Personal Identification using Palmprint Images

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Abstract **- Biometric identifiers take distinctive characteristics into consideration which are robust parameters for recognition. In this paper, we present a novel and efficient approach for personal identification using texture based palmprint technology. The method has three steps – preprocessing, feature extraction and matching. In preprocessing, we have proposed a new method for ROI extraction using three valley points and two additional points on the hand image. Features are extracted using discrete cosine transform (DCT) and finally five distance classifiers are used to find the recognition rate. CASIA palmprint database is used to evaluate the performance of the model. The experimental results offer 97% recognition rate with total execution time less than 200ms per test, which is suitable for on-line identification system as well. It has been observed that the holistic DCT is little faster than the block-wise DCT for the proposed method. MATLAB R2015a is used to simulate the model.**

Keywords - Biometrics; Palmprint; ROI; DCT; MATLAB

I. INTRODUCTION

In biometric security system, human identification can be done using human physiological characteristics such as fingerprint, iris pattern, palmprint etc. Among them, fingerprint technology was mostly used for last 25 years. After that many biometric techniques for personal authentication have successfully developed. Now-a-days, palmprint technology is on the point of main attraction. Palmprint contains more discriminative features and larger pattern area than fingerprint, so recently it is receiving increasing attention [1]. Palmprint technology identify individual person calculating palm's principal lines, wrinkles, ridges, minutiae points, singular points, textures etc.

Palmprint technology can be classified into three major categories viz.; line-based; subspace-based and texture based [2]. Principal lines, ridges, wrinkles etc. known as the features of line-based approach, and are the most clearly observable features in low-resolution palmprint images. Line-based approach can successfully extract all lines and ridges but its main drawback is computational complexity. Subspace-based approach deals with different method such as Principal Component Analysis (PCA), 2D PCA, Independent Component Analysis (ICA), Fisherpalm etc. In texture based approach, palmprint texture can be analyzed using different techniques such as Gabor filers, Discrete Cosine Transform (DCT), morphological techniques, Fourier transform and wavelet transform.

In this paper, we have presented a DCT based approach with a new region of interest (ROI) extraction technique for identification of low resolution palmprint images suitable for civil and commercial applications [3]. Experimental results evaluated the system's efficiency and indicated faster in operation.

II. PROPOSED METHOD

The proposed method has three major steps: image preprocessing, feature extraction and palmprint matching. In this paper, it is considered that the hand images are initially available to the authentication system. In preprocessing, region of interest (ROI) is extracted from low resolution palm image. Then, the textural features are extracted from the cropped image using discrete cosine transform (DCT). Finally, distance classifier is applied to measure similarity/dissimilarity of the feature vectors of the input image with that of templates sorted in the system database. The block diagram of the proposed method is shown in Fig. 1.

A. *Image Preprocessing*

It is important to find the proper region from hand image in palm print authenticaltion. It means to extract an area from the hand image which carries features like wrinkles and principal lines. Missing of these distinctive features may cause false recognition, consequently unstable the system. This focused area is known as region of interest (ROI). Reference [4] proposed a coordinate system for ROI detection where authors marked two points in the hand image. One locates between the index and middle fingers, and another between the ring and little fingers. After marking them, they set the third point as the midpoint of these two points. In this paper, instead of midpoint, we use the valley point between the ring and little fingers as the third point.

First we apply a low pass filter such as Gaussian Smoothing filter to blur the blobs and isolated points. Then the image is converted into binary image by means of global thresholding. After that, contour of the hand image is obtained using a boundary tracking algorithm [5].

