Face Recognition using Subspaces Techniques

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***Abstract* - With many applications in various domains, Face Recognition technology has received a great deal of attention over the decades in the field of image analysis and computer vision. It has been studied by scientists from different areas of psychophysical sciences and those from different areas of computer science. Psychologists and neuro-scientists mainly deal with the human perception part of the topic where as engineers studying on machine recognition of human faces deal with the computational aspects of Face Recognition. Face Recognition is an important and natural human ability of a human being. However developing a computer algorithm to do the same thing is one of the toughest tasks in computer vision. Research over the past several years enables similar recognitions automatically. Various face recognition techniques are represented through various classifications such as, Image-based face recognition and Video-based recognition, Appearance-based and Model-based, 2D and 3D face recognition methods. This paper gives a review of different face recognition techniques available as of today. The focus is on subspace techniques, investigating the use of image pre-processing applied as a preliminary step in order to reduce error rates. The Principle Component Analysis, Linear Discriminant Analysis and their modified methods of face recognition are implemented under subspace techniques, computing False Acceptance Rates (FAR)and False Rejection Rates (FRR) on a standard test set of images that pose typical difficulties for recognition. By applying a range of image processing techniques it is demonstrated that the performance is highly dependent on the type of pre-processing steps used and that Equal Error Rates (EER) of the Eigenface and Fisherface methods can be reduced using the method proposed in this paper.**

***Keywords*–Face Recognition, Normalization, Subspace, Eigenfece, Fisher face, Fisher Liner Disriminant.**

I. INTRODUCTION

The research on face recognition has been conducted for more than thirty years, but, still more processes and better techniques for facial extraction and face recognition are needed. This research work aims to reduce the error rates using pre-processing techniques under subspace methods of recognition. The most existing techniques like Eigen faces, Principal Component Analysis, etc., have the low dimension of the solution to classification and generalization problems. Also, it is a challenging task in a less-controlled environment like different illumination variations for large databases. In order to overcome the above limitations, new subspace framework with pre-processing is proposed.

II. FACE RECOGNITION TECHNIQUES

Face recognition is an evolving area, changing and improving instantly. Many research areas affect face recognition - computer vision, optics, pattern recognition, neural networks, machine learning, psychology, etc. Face Recognition methods are classified as following:

A. Geometric/Template Based approaches

The template based methods compare the input image with a set of templates. The set of templates can be constructed using statistical tools like Support Vector Machines (SVM), Principal Component Analysis (PCA), Linear Discriminate Analysis (LDA), Independent Component Analysis (ICA), Kernel Methods or Trace Transforms. The geometry feature-based methods analyze local facial features and their geometric relationships. E.g., EBGM, LBP, etc.

B. Piecemeal / Wholistic approaches

These methods use the entire face as data for the system.

C. Appearance-based/Model-based approaches

Appearance methods can be classified as linear or non-linear, while model-based methods can be 2D or 3D. Examples of linear methods are PCA, LDA, ICA, etc. Kernel methods are come under non linear methods. Examples of model based approaches are EBGM, 3D Morphable model, etc.

D. Template / statistical / neural network approaches

In template matching patterns are represented by samples, models, pixels, curves, textures. The recognition function is usually a correlation or distance measure. In statistical approach patterns are represented as features. The recognition function is a discriminant function. In Neural networks, the representation may vary. There is a network function in some point.

III. FACE RECOGNITION USING SUBSPACES TECHNIQUES

Face Recognition plays a vital role in many applications such as criminal detection which is considered to be the most useful and eminent techniques for identifying a criminalized person. A face recognition system is supposed to recognize faces under different illumination and lighting conditions present in the images. An efficient system to recognize human faces can be approached through the integration of different techniques viz., Normalization, Feature Extraction and Classification under subspace techniques. Fig.1. represents the conceptual diagram on how the face can be recognized under different illumination and lighting conditions by this method for the viewer-cantered images. The input image is given to the image pre-processing to remove the illuminations, shades, lighting effects by using the illumination normalization technique without affecting to the face features which are needed for further processes. Then the features from the normalized image are extracted using a proposed subspace framework. Then the extracted features are trained using subspace classifier to get the identified image.

