Palm-print Recognition Based on DCT Domain Statistical Features Extracted from Enhanced Image

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***Abstract*—In this paper, a feature extraction algorithm for palm-print recognition is proposed based on statistical features of two-dimensional discrete cosine transform (2D-DCT), which efficiently exploits the local spatial variations in a palm-print image. First, adaptive median filtering followed by Top-Hat transform is employed on a given palm-image to obtain palm-line enhancement by reducing the effect of noise and lighting variations. Unlike conventional median filtering, adaptive median filtering operates only on pixels, which are not structurally aligned and can preserve detail while performing overall smoothing operation. The entire enhanced image is segmented into several small spatial modules and 2D-DCT is performed on each module. Instead of considering all DCT coefficients, a set of statistical features are extracted in DCT domain, which drastically reduces the feature dimension and precisely captures the detail variations within the palm-print image. From our extensive experimentations on different palm-print databases, it is found that the performance of the proposed method in terms of recognition accuracy and computational complexity is superior to that of some of the recent methods.**

Keywords*—Feature extraction, discrete cosine transform, median filtering, top-hat transform, palm-print recognition, modularization, local intensity variation.

I. Introduction

Palm-prints of a human being possess some major and minor line structures along with some ridges and wrinkles. These markers, as remain stable throughout the lifetime of a person, are treated as unique biometric features for secure authentication and identification. Among different categories of biometric recognition systems, the palm-print based scheme has become very promising and reliable because of its robustness against movements of palm, ease of handling with low resolution images, low memory requirement, less time consumption and cost-effectiveness [1].

Most of the palm-print recognition methods primarily employ three types of feature extraction algorithms, such as line-based, texture-based, and statistic-based [2], [3]. In the line-based feature extraction schemes, generally, different edge detection methods are used to extract palm lines (principal lines, wrinkles, ridges, etc.) [4]. The extracted edges, either directly or being represented in other formats, are used for matching.

It is to be mentioned that in cases where more than one person possess similar principal lines, line based algorithms may result in ambiguous identification. In order to overcome this limitation, the texture-based feature extraction schemes can be used, where the variations existing in either the different blocks of images or the features extracted from those blocks are computed [5]-[8]. In this regard, generally, principal component analysis (PCA) or linear discriminant analysis (LDA) are employed directly on palm-print image data or some popular transforms, such as discrete Fourier transform (DFT) and discrete cosine transform (DCT), are used for extracting features from the image data. For example, in [7], statistical features of different sub-images are extracted from the DCT of the spatial data, whereas in [6], features are extracted from spatial modules using DFT. Apart from DFT and DCT, discrete wavelet transform (DWT) is also widely employed in palm-print recognition [8], [9], [10], [11]. In [8], 2D-PCA and in [9], kernel PCA is used to extract information from wavelet domain features. In [10], [11], dominant features are selected from locally extracted wavelet coefficients. Despite many relatively successful attempts to implement palm-print recognition system, a single approach, which combines accuracy, robustness, and low computational burden, is yet to be developed.

In order to extract distinguishable features among different persons, in this paper, we propose to extract precisely spatial variations from each local zone of the entire palm-print image instead of concentrating on a single global variation pattern. An efficient pre-processing scheme consisting of adaptive median filtering followed by Top-Hat transform is introduced, which provides a binary image consisting mostly the significant palm-lines. Next, the entire palm-print image of a person is segmented into several small modules. A DCT-domain statistical feature extraction algorithm is developed which extracts features from each spatial module of the palm-print image. It is found that variation in the significant lines among different images is well-reflected in the proposed feature space. The recognition task is carried out using distance based classifiers and the recognition performance is tested upon several standard palm databases and compared with some recent methods.

II. Proposed Method

For any type of biometric recognition, the most important task is to extract distinguishing features from the template data, which directly dictates the recognition accuracy. However, extracting a unique feature of a palm-print in the spatial domain would be much difficult as it consists not only some major and minor line structures, but also some ridges, wrinkles, and singular points. Hence, our objective is to first obtain significant image enhancement by using an efficient pre-processing technique and then extract the local variations in frequency domain corresponding to the spatial data of the palm-print image.

A. Adaptive Median Filter Based Preprocessing

Palm-print images often exhibit lighting variations, poor contrast, and noise corruption. In order to reduce these imperfections and generate images those are more suitable for distinguishing different persons, in the proposed scheme, prior to spectral domain statistical feature extraction, an efficient palm-image enhancement algorithm is incorporated.

