Face Recognition for cluttered Images using Eigen and Fisher Approach

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Abstract - Various critical face recognition applications like security have input scenario in which captured images are always with clutter or background, we need an efficient face detection and recognition system which will provide fairly good recognition rate and matching ratio. The proposed method helps in building a robust face recognition(FR) system by combining the functional advantages of conventional PCA(Principle Component Analysis) and FLDA(Fisher Linear Discriminant Analysis) in recognizing faces in spite of background clutter. Some other improvements are also suggested for common challenges like speed, illumination variances, computational complexity that are still there in designing a robust face recognition system.

Keywords-*Face, clutter, PCA, FLDA.*

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1. INTRODUCTION

Face recognition(FR) has become an important research area because of its usefulness in numerous applications. The general idea of face recognition is to extract certain data from the region of interest in a human facial image and to compare them to stored data for identification. Developing a computational model for face recognition is quite a difficult task because faces are a natural class of complex, multi-dimensional objects. The computational approaches available today can only suggest broad constraints for this problem.

1.1 Related Work

Many approaches have been attempted to solve the face recognition problem [1]–[2]. One of the very successful and popular face recognition methods is based on the principal components analysis (PCA) [1]. In 1987, Sirovich and Kirby [1] showed that if the eigenvectors corresponding to a set of training face images are obtained, any image in that database can be optimally reconstructed using a linear weighted combination of these eigenvectors. Their work explored the representation of human faces in a lower-dimensional subspace. In 1991, Turk and Pentland [2] used these eigenvectors (or eigen-faces as they are called) for face recognition. PCA was used to yield projection directions that maximize the total scatter across all faces in the training set. They also extended their approach to real time recognition of a moving face image in a video sequence [3]. Another popular scheme for dimensionality reduction in face recognition is due to Belhumeur et al.[4], Etemad and Chellappa [5], and Swets and Weng [6]. It is based on Fisher's linear discriminant (FLD) analysis. The FLD uses class membership information and develops a set of feature vectors in which variations of different faces are emphasized while different instances of a face due to illumination conditions, facial expressions and orientations are deemphasized. The FLD method deals directly with discrimination between classes whereas the eigenface recognition (EFR) method deals with the data in its entirety without paying any particular attention to the underlying class structure. It is generally believed that algorithms based on FLD are superior to those based on PCA when sufficient training samples are available. But as we go on increasing training samples, training time increases and so speed drops.

1.2 Proposed Outline

Methods such as EFR and FLD work quite well provided the input test pattern is a face, i.e., the face image has already been cropped out of a scene. The problem of recognizing faces in still images with a cluttered background is more general and difficult as one does not know where a face pattern might appear in a given image. A good face recognition system must possess the following two properties. It should: 1) detect and recognize all the faces in a scene, and 2) not misclassify background patterns as faces. Since faces are usually sparsely distributed in images, even a few false alarms will render the system ineffective.

Both methods, PCA and FLDA involves selection of eigenvectors with maximum information regarding covariance of training image dataset. PCA is based on the sample covariance which characterizes the scatter of entire dataset whereas FLDA provides eigenvectors having maximum information of minimized scatter within class(individual) and maximized scatter between any two individual classes. Proper number of and type of eigenvectors should be chosen providing good recognition accuracy and speed. Some work is already done in this regard.[4], [7].

In the proposed method, PCA based classification is used for classifying the test pattern as ‘face’ or ‘background’[8], [9] since this method is based on variance across all sample faces and FLDA based classification technique is used to classify a face image as ‘known’ or ‘unknown’, since this method considers scattering between and within classes(individuals).

2. EIGENFACE SPACE CREATION

2.1 Principal Component Analysis

Principal component analysis (PCA) is a useful statistical technique that has found application in fields such as face recognition and image compression and is a common technique for finding patterns in data of high dimensions.

Let a face image be a 2-D, N by N array of (8 bit) intensity values. This image may be considered as a vector of dimension N^2. For example, a 112x92 image can be considered as a vector of dimension 10304. Suppose, we have ‘M’ number of face images (samples) then our dataset can be considered as,

$$X = [\Gamma_1 \Gamma_2 - - - - \Gamma_M] \quad \text{---- (2.1.1)}$$

Where, Γ_i = column vector of size N^2 for i =1, 2… M.

