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FACE RECOGNITION IN 2D IMAGES USING LDA AS THE CLASSIFIER TO TACKLE POSING AND ILLUMINATION VARIATIONS

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ABSTRACT

In this paper the problem of varied illumination and poses is tackled. A person may look like another person from far away at a different angle under varied illumination conditions but, he/she may be a totally different person when viewed under optimum illumination and frontal pose. I have used two pre-processing techniques namely HE (Histogram Equalization) and BPS (Bit Plane Slicing) to process the images before they fed into the post processing system. BPS is used for data compression while HE is used for normalization of the pixels. I have used LDA as the post-processing technique for the purpose of dimensionality reduction and preservation of orthogonality. A comparison of the two techniques is performed and the results are analyzed. The recognition rate, false acceptance rate and the false rejection rate are computed and plotted for three databases namely ORL, FERET and VIT databases. Though bit plane slicing is useful for data compression, histogram equalization showed a higher recognition rate.

Keywords: LDA, BPS, HE, illumination variation, pose variation.

INTRODUCTION

Biometrics is the process of determining the characteristic traits of a person. These characteristics that are obtained from the behavior of a candidate are unique. i.e., the biometric features measured differ for each candidate [6], [7].

Biometrics can be broken down into two main types, physical and behavioral. The physical type deals with the shape of the body, color of the eyes, the geometry of hand (whether a person suffer from polydactyl, in which case he/she shall have more than five fingers in a particular hand), the ridges of the palm, the shape of the iris, the minutiae and ridges in the fingerprint. In behavioral, the walking style of a person also known as gate analysis and the vibrations of the larynx (also known as the voice box) are intricate features that are considered while working with voice recognition and they are the major components of biometrics as shown in Figure-1. The sense of security and the easy to use interface presented by biometrics speaks for itself as to why it has become popular. With methods that require the user input one needs to always remember passwords and pin numbers, while the need to do so is eliminated in the case of biometrics. The data related to a person is stored securely and with minimal access thus granting a higher level of security.

The various methods aid in identifying and recognizing a person more precisely rather the tedious methods where one has to remember the passwords and personal identification numbers.

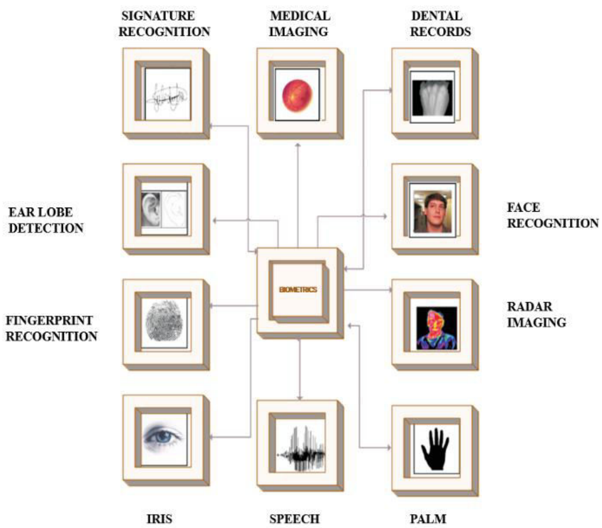

Figure-1. Biometrics - Overview.

METHODOLOGY

A. Bit plane slicing

Bit Plane Slicing is a renowned procedure used in image processing [3] [4]. Bit plane slicing is extensively used for image compression. Bit plane slicing is the transformation of images into multilevel binary image. The binary images thus obtained are compressed using various algorithms. Individually every pixel represents a sequence of numerical bits from which the binary images are extracted. Binary information regarding the image is retrieved from the binary image. The information is used on a later stage to compute the features of the images during the image retrieval process.

The approached method is based on extracting significant bit planes of the image and creating a virtual image by combining the bit planes, giving most of the information of the image multiplied by the weights [3].

