

A Novel Approach of Palmprint Recognition using PCA, DWT and Random Forest Classifier

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Abstract –Palmprint recognition being one of the important aspects of biometric technology is one of the most reliable and successful identification methods. Palmprint is an important complement and reliable biometric that can be used for identity verification because it is stable and unique for every individual. This paper is divided into two phases, training phase and testing phase. In training phase there are four sub processes; pre-processing, feature extraction and dimensionality reduction. Pre-processing is done with the help of image resizing and RGB to Gray conversion. For feature extraction, we have used Gabor Filter and Discrete Wavelet Transform (DWT). Principal Component analysis (PCA) is used for dimensionality reduction. The extracted features are then stored in database. In the testing phase the same process is done up to the PCA and then the similarity measure with database is done. Random Forest Classifier is used for similarity measure. The MATLAB image processing tool box is used to implement proposed Palmprint recognition system.

Keywords – DWT, PCA, RGB to Gray, Random Forest Classifier.

I. INTRODUCTION

Biometric identification technique is based on the main physical characteristic that lends itself to biometric identification. Palmprint has become an important complement to personal identification because of its advantages such as low resolution, low cost, non-intrusiveness and stable structure features. The palm, the inner surface of the hand between the wrist and the fingers, consists of three parts: principal lines, wrinkles and ridges. There are three principle lines made by flexing the hand and wrist in the palm, which are usually defined as life line, heart line, and head line. Wrinkles and ridges are the coarse and fine lines of the palmprint respectively. The high resolution images can generally extract all the features while in low resolution only principal lines, wrinkles can be extracted. For real time applications low resolution images are used as they have less storage memory and fast matching speed.

Palmprint is one of the most important features for the identification of human. We can recognize the palmprint by its texture or colour feature. But among the two features texture based feature is most important as the colour of the palmprint of different people can be same in many cases. So, by considering the colour feature we may not be able to recognize the human correctly. From statistics it can be noted that, different people has different texture of palmprint. So, it is better to concentrate on the texture feature of the palmprint to recognize the human being more correctly.

Figure 2.3 shows the basic palmprint recognition system.

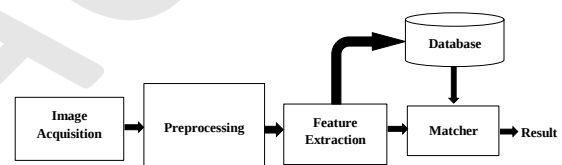


Figure 1: Basic block diagram of palmprint recognition system

II. PROPOSED METHOD

Palm-print recognition system is developed using Gabor filter, Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA) and Random Forest Classifier. The proposed flow for this research work is shown in figure 2.

As per the flow diagram it is clear that there are two phases of this research; training phase and testing phase.

Training Phase

In the first step of training phase we take input images one by one. Then the image is fed into Pre-processing block. Preprocessing is done with the help to two sub processes namely; Resize the image and RGB to Gray conversion. Since most of digital filters work on 2-dimensional data rather than multi-dimensional data, so RGB to Gray conversion is used. Moreover Histogram Equalization method is used for the equalization of image pixel intensity.

Now the preprocessed image data is fed to Feature Extraction block. This block also contains two processes that are used for feature extraction namely; Gabor filter and Discrete Wavelet Transform (DWT). Principal Component Analysis (PCA) is used for dimension reduction. Principal

component from the transformed output of DWT is extracted. This principal component is stored in the database. This all is done in the training process.

