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Face recognition using apperance based analysis

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ABSTRACT

Face recognition technology has evolved as a popular identification technique to perform verification of human identity. By using the feature extraction methods and dimensionality reduction techniques in the pattern recognition applications, a number of facial recognition systems have been produced with distinct measure of success. Various face recognition algorithms and their extensions; have been proposed in the past two decades. However, face recognition faces challenging problems in real life applications because of the variation in the illumination of the face images, facial expression and background variation. This paper provides a classification of back ground variation includes uniform background and non-uniform background along with facial expression, orientation of the image and illumination invariant using Principal Component Analysis (PCA) and Linear Discriminate Analysis (LDA) face recognition system.

Introduction

Face recognition systems have been grabbing high attention from commercial market point of view as well as pattern recognition field. Face recognition has received substantial attention from researches in biometrics, pattern recognition field and computer vision communities. The face recognition systems can extract the features of face and compare this with the existing database. The faces considered here for comparison are still faces.

The present paper is formulated based on still images captured by a digital camera. The face recognition system detects only the faces from the image scène, extracts the descriptive features. It later compares with the database of faces, which is collection of faces in different poses. The present system is trained with the database; where the images are taken with uniform background and non uniform background along with facial expressions, illumination variation and orientation of the image.

Principal Componenet Analysis (PCA)

Given an *s*-dimensional vector representation of each face in a training set of *M* images, Principal Component Analysis (PCA) [1] tends to find a *t*-dimensional subspace whose basis vectors correspond to the maximum variance direction in the original image space.

This new subspace is normally lower dimensional ($t << s$). New basis vectors define a subspace of face images called *face space*. All images of known faces are projected onto the face space to find a set of weights that describes the contribution of each vector. To identify an unknown image, that image is projected onto the face space to obtain its set of weights. By comparing a set of weights for the unknown face to sets of weights of known faces, the face can be identified. If the image elements are considered as random variables, the PCA basis vectors are defined as eigenvectors of the scatter matrix *ST* defined as:

$$ST = \sum_{i=1}^{M} (xi-\mu).(xi-\mu)^T$$

Where μ is the mean of all images in the training set (the *mean face*) and *xi* is the *i*-th image with its columns concatenated in a vector.

The projection matrix is represented as *WPCA* is composed of *t* eigenvectors corresponding to *t* largest Eigen values, thus creating a *t*-dimensional face space. For details on PCA please refer to [1].

Implementation

It includes 3 steps

Creation of Database:

The data set consists of two sets of images (a) uniform background along with illumination variations, facial expression and orientation of image, (b) non-uniform background along with illumination variations, facial expression and orientation of image.

All images in the data set are of the size 180X200 pixels.

Preprocessing:

All algorithms and all image preprocessing steps were implemented in MATLAB. The following steps are used to calculate the Eigen face.

(a) All the 2D images of the training database are converted into 1D column vectors.

Then, these 1D column vectors are put in a row to construct 2D matrix 'T', where ‘T’ is the 2D matrix consisting of 1D column vectors.

(b) Calculating the mean of training database.

(c) Calculating the deviation of each image from mean image of training database.

(d) Calculation of Eigen values, Sorting and eliminating Eigen values and calculating the eigenvectors of covariance matrix.

Recognition:

(a) Extracting the PCA features from test image

(b) Manhattan distances between the projected test image and the projection of all centered training images are calculated.

(c) Test image is supposed to have minimum distance with its corresponding image in the training database.

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Output

Fig 2.1 Uniform background along with facial expression along with normal lightening condition with glasses

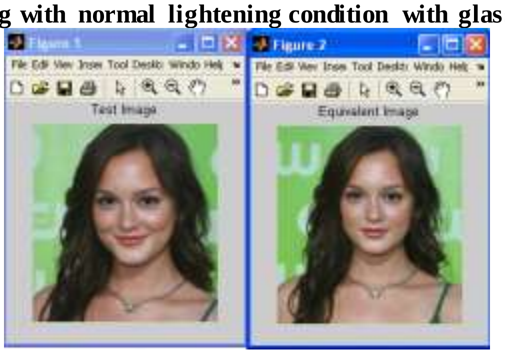

Fig 2.2 Non –uniform background along with facial expression and orientation of the image

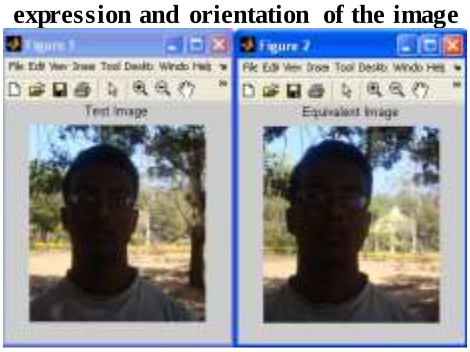

Fig 2.3 Non –uniform background along with illumination invariant with glasses

Linear Discriminant Analysis (LDA)

