In this paper, a novel pre-processing algorithm is introduced to identify the principal lines from a palm-print image and a frequency domain feature extraction algorithm is then employed for palm-print recognition, which can efficiently capture the spatial variations in the principal lines of a palm-print image. The entire image is segmented into several small spatial modules. The task of feature extraction is carried out in local zones using two dimensional discrete Fourier transform (2D-DFT). 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. It is shown that because of the pre-processing step, the discriminating capabilities of the proposed features are enhanced, which results in a very high within-class compactness and between-class separability of the extracted features. A principal component analysis is performed to further reduce the feature dimension. 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: Frequency domain feature extraction; principal component analysis; binary palm image; two-dimensional discrete Fourier transform; classification; palm-print recognition; entropy; modularization.

1. Introduction

Conventional ID card and password based identification methods, although very popular, are no more reliable as before because of the use of several advanced techniques of forgery and password-hacking. As an alternative, biometrics, such as palm-print, finger-print, face and iris being used for authentication and criminal identification [1]. The main advantage of biometrics is that these are not prone to theft and loss, and do not rely on the memory of their users. Moreover, they do not change significantly over time and it is difficult for a person to alter own physiological biometric or imitate that of other person’s. Among different biometrics, in security applications with a scope of collecting digital identity, the palm-prints are recently getting more attention among researchers [2,3]. Palm-print recognition is a complicated visual task even for humans. The primary difficulty arises from the fact that different palm-print images of a particular person may vary largely, while those of different persons may not necessarily vary significantly. Moreover, some aspects of palm-prints, such as variations in illumination, position, and scale, make the recognition task more complicated [4].

Palm-print recognition methods are based on extracting unique major and minor line structures that remain stable throughout the lifetime. In this regard, generally, either line-based or texture-based feature extraction algorithms are employed [5]. In the line-based schemes, generally, different edge detection methods are used to extract palm lines (principal lines, wrinkles, ridges, etc.) [6,7]. The extracted edges, either directly or being represented in other formats, are used for template matching. 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 [8]-[13]. 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 Fourier and discrete cosine transforms (DCT), are used for extracting features from the image data. Given the extracted features, various classifiers, such as decision-based neural networks and Euclidean distance based classifier, are employed for palm-print recognition [6,7]. Despite many relatively successful attempts to implement face or palm-print recognition system, a single approach, which combines accuracy, robustness, and low computational burden, is yet to be developed.

The objective of this paper is to identify the principal lines from a palm-print image and 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 small modules. An efficient feature extraction scheme using 2D-DFT, which offers an ease of implementation in practical applications, is developed, which operates within those local zones to extract dominant spectral features. It is shown that the discriminating capabilities of the proposed features, that are extracted from the sub-images, are enhanced because of the pre-processing step and also for the modularization of the palm-print image. A principal component analysis is performed to further reduce the feature dimension. Finally, recognition task is carried out using a distance based classifier.

2. Pre-processing

A key issue to be solved for successful palm-print recognition is preprocessing of the palm-print image to gain a proper sub-area for feature extraction and classification. Due to the images obtained by a digital scanner without any constraint of pegs, distortions including rotation, shift and translation may be present in the palm images, which make it hard to locate at correct position in the same direction. Preprocessing is used to align different palm-print images and to segment the center 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 and (5) extracting the central parts.

2.1. Extracting Major Lines

In order to identify only the major lines from a palm image, first, only the center portion of the palm-print image is extracted from the raw images omitting the black background portion as well as those consisting the fingers. The cropped portion is then filtered using a simple 2D low pass filter (2D-LPF). The low-pass filtering is performed to blur the image, i.e., to reduce the effect of the minors. It affects the majors but since the major lines are much thicker than the minor ones and also most of the unwanted minors are narrow, using a low-pass filter greatly reduces the unwanted minors but affects the majors only slightly. In Fig. 1, palm-print images after cropping are shown along with their filtered versions.
Our objective is to check whether it were possible to find out the trajectory of the major lines of the palm-print image since the minors are much more vulnerable to aging than the majors. Furthermore, two or three major lines are the most-prominent in general. Therefore, the cropped palm-print image is segmented into two or more smaller horizontal portions so that the minors become even smaller than before and can be easily eliminated in the trajectory-tracing step. Since, projection search is used to extract the trajectory of the majors, slight rotation does not affect the major line extraction much. Finally, from the selected low intensity pixels, searching for some continuous or quasi-continuous pattern of the major lines using the nonlinear placement of an arbitrary mask and replacing the pixel values outside the patterns with the same high values accomplishes the juxtaposition of the subdivisions.