A. Normalisation

A pre-processing method which reduces the effect of various illumination conditions in the image is used. In Normalization, the pre-processing chain mainly categorized under five steps viz., RGB Image to Gray Scale Image, Gamma Correction, Difference of Gaussian, Masking and Equalization of Normalization. The pre-processing is an efficient method through which the darkness from the image is removed, still preserving the necessary information from the input image for further processing of feature extraction. Fig.1. shows the sequential steps of the effective pre-processing chain used in this paper as it is the first step in eliminating the noise or darkness from the input face image.

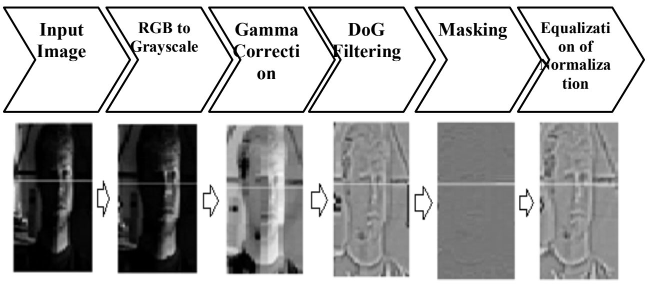


Fig.1. Sequence of Image Pre-processing Chain

1) Input image

The Input Images in Image Pre-processing Chain has the dimension of 150 x 130 which has been taken from the Yale–B database which are subjected to different variations. One input face image is projected to ten different illumination variations. Apart from the Yale–B dataset, the other test images which are RGB images are also considered for testing so that the image should be recognized even if the produced image is a RGB image.

2) RGB Image to Greyscale

The true colour RGB image is converted to gray scale intensity level so that the pixels can be set to 0 and 1 instead of 0 to 255 colours. The reason for not considering the image as RGB image itself is that it becomes a hectic process for identifying the location of a pixel. This conversion also helps in eliminating the hue and saturation information still retaining the luminance.

3) Gamma Correction

Gamma correction is nonlinear gray-level transformation used to correct the power-law transformation phenomena which perform the transformation of an input image to its original appearance. This transformed gamma-corrected image is free from the darkness by compressing all the dark regions into bright regions. It replaces the original gray-level I with I^{γ} by considering $\gamma > 0$, but lies between 0 and 1 (i.e., $\gamma \in [0, 1]$). The underlying principle behind the gamma correction is that the intensity of the light reflected from an object is the product of the incoming illumination and the local surface reflectance. Here, the obtained image after gamma correction should be an illumination free image. The gamma value from 0 to 1 is considered to be a full log transformation which is very strong to convert the dark regions. Hence the value of γ can be range from [0, 0.5] and by default the value of $\gamma = 0.2$ is to be considered. Fig 2. shows the image and a histogram after gamma correction.

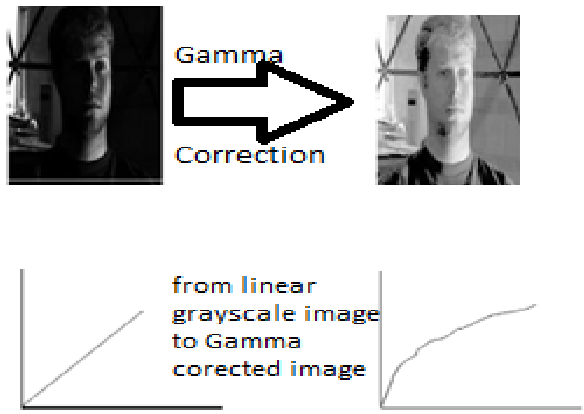


Fig.2. Gamma Corrected Image and its corresponding histogram

4) Difference of Gaussian

Gamma Correction does not remove the complete darkness, but, the local shadings can be removed by applying the high-pass filtering thus by simplifying the recognition problem. The high-pass filter attenuates low frequencies while passing high frequencies so that the edges of the image become sharper. Hence by implementing the filters using explicit convolution, boundary effects can be minimized. The process of convolution creates the mask from pixel to pixel in an image and thus computes the predefined quantity at each pixel. In order to significantly reduce the performance of the boundary conditions, Forward Fourier Transform (FFT) is utilized. Thus by establishing this filters, obviously produces a good result for the recognition of the features. Gaussian filters are the special analysis tools which are easy to manipulate.

