A DCT-based Feature Extraction Algorithm for Palm-print Recognition

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Abstract— **In this paper, a frequency domain feature extraction algorithm for palm-print recognition is proposed, which efficiently exploits the local spatial variations in a palm-print image. The entire image is segmented into several narrow-width spatial bands and a palm-print recognition scheme is developed based on extracting dominant spectral features from each of these bands using two-dimensional discrete cosine transform (2D-DCT). The proposed dominant spectral feature selection algorithm offers an advantage of very low feature dimension and it is capable of capturing precisely the detail variations within the palm-print image, which results in a very high within-class compactness and between-class separability of the extracted features. 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, classification, discrete cosine transform, dominant spectral feature, palm-print recognition*

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.

Most of the palm-print recognition methods primarily employ three types of feature extraction algorithms, such as line-based, texture-based, and statistic-based [1]. In the line-based feature extraction schemes, generally, different edge detection methods are used to extract palm lines (principal lines, wrinkles, ridges, etc.) [2]-[4]. The extracted edges, either directly or being represented in other formats, are used for matching. In [2], Canny edge detector is used for detecting palm lines, whereas in [3], Sobel masks and thresholds are employed to construct binary edge images. In [4], feature vectors are formed based on a low-resolution edge maps.

It is evident that adopting some palm lines as the biometric features would result in the possibility for more than one person having similar principal lines. 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], [6]. In this regard, generally, principal component analysis (PCA) or linear discriminant analysis are employed directly on palm-print image data and some popular transforms, such as Fourier, wavelets and Gabor transforms, are used for extracting features from the image data. In statistical approaches, the statistical properties, such as means and variances of the transform coefficients of the entire image are commonly treated as features. In some cases, the transformed images are divided into several small regions and statistical features of each small region are utilized [7], [8]. Given the extracted features, various classifiers, such as decision-based neural networks and Euclidean distance based classifier, are employed for palm-print recognition [2], [4].

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. In the proposed palm-print recognition scheme, the entire palm-print image of a person is segmented into several narrow-width spatial bands. A frequency domain feature extraction algorithm using two dimensional discrete cosine transform (2D-DCT) is developed, which operates within those local zones to extract dominant spectral features. In comparison to the discrete Fourier transform, the DCT is used as it can efficiently handle the phase unwrapping problem and offer energy compactness as well as computational advantages. Finally, recognition task is carried out using a distance based classifier.

II. PROPOSED METHOD

A. DCT Domain Spectral Feature Extraction

In comparison to person recognition based on face or voice biometrics, palm-print based recognition becomes very difficult even for a human being. For any type of biometric recognition, feature extraction is an important task, which directly dictates the recognition accuracy. As far as palm-print recognition is concerned, obtaining a significant feature space with respect to the spatial variation in a palm-print image is very crucial. In particular, 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 extract the local variations

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in frequency domain corresponding to the spatial data of the palm-print image. Fourier transform based frequency domain 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

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

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

Clearly, it is observed that considering all the 2D-DCT coefficients would definitely result in a feature vector with a very large dimension. In view of reducing the feature dimension, we propose to utilize the magnitudes corresponding to the dominant DCT coefficients as spectral features. The 2D-DCT coefficient corresponding to the maximum magnitude is treated as the dominant coefficient. Considering the magnitudes of the 2D-DCT coefficients in descending order, magnitude values other than the dominant one may also be treated as possible candidates for desired features. In accordance with their magnitude values, these dominant magnitudes are termed as second-dominant ($D2$), third-dominant ($D3$), and so on.

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 DCT 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 narrow-width bands, which are capable of extracting variations in image geometry locally. If the magnitude variations along all the narrow-width bands for the case of different dominant magnitudes remain similar, it would be very difficult to select one of those dominant magnitudes as a desired feature.

In order to demonstrate the characteristics of the dominant magnitudes in different narrow-width bands, sample palm-print images of two different persons are shown in Fig. 1. In Fig. 2, four dominant magnitudes ($D1$,$D2$,$D3$, and $D4$) obtained from all the narrow-width bands of the sample palm-print image of Person 1 appeared in Fig. 1 are shown. In this figure, the sample palm-print image is divided

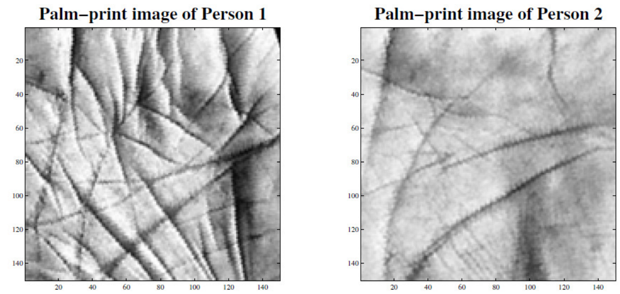

Fig. 1. Sample palm-print images of two persons.

