Comparative Study on Color Components for PCA-Based Face Recognition

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Summary Using color information can significantly improve the face recognition rate instead of using the grayscale luminance image. However, there are few works that try to compare the color space models on face recognition. In this paper, we investigate thirty different color space models on face recognition using the classical principal component analysis (PCA). Through the extensive experiments we find that after successfully diminishing the influence of the illumination the recognition accuracy can be improved by 4.6~5.5 percent points.

Keywords: face recognition, color space, principal component analysis

1. Introduction

The principal component analysis (PCA) has been widely used in various kinds of areas for face recognition\(^1\)~\(^3\) because of its outstanding performance since it was proposed by Turk and Pentland in 1991\(^1\). These areas include such as computer vision, pattern recognition and machine vision. Even though the PCA-based method is simple and has high recognition accuracy, the PCA method is not very effective under the condition of varying illumination\(^4\).

We consider that using the grayscale luminance (or non-chromatic) image as the input of PCA is one possible reason why the classical PCA-based method has low recognition accuracy when the lighting condition varies. As we know, the RGB color space does not differentiate the luminance information from the color information. In the RGB color space, the R, G and B components represent not only color but also luminance. Luminance may vary from image to image. Compared to luminance component the chrominance components are more stable even under different lighting conditions. If we can successfully remove the influence of luminosity before recognition we can expect higher recognition rate than using non-chromatic information under varying lighting conditions.

To eliminate luminance, an image can be transformed into other kinds of color space models. For example, in YCrCb color space model the luminance information is stored in the Y component and the chrominance information is stored in the Cr and Cb components. The chromatic information is independent of the luminance information.

Color information has important roles in detecting face region in color images with complex background. Many face detection algorithms have been proposed using color information\(^5\)~\(^7\). However, the effectiveness of using color information in face recognition field is not studied sufficiently. Although Yin et al. presented a comparative study on different color space models for skin color segmentation\(^10\), the effectiveness for face recognition had not been discussed. In order to improve the recognition accuracy under varying lighting condition, in this work we attempt to use the color information alone. Torres et al. first demonstrated that color information can provide additional accuracy for the PCA-based
face recognition\(^3\),\(^9\). They compared the use of PCA method on monochrome images, RGB color images, YUV color images and HSV images. However, they did not investigate applying PCA to each component of color spaces separately. In this work, we applied the classical PCA-based face recognition method to each component of thirty different color spaces in order to investigate the influence of using different color information on face recognition. The main difference of our work from that of Torres et al. is that while they tried to find out the most suitable color space, we investigate the most suitable color component among all the color components.

Our aim of this paper is to research the various color space models and to determine which color component would be the most suitable for face recognition when using the classical PCA-based method. The rest of this paper is organized as follows: Section 2 covers the color space models, and section 3 describes the PCA-based face recognition algorithm. In section 4, a number of experimental results are demonstrated for evaluating PCA-based face recognition method using different color components. Finally, conclusions are drawn based on the experimental results.

2. Color Space Models

In this work, we compare the following thirty color space models\(^1\),\(^2\),\(^3\): YIQ, YUV, YCrCb, XYZ, YPrPb, nRGB, sRGB, LMS, CMY, CIE-L*a*b*, CIE-L*u*v*, Hunter-Lab, U*V*W*, LCH, HIS, HSV, HSL, I1I2I3, AC1C2, CIECAM02, CIEYUV, UCS, IPT, TSL, P1P2, CIEUYUpVp, CIEYxy, YES, RGYeBWhBi, and RGB.

For the conversion from RGB to YIQ, YUV and YCrCb we used the following equations.

\[
\begin{bmatrix}
    Y \\
    I \\
    Q
\end{bmatrix} = \begin{bmatrix}
    0.299 & 0.587 & 0.114 \\
    0.596 & -0.274 & -0.322 \\
    0.212 & -0.523 & 0.311
\end{bmatrix} \begin{bmatrix}
    R \\
    G \\
    B
\end{bmatrix}
\]

\[
\begin{bmatrix}
    Y \\
    U \\
    V
\end{bmatrix} = \begin{bmatrix}
    0.299 & 0.587 & 0.114 \\
    -0.147 & -0.289 & 0.437 \\
    0.615 & -0.515 & -0.100
\end{bmatrix} \begin{bmatrix}
    R \\
    G \\
    B
\end{bmatrix}
\]

\[
\begin{bmatrix}
    Y \\
    Cr \\
    Cb
\end{bmatrix} = \begin{bmatrix}
    0.2215 & 0.7154 & 0.0721 \\
    -0.1145 & -0.3855 & 0.5000 \\
    0.5016 & -0.4556 & -0.0459
\end{bmatrix} \begin{bmatrix}
    R \\
    G \\
    B
\end{bmatrix}
\]

