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Evaluate robustness of PCA feature vector to noise in a touchless Palm Print Biometric Identification System

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Abstract

Palm prints have many features which can be used for the purpose of biometric identification.A contactless Palm print recognition system has more user acceptability but the acquisition of palm images in such a setup issensitive to environmental conditions and noise. In order to achieve high performance accuracy, it is essential that the system has to be immune to noise in the acquired image. This paper presents use of Principal Component Analysis for feature extraction of palm print images for biometry. Feature matching has been done with Weighted Euclidean distance.The palm images have been degraded with salt and pepper noise, Gaussian noise and blurring and then subjected to identification for determining the robustness of the system.

Keywords: Palm print Biometric, Principal Component Analysis, weighted Euclidean distance, salt and pepper noise, Gaussian noise, blurring.

I. INTRODUCTION

There are increasing applications which require biometric methods for verifying the identity of a person. Palm prints are rich in features, can be easily acquired and hence different Palm print features are used for the purpose of biometric identification.

There are many different approaches to extract palm print features- line based, texture based, coding based and appearance based. In line based methods, the line patterns like principle lines, wrinkles, ridges, and creases are extracted for recognition. Edge detection methods, modified radon transform, filiformity are different techniques used to extract line features [1] [2] [4]. However, these principal lines are not sufficient to represent the uniqueness of each individual's Palm print because different people may have similar principal lines [6].In texture based methods, the three approaches generally used are statistical, structural and spectral. Statistical measures such mean, variances etc. are used as features. Structural techniques deal with the arrangement of image primitives. Spectral techniques are based on the properties of the Fourier spectrum [5]. The advantage of texture analysis is that the information can be extracted from low resolution palm print images. The problem with texture method is that the abundant textural details of a palm are ignored and the extracted features are greatly affected by the lighting conditions [6]. In coding based methods, the palm print features are represented by binary codes. Palm code, Fusion code, Competitive code, orientation code and ordinal code are the codes generated for palm prints [4].Generally the matching speed of the coding algorithms is slow [6]. In appearance based methods, generally analyses such as Principle Component Analysis (PCA), Linear Discriminant Analysis (LDA) and Independent Component Analysis (ICA) are used [3] [4].

Principal component analysis (PCA) is a mathematical procedure that uses KL transformation and is defined in such a way that the first principal components account for the variability in the data in decreasing order.It has also been found that principal components offer good characteristics for palmprint recognition. Based on the Karhunen–Loeve (K–L) transform, the original palmprint images used in training are transformed into a small set of characteristic feature images, called ''Eigenpalms'', which are the eigenvectors of the training set. Then, feature extraction is performed by projecting a new palmprint image into the subspace spanned by the ''Eigenpalms'' [6].The Eigen bases generated from the set of Palmprint images have the same dimension as the original images and are like Palmprint in appearance [12].Considering the advantages of PCA, these components have been chosen for study in this work.

The palm print acquisition methods can be touch based or contactless. The major drawbacks of touch based systems are distortion, dirt and user acceptability. Distortions are caused by non- uniform pressure of the hand on the sensor. Dirt accumulated after repeated acquisitions and can reduce the quality of acquisitions. Also people dislike using a sensor which has been touched by many people, particularly in areas where hygiene is important [20].

Hence, the touchless approach is preferred to overcome these drawbacks. But the development of a touchless palm print recognition system is not easy. The touchless methods have lower contrast, more complex background, and non uniform acquisition distances. They are sensitive to lighting conditions and noise. Also the main challenge of touchless acquisition systems is the need for fast image capture so as to avoid motion blur effects [20]. The hand position of the users may change. There can be rotation, scale variability and palm stretching. The presence of noise/degradation may reduce recognition accuracy. Preprocessing techniques have to be incorporated to reduce the effect of noise [17][18].

Image enhancement using local histogram equalization and adaptive thresholding (LHEAT) have been used to improve the recognition accuracy for images degraded with salt and pepper noise and with motion blur [17]. Noise cleaning with the use of median filtering on preprocessed image has also been incorporated. This approach makes the recognition approach robust with respect to salt and pepper noise [18]. An efficient palm image enhancement algorithm that consists of adaptive median filtering followed by Top Hat transform has been used to reduce noise corruption [19].Denoising models have been proposed for fingerprint images. Some of the important denoising models are Gabor filters with FFT based FPI, fusion and context switching frameworks, segmentation algorithm based FPI denoising, Gaussian denoising and histogram based processing. Denoising model based on pixel component analysishas been effectively used for fingerprints [23]. In this way different methods of preprocessing to reduce noise have been studied.

