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A Wavelet-based Feature Selection Scheme for Palm-print Recognition

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ABSTRACT

In this paper, a multi-resolution feature extraction algorithm for palm-print recognition is proposed based on two-dimensional discrete wavelet transform (2D-DWT), which efficiently exploits the local spatial variations in a palm-print image. The entire image is segmented into several small spatial modules and a palm-print recognition scheme is developed, which extracts histogram-based dominant wavelet features from each of these local modules. This not only drastically reduces the feature dimension but also results in a very high within-class compactness and between-class separability of the extracted features. Moreover, the improvement of the quality of the extracted features as a result of illumination adjustment has also been analyzed. 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 **- Feature extraction, classification, discrete wavelet transform, entropy based information content, histogram, dominant wavelet-domain feature, palm-print recognition, modularization**

I. 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 [9]. 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 [4, 11].

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 [8].

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 [16, 17]. In the line-based schemes, generally, different edge detection methods are used to extract palm lines (principal lines, wrinkles, ridges, etc.) [15, 12]. The extracted edges, either directly or being represented in other formats, are used for template matching. Canny edge detector is used for detecting palm lines in [15], whereas in [12], feature vectors are formed based on a low-resolution edge maps. 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 [1, 2, 3, 6, 14]. 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, wavelets and discrete cosine transforms (DCT), are used for extracting features from the image data. Because of the property of shift-invariance, it is well known that wavelet based approach is one of the most robust feature extraction schemes, even under variable illumination [7]. Given the extracted features, various classifiers, such as decision-based neural networks and Euclidean distance based classifier, are employed for palm-print recognition [15, 12]. 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.

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 small modules. A wavelet domain feature extraction algorithm using 2D-DWT is developed to extract histogram-based dominant wavelet coefficients corresponding to the spatial modules residing within the image. In comparison to the discrete Fourier transform, the DWT is used as it possesses a better space-frequency localization. Moreover, the improvement of the quality of the extracted features as a result of illumination adjustment has also been analyzed. Apart from considering only the dominant features, further reduction of the feature dimension is obtained by employing the PCA. Finally, recognition task is carried out using a distance based classifier.

II. Brief Description of the Proposed Scheme

A typical palm-print recognition system consists of some major steps, namely, input palm-print image collection, pre-processing, feature extraction, classification and template storage or database, as illustrated in Fig. 1. The input palm-print image can be collected generally by using a palm-print scanner. In the process of capturing palm images, distortions including rotation, shift and translation may be present in the palm images, which make it difficult to locate at the correct position. Pre-processing sets up a coordinate system to align palm-print images and to segment a part of palm-print image for feature extraction. For the purpose of classification, an image database is needed to be prepared consisting template palm-images of different persons. The recognition task is based on comparing a test palm-print image with template data. It is obvious that considering images themselves would require extensive computations for the purpose of comparison. Thus, instead of utilizing the raw palm-print images, some characteristic features are extracted for preparing the template. It is to be noted that the recognition accuracy strongly depends upon the quality of the extracted features. Therefore, the main focus of this research is to develop an efficient feature extraction algorithm.

The proposed feature extraction algorithm is based on extracting spatial variations precisely from the spatial modules of the palm-print image instead of utilizing the image as a whole. In view of this, a modularization technique is employed first to segment the entire palm-print into several small segments. It should be noted that variation of illumination of different palm-print images of the same person may affect their similarity. Therefore, prior to feature extraction, an illumination adjustment step is included in the proposed algorithm. After feature extraction, a classifier compares two palm-print features and a database is used to store registered templates and also for verification purpose.

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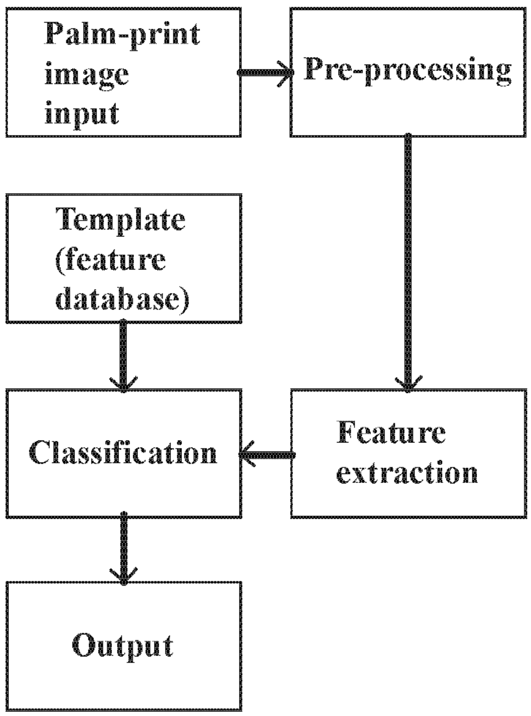


Figure 1: Block diagram of the proposed method.