Utilizing the characteristics of Gaussian function, the gamma corrected image generates the informative image using the difference between the two Gaussian filters according to the local contrast information of the images. The two Gaussian filters with the variances $\sigma 1 = 1.0$ and $\sigma 2 = 2.0$ by default (always $\sigma 1 < \sigma 2$) can be considered. Though gamma correction produces an informative image, still without DoG filtering, the resulting images suffer from reduced local contrast in shadowed regions.

5) Equalization of Normalization

The last step of the pre-processing chain is the equalization of normalization which rescales the image intensity, thus highlights the most of the information by preserving the essential elements of visual appearance. This is done using the median of the absolute value of the signal based on following formula.

$$I(x,y) \leftarrow \frac{I(x,y)}{\left(\text{mean}\left(|I(x',y')|^{a}\right)\right)^{1/a}} \qquad (1)$$

$$I(x,y) \leftarrow \frac{I(x,y)}{\left(\text{mean}\left(\min\left(\tau,|I(x',y')|\right)^{a}\right)\right)^{1/a}} \qquad (2)$$

Here is a strongly compressive exponent that reduces the influence of large values, τ is a threshold used to truncate the large values after the first phase of normalization, and the *mean* is over the whole unmasked part of the image. By default, the values of = 0.1 and τ = 10 is used. Now, the image is well-scaled, but still has the extreme values. To reduce this, the hyperbolic tangent $I(x,y) \leftarrow \tau \tanh\left(\frac{I(x,y)}{\tau}\right)$ can be used and thus limiting I to the range (-τ, τ).

6) Histogram and Computation Time

The difference between the input face image's histogram before and after the proposed pre-processing stage is shown in the Fig. 3. This illustrates clearly how important the pre-processing to be done in order to reduce the unwanted noise or the highly variable lighting differences from the images to get the fruitful information for extracting of the features for the agent. Run time is considered to be very important. The computational time taken by the Matlab 7.4 is only about 60ms for 150 x 130 dimension image.

B. BDPCA+LDA: A subspace Feature Extractor

This section proposes a fast feature extraction technique, Bi-Directional PCA plus LDA(BDPCA+LDA), which performs LDA in the BDPCA subspace. Compared to any subspace feature extraction method, BDPCA+LDA requires less computational and memory needs and can achieve competitive recognition accuracy. Apart from the various challenges that already addressed in preprocessing, this framework addresses singularity, over fitting and robustness.

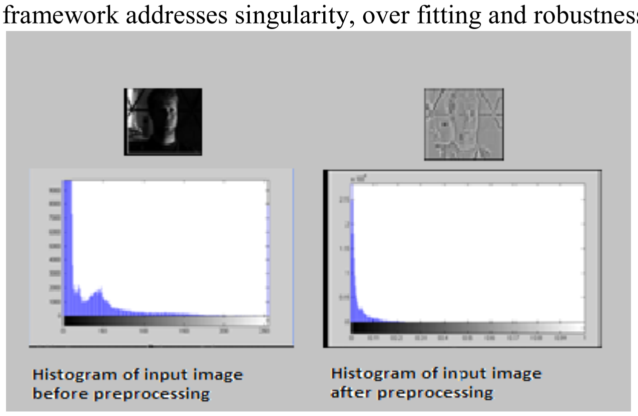


Fig.3. Difference between the histograms before and after preprocessing of the image under dim light condition

1) The BDPCA+LDA: algorithm

BDPCA+LDA is an LDA approach that is applied on a low-dimensional BDPCA subspace, and thus can be used for fast facial feature extraction. Since less time is required to map an image matrix to BDPCA subspace, BDPCA+LDA is, at least, computationally faster than any subspace method. BDPCA+LDA first uses BDPCA to obtain feature matrix Y. The feature matrix Y is then transformed into feature victor y by concatenating the columns of Y. The LDA projector - $W_{LDA}=[\varphi_1, \varphi_2, \ldots \varphi_m]$ is calculated by maximizing Fisher's criterion:

$$J(\varphi) = \frac{\varphi^T S_b \varphi}{\varphi^T S_w \varphi} \qquad (3)$$

where φ_i is the generalized eigenvector of S_b and $S_w$corresponding to the i^{th} largest eigen value λ_i.

$$S_b \varphi i = \quad S_w \varphi w \qquad (4)$$

And $\mathbf{S}_b$ is the between-class scatter matrix of **y**

$$S_b = \frac{1}{N} * \sum_{i=1}^{C} Ni\,(\mu i - \mu) * (\mu i - \mu)^T \qquad (5)$$

And$S_w$is the within-class scatter matrix of **y**,

$$S_w = \frac{1}{N} * \sum_{i=1}^{C} (Yi,j - \mu i) * (Yi,j - \mu i)^T \qquad (6)$$

Where N_i, $\mathbf{y}_{i,j}$ and $\boldsymbol{\mu}_i$ are the number of feature vectors, the jth feature vector and the mean vector of class i, C is the number of classes, and $\boldsymbol{\mu}$ is the mean vector of all the feature vectors.

