Chapter 16
Color Image Spaces

Abstract. The subject of this chapter is color image spaces. In the chapter we provide a brief summary of the different color spaces.

16.1 Introduction

A color space is a means by which color can be specified, created and visualized. In many applications the choice of color space is critical. The reason is that in one color space we may emphasize specific characteristics in an input image which would not be easily identified in a different color space. This is illustrated in the following example.

Example 16.1. Foreground and Shadow Detection in Traffic Monitoring [7]. Segmenting foreground objects is an important step in vehicle tracking and traffic surveillance. Ref [7] is a comparative study of different color spaces for the detection of foreground objects and their shadows in image sequences. The comparative true detection and false detection are listed in Table 16.1.

Table 16.1 Comparative True and False Detection Probabilities

Color Space	Probability of True Detection	Probability of False Detection
RGB	97.3%	0.7%
HSV	88.1%	5.8%
YC_rC_b	97.7%	0.4%
XYZ	96.7%	0.3%
rgb	91.5%	0.4%

Many different color spaces have been proposed in the literature. The commonly used color spaces may be divided into four families [11]:

Primary Systems. The primary color spaces are based on the trichronomatic theory and assume it is possible to match any color by mixing appropriate amounts of the three primary colors. Primary color spaces include RGB, XYZ and rgb. See Fig. 16.1.

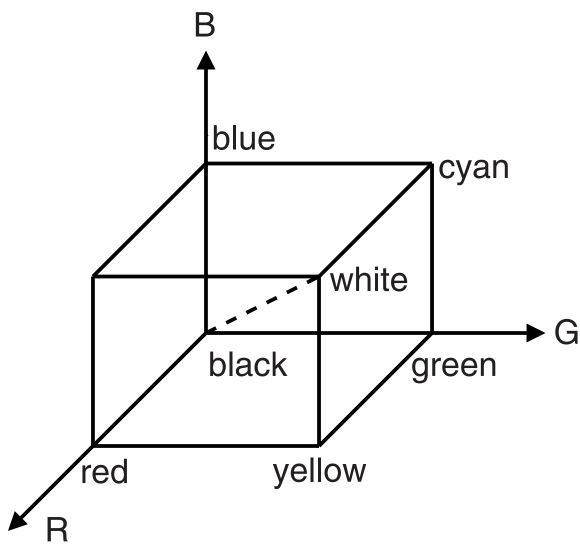

Fig. 16.1 Shows the RGB color space. Several colors are shown mapped into their location in the RGB color space.

Luminance-Chrominance Systems. The luminance-chrominance color spaces use one component to represent the luminance and two components to represent the chrominance. The luminance-chrominance spaces include YC_1C_2, AC_1C_2, $L^*u^*v^*$ and $L^*a^*b^*$.

Perceptual Systems. The perceptual spaces try to quantify the subjective human color perception by means of the intensity, hue and saturation. The perceptual color spaces include IHS, HSV, HLS and IHLS.

Statistical Independent Component Systems. The statistical independent component color spaces use statistical methods to generate components which are minimally correlated. The statistical independent component spaces include $I_1I_2I_3$ and $H_1H_2H_3$.

16.2 Perceptual Color Models

The basic process behind the perceptual color model and the transformation from an RGB coordinate system to a hue, saturation and brightness coordinate system is as follows. For 24-bit deep input image (RGB), we define the achromatic axis in RGB space as the line joining $(0,0,0)$ and $(255,255,255)$ and the chromatic plane as a plane which is perpendicular to the achromatic axis and intersects it at the origin. We then choose a function $L(C)$ which calculates the brightness or intensity of the color $C = (R,G,B)$. The projection of $L(C)$ onto the chromatic plane defines the hue and saturation of C, where the hue corresponds to the angular coordinate around the achromatic axis and the saturation corresponds to a distance from the achromatic axis. *Note*: The hue corresponds to an angular coordinate and is therefore measured in radians or degrees. Fig. 16.2 illustrates the construction of a perceptual color model.

