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Comparison of Colour Image Discriminant and Fisher Linear Discriminant Algorithms

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Abstract: Recognition by face is one of the biometric methods used commonly for identification. The Colour Image Discriminant (CID) model tries to combine the colour image exemplification and recognition tasks into one framework. Basic CID colour space, extracts multiple features in the colour image, where three new colour component images D1, D2 and D3 are derived using an iterative algorithm.The classical FLD method involves only one set of variables: one or multiple discriminant projection basis vectors, for image discrimination. Experimental results using two face databases, namely, Face96 and Indian Face dataset of IIT Kanpur and then with live still images succeeds in gender recognition. The method achieves the recognition rate of 88.43% with ROC of 0.903 showing the effectiveness of CID algorithm.

Keywords: Colour component images, colour image discriminant (CID) colour space, gender recognition, Fisher linear discriminant analysis (FLD or LDA).

I. INTRODUCTION

A colour space is a method by which we can identify, construct and imagine colour. A colour is thus usually specified using three parameters describing the position of the colour within the colour space being used. Colour provides a useful feature for object finding, tracing and recognition, image (or video) segmentation, etc. Different colour spaces (or colour models) hold different characteristics and are suitable for different visual tasks. Although colour has been demonstrated helpful for face detection and tracing, some previous research suggests that colour appears to advise no significant face recognition advantage beyond the luminance information. Latest research efforts, however, reveal that colour may provide useful information for face recognition at lower resolutions. The experimental results in [2] show that the principal component analysis (PCA) method using colour information can improve the recognition rate compared to the same method using only luminance information. The results in [3] further demonstrate that colour cues can significantly improve recognition performance compared with intensity-based features for coping with low-resolution face images.

Most face recognition (FR) methods have been developed under the hypothesis that face image sets consist of grey scale still images. Indeed, the use of grey scale images is a common practice for conventional FR applications. However, recently, considerable research efforts have been done to the development of face recognition methods that utilize colour information. Outcomes reported in these works indicate that colour information can play an important role in face recognition and it can be used to considerably enhance face recognition performance. Face recognition has been attracting large attention from the researchers in the computer vision, pattern recognition, and machine learning groups. In contrast to the classical FLD method, which involves only one set of variables (one or multiple discriminant projection basis vectors) [4], Colour image discriminant (CID) model pursues a meaningful representation and effective recognition method of colour images in a single entity framework, integrating colour image exemplification and recognition into one analysis model [1].

II. MOTIVATION

Different colour spaces (or colour models) have different characteristics and have been applied for different visual tasks. One practice is to choose an existing colour space or a colour component configuration for achieving good recognition performance with respect to a specific recognition method. One practice is to linearly combine its three colour components into one intensity image before applying a face recognition algorithm for recognition.

$$I = \frac{1}{3}R + \frac{1}{3}G + \frac{1}{3}B \qquad (1)$$

The intensity image I is then used to symbolize A for recognition. However, hypothetical explanation is lacking in supporting that such an intensity image is a good representation of image A for image recognition. Here the goal of colour image discriminant (CID) model, is to find a set of ideal coefficients to combine the R, G, and B colour components within a discriminant analysis framework so that is the best representation of the colour image for image recognition. Specifically, let D be the combined image given below:

$$D = x_1 R + x_2 G + x_3 B \qquad (2)$$

Where, x1, x2 and x3 are the colour component combination coefficients.

III. COLOUR IMAGE DISCRIMINANT MODEL

A CID model is first derived for two-class recognition problems. The CID model holds one colour component combination coefficient vector and one discriminant

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projection basis vector. Lagrange multiplier method and generalized Eigen equation iterative is used to solve the problem in CID model. The task is to find a set of ideal coefficients so that D is the best representation of the colour image A for image recognition. Given the set of training colour images with class labels, create a combined image D for each image A = [R, G, B]. The idea of Fisher linear discriminant analysis (FLD) is used to build the pattern vector space D formed by all combined images defined by equation (2). Note that the CID model is fairly different from the classical FLD model because it involves an additional set of variables: the colour component combination coefficientsx_1 , $x_2$and x_3. To avoid the negative effect of magnitude supremacy of one component image over the others, apply a basic image normalization method by removing the mean and normalizing the standard deviation of component image. The minimum distance classifier is used to classify all query images and the classification is done.