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Weights are selected such that higher order bit planes carry more weights. I have combined the bit planes 1, 2, 6, 7, and 8 for the use of face recognition.

Let Γ_i denote the mth image of the ith person (m=1, 2..., M, i=1, 2..., I), the mean image is given as in Equation (1)

$$\Psi = \frac{1}{M}\sum_{i=1}^{M}\Gamma_i \quad (1)$$

The bit-plane extraction is performed on Γ_i to get its five bit planes and mark them as $B_{i,}$ i is the 1, 2, 6, 7, 8). A new virtual face of the mth image of the ith person is thus given by
Computation of virtual image

$$V = \sum_{i=1,2,6,7,8} B_i \alpha_i \quad (2)$$

In the above equation, (Equation (2)), the parameters α_i is non-negative coefficients determined by a trial procedure.

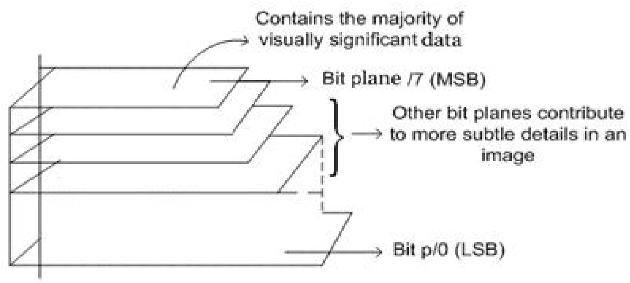

Figure-2. Bit plane slicing.

Among 8 single bit-planes, bit-plane 0 to 3 have a very low information, and have lower than Recognition rate of 60%, while bit-planes 4, 5, 6, and 7 achieve over 88% accuracy for face recognition. The higher order bit-planes have better performance because they are considered as visually significant data, which contain enough information for recognition. Here I have used bit planes 1, 2, 6, 7 and 8 to achieve higher recognition rate.

The output for the pre-processing of ORL using Bit Plane Slicing is shown in the following Figure-3. I have combined the bit planes 1, 2, 6, 7 and 8 to achieve an acceptable recognition rate. These extracted features from the pre-processing stage aid us in overcoming the illumination [2] [3] challenges faced while face recognition and are used as the input for the post-processing stages.

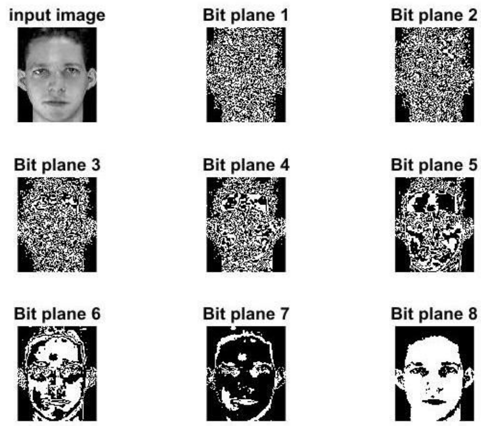

Figure-3. Illustration of BPS using ORL database.

Figure-4. Bit Plane slicing output for ORL database.

B. Histogram equalization

Histogram equalization [1] [2] is a technique for varying image intensities to enhance contrast. This technique typically escalates the overall contrast of many images, exclusively when the usable data of the image is represented by close contrast values. Through this modification, the intensities will evenly have distributed on the histogram. This improves the contrast of the local areas with lower contrasts and modifies them such that they are on par with the global areas. It achieves this upon efficiently scattering out the most recurrent intensity values. This method is a viable option for images with varying lighting conditions for the backgrounds and foregrounds.

To understand how actually the Histogram Equalization is done we will take this example:

Consider a 3x3 Matrix

$$A = \begin{matrix} 1 & 4 & 2 \\ 5 & 1 & 3 \\ 1 & 2 & 4 \end{matrix}$$

With number of bins=5

Step 1: Find the frequency of each pixel value. The pixel value 1 occurs 3 times; similarly pixel value 2 occurs 2 times and so on.

