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Recognition of Face Images Through the Fusion Approach

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Abstract: Face Recognition System should be able to automatically detect a face in images. This involves extraction of its features and then recognizes it, regardless of lighting, ageing, occlusion, expression, illumination and pose. Color local texture method do not easy to recognize the face and if variation in face means do not get proper results. Linear Discriminant Analysis (LDA) is commonly used technique for data classification and dimensionality reduction. LDA approach overcomes the above problem. The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible. Linear discriminant analysis is also known as Fisher's discriminant analysis and it searches for those vectors in the underlying space that best discriminate among classes.

Key words: Color face recognition, color local texture features, combination, principal component analysis, linear discriminant analysis

INTRODUCTION

Face recognition is widely used in biometric systems. Face recognition is also useful in human computer interaction, virtual reality, database retrieval, multimedia, computer entertainment, information security, e.g., operating system, medical records, online banking., biometric, e.g., personal identification-passports, driver licenses, automated identity verification-border controls, law enforcement, e.g., video surveillances, investigation, personal security-driver monitoring system, home video surveillance system. There are different types of approaches-Appearance-based method, Feature-based approach and hybrid approach. In holistic approach the whole face region is taken into account as input data into face detection system.

One of the best example of Holistic Methods are eigen faces most widely used method for face recognition, In this methods local features such as eyes, nose and mouth are first extracted and their locations and local statistics (geometric and/or appearance) are fed into a structural classifier.

A big challenge for feature extraction methods is feature "restoration", this is when the system tries to recover features that are invisible due to large variations, e.g., head pose. There are different extraction methods, the first is generic methods based on edges, lines and curves, the second is feature-template-based methods and the third is structural matching methods that take into consideration geometrical constraints on the features. Hybrid approach uses a combination of both holistic and feature-based approaches.

Principal Component Analysis (PCA) is one of the most popular holistic approach, i.e., appearance-based methods used for dimensionality reduction for compression and face recognition problems. Linear Discriminant Analysis (LDA) is another powerful dimensionality reduction technique which is also known as Fisher's discriminant analysis. It has been used widely in many applications such as face recognition, image retrieval, etc.

PREPROCESSING PROCEDURE

Preprocessing procedure is very important step for facial expression recognition. The ideal output of processing is to obtain pure facial expression images which have normalized intensity, uniform size and shape. It also should eliminate the effect of illumination and lighting. The preprocessing procedure of the system performs the following five steps:

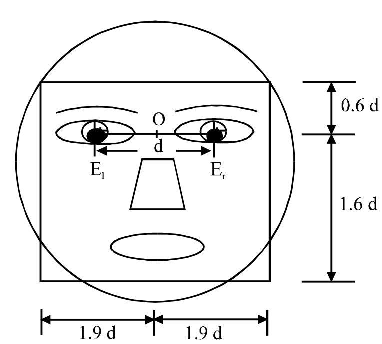

Fig. 1: Facial Model

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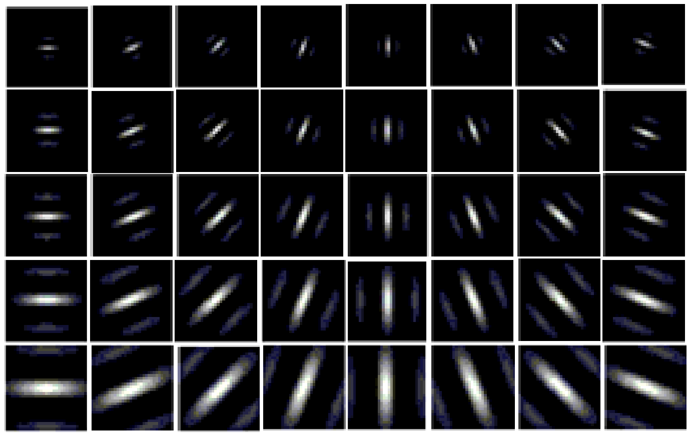

Fig. 2: The real part of the Gabor filters with five frequencies and eight orientations for $\omega_{max} = \pi/2$, the row corresponds to different frequency ω_m, the column corresponds to different orientation θ_n