Let c be the number of pattern classes, A_{ij}be the j^{th} colour image in class i, where i = 1,2,……,c, j = 1,2,……….M_i, and M_i denote the number of training examples in class i. The mean image of the training examples in class i is

$$\overline{A_i} = \frac{1}{M_i}\sum_{j=1}^{M_i} A_{ij} = [\overline{R_i}, \overline{G_i}, \overline{B_i}] \quad (3)$$

The mean image of all training examples is

$$\overline{A} = \frac{1}{M}\sum_{i=1}^{c}\sum_{j=1}^{M_i} A_{ij} = [\overline{R}, \overline{G}, \overline{B}] \quad (4)$$

where, M is the total number of training examples.

The combined image of three colour components of the colour image A_{ij}= [R_{ij}, G_{ij}, B_{ij}] is given by

$$D_{ij} = [R_{ij}, G_{ij}, B_{ij}]X \quad (5)$$

where, X = [x_1, x_2, x_3]^T is a colour component combination coefficient vector.

Let, Di be the mean vector of the combined images in class i and D be the grand mean vector

$\overline{D_i} = \overline{A_i}\,X$(6)

$\overline{D} = \overline{A}\,X$(7)

The earlier criterion is equivalent to the following criterion:

$$J(X) = \frac{X^T L_B X}{X^T L_W X} \quad (10)$$

where, L_B and L_W are the colour space between-class scatter matrix and colour space within-class scatter matrix, and they are both 3 by 3 matrices.For the CID Algorithm first, state the colour-space between-class scatter matrix $L_b(\varphi)$ and the colour-space within-class scatter matrix L_w (φ) as follows:

$$L_b(\varphi) = \sum_{i=1}^{c} P_i[(\overline{A_i} - \overline{A})^T \varphi\, \varphi^T (\overline{A_i} - \overline{A})] \quad (11)$$

$$L_w(\varphi) = \sum_{i=1}^{c} P_i \frac{1}{M_i - 1} \times \sum_{j=1}^{M_i}[(\overline{A_i} - \overline{A})^T \varphi\, \varphi^T (\overline{A_i} - A \quad (12)$$

where, P_i is the prior probability for class I and commonly evaluated as P_i = M_i /M.$L_b(\varphi)$ and $L_w(\varphi)$ are, therefore, 3×3 nonnegative-definite matrices. Actually, $L_b(\varphi)$ and $L_w(\varphi)$ can be viewed as dual matrices of $S_b(X)$ and $S_w(X)$. If X is fixed, the maximum point φ* of JF(φ, X) can be chosen as the eigenvector of the generalized equation Sb(X)φ = λSW(X)φ equivalent to the largest eigenvalue, and if φ is fixed, the maximum point X* of JF(φ, X) can be chosen as the eigenvector of the generalized equation Lb(X)φ = λLW(X)φ corresponding to the largest eigenvalue. Based on this conclusion, we can design an iterative algorithm to calculate the maximum points φ* and X*. Let X = X[k] be the initial value of the combination coefficient vector in the k^{th} iteration. In the first step, we construct Sb(X) and Sw(X) and calculate their generalized eigenvector φ = φ[k+1] corresponding to the largest eigenvalue. In the second step, we build Lb(φ) and Lw(φ) and calculate their generalized eigenvector X[k+1] equivalent to the largest eigenvalue. X = X[k+1] is used as initial value in the next iteration. The CID algorithm performs the previous two steps successively until it meets when the value of the criterion function stops changing. Specifically, after k+1 times of iterations, if J($\varphi^{[k+1]}$, $X^{[k+1]}$) - J($\varphi^{[k]}$, $X^{[k]}$) |< ε, we think the algorithm converges. Then, we choose φ* = φ[k+1] and X* = X[k+1].