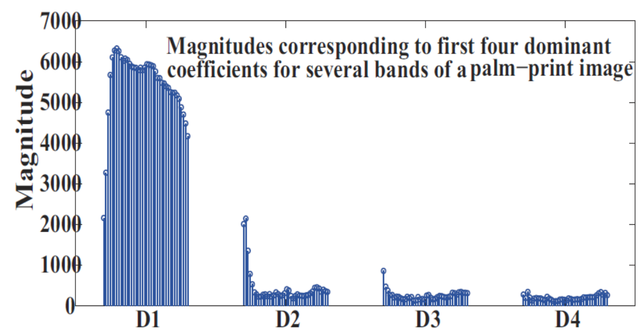

Fig. 2. Proposed dominant magnitude-features.

into 40 bands and dominant magnitudes are obtained in each band of the image by using 2D-DCT as in (1). It is found that the first dominant magnitude ($D1$) exhibits completely different characteristics in comparison to other dominant magnitudes. The characteristics of all other dominant magnitudes, in comparison to those of ($D1$), remain almost similar. An analogous behavior is obtained for Person 2 of Fig. 1. It is evident from the figure that $D1$ is the most significant among all the dominant magnitudes and thus, it is sufficient to consider only $D1$ as a desired feature, which also offers an advantage of reduced feature dimension. Computing $D1$ in each narrow-width band of a palm-print image, the proposed feature vector is obtained.

Next, we present an experimental result in order to demonstrate the advantage of extracting the dominant feature ($D1$) from the narrow-width bands of a palm-print image instead of considering the entire image as a whole. In Fig. 3, centroids of the dominant features obtained from several sample palm-print images of two different persons (as appeared in Fig. 1) 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-centroids 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

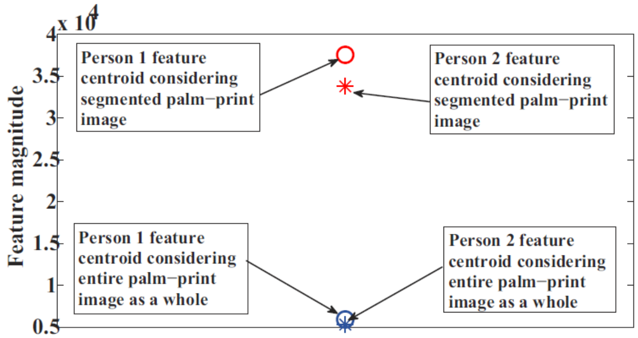

Fig. 3. Centroids of dominant features.

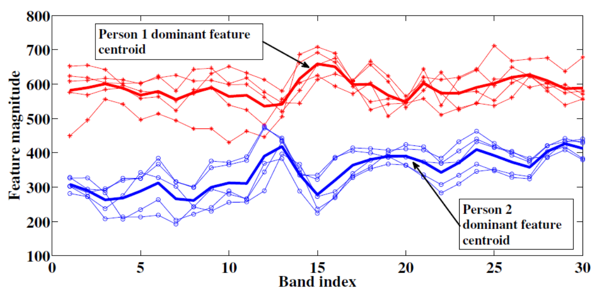

Fig. 4. Variation of dominant features with narrow-width bands for several palm-print images of two persons.