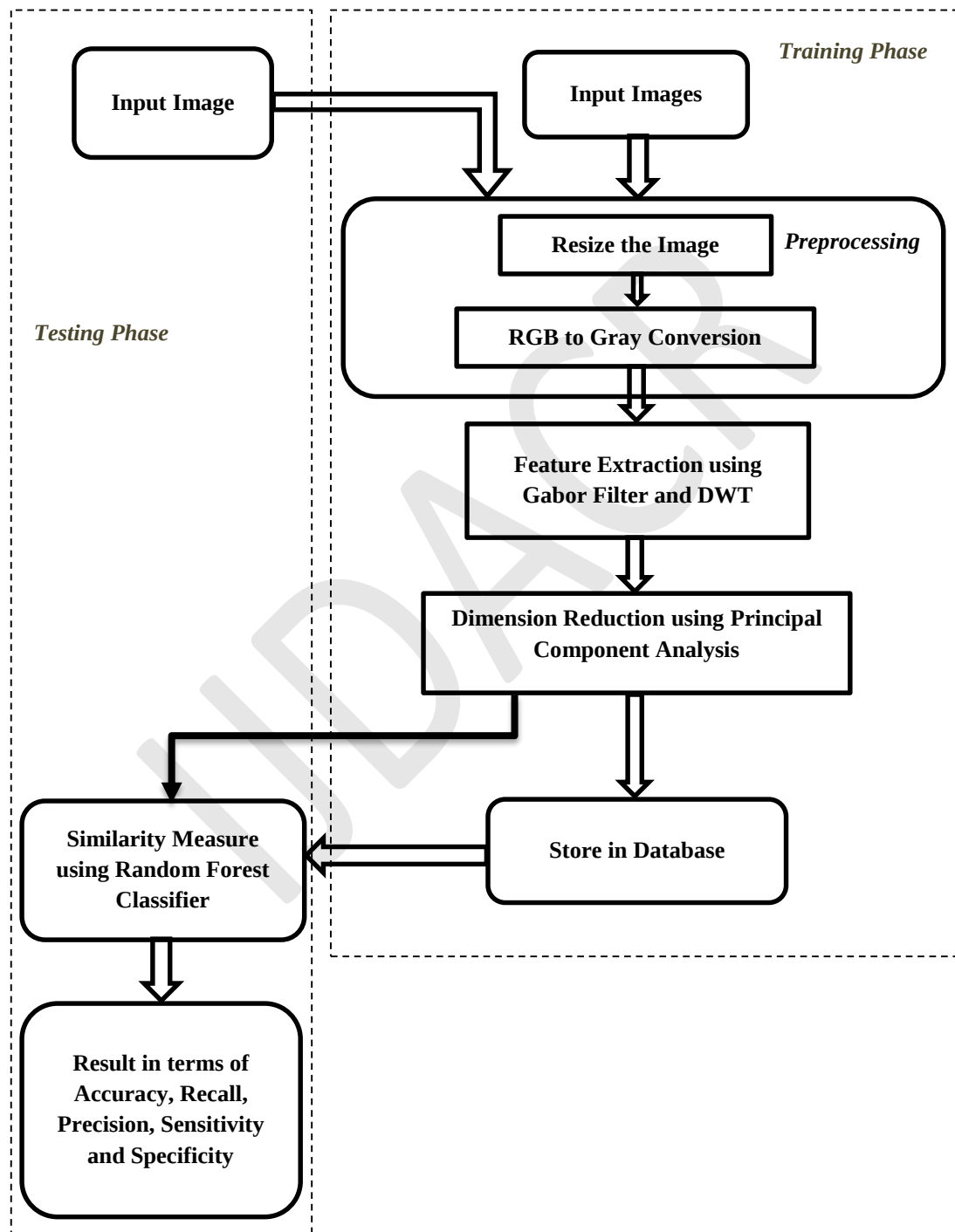


Figure 2: Flowchart for training and testing process for Palm-print recognition

Testing Phase

In the testing phase an input image is processed similar to training phase. Pre-processing and Post-processing are done same as training phase. And the principal component extracted from the Post processing is matched using random forest classifier method with other principal components present in the database. And the recognition is completed using the parameters namely; Accuracy, Recall, Precision, Sensitivity and Specificity.

Pre-Processing Block

The steps involved in pre-processing are shown in Figure 2. The details are as follows:

1. The input image to this block is resized using the inbuilt resize function available in MATLAB. We have resized the image to 250×250 pixels.
2. After resizing, the RGB image is converted to a grey scale image using rgb2gray function.

