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Palmprint Recognition using DCT-mod2 Features and Backpropagation Neural Network

Sarita Salawadgi
Department of CSE
SECAB Institute of Engineering & Technology,
Bijapur, Karnataka, India

Abstract: A biometric system recognizes or authenticates individual based on some physical or behavioural characteristics that are intrinsically unique. Human palmprint image contains some unique features that can easily identify people, which make it a challenging topic for research. This paper proposes a new method for identification of person using palmprint. In this paper, IIT Delhi palmprint database is used. Here DCT-mod2 features are extracted. The dimensionality of the extracted features is reduced using Principal Component Analysis (PCA).Back propagation neural network (BPNN) is used for the matching.

Keywords: Biometric system, BPNN, DCT-mod2, Palmprint, PCA.

I. INTRODUCTION

Human palmprint image has many features that can be used for personal identification. Principal lines, wrinkles, ridges, minutiae points, singular points and texture are regarded as useful features for palmprint representation. Various features can be extracted at different image resolutions. For features such as minutiae points, ridges and singular points, a high-resolution image, with at least 400 dpi(dots per inch),is required for feature extraction. However features like principal lines and wrinkles, a low-resolution image, with less than 100 dpi(dots per inch) is required. Palmprint identification can be divided into two categories, on-line and off-line. For off-line identification, all palmprint samples should be inked on a paper, and then transmitted to a computer through scanner. For on-line palmprint identification, the samples can be directly obtained by palmprint input equipment. It is evident that on-line identification is more important for many real-time applications of personal authentication.

Palm print identification can be divided into two categories: high-resolution or low-resolution images. High resolution images are most suitable for forensic applications such as criminal detection whereas low resolution images are suitable for civil and commercial applications such as access control. Points and minutia are features from high resolution images while in low resolution images principal lines, wrinkles and texture features are extracted.

Initially, palmprint research focused on high resolution images but now almost all research is on low resolution images for civil and commercial applications. There are three key issues [1] to be considered in developing online palmprint identification systems are:

Palmprint Acquisition: How do we obtain a good quality palmprint image within short time interval such as 1 second? What kinds of devices are suitable for data acquisition?

Palmprint Feature Representation: Which types of palmprint features are suitable for identification? How to represent different palmprint features?

Palmprint Identification: How do we search for a queried palmprint in a given database and obtain a response within a limited time?

II. LITERATURE REVIEW

Palmprint recognition has been investigated over the past ten years. During this period, many different problems related to palmprint recognition have been addressed. Researchers have focused on developing accurate verification algorithms. Various feature extraction and matching algorithms have been proposed. To achieve high verification accuracy, researchers combine different biometric traits with palmprints.

A biometric approach to online identification using palmprint technology is proposed [1], where online palmprint identification system employs low resolution palmprint images to achieve effective identification. The system consists of two parts: a novel device for palmprint acquisition and an efficient algorithm for fast palmprint recognition. A robust image coordinate system is defined to facilitate image alignment for feature extraction. Victor S Viera and Joao Marquez