Mean of these sample dataset is denoted by,

$$\Psi = \frac{1}{M}\sum_{n=1}^{M}\Gamma_n \quad \text{---- (2.1.2)}$$

And Covariance matrix of the dataset is,

$$C = \frac{1}{M}\sum_{n=1}^{M}(\Gamma_n - \Psi)(\Gamma_n - \Psi)^T \quad \text{---- (2.1.3)}$$

Each face differs from the mean by a vector, Φi = гi-ψ. Hence, data matrix of centered face images can be written as,

$$A = [\Phi_1 \Phi_2 - - - \Phi_M] \quad \text{---- (2.1.4)}$$

Hence equation, (2.1.3) becomes,

$$C = \frac{1}{M}\sum_{n=1}^{M}\Phi_n\Phi_n^T \quad \text{Or,} \quad C = AA^T \quad \text{---- (2.1.5)}$$

For this symmetric covariance matrix C, we can calculate an orthogonal basis by finding its eigenvalues and eigenvectors. The eigenvectors, νi with the eigenvalues, λi are the solutions of the equation,

$$Cv_i = \lambda_i v_i \quad \text{for, i =1, 2,……, } N^2 \quad \text{---- (2.1.6).}$$

These eigenvectors (principal components) calculated forms an orthogonal basis which best describes the distribution of the data and the corresponding eigenvalues indicates how much percentage the principal component represents the total tendency of variation. Hence, by ordering the eigenvectors in the order of descending eigenvalues, one can create an ordered orthogonal basis with the first eigenvector (with largest eigenvalue) having direction in which the data set has the most significant amount of energy and largest variance.

2.2 Decrementing Dimensions

Above literature clearly indicates that we have to solve for the covariance matrix, C of size N2XN2 determining N2 eigenvectors and eigenvalues which is quite a cumbersome task.

Fortunately if number of samples (no. of data points in space) is less than number of pixels in a image (no. of dimensions of space) or, if M<<N2 then we can solve for N2 dimensional eigenvectors by first solving for eigenvectors of MXM matrix and then taking appropriate linear combinations of face images Φi, as per [2] .

If we find out eigenvectors, νi of matrix ATA(MXM) such that,

$$A^TAv_i = \lambda_i v_i \quad \text{for, i=1,2,……,M} \quad \text{---- (2.2.1)}$$

Pre-multiplying both sides by A, we get

$$AA^TAv_i = \lambda_i Av_i \quad \text{---- (2.2.2)}$$

Comparing above equation with basic eigenvalue problem, Cν=λν, we observe that Aνi are the eigenvectors of C=AAT.

Hence, we construct matrix, L=ATA (MXM) and find M eigenvectors νl of L. These eigenvectors determine linear combinations of M training set face images to form eigenfaces μl as,

$$\mu_l = \sum_{k=1}^{M} v_{lk}\Phi_k \quad \text{---- (2.2.3)}$$

With this analysis, the calculations are greatly reduced from the order of number of pixels in the images (N2) to the order of number of images in the training set (M).

2.3 Using Eigenfaces to Classify Image

The eigenvectors seem adequate for describing images under very controlled conditions, hence decided to investigate their usefulness as a tool for identification. In practice, as evaluated by Sirovich and Kirby [1] and [10], a smaller M’ is sufficient for identification, since accurate reconstruction of the image is not a requirement. The eigenvector span a M’ dimensional subspace of the original N2 image space by choosing M’ eigenvectors with highest associated eigenvalues out of M eigenvectors of matrix L.

This group of M’ eigenvectors forms the “Eigenface space” on which to operate for classifying input image as face or clutter/background image in the proposed method.

A new face image, (Γ) is transformed into its eigenface components (projected onto eigenface space) by a simple operation,

$$\omega_k = u_k^T(\Gamma - \Psi) \quad - (2.3.1) \qquad \text{for } k=1, 2,\ldots, M'.$$

The weights form a vector, Ω= [ω1,ω2, ………ωM'] describes the contribution of each eigenface in representing the input face image, treating the eigenfaces as a basis set for face images.

2.3.1 Calculation of threshold, Θ_FEFS:

Θ_FEFS defines maximum allowable distance from eigenface space.

For this, we have to calculate for the projection of normalized training images on "eigenface space" as:

$$\Phi_{f,j} = \sum_{i=1}^{M} \omega_i u_i \qquad \text{---- (2.3.1.1)}$$

for i=1,2,…….,M' and j=1,2,……,M.

Then Euclidian distance between Φj and Φf,j is calculated as:

$$\theta_j^2 = \|\Phi_j - \Phi_{f,j}\|^2 \qquad \text{---- (2.3.1.2)}$$

Where, Φj = rj -ψ.

