3-20

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Investigation of Color Spaces for Face Recognition

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Abstract

This paper presents color processing for face recognition systems and proposes new directions for them. We show that color information helps performance of face recognition and found that specifically YCbCr and YCg'Cr' color spaces are the most appropriate for face recognition. In this paper, the performance of the principal component analysis (PCA)-based face recognition algorithm is performed in various color spaces including RGB, HSV, YCbCr, and YCg'Cr'. The performance evaluation was conducted with the color FERET database in terms of the recognition rate. In our experimentation, robustness of the independent PCA-based algorithms with different color domains is investigated for different facial expressions and aging.

1. Introduction

Light reflected from an object is multi-spectral, and human beings recognize the object by perceiving color spectrum of the visible light [1]. However, most of face recognition systems have used only luminance information. Many face recognition systems convert the color input images to grayscale images by discarding the color information and use only luminance information.

Only a limited number of face recognition researches using color information have been attempted. Torres *et al*. proposed a global eigen scheme to make use of color components independently [2]. They reported potential improvement of face recognition using color information. Rajapakse *et al*. proposed a non-negative matrix factorization (NMF) method to recognize color face images and showed that the color image recognition method is better than grayscale image recognition approaches [3]. Yang *et al*. presented the complex eigenface method that combines saturation and intensity components in the form of a complex number [4]. This literature shows that multi-variable principle component analysis (PCA) method outperforms traditional grayscale eigenface methods.

Color images include more visual clues than grayscale images, and the above-mentioned works showed the effectiveness of color information for face recognition. However, there is lack of analysis and evaluation regarding the recognition performance in diverse color spaces. In this paper, we investigate different color spaces for face recognition by using the eigenface method. For the evaluation, we use the color FERET database which contains a number of face images with wide variation of facial expressions and aging. Experimental results show that the use of color information gives a significant improvement in terms of the recognition rate, and YCbCr and YCg'Cr' spaces are the most appropriate for face recognition.

Section 2 reviews the fundamental eigenface method. In Section 3, the independent PCA-based face recognition algorithm to efficiently utilize the color information is described. The performance comparison of the face recognition for several color domains is presented in Section 4. Finally, Section 5 gives conclusions and future works.

2. Fundamental Eigenface Face Recognition

Turk and Pentland proposed the eigenface-based face analysis that is based on the PCA for efficient face recognition [5]. In the training phase of the eigenface method, eigenvectors are calculated with a number of training faces. The computed eigenvectors are called as eigenfaces. Then, faces are enrolled in the face recognition system by their projection onto the eigenface space. In the recognition phase, an unknown input face can be identified by measuring the distances of the projected coefficients between the input face and the enrolled faces in database.

2.1. Eigenface space composition

Dimension of an image space is so high that it is often impractical to deal with all the data of images in their own dimensions. PCA enables to optimally reduce the dimensionality by constructing the eigenface space that is composed of the eigenvectors [5].

Let $\{\mathbf{x}_1, \mathbf{x}_2, \cdots, \mathbf{x}_{M_t}\}$ be a training set of face images, and $\mathbf{x}_i$ represents a training face image which is expressed as an N×1 vector. Note that M_t is the number of training images and N denotes the number of pixels in an image. The mean vector $\boldsymbol{\mu}$ of the dataset is defined by

$$\boldsymbol{\mu} = \frac{1}{M_t}\sum_{i=1}^{M_t}\mathbf{x}_i. \tag{1}$$

Then, the N×N covariance matrix $\mathbf{C}$ of the dataset is computed by

$$\mathbf{C} = \frac{1}{M_t}\sum_{i=1}^{M_t}(\mathbf{x}_i - \boldsymbol{\mu})(\mathbf{x}_i - \boldsymbol{\mu})^T, \tag{2}$$

where the superscript T denotes the transpose operation. The eigenvalues and the corresponding eigenvectors of

C can be computed with the singular value decomposition (SVD). Let $\lambda_1, \lambda_2, \ldots, \lambda_N$ be eigenvalues of **C**, where the eigenvalues are ordered in decreasing order, and $\mathbf{u}_1, \mathbf{u}_2, \ldots, \mathbf{u}_N$ represent N eigenvectors of **C**. Note that the ith eigenvalue, λ_i is associated with the ith eigenvector, $\mathbf{u}_i$. The eigenvector having larger λ_i is more dominant to represent the training face images. We can choose N' eigenvectors as the eigenfaces space for face recognition ($N' << N$).