- Detecting facial feature points manually including eyes, nose and mouth
- Rotating to line up the eye coordinates
- Locating and cropping the face region using a rectangle according to face model (Zou *et al*., 2007) as shown in Fig. 1. Suppose the distance between two eyes is d, the rectangle will be 2.2×1.8 d
- Scaling the image to fixed size of 128×96, locating the center position of the two eyes to a fixed position
- Using a histogram equalization method to eliminate illumination effect

GABOR FEATURE EXTRACTION

The Gabor filters, whose kernels are similar to the 2D receptive field profiles of the mammalian cortical simple cells, have been considered as a very useful tool in computer vision and image analysis due to its optimal localization properties in both spatial analysis and frequency domain.

GABOR FILTERS

In the spatial domain, a Gabor filter is a complex exponential modulated by a Gaussian function (Drimbarean and Whelan, 2001). The Gabor filter can be defined as follows (Fig. 2):

$$\psi(x, y, \varpi, \theta) = \frac{1}{2\pi\sigma^2} e^{-\left(\frac{x'^2+y'^2}{2\sigma^2}\right)} \left[e^{i\varpi x'} - e^{-\frac{\varpi^2\sigma^2}{2}} \right]$$

$$x' = x\cos\theta + y\sin\theta,\ y' = -x\sin\theta + y\cos\theta$$

Where:

(x, y) = The pixel position in the spatial domain
θ = The radial center frequency
ϖ = The orientation of Gabor filter
σ = The standard deviation of the round Gaussian function along the x and y-axes

GABOR FEATURE REPRESENTATION

The Gabor feature representation of an image $I(x, y)$ is the convolution of the image with the Gabor filter bank $\psi(x, y, \varpi_m, \theta_n)$ as given by:

$$O_{m,n}(x, y) = I(x,y) * \psi(x, y, \varpi_m, \theta_n)$$

where, * denotes the convolution operator. The magnitude of the convolution outputs of a sample image (Fig. 1) corresponding to the filter bank.

PRINCIPAL COMPONENT ANALYSIS

Principal Component Analysis (PCA) is a dimensionality reduction technique which is used for compression and face recognition problems. PCA calculates the eigen vectors of the covariance matrix and projects the original data onto a lower dimensional feature space which is defined by eigen vectors with large eigen values. PCA has been used in face representation and recognition where the eigen vectors calculated are referred to as eigen faces.

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 dimension. It is one of the more successful techniques of face recognition. PCA is to reduce the dimension of the data. No data redundancy is found as components are orthogonal. With help of PCA, complexity of grouping the images can be reduced. The application of PCA is made in criminal investigation,

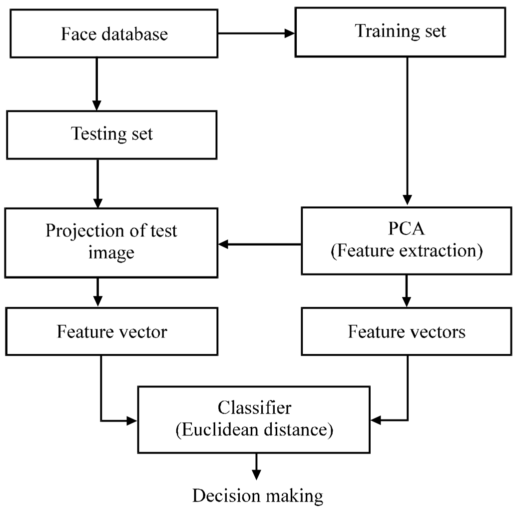

Fig. 3: PCA approach for face recognition

access control for computer, online banking, post office, passport verification and medical records, etc. (Fig. 3).

Methodology: Find the principal component use the following method:

Step 1: Get the data: suppose X1, X2,..., XM is N×1 Vectors:

$$X = \frac{1}{M\sum_{i=1}^{M} Xi}$$

Step 2: Subtract the mean:

$$\Phi i = \bar{X}i - X$$

Step 3: Calculating the covariance matrix: form of matrix A = [Φ1, Φ2, ..., ΦM] (N×M matrix) then compute:

$$C = \frac{1}{M\sum_{n=1}^{MT} \Phi n \Phi n} = AA$$

Step 4: Calculating the eigen vector and eigen value of the covariance matrix.