Once contour is obtained, then three valley points between index, middle and little fingers are detected by tracking the local minima of the hand image, and are marked as P_1, P_2 and P_3 (see Fig. 2(a)). Draw line $\overline{P_1P_2}$ and $\overline{P_2P_3}$. Let the line lenghts are a and b respectively. Now we detect another two points P_4 and P_5 in such a way that P_4 is $a/2$ distance away from P_1 along the P_2P_1 axis whereas P_5 is $b/2$ distance away from P_3 along the P_2P_3 axis (see Fig. 2(b)). Draw line L_1 connecting points P_4 and P_5. Angle of line L_1 and horizontal axis can be determined by:

$$\theta = \tan^{-1}\left(\frac{y_{p5} - y_{p4}}{x_{p5} - x_{p4}}\right) \tag{1}$$

Let the length of line L_1 is c. Now Draw another two lines L_2 and L_3 having of length c such that $L_2 \perp L_1$ and $L_3 \perp L_1$ using the relation of perpendicular lines $m_1 m_2 = -1$. Connect the terminals of line L_2 and L_3 to get line L_4 (see Fig. 2(c)). Then the image is rotated to align the square [$L_1L_2L_3L_4$] along the horizontal and vertical axes (see Fig. 2(d)). Finally, the square is cropped and resized to a 128×128 image. Fig. 3 shows ROI of four different persons.

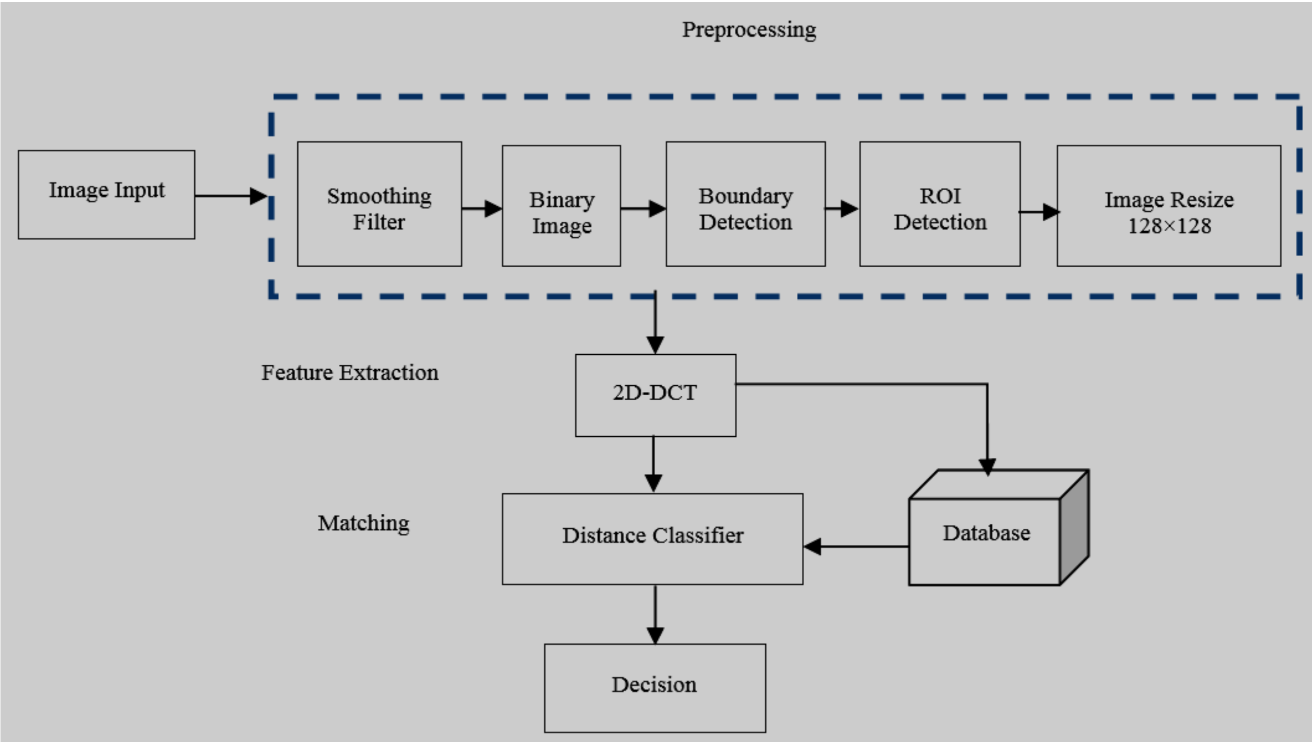


Fig.1. Block diagram of the proposed palm print based recognition system.

