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A NOVEL METHODOLOGY TO PERFORM MULTIBIOMETRICS BY COMBINING LEFT AND RIGHT PALMPRINT IMAGES:A REVIEW

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ABSTRACT

Palm print recognition has gained significant importance in biometric and multi- biometric identification systems and it has been widely used in most of the security projects. The reason behind this is that a palmprint is a unique sample for each individual person. It is a biometric signature of fix shape; a born baby holds the same shape up to death. Nowadays most of the studies focus on enhancing the recognition rate and determining the age and gender of palmprint images. In this thesis, three different feature extraction techniques have been applied on images of a well know palmprint database.This paper provides an overview of current palm- print research, describing in particular capture devices, preprocessing, and verification algorithms. The purpose of this article is to provide an updated survey of palmprint recognition methods, and present a comparative study to evaluate the performance of the state-of-the-art palmprint recognition methods.

I. INTRODUCTION

With the increasing demand of biometric solutions for security systems, palmprintrecognition , a relatively novel but promising biometric technology, has recently received considerable interest. The inner surface of the palm normally contains three flexion creases, secondary creases and ridges. The flexion creases are also called principal lines and the secondary creases are called wrinkles. The flexion and the major secondary creases are formed between the third and fifth months of pregnancy and superficial lines appear after

we born. Although the three major flexion's are genetically dependent, most of other creases are not. Even identical twins have different palm prints. These non-genetically deterministic and complex patterns are very useful in personal identification. Human beings were interested in palmlines for fortune telling long time ago. Scientists know that palm lines are associated with some genetic diseases including Down syndrome, Aarskog syndrome, Cohen syndrome and fetal alcohol syndrome. Scientists and fortune tellers name the lines and regions in palm differently .

Palmprint research employs either high or low resolution images. High resolution images aresuitable for forensic applications such as criminal detection .Low resolution images are more suitablefor civil and commercial applications such as access control. Generally speaking, high resolution refers to 400dpi or more and low resolution refers to 150dpi or less.

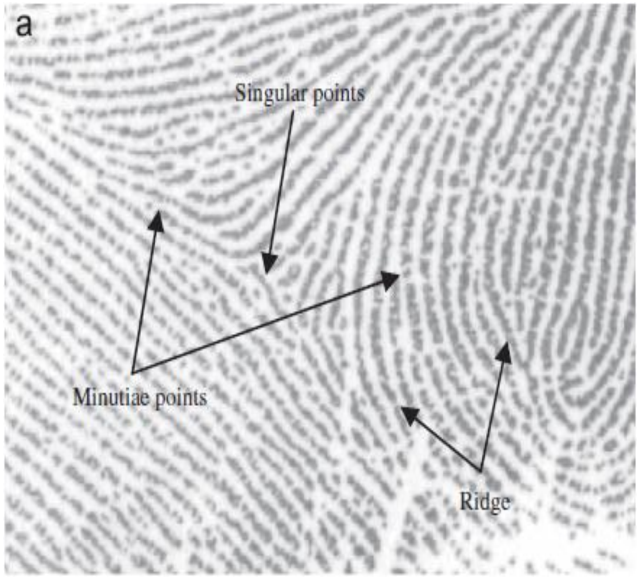
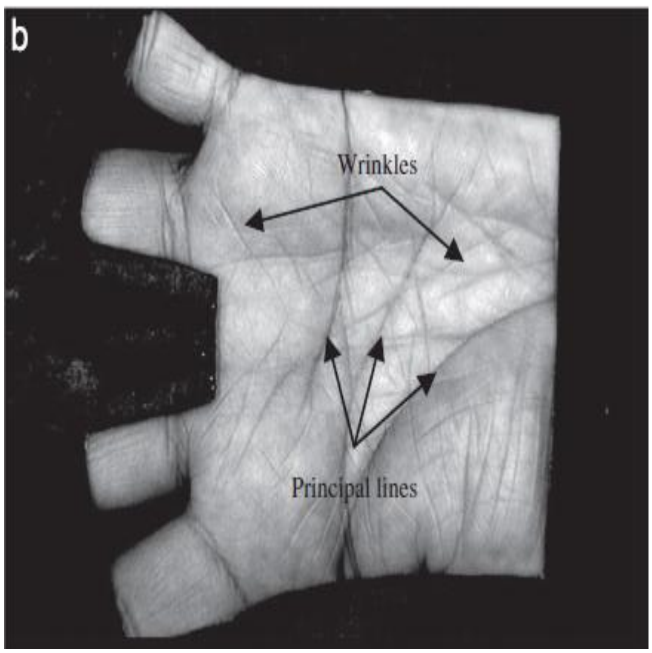