III. 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 wavelet 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 wavelet domain transform.

A. Wavelet-based Feature Extraction from Spatial Modules

For biometric recognition, feature extraction can be carried out using mainly two approaches, namely, the spatial domain approach and the frequency domain approach [13]. 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. Recently, multi-resolution analysis, such as wavelet analysis, is also getting popularity among researchers. In what follows, we intend to develop a feature extraction algorithm based on multi-resolution transformation.

It is well-known that Fourier transform based palm-print recognition algorithms involve complex computations and choices of spatial and frequency resolution are limited. In contrast, DWT offers a much better space-frequency localization. This property of the DWT is helpful for analyzing images, where the information is localized in space. The wavelet transform is analogous to the Fourier transform with the exception that it uses scaled and shifted versions of wavelets and the decomposition of a signal involves sum of these wavelets. The DWT kernels exhibit properties of horizontal, vertical and diagonal directionality.

The continuous wavelet transform (CWT) of a signal $s(t)$ using a wavelet $\psi(t)$ is mathematically defined as

$$C(a,b) = \frac{1}{\sqrt{a}} \int s(t)\psi(\frac{t-b}{a})dt, \quad (1)$$

where a is the scale and b is the shift. The DWT coefficients are obtained by restricting the scale (a) to powers of 2 and the position (b) to integer multiples of the scales, and are given by

$$c_{j,k} = 2^{j/2} \int_{-\infty}^{\infty} s(t)\psi(2^j t - k)dt, \quad (2)$$

where j and k are integers and $\psi_{j,k}$ are orthogonal baby wavelets defined as

$$\psi_{j,k} = 2^{j/2}\psi(2^j t - k) \quad (3)$$

The approximate wavelet coefficients are the high-scale low-frequency components of the signal, whereas the detail wavelet coefficients are the low-scale high-frequency components. The 2D-DWT of a two-dimensional data is obtained by computing the one-dimensional DWT, first along the rows and then along the columns of the data. Thus, for a 2D data, the detail wavelet coefficients can be classified as vertical, horizontal and diagonal detail.

Palm-prints of a person possess some major and minor line structures along with some ridges and wrinkles. A person can be distinguished from another person based on the differences of these major and minor line structures. Fig. 2 shows sample palm-print images of two different persons. The three major lines of the two persons are quite similar. They differ only in minor line structure. In this case, if we considered the line structures of the two images locally, we may distinguish the two images.

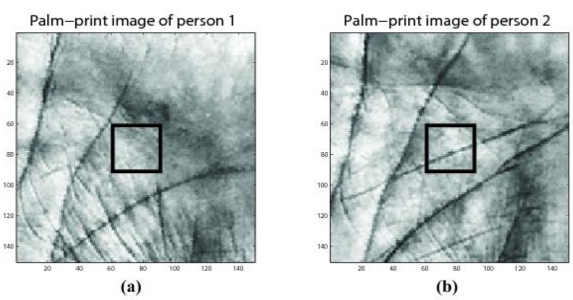
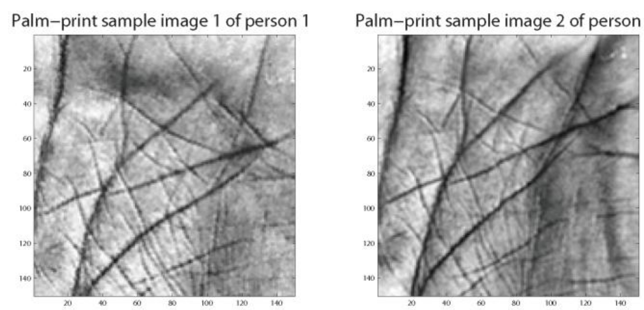


Figure 2: Sample palm-print images of two persons. Square block contains portion of images (a) without any minor line (b) with a minor line

B. Effect of Illumination

It is intuitive that palm-images of a particular person captured under different lighting conditions may vary significantly, which can affect the palm-print recognition accuracy. In order to overcome the effect of lighting variation in the proposed method, illumination adjustment is performed prior to feature extraction. Given two palm-print images of a single person having different intensity distributions due to variation in illumination conditions, our objective is to provide with similar feature vectors for these two images irrespective of the difference in illumination conditions. Since in the proposed method, feature extraction is performed in the DWT domain, it is of our interest to analyze the effect of variation in illumination on the DWT-based feature extraction.

