

Color Space Learning for Face Representation and Recognition

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Color Cue in Vision

- Color provides useful and important information for object detection (e.g. face detection) and tracking, image (or video) segmentation, indexing and retrieval, etc.
- Different color spaces (or color models) possess different characteristics as applied to different visual tasks.

Role of Color in Face Recognition

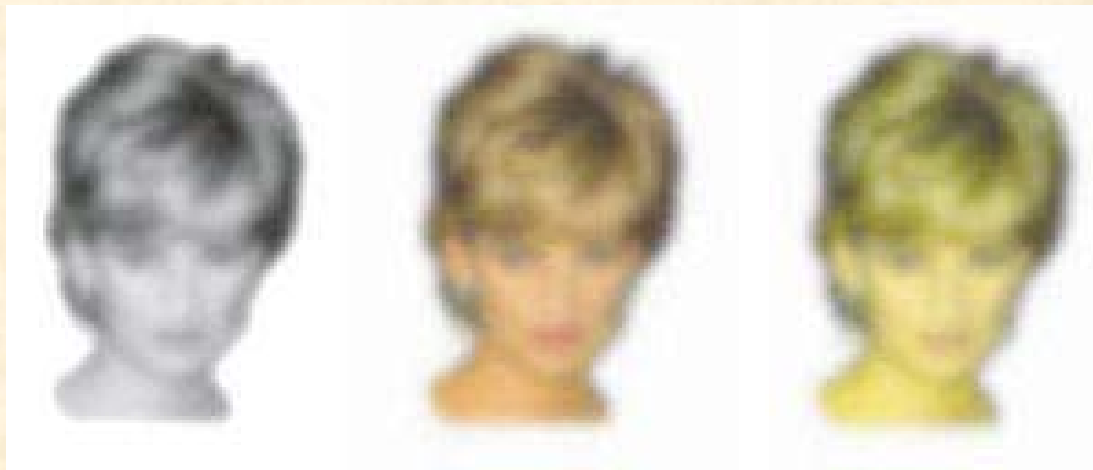
- Does color help face recognition?
- A previous answer:

Color appears to confer no significant face recognition advantage beyond the luminance information

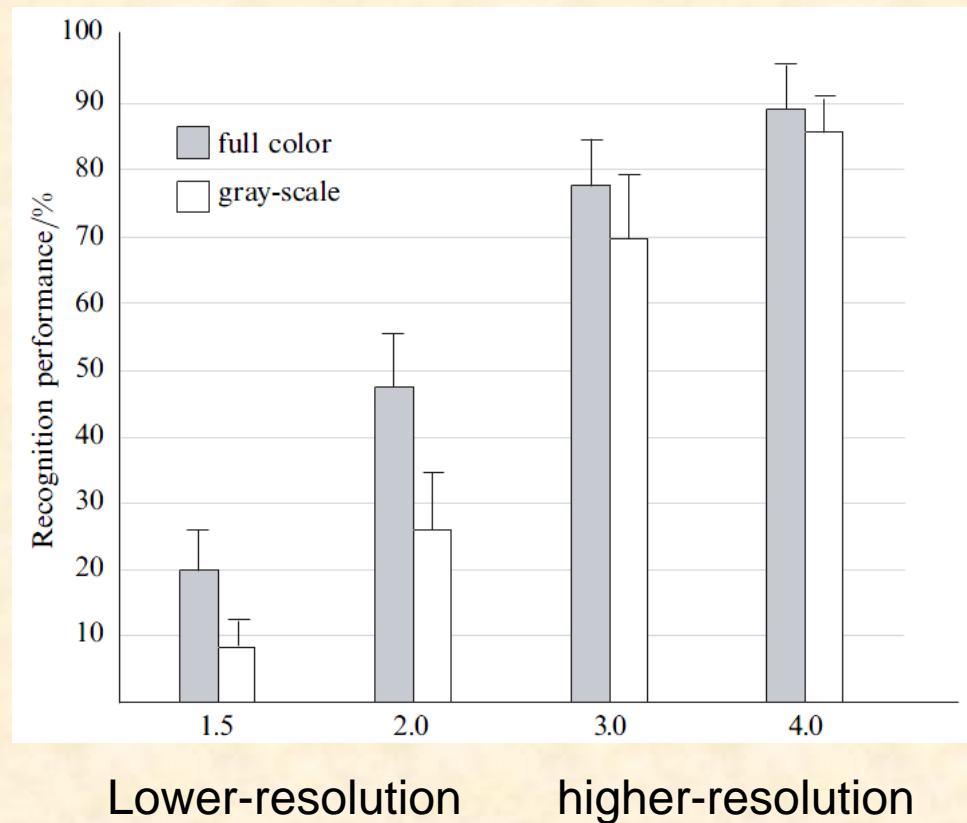
Kemp, R. et al. (1996). Perception and recognition of normal and negative faces: the role of shape from shading and pigmentation cues. *Perception*, 25, 37-52.

