Physics-based face database for color research

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Abstract. Most face databases are meant for pattern recognition use. We report the creation of a unique face database which may be used for color-related studies of faces. We describe it as physics-based because it not only contains color images but also data on color image formation such as spectral reflectance measurements from facial skin, illuminant spectral power distribution, and camera spectral response. We demonstrate the usefulness of the database by an approach we developed to color correct face images taken under different illumination conditions. © 2000 SPIE and IS&T.

1 Introduction

For many years, researchers in computer vision have built face databases for the purpose of testing face recognition and detection algorithms that can support applications such as surveillance and security, telecommunications, digital libraries, multimedia, and medicine. Recently, color has become a popular cue for detecting persons in a scene because skin color is distinct. Since color is a low-level image attribute, operations performed with color at the pixel level are fast. However, captured colors change as lighting condition changes thus illumination-invariant detection techniques are still being sought.

Besides face detection, there are other face-related areas of research that have a need for color. For example, in computer graphics, skin color models can help animators render more realistic looking faces. In the cosmetics industry, facial skin color and make-up under different illuminants must be known by make-up manufacturers. Skin color has also been used for correcting color reproduction in TV.

There are face databases made up of color images but they cannot adequately support color research. Our goal was to create one that can be used not only for face recognition and detection but for color image analysis as well. Two aspects make our database unique: (1) we took images of faces under different illuminants and different camera calibration conditions, thus capturing the variety of color facial skin can be observed in, and (2) we included features that affect the color of an image, such as the spectral reflectance of skin, illuminant spectral power distribution, and camera spectral sensitivities. The database is available in compact disc.

Using the database we developed a method to correct color shifts in the face under different illumination and camera calibration conditions. The method utilizes the eigenface approach applied to color images. By providing calibrated and color shifted images we explain how our database can support color constancy and color-based face segmentation experiments.

The rest of the article is organized as follows. In Sec. 2, principles of physics-based color machine vision and human skin properties are reviewed. Section 3 presents information on the creation of the physics-based face database. In Sec. 4 we discuss applications of the database, and in Sec. 5 we give our conclusions and recommendations.

2 Color Imaging of Skin

The output signal \( I_{(x,y)} \) of the \( i \)th camera channel \( (i = \text{blue, green, red}) \) at a pixel location can be presented in the form

\[
I_i = \frac{K \int_{\lambda_1}^{\lambda_2} S_{\text{cur}}(\lambda) \rho(\lambda) \eta_i(\lambda) d\lambda}{\int_{\lambda_1}^{\lambda_2} S_{\text{ref}}(\lambda) \eta_i(\lambda) d\lambda},
\]

where

\[
S_{\text{cur}}(\lambda) = \sum_{n=1}^{N} S_{n}(\lambda) \quad \text{and} \quad S_{\text{ref}}(\lambda) = \sum_{n=1}^{N} S_{n}(\lambda)
\]

are the spectral reflectance functions of facial skin and the illuminant, respectively, in the range \([\lambda_1, \lambda_2]\) of the camera spectral response. \( \rho(\lambda) \) is the camera spectral response and \( \eta_i(\lambda) \) is a weighting function that characterizes the illuminant under which the image is taken.

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where \( S_{\text{cur}} \) is the spectral power distribution (SPD) of the current illuminant, \( \rho \) is the spectral reflectance of the object, \( \eta_i(\lambda) \) is the spectral sensitivity of the \( i \)th camera channel, \( K \) is a geometric term, \( S_{\text{ref}} \) is the SPD of the reference illuminant for calibration, and \( \lambda_1 \) and \( \lambda_2 \) are the upper and lower limits of integration, respectively. When \( S_{\text{cur}} \) is the same as \( S_{\text{ref}} \), the camera is said to be white balanced for that illuminant.

The product \( S_{\text{cur}}(\lambda) \rho(\lambda) \) is called the color stimulus and represents the light reflected off an object. Points on the object surface can reflect light in one of the following ways: regular, diffuse, or mixed.\(^{21} \) When mixed reflection occurs, the reflectance \( \rho(\lambda) \) can be expressed as the sum of two parts,

\[
\rho(\lambda) = \rho_d(\lambda) + \rho_r(\lambda) = \rho_d(\lambda) + \rho_r, \tag{2}
\]

where \( \rho_d(\lambda) \) is the diffuse or body reflectance and \( \rho_r(\lambda) \) is the regular (or directional) reflectance. The regular reflectance possesses surface structure information, and is determined by Fresnel’s law. It can be considered constant in the visible spectrum for dielectric materials, while the diffuse reflectance is dependent on wavelength \( \lambda \) and carries information on the chromaticity of the material. The phenomena described form the basis of dichromatic reflection models\(^{22-24} \) that are often used in physics-based machine vision.