2.2. Projection onto the Eigenface Space

A face image is transformed by projecting it onto the eigenface space. Let $\{\mathbf{y}_1, \mathbf{y}_2, \cdots, \mathbf{y}_{M_g}\}$ be a gallery set of face images, where M_g is the size of the gallery set. Then, the weight ω_{ik} of $\mathbf{y}_i$ with respect to the kth eigenface can be obtained by

$$\omega_{ik} = \mathbf{u}_k^T(\mathbf{y}_i - \boldsymbol{\mu}), \tag{3}$$

and all the weights are represented by a weight vector, $\mathbf{\Omega}_i = [\omega_{i1}\ \omega_{i2} \cdots \omega_{iN'}]^T$.

2.3. Classification

Given an unknown face image, we obtain the weight vector, $\mathbf{\Omega} = [\omega_1\ \omega_2 \cdots \omega_{N'}]^T$, by projecting it onto the eigenface space. Then, the face image can be classified using the nearest neighborhood classifier. The distances between the input face and the other faces in the gallery are computed in the eigenface space. The Euclidean distance between the input face and the ith face image in the gallery set is defined by

$$d_e(\mathbf{\Omega}, \mathbf{\Omega}_i) = \sum_{k=1}^{N'} |\omega_k - \omega_{ik}|, \tag{4}$$

whereas the Mahalanobis distance is defined by

$$d_m(\mathbf{\Omega}, \mathbf{\Omega}_i) = \sum_{k=1}^{N'} \frac{1}{\sqrt{\lambda_k}} |\omega_k - \omega_{ik}|. \tag{5}$$

The identity of the input face image can be determined by finding the minimum distance with the above-mentioned distance function. The decision rule for face recognition can be expressed by

$$i_{matching} = \arg\min_{1 \le i \le M_g} d(\mathbf{\Omega}, \mathbf{\Omega}_i), \tag{6}$$

where $i_{matching}$ is the index indicating the identified person.

3. Face Recognition with Multiple Color Components

3.1. Face recognition system

Generally, color images have three channels (R, G, and B). We applied the eigenface method to each color component independently and combine the results to make a final decision [2]. Fig. 1 shows the block diagram of the face recognition system for multi-spectral face images.

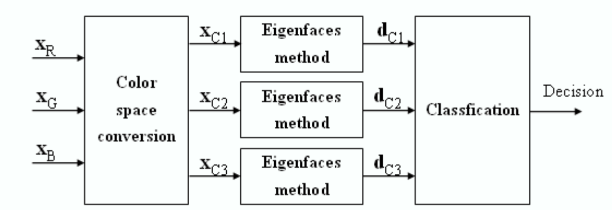


Figure 1. Block diagram of the face recognition system using color information.

$\mathbf{x}_R$, $\mathbf{x}_G$, and $\mathbf{x}_B$ are $N \times 1$ vectors, denoting red, green, and blue components of an input face image, respectively. First, these components of RGB are converted to three other components $\mathbf{x}_{C1}$, $\mathbf{x}_{C2}$, and $\mathbf{x}_{C3}$. At the second stage, the eigenface analysis is performed for each component, independently. And then, the three distance vectors, $\mathbf{d}_{C1}$, $\mathbf{d}_{C2}$, and $\mathbf{d}_{C3}$ are combined with weighting factors and the person of the face image is identified at the end.

3.2. Color spaces for face recognition

Even though most of digital image acquisition devices produce R, G, and B components, the RGB color space is converted into different color spaces depending on applications. For face recognition, the eigenface analysis in the RGB domain may not be effective, because R, G, and B components are largely correlated with each other. Some literatures also showed the inefficiency of the face recognition in the RGB domain [2]. Therefore, we need to find the color space that is less correlated between its components for improvement of face classification performance. Here, we will look into effective color spaces for face recognition.

The HSV space is the well-known color space reflecting the human visual perception and it is composed of hue, saturation, and value [6]. The conversion equations are defined by

$$H = \begin{cases} \theta & \text{if } B \le G \\ 360 - \theta & \text{if } B > G \end{cases}$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \tag{7}$$

$$V = \max(R,G,B),$$

where

$$\theta = \cos^{-1}\left\{\frac{0.5[(R-G)+(R-B)]}{[(R-G)^2 + (R-B)(G-B)]^{1/2}}\right\}.$$

The YCbCr color domain was developed for efficient image compression by separating luminance (Y) and chrominance (Cb, Cr) components. This space is also known as an effective space for skin color segmentation [7] and the conversion matrix is defined by

$$\begin{bmatrix} Y \\ Cb \\ Cr \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.148 & -0.291 & 0.439 \\ 0.439 & -0.368 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix}. \tag{8}$$