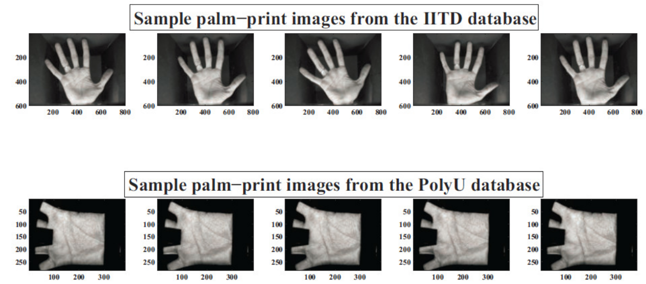

Fig. 5. Sample palm-print images

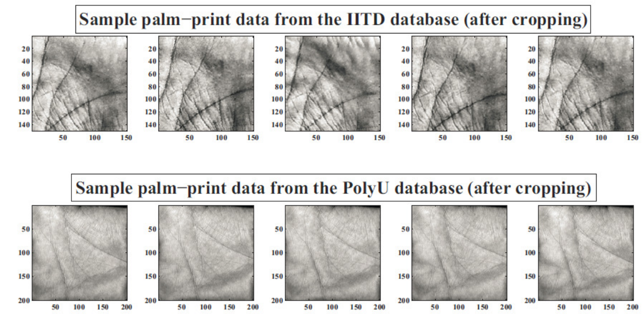

Fig. 6. Sample palm-print images after cropping

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 dominant features, we consider five sample palm-prints for each of the two persons as appeared in Fig. 1. Fig. 4 shows the proposed dominant features obtained from different narrow-bands of all the sample palm-prints of two different persons. For each person, the centroid of the proposed feature vectors is also shown in the figure. It is to be noted that the feature centroids of the two different persons are well-separated even though the major lines of the two palm-print images are quite similar considering the pattern and position. It is also observed that a low degree of scattering exists among the features around their corresponding centroids. Hence, the dominant 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.

B. Distance Based Palm-print Recognition

In the proposed method, for the purpose of recognition using the extracted dominant 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 f -th test sample image 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 is defined as

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

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

$$D_j^f \le D_g^f, \ \forall j \ne g \text{ and } \forall g \epsilon \{1, 2, ..., p\} \tag{5}$$

III. Experimental Results

Extensive simulations are carried out in order to demonstrate the effectiveness of the proposed method for palm-print recognition using proposed feature vectors. We investigate the recognition accuracy for the palm-print images of two well-known databases. The performance of the proposed method in terms of recognition accuracy is obtained and compared with those of some recent methods [9], [10]. Moreover, we investigate the effect of variation of the widths of the narrow-bands upon the palm-print recognition accuracy.

A. Palm-print Databases Used in Simulation

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

TABLE I
COMPARISON OF RECOGNITION ACCURACIES

Method	PolyU database	IITD database
Proposed method	99.97%	99.92%
Method [9]	97.50%	N/A
Method [10]	98.00%	N/A

namely, the PolyU palm-print database (version 2) [11] and the IITD palm-print database [12]. Fig. 5 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. 5 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. 6.

B. *Performance Comparison*

In the proposed feature extraction scheme, the palm-print images are divided into bands of width N pixels. In our simulations, N =20for the PolyU database and N =15 for the IITD database are chosen. Proposed dominant spectral features are extracted from the narrow-width bands using 2DDCT. Spectral features obtained from all the segments of a particular palm-print image are used to form the feature vector of that image and the recognition task is carried out on the reduced feature space as described in Section II-B.

For the purpose of comparison, recognition accuracy obtained using the proposed method along with those reported in [9] and [10] are listed in Table I. Here, in case of the IITD database, the recognition accuracy for the method in [9] and [10] are denoted as not available (N/A). 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 experiments were performed following the leave-one-out cross validation rule. In order to demonstrate the effect of variation of widths of the narrow-bands on the recognition accuracy, we present Fig. 7, where the recognition accuracies for various band widths for both the databases are shown. It is evident from the figure that better recognition accuracies are achieved for smaller band-widths, which is an indication that variations in the image geometry and intensity, i.e., variations in local information are captured more successfully in smaller-width bands.

IV. CONCLUSIONS

In the proposed DCT-based palm-print recognition scheme, instead of operating on the entire palm-print image at a time, dominant spectral features are extracted separately from each of the narrow-width band obtained by image - segmentation. It has been found that the proposed feature extraction scheme offers two-fold advantages. First, it can precisely capture local variations that exist in the 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. 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.

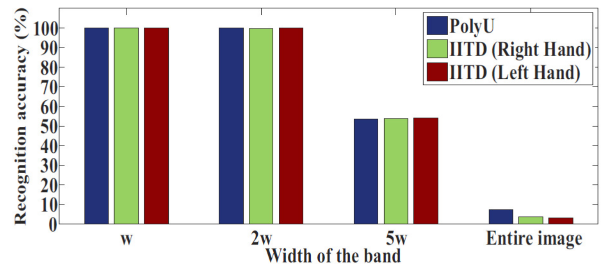

Fig. 7. Variation of recognition accuracy with band width for the PolyU and the IITD databases

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