In summary, the main steps in **B**DPCA+LDA feature extraction are to first transform an image matrix **X** into BDPCA feature subspace **Y** by equation (7).

$$Y = W_c^T X W_r \qquad (7)$$

and map **Y** into its 1Drepresentation **y** and then to obtain the final feature vector **z** by

$$Z = W_{LDA}^T Y \qquad (8)$$

C. The Classifier

The classifier considered in this paper is a subspace classifier, the most existing method – Fisher Liner Discriminate (FLD) that classifies unlabeled features based on their similarity with features in their training sets. Fisher's linear discriminant is a classification method that projects high-dimensional data onto a line and performs classification in this one-dimensional space. The projection maximizes the distance between the means of the two classes while minimizing the variance within each class. This defines the Fisher criterion, which is maximized over all linear projections, w:

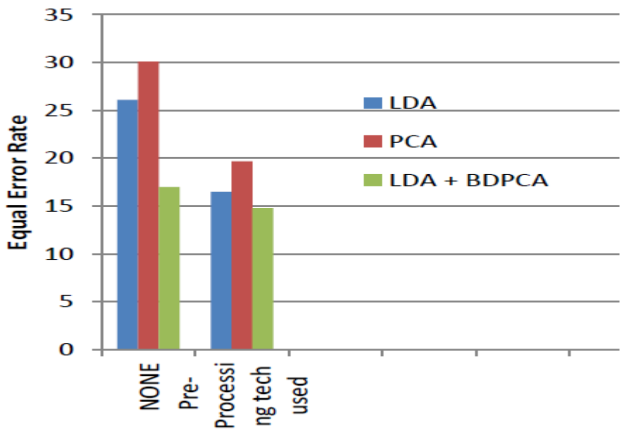
$$J(w) = \frac{|m1 - m2|^2}{s1^2 + s2^2} \qquad (9)$$

where m represents a mean, s^2 represents a variance, and the subscripts denote the two classes. In signal theory, this criterion is also known as the signal-to-interference ratio. Maximizing this criterion yields a closed form solution that involves the inverse of a covariance-like matrix. This method has strong parallels to linear perceptrons that significantly improves the results.

IV. EXPERIMENTS

To evaluate the proposed method a standard image set, FARET is used. A subset of the FERET database is chosen to evaluate this method. Several images of each individual with varied illumination are taken. The facial portion of each original image was cropped to a size of 80□80 and pre-processed using the proposed normalization, a pre-processing chain. We also compare BDPCA+LDA with other subspace methods, including Fisher faces, Eigenfaces. Since the aim is to evaluate the efficacy of feature extraction methods, the most existing classifier Fisher's Linear Discriminant (FLD). To reduce the variation of recognition results, mean of 10 runs as the average recognition rate (ARR) is taken.

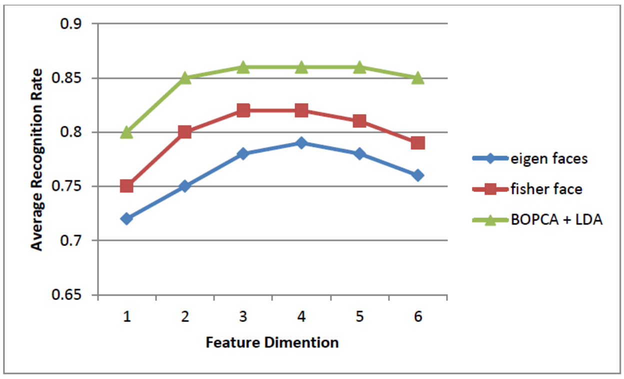
The EER of a system can be used to give a threshold independent performance measure. The lower the EER is the better is the system's performance, as the total error rate which is the sum of the FAR and the FRR at the point of the EER decreases.