In Fig. 3(a), two palm-print images of the same person are shown, where the second image has a slightly lower average illumination level. 2D-DWT operation is performed upon each image, first without any illumination adjustment and then after performing illumination adjustment. Considering all the 2D-DWT approximate coefficients to form the feature vectors for these two images, a measure of similarity can be obtained by using correlation. In Figs. 3(b) and (c), the cross-correlation values of the 2D-DWT approximate coefficients obtained by using the two images without and with illumination adjustment are shown, respectively. It is evident from these two figures that the latter case exhibits more similarity between the DWT approximate coefficients indicating that the features belong to the same person.



(a)

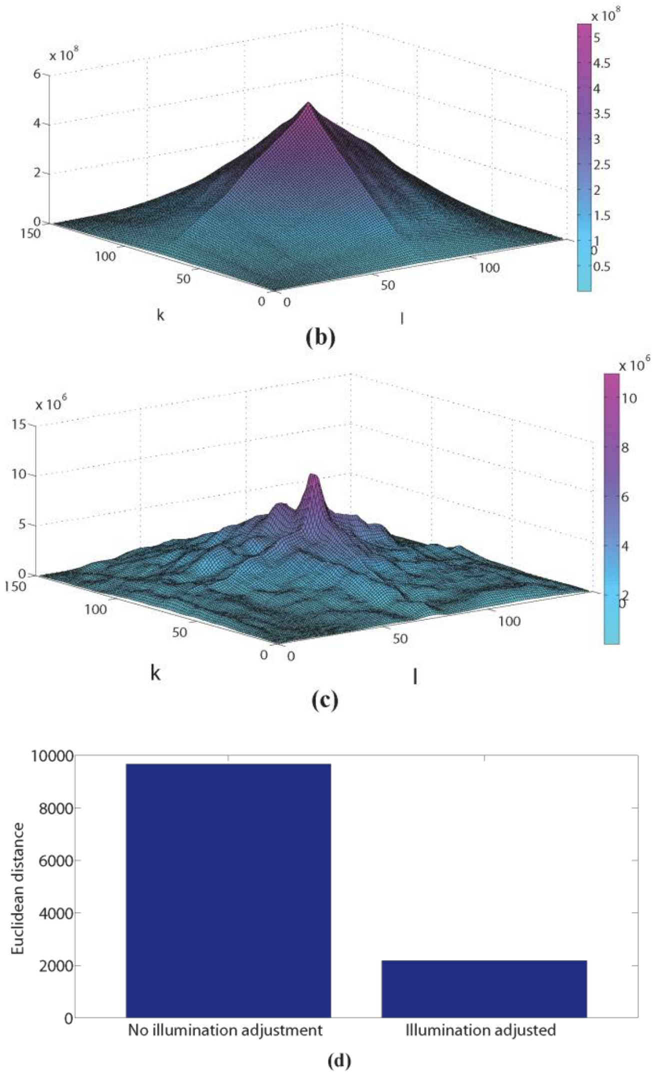


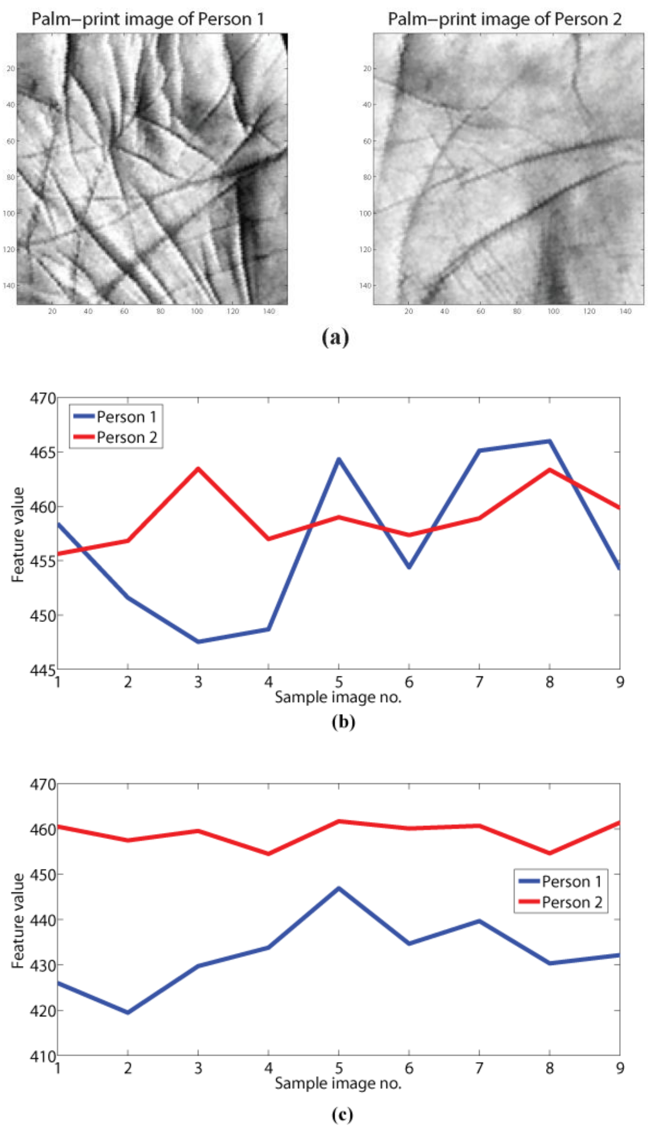
Figure 3: (a) Two sample palm-print images of the same person under different illumination; correlation of the 2D-DWT approximate coefficients of the sample palm-print images shown in Fig. 3(a): (b) no illumination adjustment (c) illumination adjusted; and (d) Euclidian distance between 2D-DWT approximate coefficients of sample palm-print images

The similarity measure in terms of Euclidean distances between the 2D-DWT approximate coefficients of the two images for the aforementioned two cases are also calculated and shown in Fig. 3(d). It is observed that there exists a huge separation in terms of Euclidean distance when no illumination adjustment is performed, whereas the distance is very small when illumination adjustment is performed, as expected, which clearly indicates that a better similarity between extracted feature vectors.

C. Proposed Wavelet Domain Dominant Feature