Salomao [2] used Gaussian filter for principle line extraction. Debauchies wavelet transform is applied four times to get features. Nirupama Srinivasanet al., [3] describe an approach to palmprint recognition. A corner finding algorithm is developed to detect the finger tips and trough corners of a palm. Based on this, a consistent region of interest is extracted for each palm. A feature vector is computed for each ROI and similarity index is computed for palms. Xiang-Qian et al.,[4] describe a palmprint feature called wavelet energy features. This feature is defined employing wavelet, which is powerful tool of multi-resolution analysis.WEF can reflect wavelet energy distribution of principal lines, wrinkles, and ridges in several directions at different wavelet decomposition level, so its ability to discriminate palm is very strong. Vamsi Krishna Madasu [5] describe that fuzzy logic based edge detectors for feature extraction in biometric systems. Edge detection is carried out by means of local and global information. The local information is fuzzified by using modified Gaussian membership function. Using the contrast intensification operator, the image is enhanced to required level of visual quality by entropy optimization of fuzzification parameters.Xiangqian Wu et al., [6] described a approach in which principal lines and wrinkles can be extracted in low resolution images. To extract palm a set of directional line detectors are used and then these detectors are used to extract these lines in different directions. To avoid loosing the details of palm line structure, these irregular lines are represented using their chain codes. Here, to match palm lines, a matching score is defined between two palms according to points of their palm lines. Lie Zhang and David Zhang [7] describe a palmprint identification scheme that characterizes a palmprint using a set of statistical signatures. The palmprint is first transformed into wavelet domain, and the directional context of each wavelet subband is defined and computed in order to collect the predominant coefficients ofits principal lines and wrinkles. A set of statistical signatures, which includes gravity center, density, spatial dispersivity and energy, is then defined to characterize the palmprints with selected directional context values. A classification and identification scheme based on these signatures is subsequently developed. This scheme uses a much smaller amount of data signatures. Zhenan and Tieniu [8] present a novel palmprint representation ordinal measure, which unifies several major existing palmprint algorithms into general framework. In this framework, a novel palmprint representation method, namely orthogonal line ordinal feature, is proposed. The basic idea of this of this method is to qualitatively compare two elongated, line like image regions, which are orthogonal in orientation and generate one bit feature code. A palmprint pattern is represented by thousands of ordinal feature code. Yofie Han et al. propose a practical palmprint recognition algorithm using two-dimensional (2D) phase information. The algorithm proposed by Satoshi Iitsuka and Koichi Ito [9] reduces the registered data size by registering quantized phase information and deals with nonlinear distortion between palmprint images by local block matching. Saroj Kumar Panigrahy et al. [10] proposed efficient approach to the palmprint preprocessing scheme. In real-time palmprint verification the input subject to the scanner for image acquisition may suffer rotational as well as translational variation. Because when the user puts his/her palm on the scanner, the angle and position of the palm may change. So, different images are acquired by the scanner according to the input each time. Masayoshi[11], proposed an algorithm for fingerprint image recognition. The proposed algorithm involved two stages, which is pre-processing of fingerprint image and feature extraction based on DCT.

The extracted DCT data is used as input for the back propagation neural network training for personal identification.Adams Kong et al.,[12] proposed a feature-level fusion approach for improving the efficiency of palmprint identification. Multiple elliptical Gabor filters with different orientations are employed to extract the phase information on a palmprint image, which is then merged according to a fusion rule to produce a single feature called the Fusion Code. The similarity of two Fusion Codes is measured by their normalized hamming distance. A dynamic threshold is used for the final decisions. Xing Peng [13] et al., proposed an improved 2DLPP method on Gabor features (I2DLPPG) for palmprint recognition in this paper. 2DPCA is first utilized for dimensionality reduction of Gabor feature space maintaining most prominent 2D information. Thus similarity matrix corresponding to elements is easily constructed and the followed 2DLPP can be implemented directly in the reduced feature space. Wangmeng Zuo et al., [14] presented a multiscale competitive code method for efficient palmprint representation and matching. In filterbank design, the log-Gabor wavelets are used because of its less overlapping in the frequency domain. In palmprint representation, competitive code is used to encoding the dominant orientation of the filter responses in each scale. In palmprint matching, a fusion rule is proposed to combine the distances obtained using different scales.Yanquing Zhang et al., [15] applied the laplacian transform to palm and middle finger images which are fused together and the feature extraction is done by PCA. Matching is done by Nearest Neighbor Classifier. ShuangXu et al., [16] used Gabor wavelet for feature extraction and represent as a matrix by B2DPCA and further reduced by PCA. RunbinCai et al., [17] fused the visible and infrared images of palmprints. This is then decomposed by DTCWT. The entropy of the fused image and the source image is used for identification. K.Vaidehi, et al., [18] apply DWT DB4 and then DCT for feature extraction. The dimension of DCT is reduced by PCA. Peng –FeiYu et al., [19] used modified discrete cosine transform based feature extraction method to obtain palmprint features. Furthermore, a radial basis function neural network is employed for palmprint classification. principal components analysis is applied to reduce these features to a reasonable dimension. K B Nagasundara and D S Guru [20] propose a multi algorithm based feature extraction. Features are extracted using both Haar wavelet and Zernike moments. The fused features are then indexed using KD-Tree, which results in faster identification.

III. IMPLEMENTATION

Every Palmprint recognition system consist of four steps: palmprint acquisition, preprocessing, feature extraction and matching as shown in Fig. 1.