The YCgCr color space was proposed for fast face segmentation [8]. This space produces another chrominance component Cg instead of Cb. Moreover, the YCg'Cr' space was derived by rotating the CgCr plane for face segmentation [9]. YCgCr and YCg'Cr' are defined by

$$\begin{bmatrix} Y \\ Cg \\ Cr \end{bmatrix} = \begin{bmatrix} 0.257 & 0.504 & 0.098 \\ -0.317 & 0.438 & -0.121 \\ 0.438 & -0.366 & -0.071 \end{bmatrix} \begin{bmatrix} R \\ G \\ B \end{bmatrix} + \begin{bmatrix} 16 \\ 128 \\ 128 \end{bmatrix} \qquad (9)$$

$$\begin{aligned} Cg' &= Cg\cos 30^\circ + Cr\sin 30^\circ - 48 \\ Cr' &= -Cg\sin 30^\circ + Cr\cos 30^\circ + 80 \end{aligned} \qquad (10)$$

4. Experimental Results and Discussions

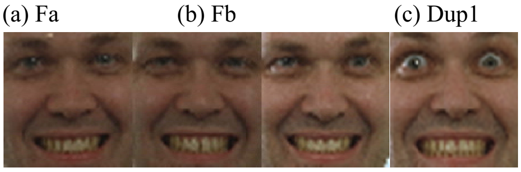
In our experiments, we used the color FERET database [10][11]. The database provides standard testing subsets that constitute one gallery set (Fa) and three probe sets (Fb, Dup1, and Dup2). The set Fb has face images with different facial expressions, while Dup1/Dup2 contain short/long-term aging faces additionally.

We made use of 194 Fa images as gallery set, while 194 Fb images were used as probe set 1, 269 Dup1 images as probe set 2, and 150 Dup2 images as probe set 3. Other 386 face images were used to construct the eigenface space. Fig. 2 shows example faces for each data set. To remove the effect of background and hair style variations, we cropped face region by excluding background and hair regions. They were rescaled to 50×50 in pixel and rotated to make the line between two eye-centers horizontal. Each color component was normalized to zero-mean and unit-variance.

Diverse color spaces including RGB, HSV, YCbCr, and YCgCr were investigated in the PCA-based color face recognition system. We also evaluated the performance of the conventional eigenface method using only luminance information. The luminance component image were generated in two ways by two conversions, i.e., $Y = 0.3R + 0.59G + 0.11B$ and $I = (R + G + B) / 3$.

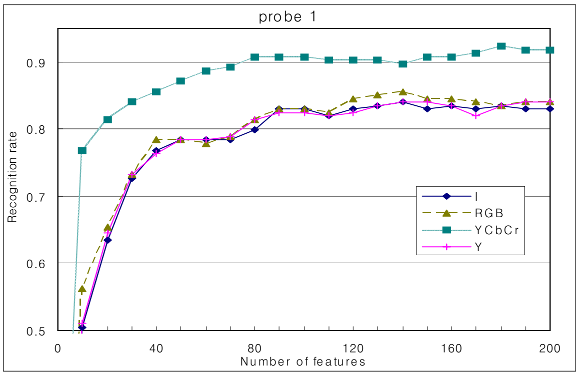
Fig. 3 illustrates the recognition rates when the number of features varies from 10 to 200, and Table 1 shows each maximum recognition rate in different spaces including two luminance spaces. The recognition rate is defined by the ratio of the number of correct recognitions to the size of the probe set.

(a) Fa (b) Fb (c) Dup1

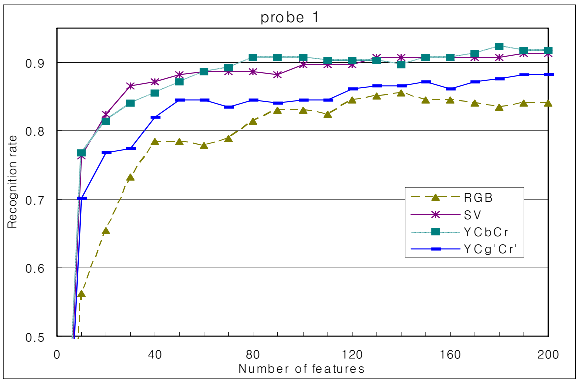


(d) Dup2

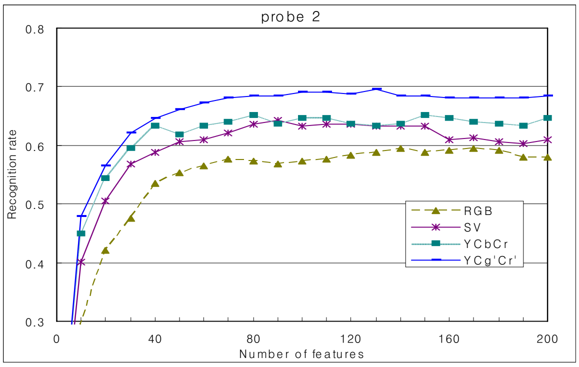
Figure 2. Color FERET database: (a) a face image in the Fa set used as the gallery, (b) a face image in the Fb set as probe set 1, (c) faces in the Dup1 set as probe set 2, (d) faces in the Dup2 set as probe set 3.



