filter. Other methods, such as two-stage filtering, have also been applied to palm line detection [Wang and Ruan 2006c]. Another topic in the line-based method is local line matching, where a score is produced by matching two line images. An ordinary matching method is calculating the number (or proportion) of the line pixels that are in the same location as the two line images. However, the performance of this method would be unsatisfactory due to several unavoidable factors, such as the translation, rotation, and deformation of the palm print images. To improve the line matching performance, Wu et al. [2006b] proposed dilating the template line image before matching, and Leung et al. [2007] used the line segment Hausdorff distance to denote the matching score of two line images [Gao and Leung 2002; Li and Leung 2006].

6. Statistical approaches

Statistical approaches are either local or global statistical approaches. Local statistical approaches transform images into another domain and then divide the transformed images into several small regions. Local statistics such as means and variances of each small region are calculated and regarded as features. Gabor, wavelets and Fourier transforms have been applied. The small regions are commonly square but some are elliptical and circular. To our knowledge, no one has yet investigated high order statistics for these approaches.

V. Fusions in Biometrics

Unlike biometric systems utilizing a single biometric characteristic (unimodal systems), multimodal biometric systems combine multiple characteristics in order to improve the system performance and make the system more reliable to spoofing attacks. A multimodal biometric system requires an integration scheme to fuse the information obtained from the individual modalities. The fusion can be performed at the four different levels:

(1) At the sensor level
(2) At the feature level
(3) At the match score level
(4) At rank level
(5) At the decision level

Multimodal biometrics systems take input from single or multiple sensors measuring two or more different modalities of biometric characteristics. The key to multimodal biometrics is the fusion of various biometric modes [2]. A generic multimodal biometric system has four important modules:

1. Sensor level: This fusion strategy requires the raw data to be acquired from multiple sensors which can be further processed and integrated to generate new data from which features can be extracted. Sensor level fusion can be done only if the multiple cues of the same biometric are obtained from multiple compatible sensors.

2. Feature level: The feature set is extracted from the multiple sources of information and is further concatenated into a joint feature vector. This new high dimensional feature vector represents an individual. In case of feature level fusion some reduction technique must be used in order to select only useful features.

3. Match score level: Match score is a measure of the similarity between the input biometric and template biometric feature vectors. Based on the similarity of feature vector and the template, each subsystem calculates its own match score value. These individual scores are finally combined to obtain a total score, which is then passed to the decision module, after which recognition is performed.

4. Rank level: Rank level fusion is generally adopted for the identification of the person rather than verification. Thus, fusion entails consolidating the multiple ranks associated with an identity and determining a new rank that would aid in establishing the final decision.

5. Decision level: In a multi biometric system, fusion is carried out at this level when only the decisions output by the individual biometric matchers are available. Here, a separate authentication decision is computed for each biometric trait which is then combined to result in a final vote. Different strategies are available to combine the distinct decisions of individual modality to a final authentication decision. Fusion at this level is considered to be rigid compared to the other fusion schemes due to the availability of limited information.

VI. PERFORMANCE METRICS

The recognition results of a palm print recognition system should be reported with commonly used performance evaluation tools to simplify system comparisons. Following are the most widely used standard metrics for analyzing the accuracy and performance of a biometric system.

False acceptance rate (FAR): FAR is the ratio of the number of unauthorized (unregistered) users accepted by the biometric system to the total of identification attempts made.

False rejection rate (FRR): FRR is the ratio of the number of number of authorized users rejected by the biometric system to the total number of attempts made.
Equal-Error-Rate (EER) is defined as the rate at which the FAR is equal to the FRR.

VII. CONCLUSIONS

In this paper we have reviewed the various existing methods used for palm print verification system. We recommend D.Zhang et al. Work [5] for palm print acquisition which uses CCD based scanner. We also recommend Kong's phd thesis because it contains palm code, fusion code, competitive code and the theory of coding method. We suggest Adams Kong et al. Competitive coding scheme for palm print verification [54].Palm print recognition is an emerging field and only limited works were carried out which paves way for the researchers to invent new methods to reduce the error rates and to improve the accuracy and speed of the system.

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