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Effective Face Recognition Through Color Local Texture Features

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Abstract: The new color local texture features that means Color Local Gabor Wavelets (CLGWs) and Color Local Binary Pattern (CLBP), for the purpose of Face Recognition (FR). This method is able to provide excellent recognition rates for face images taken under severe variation in illumination as well as for small (low) resolution face images. In addition, the feasibility of color local texture features has been successfully demonstrated by making comparisons with other state of the art color FR Methods. 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 (FR) has received a significant interest in pattern recognition and computer vision due to the wide range of applications including video surveillance, biometric identification and face indexing in multimedia contents. As in any classification task, feature extraction is of great importance in the FR process.

Recently, 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. In particular, Gabor wavelets and Local Binary Pattern (LBP) texture features have proven to be highly discriminative for FR due to different levels of locality.

In three grayscale texture techniques including local linear transform, Gabor filtering and co-occurrence methods are extended to color images. This study reports that the use of color information can improve classification performance obtained using only grayscale texture analysis techniques.

In incorporating color into a texture analysis can be beneficial for classification recognition schemes. In particular, researchers showed that perceptually uniform color spaces and YCbCr for color texture analysis. Following the aforementioned studies, it is natural to expect better FR performance by combining color and texture information than by using only color or texture information. However, at the moment how to effectively make use of both color and texture information for the purpose of FR still remains an open problem. The aim of this study is to suggest a new color FR framework.

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 5 steps:

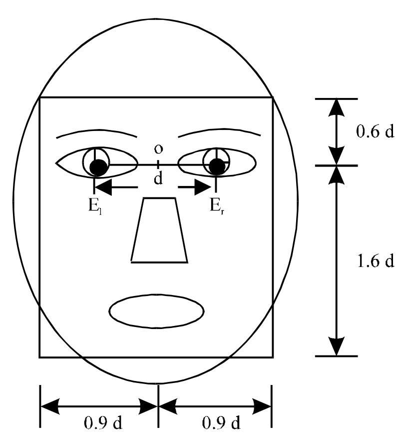

Fig. 1: Facial model

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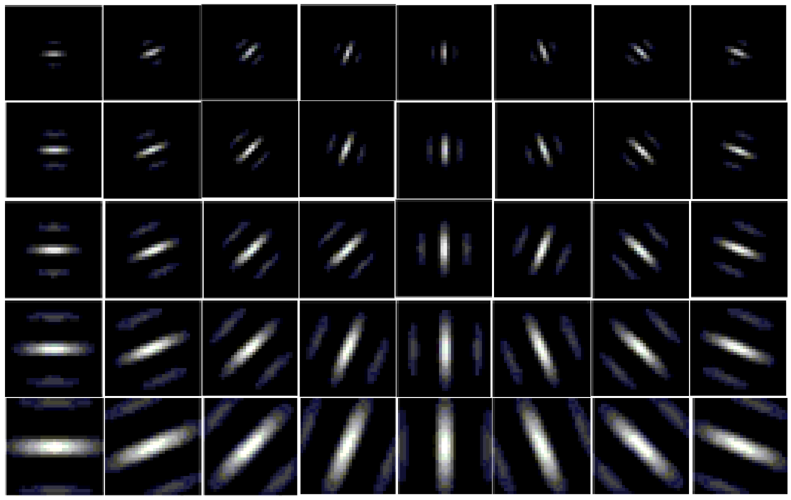

Fig. 2: The real part of the Gabor filters with 5 frequencies and eight orientations for $\omega_{max} = \pi/2$, the row corresponds to different frequency ω_m, the column corresponds to different orientation θ_n

- 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 2 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 2 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) (Fig. 2). The Gabor filter can be defined as follows:

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

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

Where:

(x, y) = The pixel position in the spatial domain

ϖ = The radial center frequency

θ = 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 $\psi(x, y, \omega_m, \theta_n)$ as given by:

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

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

PRINCIPAL COMPONENT ANALYSIS

Let us consider a set of N sample images $\{x_1, x_2, ..., x_N\}$ represented by t-dimensional Gabor feature vector. The PCA can be used to find a linear transformation mapping the original t-dimensional feature space into an f-dimensional feature subspace where normally f<<t. The new feature vector are defined as (Fig. 3):

$$y_i = W_{pca}^T x_i \; (i = 1, 2, ..., N)$$

Where:

W_{pca} = The linear transformations matrix

i = The number of sample images

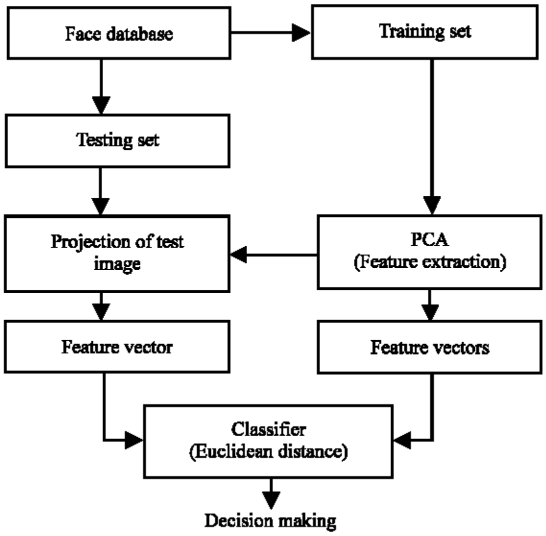

Fig. 3: PCA approach for face recognition

The columns of W_{pca} are the f eigenvectors associated with the f largest eigen values of the scatter matrix S_T which is defined as:

$$S_T = \sum_{i=1}^{N} (x_i - \mu)(x_i - \mu)^T$$

where, μ is the mean image of all samples. The disadvantage of PCA is that it may lose important information for discrimination between different classes.

LINEAR DISCRIMINANT ANALYSIS

LDA is a supervised learning method which utilizes the category information associated with each sample. The goal of LDA is to maximize the between-class scatter while minimizing the within-class scatter. Mathematically speaking, the within class scatter matrix S_w and between class scatter matrix S_b are defined as (Fig. 4):

$$S_w = \sum_{j=1}^{c} \sum_{i=1}^{N_j} (x^j_i - \mu_j)(x^j_i - \mu_j)^T$$

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

Where:

x_i = The ith sample of class j
μ_j = The mean of class j
μ = The mean image of all classes
c = The number of classes
N_j = The number of samples of class j

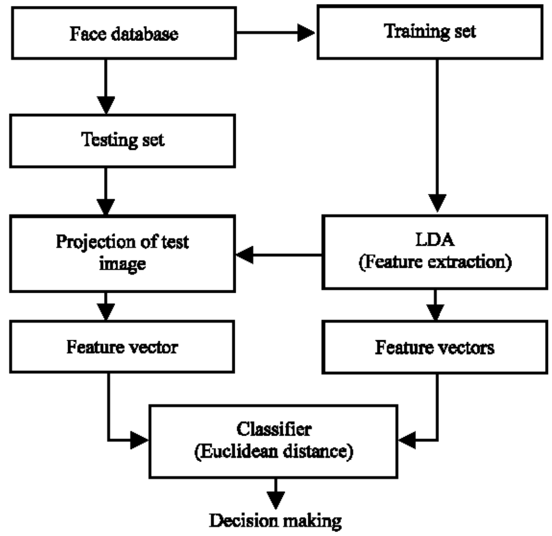

Fig. 4: LDA approach for face recognition

RELEVANT WORK

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.* (2011), to find the best color local texture features, each of which corresponding to a particular local face region. Su *et al.* (2009) reports that the use of color information can improve classification performance obtained using only grayscale texture analysis techniques.

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. (Zou *et al.*, 2007; Liu and Liu, 2010; Mukherjee *et al.*, 2008; Phillips *et al.*, 2000; Sim *et al.*, 2009; Torres *et al.*, 1999; Turk and Pentland, 1991; Xie *et al.*, 2010). Researchers propose the FR Method that fuses multiple global and local features derived from a hybrid color space RcrQ (Liu and Liu, 2010).

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.* (2009) proposed useful 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

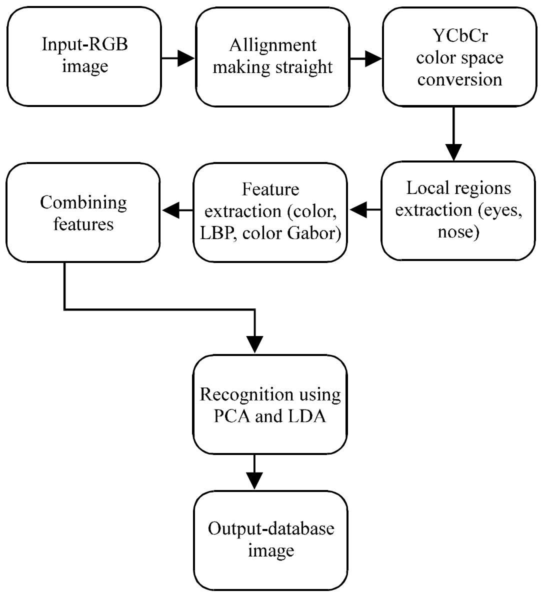

Fig. 5: System block diagram of color FR framwork based on color local texture features

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. 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).

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.

Table 1: Performance of PCA and LDA

Training images	Testing images	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

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

The existing face recognition approaches shows that the FR approach using color local texture features achieves better FR performance than the FR approach relying only on color or texture information. The color local texture features are highly effective for low resolution images and are robust against severe variation in illumination (caused by the interruption of background colored light and cast shadow) as compared with conventional grayscale texture features. The two effective color local texture features, i.e., Color Local Gabor Wavelets (CLGWs) and Color LBP (CLBP) both of which are able to encode the discriminative features derived through linear discriminant analysis for improving FR performance. The FR approaches using color local texture features impressively yield better recognition rates than FR approaches using only color or texture information when compared with those obtained using other recent advanced color FR Methods.

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