Although the pixel intensity of background is usually higher than that of palm-lines, the intensity values of some background pixels may be comparable to those of palm-line pixels. This effect can deteriorate the performance of the palm-print recognition system. In order to improve the performance of the proposed method, adaptive median filtering is utilized. Unlike conventional median filtering, adaptive median filtering operates only on pixels those are not structurally aligned. It can handle noise with high spatial density. First, it performs spatial processing to determine which pixels in an image have been affected by noise. It classifies pixels as noise by comparing each pixel in the image to its surrounding neighborhood pixels. The size of the neighborhood is adjustable, as well as the threshold for the comparison. A pixel that is different from a majority of its neighbors, as well as being not structurally aligned with those pixels to which it is similar, is labeled as noise pixel. These noise pixels are then replaced by the median pixel value of the pixels in the neighborhood that have passed the noise labeling test. A benefit of the adaptive median filter is that it seeks to preserve detail while performing overall smoothing operation on the image.

In view of obtaining further enhancement of palm-lines in the resulting image I_γ, in the proposed pre-processing scheme, Top-Hat transform is employed. Top-Hat transform is achieved by subtracting a morphologically opened image from the original image. It returns an image, containing those objects or elements of an input image that are smaller than the structuring element (i.e., places where the structuring element does not fit in). Top-Hat Transform is performed on the complementary image of I_γ.

In Fig. 1, resultant images obtained by using the proposed pre-processing steps are shown. It is observed that in the resulting image, palm-lines possess better visibility and distinguishability than those of the original palm-image.

B. Proposed Modularized DCT-domain Feature Extraction

It is well-known that Fourier transform or wavelet transform based palm-print recognition algorithms involve complex computations. In contrast, DCT of real data avoids complex arithmetic and offers ease of implementation in practical applications. Moreover, DCT can efficiently handle the phase unwrapping problem and exhibits a strong energy compaction property, i.e., most of the signal information tends to be concentrated in a few low-frequency components of the DCT. Hence, we intend to develop an efficient feature extraction scheme using 2D-DCT. For a function $f(x, y)$ with dimension of $M \times N$, the 2D-DCT $F(u, v)$ also has dimension $M \times N$ and is computed as

$$F(u,v) = \alpha_u \alpha_v \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) cos \frac{(2x+1)u\pi}{2M} cos \frac{(2y+1)v\pi}{2N}, \quad (1)$$

where

$$\alpha_u = \begin{cases} \sqrt{\frac{1}{M}} & ; \text{if } u = 0 \\ \sqrt{\frac{2}{M}} & ; \text{if } 1 \le u \le N-1 \end{cases} \quad (2)$$

$$\alpha_v = \begin{cases} \sqrt{\frac{1}{N}} & ; \text{if } v = 0 \\ \sqrt{\frac{2}{N}} & ; \text{if } 1 \le v \le N-1 \end{cases} \quad (3)$$

One advantage in terms of computational burden is that the DCT operation will be carried out on the pre-processed image, which is binary. However, considering all the 2D-DCT coefficients would definitely result in a feature vector with a very large dimension.

Instead of using all DCT values obtained in a module, it is more logical to consider a set of statistical features, which can efficiently represent the block characteristics. In view of this, several conventional statistical parameters are investigated and only four are selected:

- statistical mean of the DCT coefficients of the enhanced spatial segment
- statistical mode of the DCT coefficients of the enhanced spatial segment
- difference of statistical mean from maximum of the DCT coefficients of the enhanced spatial segment
- difference of statistical mean from minimum of the DCT coefficients of the enhanced spatial segment

Average DCT value of the module Presence of thick major lines along with densely spaced major lines will cause increase in dark portion resulting in decrease in overall spatial energy, which may tend to reduce spectral energy and thus the average of the DCT coefficients is expected to be lower. This would be different for different persons as palm-prints of different persons would have different setting of major and minor palm-lines. Similarly, the statistical mode of the DCT coefficients of a segment also reflects the presence of major/minor lines with respect to background. Finally, the difference of statistical mean from maximum and minimum of DCT coefficients of the particular block is also considered. These four values selected from each block is considered as the feature vector of that block and concatenating the feature vectors of each block of a palm-image constructs the feature vector of the particular palm-image.