Step 2: Find the probability of each frequency. The probability of pixel value 1's occurrence= frequency (1)/no. of pixels. i.e., 3/9.

Step 3: Find the cumulative histogram of each pixel:
The cumulative histogram of 1= 3
The Cumulative histogram of 2= cumulative histogram of 1 + frequency of 2 = 5
Cumulative histogram of 3= cumulative histogram of 2+ frequency of 3 = 5+1=6

Step 4: Find the cumulative distribution probability of each pixel
Cdf of 1 = cumulative histogram of 1/ no. of pixels= 3/9

Step 5: Calculate the final value of each pixel by multiplying Cdf with no. of bins
Cdf of 1 = (3/9)*5= 1.667. Round off the value.

Step 6: Now replace the final values:

The final value for bin 1 is 2. It is placed in place of 1 in the matrix.

$$A = \begin{matrix} 2 & 4 & 2 \\ 5 & 2 & 3 \\ 2 & 3 & 4 \end{matrix}$$

The histogram equalized pre-processed database is shown in Figure-5 for the VIT database that has been created. This pre-processed database is the subjected to post processing using LDA.

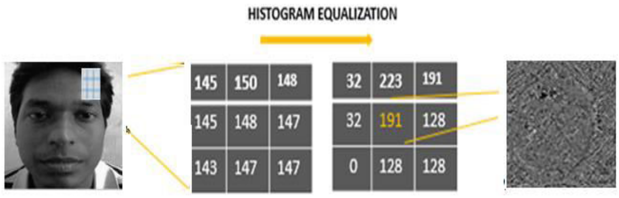

Figure-5. Illustration of HE using VIT database.

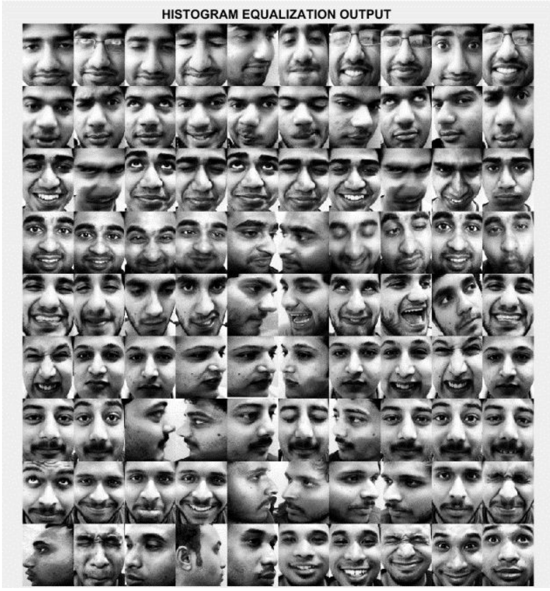

Figure-6. Histogram equalization output for VIT database.

C. Linear discriminant analysis

Face Recognition using LDA [5] [8] is a feature extraction technique and a well-known example of dimensionality reduction. LDA was developed because PCA does not project lower dimensional data and performance was poor (Yanwei Pang *et al.*, 2004). The elementary principle of LDA is that it tries to find the best projection direction in the databases belonging to various classes that are well separated. The block diagram of LDA is shown in Figure-7.

The images are first converted to grayscale (Shami Jhodge *et al.*, 2012; Beveridge *et al.*, 2001; Steven Fernandes and Josemin Bala, 2013) followed by averaging and reshaping for the proper alignment of images. This is done because every single image in the database may be of different size variant pose and differently illuminated and hence in order to make them into same size, reshaping is done. Meanwhile the input test image is sent to the block of feature extraction where every part of sensory organs like eyes, nose, and teeth are extracted.

Now the database images and input test image are classified into either within the class and between the class variance where the outcome is a projected vector of weights. Using these projected vectors, co-variance matrix is calculated for both input and database images. Using co-variance matrices Fisher values are obtained. Now the Euclidean Distance is computed and finally matched image is obtained (Ajay Kumar Bansal and Pankaj Chawla, 2013; Raj Kumar Sahu *et al.*, 2013).