This paper deals with study of effect of noise on palm print identification to estimate robustness of the PCA algorithms with minimal preprocessing.The test images have been degraded with various types of noise namely blurring with motion filter and disk filter, and additive noise such as salt & pepper noise and Gaussian noise associated with touchless palm print acquisition system. Also, the parameters of the noise have been varied.

The preprocessing and recognition algorithm adopted is described in Section II of this paper. The methodology and the sequence of processing is discussed in Section III and the experimental work undertaken is given in Section IV. Finally, the results and discussion is given in Section V.

II. ALGORITHM

The initial step undertaken in apalm print recognition system is to obtain a Region of Interest (ROI) from the palm image. Square based ROIs are commonly used. The general method of selecting the ROI is to extract the boundary, then convert the image to binary and extract the key points of the image. These key points are used to set a coordinate axis and then a fixed size square is determined and clipped [14].

A novel pre-processing technique has been developed to overcome the difficulties in hand position, which allows the palm to be facing the sensor but in any orientation. The algorithm is simple and works in two stages. The first stage orients the image in the vertical direction with fingers upwards. The second stage deals with the fine alignment of the image based on the outer edge of the palm. The algorithm for extracting a central square shaped region has been developed which considers the palm geometry by making use of the bounding box values [24].

Once the ROI is obtained, further preprocessing is done for normalization of all ROIs. In this work, normalization is done with respect to mean and variance.Let the gray level at (x, y) in a palm print image be represented by I(x, y). The mean and variance of the image, μ and ρ, respectively, can be computed from the gray levels of the pixels. The normalized image I'(x, y) is computed using pixel wise operations as follows:

$$I'(x, y) = \mu_d + \lambda \qquad \text{if } I(x, y) > \mu$$

$$I'(x, y) = \mu_d - \lambda \qquad \text{otherwise}$$

$$\text{Where } \lambda = \sqrt{\frac{\rho_d(I(x,y) - \mu)^2}{\rho}}$$

where $\mu_d$and ρ_d are the desired vales for mean and variance respectively [11].

Finally, the ROIs are sharpened with the help of Laplacian filter.This ROI has been used to extract the feature vector. Principal Component Analysis is an appearance based methods and transforms the data with significantly fewer dimensions and thus it finds optimal basis for image representation [8] [9] [10] [13]. The steps to extract PCA features are to calculate the eigenvectors and eigenvalues from covariance matrix and then Retain only the eigenvectors with the largest eigenvalues [7] [8].

The recognition accuracy for different number of principal components has been tested and based on the results obtained, an optimum number of 40 principal components have been retained. Then the mean-shifted images have been projected into the Eigen space using the retained eigenvectors. A weight matrix has been generated for each image. The weights obtained by this method have been used as feature vector for the purpose of identification.

III. METHODOLOGY

The work presented in this paper deals with study of effect of noise on recognition accuracy of a contactless Palmprint recognition system. Preprocessing has been carried out for extracting and normalizing the ROIs. Various types of noise have been added to all the test images and feature vector based on PCA components has been derived. The recognition accuracy is evaluated in each case.

Images of 99 persons from standard databases CASIA and IITD have been selected. In the study with images from CASIA database, 6 images of each person are considered as enrolment and the features of these images are stored in enrolment database for comparison. These 6 images and 2 additional images i.e. 8 images of each person are considered for testing. During enrolment procedure, the ROIs are not degraded. The feature vector is evaluated and stored in the enrolment database. But during identification mode, all the ROIs are degraded with different noise such as blurring with motion filter and disk filter; addition of salt & pepper noise and Gaussian noise with varying parameters. The features of the degraded ROIs are compared with the features stored in enrolment database to take a decision on matching and identifying the person.

In this work, weighted Euclidean distance has been used. The weighted Euclidean distance is given by

$$dk = \sum_{i=1}^{N} \left(\left(\frac{(f(i) - f_k(i))^2}{(s_k)^2} \right) \right)$$

Where f is the feature vector of the unknown palmprint, f_k and s_k denote the k^{th} feature vector and its standard deviation, and N is the feature length [6].

IV. **EXPERIMENTAL WORK**

The Image processing Toolbox of MATLAB R2016 has been used for the experimentation. For the study undertaken, 99 persons have been consideredfrom CASIA and IITD databases.