It is to be noted that within a particular palm-print image, the change in information over the entire image may not be properly captured if the feature extraction operation is performed upon the image as a whole because of the difference in patterns and positions of principal lines, ridges and wrinkles. Even if it is performed, it may offer spectral features with very low between-class separation. In order to obtain high within-class compactness as well as high between-class separability, we propose to segment the palm-print image into some small

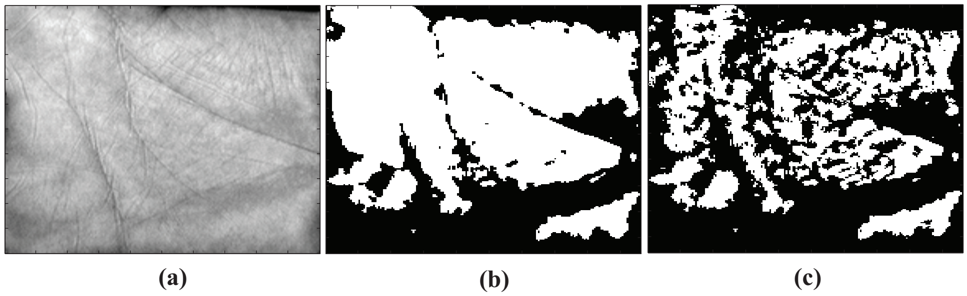

Fig. 1. (a) A sample palm-print image, (b) image resulting from adaptive median filtering and (c) the final pre-processed image after top-hat transform

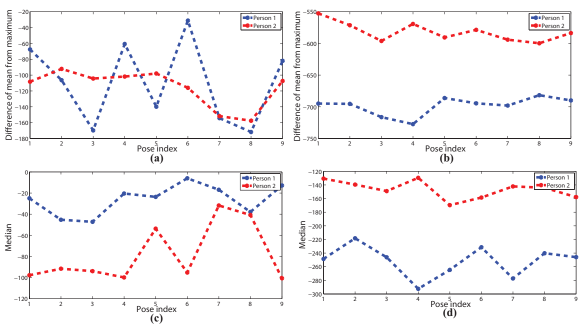

Fig. 2. Feature values of different images for (a) and (c) un-modularized palm-print image; (b) and (d) modularized palm-print image

spatial segments, which are capable of extracting variations in image geometry locally.

Next, we present an experimental result in order to demonstrate the advantage of extracting the selected features from the segments of a palm-print image instead of considering the entire image as a whole. In Fig. 2, the statistical features obtained from several sample palm-print images of two different persons are shown considering two different cases: (i) when features are extracted considering the entire palm-print image as a whole and (ii) when features are extracted from each narrow-width band separately. It is observed from the figure that, in the first case, the distance between the feature-values is extremely small, which strongly discourages to extract a single global variation pattern from the entire image at a time. However, the large between class separability in the second case supports the proposed feature selection algorithm, which extracts the features from the entire image considering each local zones separately.

It is observed that a significant variation may occur in the palm-print images of a single person taken under different conditions. In view of demonstrating the effect of such variations on the proposed features, we consider nine sample palm-prints for each of the two persons discussed before. Fig. 3(a) shows the proposed statistical features obtained from the entire image of all the sample palm-prints of two different persons, whereas Fig. 3(b) shows the proposed statistical features obtained from one segment of all the sample palm-prints of those two different persons. It is observed from these figures that for unsegmented feature extraction, the variation of a single feature might be high enough to overlap with other features of the same person whereas for segmented palm-print feature extraction, the feature values are well separated and coherent among different sample palm-images. Hence, the features extracted locally within a palm-print image offer not only a high degree of between-class separability but also a satisfactory within-class compactness.

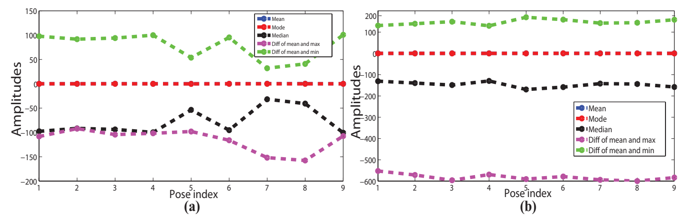

Fig. 3. Feature values for (a) un-modularized image and (b) modularized image

C. Distance Based Palm-print Recognition

In the proposed method, for the purpose of recognition using the extracted features, a distance-based similarity measure is utilized. The recognition task is carried out based on the distances of the feature vectors of the training palm-images from the feature vector of the test palm-image. Given the m-dimensional feature vector for the k-th sample image of the j-th person be $\{\gamma_{jk}(1), \gamma_{jk}(2), ..., \gamma_{jk}(m)\}$ and a test sample image f with a feature vector $\{v_f(1), v_f(2), ..., v_f(m)\}$, a similarity measure between the test image f of the unknown person and the sample images of the j-th person, namely *average sum-squares distance,* Δ, is defined as

$$\Delta_j^f = \frac{1}{q}\sum_{k=1}^{q}\sum_{i=1}^{m}|\gamma_{jk}(i) - v_f(i)|^2, \tag{4}$$

where a particular class represents a person with q number of sample palm-print images. Therefore, according to (4), given the test sample image f, the unknown person is classified as the person j among the p number of classes when

$$\Delta_j^f \leq \Delta_g^f, \ \forall j \neq g \text{ and } \forall g \epsilon \{1, 2, ..., p\} \tag{5}$$