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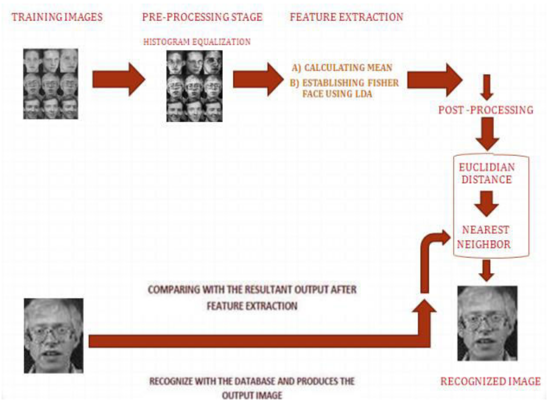

Figure-7. Block diagram of LDA.

The various steps used in LDA are explained below:

Step 1: Both input test image and training database images are taken and converted into matrix form.

Step 2: Compute the mean for test image and database each class images are calculated.

Step 3: The sample images $\{x_1, x_2 ... xn\}$ are projected face space taken by *c* classes $\{X_1, X_2 ... Xj\}$.

Where n is total number of images and j is total number of persons and $c = (1, 2... j)$

The mean of each class face space is given by

$$\mu_j = \frac{1}{M}\sum_{k=1}^{j} X_k \tag{3}$$

A class is a set of 10 images of a single person. The total of 200 sample test images comprises of 20 classes. A class is just a descriptive term for a set of images of the same person within the database used. The mean value and the mean of each class are calculated using MATLAB by implementing the formula depicts in the Equation (3) and Eq. (4). The explanation of the terms is given in Equation (5) and Equation (6)

The total mean of projected face space is given by

$$\mu = \frac{1}{M}\sum_{k=1} \mathrm{X_K} \tag{4}$$

Where X_k is the projected face space

$$X_K = (\mathrm{AVi}) * (\mathrm{Ti} - \psi) \tag{5}$$

Where $T_i$is the training images and ψ is the mean of the training images

Where i=1, 2, 3..., n, difference matrices

$$A = [\Phi_1, \Phi_2, \Phi_3, \dots, \Phi_M] \tag{6}$$

Fisher faces: Fisher Faces represent the extracted features of the images. Most of the information required is contained in these faces and are sufficient enough to make an efficient system. Practically, we process thousands of images for which we require a fast and efficient system. In order to avoid a system lag, we extract features which will save space as well as time. Moreover, the extracted features are sufficient to recognize images.

Step 4: Projected Fisher image is calculated by the Fisher vector and projected face space

Step 5: Fisher vector is calculated using Equation (7) and Equation (8) (S_b, S_w) = [Eigen vectors, Eigen value]
S_b = between-class scatter matrix; Sw = within-class scatter matrix.

$$S_b = \sum_{j=1}^{c}(\mu_j - \mu)(\mu_j - \mu)^T \tag{7}$$

Where j=*1, 2... c*

X_j	is the number of classes or persons
μ_j	is the mean calculated for each person in projected face space
μ	is the mean calculated for total Fisher face.

The between-class scatter matrix is calculated in

MATLAB by implementing Equation (7). It is later used to calculate the Fisher vector.

$$S_w = \sum_{j=1}^{C}\sum_{i=1}^{N_j}\left(\Gamma_i^j - \mu_j\right)\left(\Gamma_i^j - \mu_j\right)^T \tag{8}$$

Where Γ_i^j , the i^{th} sample of class j, μ_j is the mean of class j, C is the number of classes, $N_j$is the number of samples in class j.