For the conversion from RGB to XYZ we used the following procedures.

\[
\begin{align*}
    r &= R/255, \quad g = G/255, \quad b = B/255 \\
    \text{if } r > 0.04045 & \quad \text{then } r = ((r + 0.055)/1.055)^{2.4} \\
    \text{else } r &= r/12.92 \\
    \text{if } g > 0.04045 & \quad \text{then } g = ((g + 0.055)/1.055)^{2.4} \\
    \text{else } g &= g/12.92 \\
    \text{if } b > 0.04045 & \quad \text{then } b = ((b + 0.055)/1.055)^{2.4} \\
    \text{else } b &= b/12.92 \\
    r &= r \times 100.0, \quad g = g \times 100.0, \quad b = b \times 100.0
\end{align*}
\]

\[
\begin{bmatrix}
    X \\
    Y \\
    Z
\end{bmatrix} = \begin{bmatrix}
    0.4124 & 0.3576 & 0.1805 \\
    0.2126 & 0.7152 & 0.0722 \\
    0.0193 & 0.1192 & 0.9505
\end{bmatrix} \begin{bmatrix}
    r \\
    g \\
    b
\end{bmatrix}
\]

The description of other models are omitted here. Please find them in the referenced papers. After the color space transformation, normalization is processed using the following equation.

\[
\hat{I}^c_i(x, y) = \left( \frac{I^c_i(x, y) - \text{MIN}_c}{\text{MAX}_c - \text{MIN}_c} \right) \times 255,
\]

where \(I^c_i(x, y)\) is the pixel value of \(i\)th component of color space \(c\), and \(\text{MIN}_c^i\) and \(\text{MAX}_c^i\) are the minimum and maximum pixel values of \(i\)th component.
of color space $c$. Fig. 1 illustrates some normalized sample images of the color components.

3. PCA-Based Face Recognition Algorithm

The PCA-based face recognition method is based on an information theory approach that decomposes face images into a small set of characteristic feature images called eigenfaces. Eigenfaces are the eigenvectors of the covariance matrix corresponding to the original face images, and they are face-like in appearance. The eigenfaces define the subspace of face images, which is called face space. Each face image in the training set can be represented exactly in terms of a linear combination of the eigenfaces, followed by computing the distance between the position in the face space and those of known face classes.

The main processes of computing the eigenfaces and recognition using eigenfaces is described below.

3.1 Computation of Eigenfaces (Training Stage)

Suppose the training set consists of $M$ face images from all the face classes and the size of each image is $N \times N$. We consider $N$ by $N$ face image as an $N^2$-dimensional vector. The input image will also be $N \times N$.

Step 1: Compute mean face as

$$\Psi = \frac{1}{M} \sum_{n=1}^{M} \Gamma_n,$$

where $\Gamma_1, \Gamma_2, \Gamma_3, \ldots, \Gamma_M$ denote the images in the training set.

Step 2: Subtract the mean face from each image in training set and find difference vectors (difference face image) as

$$\Phi_n = \Gamma_n - \Psi, \quad n = 1, \ldots, M.$$

Step 3: Construct $N^2 \times N^2$ covariance matrix $C$ as

$$C = \frac{1}{M} \sum_{n=1}^{M} \Phi_n \Phi_n^T,$$

where $\Phi_n^T$ is transpose of $\Phi_n$.

Step 4: Compute the eigenvectors of the covariance matrix $C$. Let $u_l$ ($l = 1 \sim M$) be the eigenvectors of $C$. To compute $N^2$ eigenvectors and eigenvalues for typical image sizes of covariance $C$ is not computationally efficient when the number of training images is smaller than the number of pixels in an image. In this case, the eigenvectors of $C$ are computed by first finding the eigenvectors of $M \times M$ matrix $L$.

$$L = A^T A, \quad A = [\Phi_1, \Phi_2, \ldots, \Phi_M]$$

Then the eigenvectors $u_l$ of $C$ are calculated by a linear combination of the difference face images and eigenvectors $v_l$ of $L$.

$$u_l = \sum_{k=1}^{M} v_k \Phi_k, \quad l = 1, \ldots, M$$

Step 5: Keep only $K$ eigenvectors corresponding to $K$ largest eigenvalues ($K \leq \min \{M, N^2\}$).