III. Experimental Results

Extensive simulations are carried out in order to demonstrate the effectiveness of the proposed method of palm-print recognition using the palm-print images of several well-known databases. Different analyses showing the effectiveness of the proposed feature extraction algorithm have been shown. The performance of the proposed method in terms of recognition accuracy is obtained and compared with those of some recent methods [7], [12].

A. Palm-print Databases Used in Simulation

Performance of the proposed palm-print recognition scheme has been tested upon two standard databases,

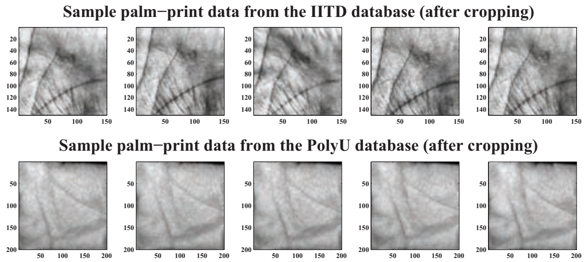

Fig. 4. Sample palm-print images after cropping

TABLE I. COMPARISON OF RECOGNITION ACCURACIES

Method	PolyU database
Proposed method	98.59%
Method [7]	97.50%
Method [12]	98.00%

namely, the PolyU palm-print database (version 2) http://www4.comp.polyu.edu.hk/~biometrics/ and the IITD palm-print database http://web.iitd.ac.in/~ajaykr/Database_Palm.htm. Fig. 4(a) shows sample palm-print images from the two databases. The PolyU database (version 2) contains a total of 7752 palm-print images of 386 persons. Each person has 18 to 20 different sample palm-print images taken in two phases. The IITD database, on the other hand, consists a total of 2791 images of 235 persons, each person having 5 to 6 different sample palm-print images for both left hand and right hand. It can be observed from Fig. 4 that not all the portions of the palm-print images are required to be considered for feature extraction. The portions of the images containing fingers and the black regions are discarded from the original images to form the regions of interest (ROI) as shown in Fig. 4(b).

B. Performance Comparison

In the proposed method, features are extracted from the 2D-DCT coefficients obtained from all the modules of the pre-processed palm-print image. The recognition task is carried out using a simple Euclidean distance based classifier as described in Section II-C. The experiments were performed following the leave-one-out cross validation rule.

For simulation purposes, the module size for the PolyU database and the IITD database has been chosen as 16×16 pixels and 8×8 pixels, respectively. The size of disc in adaptive median filtering is taken as 4×4. The statistical parameters of DCT coefficients are then selected. For the purpose of comparison, recognition accuracy obtained using the proposed method along with those reported in [7], [12] are listed in Table I. It is evident from the table that the recognition accuracy of the proposed method is comparatively higher than those obtained by the other methods. The performance of the proposed method is also very satisfactory for the IITD database (for both left hand and right hand palm-print images). An overall recognition accuracy of 98.46% is achieved.

IV. CONCLUSION

In the proposed DCT-domain statistical feature-based palm-print recognition scheme, instead of directly operating on the entire palm-print image at a time, features are extracted separately from each of the modules obtained by segmenting enhanced images. The novelty of the proposed method lies in introducing the idea of extracting statistical features in DCT domain from pre-processed and modularized palm-print image. It is found that variation in the significant lines among different images is well-reflected in the proposed feature space. The proposed feature extraction scheme is shown to offer three-fold advantages. First, it can precisely capture local variations that exist in the major and minor lines of palm-print images, which plays an important role in discriminating different persons. Second, it utilizes a very low dimensional feature space for the recognition task, which ensures lower computational burden. Third, DCT is performed upon binary images further reducing computational burden. For the task of classification, an Euclidean distance based classifier has been employed and it is found that, because of the quality of the extracted features, such a simple distance-based classifier can provide a very satisfactory recognition performance and there is no need to employ any complicated classifier. From our extensive simulations on different standard palm-print databases, it has been observed that the proposed method, in comparison to some of the recent methods, provides excellent recognition performance.

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