Instead of considering the DWT coefficients of the entire image, the coefficients obtained form each modules of the palm-print image are considered to form the feature vector of that image. However, if all of these coefficients were used, it would definitely result in a feature vector with a very large dimension. In view of reducing the feature dimension, we propose to utilize wavelet coefficients, which are playing the dominant role in the representation of the image. In order to select the dominant wavelet coefficients, we propose to consider the frequency of occurrence of the wavelet coefficients as the determining characteristic. It is expected that coefficients with higher frequency of occurrence would definitely dominate over all the coefficients for image reconstruction and it would be sufficient to consider only those coefficients as desired features. One way to visualize the frequency of occurrence of wavelet coefficients is to compute the histogram of the coefficients of a segment of a palm image. In order to select the dominant features from a given histogram, the coefficients having frequency of occurrence greater than a certain threshold value are considered.

It is intuitive that within a palm-print image, the image intensity distribution may drastically change at different localities. In order to select the dominant wavelet coefficients, if the thresholding operation were to be performed over the wavelet coefficients of the entire image, it would be difficult to obtain a global threshold value that is suitable for every local zone. Use of a global threshold in a palm-print image may offer features with very low between-class separation. In order to obtain high within-class compactness as well as high between-class separability, we have considered wavelet coefficients corresponding to the smaller spatial modules residing within a palm-print image, which are capable of extracting variation in image geometry locally. In this case, for each module, a different threshold value may have to be chosen depending on the wavelet coefficient values of that segment.