Graph.1. Equal Error Rates of face recognition methods with image preprocessing technique used and not used

Both the Fisher face and Eigen face methods would perform best when used with preprocessing technique, achieving low EER than that of no preprocessing is used. The LDA+BDPCA method would achieve the lowest EER when used with the proposed normalization pre- processing technique. Lowest computational time and less memory requirements are expected with this method.

Average recognition rates and Equal error rates are compared with other subspace techniques such as fisher faces and eigen faces and better accuracy rates and low ERR would be achieved over the other subspace methods.



Graph 2. Comparisons of the recognition rates obtained using different methods on the FERET subset.

Table 1. Recognition performance of various subspace face recognition methods on the FERET database

Methods	Eigen faces	Fsherfaces	LDA+BDPCA
ARR%	78.26	84.69	87.16
ERR%	19.1	16.6	14.8

V. CONCLUSION

The approach in this work is primarily to reduce the error rates by using preprocessing techniques and recognizing using subspace methods. A new subspace framework is used in this paper for better recognition. The subspace framework applied to this work would give significant results. Experiments would be done on standard set of data bases and FAR and FRR would be computed in order to find the error rates (ERR). This proposed approach would reduce the ERR of the subspace methods.

REFERENCES

[1] W. ZHAO, R. CHELLAPPA, P. J. PHILLIPS "Face Recognition: A Literature Survey" ACM Computing Surveys, Vol. 35, No. 4, December 2003, pp. 399–458.

[2] Xiaoyang Tan and Bill Triggs, *"Enhanced Local Texture Feature Sets for Face Recognition Under Difficult Lighting Conditions"*, IEEE Trans, on Image Processing, Vol. 19, No.6, June 2010.

[3] Belhumeur, P., Hespanha, J., &Kriegman, D. (1997). Eigenfaces vs. Fisherfaces: Recognition Using Class Specific Linear Projection. *IEEE Transactions on Pattern Analysis and Machine Intelligence,* 19(7).

[4] Wolf, Lior. (2009) Face Recognition, Geometric vs. Appearance-Based. *Encyclopedia of Biometrics*, Vol. 2.

[5] Wolf, Lior. (2009) Face Recognition, Geometric vs. Appearance-Based. *Encyclopedia of Biometrics*, Vol. 2.

[6] Starovoitiv, V., &Samal, D. (1999).A geometric approach to face recognition.*Proc. IEEE-EURASIP Workshop on Nonlinear Signal and Image,* 2, 210-213.

[7] Baeka, J. &Kimb, M. (2004) Face recognition using partial least squares components. *Pattern Recognition*, Vol.37, 1303-1306.

[8] Bartlett, M.S.;Movellan, J.R. &Sejnowski, T.J. (2002) Face Recognition by Independent Component Analysis. *IEEE Trans. Neural Network*, Vol.13, No.6, 1450-1464.

[9] Belhumeur, P. N.; Hespanha, J. P. &Kriegman, D. J. (1997) Eigenfaces vs Fisherfaces: recognition using class specific linear projection. *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol.20, No.7, 711-720.

[10] Cevikalp, H.; Neamtu, M.; Wilkes, M. &Barkana, A. (2005) Discriminative common vectors for face recognition. *IEEE Trans Pattern Analysis and Machine Intelligence*, Vol. 27, No.1, 4-13.
[11] Liu, C. (2004) Gabor-based kernel PCA with fractional power polynomial models for face recognition", *IEEE Trans. Pattern Analysis and Machine Intelligence*, Vol. 26, No. 5, 572-581.
[12] Liu, C. & Wechsler, H. (1998) Enhanced Fisher linear discriminant models for face recognition.*Proc. 14th Int'l Conf. Pattern Recognition*, Vol. 2, pp. 1368-1372.
[13] Liu, C. & Wechsler, H. (2002) Gabor feature based classification using the enhanced fisher linear discriminant model for face recognition. *IEEE Trans. Image Processing*, Vol.10, No.4, 467-476.
[14] Liu, K.; Cheng, Y.-Q. & Yang, J.-Y. (1993) Algebraic feature extraction for image recognition based on an optimal discriminant criterion. *Pattern Recognition*, Vol.26, No.6, 903-906.