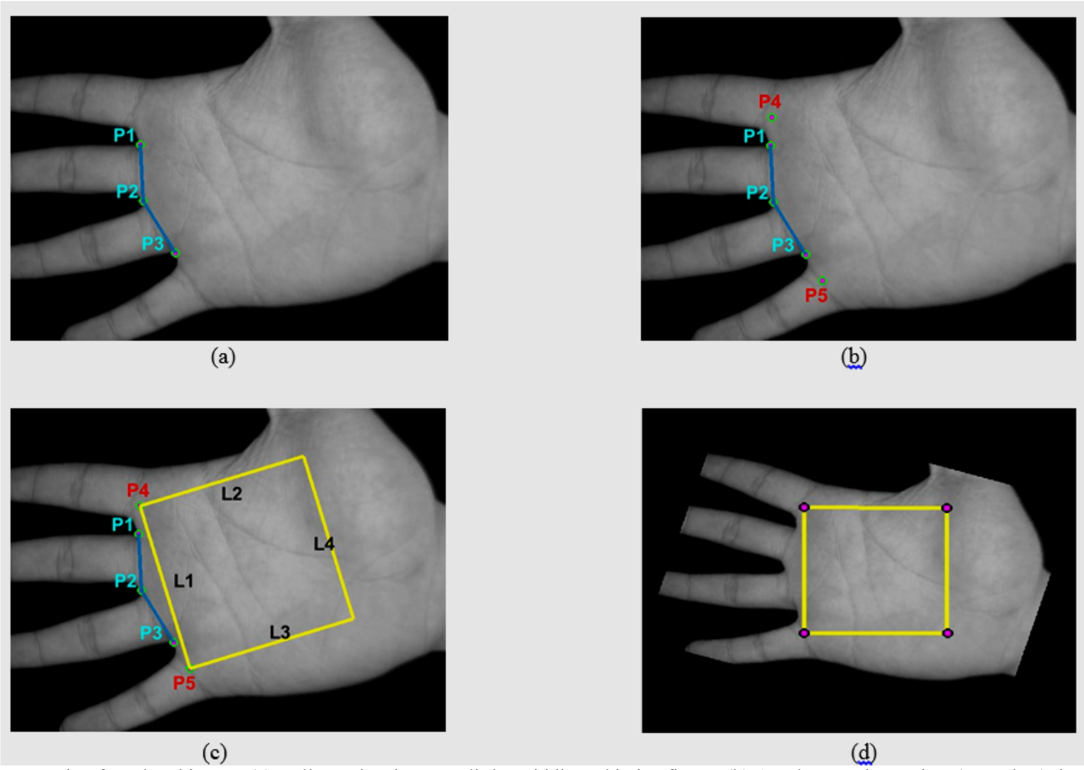


Fig. 2. ROI extraction from hand image. (a) Valley points between little, middle and index finger, (b) Another two key points (P_4 and P_5) detected on the hand image, (c) ROI located on the hand image, (d) Image after rotation.

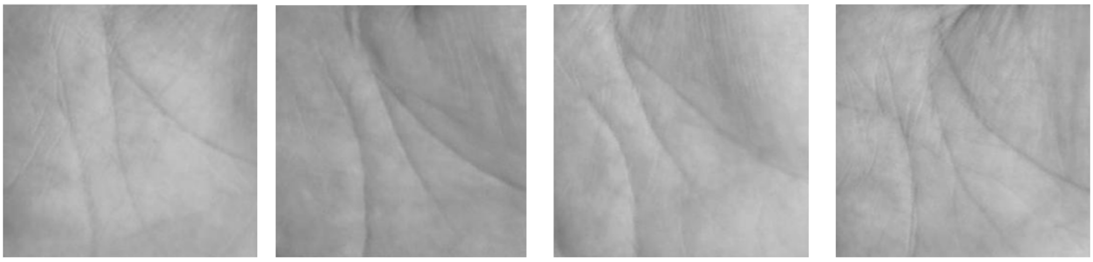


Fig. 3. ROI of four different persons

B. *Feature Extraction*

Discrete cosine transform, shortly known as DCT, is a very popular method in image processing and signal analysis due to its 'energy compaction' property [6]. In this paper, 2D-DCT is used for extracting features from ROI. The general equation of 2D-DCT for a N × M image is defined as follows:

$$F(u,v) = \sqrt{\frac{2}{N}}\sqrt{\frac{2}{M}}\sum_{i=0}^{N-1} A(i) * \cos\left(\frac{u(2i+1)\pi}{2N}\right) * \sum_{j=0}^{M-1} A(i) * \cos\left(\frac{v(2j+1)\pi}{2M}\right) * f(i,j) \quad (2)$$