Role of Color in Face Recognition

- Recent research efforts, however, reveal that color may provide useful information for face recognition.
- Color cues do play a role in face recognition and their contribution becomes evident when shape cues are degraded (e.g. blurred images)



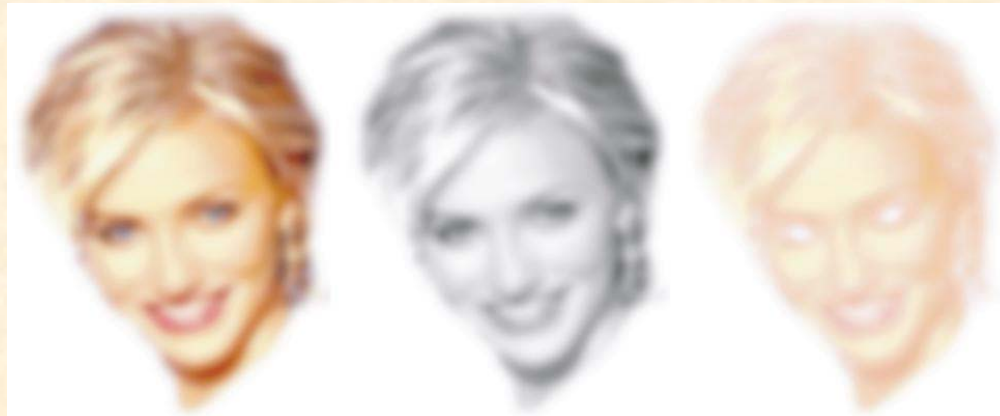
Role of Color in Face Recognition



A. Yip and P. Sinha, "Contribution of color to face recognition", *Perception*, 2002, volume 31, 995-1003.

Why does Color Aid Face Recognition?

- Color provides discriminative information, e.g. the color of eye or skin may help us identify the individual (in particular the race)
- Color might facilitate low-level image analysis (segment face features like eyes and lip), and thus indirectly aid face recognition



How should we represent color images for the recognition purpose?

- A common way is to linearly combine the three color components into one intensity image:

$$\mathbf{E} = \frac{1}{3} \mathbf{R} + \frac{1}{3} \mathbf{G} + \frac{1}{3} \mathbf{B}$$

The intensity image \mathbf{E} is then used for recognition.

- This representation is not theoretically optimal
 - (1) The color information is lost;
 - (2) The combination coefficients are not necessary optimal

How should we represent color images for the recognition purpose?

- The other research effort is to choose an existing color space or to build a hybrid color space by experience for achieving good recognition performance
- Different color spaces used:
 - RGB, Rajapakse et al. 2004
 - YUV, Torres et al. 1999
 - $\lg(r-g)$, Kittler and Sadeghi, 2004
 - YQC_r , Shih and Liu, 2006,
where Y and Q are from the YIQ color space and C_r is from the YC_bC_r color space

Which color space is the best for face recognition?

From the previous research, we conclude

- There is no consistent result for color space selection
- Color space selection seems to be data-dependent

Thus, for a given new database, we still don't know which color space we should choose

Motivation and Idea

- Our motivation is to learn an optimal color space for a given face database
- Starting from the common RGB color space, our goal is to find a set of optimal coefficients to combine the **R**, **G**, and **B** color components. Let **D** be the combined image given below:

$$\mathbf{D} = x_1 \mathbf{R} + x_2 \mathbf{G} + x_3 \mathbf{B}$$

- The remaining task is to find a set of optimal coefficients with respect to a given criterion

Discriminant Color Model I:

- A model focuses on color space learning
- Criterion: In the D -space, the between-class scatter is maximal and the within-class scatter is minimal, i.e.

$$J(\mathbf{X}) = \frac{\text{tr}(\mathbf{S}_b)}{\text{tr}(\mathbf{S}_w)}$$

where $\mathbf{X} = [x_1, x_2, x_3]^T$, \mathbf{S}_b and \mathbf{S}_w are the between-class scatter matrix and the within-class scatter matrix in the D -space.