Feature Extraction Block

Gabor Filter

An image represented in terms $f(x, y)$ where x and y signifies the coordinates of pixels having size $M \times N$ is convoluted in frequency domain. The Fourier transform is applied as the solution for this step:

$$\begin{aligned} F\{f(x, y)\} &= F(u, v) \\ &= \int_{-\infty}^{M-1} \int_{-\infty}^{N-1} f(x, y) e^{-j2\pi(\frac{ux}{M} + \frac{vy}{N})} dx dy \end{aligned} \quad (1)$$

In frequency domain the Gabor feature for an image $f(x, y)$ is the multiplication of convoluted image with Gabor filter bank $\Psi(x, y, \omega_m, \theta_n)$ given by:

$$O_{m,n}(x, y) = F(u, v) * \Psi(u, v, \omega_m, \theta_n) \quad (2)$$

Where, $*$ is the convolution operator. The filter bank is created using m frequencies and n rotations

$G(m \times n)$ that provides features points and is saved in form of vector.

Generate Feature Vector: Feature vectors are the matching templates that calculate the distance among the features of exerted information. For an $M \times N$ image with centre points (c_i, c_j) , the spatial tessellation of region under interest is given by collection of sectors (S_i is the i^{th} sector)

$$S_i = \{(x, y) | b(T_i + 1) \cdot r < b(T_i + 2), \theta_i \leq \theta \leq \theta_{i+1}, 1 \leq x \leq N, 1 \leq y \leq M\} \quad (3)$$

Where, (Let's say $b=10$ pixels, $K=8$ Sectors in each band) and

$$T_i = i \text{ div} \quad (4)$$

$$\theta_i = (i \bmod k) \left(\frac{2\pi}{k} \right) \quad (5)$$

$$r = \sqrt{(x - x_c)^2 + (y - y_c)^2} \quad (6)$$

$$\theta = \tan^{-1} \left(\frac{(y - y_c)}{(x - x_c)} \right) \quad (7)$$

On application of Gabor filter, the planes of Gabor response is generated is equal to the number of angles. The mean and standard deviation of Gabor response provides feature vector of single plane and thus in this manner total feature vector can be generated.

Discrete Wavelet Transform (DWT)

The extracted feature form Gabor filters is too big for computation. It creates additional overhead for training to classifier. There is need of dimension reduction of Feature vector. Discrete Wavelet Transform (DWT) is a mathematical tool for hierarchically decomposing an image. It is useful for processing of non-stationary signals. The transform is based on small waves, called wavelets, in time and frequency domain. Unlike conventional Fourier transform, temporal information is retained in this transformation process. Wavelets are created by translations and dilations of a fixed function called mother wavelet. This section analyses suitability of DWT for feature extraction and gives advantages of using DWT as against other transforms.

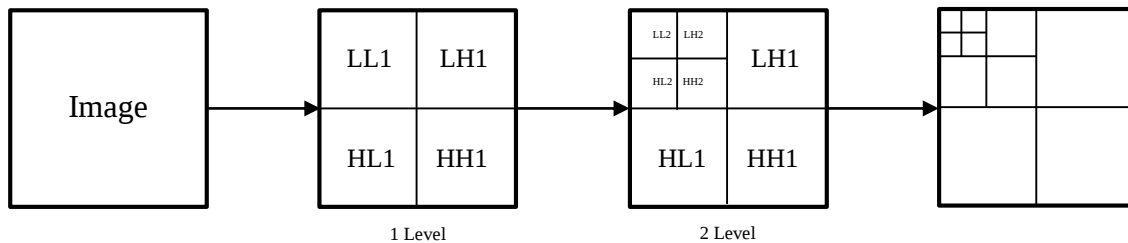


Figure 3: The workflow of discrete wavelet transform

After applying a 1-level DWT on image, we get the approximation sub-band LL, the horizontal sub-band LH, the vertical sub-band HL, and the diagonal sub-band HH. Moreover, if we apply a 2-level DWT on the image, we just simply apply another 1-level DWT on the approximation sub-band LL. After applying a 2-level DWT, we also get the approximation sub-band LL2, the horizontal sub-band LH2, the vertical sub-band HL2, and the diagonal sub-band HH2 of the approximation sub-band LL other than sub-bands LH, HL, HH. Applying IDWT to LL, HL, LH, and HH, we can get four different frequency's images that are low frequency image, middle-low frequency image, middle high frequency image, high frequency image separately.