During experimentation on CASIA database, six images each of 99 personsi.e. 594 images have been used for training and eight images i.e. 792 images have been used for testing. ROIs have been extracted for all the images. Feature vectors based on 40 principal components have been computed. The performance parameters False Acceptance Rate (FAR), False Rejection Rate (FRR) and Genuine Acceptance Rate (GAR) of recognition have been evaluated. It is found that threshold value of 30has Equal Error rate (EER). Figure 1 shows the ROC curve for ROI’s without noise.

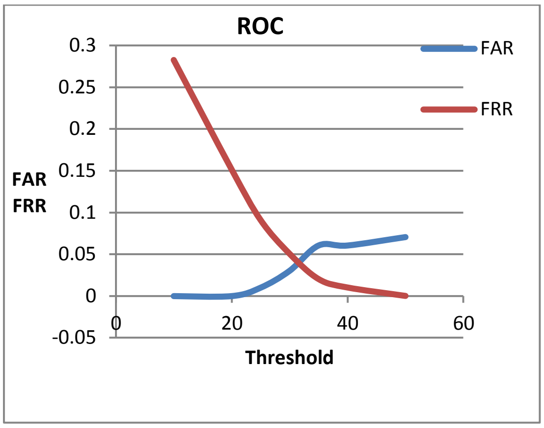

Figure 1: ROC for CASIA

The experiments with threshold value 30 have resulted in 99% recognition accuracy.

Similar procedure has been followed during experimentation on IITD images. 4 images each of 99persons i.e.total of 396 images have been considered for training.Noise is not added to these training ROIs.Feature vectors based on 40 principal components have been computed. Five images of each person i.e. 495 images have been considered for testing. Initially, the test images have not been degraded and performance parameters evaluated. Figure 2 shows the ROC obtained.

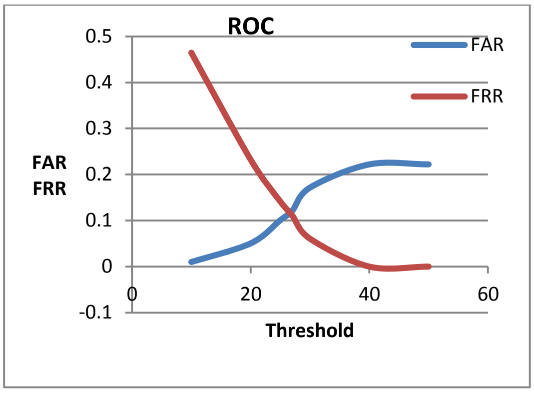

Figure 2: ROC for IITD

Threshold value of 27 gives EER. Recognition accuracy of 95.4% has been obtained.

To evaluate the robustness of the system to noise, all the test images have been degraded with blur and noise. Motion blur approximates the linear motion of palm. This type of blur can result when the palm is rapidly moved while acquisition. The parameters of motion blur are 'len' and 'theta' where len is the linear motion in pixels and theta is the angle of rotation in degrees in a counterclockwise direction. The default len is 9 and default theta is 0, which corresponds to a horizontal motion of 9 pixels. Figure 3 shows a sample test image degraded with motion blur with parameters len=5, theta=90, len=10, theta=180 and len=15, theta=0.

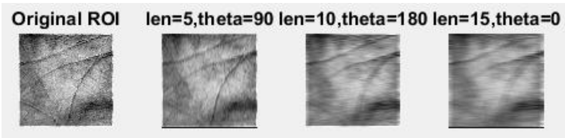

Figure 3: Sample test ROI with motion blur

Blur with disk filter is a circular averaging filter. The parameter of this filter is radius, which is the radius of the disk within the square matrix of size 2*radius+1. The default radius is 5. Figure 4 shows a sample test image degraded with blur using disk filter with radius 5 and 10.

Figure 4: Sample test ROI with blur using disk filter

Salt and pepper noise is used to model defects in the acquisition of image. The parameter of this noise is'd' the noise density. When the noise is added to image I, it affects approximately d*numel (I) pixels. The default for d is 0.05. Figure 5shows a sample test image with salt and pepper noise with d as 0.05, 0.1 and 0.15

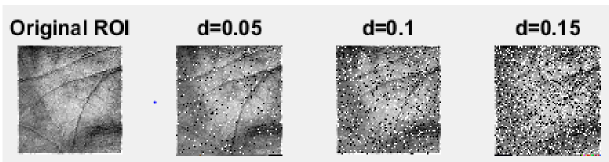

Figure 5: Sample test ROI with salt & pepper noise

Principal sources of Gaussian noise arising during acquisition are poor illumination or high temperature. The parameters are mean m and variance v. The default is zero mean with 0.01 variance. Figure 6 shows a sample test image with Gaussian noise with m=0 & v=0.01, m=0 & v=0.05 and m=0 & v=0.1.

