Evaluation of CIE-XYZ System for Face Recognition Using Kernel-PCA

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Abstract. paper evaluates the performance of face recognition with different CIE color spaces. The XYZ and L*a*b* color spaces are compared with the gray image (luminance information Y). The face recognition system consists of a feature extraction step and a classification step. The Kernel-PCA is used to construct the feature space. Kernel-PCA is a nonlinear form of Principal Component Analysis (PCA). The k-nearest neighbor classifier with cosine measure is used in the classification step. Experiments using FEI color database with 200 subjects, show that the b* color component can improve the recognition rate.

Keywords: face recognition, CIE-XYZ color space, kernel-PCA.

1 Introduction

Face recognition from images is a sub-area of the general object recognition problem. Most face recognition methods have been developed using gray scale still images. Over the last several years, Color information provides important information in face recognition. Recent research has evinced that color cues contribute in recognizing faces, especially when shape cues of the images are degraded [1]. Various color spaces have been developed by the researchers for face recognition [2, 3].

Feature extraction is important step in the to perform face recognition process in real time. One needs to reduce the huge amounts of pixels in the raw face image to save time for the decision step. Feature extraction refers to transforming face space into a feature space. The most popular method to achieve this target is through applying the Eigenfaces algorithm [4]. The Eigenfaces algorithm is a classical statistical method using the linear Karhumen-Loeve transformation (KLT) (also known as Principal component analysis (PCA)). In contrast to linear PCA, Schölkopf et al. [5] extended principal component analysis to a nonlinear form based on kernel methods.

In this paper, the XYZ and L*a*b* color spaces are compared with the gray image (luminance information Y). The kernel-PCA has been applied on each color component independently. The remainder of this paper is organized as follows. The next section provides related works about color face recognition. In Section 3 the

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research describes the CIE-XYZ color space. Section 4 explains the Kernel-PCA and classification rule. Section 5 discusses the results. The paper concludes in section 6.

2 Related Works

Recent research provides that color may provide useful information for face recognition. Choi et al. [1] studied how color features affect the recognition performance with respect to changes in face resolution. The effectiveness of color on low-resolution faces has been tested on eigenfaces, fisherfaces, and Bayesian. The results show that color features decrease the recognition error rate by at least an order of magnitude over intensity-driven features when low-resolution faces (25×25 pixels or less) are applied to three face recognition methods.

In [6], the color local Gabor wavelets (CLGWs) and color local binary pattern (CLBP) were proposed for face recognition. The results show that the proposed color local texture features are able to provide excellent recognition rates for face images taken under severe variation in illumination, as well as for small- (low-) resolution face images. Wang et al. [7] has been presented RGB matrix-representation model to describe the color face image. The color-Eigenfaces are computed for feature extraction using 2DPCA. Nearest neighborhood classification approach is adopted to identify the color face samples. Experimental results on CVL and CMU PIE color face database has been shown a good performance of the proposed color face recognition approach.

Shih and Liu [2] assessed comparatively the performance of content-based face image retrieval in different color spaces using the standard algorithm Principal Component Analysis (PCA). Experimental results using FERET database have been shown that some color configurations, such as R in the RGB color space and V in the HSV color space, help improve face retrieval performance. Liu and Liu [3] presented a robust face recognition method using novel hybrid color space, the RCrQ color space. Wang et al. [8] presented the tensor discriminant color space (TDCS) model which optimizes one color space transformation matrix and two discriminant projection matrices simultaneously. Experimental results on the AR and Georgia Tech color face database have been systematically performed.

3 CIE-XYZ Color Space

Commission International de l'Eclairage (CIE) considered the tri-stimulus values for red, green, and blue to be undesirable for creating a standardized color model [9]. The reformulated tri-stimulus values were indicated as XYZ. The CIE-XYZ system is at the root of all colorimetry. It is defined such that all visible colors can be defined using only positive values, and, the Y value is luminance. The transformation from the RGB color space to the XYZ color space is as follows [10].

$$\begin{bmatrix} X \\ Y \\ Z \end{bmatrix} = \begin{bmatrix} 0.607 & 0.174 & 0.201 \\ 0.299 & 0.587 & 0.114 \\ 0.000 & 0.066 & 1.117 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} \quad (1)$$

