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Gender Face Classification Using Color Image Discrimination Model

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Abstract: The biometric schemes are commonly used for the identification of human beings. Face recognition is one of the biometric methods, to identify given face image using main features of the face. The objective of face recognition involves the extraction of different features of the human face from the face image for discriminating it from other persons. To seek a meaningful representation and an effective recognition method of color images in a unified framework, color image representation and recognition is integrated into one discriminant analysis model: color image discriminant (CID) model. The two sets of variables can be determined optimally and simultaneously by the CID algorithms. Gender is an important demographic attribute of people. An Basic CID algorithm with two class recognition problem is for gender classification.

Keywords: Color image discriminant (CID) color space, face recognition, color images, gender classification.

I. INTRODUCTION

Color is the brains reaction to a specific visual stimulus. Although we can precisely describe color by measuring the intensity of the visible electro-magnetic radiation at many discrete wavelengths which leads to a large degree of redundancy. The reason for this redundancy is that the eye's retina samples color using only three broad bands, roughly corresponding to red, green and blue light. The signals from these color sensitive cells (cones), together with those from the rods (sensitive to intensity only), are combined in the brain to give several different "sensations" of the color. A color space is a method by which we can specify, create and visualize color. A color is thus usually specified using three co-ordinates, or parameters. These parameters describe the position of the color within the color space being used.

Color provides a useful feature for object detection, tracking and recognition, image (or video) segmentation, etc. Color constancy algorithms and color histogram techniques provide efficient tools for object recognition under varying lighting conditions. Different color spaces (or color models) possess different characteristics and are suitable for different visual tasks. For instance, the HSV color space and the YC_bC_r color space are effective for face detection, while the modified L*u*v* color space is useful for image segmentation. Recently, a selection and fusion scheme of multiple color models was investigated and applied for feature detection in images.

The luminance structure of face images is undoubtedly of great significance for recognition. Past research has suggested that the use of these cues may adequately account for face identification performance with little remaining need to posit a role of color information. However, the experimental results by A Yip, P Sinha suggest that color does in fact play an important role in face recognition and that its contribution becomes evident under conditions that degrade available shape information. The recognition performance with gray- scale images is not significantly different from that with color images at high resolutions. However, performance for the two groups diverged as image resolution is progressively decreased. At low resolutions, performance with color images is significantly better than that with gray-scale images. This evidence of the contribution of color to face recognition brings up an interesting question regarding the specific role it plays. One possibility is that color provides diagnostic information. The expression `diagnostic information' refers to color cues that are specific to an individual, for instance the particular hue of hair or skin that may allow us to identify the individual. On the other hand, color might facilitate low-level image analysis, and thus indirectly aid face recognition [12]. Recent research efforts reveal that color may provide useful information for face recognition. The experimental results in [2] show that the principal component analysis (PCA) method using color information can improve the recognition rate compared to the same method using only luminance information. The results in [3] further demonstrate that color cues can significantly improve recognition performance compared with intensity-based features for coping with low-resolution face images.

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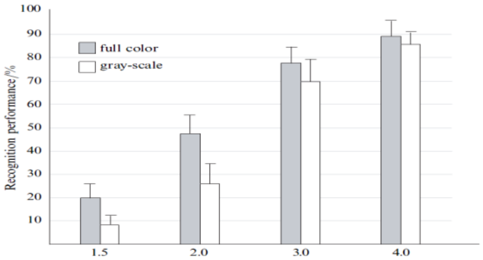

Fig.1. Face-recognition performance with full-color and gray-scale images as a function of image resolution [12].

Face recognition has been attracting substantial attention from the researchers in the computer vision, pattern recognition, and machine learning communities. An effective effort to seek a meaningful representation and an effective recognition method of color images in a unified framework integrating color image representation and recognition into one discriminant analysis model is the color image discriminant (CID) model. The CID models involve two sets of variables: a set of color component combination coefficients for color image representation and one or multiple discriminant projection basis vectors for image discrimination. The two sets of variables can be determined optimally and simultaneously by the CID algorithms [1].

II. MOTIVATION FOR CID MODEL

Different color spaces (or color models) possess different characteristics and have been applied for different visual tasks. One common practice is to convert color images in the RGB color space into an intensity image by averaging the three color component images before applying a face recognition algorithm for recognition. However, there are neither theoretical nor experimental justifications for supporting the fact that such an intensity image is a good representation of the color image for the recognition purpose. Other research effort is to choose an existing color space or a color component configuration for achieving good recognition performance with respect to a specific recognition method. One common practice is to linearly combine its three color components into one intensity image.

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

The intensity image I is then used to represent A for recognition. The goal of color image discriminant model, is to find a set of optimal coefficients to combine the R, G, and B color components within a discriminant analysis framework so that is the best representation of the color 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, x_1 , x_2 and x_3 are the color component combination coefficients.

III. COLOR IMAGE DISCRIMINATION MODEL

The CID model contains one color component combination coefficient vector and one discriminant projection basis vector. Lagrange multiplier method is used to solve the problem that the CID model involves and design a CID algorithm to seek the optimal solution by solving two associated, generalized eigen equations iteratively [1].