Where,

$$A(i) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } u = 0 \\ 1 & \text{otherwise} \end{cases}$$

$$A(j) = \begin{cases} \frac{1}{\sqrt{2}} & \text{for } v = 0 \\ 1 & \text{otherwise} \end{cases}$$

f(i,j) is the 2D input sequence.

Low frequency coefficients are located at the upper left corner of the DCT matrix, and generally carry much of the signal energy [7]. Since, high frequency coefficients, located at lower right corner of the DCT matrix, are often very small, so they can be neglected with little visible distortion. In this paper, we consider holistic and block-wise DCT approach for feature extraction.

Holistic approach

In holistic approach, DCT is taken for the whole input image resulting a DCT matrix having same size as the original image. Next, the DCT matrix is converted into a one-dimensional vector using zigzag scanning, which rearranges the components according to the frequency in ascending order (see Fig. 4). Finally, low frequency components are stored and proceeded to distance classifier.

Block-wise approach

In this approach, image is divided into small blocks first. Then, DCT is applied to each block. If the block size is 8×8 pixels, then it divides the ROI of 128×128 pixels, into 256 sub-images. Consequently, DCT is found for each sub-image (see Fig. 5). In this paper, we store the upper leftmost coefficient of each sub-image for further processing.

C. *Palmprint matching*

Once the features are obtained, they are compared with templates stored in the database to find the similarity/dissimilarity among them. Various distance classifiers can be used in this regard. In this paper, five widely used distance based measurements have been used to evaluate the performance of the system. They are – Euclidean distance, Cosine distance, Correlation coefficient distance, Canberra distance and Manhattan or City-block distance. The summery of these distances are shown in bellow:

(1) Euclidean distance

$$d(x,y)=\sqrt{\sum_{i=1}^{n}\left|x_i-y_i\right|^2} \quad (3)$$

(2) Manhattan or City-Block distance

$$d(x,y)=\sum_{i=1}^{n}\left|x_i-y_i\right| \quad (4)$$

(3) Cosine distance

$$d(x,y)=-\cos(x,y)$$

$$\cos(x,y)=\frac{\sum_{i=1}^{n}x_i y_i}{\sqrt{\sum_{i=1}^{n}x_i^2\sum_{i=1}^{n}y_i^2}} \quad (5)$$

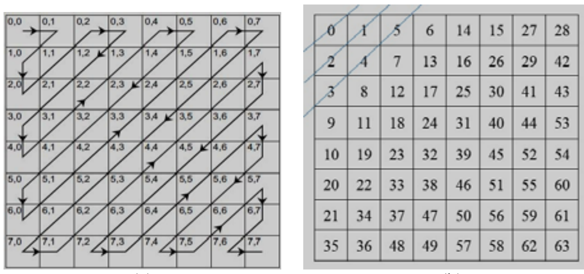
(4) Canberra distance

$$d(x,y)=\sum_{i=1}^{n}\frac{\left|x_i-y_i\right|}{\left|x_i\right|+\left|y_i\right|} \quad (6)$$

(5) Correlation coefficient-based distance

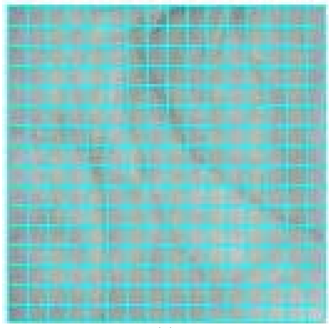
$$d(x,y)=-r(x,y) \quad (7)$$

$$r(x,y)=\frac{n\sum_{i=1}^{n}x_i y_i-\sum_{i=1}^{n}x_i\sum_{i=1}^{n}y_i}{\sqrt{\left(n\sum_{i=1}^{n}x_i^2-\left(\sum_{i=1}^{n}x_i\right)^2\right)\left(n\sum_{i=1}^{n}y_i^2-\left(\sum_{i=1}^{n}y_i\right)^2\right)}}$$