The within-class matrix is obtained by implementing the Equation (8) in MATLAB. It is used to calculate the Fisher vector along with the between-class scatter matrix. The subspace for LDA is spanned by a set of vectors $W = [W_1, W_2 ... W_M]$, satisfying Equation (9).

$$J(W) = \arg max \left|\frac{W^T S_b W}{W^T S_w W}\right| \tag{9}$$

The within class scatter matrix represents how face images are distributed closely within classes and between class scatter matrix describes how classes are separated from each other. When face images are projected into the discriminant vectors *W*, face images should be distributed closely within classes and should be separated between classes, as much as possible. In other words, these discriminant vectors minimize the denominator and maximize the numerator in eq. (4.8). *We* can therefore be constructed by the Eigen vectors of $S_w^{-1}S_b$.

Step 6: Using the above criterion we can construct *W* by finding the Fisher Eigen vectors (Eq. (10)) of

$$S_b W = \lambda\, S_w \tag{10}$$

Step 7: Given a test image is projected in the subspace and feature vectors are generated, these vectors are compared to the database vectors using Euclidean Distance.

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Step 8: Now we find the minimum Euclidian distance using the formula in Eq. (11)

$$\text{Euclidean distance} = \sum_{i=1}^{K}(\rho_i - \rho_t)\text{Eq.} \qquad (11)$$

Step 9: The minimum Euclidian distance will give the corresponding Recognized index which is the particular image to find out. Let say, if "18" is the recognized index then the 18th image in the database will be recognized.

Step 10: To Calculate the Recognition Rate, we will prepare test database of 40, 50,100,150,200 respectively and see howmany images are correctively recognized. So the recognition rate (RR) would be:

$$RR = \frac{Number\text{of images correctly recognized}}{Total\ images\ in\ TD}\ X\ 100$$

Step 11: To calculate False Acceptance ratio, we use formula

$$FAR = \frac{Number\ of\ unauthorized\ persons\ accepted}{number\ of\ authorized\ persons} X100$$

False acceptance is the acceptance of an image as an image from the database

Step 12: To calculate False Rejection Rate we us the formula

$$FRR = \frac{Number\ of\ authorized\ persons\ Rejected}{number\ of\ authorized\ persons.} X100$$

SUMMARY

Two techniques have been compared to get an efficient result. The pre-processing techniques like BPS and Histogram Equalization the open-source databases like FERET, ORL the newly generated VIT database have been used for analysis. After performing an extensive analysis on all these databases, it has been found out that HE is the most efficient technique among its peer methods that gives a high recognition rate. By using all these methods, efficient and satisfying results have been obtained. There are various methods other than the methods used in this thesis which can be used for the purpose of facial recognition and they can also give efficient LDA.

Table-1. Performance analysis of ORL, FERET and VIT database.

No. of test images/ No. of persons	ORL						FERET						VIT					
	% RR		% FAR		% FRR		% RR		% FAR		% FRR		% RR		% FAR		% FRR	
	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE
15/3	67	87	33	14	34	10	67	80	25	10	35	20	60	83	40	25	40	17
20/2	70	90	30	10	30	9	65	90	20	8	35	10	67	84	39	20	39	16
50/5	75	94	25	6	35	7	70	94	12	7	30	6	75	85	26	15	25	15
100/10	83	92	17	4	20	4	85	95	15	6	15	5	83	88	22	10	20	12
200/20	92	94	8	6	12	3	94	95	9	3	6	5	91	94	10	8	12	6

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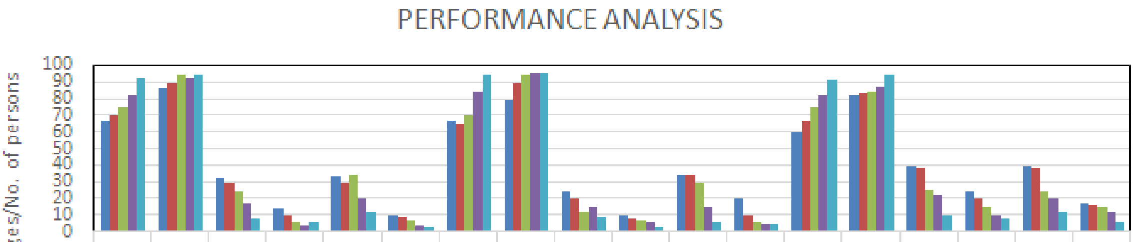