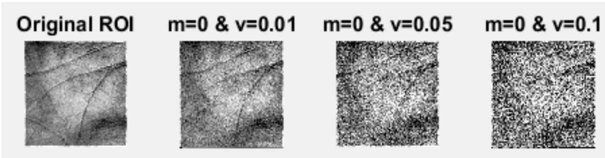

Figure 6: Sample test ROI with Gaussian noise

The performance parameters False Acceptance Rate FAR, False Rejection Rate FRR and Genuine Acceptance Rate GAR have been found for each case.

V. RESULTS AND DISCUSSION

The Region of Interest of different images has been extracted for 99 persons. Principal Component Analysis (PCA) has been done on these ROIs. The test images have been degraded with noise and compared with all the images in the enrolment database for the purpose of identification. The parameters of noise have been varied. The performance parameters have been determined for each case. Tables 1, 2, 3 and 4 show the effect of motion blur, blur with disk filter, salt& pepper noise and Gaussian noise respectively on a sample ROI.

Table 1: Effect of motion blur on CASIA images

	Parameters	FAR	FRR	GAR
Without degradation	--	0.4%	0.6%	99%
Degrading by blur with motion filter	Len=5 Theta=0	0.4%	0.6%	99%
	Len=5 Theta=30	0.4%	0.6%	99%
	Len=5 Theta= 60	0.4%	0.6%	99%
	Len=5	0.4%	0.6%	99%

	Theta= 90			
	Len= 5 Theta= 180	0.4%	0.6%	99%
	Len=10 Theta=0	0.4%	0.6%	99%
	Len=10 Theta=10	0.4%	0.6%	99%
	Len=10 Theta=60	0.4%	0.6%	99%
	Len=10 Theta=90	0.4%	0.6%	99%
	Len=10 Theta=180	0.4%	0.6%	99%
	Len=15 Theta=0	0.6%	0.6%	98.8%
	Len=15 Theta=10	0.6%	0.6%	98.8%
	Len=15 Theta=60	0.7%	0.6%	98.7%
	Len=15 Theta=90	0.1%	0.4%	98.5%
	Len=15 Theta=180	0.6%	0.6%	98.8%

Table 2: Effect of blur with disk filter on CASIA images

	Parameters	FAR	FRR	GAR
Without degradation	--	0.4%	0.6%	99%
Degrading by blur with disk	Radius=5	0.5%	0.5%	99%
	Radius=7	1.0%	0.5%	98.5%
	Radius=10	1.4%	0.6%	98%

Table 3: Effect of Salt and Pepper noise on CASIA images

	Parameters	FAR	FRR	GAR
Without degradation	--	0.4%	0.6%	99%
Degrading with salt & pepper noise	Noise density=0.05	0.4%	0.6%	99%
	Noise density=0.10	0.6%	0.6%	98.8%
	Noise density=0.15	0.6%	0.6%	98.8%

Table 4: Effect of Gaussian noise on CASIA images

	Parameters	FAR	FRR	GAR
Without degradation	--	0.4%	0.6%	99%
Degrading with Gaussian noise	Mean=0 Variance=0.01	0.4%	0.6%	99%
	Mean=0 Variance=0.05	0.4%	0.6%	99%
	Mean=0 Variance=0.1	0.6%	0.6%	98.8%

Tables 5, 6, 7 and 8 show the effect of motion blur, blur with disk filter, salt& pepper noise and Gaussian noise respectively on the ROI images selected from IITD database.

Table 5: Effect of motion blur on IITD ROI images

	Parameters	FAR	FRR	GAR
Without degradation	--	2.4%	2.2%	95.4%
Degrading by blur with motion filter	Len=5 Theta=0	2.6%	2.0%	95.4%
	Len=5 Theta=30	2.4%	2.2%	95.4%
	Len=5 Theta= 60	2.4%	2.2%	95.4%
	Len=5 Theta= 90	2.4%	2.2%	95.4%
	Len= 5 Theta= 180	2.4%	2.2%	95.4%
	Len=10 Theta=0	2.8%	1.8%	95.4%
	Len=10 Theta=30	2.8%	2.0%	95.2%
	Len=10 Theta=60	2.6%	2.0%	95.4%
	Len=10 Theta=90	2.8%	1.8%	95.4%
	Len=10 Theta=180	2.8%	1.8%	95.4%
	Len=15 Theta=0	3.4%	1.4%	95.4%
	Len=15 Theta=30	2.6%	1.8%	95.4%
	Len=15 Theta=60	2.4%	2.2%%	95.4%
	Len=15 Theta=90	2.6%	2.0%	95.4%
	Len=15 Theta=180	3.4%	1.4%	95.2%