Discriminant Color Model I

- The foregoing criterion is equivalent to the following criterion

$$J(\mathbf{X}) = \frac{\mathbf{X}^T \mathbf{L}_b \mathbf{X}}{\mathbf{X}^T \mathbf{L}_w \mathbf{X}}$$

where \mathbf{L}_b and \mathbf{L}_w are the *color space between-class scatter matrix* and *color space within-class scatter matrix*, and they are both 3 by 3 matrices.

Discriminant Color Model I

- Maximizing the criterion, we achieve a set of optimal combination coefficient vectors \mathbf{X}_1 , \mathbf{X}_2 and \mathbf{X}_3 .
- The three discriminant color components of image \mathbf{A} can be obtained by

$$\mathbf{D}^i = \mathbf{A} \mathbf{X}_i = [\mathbf{R}, \mathbf{G}, \mathbf{B}] \mathbf{X}_i, \quad i = 1, 2, 3$$

Illustration of three discriminant color component images

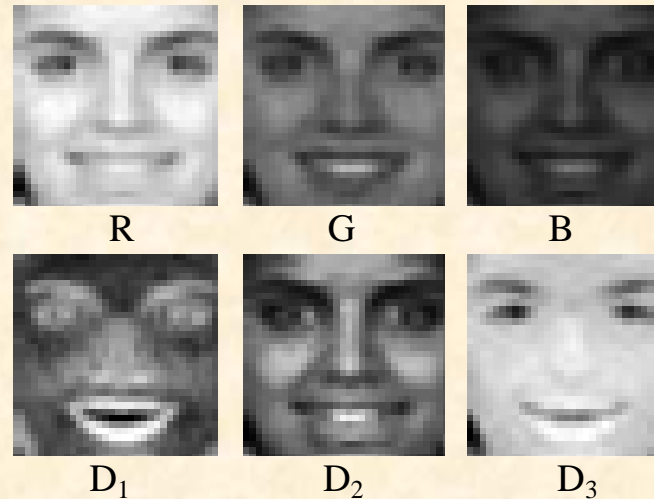
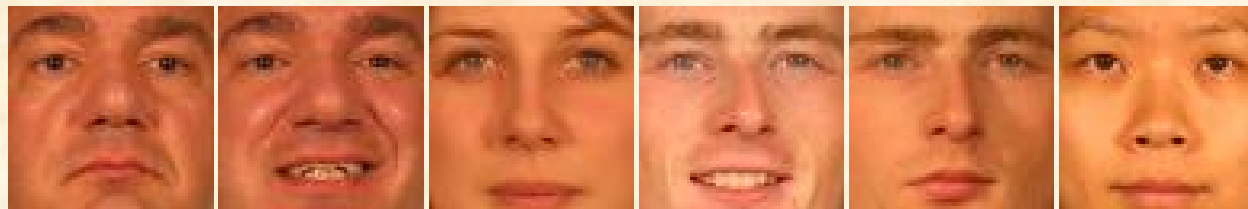


Figure Illustration of R, G, B color component images and the three discriminant color component images generated by the proposed method

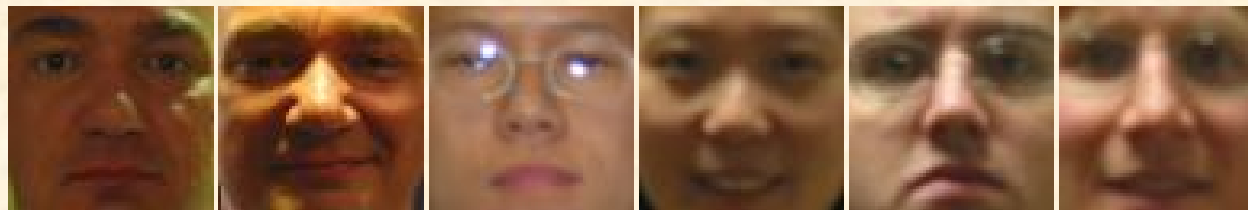
The FRGC Database (v2)

- The Face Recognition Grand Challenge (FRGC) version 2 database contains 12,776 training images, 16,028 **controlled** target images, and 8,014 **uncontrolled** query images for the FRGC Experiment 4.
- 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.