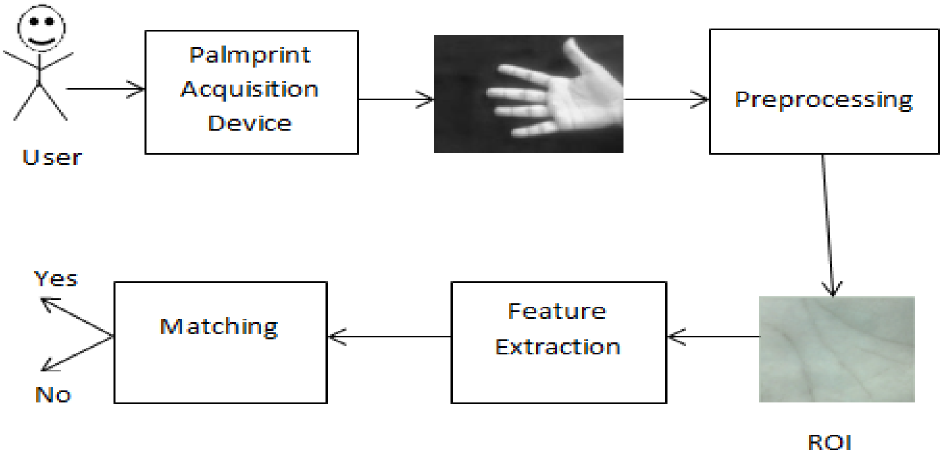


Fig.1. Proposed palmprint recognition model

The palmprint acquisition device such as scanner collects palmprint images. Preprocessing sets up a coordinate system to align palmprint images and to segment a part of palmprint image for feature extraction. Feature extraction obtains effective features from the preprocessed palmprints. A matcher compares two palmprint features.

Before implementing algorithms, let us see the brief description about the database. Firstly, the database used consists of gray scale images with the resolution of 800 x 600 pixels. The database was obtained from IIT, Delhi touchless palmprint database. All the implementations were carried out in MATLAB R2011b.

A. Preprocessing

In preprocessing we define a coordinate system that is used to align different images for matching. To extract central part of palmprint, we use the gaps between the fingers as reference points to determine a coordinate system. The five major steps in preprocessing are:

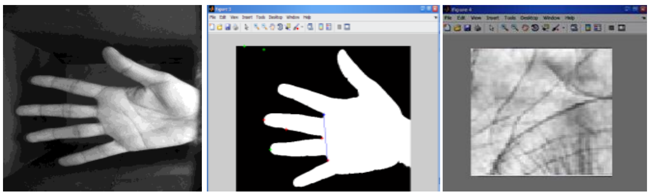
Step 1: Apply a lowpass filter,$L(u, v)$, such as Gaussian smoothing, to the original image$O(x, y)$. A threshold, t_p, is used to convert the convolved image to binary image, $B(x, y)$.

Step 2: Obtain the boundaries of the gaps, between the fingers using boundary tracking algorithm. The boundary of gap between the ring and middle fingers is not extracted since it is not useful for following processing.

Step 3: Compute the tangent of the two gaps. Let (x_1,y_1) and (x_2,y_2) be any points on($F_1 x_j$, $F_1 y_j$) and ($F_2 x_j$, $F_2 y_j$) respectively. If the line ($y = mx + c$) passing through these points satisfies the inequality, $F_i y_j \leq mF_i x_j + c$, for all iandj, then the line($y = mx + c$ is considered to be the tangent of two gaps.

Step 4: Line up (x_1,y_1)and (x_2,y_2) to get the Y-axis of palmprint coordinate system, and use a line passing through the midpoint of these two points, which is perpendicular to the Y-axis, to determine the coordinate system's origin.

Step 5: Extract the fixed sized subimage based on the coordinate system. The subimage is located at a certain area of the palmprint image for feature extraction.



(a) (b) (c)

Fig.2. Preprocessing: (a) original image (b)binary image (c)preprocessed result

B. Feature Extraction

A palmprint can be represented by some line features from a low resolution image. Principal lines are not sufficient to represent the uniqueness of each individual's palmprint because different people may have similar principal lines in their palmprint. As result we try to extract dctmod2 features.

DCT-mod2 features

DCT is a signal analysis method used in image compression and other image processing applications [19]. It has been used as feature extraction methods in many researches on biometric recognition, for example, fingerprint recognition, face recognition and many more.