Table 6: Effect of blur with disk filter on IITDROI images

	Parameters	FAR	FRR	GAR
Without degradation	--	2.4%	2.2%	95.4%
Degrading by blur with disk	Radius=5	3.2%	1.8%	95%
	Radius=7	3.4%	1.6%	95%
	Radius=10	4.2%	1.6%	94.2%

Table 7: Effect of Salt and Pepper noise on IITD ROI images

	Parameters	FAR	FRR	GAR
Without degradation	--	2.4%	2.2%	95.4%
Degrading with salt & pepper noise	Noise density=0.05	2.6%	2.6%	95%
	Noise density=0.10	3.0%	2.6%	94.4%
	Noise density=0.15	3.0%	2.6%	94.4%

Table 8: Effect of Gaussian noise on IITD ROI images

	Parameters	FAR	FRR	GAR
Without degradation	--	2.4%	2.2%	95.4%
Degrading with Gaussian noise	Mean=0 Variance=0.01	2.4%	2.4%	95.2%
	Mean=0 Variance=0.05	2.8%	2.7%	94.5%
	Mean=0 Variance=0.1	3.2%	3.1%	93.7%

It has been observed that the recognition accuracy is not affected by test images blurred due to motion by linear motion upto 10 pixels and rotation of the hand upto 180°. Similarly, the recognition rate is found to be similar in the presence of salt and pepper noise for noise density of 0.05. With increase in noise density, the performance slightly decreases. Also, there is slight decrease in performance when the test images are blurred due to disk filter and the radius of the disk increases.In presence of Gaussian noise, the system is unaffected for zero mean and variance less than 0.05. The recognition rate is found to be affected when mean and variance are higher than these values.

CONCLUSION

In this work, the palm image is first appropriately aligned, ROI extracted, normalized and sharpened. Then the features are extracted based on PCA. It is seen that the recognition accuracy is high and the algorithm is robust to noise.

Effects of salt and pepper noise and motion blur with default parameters have been reported in literature [17]. Table 9 shows the comparison of resultsreported in literature and the results of experimentation in our work using salt and pepper noise and motion blur using the default parameters.

Table 9: Comparison of results with reported results

Method	Without noise degradation	Salt and pepper noise	Motion blur
Image enhancement and IFkNCN classifier [17]	98.96%	94.11%	92.45%
Proposed PCA based experiments on CASIA images	99%	99%	99%
Proposed PCA based experiments on IITD ROI images	95.4%	95.4%	95.4%

In literature, study has been restricted to motion blur and salt & pepper noise. The papers report results based on default parameters of noise degradation and the number of users is limited to 40. There are other papers reporting noise based preprocessing [18] [19]. But the results comparing system performance with and without noise degradation have not been included.

In the study presented in this paper, other types of noise such as blur with disk filter and Gaussian noise have also been applied for test image degradation. The parameters like density, mean, variance etc. of noise have been varied. The number of users has also been increased to 99. Moreover, there is minimal preprocessing on the ROIs. The results show that the recognition accuracy is comparable to the accuracy obtained with test images having minimal noise indicating thatappropriate preprocessing, ROI extraction, feature extraction method based on PCA is less sensitive to noise effects. The recognition accuracy does not deteriorate with motion blur upto 10 pixels and is independent of rotation as well as blur with disk filter upto radius of 5. Salt and pepper noise of density 0.05 and Gaussian noise with zero mean and variance less than 0.05 do not affect performance of the system.

Touchless palmprint recognition methods avoid the problems related with touch based methods and hence have increased usability and acceptability by the users. But the main challenges in the design of a touchless system are flexible distance from sensor, fewer restrictions on the placement of the palm with respect to position and orientation, variation in illumination and movement of palm or sensor. These variations contribute in introducing noise in the acquired images. A touchless Palmprint based biometric identification system must use an efficient preprocessing, ROI extraction, feature extraction method so that the final identification results are tolerant to noise. The results given in this paper indicate that the preprocessing, ROI extraction followed by PCA is a robust method tolerant to motion blur and limited salt and pepper as well as Gaussian noise.

In future, study shall be undertaken to examine the robustness to noise for other feature extraction methods such as discrete wavelet transform and statistical techniques. Similarly performance of neural networks and other pattern classifiers shall be evaluated.

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