Dimension Reduction using Principal Component Analysis (PCA)

Dimension Reduction of palmprint features is done using the PCA method. Let there are R images in the training set and each image X_i is a 2-dimensional array of size $m \times n$ of intensity values. An image X_i can be converted into a vector of D ($D = m \times n$) pixels, where $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. The rows of pixels of the image are placed one after another to form the vector.

Define the training set of R images by:

$$X = (X_1, X_2, \dots, X_R) \subset \mathbb{R}^{D \times R} \quad (8)$$

The covariance matrix is defined as follows:

$$\text{con}(X, Y) = \frac{\sum_{i=1}^n (X_i - \bar{X})(Y_i - \bar{Y})}{(n-1)} \quad (9)$$

$$= \Phi \Phi^T$$

Where,

$\Phi = (\Phi_1, \Phi_2, \dots, \Phi_R) \subset \mathbb{R}^{D \times R}$ and $\bar{X} = \frac{1}{(n-1)} \sum_{i=1}^n X_i$ which is the mean image of the training set. The dimension of the covariance matrix Γ is $D \times D$. Then, the eigenvalues and eigenvectors are calculated from the covariance matrix Γ . Let $Q = (Q_1, Q_2, \dots, Q_R) \subset \mathbb{R}^{D \times R} (r < R)$ be the r eigenvectors corresponding to r largest non-zero eigenvalues. Now, each of the images of the training set X_i is projected into the eigenvector to obtain its corresponding feature $Z_i \subset \mathbb{R}^{D \times R}$ which is defined as follows:

$$Z_i = Q^T Y_i, i = 1, 2, \dots, R \quad (10)$$

Where, Y_i is the reduced dimension image of X_i .

Similarity Measure using Random Forest Classifier

Random forests are recently proposed statistical inference tools, deriving their predictive accuracy from the nonlinear nature of their constituent decision tree members and the power of ensembles. Random forest committees provide more than just

predictions; model information on data proximities can be exploited to provide random forest features. Variable importance measures show which variables are closely associated with a chosen response variable, while partial dependencies indicate the relation of important variables to said response variable.

The Generalization error (PE^*) of Random Forest is given as,

$$PE^* = P_{x,y}(mg(X, Y)) < 0 \quad (11)$$

Where, $mg(X, Y)$ is Margin function. The Margin function measures the extent to which the average number of votes at (X, Y) for the right class exceeds the average vote for any other class. Here X is the predictor vector and Y is the classification.

III. SIMULATION AND RESULTS

The simulation is carried out by using MATLAB software image processing toolbox.

Output Class	1	15 18.8%	0 0.0%	0 0.0%	0 0.0%	6 7.5%	71.4% 28.6%
	2	1 1.3%	15 18.8%	0 0.0%	0 0.0%	2 2.5%	83.3% 16.7%
	3	0 0.0%	0 0.0%	16 20.0%	1 1.3%	0 0.0%	94.1% 5.9%
	4	0 0.0%	1 1.3%	0 0.0%	15 18.8%	1 1.3%	88.2% 11.8%
	5	0 0.0%	0 0.0%	0 0.0%	0 0.0%	7 8.8%	100% 0.0%
		93.8% 6.3%	93.8% 6.3%	100% 0.0%	93.8% 6.3%	43.8% 56.3%	85.0% 15.0%
		1	2	3	4	5	
		Target Class					

Figure 4: Confusion matrix plot for palmprint recognition using random forest classifier

The row and column are the class of CASIA database. There are 5 set of classes and each class having different set of detection. For training only 16 samples are taken from every set. The confusion plot indicates the accuracy i.e. 85% for proposed algorithm.