In DCTmod2 feature extraction, for a given image f(x, y), the two dimensions DCT is defined as:

$$C(u, v) = \frac{2}{N} G(u) G(v) \sum_{x=0}^{N-1} \sum_{y=0}^{M-1} f(x, y)\, \beta(x, y, u, v) \quad (1)$$

For $u, v = 0,1,2 \ldots \ldots . . N - 1$

Where, $G(u)G(v)=\frac{1}{\sqrt{2}}$, for $u = 0, v = 0$

Otherwise, $G(u)G(v) = 1$ and $\beta(x, y, u, v) = cos\frac{(2x+1)\pi u}{2N} cos\frac{(2y+1)\pi v}{2N}$

The DCT features are sensitive to changes in the illumination direction. Hence, we use some modified DCT based methods. Among these DCT derived methods, DCT-mod2 method divides a given image into blocks, where each block is of size $N_P \times N_P$ (Here we use $N_p = 8$) and each block overlaps neighboring horizontally and vertically adjacent blocks by 20% pixels. Subsequently, 2-D DCT transform is performed on each block, and the first M of zigzag scanned sequence DCT coefficients are selected to build a feature vector:

$$\vec{x}=[c_0{}^{(b,a)}, c_1{}^{(b,a)}, c_2{}^{(b,a)}, \ldots\ldots\ldots\ldots.. c_{M-1}{}^{(b,a)}]^T \quad (2)$$

Since the first three coefficients are sensitive to illumination changes, they are discarded from the above vector, and then replaced by their horizontal and vertical polynomial coefficients. As a result, the effects of illumination changes are reduced. The DCT-mod2 feature is defined as follows:

$$\vec{x}=[\Delta^h c_0^{(b,a)}, \Delta^v c_0^{(b,a)}, \Delta^h c_1^{(b,a)}, \Delta^v c_1^{(b,a)}, \Delta^h c_2^{(b,a)}, \Delta^v c_2^{(b,a)} \ldots\ldots c_{M-1}^{(b,a)}]T \quad (3)$$

Where, $\Delta^h c_i^{(b,a)}$ and $\Delta^v c_i^{(b,a)}$ are the horizontal and vertical polynomial coefficients respectively. These two coefficients are computed using DCT coefficients calculated from neighboring blocks:

$$\Delta^h c_i^{(b,a)} = \sum_{k=-1}^{1} h_k\, c_i^{(b,a)} (4) \text{ and } \Delta^v c_i^{(b,a)} = \sum_{k=-1}^{1} h_k\, c_i^{(b,a)} \quad (4)$$

Where, h_k is an element of a three dimensional symmetric vector.

Further, we apply Principal Component Analysis (PCA) to reduce the dimensionality of the obtained feature vector using DCT. We obtain mean, variance and Eigen values by applying PCA.

C. Matching

This work also involves developing a suitable neural network model (BPNN). The extracted features are presented to BPNN, which recognizes palmprint images. The neural network architecture is trained itself accordingly. The training takes place such that the neural network learns that each entry in the input file has a corresponding entry in the output file.

In testing, input image from testing set is selected and its features are extracted and given to the trained model, the trained BPNN model classifies given sample and produces output.

1) *Backpropagation Neural Network:* Backpropagation Neural network is a supervised learning method, and is a generalization of the delta rule. It requires a dataset of the desired output for many inputs, making up the training set. It is most useful for feed-forward networks (networks that have no feedback, or simply, that have no connections that loop). Backpropagation requires that the activation function used by the artificial neurons (or "nodes") be differentiable.

2) *Creating BPNN:* The Neural Network is designed and implemented using the in MATLAB R2011b with Neural Network Toolbox 4.0. Jayas et al. (2000) have indicated that Back Propagation Neural Network (BPNN) suits the best in these applications. We have adopted a four layer BPNN for palmprint classification.

The number of neurons in the first layer is n (n=16 in this work) which is equal to the dimensionality of the input pattern vectors (Number of input nodes equals number of input features used). The number of neurons in the output layer is 5 which are equal to the number of pattern classes.

The number of nodes in the hidden layer is calculated using the (5).

$$n = \frac{I+O}{2} + y^{0.5} \quad (5)$$

Where n=number of nodes in the hidden layer, I=number of nodes in the input layer, O=number of nodes in the output layer, and y=number of input patterns in the training set.

3) *Training of BPNN:* Training is the process of altering the weights of a network systematically so as to yield a proper mapping between input and output patterns. The connection weights are adjusted from the output layer toward the inputs (error back-propagation). When all the patterns in the training set are sequentially introduced to the network and weights are adjusted accordingly, a training cycle is completed. Training cycles are repeated until the network error reaches a predetermined error value or a specified number of training cycles is. In this work, back propagation algorithm is used for training the developed BPNN. BPNN are trained to do a specific task.