Sample images from FRGC

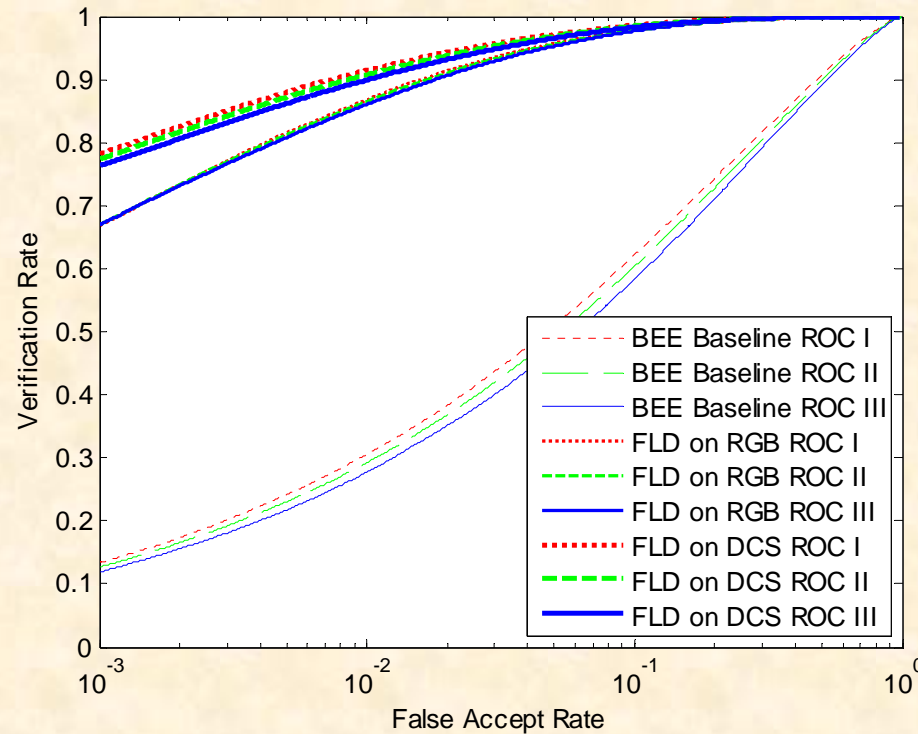


Images taken in **controlled** environment



Images taken in **uncontrolled** environment

Experimental Results



ROC curves corresponding to different color spaces using FLD and image-level fusion strategy

Discriminant Color Model II:

- A model integrates color space and image subspace learning
- Use the following criterion

$$J(\varphi, \mathbf{X}) = \frac{\varphi^T \mathbf{S}_b(\mathbf{X}) \varphi}{\varphi^T \mathbf{S}_w(\mathbf{X}) \varphi}$$

where φ is a discriminant projection vector and \mathbf{X} a color component combination coefficient vector. $\mathbf{S}_b(\mathbf{X})$ and $\mathbf{S}_w(\mathbf{X})$ are the between-class scatter matrix and the within-class scatter matrix in D -space, which are defined by

Discriminant Color Model II

$$\mathbf{S}_b(\mathbf{X}) = \sum_{i=1}^c P_i [(\bar{\mathbf{A}}_i - \bar{\mathbf{A}})\mathbf{X}\mathbf{X}^T(\bar{\mathbf{A}}_i - \bar{\mathbf{A}})^T]$$

$$\mathbf{S}_w(\mathbf{X}) = \sum_{i=1}^c P_i \frac{1}{M_i - 1} \sum_{j=1}^{M_i} [(\mathbf{A}_{ij} - \bar{\mathbf{A}}_i)\mathbf{X}\mathbf{X}^T(\mathbf{A}_{ij} - \bar{\mathbf{A}}_i)^T]$$

Maximizing the criterion is equivalent to solving the following optimization model

$$\begin{cases} \max_{\boldsymbol{\varphi}, \mathbf{X}} \boldsymbol{\varphi}^T \mathbf{S}_b(\mathbf{X}) \boldsymbol{\varphi} \\ \text{subject to } \boldsymbol{\varphi}^T \mathbf{S}_w(\mathbf{X}) \boldsymbol{\varphi} = 1, \end{cases}$$