3. 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. In comparison to person recognition based on face or voice biometrics, palm-print recognition is very challenging even for a human being. For the case of palm-print recognition, obtaining a significant feature space with respect to the spatial variation in a palm-print image is very crucial. Moreover, a direct subjective correspondence between palm-print features in the spatial domain and those in the frequency domain is not very apparent. In what follows, we are going to demonstrate the proposed feature extraction algorithm for palm-print recognition, where spatial domain local variation is extracted from frequency domain transform.
3.1. Proposed Spectral Feature

For biometric recognition, feature extraction can be carried out using mainly two approaches, namely, the spatial domain approach and the frequency domain approach [14]. The spatial domain approach utilizes the spatial data directly from the palm-print image or employs some statistical measure of the spatial data. On the other hand, frequency domain approaches employ some kind of transform over the palm-print image for feature extraction. In case of frequency domain feature extraction, pixel-by-pixel comparison between palm-print images in the spatial domain is not necessary. Phenomena, such as rotation, scale and illumination, are more severe in the spatial domain than in frequency domain. Hence, in what follows, we intend to develop a feature extraction algorithm based on frequency domain transformation.

It is well-known that Fourier transform based algorithms offer ease of implementation in practical applications. Hence, we intend to develop an efficient feature extraction scheme using two dimensional Fourier transform. For a function $f(x,y)$ of size $M \times N$ with two-dimensional variation, the 2D-DFT is given by [15]

$$F(u,v) = \frac{1}{MN} \sum_{x=0}^{M-1} \sum_{y=0}^{N-1} f(x,y) e^{-j2\pi \left( \frac{ux}{M} + \frac{vy}{N} \right)}$$

(1)

where $u = 1, 2, ..., M - 1$ and $v = 1, 2, ..., N - 1$.

In the proposed palm-print recognition scheme, 2D-DFT is used for feature extraction. Several palm-print images of different persons have been investigated and it is observed that there exist some correspondences between palm-print features on the spatial domain image and those on the corresponding frequency domain transform. In general, the stronger the majors are on the spatial domain image, the less compact the information is on the frequency domain transform. And if a palm-print image in the spatial domain has a strong line, in the frequency domain there will be more information in the line’s perpendicular direction [9].

In order to demonstrate the effect of rotation on the extracted features in frequency domain, Fig. 3 shows two synthetic palm-print images. Two palm-prints are basically the same, except that the second one is derived by rotation of the first one by $30^\circ$. The Euclidean distances between the raw palm-prints and their corresponding 2D-DFT coefficients are shown in Fig. 4. It is evident from the figure that the latter one provides orders of magnitude lower Euclidean distance as opposed to the earlier one, which shows sharp correlation signifying better match.
3.2. Proposed Dominant Spectral Feature Selection

In the proposed method, instead of taking the DFT coefficients of the entire image, the coefficients obtained from each module of the binary image are considered to form a feature vector. However, if all of these coefficients were used, it would definitely result in a feature vector with a very large dimension. One advantage of working in the Fourier domain is that a few coefficients with higher magnitudes would be sufficient to represent an image or a portion of an image. Hence, in view of reducing the feature dimension, we propose to utilize the magnitudes and 2D-frequencies corresponding to the dominant DFT coefficients as spectral features. The 2D-DFT coefficient corresponding to the maximum magnitude is treated as the dominant coefficient \( D_1 \) and the corresponding 2D-frequencies are termed as the dominant frequencies. Considering the magnitudes of the 2D-DFT 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 \( D_2 \), third-dominant \( D_3 \), and so on. If the magnitude variations along all the segments 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 modules, sample binary palm-print images of two different persons are shown in Fig. 5. In Fig. 6, four dominant magnitudes $D1, D2, D3$ and $D4$ obtained from all the modules of the sample palm-print image of Person 1 appeared in Fig. 5(a) are shown. In this figure, the sample palm-print image is divided into 30 segments. It is found that different dominant magnitudes obtained from the spatial modules exhibit completely different characteristics. However, the magnitude value for the first dominant $D1$ is found reasonably higher than other dominant magnitudes. An analogous behavior is obtained for Person 2 of Fig. 5(b). It is evident from Fig. 6 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 $D1$ and the corresponding 2D-frequencies $(\omega_{D1x}^1, \omega_{D1y}^1)$ in each segment of the palm-print image, the proposed feature vector is obtained.

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. 5. In Fig. 7, the proposed dominant features obtained from different segments of all the sample palm-prints of two different persons are shown.
For each person, the centroid of the proposed feature vectors is also shown in the figure (in thick continuous lines). 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.

3.3. Reduction of the Feature Dimension

For the cases where the acquired palm-print are of very high resolution, even after selection of dominant features from the small segments of the palm-print image, the feature vector length may still be very high. Further dimensionality reduction may be employed for reduction in computational burden.