The developed BPNN is trained with palmprints of different persons. Large numbers of images are required to ensure proper training of the BPNNs. The extracted features of the palmprint are used after normalization to train the developed model. Some initial runs showed that these settings appeared to be sufficient for this study. During the training procedure of the BPNNs, the maximum acceptable Mean Square Error (MSE) is empirically set at 1 x 10^-3. Each traverse through all of the training input target vectors is called s pass or epoch. The training process is carried out with fast back propagation, with 500-5000 epochs (cycles) or till maximum acceptable MSE is reached.

4) *Testing using trained BPNN:* In testing, input image from untrained set of samples is selected and its features are extracted and given them to the trained model, the trained BPNN model classifies given sample and produces output.

IV. EXPERIMENTATION

In order to evaluate designed system's performance, two experiments have been carried out. The database was obtained from IIT, Delhi touchless palmprint database. Ten palmprints of each person were taken. The palmprint images were of right hand. All the implementations were carried out in MATLAB R2011b.

Experiment

The first experiment has been performed on a palmprint database where dct-mod2, Eigenvalues, mean and variance features of each palmprint are extracted. Recognition rate resulted from this experiment is shown in the Fig. 3, where x-axis indicates number of persons and y-axis indicate performance rate. The system reached 97% recognition rate for the database of 20persons.

The second experiment has been performed on a palmprint database where, the numbers of persons were increased to 40.The recognition rate resulting from this experiment is 94%.
By this experiment we can conclude that as the number of persons increases the performance rate decreases.

TABLE I
PERFORMANCE OF TWO EXPERIMENTS

Experiment	No of persons	Performance Rate
Experiment 1	10 persons	97%
Experiment 2	20 persons	94%

The performance plot of two experiments is shown below.

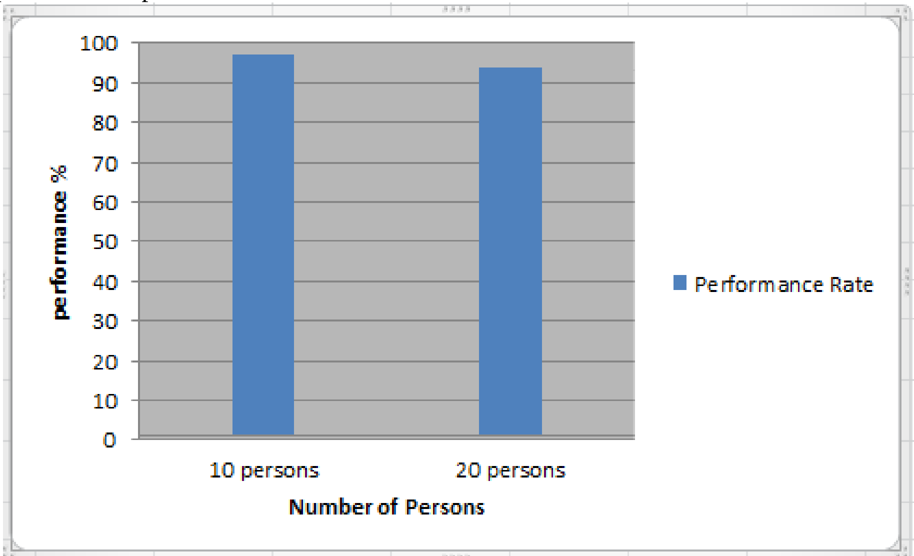


Fig.3. Performance plot of two experiments.

V. CONCLUSION AND FUTURE WORK

Palmprint recognition is an important biometric method and has wide applications. The proposed system has used DCT-mod 2 along with PCA as feature extraction method. Neural network is used as classifier to recognize palmprints. It has been observed that features extracted using DCT-mod 2 and PCA are found to be efficient for palmprint recognition. We achieved the accuracy rate ranging from 97-94% for enrolment of 10 to 20 persons. There is an improvement of identification rate. But neural network takes more time for processing as the number of persons in the database increase. The accuracy of recognition can also be increased by increasing number of trained images for each person.

Future work of this project include an analyses of new features of palmprint image and combining those with the feature vectors used in this work to obtain better accuracy than the accuracy of present work.

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