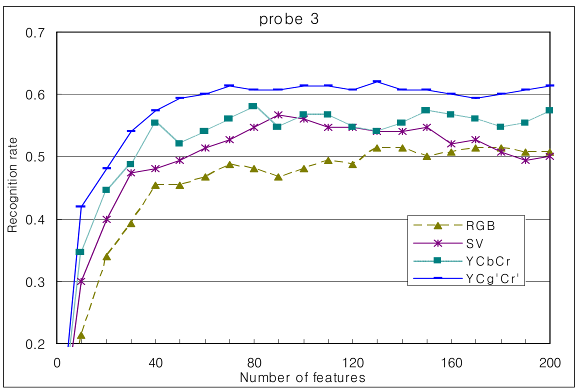
(a) Gray level vs. Color



(b) Probe set 1



(c) Probe set 2



(d) Probe set 3

Figure 3. Comparison of recognition rate in terms of the number of features in different color spaces.

Table 1. Maximum recognition rates in various spaces on probe sets 1, 2, and 3.

Spaces	Y	I	RGB	SV	YCbCr	YCg'Cr'
Probe set 1	0.840	0.840	0.876	0.912	0.923	0.881
Probe set 2	0.599	0.599	0.595	0.643	0.651	0.695
Probe set 3	0.507	0.507	0.513	0.567	0.580	0.620
Spaces	YUV	YIQ	HSV	HSI	SI	RSV
Probe set 1	0.923	0.851	0.881	0.881	0.902	0.912
Probe set 2	0.651	0.576	0.602	0.599	0.632	0.628
Probe set 3	0.580	0.467	0.520	0.507	0.547	0.553

Fig. 3(a) shows that the performance of face recognition with color information is significantly improved. The recognition rate using the YCbCr space is approximately 8 % better than that using only a luminance component. Note that the performance of the RGB space is similar to that of the luminance space. The use of RGB components produce little benefit to generate distinguishable features, since all the three components of the RGB space are strongly correlated with each other. On the other hand, the YCbCr space is effective because its components are less correlated with each other through separation of luminance and chrominance components.

For probe set 1 having facial expression variation, the best performance is observed with the YCbCr space, as shown in Fig. 3(b). The adoption of the SV (saturation and value) space also produces improvement, but it's slightly lower than that of the YCbCr space. Since the components of the HSV space have low correlation with each other, the performance in the HSV domain is better than that in the gray level. By assigning zero-weight to hue component, we obtained better performance because hue component is sensitive to illumination condition.

Figs. 3(c) and (d) shows the recognition rates for the probe sets 2 and 3 containing both aging and facial expression variations. As shown in the figures, the YCg'Cr' space yields the best performance. The maximum recognition rate with the YCg'Cr' space is 4% higher than that with the YCbCr and 10% better than that with the RGB. Similarly to the YCbCr space, the YCg'Cr' space is constructed by decomposing luminance (Y) and chrominance (Cg, Cr), with less correlation. We also found that the Cg'Cr' components are more robust to illumination variation than the CbCr components in that YCg'Cr is more efficient than YCbCr with probe set 2 and 3 which have illumination changes.

The performances in other color spaces such as YUV, YIQ, HSI, and RSV were examined as well. The RSV space is composed of red component from RGB, saturation and value components from HSV. Since red and value components are largely correlated, the space yields similar performance to the SV space. The YUV space produced almost the same performance to the YCbCr. In fact, the YCbCr space is an off-set version of the YUV space. The maximum recognition rates for these color spaces are listed in the lower part of Table 1.

5. Conclusions

In this paper, we evaluated the PCA-based face recognition algorithm in diverse color spaces and analyzed their performance in terms of the recognition rate. Experimental results with plentiful face images showed that color information is beneficial for face recognition and the YCbCr and YCg'Cr' spaces are the most appropriate spaces for face recognition. The YCbCr space is shown to be effective to facial expression variation, while YCg'Cr' is especially robust to aging faces.

Further works will focus on analysis of inter-color correlation and investigation of illumination-invariant color features for face recognition.

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