Step 5: Choosing components and forming a feature vector: once eigen vectors are found from the covariance matrix, the next step is to order them by eigen value, highest to lowest. This gives the components in order of significance. The eigen vector with the highest eigen value is the principle component of the data set. Choose the highest eigen value and forming a feature vector.

Step 6: Deriving the new datasets: once chosen the components (eigen vectors) that wish to keep in the data and formed a feature vector, imply take the transpose of the vector and multiply it on the left of the original data set, transposed.

Final data = Row feature vector * Row data adjust

The above equation getting the features of images, the Euclidean distance is calculated between the mean adjusted input image and the projection onto face space. The low values indicate that there is a face and display the face.

LINEAR DISCRIMINANT ANALYSIS

Linear Discriminant Analysis (LDA) is commonly used technique for data classification and dimensionality reduction. Linear discriminant analysis is also known as Fisher's discriminant analysis and it searches for those vectors in the underlying space that best discriminate among classes. The objective of LDA is to perform dimensionality reduction while preserving as much of the class discriminatory information as possible. The goal of LDA is to maximize the between-class scatter matrix measure while minimizing the within-class scatter matrix measure.

The PCA+LDA Method where PCA is used to project images from the original image space to the low dimensional space and make the within-class scatter non-degenerate.

However, the first dimensionality reduction using PCA can also remove the discriminant information that is useful for classification. The most efficient method was proposed which projects the between-class scatter into the null space of the within-class scatter and chooses the eigenvectors corresponding to the largest Eigen values of the transferred between-class scatter (Fig. 4).

Methodology: The steps in LDA are as follows:

Step 1: Samples for class1 and 2.

Step 2: Calculate the mean of class1 and 2, i.e., Mu1 and Mu2.

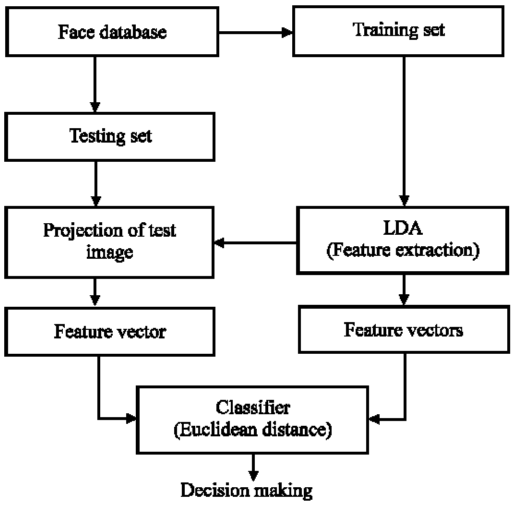

Fig. 4: LDA approach for face recognition

Step 3: Covariance matrix of the 1st and 2nd class, i.e., S1 and S2.

Step 4: Calculate within-class scatter matrix by using given equation:

$$Sw = S1+S2$$

Step 5: Calculate between-class scatter matrix by using given equation:

$$SB = (Mu1-Mu2)*(Mu1-Mu2)$$

Step 6: Calculate the mean of all classes.

Step 7: Compute the LDA projection:

$$invSw = inv(Sw)\ invSw\_by\_SB = invSw*SB$$

Step 8: The LDA projection is then obtained as the solution of the generalized eigen value problem:

$$Sw\text{-}1SBW = \lambda W$$

$$W = eig(Sw\text{-}1\ sb)$$

where, W is projection vector.

RELEVANT RESEARCH

Researchers survey the techniques and method relevant to better face recognition rate for low resolution images. Many researchers have given their contributions to face identification and provide solutions to the above mentioned problems.

Ahonen *et al.* (2006) proposed a local binary pattern features. Choi *et al.* (2012) to find the best color local texture features each of which corresponding to a particular local face region. Drimbarean and Whelan (2001) this study reports that the use of color information can improve classification performance obtained using only grayscale texture analysis techniques.