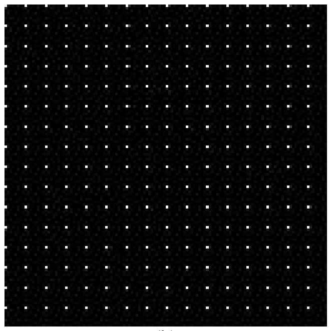


(a) (b)

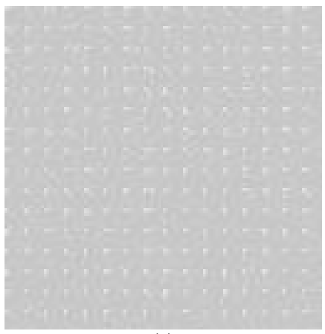
Fig. 4. (a) Zigzag scanning, (b) Area of interest indicating low frequency components.



(a)



(b)



(c)

Fig. 5. Block-wise DCT. (a) Image divided into blocks of 8×8, (b) DCT transform of the sub-images, (c) Histogram equalized sub-images.

III. DATABASE

In our experiments, palm images are collected from CASIA Palmprint Image Database [8]. It contains total 5502 palmprint images corresponding to 312 different subjects including images from both left and right hands. All palmprint images are 8-bit gray-level JPEG files captured by a CMOS camera. We have used palmprint images of right hands in our experiments.

IV. EXPERIMENTAL RESULTS

For experiments, we have chosen 100 persons randomly from CASIA database. We have taken 7 right hand palmprint images of each person for training and one for testing. Thus, total 700 training and 100 testing images are stored. Also, ROI dimension is set up to 128×128 in the experiments. Features of ROI are extracted using 2D-DCT. Before applying to classifiers, features are collected in two different ways – holistic DCT and block-wise DCT. In holistic approach, coefficients located at the upper left corner of the DCT matrix have been used, whereas, in block-wise DCT, images are divided into blocks of different sizes, and then upper leftmost component of each block is stored. Recognition rate is defined as the fraction of test samples which are correctly recognized by the identification system [9]. Table I and Table II show the recognition rate of five distance classifiers for holistic and block-wise DCT approach respectively. In holistic DCT, best performance is achieved using minimum 28 coefficients, whereas, 16×16 blocks show maximum efficiency for block-wise DCT. Fig. 6 and Fig. 7 are the Receiver Operating Characteristic (ROC) curves (False acceptance rate vs Genuine acceptance rate), where cosine distance shows slightly better performance for block-wise DCT and Manhattan distance for holistic DCT.

TABLE I. PERCENTAGE RECOGNITION RATE FOR DIFFERENT MATCHING MEASUREMENTS FOR HOLISTIC APPROACH

S/ N	Coeffi- cients	Euclidean	Cosine	Correlation	Canberra	Man- hattan
1	3	62	28	13	42	63
2	6	89	78	74	74	89
3	10	92	89	89	80	90
4	15	94	94	93	88	96
5	21	96	96	96	94	96
6	**28**	**97**	**97**	**97**	**96**	**97**
7	36	97	97	97	96	97
8	45	97	97	97	96	97

TABLE II. PERCENTAGE RECOGNITION RATE FOR DIFFERENT MATCHING MEASUREMENTS FOR BLOCK-WISE DCT APPROACH

S/ N	Block size	Euclidean	Cosine	Correla- tion	Canberra	Man- hattan
1	64×64	79	54	27	79	79
2	32×32	94	91	89	94	94
3	**16×16**	**97**	**97**	**97**	**97**	**97**
4	8×8	97	97	97	97	97
5	4×4	97	97	97	97	97
6	2×2	97	97	97	97	97