3.2 Face Recognition Using Eigenfaces (Recognition Stage)

Given an unknown face image $\Gamma$.

Step 1: Normalize $\Gamma$ as

$$\Phi = \Gamma - \Psi.$$

Step 2: Project $\Phi$ on the eigenspace as

$$w_i = u_i^T \Phi, \quad i = 1, \ldots, K.$$

Let $\Omega = [w_1 w_2 \ldots w_K]^T$. $\Omega$ describes the contribution of each eigenface in representing the input face image.

Step 3: Find

$$\varepsilon_k^2 = \|\Omega - \Omega_k\|^2,$$

where $\Omega_k$ is a vector describing $k$th face class.

If we find the face class $k$ that minimizes the Euclidean distance $\varepsilon_k$ then we can classify the input face image as belong to the face class $k$.

4. Experimental Results and Discussion

For testing the recognition accuracy of each color component we used CIT face database$^{24}$. CIT database includes frontal face images collected by Webber at California Institute of Technology. CIT database is taken under different lighting conditions with various expressions and complex backgrounds. We manually cropped face images and normalized them to $64 \times 64$. From the CIT database we collected 413 images of 21 individuals. Out of the total images, 304 images are used for training and the remainder are used for testing the recognition. Fig. 2 shows some sample images of training set and testing set.

Two experiments were involved with the number of eigenvectors. Generally, there are two kinds of

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assumptions when we face the problem of selecting the number of eigenvectors. First one is, eigenvectors corresponding to the smaller eigenvalues would not contribute to the recognition so much and to remove these eigenvectors from the representation of feature space (eigen space, face space) would improve the recognition performance. And the second one is, the low order (low order refers to the index of eigenvalues sorted decreasing order) eigenvectors encode variations such as lighting changes, then performance may improve by removing the low order eigenvectors from the representation). We followed the first assumption and discarded the eigenvectors corresponding to the smaller eigenvalues as the first choice of evaluating the performance of PCA-based face recognition method. To the second assumption, since in our research we had separated the chrominance information from the luminance information, in this case we did not exclude the first or the second eigenvector. We carried out two kinds of experiments in order to evaluate the recognition accuracy of each component. One was using first twenty eigenvectors, and the other was using first $n$ eigenvectors where $n$ was selected so that the cumulative contribution ratio was 60% (hereafter called “60% of eigenvectors”).

Table 1 and Table 2 show the recognition accuracy of each component using first twenty eigenvectors and 60% of eigenvectors, respectively. Color components that correspond to luminance values in color spaces are underlined. The recognition accuracy of grayscale image C1 derived from averaging R, G and B pixel values is 89.9% and 89.0%, when applying the first twenty eigenvectors and 60% of eigenvectors, respectively. From the experiments, a fairly good recognition accuracy 94.5% is obtained with CIEYUV$_U$ (CIEYUV$_U$ indicates the U component of CIEYUV color space), CIEYUpVp$_Up$, I1I2I3$_I2$, YIQ$_J$ when applying the first twenty eigenvectors and with CIECAM02$_S$, I1I2I3$_I2$, YES$_E$, YIQ$_J$, RGYeBWhBl$_RG$, YCrCb$_Cr$ when applying 60% of eigenvectors. These data also show that more color components achieved highest recognition accu-

### Table 1 Performance of PCA for each channel separately using first twenty eigenvectors. The bold number indicates the recognition accuracy same as C1. (The recognition accuracy of C1 for [(R+G+B)/3] is 89.9%). HsRGB$_I$ means reconstructed image with the H component of HSV color space.