The above calculations have to be done by considering each training image r_j and θ_j are calculated for i=1, 2... *M.*

Then, the threshold Θ_FEFS is obtained as the maximum value amongst all θ_j's.

$$\Theta\_FEFS = \max(\theta_j). \qquad \text{---- (2.3.1.3)}$$

3. FISHERFACE SPACE CREATION

3.1 Fisher Linear Discriminant Analysis

FLDA is capable of distinguishing image variation due to identity from variation due to other sources such as illumination and expression. It also provides dimensionality reduction while preserving as much of the class discriminatory information as possible. This method seeks to find directions along which the classes are best separated. It takes into consideration the scatter within-classes but also the scatter between-classes.

Suppose there are C classes and let μl be the mean vector of class I, i=1,2,3,...,C.. Let Mi be the number of samples within class I and let M equal to the summation of Mi for all classes be the total number of samples. Then, Fisher-LDA considers maximizing the following objective:

Maximize,

$$J = \frac{det(S_B)}{det(S_W)} \qquad \text{---- (3.1.1)}$$

where SB is the "between classes scatter matrix" and SW is the "within classes scatter matrix". Note that due to the fact that scatter matrices are proportional to the covariance matrices we could have defined J using covariance matrices – the proportionality constant would have no effect on the solution. The definitions of the scatter matrices are:

$$S_W = \sum_{i=1}^{C} \sum_{j=1}^{Mi} [y_j - \mu_i][y_j - \mu_i]^T \quad \text{---- (3.1.2)}$$

$$S_B = \sum_{i=1}^{C} [\mu_i - \mu][\mu_i - \mu]^T \qquad \text{---- (3.1.3)}$$

$$\mu = \frac{1}{C}\sum_{i=1}^{C} \mu_i \quad \text{-- (mean of entire dataset)} \quad \text{---- (3.1.4)}$$

Such a transformation should retain class sap arability while reducing the variation due to sources other than identity (e.g., illumination). The eigenvectors are solutions of the generalized eigenvector problem:

$$S_W^{-1} S_B \mu_k = \lambda_k \mu_k \qquad \text{---- (3.1.5)}$$

3.2 Using Fisherfaces to Classify Image

Training Phase:

1) Take X which is the input / training data in matrix form.
2) Calculate SB and SW from X.
3) Calculate $S_W^{-1} S_B$.
4) Calculate Eigen vectors and Eigen values of $S_W^{-1} S_B$.
5) Let c be the number of dimensions you want in reduced form.
6) Select c Eigen vectors corresponding to c highest Eigenvalues.
7) These c eigen vectors together forms w (fisherface).

Testing Phase:: When a test image, x is multiplied with W^T, it lowers down in dimensionality and its distance from all fisherfaces (i.e, projections) of training classes are threshold for recognition.

We are **going** to use the above FLDA technique for recognizing the face as "known" or "unknown", once the test sub-image is classified as "face" image by PCA method.

4. RECOGNITION WITH CLUTTERED IMAGE

4.1 Training Phase

The proposed face recognition system has to be initially trained for getting ready for the use. As shown in figure 3.1 , training phase involves creation of eigenface space using PCA and threshold(maximum distance allowed from eigenface space) for classifying input image as "face" or "clutter" image. Secondly, training phase also involves formation of fisher space using FLDA and threshold(maximum distance allowed from fisherfacespace) to classify an input face image as "known" or "unknown" .

4.2 Testing Phase

When cluttered test image is captured by camera as a input probe, it has to firstly sampled into number of sub-images each of size equal to the size of training image. Then eigenbackground space of test image is created by learning background of test image, on the fly (using N x N sub-images of test image like training set). For recognizing a face-like sub-image in the probe, classify each sub-image, y of test image as 'face image', if the following condition satisfies otherwise as 'background pattern'.

$$\| y - \hat{y}_f \|^2 < \| y - \hat{y}_b \|^2 \ \& \ \| y - \hat{y}_f \|^2 < \Theta\_FEFS$$

If the sub-image is classified as 'face image' then classify it as 'known' image if the distance of its projection in fisherface space is less than the threshold, Θ_IFFS.

