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CREATING RGB IMAGES FROM HYPERSPECTRAL IMAGES USING A COLOR MATCHING FUNCTION

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ABSTRACT

Hyperspectral images (HSI) are composed of hundreds of spectral bands, covering a broad range of the electromagnetic spectrum. However, images can only be visualized using three spectral channels for red, green, and blue (RGB) colors. Generating realistic RGB images using HSI is seldom the main focus of remote sensing researchers, and is therefore sometimes lacking. In this paper, we present an algorithm which creates realistic color images of HSI, using standardized methods. Research, conducted on the human perception of color in the 1920s culminated in the CIE 1931 XYZ color space. The algorithm maps every spectral band in the visible spectrum to the XYZ color space, using D65 as the reference illuminant, and then maps the XYZ to the sRGB (standard Red Green Blue) color space. The image is gamma-corrected and finally thresholded to improve contrast. The method was validated using two HSIs, creating realistic color images.

1. INTRODUCTION

Photographic interpretation refers to the manual work where a human analyses a photo and extracts information from it. It is based on the premise that the image, depicts the objects of the image realistically. Images are visualized either in black and white, using one channel, or in color using three channels. The problem facing HSI is how to display the image, which contains 100s of spectral bands, using only three channels, without losing valuable spectral information. A common approach is choosing one band for blue (450-485 nm), green (500-565 nm), and red (625-740 nm) [1], respectively. Band selection is not standardized, and it varies between researchers how spectral bands are selected. Therefore, color images of common HSI datasets can differ vastly between papers. In addition to this, researchers seldom apply gamma correction, which leads to overly dark images.

   Color is perceived through cone cells in the eyes. There are three different types of cone cells, each sensitive to specific wavelengths of light: blue, green, and red; or short,

medium, and long wavelengths [2]. In 1931, the International Commission on Illumination (CIE), created the CIE 1931 XYZ and CIE 1931 RGB color spaces [3]. These color spaces cover the whole gamut of perceivable colors. They were based on a series of experiments conducted on the human perception of color. Researchers found that every perceivable color could be recreated by combining light of different wavelengths. In the experiments, subjects were asked to match a reference color by blending the three primary light colors: red, green, and blue. Subjects were able to tune the brightness of each light source until the correct match was found. Not every color was reproducible using these three lamps. However, when the red light was directed at the reference color, subjects were able to recreate the color using the green and blue light. Adding a primary color to the reference color was referred to as "negative light". To get around negative values for light, the researchers formulated the XYZ color space. The CIE 1931 RGB color space was mapped to a space were every value was positive, called the CIE 1931 XYZ color space.
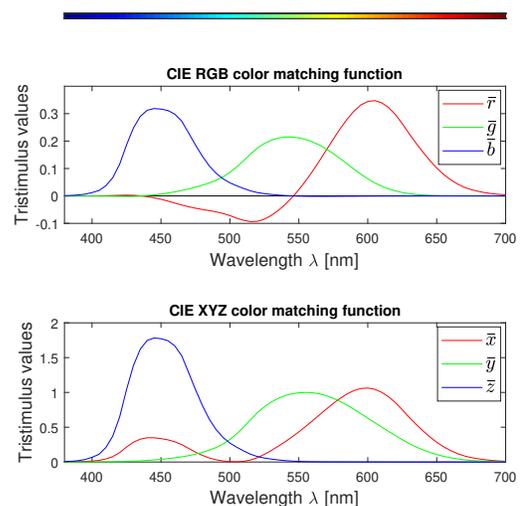
Fig. 1: The CIE RGB (above) and XYZ (below) color matching functions.

Fig. 1 shows the two-color matching functions that were derived from the experiments. The upper plot shows how negative values ("negative light") of $\bar{r}$ were needed to create cyan, in contrast to the graph below where every value is positive.

The CIE XYZ color space is a mathematical description of every perceivable color and, therefore, it is device-independent. However, no electronic monitor can replicate the whole gamut of the XYZ color space. For that reason, other color spaces were created to standardize the reproduction of color. An RGB color space is defined by the XYZ coordinates of its red, green, and blue primaries; and its white color. The boundary defined by those coordinates, specifies which color the color space can reproduce. A linear transform describes the relationship between the XYZ color space and other RGB color spaces [4]. Standard Red Green Blue (sRGB) [5] was developed by Hewlett-Packard and Microsoft in 1996 as the standard color space for the internet and electronic devices. It covers a much smaller color spectrum than the human eye can perceive, but it can be used by every monitor, printer, and digital camera, ensuring that the color is reproduced the same way. A two-dimensional representation of the XYZ and sRGB color space is shown in Fig. 2.
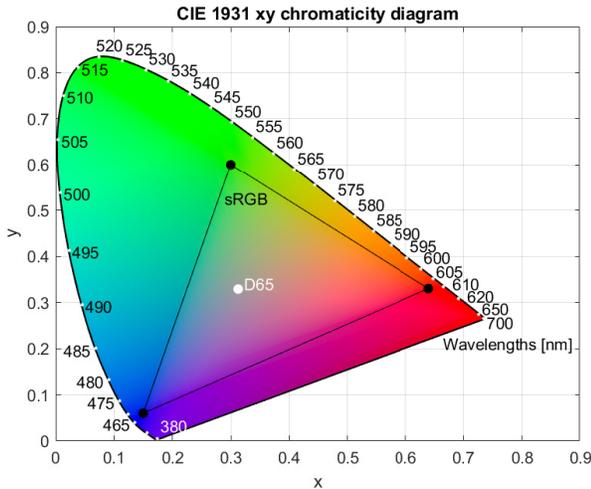
Fig. 2: CIE 1931 xy chromaticity diagram [2], which is a hyper plane of the XYZ color space for a fixed luminance Y, $x = X/(X + Y + Z)$, $y = Y/(X + Y + Z)$. Wavelengths of light are shown around the edges. The triangle shows the gamut of colors that sRGB can recreate. D65 is the reference illuminant, which specifies the white point.