<table>
<thead>
<tr>
<th>Color component</th>
<th>Accuracy</th>
</tr>
</thead>
<tbody>
<tr>
<td>HSV$_I$, HSL$_H$</td>
<td>52.3%</td>
</tr>
<tr>
<td>HIS$_H$</td>
<td>55.0%</td>
</tr>
<tr>
<td>CIECAM02$_h$, LCH$_H$</td>
<td>67.0%</td>
</tr>
<tr>
<td>HIS$_S$</td>
<td>78.9%</td>
</tr>
<tr>
<td>HSL$_S$, LCH$_C$</td>
<td>79.8%</td>
</tr>
<tr>
<td>CMY$_C$</td>
<td>80.7%</td>
</tr>
<tr>
<td>AC1C2$_C1$, Lab$_L$</td>
<td>82.6%</td>
</tr>
<tr>
<td>CMY$_M$, YIQ$_Q$, UCS$_L$</td>
<td>83.5%</td>
</tr>
<tr>
<td>P1P2$_P1$, TSL$_S$</td>
<td>84.4%</td>
</tr>
<tr>
<td>AC1C2$_C2$, P1P2$_P2$, nRGB$_nG$, nRGB$_nB$</td>
<td>85.3%</td>
</tr>
<tr>
<td>LMS$_S$, sRGB$_sG$</td>
<td>86.2%</td>
</tr>
<tr>
<td>AC1C2$_A$, CIECAM02$_C$</td>
<td>87.2%</td>
</tr>
<tr>
<td>CIECAM02$_M$, CMY$_Y$, LMS$_L$, Luv$_v$</td>
<td>88.1%</td>
</tr>
<tr>
<td>UsVsWsVs$_V$, RGB$_B$, sRGB$_sB$, nRGB$_nB$, XYZ$_X$, XYZ$_Z$</td>
<td>88.1%</td>
</tr>
<tr>
<td>CIEYUpVp$_Up$, CIEYUV$_U$, CIEYxy$_Y$</td>
<td>89.9%</td>
</tr>
<tr>
<td>Hlab$_H$, Hlab$_Hb$, HIS$_L$, I1I2I3$_I3$, UsVsWsUs$_V$, UCS$_L$_j, nRGB$_nR$, sRGB$_sR$, XYZ$_X$, XYZ$_Z$</td>
<td>90.8%</td>
</tr>
<tr>
<td>LMS$_M$, Lab$_L$, Luv$_v$, Luv$_vW$</td>
<td>91.7%</td>
</tr>
<tr>
<td>LCH$_H$, UsVsWsWs$_W$, UCS$_G$, RGB$_G$, RGB$_G$, CIECAM02$_Q$, CIEYUV$_V$, HSL$_L$, I1I2I3$_I3$, TSL$_S$, TSL$_S$, YCrCb$_Cr$, YPrPb$_Pb$, RGYeBWhBl$_WhBl$, CIEYUpVp$_Up$</td>
<td>92.7%</td>
</tr>
<tr>
<td>CIEYxy$_Y$, HSV$_S$, HSV$_V$, YES$_E$, YIQ$_Y$, YIQ$_Y$, TSL$_S$, Lab$_L$, YUV$_V$, YUV$_U$, YPrPb$_Pr$</td>
<td>92.7%</td>
</tr>
<tr>
<td>CIECAM02$_S$, CIEYxy$_Y$, YES$_S$, YUV$_V$, YCrCb$_Cr$, YPrPb$_Pr$</td>
<td>94.3%</td>
</tr>
<tr>
<td>CIEYUpVp$_Up$, CIEYUV$_U$, I1I2I3$_I2$, YIQ$_J$</td>
<td>94.5%</td>
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</table>
Table 2: Performance of PCA for each channel separately using 60% of eigenvectors. The bold number indicates the recognition accuracy same as C1. (The recognition accuracy of C1 for [(R+G+B)/3] is 89.0%.)

<table>
<thead>
<tr>
<th>Color component</th>
<th>Accuracy</th>
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<tbody>
<tr>
<td>HSV</td>
<td>x</td>
</tr>
<tr>
<td>HIS</td>
<td>x</td>
</tr>
<tr>
<td>LCH</td>
<td>x</td>
</tr>
<tr>
<td>CIECAM02</td>
<td>x</td>
</tr>
<tr>
<td>LCH</td>
<td>C</td>
</tr>
<tr>
<td>HIS</td>
<td>x, HIS, nRGB</td>
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<tr>
<td>CMY</td>
<td>M, P1P2</td>
</tr>
<tr>
<td>AC1C2</td>
<td>x, CIEXy</td>
</tr>
<tr>
<td>CIEXy</td>
<td>Y, LMS, RGB, XYZ, YCrCb</td>
</tr>
<tr>
<td>LMS</td>
<td>x, sRGB</td>
</tr>
<tr>
<td>CMY</td>
<td>C, LMS, M, P1P2,P1, Lab</td>
</tr>
<tr>
<td>AC1C2</td>
<td>x, CIEXyUp</td>
</tr>
<tr>
<td>CMY</td>
<td>Y, YES, YIQ, YUV, TSL, Lab, Lu, LCH, L, UsVsWs, Ws, RGB, nRGB, nRGB, YUV</td>
</tr>
<tr>
<td>AC1C2</td>
<td>x, AC1C2</td>
</tr>
<tr>
<td>CIECAM02</td>
<td>, HSL, RGB, sRGB, sRGB, nRGB, nRGB, YUV, YCrCb, Cr, YPrPb, Y, CIECAM02</td>
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<td>, HSL, RGB, sRGB, sRGB, nRGB, nRGB, YUV, YCrCb, Cr, YPrPb, Y, CIECAM02</td>
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</table>