Discriminant Color Model II

To solve the model, we need construct the general color-space between-class scatter matrix and the general color-space within-class scatter matrix as follows:

$$\mathbf{L}_b(\varphi) = \sum_{i=1}^c P_i [(\bar{\mathbf{A}}_i - \bar{\mathbf{A}})^T \varphi \varphi^T (\bar{\mathbf{A}}_i - \bar{\mathbf{A}})],$$

$$\mathbf{L}_w(\varphi) = \sum_{i=1}^c P_i \frac{1}{M_i - 1} \sum_{j=1}^{M_i} [(\mathbf{A}_{ij} - \bar{\mathbf{A}}_i)^T \varphi \varphi^T (\mathbf{A}_{ij} - \bar{\mathbf{A}}_i)]$$

Discriminant Color Model II

- Finding the optimal solutions φ^* and \mathbf{X}^* of the optimization problem is equivalent to solving the following generalized eigen-equation set:

$$\begin{cases} \mathbf{S}_b(\mathbf{X})\varphi = \lambda \mathbf{S}_w(\mathbf{X})\varphi \\ \mathbf{L}_b(\varphi)\mathbf{X} = \lambda \mathbf{L}_w(\varphi)\mathbf{X} \end{cases}$$

Iterative Algorithm for Model II

Step 0. Set $k = 0$, and provide an initial value for \mathbf{X} : $\mathbf{X} = \mathbf{X}^{[0]}$.

Step 1. Construct $\mathbf{S}_b(\mathbf{X})$ and $\mathbf{S}_w(\mathbf{X})$ based on $\mathbf{X} = \mathbf{X}^{[k]}$. Calculate their generalized eigenvectors

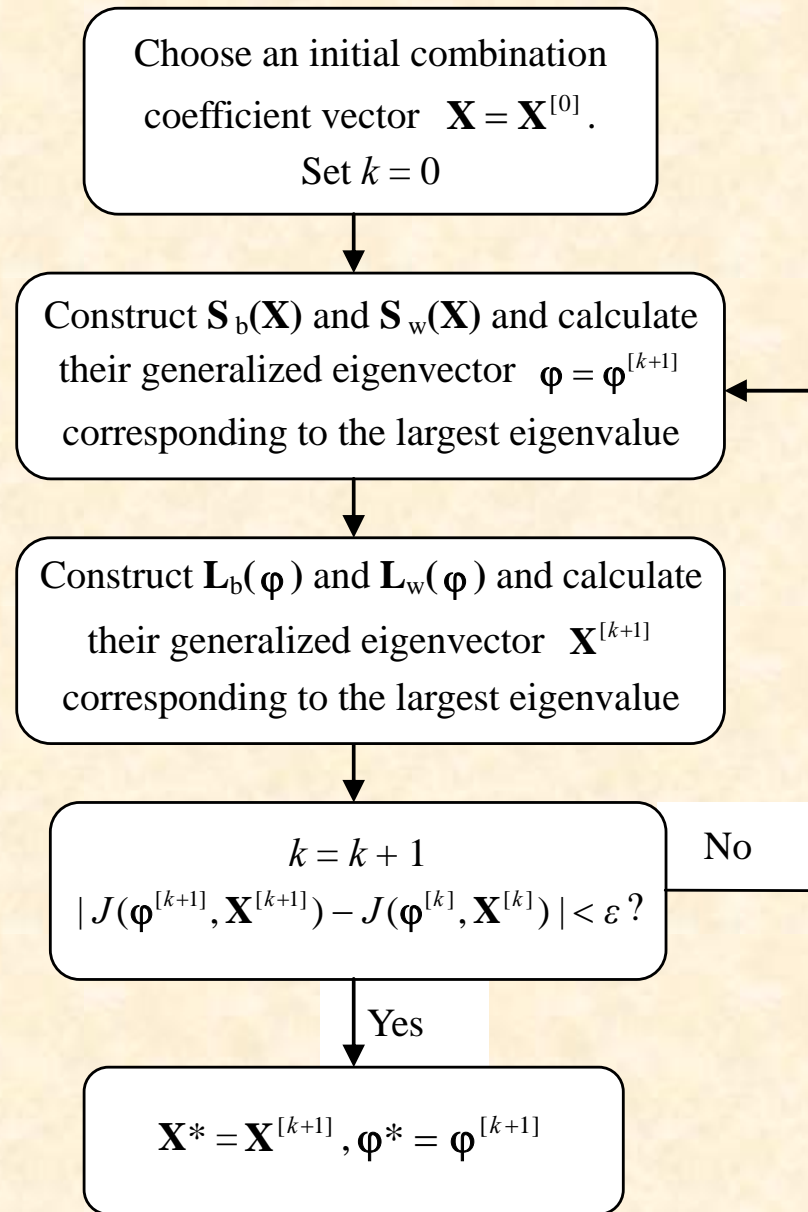
$\varphi_1, \varphi_2, \dots, \varphi_d$ corresponding to the d largest eigenvalues. Let $\mathbf{P}^{[k+1]} = [\varphi_1, \varphi_2, \dots, \varphi_d]$.