Figure 1.Palmprint features in (a) a high resolution image



(b) a low resolution image.

Figure 1(a,b) illustrates a part of a high resolution palm print image and a low resolution palm print image. Researchers can extract ridges ,singular points and minutia points as features from high resolution images while in low resolution images they generally extract principal lines,wrinkles and texture. Initially palm print research focused on high resolution images but now almost all research is on low resolution images for civil and commercial applications. Camera based biometrics allows for easy to use system modality for a user by following a flexible image capturing process. This flexibility entails fluctuations in the image quality and results in loss of texture and other variations viz. illumination, noise, pose variations etc. These variations have an adverse effect on the recognition accuracy. To overcome this problem, require new algorithms designed to handle weak templates and to make use of the information available to us in the best possible way.

A typical palmprint recognition system consists of five parts: palm print scanner ,preprocessing, feature extraction, matcher and database illustrated in Fig.2.

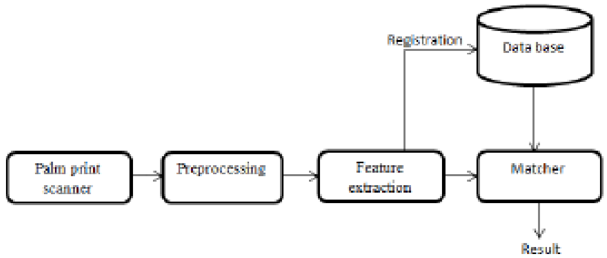


Figure. 1.2. An illustration of a typical palm print recognition system

The palmprint scanner collects palm print images. Preprocessing sets up a coordinate system to align palmprint images and to segment apart of palmprint image for feature extraction. Feature extraction obtains effective features from the preprocessed palmprints. A matcher compares two palmprint features and a data base stores registered templates.

II. PALM PRINT RECOGNITION METHODS

Personal authentication using palmprint images is an emerging biometric security research area. A number of approaches have been proposed for the palmprintmatching.Thereare two popular approaches to palmprint recognition. The first approach is based on the palmprint statistical features while the other on structural features.On the basis of extracted features the Palmprint authentication can be broadly classified into three categories: namely line based, subspace based, and statistical based. Some other coding methods are used for palmprint recognition, such as Palm Code, Fusion Code, Competitive Code, Ordinal Code,In the past decade, some appearance-based approaches were also applied to biometrics including palmprint recognition.

A. Line- based approaches:

Lines are the basic feature of palmprint and line based methods play an important role in palmprint verification and identification. Line-based approaches either develop edge detectors or use existing edge detection methods to extract palm lines. These lines are either matched directly or represented in other formats for matching. In general, most palms have three principal lines: the heartline, headline, and lifeline, which are the longest and widest lines in the palmprint image and have stable line shapes and positions. Thus, the principal line based method is able to provide stable performance for palmprint verification.

Wu etal. Use Canny edge operator to detect palmlines. The orientations of the edge points are passed into four membership functions representing four directions.For each direction, the authorscompute $E_{R,i} = \sum_{(x,y)\in R}(\mathrm{Mag}(x,y) * \mu_i(x,y))^2$,where μ_i represents one of the membership functions; Mag represents the magnitude of the lines and R is a local region. The feature value,$E_{R,i}$ is normalized. Finally, Euclidean distance is used for matching.