CIE adopted two different uniform diagrams, CIELuv and CIELab. The Yxy, Yuv, L*u*v*, L*a*b*, and L*ch color spaces are a transformation of CIE- XYZ. The CIE-L*a*b* is a color space that describes all colors visible to the human eye [9]. It was created to serve as a device independent model to be used as a reference. The L*a*b* color space is separated into lightness (L*) and color information (a*, b*). L* scales from 0 to 100. The a* and b* axes have no specific numerical limits. Positive a* is red and negative is green. Positive b* is yellow and negative is blue. The L*a*b* color space is defined based on XYZ tri-stimulus as follows:

$$L^* = \begin{cases} 116(\frac{Y}{Y_0})^{1/3} - 16 & if \ \frac{Y}{Y_0} > 0.008856 \\ 903.3(Y/Y_0) & otherwise \end{cases} \quad (2)$$

$$a^* = 500\left[f\left(\frac{X}{X_0}\right) - f\left(\frac{Y}{Y_0}\right)\right], b^* = 200\left[f\left(\frac{Y}{Y_0}\right) - f\left(\frac{Z}{Z_0}\right)\right] \quad (3)$$

where $f(U) = U^{1/3}$ if U > 0.008856 and f(U) = 7.787U+(16/116) otherwise, and X_0, Y_0, and Z_0 are the tri-stimulus values of the reference illuminant (light source.

4 Kernel PCA and Nearest Neighbor Classifier

Schölkopf et al. [5] have developed a nonlinear PCA called Kernel-PCA. The kernel-PCA is not interested in principal components in input space, but rather in principal components of variables which are nonlinearly related to the input variables [11]. They compute PCA in another dot product feature space F, which is related to the input space RMN by a possibly nonlinear map, $\varphi\mathbf{:R}^{MN}\rightarrow\mathbf{F}$.

The $\{\boldsymbol{\varphi}(x_i)\}$, $i = 1, 2, \ldots, n$, denote the images of center input vectors x_i included in the feature space [12]. It is assumed that preprocessing has been done to satisfy the zero mean condition of all feature vectors over the training sample, i.e. $1/n\sum_{i=1}^{n}\varphi(x_i)$. Kernel function is the inner product term and denote as the scalar, $k(x,x_i) = \varphi^T(x_i)\,\varphi(x)$, $i = 1, 2, ..., n$. Compute the $k(x_i, x_j)$ as the ij-th element of the n-by-n matrix K, $K = \{k(x_i, x_j)\} = \{\varphi^T(x_i)\,\varphi(x_j)\}_{i,}\ j = 1, 2, ..., n$ (4)

The covariance matrix in **F** is $R = \frac{1}{n}\sum_{i=1}^{n}\varphi(x_i)\varphi^T(x_i)$ (5)

One now solves the *eigenvalue problem* $\mathbf{RV} = \lambda\ V$ (6)

where λ is an eigenvalue of R and V is the associate eigenvector. Then

$$K\alpha = n\lambda\alpha \quad (7)$$

where λ is an eigenvalue of K and α is the associate eigenvector. For the purpose of principal component extraction one needs to compute projections onto the eigenvectors V=[v_1, v_2, …, v_n] in F. Let x be a test point, with an image φ(x) in F, then

$$y_q = v_q^T \varphi(x) = \sum_{j=1}^{n} \alpha_{q,j} \varphi^T(x_j) \varphi(x) \tag{8}$$

In brief, the following steps were necessary to compute the principal components: first, compute the dot product matrix K defined by eq (4); second, compute its eigenvectors (eq. (7)) and normalize them in F; third, compute projections of a test point onto the eigenvectors by eq. (8).

In our work, the Gaussian kernel functions are used. The Gaussian kernel, also called Radial basis kernel is k(x, y) = exp $(-\frac{\|x-y\|^2}{2\sigma^2})$, where the width σ, common to all the kernels, is specified a priori by the user.

The k-nearest neighbor classifier (k-NN) is used in our experiments to classify objects by finding the closest k neighbors in the feature space [13]. The k-NN rule classifies finds the k neighbors of the query point z with the minimum distances between z and all prototype feature points $\{z_{ci}, 1 \leq c \leq C, 1 \leq i \leq n_c\}$. Different parameters are used with k-NN, such as value of k nearest neighbors and distance model. In our work, the Euclidean norm distance $d(z, z_{ci}) = \|z - z_{ci}\|$ is used at the place of distance model. Besides, the cosine similarity measure $cos(z, z_{ci}) = (z^T z_{ci})/(\|z\|.\|z_{ci}\|)$ is used at the place of distance model. We choose k = 1 to find the class of the closest query point.

5 Experiments

In our experiments, eight images for 200 subjects from the FEI database are used with a total of 1600 images. The FEI face database is a Brazilian face database that contains a set of face images taken at the Artificial Intelligence Laboratory of FEI in São Bernardo do Campo, São Paulo, Brazil[1]. We cropped the face region of each face image and resized to a resolution of 55 × 77 pixels. Fig. 1 shows some samples of one person used in our experiments.