IV. RESULTS

To assess the performance of the model and algorithm a colour image database is required. The controlled images have good image quality, while the uncontrolled images display poor image quality, such as large illumination variations, low resolution of the face region, and possible blurring.

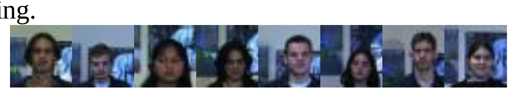

Fig. 1 Colour Images Cropped in 32 X 32

The CID algorithm is tested on 345 images. The original colour image size from the data base Face96, taken, is 196 × 196, which contains males and female subjects. In CID model experiments, the face region of each image is first cropped from the original high-resolution still images and resized to a spatial resolution of 32 × 32. To evaluate algorithms experiment is designed by apply CID algorithm to a two class recognition problem: gender classification. Manually label male or female for each image in the data base, then train the CID algorithm using the standard training set, which contains 258 male images and 87 female images.

Fig. 2 Mean image of classes

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The initial value of the basic CID algorithms is chosen as $X^{[0]} = [1/5, 1/5, 1/5]$, which is the combination coefficient vector of the intensity image. The convergence threshold of the algorithm is set to be $\varepsilon = 0.01$. After the algorithm converges, an optimal colour component combination coefficient vector $X^* = [-1.00, 0.2764, 0.1902]^T$ and one discriminant projection vector (because there are two classes for gender recognition) is obtained. Represent each colour image A = [R, G,B] by its combined image D = [R, G, B]X^*. Then project all target and query images onto the discriminant projection vector and get their 1-D features. Based on the features of the target images, we calculate the class means of the male and the female, respectively.

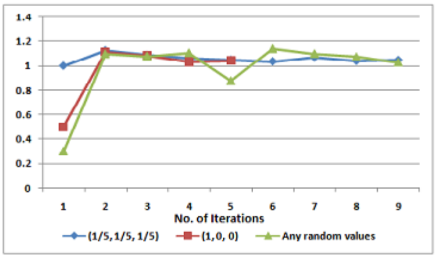

Fig. 3 Illustration of the convergence of the CID algorithm

The minimum distance classifier is used to classify all query images and the classification results are shown in Table I. For comparison, the results from the various papers are used. With reference to the paper presented by S. T. Gandhe, K. T. Talele and A. G. Keskar, "Face Recognition Using DWT+PCA", the recognition rate is dependent on the selected wavelet function and the level of decomposition for PCA and for DWT+PCA [12].

TABLE I: COMPARISON FOR GENDER RECOGNITION

Sr. No.	Parameters	FLD	CID
1	Recognition Rate	82.49%	88.43%
2	Area under curve	0.853	0.903

Table I shows that the CID algorithm achieves better gender recognition performance than the FLD algorithm, PCA algorithm and the DWT+PCA algorithm.

V. CONCLUSION

CID model thus is a meaningful exemplification and an effective recognition method of colour images in a combined framework; integrating colour image exemplification and recognition tasks into one discriminant model. Results reported in these works indicate that face colour information can play an important role in face recognition and it can be used to considerably enhance face recognition performance. All of our experiments show that the CID algorithms converge fast and do not depend on the choice of the initial value.

VI. FUTURE SCOPE

Gender classification refers to designate an image of a person into one of the categories of male or female. Computer vision systems not only boost existing HCI systems but can also assist passive observation and control of areas and lands (e.g., restricting entry to certain premises based on gender), performing valuable analysis (e.g., comparing the consumption of specific items of men's wear and women's wear in a super store), voice recognition purposes (e.g., identifying gender of the speaker in the audio/video files) and reducing uncertainties in audio-visual aids (e.g., relating only female voice to a female appearance). The CID model and algorithm is suitable for two-class recognition problems, such as gender recognition.

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BIOGRAPHY

Dipti Pandit received her Master's and Bachelor's in Electronics from Pune University. Her special interest is in subjects like Embedded Systems, Image Processing.