Fig. 3: Sample images of the first three high recognition accuracy and some low recognition accuracy faces when using the first twenty eigenvectors. C1: Correct Recognition, W: Wrong Recognition. C1: [(R+G+B)/3] and C2: [I1 I2 I3] when C1 did not.)

Table 3: Matched and mismatched sample faces when using the first twenty eigenvectors. C1: Correct Recognition, W: Wrong Recognition. C1: [(R+G+B)/3], C2: [I1 I2 I3], C3: YIQ, C4: CIEXYUV, C5: CIEXYUV. (The bold FaceID means correctly recognized faces by C2~C5 when C1 did not.)

<table>
<thead>
<tr>
<th>FaceID</th>
<th>C1</th>
<th>C2</th>
<th>C3</th>
<th>C4</th>
<th>C5</th>
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<td>3</td>
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<td>C</td>
<td>C</td>
<td>C</td>
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</table>

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higher recognition accuracy compared with the C1 (See Table 1 and Table 2). The recognition accuracy is improved by 4.6~5.5 percent points compared with using C1.

Fig. 3 displays sample images of the first three high recognition accuracy and some low recognition accuracy. From Fig. 1 and Fig. 3, we can observe the features of face image (i.e., nose, eyes, mouth and their positions) more precisely with the reconstructed images corresponding to the higher recognition accuracy. And these images (such as YIQ_I and I1I2I3 chrominance images) seem to have few influence of varying lighting condition compared to the luminance images (such as CMY_Y and YIQ_Y).

Components of normalized color space (such as nRGB) and some color spaces which did not discriminate the luminance information and color information (such as RGB, sRGB, XYZ and CMY) did not show high recognition accuracy compared to C1. The recognition accuracies of luminance images have similar results 89.0%~89.9%. Fig. 1 and Fig. 3 show that the reconstructed images of hue component lose lots of information. As the result, the recognition accuracy is the worst. Table 3 and Table 4 show that the recognition accuracy of C2~C9 are higher compared to C1, and the set of successfully recognized faces by each component are different. And most of the face which is not recognized by C1 is correctly classified by C2~C9, successfully. Due to the fact that correctly recognized faces are diverse among the components, from these experimental observation we can consider combining the results in order to obtain higher recognition accuracy.

These results demonstrate that the recognition accuracy of the PCA-based method could be improved after diminishing the influence of the illumination. These two experiments indicate that as a possible consideration to improve the recognition accuracy under the different lighting conditions, it is desirable to use the chrominance component alone (i.e., I component in YIQ, I2 component in I1I2I3) instead of using grayscale luminance image.

### 5. Conclusions

In this paper, we investigated thirty different color space models for the performance of recognizing faces by the PCA-based face recognition method. We applied the PCA-based method to each component of different color spaces. Through the experiment we found that after successfully removing the luminance effect on image the recognition accuracy improved from 4.6 to 5.5 percent points compared to using simple grayscale image obtained by averaging RGB values as the input of the system. We achieved high recognition accuracy 94.5% with the following color components: CIEY_Up, CIEYUV_U, I1I2I3_I2, YIQ_I, CIECAM02_S, YES_E, RGYeB_WhBl_RGB, YCrCb_Cr.

This is the first approach using amount of color space models to investigate the effect of using each color component to face recognition. Through experiment, we have shown that the use of color information is able to improve the recognition accuracy of the classical PCA-based method.
Paper: Comparative Study on Color Components for PCA-Based Face Recognition

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