In the Kernel-PCA feature extraction method, we choose the Gaussian function as the Kernel function. The performance of the Gaussian kernel function is affected by its width σ. We choose the width σ equal 3000 [14]. The performance of the kernel-PCA is affected by varying the number of principal components that projected from the PCA. For the experiments, we choose 200 principal components [14]. For each color space used in this paper, we define three individual color component images. Before apply the kernel-PCA, each color component image is normalized to zero mean and unit variance.

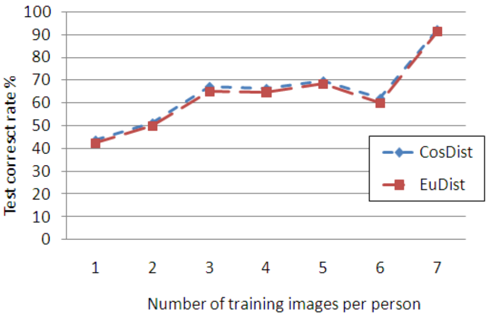
In the 1-nearest neighbor classifier, we compare between two distance models, the Euclidean distance and cosine measure, to find out the true class of the test patterns. Two different sets are randomly selected for training, starting from 1 training image per person until 7 training images per person. The remaining set (unseen during

[1] This database is publicly available on
http://www.fei.edu.br/~cet/facedatabase.html

training) is used for testing; so every experiment is repeated two times. The correct recognition rate is considered to evaluate the performance of different color spaces.

The first set of experiments was performed to determine the impact of changed the distance model in the 1-nearest neighbor classifier. Fig. 2 shows the performance of Euclidean distance and cosine measure on the gray image (luminance Y component). The correct recognition rates expressed as functions of the number of training samples per person. One can observe from fig. 2 that the cosine measure outperforms the Euclidean distance. Therefore, the cosine measure is used in the remaining experiments.

Fig. 1. Some sample images of one person of the FEI database



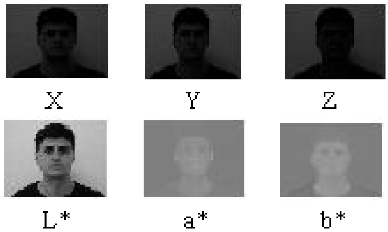


Fig. 2. Performance of *Kernel*-PCA with Euclidean distance and cosine measure on the gray image

Fig. 3. Illustration of X, Y and Z components of XYZ color space, and L*, a*, and b* of L*a*b* color space

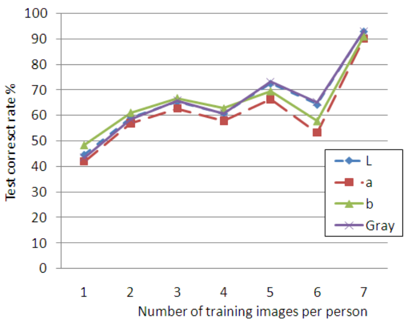


Fig. 4. Performance of Kernel-PCA with X, Y, and Z color components independently, and the gray image

Fig. 5. Performance of Kernel-PCA with L*, a*, and b* color components independently, and the gray image

The second set of experiments was performed to compare between the color spaces XYZ, and L*a*b* on the performance of the face recognition. The results are compared with the gray image (luminance information Y). The kernel-PCA has been applied to each color component independently. Fig. 3 illustrates the three color components corresponding to the XYZ and L*a*b* color spaces.

Fig. 4 and Fig. 5 show the performance of the XYZ color space and L*a*b* color space, respectively. For the XYZ color space, the performance with Z component declined the recognition rate. The gray image (luminance Y component) is more effective than the use of one individual XYZ color components. With 7 images per person during the training phase, the average test correct recognition rate by gray image (luminance Y component) is 92%, 186 images correctly of the 200 test faces (93 %) in the first experiment and 182 images correctly of the 200 test faces (91 %) in the second repeat experiment. For the L*a*b* color space, one can observe from Fig. 5 that the b* color component perform better than L* and a* color components by using few numbers of images per person. Fig. 5 shows that with few numbers of images per person, the L* and gray image have a little variation in performance.

6 Conclusion

This paper evaluates the performance of different CIE color spaces in face recognition. We compare the gray image with the individual color components of XYZ and L*a*b* color spaces. The face recognition system used the Kernel-PCA and cosine classifier. In our work, the experiments are performed on the FEI database. Experimental results using eight images for 200 subjects show that the gray images performed a recognition rate of 92%. The b* from the L*a*b* color space outperforms all the used color components.

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