Principal component analysis (PCA) is a very well-known and efficient orthogonal linear transformation [16]. It reduces the dimension of the feature space and the correlation among the feature vectors by projecting the original feature space into a smaller subspace through a transformation. The PCA transforms the original \( p \)-dimensional feature vector into the \( L \)-dimensional linear subspace that is spanned by the leading eigenvectors of the covariance matrix of feature vector in each cluster \( (L < p) \). PCA is theoretically the optimum transform for given data in the least square sense. For a data matrix, \( X^T \), with zero empirical mean, where each row represents a different repetition of the experiment, and each column gives the results from a particular probe, the PCA transformation is given by:

\[
Y^T = X^T W = V \sum^T
\]

where the matrix \( \sum \) is an \((m \times n)\) diagonal matrix with nonnegative real numbers on the diagonal and \( W \sum V^T \) is the singular value decomposition of \( X \). If \( q \) sample palm-print images of each person are considered and a total of \( M \) dominant DFT coefficients are selected per image, the feature space per person would have a dimension of \( q \times M \).

For the proposed dominant spectral features, implementation of PCA on the derived feature
space could efficiently reduce the feature dimension without losing much information. Hence, PCA is employed to reduce the dimension of the proposed feature space.

3.4. 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 \( \{\gamma_{jk}(1), \gamma_{jk}(2), \ldots, \gamma_{jk}(m)\} \) and a test sample image \( f \) with a feature vector \( \{\nu_{jk}(1), \nu_{jk}(2), \ldots, \nu_{jk}(m)\} \), 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, \( \Delta \), is defined as

\[
\Delta_f^j = \frac{1}{q} \sum_{k=1}^{q} \sum_{i=1}^{m} \left| \gamma_{jk}(i) - \nu_f(i) \right|^2,
\]

where a particular class represents a person with \( q \) number of sample palm-print images. Therefore, according to (3), given the test sample image \( f \), the unknown person is classified as the person \( j \) among the \( p \) number of classes when

\[
\Delta_f^j \leq \Delta_f^g, \forall j \neq g \text{ and } \forall g \in \{1,2,\ldots,p\}
\]

4. 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 [12,17].
4.1. Palm-print Databases Used in Simulation

Fig. 8. Sample palm-print images from the IITD database

Fig. 9. Sample palm-print images from the IITD database after cropping
In this section, palm-print recognition performance obtained by different methods has been presented using two standard databases, namely, the PolyU palm-print database (version 2) [18] and the IITD palm-print database [19]. In Figs. 8 and 10, sample palm-print images from the PolyU database and the IITD database are shown, respectively. 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 different instances. 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 Figs. 8 and 10 that not all the portions of the palm-print images are required to be considered for feature extraction [2]. 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 Figs. 9 and 11.

4.2. Performance Comparison

In the proposed method, dominant spectral features (magnitudes and frequencies) obtained from all the modules of a palm-print image are used to form the feature vector of that image and feature dimension reduction is performed using PCA. The recognition task is carried
out using a simple Euclidean distance based classifier as described in Section 3.4. 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 $20 \times 20$ pixels and $15 \times 15$ pixels, respectively. For the purpose of comparison, recognition accuracy obtained using the proposed method along with those reported in [12] and [17] are listed in Table 1. 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 99.91% is achieved.

Table 1. Comparison of recognition accuracies

<table>
<thead>
<tr>
<th>Method</th>
<th>PolyU database</th>
</tr>
</thead>
<tbody>
<tr>
<td>Proposed method</td>
<td>99.96%</td>
</tr>
<tr>
<td>Method [12]</td>
<td>97.50%</td>
</tr>
<tr>
<td>Method [17]</td>
<td>98.00%</td>
</tr>
</tbody>
</table>

As mentioned earlier, dominant spectral features are extracted from the small modules of the palm-print images. Next, we intend to demonstrate the effect of variation of module width upon the recognition accuracy obtained by the proposed method. In Fig. 12, the recognition accuracies obtained for different module sizes are shown. It is observed from the figure that better recognition accuracies are achieved for smaller segments, which is an indication that variations in the image geometry and intensity, i.e., variations in local information are captured more successfully in case of smaller sized segments. Note that, in case of considering the entire image as a whole instead of any modularization, the recognition accuracy drastically falls to a value less than 20% for both the databases, as expected.

In view of reducing computational complexity, dimension reduction of the feature space plays an important role. In the proposed method, the task of feature dimension reduction is performed using PCA. In Fig. 13, the effect of dimension reduction upon recognition accuracy is shown. It is found from this figure that even for a very low feature dimension, the recognition accuracies remain very high for both the databases.

![Fig. 12. Variation of recognition accuracy with module size for the PolyU and the IITD databases](image-url)
5. Conclusions

In the proposed palm-print recognition scheme, instead of operating on the entire palm-print image at a time, dominant spectral features are extracted from binary palm-print images consisting only two/three major lines. It has been shown that because of the novel pre-processing step and the modularization of the palm-print image, the proposed dominant spectral features, that are extracted from the sub-images, attain better discriminating capabilities. The effect of variation of module size upon recognition performance has been investigated and found that the recognition accuracy does not depend on the module size unless it is extremely large. The proposed feature extraction scheme is shown to offer two-fold advantages. First, it can precisely capture local variations that exist in the major 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. 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 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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