Equation (1) can therefore be written as

\[
I_i = K_b \int_{\lambda_1}^{\lambda_2} S_{\text{cur}}(\lambda) \rho_d(\lambda) \eta_i(\lambda) d\lambda + K_r \int_{\lambda_1}^{\lambda_2} S_{\text{ref}}(\lambda) \eta_i(\lambda) d\lambda = C_{ib} + C_{is}, \tag{3}
\]

where \( K_b \) and \( K_r \) are geometric terms for body and surface components, respectively, and \( C_{ib} \) and \( C_{is} \) are color terms for body and surface components, respectively, for the \( i \)th camera channel.

Skin has a layer structure with colorants in each layer. The topmost, the epidermis, contains the brown pigment melanin. As skin cells increase in size, they die out and litter the skin surface. The second and third layers, the dermis, and subcutaneous fat, have the orange pigment carotene. Capillaries across the dermis carry hemoglobin which could be reddish if the blood is oxygenated or bluish if deoxygenated. Light striking skin is transmitted, absorbed, and reflected through each layer. The light that emerges from the skin bears the imprint of these colorants thus skin reflectance is higher in the orange to red wavelengths. Because the uppermost layer of skin is covered with dead cells, it allows us to conclude that the surface of normal skin is more likely a diffusional surface if not covered with additional creams, skin oil, or sweat.

3 Data Acquisition

Section 3 describes the creation of our database. Data acquisition consists of two parts, color image capture and skin reflectance measurements. The illuminant spectral power distribution and camera spectral sensitivities were derived from manufacturer specifications.
Fig. 2 Example of image series from physics-based face database arranged in increasing color temperature order where columns represent the current illuminant and rows represent the reference illuminant. Each image is described by RC where R is the reference illuminant for camera white balancing and C is the current illuminant where the face is captured (H=horizon, A=incandescent A, T=fluorescent TL84, D=daylight).

Fig. 7 Color correction of the image series in Fig. 1 using RGB eigenfaces.
reference illuminant for calibration, \(c\) is the current illuminant, and XXX is the person number. For example, the file ah94.bmp is the image of person No. 94 taken under illuminant H with the camera white balanced for illuminant A. If the person had glasses on, an additional 16 images of the person wearing them were taken and the file names are rclXXX.bmp.

Figure 2 shows an image array for one face when arranged in increasing illuminant correlated color temperature order, where columns represent the current illuminant and rows represent the illuminant for calibration. In this manner, the diagonal represents the calibrated cases where the current illuminant is the same as the reference illuminant. Off-diagonal elements represent uncalibrated or non-ideal cases where the reference and current illuminants differ. Figure 1 illustrates the variety of colors a face may have under different camera and illuminant conditions.

### 3.2 Skin Reflectance Measurements

Skin spectral reflectance was measured with a Minolta CM 2002 spectrophotometer with the surface or specular component excluded [(SCE) option] on three positions on the face: the forehead and the left and right cheeks. The mea-
measurements were from 400 to 700 nm in steps of 10 nm. Women’s faces were measured and imaged without make-up. Figure 3 shows an example of the measurements of one person.

3.3 Contents
At present the database involves 111 individuals of different ethnic origins, sexes, and ages (from 15 to 65). In terms of the three major complexions there are 100 persons with pale skin (of European descent), 5 with yellowish skin (of Asiatic descent), and 6 with dark skin (of African descent). The total number of images is 2112 (90×16) (without glasses)+21×32 (with glasses). The total number of spectral reflectance measurements is 333. A supplement to the database contains 60 (5×3×20) spectral reflectances of 20 faces taken with the specular component included [SCI option]. In addition, the database includes the red, green, blue (RGB) spectral sensitivities of the 3CCD Sony DXC-755P camera and the relative spectral power distributions of illuminants CIE D65, CIE A, TL84, and horizon daylight.

4 Experiments and Potential Applications
4.1 Analysis of Spectral Characteristics
The total spectral reflectance, \( \rho(\lambda) \), measured with the SCI option, for each individual shows slightly higher values than diffuse reflectances, \( \rho_d(\lambda) \), measured with the SCE option (Fig. 4). According to Eq. (2) the regular spectral reflectance, \( \rho_s(\lambda) \), is evaluated as the difference of spectral reflectances, \( \rho(\lambda) \) and \( \rho_d(\lambda) \), measured for the same place on individual faces with options SCI and SCE, respectively. The values obtained showed that, for each wavelength, the regular spectral reflectance, \( \rho_s(\lambda) \), is almost constant \( \rho_r \), and for different persons it is about 1%–1.8% (on a scale of reflectance of 100%). This implies that skin is mostly a matte finish.