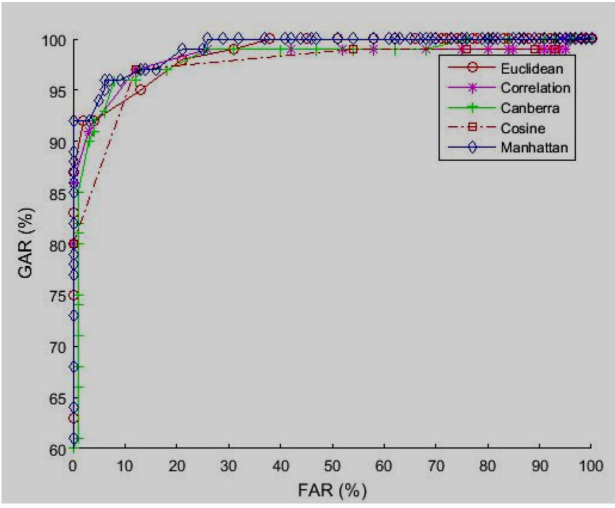


Fig. 6. ROC curve for holistic DCT

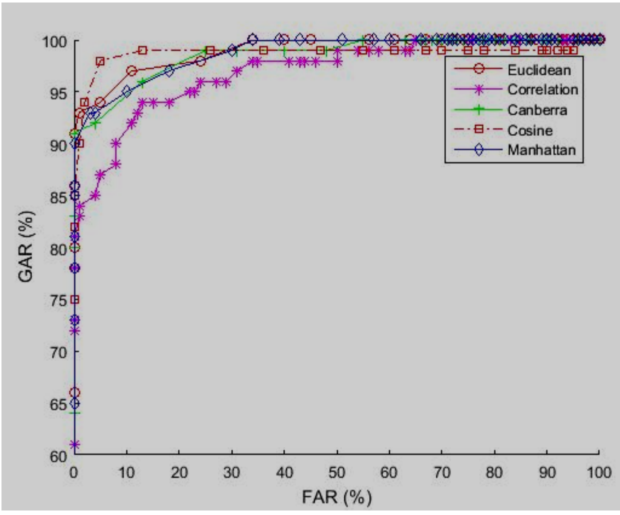


Fig. 7. ROC curve for block-wise DCT

V. SPEED

MATLAB R2015a has been used on a PC using Core i3, 2.30GHz processor with 2GB RAM. The execution time (summation of ROI extraction time, feature extraction time and matching time) of 100 test images for holistic approach with 28 coefficients and for block-wise approach with block size 16×16 is shown in Fig. 8.

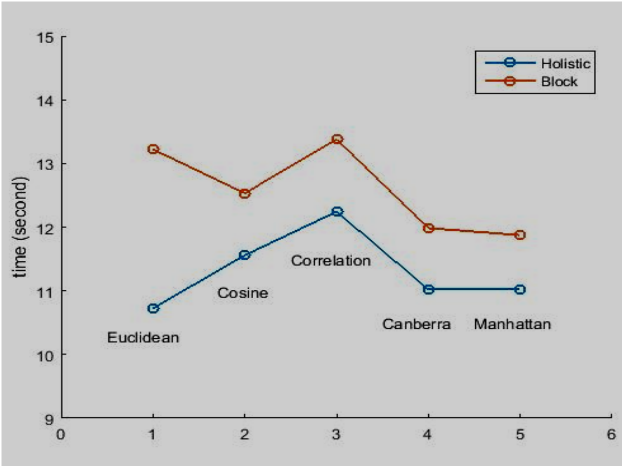


Fig. 8. Execution time for 100 test images for different distance classifiers.

VI. CONCLUSION

A new approach for region of interest (ROI) extraction from palmprint image has been proposed. Unlike other methods [2], it requires fewer points to extract ROI with less mathematical complexity. Discrete cosine transform (DCT) is used for feature extraction. Five popular distance classifiers are used to evaluate the performance of the system. Both holistic and block-wise DCT approach show good accuracy for these classifiers. Optimal number of coefficients found for holistic approach is 28, whereas, the optimal block size is 16×16 for block-wise DCT approach. ROC curves for the both approaches are demonstrated. Finally, speed of the system is measured. It has been seen that the average execution time is little higher for block-wise approach compared to the holistic approach. Nevertheless, execution time remains below 200ms for each test image, indicating fast enough for on-line identification.

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