	ORL						FERET						VIT					
	% Recognition rate		% False acceptance rate		% False rejection rate		% Recognition rate		% False acceptance rate		% False rejection rate		% Recognition rate		% False acceptance rate		% False rejection rate	
	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE	BPS	HE
15/3	67	87	33	14	34	10	67	80	25	10	35	20	60	83	40	25	40	17
20/2	70	90	30	10	30	9	65	90	20	8	35	10	67	84	39	20	39	16
50/5	75	94	25	6	35	7	70	94	12	7	30	6	75	85	26	15	25	15
100/10	83	92	17	4	20	4	85	95	15	6	15	5	83	88	22	10	20	12
200/20	92	94	8	6	12	3	94	95	9	3	6	5	91	94	10	8	12	6

Figure-8. Performance analysis of ORL, FERET and VIT database.

CONCLUSIONS

The Table-1 shows the percentage of recognition rate, false acceptance rate and the false rejection rate. The Figure-10 shows the graphical representation of the Table-1.

On the whole it can be summarized that LDA is an effective method for dimensionality reduction and for preserving as much as information possible. it can be inferred from the results that histogram equalization is a better approach to facial recognition as compared to bit plane slicing which is rather suited for image compression in case of huge data quantities, for when there are millions of images to be sorted through to find a single individual.

REFERENCES

[1] Omprakash Patel *et al.* 2013. A Comparative Study of Histogram Equalization Based Image Enhancement Techniques for Brightness Preservation and Contrast Enhancement. Signal & Image Processing: An International Journal (SIPIJ). 4(5).

[2] Ping-Han Lee, Szu-Wei Wu and Yi-Ping Hung. 2012. Illumination Compensation Using Oriented Local Histogram Equalization and Its Application to Face Recognition. IEEE Transactions on Image Processing. 21(9): 4280-4289.

[3] Yi Dai, Guoqiang Xiao and KaijinQiu. 2009. Efficient face recognition with variant pose and illumination in video. Proceedings of 4th International Conference on Computer Science and Education, IEEE. pp. 18-22.

[4] Jasmine Pemeena Priyadarsini, M., K. Murugesan, Srinivasa Rao Inabathini, Visal Kumar. 2012. Efficient Face Recognition in Video by Bit Planes Slicing. Journal of Computer Science, ISSN 1549-3636, 8(1): 26-30.

[5] Suman Kumar Bhattacharyya and Kumar Rahul. 2013. Face Recognition by Linear Discriminant Analysis. International Journal of Communication Network Security. 2(2, 3): 1-35.

[6] Ambika Ramchandra and Ravindra Kumar. 2013. Overview of Face Recognition System Challenges, International Journal of Scientific and Technology Research. 2(8): 234-236.

[7] Anil K. Jain, Arun Ross and SalilPrabhakar. 2004. An Introduction to Biometric Recognition. IEEE Transactions on Circuits and Systems for Video Technology. 14(1): 4-20.

[8] Dominik Jelšovka, RóbertHudec, and Martin Brezňan. 2012. Face Recognition on FERET Face Database Using LDA and CCA Methods, International Journal of Computer Science and Network Security. 12(5): 77-84.

[9] Rafael C Gonzalez and Richard E.Woods. 2004. Digital image processing by. Pearson Peintice Hall, Pearson, 5th Edition. pp. 1-577.

[10] Ruo Du, Qiang Wu *et al.* 2009. Facial Expression Recognition using Histogram Variances Faces. IEEE Applications of Computer Vision (WACV), 2009 Workshop. pp. 1-7.