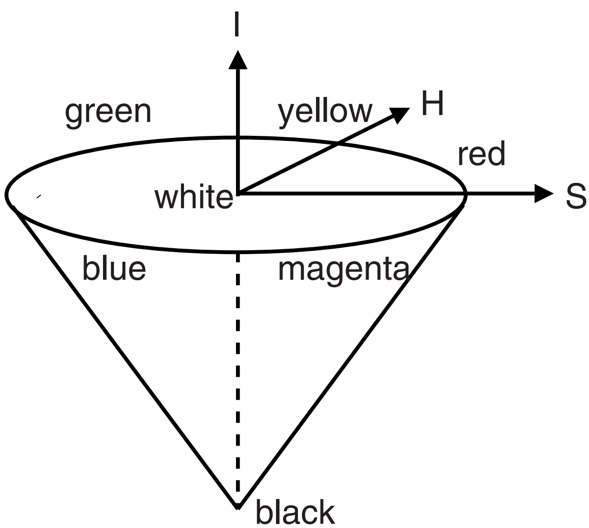

Fig. 16.2 Shows the perceptual color spaces. It has a cone shape where the central axis represents the intensity. Along this axis are all grey colors, with black at the pointed end of the cone and white at its base. The greater the distance along this axis the higher the intensity.

16.2.1 IHS

For image analysis, the most widely used perceptual color model is the IHS model. In the classical IHS model, the brightness, saturation and hue expression are:

$$L_{IHS} = \frac{1}{3}(R+G+B)\,, \tag{16.1}$$

$$S_{IHS} = 1 - \frac{3\min(R,G,B)}{R+G+B}\,, \tag{16.2}$$

$$H_{IHS} = \cos^{-1}\left(\frac{R-\frac{1}{2}(G+B)}{\sqrt{(R-G)(R-G)+(R-B)(G-B)}}\right). \tag{16.3}$$

Sometimes the following algorithm is used to calculate the hue. It contains fewer multiplications and avoids the square root operation:

Example 16.2. Fast Hue Calculation.

if $R=G=B$ then
  $H_{IHS} =$ undefined
else
  if $R \geq B$ and $G \geq B$ then
    $H_{IHS} = \frac{\pi}{3} + \tan^{-1}\left(\frac{\sqrt{3}(G-B)}{G+R-2B}\right)$
  else if $G > R$ then
    $H_{IHS} = \pi + \tan^{-1}\left(\frac{\sqrt{3}(B-G)}{B+G-2R}\right)$
  else
    $H_{IHS} = \frac{5\pi}{3} + \tan^{-1}\left(\frac{\sqrt{3}}{R+B-2G}\right)$
  end
end

There are also many simpler approximate formulas for calculating the IHS transformation. Two widely used approximate transformations are HSV and HLS. However [3, 4] has suggested a better approximate model is the improved HLS (IHLS) transformation.

16.2.2 HSV

The brightness function used in the HSV model is

$$L_{HSV} = \max(R,G,B)\,,$$

and the corresponding HSV saturation and hue expressions are:

$$S_{HSV} = \begin{cases} \dfrac{C_{\max} - C_{\min}}{C_{\max}} & \text{if } C_{\max} \neq 0 \,, \\ 0 & \text{otherwise} \,, \end{cases}$$

$$H_{HSV} = \begin{cases} \text{undefined} & \text{if } S_{HSV} = 0 \,, \\ \left(\dfrac{\pi(G-B)/3}{C_{\max} - C_{\min}} + 2\pi\right) \text{mod}(2\pi) & \text{if } R = C_{\max} \,, \\ 2\pi/3 + \dfrac{\pi(B-R)/3}{C_{\max} - C_{\min}} & \text{if } G = C_{\max} \,, \\ 4\pi/3 + \dfrac{\pi(R-G)/3}{C_{\max} - C_{\min}} & \text{if } B = C_{\max} \,, \end{cases}$$

where $C_{\max} = \max(R,G,B)$ and $C_{\min} = \min(R,G,B)$.

16.2.3 HLS

The brightness function used in the HLS model is

$$L_{HLS} = \frac{C_{\max} + C_{\min}}{2} \,,$$

and the corresponding HLS model saturation and hue expressions are:

$$S_{HLS} = \begin{cases} 0 & \text{if } C_{\max} = C_{\min} \,, \\ \dfrac{C_{\max} - C_{\min}}{C_{\max} + C_{\min}} & \text{if } L_{HLS} \leq 0.5 \,, \\ \dfrac{C_{\max} - C_{\min}}{2 - (C_{\max} + C_{\min})} & \text{if } L_{HLS} > 0.5 \,, \end{cases}$$

$$H_{HLS} = \begin{cases} \text{undefined} & \text{if } S_{HSV} = 0 \,, \\ \left(\dfrac{\pi(G-B)/3}{C_{\max} - C_{\min}} + 2\pi\right) \text{mod}(2\pi) & \text{if } R = C_{\max} \,, \\ 2\pi/3\,\text{deg} + \dfrac{\pi(B-R)/3}{C_{\max} - C_{\min}} & \text{if } G = C_{\max} \,, \\ 4\pi/3 + \dfrac{\pi(R-G)/3}{C_{\max} - C_{\min}} & \text{if } B = C_{\max} \,, \end{cases}$$