Zou *et al.* (2007), Liu and Liu (2010), Mukherjee *et al.* (2008), Phillips *et al.* (2000), Sim *et al.* (2003), Torres *et al.* (1999), Turk and Pentland (1991) and Xie *et al.* (2010) local texture features have gained reputation as powerful face descriptors because they are believed to be more robust to variations of facial pose, expression, occlusion, etc. Liu and Liu (2010), propose the FR Method that fuses multiple global and local features derived from a hybrid color space RcrQ. Color local texture features are much more robust to variation in face resolution than gray scale texture feature (Mukherjee *et al.*, 2008). Phillips *et al.* (2000), provides the best face recognition performance. Sim *et al.* (2003) useful for detailed and photometric modeling of objects. The RGB, HSV, YUV color spaces were examined in the context of FR (Torres *et al.*, 1999).

The results show that facial color contains complementary information and that the accuracy of FR is affected by the color space chosen. Turk and Pentland (1991) provides excellent recognition rate for face images taken under severe variation in illumination as well as for small (low) resolution face images. Yang *et al.* (2010) found out a common characteristic of a powerful color space for FR by analysing the transformation matrix of the different color spaces from the RGB color space. In (Su *et al.*, 2009) texture features have proven to be highly discriminative for FR due to different levels of locality.

PROPOSED METHODOLOGY

In this study, researchers present a best face recognition rate for low resolution face images. The proposed modules: color space conversion and partition, feature extraction, combination and classification.

Color space conversion and partition: A face image represented in the RGB color space is first translated, rotated and rescaled to a fixed template, yielding the corresponding aligned face image. Subsequently, the aligned RGB color image is converted into an image represented in another color space.

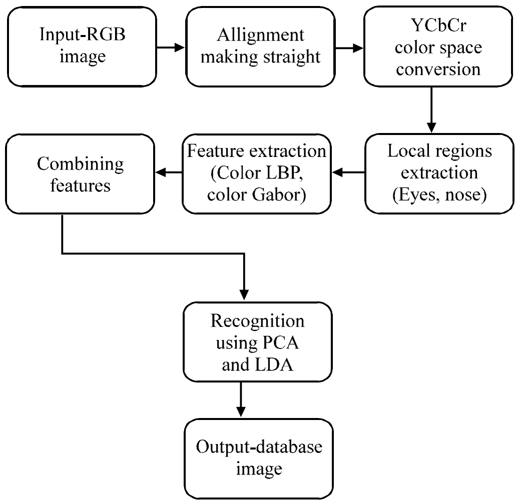

Fig. 5: System block diagram of color FR framework based on color local texture features

Table 1: Performance of PCA&LDA

Training images	Testing images	PCA	PCA+LDA
2	8	71	78
3	7	73	82
4	6	77	87
5	5	78	87
6	4	89	93
7	3	92	95
8	2	94	96

Feature extraction: Each of the color component images of current color model is then partitioned into local regions. Texture feature extraction is independently and separately performed on each of these local regions. Since, texture features are extracted from the local face regions obtained from different color channels, they are referred to as color local texture features.

Combination and classification: Since, N color local texture features (each obtained from the associated local region and spectral channel) are available to combine them to reach the final classification (Fig. 5).

SYSTEM PERFORMANCE

The performances of the proposed systems are measured by varying the number of faces of each subject in the training and test faces. Table 1 shows the performances of the proposed PCA and LDA based on the euclidean distance classifier. The recognition performances increase due to the increase in face images in the training set. This is obvious because more sample images can characterize the classes of the subjects better in the face space.

CONCLUSION

In this study, researchers proposed a novel local Gabor filter bank for feature extraction. A minimum distance classifier was employed to evaluate the recognition performance in different experiment conditions. The experiments suggest the following conclusions:

- Local Gabor filter reducing the high dimensional feature, decreasing the required computation and storage, even achieving better performance in some situations
- PCA can significantly reduce the dimensionality of the original feature without loss of much information in the sense of representation but it may lose important information for discrimination between different classes
- When using PCA+LDA Method, the dimensionality reduced to and the recognition performance is improved

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