Wu et al. designed two masks to compute the vertical first- order derivative and the second-order derivative of palmprint images. The directional first-order and second-order derivatives can be obtained by rotating the two standard marks. They use the zero- crossings of the first-order derivatives to identify the edge points and corresponding directions. The magnitude of the corresponding second-order derivative is considered as the magnitude of the lines. They retain only the positive magnitude because palm lines are valleys. The weighted sum of the local directional magnitude is regarded as an element in the feature vector. This feature is normalized by its maximum and minimum components. Euclidean distance is used for matching.

Wu et al. Propose another algorithm, which use Sobel masks to compute the magnitude of palm lines. These magnitudes are projected along both x and y directions to form histograms. These histograms are considered as inputs of Hidden Markov Models(HMMs).

Boles et al.useSobel masks and thresholds to construct binary edge images and then employ Hough transform to extract the parameters of the six lines with highest densities in the accumulator array for matching.

Kung et al. formed a feature vector based on a low-resolution edge map. The feature vector is passed into decision-based neural networks. This was the first paper to report an online palm print recognition method.

Pedro et al. employ Sobel masks to enhance edge in formation and the statistical information in the processed images is used to estimate an optimal threshold for extracting the edges The authors then utilize a thinning algorithm to further process the edges. Several descriptors of the edges are computed as features for matching.

Huang et al. proposed a two-level modified finite radon transform and a dynamic threshold to extract major wrinkles and principal lines. Two binary edge maps are compared based on a matching scheme called pixel-to-area comparison. The authors claim that the proposed algorithm has a better high false acceptance rate than a classical palmprint identification algorithm Palm Code .However, Palm Code still has a better at low false acceptance rate. Even though some strong wrinkles are included in the edge maps, the major features in this method are principal lines, which are genetically dependent.

The pixel-to-area matching strategy is adopted for principal lines matching in Robust Line Orientation Code (RLOC) method ,which defines a principal lines matching score as follows:

$$S(A,B)=\sum_{i=1}^{m}\sum_{j=1}^{n} A(i,j)\&\overline{B}(i,j))/N_A \qquad (1)$$

whereA and B are two palmprint principal lines images, “&” represents the logical “AND” operation, NA is the number of pixel points of A, and .$\overline{B}$ (i, j) represents a neighbor area of B(i, j). For example, $\overline{B}$ (i, j) can be defined as a set of five pixel points, B(i −1, j), B(i +1,j), B(i, j), B(i, j −1), and B(i, j +1). The value of A(i, j) & .B(i, j) will be 1 if A(i, j) and at least one of $\overline{B}$ (i, j) are simultaneously principal lines points, otherwise, the value of A(i, j) &$\overline{B}$ (i, j) is 0. S(A, B) is between 0 and 1, and the larger the matching score is, the more similar A and B are. Thus, the query palmprint can be classified into the class that produces the maximum matching score.

The drawback of line based approaches is that The performance of this method would be unsatisfactory due to several unavoidable factors, such as the translation, rotation, and deformation of the palmprint images. The designing of palm print line classification systems requires highly equipped devices.

B. Subspace based approaches:

Subspace-based approaches also called appearance-based approach in the literature of face recognition. They use principal component analysis (PCA), linear discriminant analysis (LDA) and independent component analysis (ICA).The subspace coefficients are regarded as features. Various distance measures and classifiers are used to compare the features. In addition to applying PCA, LDA and ICA directly to palmprint images, researchers also employ wavelets, Gabor, discrete cosine transform (DCT) and kernels in their methods.

PCA finds a set of orthogonal basis vectors which describe the major variations among the training images, and with minimum reconstruction mean square error. This is useful as it helps to decrease the dimensions used to describe the set of images and also scale each variable according to its relative importance in describing the observation.Eigen bases have the same dimension as the original and called eigenpalms. While PCA only impose independence only up to the second order ICA computes the basis components that are statistically independent or as independent as possible A separating matrix is learnt by ICA to recover a set of statistically independent basis images subspace-based approaches do not make use of any prior knowledge of palmprints.

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In the subspace palmprint identification method, the query palmprint image is usually classifiedinto the class which produces the minimum Euclidean distance with the query sample in the low-dimensional feature space.