16.2.4 IHLS

The brightness function used in the improved HLS or IHLS model [3, 4] is

$$L_{IHLS} = 0.2126R + 0.7152G + 0.0722B\,,$$

and the corresponding IHLS model saturation and hue expressions are:

$$\begin{aligned} S_{IHLS} &= C_{\max} - C_{\min}\,, \\ H_{IHLS} &= \begin{cases} 2\pi - H_{HSI} & \text{if } B > G\,, \\ H_{HSI} & \text{otherwise}\,, \end{cases} \end{aligned}$$

Apart from the above (direct) transformations, there are also indirect IHS transformations.

16.2.5 Indirect IHS Transformation

An indirect IHS transformation consists of linear transformation followed by a non-linear transformation. The following is a common indirect IHS transformation:

Linear Transformation

$$\begin{pmatrix} I \\ v_1 \\ v_2 \end{pmatrix} = \begin{pmatrix} \frac{1}{3} & \frac{1}{3} & \frac{1}{3} \\ -\frac{\sqrt{2}}{6} & -\frac{\sqrt{2}}{6} & \frac{2\sqrt{2}}{6} \\ \frac{1}{\sqrt{2}} & -\frac{1}{\sqrt{2}} & 0 \end{pmatrix} \begin{pmatrix} R \\ G \\ B \end{pmatrix}.$$

Non-linear Transformation

$$\begin{aligned} H &= \tan^{-1}(v_2/v_1)\,, \\ S &= \sqrt{v_1^2 + v_2^2}\,. \end{aligned}$$

The following example illustrates the merging of infrared and RGB color images using a contrast enhanced fusion method based on the linear $\mathrm{Iv_1v_2}$ transformation.

Example 16.3. Merging Infrared and RGB Color Images [8]. Ref. [8] describes the contrast enhanced fusion of a color (RGB) electro-optical image EO and an infra-red image IR. The principal steps in the algorithm are as follows:

1. Transform the EO image into $\mathrm{Iv_1v_2}$ space.
2. Match the infrared grayscale image IR to the electro-optical intensity image I using second-order statistics (Sect. 6.4) [8]. Let $\widetilde{IR}$ denote the transformed IR image.
3. Fuse $\widetilde{IR}$ and I using any pixel-by-pixel fusion operator (Chapt. 7). Let $\widetilde{I}$ denote the fused intensity image.

4. Obtain the enhanced color image, $(\widetilde{R}\widetilde{G}\widetilde{B})$, by performing the inverse $\mathrm{Iv_1v_2}$ transformation:

$$\begin{pmatrix} \widetilde{R} \\ \widetilde{G} \\ \widetilde{B} \end{pmatrix} = \begin{pmatrix} 1 & -\frac{1}{\sqrt{6}} & \frac{3}{\sqrt{6}} \\ 1 & -\frac{1}{\sqrt{6}} & -\frac{3}{\sqrt{6}} \\ 1 & \frac{2}{\sqrt{6}} & 0 \end{pmatrix} \begin{pmatrix} \widetilde{I} \\ v_1 \\ v_2 \end{pmatrix} .$$

16.2.6 Circular Statistics

In perceptual color spaces, standard statistical formula may be used to calculate statistical descriptions of the brightness and saturation values. However the hue is an angular value and so circular statistical formula must be used to calculate statistical descriptors of its values. The following example illustrates the concept of circular statistics.

Example 16.4. Circular Statistics. Given N hue values $H_i, i \in \{1,2,\ldots,N\}$, we may calculate a chrominance vector

$$C = \left(\frac{A}{N}, \frac{B}{N}\right)^T ,$$

where

$$A = \sum_{i=1}^{N} \cos H_i \qquad \text{and} \qquad B = \sum_{i=1}^{N} \sin H_i .$$

The spread of the H_i values around C is

$$V = 1 - \frac{R}{N} ,$$

where

$$R = \sqrt{A^2 + B^2} .$$

In analyzing color images we find it advantageous to use saturation weighted hue statistics. In this case, the corresponding equations are:

$$C_S = \left(\frac{A_S}{N}, \frac{B_S}{N}\right)^T ,$$

where

$$A_S = \sum_{i=1}^{N} S_i \cos H_i \qquad \text{and} \qquad B_S = \sum_{i=1}^{N} S_i \sin H_i .$$

The spread of the H_i values around C_S is

$$V_S = 1 - \frac{R_S}{N} ,$$

where

$$R_S = \sqrt{A_S^2 + B_S^2} .$$

The following example illustrates K-means clustering of the hue space.