Linear Discriminant Analysis (LDA) [2], [3] finds the vectors in the underlying space that best discriminate among classes. For all samples of all classes the between-class scatter matrix *SB* and the within-class scatter matrix *Sw* are defined by

$$SB = \sum_{i=1}^{c} Mi\,(xi-\mu).\,(xi-\mu)^{T}$$

$$Sw = \sum_{i=1}^{c} \sum_{xk \in xi} Mi\,(xi-\mu i).\,(xi-\mu i)^{T}$$

Where *Mi* is the number of training samples in class *i*, *c* is the number of distinct classes, µ*i* is the mean vector of samples belonging to class *i* and *xi* represents the set of samples belonging to class *i* with *xk* being the *k*-th image of that class. *Sw* represents the scatter of features around the mean of each face class and *SB* represents the scatter of features around the overall mean for all face classes. The goal is to maximize *SB* while minimizing *Sw* in other words, maximize the ratio det| *SB* | / det| *Sw* |. This ratio is maximized when the column vectors of the projection matrix (*WLDA*) are the eigenvectors of *Sw -1*. *SB*. In order to prevent *Sw* to become singular, PCA is used as a preprocessing step and the final transformation is $Wop^{tT} = WLDA^{T}.WPCA^{T}$. For details on LDA please refer to [2].

Implementation

It includes 3 steps

Creation of Database:

The data set consists of two sets of images (a) uniform background along with illumination variations, facial expression and orientation of image, (b) non-uniform background along with illumination variations, facial expression and orientation of image. All images in the data set are of the size 180X200 pixels.

Preprocessing:

All algorithms and all image preprocessing steps were implemented in MATLAB. The following steps are used to calculate the Fisher Linear Discriminant (FLD) to determine the most discriminating features between images of faces using Principal Component Analysis (PCA).

(a)All the 2D images of the training database are converted into 1D column vectors. Then, these 1D column vectors are put in a row to construct 2D matrix 'T', where 'T' is the 2D matrix consisting of 1D column vectors.

(b) Calculating the mean of training database.

(c) Calculating the deviation of each image from mean image of training database.

(d) Calculation of Eigen values. Sorting and eliminating Eigen values and calculating the eigenvectors of covariance

(e) Projecting centered image vectors onto Eigen space.

(f) Calculating the mean of each class in eigenspace.

(g) Calculating Fisher discriminant basis's

(h) Eliminating zero Eigen's and sorting in descend order.

(i) Projecting images onto Fisher linear space.

Recognition:

(a) Extracting the linear discriminant features from test image.

(b) Manhattan distances between the projected test image and the projection of all centered training images are calculated.

(c) Test image is supposed to have minimum distance with its corresponding image in the training database.

Output

Fig 3.1 uniform/Black background along with facial expression &orientation of the image

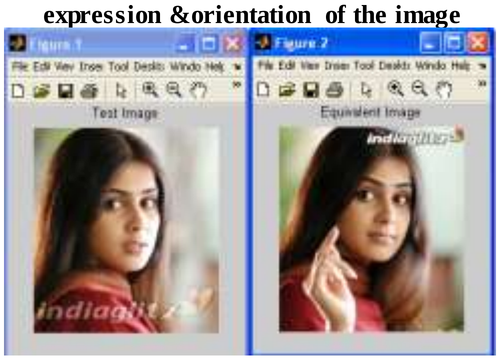

Fig 3.2 Non-uniform background along with orientation of the image

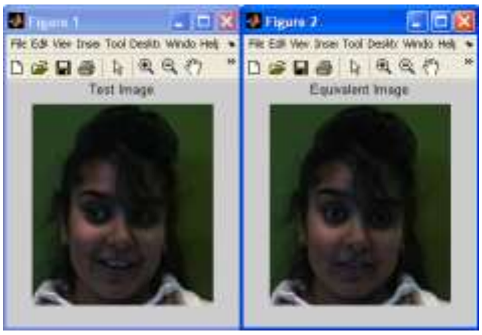

Fig 3.3 Uniform background with illumination invariant along with eye movement

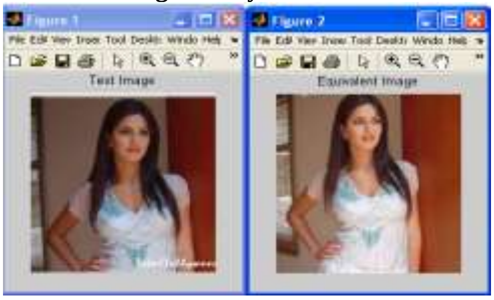

Fig 3.4 Non-uniform background along with illumination Invariant in the test image

Result

Table showing the success and error rates of face recognition on self created database consisting of 36 training images and 18 test images for facial expression along with orientation.

Method	Background	Lightning condition	Success	Error
Principal component analysis (PCA)	Uniform	Normal	100.00	0.00
	Uniform	Illumination invariant	90.00	10.00
	Non-uniform	Normal	100.00	0.00
	Non-uniform	Illumination invariant	100.00	0.00
Linear discriminanat analysis (LDA)	Uniform	Normal	100.00	0.00
	Uniform	Illumination invariant	80.00	20.00
	Non-uniform	Normal	80.00	20.00
	Non-uniform	Illumination invariant	50.00	50.00

Conclusion

The tests conducted on various images for uniform and non-uniform background along with facial expression with orientation &normal lighting condition and facial expression with orientation &illumination invariant has been satisfactory for self created database consisting of 40 training images and 20 test images, the PCA has produced with overall accuracy for both uniform and non-uniform condition results in 94.44% but for LDA the overall accuracy for both uniform and non-uniform condition results in77.8%.

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