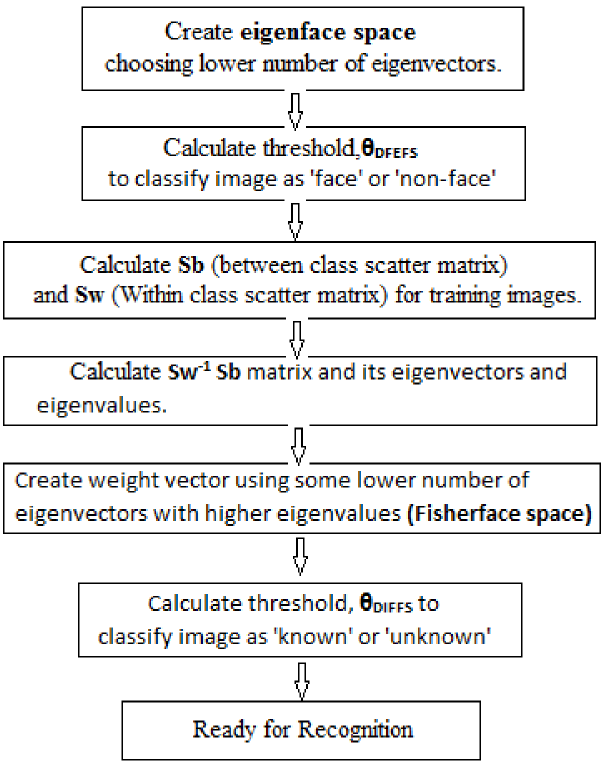

Fig.(4.1): Training Phase

5. CONCLUSION

In the literature, the eigenface technique has been demonstrated to be very useful for face recognition. However, when the scheme is directly extended to recognize faces in the presence of background clutter, its performance degrades as it cannot satisfactorily discriminate against non-face patterns. In this paper, we have proposed a idea regarding robust scheme for recognizing faces in still images of natural scenes. We argue in favor of constructing an eigen-background space from the background images of a given scene. The background space which is created "on the fly" from the test image is shown to be very useful in distinguishing non-face patterns. The scheme outperforms the traditional EFR technique and gives very good results with almost no false alarms, even on fairly complicated scenes.

Functional advantages of conventional PCA for reducing computational complexity when crucial details are not required for classification and FLDA for recognizing faces in spite of fair presence of illumination and expression variations in probe images with background clutter can be very used in designing a robust face recognition system.

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7. REFERENCES

[1] L. Sirovich and M. Kirby, "Low-dimensional procedure for the characterization of human faces," J. Opt. Soc. Amer. A, vol. 4, pp. 519–524, 1987.

[2] M. Turk and A. Pentland, "Eigenfaces for recognition," J. Cogn. Neurosci., vol. 3, pp. 71–86, 1991.

[3] A. Pentland, "Looking at people: Sensing for ubiquitous and wearable computing," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 1, pp.107–119, Jan. 2000.

[4] P. Belhumeur, J. Hespanha, and D. Kriegman, "Eigenfaces vs. Fisher-faces: Recognition using class specific linear projection," IEEE Trans.Pattern Anal. Mach. Intell., vol. 19, no. 5, pp. 711–720, May 1997.

[5] K. Etemad and R. Chellappa, "Discriminant analysis for recognition of human face images," J. Opt. Soc. Amer. A, vol. 14, pp. 1724–1733, 1997.

[6] D. L. Swets and J. Weng, "Using discriminant features for image retrieval," IEEE Trans. Pattern Anal. Mach. Intell., vol. 18, no. 6, pp.831–836, Jun. 1996.

[7] " Features vs templates", R. Brunelli and T. Poggio. Face recognition, *IEEE Trans. Pattern Anal. Mach. Intelligence*, 15(10):1042–1053, 1993.

[8] " Background Learning for Robust Face Recognition with PCA in the Presence of Clutter", A. N. Rajagopalan, Rama Chellappa, *Fellow*, *IEEE*, and Nathan T. Koterba, IEEE TRANSACTIONS ON IMAGE PROCESSING, VOL. 14, NO. 6, JUNE 2005.

[9] "Automatic Door Access System Using Face Recognition", Hteik Htar Lwin, Aung Soe Khaing, Hla Myo Tun, INTERNATIONAL JOURNAL OF SCIENTIFIC & TECHNOLOGY RESEARCH VOLUME 4, ISSUE 06, JUNE 2015.

[10] M. Kirby and L. Sirovich, 1990 "Application of Karhunen-Loeve Procedure for the Characterization of Human faces," IEEE Transactions on Pattern Analysis and Machine Intelligence, 12(1).