Human skin, as with most natural objects, can have some variations in color or surface. To check the uniformity of the spectral reflectance of each human face, the measurements were performed at three different places on the face. To determine the overall goodness of the fit of the measured spectra, the averages \( \Delta \delta_{avg,k} \) of the absolute values of differences averaged over the wavelength band \( \lambda \) for each of pair of curves, \( i \) and \( k \), were calculated as follows:
where $N$ is the number of wavelengths.

Figure 5 shows the average skin spectral reflectance per complexion group. All spectra are similar in shape, have no sharp peaks, and differ mostly by a bias. These observations imply that (1) the spectral reflectance for all complexions can be modeled by a small number of basis vectors and (2) the skin chromaticity for all complexions will be very close and will vary only in the degree of lightness.

For all skin types, the spectral reflectances from three places on the human face are very similar: in most cases (90% of the whole group), all three curves almost overlap or are very close to each other [Fig. 6(d)]; in 10% of the cases, spectral reflectances of the cheeks were very similar [Fig. 6(a)] whereas spectral reflectances of the forehead have slightly smaller values over all wavelength bands [Figs. 6(b) and 6(c)].

### 4.2 Color Image Analysis

From Eq. (1) it can be noted that if the camera is white balanced with light whose SPD is more dominant in higher wavelengths (i.e., reddish, e.g., H or A), images will appear bluish when cast under light with higher power in the lower wavelengths (e.g., D) and vice versa. Each row in the array of Fig. 2 shows the color shifts that a facial image underwent when a camera white balanced for one illuminant is used under a different illuminant. Since the illuminants used are typical of what we encounter in real life, this represents a more realistic scenario than capturing color shifted images by putting red, green, or yellow filters on a light source. If a face segmentation algorithm uses a static skin color model trained under condition HH, it will likely fail in AH unless color correction is performed on the image. Using the database color constancy, techniques can be tested with the calibrated images serving as ground truth. Color constancy can be thought of as getting a transformation matrix that will map the colors observed under some illuminant into colors observed under a canonical illuminant.\(^{26}\)

If the RGB responses are narrow band, the transformation can be simple scaling of the channels.\(^{27}\) One way is by dividing each channel by the observed white ($\rho = 1$) in the current illuminant. From Eq. (1) this is equal to

$$\Delta \delta_{avg,k} = \frac{1}{N} \sum_{i=1}^{N} |\delta_i - \delta_k|, \quad i, k = 1, 2, 3; \quad i \neq k, \quad (4)$$

4.3 **Color Correction by RGB Eigenfaces**

We have developed a method to correct color shifts in face images when captured under different illuminants.\(^{28}\) The eigenface technique for reducing the dimensionality of images\(^{2,29}\) is applied to color images by splitting the image into its R, G, and B channels and performing a singular value decomposition on an ensemble. When ordered according to decreasing eigenvalues, the first few eigenfaces deliver illumination information while the higher eigenfaces hold facial details. Color image reconstruction is accomplished by overlaying the reconstruction from each channel.

Reconstructing an image using only the first three RGB eigenfaces gives an image with color information but little facial details while reconstructing an image using all but the first three RGB eigenfaces gives facial details but little color information. If we then reconstruct a nonideal image using the first three eigenfaces and their coefficients obtained from the calibrated case and retain the reconstruction from the remaining eigenfaces and their coefficients, then we will obtain an image with the original facial details but with corrected coloring.

We have shown in Ref. 28 that transformation of the coefficients of the first three eigenfaces towards ideal values can be learned by a neural network. Figure 7 shows the resulting color correction of the face series in Fig. 2 using this method. Except for the HD condition which has clipped colors, qualitative improvement in facial color is achieved. This method uses only one neural network for various illumination conditions. In contrast, color constancy techniques require one transformation matrix per condition.

### 5 Conclusions

We have reported the creation of a database which can be used for color-related research on faces. It is unique because not only does it contain color images it also contains spectral information from the skin, camera, and illuminants. From the analysis of spectral characteristics of facial skin it was shown that skin is predominantly diffusional and similar across the face. We show the usefulness of the database by a color correction scheme we developed which uses RGB eigenfaces. Potential applications of the database in color constancy and face segmentation were also discussed.

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