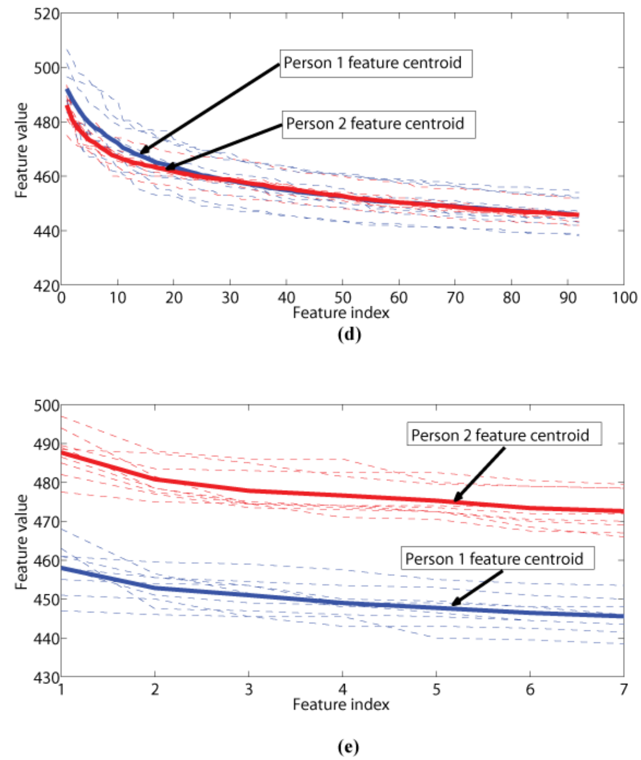


Figure 4: (a) Sample palm-print images of two persons; Feature centroids of different images for: (b) un-modularized palm-print image (c) modularized palm-print image; Feature values for: (d) un-modularized palm-print image (e) modularized palm-print image

We propose to utilize the coefficients (approximate and horizontal detail) with frequency of occurrence greater than $\theta\%$ of the maximum frequency of occurrence for the particular module of the palm-print image and are considered as dominant wavelet coefficients and selected as features for the particular segment of the image. This operation is repeated for all the modules of a palm-print image.

Next, in order to demonstrate the advantage of extracting dominant wavelet coefficients corresponding to some smaller modules residing in a palm-print image, we conduct an experiment considering two different cases: (i) when the entire palm-print image is used as a whole and (ii) when all the modules of that image are used separately for feature extraction. For these two cases, centroids of

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the dominant approximate wavelet coefficients obtained from several poses of two different persons (appeared in Fig. 4(a)) are computed and shown in Figs. 4(b) and (c), respectively. It is observed from Fig. 4(b) that the feature-centroids of the two persons for different sample palm-print images are not well-separated and even for some images they overlap with each other, which clearly indicates poor between-class separability. In Fig. 4(c), it is observed that, irrespective of the sample images, the feature-centroids of the two persons maintain a significant separation indicating a high between-class separability, which strongly supports the proposed local feature selection algorithm.

We have also considered dominant feature values obtained for various sample images of those two persons in order to demonstrate the within class compactness of the features. The feature values, along with their centroids, obtained for the two different cases, i.e., extracting the features from the palm-print image without and with modularization, are shown in Figs. 4(d) and (e), respectively. It is observed from Fig. 4(d) that the feature values of several sample palm-print images of the two different persons are significantly scattered around the respective centroids resulting in a poor within-class compactness. On the other hand, it is evident from Fig. 4(e) that the centroids of the dominant features of the two different persons are well-separated with a low degree of scattering among the features around their corresponding centroids. Thus, the proposed 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.

D. Feature Dimensionality Reduction

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 [10]. 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:

$$Y^T = X^T W = V\Sigma^T \tag{4}$$

where the matrix Σ is an $m \times n$ diagonal matrix with nonnegative real numbers on the diagonal and $W\Sigma V^T$ is the singular value decomposition of X. If q sample palm-print images of each person are considered and a total of M dominant DWT coefficients (approximate and horizontal detail) are selected per image, the feature space per person would have a dimension of $q \times M$. For the proposed dominant features, implementation of PCA on the derived feature space could efficiently reduce the feature dimension without loosing much information. Hence, PCA is employed to reduce the dimension of the proposed feature space.

E. 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 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

$$\Delta_j^f = \frac{1}{q}\sum_{k=1}^{q}\sum_{i=1}^{m} |\gamma_{jk}(i) - v_f(i)|^2, \quad (5)$$

where a particular class represents a person with q number of sample palm-print images. Therefore, according to (5), given the test sample image f, the unknown person is classified as the person j among the p number of classes when

$$\Delta_j^f \leq \Delta_g^f,\ \forall j \neq g \ and \ \forall g \varepsilon \{1,2,\ldots,p\} \quad (6)$$