Figure. 3. The architecture of subspace approach

Figure 3.illustrates the architecture of subspace approach. Some researchers have developed new subspace approaches and examined them on palmprints. Generally speaking, subspace-based approaches do not make use of any prior knowledge of palmprints.But it requires more processing time.

C. Coding based approaches

Coding based methods are the most influential palmprint identification methods Representative coding based methods include the competitive code method, ordinal code method, palmcode method and Binary Orientation Co-occurrence Vector (BOCV) method, and so on.

The competitive code method [6] uses six Gabor filters with six different directions $\theta j = j\pi/6$, $j \in \{0, 1, \ldots, 5\}$, to extract orientation features from the palmprint as follows. Six directional Gabor templates are convoluted with the palmprint image respectively. The dominant direction is defined as the direction with the greatest response, the index j (j = 0 . . . 5) of which is indicated as the competitive code

In the matching stage of the competitive code method, the matching score between two palmprint images is calculated by using the angular distance, which can be defined as:

$$S_D = \frac{1}{3N^2} \sum_{i=1}^{N} \sum_{j=1}^{N} F(D_d(i,j), D_t(i,j)) \qquad (2)$$

whereDd and Dt be two index code planes of two palmprint images and $F(\alpha, \beta) = \min(|\alpha - \beta|, 6 - |\alpha - \beta|)$. The N is the number of the pixels of the palmprint image. SD is in the range of 0 to 1. The smaller the SD is, the more similar the two samples are.

The competitive code can be represented by three bit binary codes. Then the Hamming distance can be used to measure the similarity between two competitive codes, which can be calculated by

$$D(P,Q)=\frac{\sum_{y=1}^{N} \sum_{x=1}^{N} \sum_{i=1}^{3} (P_i(x,y) \otimes Q_i(x,y))}{3N^2} \qquad (3)$$

where Pi (Qi) is the i th bit binary code plane. "⊗" is the logical "XOR" operation. The smaller the Hamming distance (angular distance) is, the more similar the two samples are. Therefore, the query palmprint is assigned to the class that produces the smallest angular distance.

Differing from the competitive code method, the palmcodemethod uses only one optimized 2D Gabor filter with direction of $\pi/4$ to extract palmprint 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 palmprint feature vectors. In the ordinal code method [8], three integrated filters, each ofwhich is composed of two perpendicular 2D Gaussian filters, are employed to convolute a palmprint 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 palmprint ordinal codes. In the fusion code method multiple elliptical Gabor filters with four different directions are convoluted with palmprint 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 palmprint verification. In the BOCV method, the same six filters as the competitive code method are convoluted with the palmprint image, respectively. All six orientation features are encoded as six binary codes successively, which are joined to calculate the Hamming distance between the query palmprint and the gallery palmprint. The Sparse Multiscale Competitive Code (SMCC) method 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.

D. 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. In addition to directly describing the local region by statistics, Wang et al. use histograms of local binary pattern as features .Global statistical approaches compute global statistical features directly from the whole transformed images. Moments, centers of gravity and density have been regarded as the global statistical features.

III. CONCLUSION

This article presented a survey of palm print feature extraction methods. Palmprint features are generally described by forensic experts at three levels of detail. However, not all palmprint features that are utilized in manual Palmprint matching are employed in automatic matching systems. Palmprint recognition has considerable potential as a personal identification technique as it shares most of the discriminative features with fingerprints and in addition possesses a much larger skin area and other discriminative features such as principal lines, ridges and wrinkles which are very useful in biometric security.This paper presented an overview of palmprint identification, in which the definition of a palmprint, the formation and structure of palmprint features, and palmprint identification methods were discussed. In our survey, we grouped current palmprint recognition methods into different categories. In line-based approaches either develop edge detectors or existing edge detection methods extract palm lines . In feature-based methods, coding-based methods, which usually encode the response of a bank of filters into bitwise codes, may be one class of the most efficient palmprint recognition algorithms in terms of recognition accuracy, computational, and memory requirements. Based on the categorization of palmprint recognition methods, we also compared the complexity of different algorithms, provided a brief survey of the palmprint recognition methods for partial recognition.

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