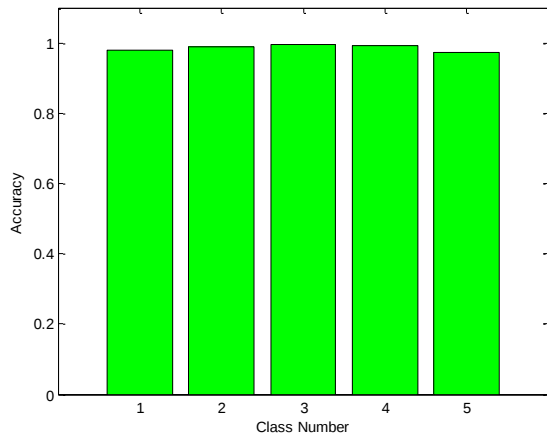


Figure 5: Accuracy graph for Random Forest Classifier based approach

Table 1: Accuracy for Random Forest Classifier based approach

Class Number	Accuracy
1	0.9795
2	0.9882
3	0.9970
4	0.9911
5	0.9725

Figure 6 shows the bar graph of accuracy for Random Forest Classifier based approach. The associated accuracy for this bar graph is shown in Table 1.

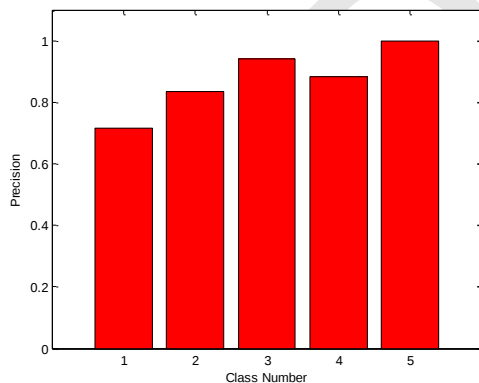


Figure 6: Precision graph for Random Forest Classifier based approach

Table 2: Precision for Random Forest Classifier based approach

Class Number	Precision
1	0.7143
2	0.8333
3	0.9412
4	0.8824
5	1.0000

Figure 6 shows the bar graph of precision for Random Forest Classifier based approach. The

associated precision for this bar graph is shown in Table 2.

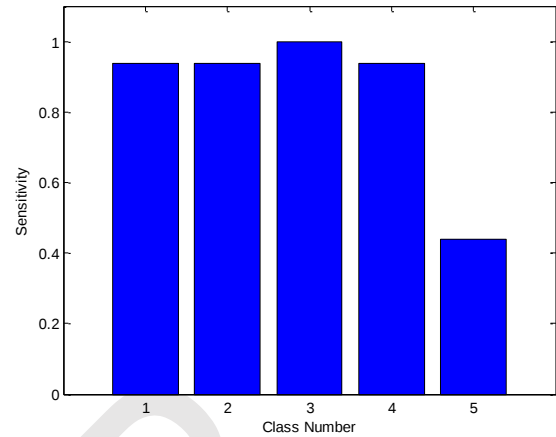


Figure 7: Sensitivity graph for Random Forest Classifier based approach

Table 3: Sensitivity for Random Forest Classifier based approach

Class Number	Sensitivity
1	0.9375
2	0.9375
3	1.0000
4	0.9375
5	0.4375

Figure 7 shows the bar graph of sensitivity for Random Forest Classifier based approach. The associated sensitivity for this bar graph is shown in Table 3.

IV. CONCLUSION

A training procedure is necessary to construct palmprint model in our approach, that is, the method is entirely dependent on the training set. Verification tests on our palmprint database are used to choose a group of optimal parameters for the proposed method. The proposed method with these appropriate parameters is used to perform accuracy test on our palmprint database and the palmprint database. There is another phase called testing phase is done with the help of random forest classifier method. The experimental results demonstrate that the proposed approach can give a better performance in terms of accuracy, recall and precision.

Following developments can be made in the future:

- Multimodel biometric recognition system.
- Optimal palmprint based biometric recognition system.

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