IV. EXPERIMENTAL RESULTS

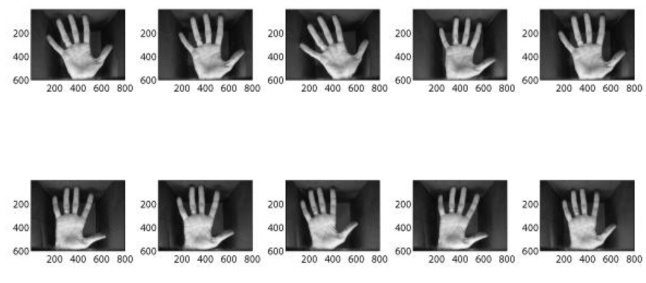
Extensive simulations are carried out in order to demonstrate the effectiveness of the proposed method of palm-print recognition using the palm-print images of several well-known databases. Different analyses showing the effectiveness of the proposed feature extraction algorithm have been shown. The performance of the proposed method in terms of recognition accuracy is obtained and compared with those of some recent methods [2, 5].

A. Palm-print Recognition

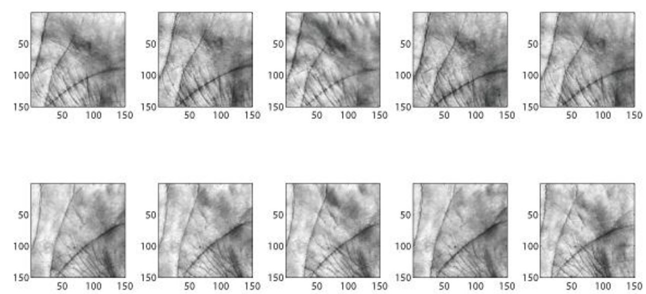
In this section, palm-print recognition performance obtained by different methods has been presented using two standard databases, namely, the PolyU palm-print database (version 2) (available at http://www4.comp.polyu.edu.hk/~biometrics/) and the IITD palm-print database (available at http://web.iitd.ac.in/~ajaykr/Databasen_Palm.htm). In Figs. 5(a) and (b), 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. 5(a) and (b) that not all the portions of the palm-print images are required to be considered for feature extraction [4]. 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. 5(c) and (d).

B. Performance Comparison

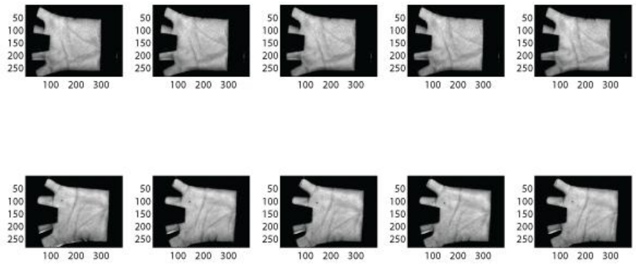
In the proposed method, dominant features (approximate and horizontal detail 2D-DWT coefficients) obtained from



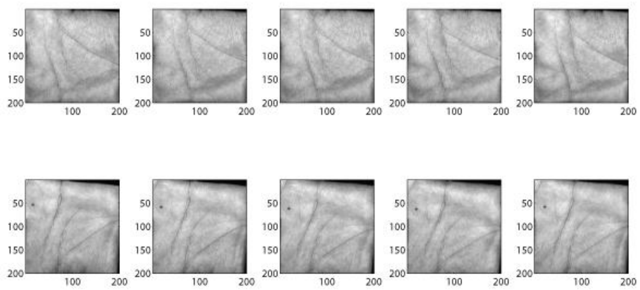
(a)



(c)



(b)



(d)

Figure 5: Sample palm-print images from: (a) the IITD database and (b) the PolyU database; Sample palm-print images after cropping: (c) from the IITD database and (d) from the PolyU database

all the modules of 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.E. 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 dominant wavelet coefficients corresponding to all the local segments residing in the palm-print images are then obtained using $\theta = 20$. For the purpose of comparison, recognition accuracy obtained using the proposed method along with those reported in [2] and [5] 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 99.82% is achieved.

Table 1: Comparison of recognition accuracies

Method	**Recognition accuracies**
Proposed method	99.79%
Method [2]	97.50%
Method [5]	98.00%

V. Conclusion

In the proposed DWT-based palm-print recognition scheme, instead of operating on the entire palm-print image at a time, dominant features are extracted separately from each of the modules obtained by image-segmentation. It has been shown that because of modularization of the palm-print image, the proposed dominant features, that are extracted from the sub-images, attain better discriminating capabilities. The proposed feature extraction scheme is shown to offer two-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. 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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