Example 16.5. K-means clustering in Hue Space. [12]. In clustering pixels in hue space we require a distance between two hues, i. e. a distance between two angles, ϕ and θ. The simplest distance between two angles is one based on the above circular statistics formulae:

$$d_{circular}(\theta,\phi) = 1 - \frac{1}{2}\sqrt{A^2 + B^2} ,$$

where

$$A = \cos\theta + \cos\phi \qquad \text{and} \qquad B = \sin\theta + \sin\phi .$$

However, $d_{circular}(\theta,\phi)$ is non-linear and distorts the spatial relationships between the patterns. For this reason we recommend using the following linear distance [12]:

$$d(\theta,\phi) = \min(|\theta-\phi|, 2\pi - |\theta-\phi|) .$$

16.3 Multiple Color Spaces

In Ex. 16.1, we showed how the choice of a color space may emphasize specific characteristics in the input image which would not be easily identified in a different color space. We now consider the use of multiple color spaces. We start with a skin classifier (binary classification) which uses an ensemble of multiple color spaces.

Example 16.6. Skin classifier [1]. Detection of skin regions in color images is a preliminary step in many applications such as image and video classification and retrieval. Many different methods have been developed for discriminating between skin and non-skin pixels. In this example we consider the fusion of several skin classifiers which work by expressly defining the boundaries of the skin cluster in a given color space.

Among the skin classifiers are:

Hseih *et al.* [5]. Uses the IHS color space. The skin pixels satisfy at least one of the following rules: (1) $I > I_1$, $S_1 \leq S \leq S_2$ and $0 < H \leq H_1$, (2) $I > I_1$, $S_1 \leq S \leq S_2$ and $H_2 \leq H \leq 360\,\text{deg}$, (3) $I > I_1$, $S_3 \leq S \leq S_4$ and $H_3 \leq H \leq (H_2 - 1)$. For 24-bit color pictures [1] recommends $I_1 = 84$, $S_1 = 26$, $S_2 = 92$, $S_3 = 82$, $S_4 = 67$, $H_1 = 13$ deg, $H_2 = 337$ deg, $H_3 = 310$ deg.

Kovac *et al.* [6]. Uses the RGB space. For uniform daylight illumination the skin pixels satisfy all of the following rules: (1) $R > R_1, G > G_1, B > B_1$, (2) $\max(R,G,B) - \min(R,G,B) < \Delta$, (3) $|R - G| > L, R > G, R > B$. For flash-light illumination the rules are: (1) $R > R_2, G > G_2, B > B_2$, (2) $|R - G| \leq L$, $B < R, B < G$. For 24-bit color pictures [1] recommends $R_1 = 111, G_1 = 77$, $B_1 = 33, \Delta = 47, L = 29, R_2 = 191, G_2 = 251, B_2 = 196$.

Tsekeridou and Pitas [10]. Uses the HSV color space. The skin pixels satisfy all of the following rules: (1) $V \geq V_1$, (2) $S_1 < S < S_2$, (3) $0 \leq H \leq H_1$ or $H_2 \leq H < 360\,\text{deg}$. For 24-bit color pictures [1] recommends $V_1 = 52$, $S_1 = 0.25, S_3 = 0.64, H_1 = 35$ deg, $H_2 = 349$ deg.

Gomez and Morales [2]. Uses the rgb color space. This is defined as follows: $r = R/(R+G+B), g = G/(R+G+B), b = B/(R+G+B)$. The skin pixels satisfy all of the following rules: (1) $r/g > k_1$, (2) $rb/(r+g+b)^2 > k_2$ and (3) $rg/(r+g+b)^2 > k_3$. For 24-bit color pictures [1] recommends $k_1 = 1.148, k_2 = 0.054, k_3 = 0.128$.

Each of the above classifiers generates a binary map $B_k(x,y)$, where

$$B_k(x,y) = \begin{cases} 1 \text{ if } k\text{th classifier declares pixel } (x,y) \text{ a skin pixel} , \\ 0 \text{ otherwise} . \end{cases}$$

The individual pixel classifications may then be combined using the majority vote operator:

$$\widetilde{B}(x,y) = \begin{cases} 1 \text{ if } \sum_k B_k(x,y) \geq K/2 , \\ 0 \text{ otherwise} . \end{cases}$$

16.4 Software

COLOR SPACE CONVERTER. Matlab m-file for color space conversion. Available from Matlab central directory. Author: Pascal Getreuer.

16.5 Further Reading

Ref. [9] discusses the issues involved in selecting different color spaces for image feature detection.

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