Step 2. Construct $\mathbf{L}_b(\mathbf{P})$ and $\mathbf{L}_w(\mathbf{P})$ based on $\mathbf{P} = \mathbf{P}^{[k+1]}$. Calculate their generalized eigenvectors

$\mathbf{X}^{[k+1]}$ corresponding to the largest eigenvalues.

Step 3. If $|J(\mathbf{P}^{[k+1]}, \mathbf{X}^{[k+1]}) - J(\mathbf{P}^{[k]}, \mathbf{X}^{[k]})| < \varepsilon$, the iteration terminates and let $\mathbf{P}^* = \mathbf{P}^{[k+1]}$ and

$\mathbf{X}^* = \mathbf{X}^{[k+1]}$. Otherwise, let $\mathbf{X} = \mathbf{X}^{[k+1]}$ and go to Step 1.



The flowchart of the iterative algorithm for Model II

Illustration of three discriminant color component images



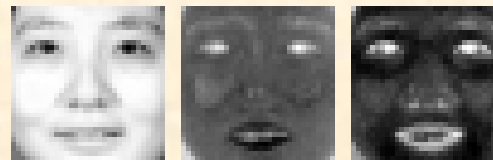
Original image



R

G

B



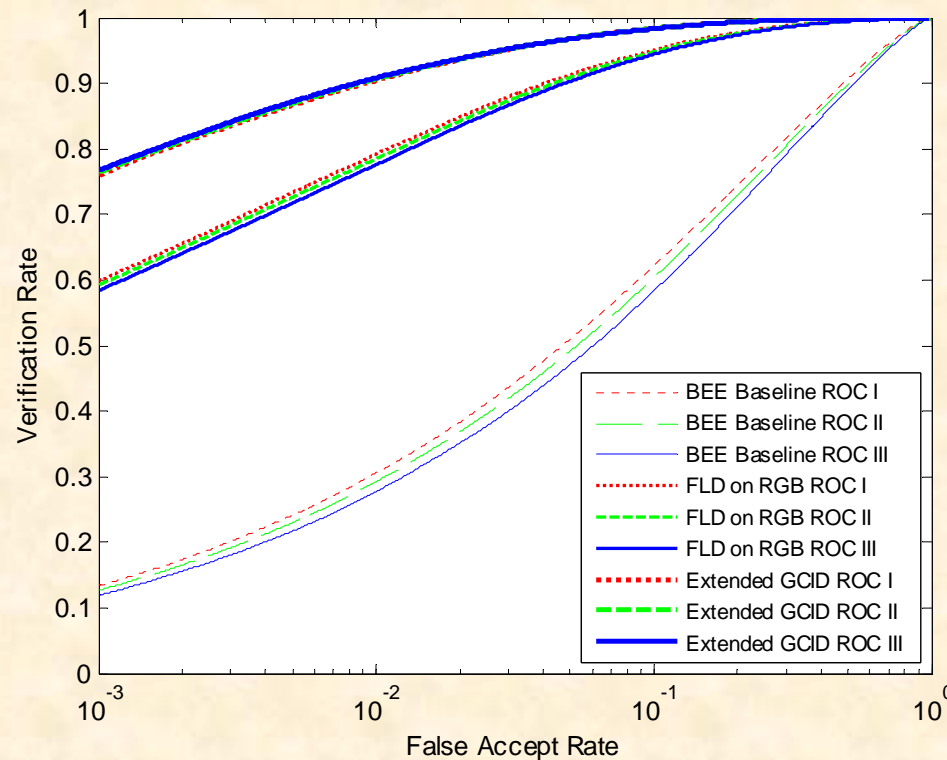
D1

D2

D3

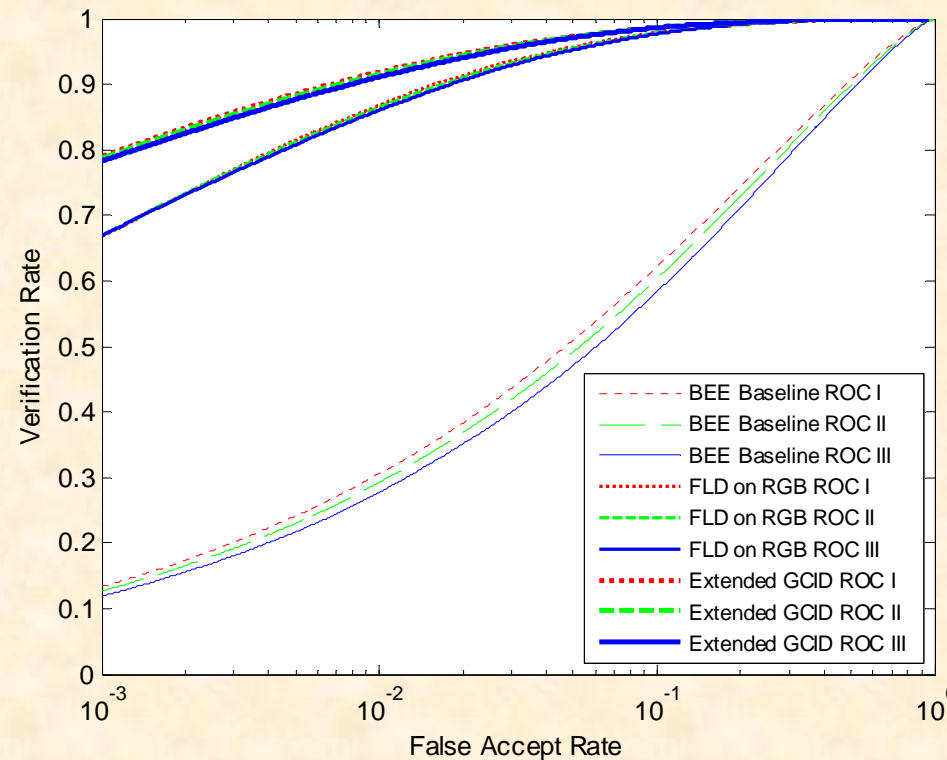
Illustration of R, G, B color component images and the three discriminant color component images generated by the proposed method

Experimental Results



ROC curves corresponding to the BEE baseline algorithm, FLD using the RGB images, and the extended GCID algorithm (for three color components) using the **decision-level fusion** strategy

Experimental Results