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

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

The mean image of all training samples is

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

where M is the total number of training samples. The combined image of three color components of the color image $A_{ij}=[R_{ij}, G_{ij}, B_{ij}]$ is given by

$$D_{ij} = x_1 R_{ij} + x_2 G_{ij} + x_3 B_{ij} = [R_{ij}, G_{ij}, B_{ij}]X \qquad (5)$$

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

The between-class scatter matrix $S_b(X)$ and the within-class scatter matrix $S_w(X)$ in the D-space are defined as follows:

$$S_b(X) = \sum_{i=1}^{c} P_i [(\overline{A}_i - \overline{A})^T X X^T (\overline{A}_i - \overline{A})] \qquad (6)$$

$$S_w(X) = \sum_{i=1}^{c} P_i \frac{1}{M_i - 1} \times \sum_{j=1}^{M_i} [(\overline{A}_i - \overline{A})^T X X^T (\overline{A}_i - \overline{A})] \qquad (7)$$

where P_i is the prior probability for class I and commonly evaluated as $P_i = M_i /M$. Because the combination coefficient vector X is an unknown variable, the elements in $S_b(X)$ and $S_w(X)$ can be viewed as linear functional of X.

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The foregoing criterion is equivalent to the following criterion:

$$J(\varphi, X) = \frac{\varphi^T S_B(X)\varphi}{\varphi^T S_W(X)\varphi} \qquad (8)$$

where φ is a discriminant projection basis vector, $\varphi \neq 0$, and $X \neq 0$. The criterion function is a generalized Rayleigh quotient if X is fixed.

From the property of the generalized Rayleigh quotient, the maximum point of the function exists on the elliptic spherical surface $\{\varphi|\varphi^T S_W(X)\varphi = 1, \varphi \in R^N\}$. Therefore, maximizing the criterion in (8) is equivalent to solving the following optimization model with max $\varphi^T S_b(X)\varphi$ for max φ, X subject to $\varphi^T S_W(X)\varphi = 1$. An iterative algorithm is designed to simultaneously determine the optimal discriminant projection basis vector φ^* and the optimal combination coefficient vector X^*.

For the CID Algorithm first, define the color-space between-class scatter matrix $L_b(\varphi)$ and the color-space within-class scatter matrix $L_w(\varphi)$ as follows:

$$L_b(\varphi) = \sum_{i=1}^{c} P_i\,[(\bar{A}_i - \bar{A})^T\,\varphi\,\varphi^T\,(\bar{A}_i - \bar{A})] \qquad (9)$$

$$L_w(\varphi) = \sum_{i=1}^{c} P_i\,\frac{1}{M_i - 1} \times \sum_{j=1}^{M_i}[\,(\bar{A}_i - \bar{A})^T\,\varphi\,\varphi^T\,(\bar{A}_i - \bar{A})] \qquad (10)$$

$L_b(\varphi)$ 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 $J_F(\varphi, X)$ can be chosen as the eigenvector of the generalized equation $S_b(X)\varphi = \lambda S_W(X)\varphi$ corresponding to the largest eigenvalue, and if φ is fixed, the maximum point X^* of $J_F(\varphi, X)$ can be chosen as the eigenvector of the generalized equation $L_b(X)\varphi = \lambda L_W(X)\varphi$ corresponding to the largest eigenvalue. Based on this conclusion, an iterative algorithm can be designed to calculate the maximum points φ^* and X^*.

The CID algorithm performs the preceding two steps successively until it converges. Convergence may be determined by observing when the value of the criterion function stops changing. Specifically, after k+1 times of iterations, if $|J(\varphi^{[k+1]}, X^{[k+1]}) - J(\varphi^{[k]}, X^{[k]})| < \varepsilon$, we think the algorithm converges. Then, choose $\varphi^* = \varphi^{[k+1]}$ and $X^* = X^{[k+1]}$.

IV. RESULTS

First manually label male or female each image in the database and then train the CID algorithm using the standard training set, which contains some male images and female images. The initial value of the 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 ε = 0.01. After the algorithm converges, an optimal color component combination coefficient vector, and one discriminant projection vector φ^* (because there are two classes for gender recognition) is obtained. Represent each color 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, calculate the class means of the male and the female, respectively. The minimum distance classifier is used to classify all query images. These experimental results are completely consistent and so, the conclusion, is that, the R component plays a more important role than the other two components, which has been revealed by our basic CID algorithm. As a matter of fact, it is not hard to understand this from the natural color property of human faces, i.e., R is the principal component in the color of human faces.

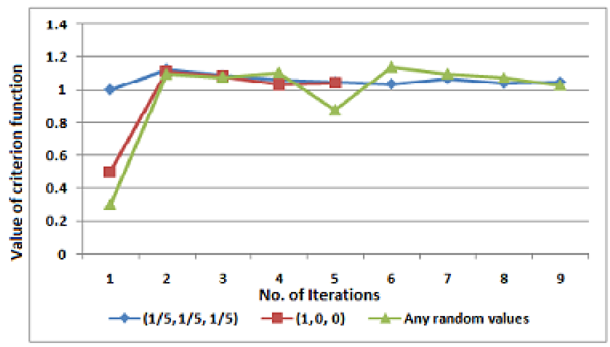

Fig. 2. Illustration of the convergence of the basic CID algorithm.

It should be pointed out that the convergence of the CID algorithm does not depend on the choice of the initial value of $X^{[0]}$. The experiment with other initial values, such as $X^{[0]} = [1,0,0]^T$ (corresponding to the R component image of an RGB color image) and a randomly generated 3-D vector. The convergence of the CID algorithm corresponding to these initial values is illustrated in Fig. 2. The convergence of the CID algorithm is independent of the choice of initial value of $X^{[0]}$. The algorithm consistently converges to a very similar value of the criterion function J(φ, X), and its convergence speed is fast: it always converges within ten iterations if ε = 0.01 is chosen

V. CONCLUSION

Color Discrimination Model is an integrate color image representation and gender recognition into one discriminant model.

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BIOGRAPHIES

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