ROC curves corresponding to the BEE baseline algorithm, FLD using the RGB images, and the extended GCID algorithm (for three color components) using the **image-level fusion** strategy

Experimental Results

Table: Verification rate (%) comparison when the false accept rate is 0.1% using all of the three color components images

Fusion strategy	Method	ROC I	ROC II	ROC III
Decision-level fusion	FLD on RGB images	59.75	59.14	58.34
	Extended GCID	75.86	76.33	76.71
Image-level fusion	FLD on RGB images	66.68	66.85	66.89
	Extended GCID	78.90	78.66	78.26

Related Publications

- Jian Yang, Chengjun Liu, “A General Discriminant Model for Color Face Recognition”, *Eleventh IEEE International Conference on Computer Vision (ICCV 2007)*, Rio de Janeiro, Brazil, October 14-20, 2007
- Jian Yang, Chengjun Liu, “Color Image Discriminant Models and Algorithms for Face Recognition”, *IEEE Transactions on Neural Networks*, 2008, 19(12), 2088-2098.
- Zhiming Liu, Jian Yang, Chengjun Liu, Extracting Multiple Features in Discriminant Color Space for Face Recognition, *IEEE Transactions on Image Processing*, 2010, vol. 19, no. 9, pp. 2502-2509.
- Su-Jing Wang, Jian Yang, Na Zhang, Chun-Guang Zhou, Tensor Discriminant Color Space for Face Recognition, *IEEE Transactions on Image Processing*, 2011, 20(9), 2490-2501.

Thank you!!!