1.1. Prior Work

Other methods have been proposed for displaying hyperspectral images in color, such as principal component analysis (PCA) [6], where the first three components are assigned to the red, green, and blue channels. PCA highlights important features in an image, though it will not recreate the true colors

of the image. The paper [7], compared a number of classification and transformation based approaches, to display HSI in color. Their aim was to maximise class separability in HSI, and not to create realistic color images. The stretched CMF was introduced in [8], where the RGB CMF in Fig. 1 was stretched to cover the whole range of the AVIRIS hyperspectral sensor. In [9], the stretched CMF and normalized information measures were used for band selection, to create natural looking HSI color images while maximizing their information content. In [10], a convolutional neural network (CNN) and an intensity-hue-saturation transform (IHS) were used to create realistic color images from hyperspectral data, utilising the whole spectral range. The downside of this approach is the training of the CNN, which can be time-consuming for larger images.

1.2. Main Contribution

We propose that authors displaying RGB images of HSIs in their publications use a color matching function (CMF), which maps the visible spectrum of hyperspectral data to the XYZ color space and from there to the sRGB color space. The method is fast, standardized, deterministic, and creates a realistic image. We define realistic as a simulation of human perception under open-air daylight illumination. The method only requires the HSI and its wavelengths. To facilitate this, we publish both Matlab and Python code that can be used for creating realistic RGB images for HSI.[1]

2. METHODS

2.1. Spectrum to XYZ

The reflectance values for the image are normalized to $[0, 1]$. The spectral bands in the visible range of the hyperspectral image are then mapped to the XYZ color space, using (1) [2], where Y is the perceived luminance, and X, Z are the perceived colors.

$$X = \frac{1}{N}\sum_\lambda S(\lambda)I(\lambda)\bar{x}, \quad Y = \frac{1}{N}\sum_\lambda S(\lambda)I(\lambda)\bar{y}$$
$$Z = \frac{1}{N}\sum_\lambda S(\lambda)I(\lambda)\bar{z}, \quad N = \sum_\lambda I(\lambda)\bar{y} \tag{1}$$

For spectral band $\lambda \in [380, 780]$ nm, $S(\lambda)$ is the spectral reflectance of the sample, $I(\lambda)$ is the spectral power distribution of the reference illuminant, and $\bar{x}$, $\bar{y}$, and $\bar{z}$ are the CIE standard observer functions. N scales the values so that $Y = 1$ is the white color. There are many possible reference illuminants, we use D65, which has a correlated color temperature of approximately 6500 degrees kelvin and represents average daylight [2].

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[1] https://github.com/JakobSig/HSI2RGB

2.2. XYZ to RGB

The transformation from XYZ to another color space is done by multiplying the $[X, Y, Z]^T$ vector by a 3×3 matrix $\boldsymbol{M}$

$$\begin{bmatrix} R \\ G \\ B \end{bmatrix} = \boldsymbol{M} \begin{bmatrix} X \\ Y \\ Z \end{bmatrix}$$

The matrix $\boldsymbol{M}$ specifies which color space XYZ is transformed to. $\boldsymbol{M}$ depends on the coordinates of the red, green, and blue primaries of the corresponding color space and which reference illuminant is used [5]. For sRGB using D65, $\boldsymbol{M}$ is

$$\boldsymbol{M} = \begin{bmatrix} 3.2406255 & -1.5372080 & -0.4986286 \\ -0.9689307 & 1.8757561 & 0.0415175 \\ 0.0557101 & -0.2040211 & 1.0569959 \end{bmatrix}$$

2.3. Gamma Correction

Computer monitors have a non-linear relationship between their input voltage, and their corresponding output luminance. Gamma correction, is used to counter the non-linear response of the monitors, so that images are displayed correctly [11]. This is done by encoding the luminance values of images. Without gamma correction, images look overly dark. The gamma function for sRGB [5], where u is R, G, or B, is as follows

$$\gamma(u) = \begin{cases} 12.92u & , u \leq 0.0031308 \\ 1.055u^{0.416} - 0.055 & , \text{otherwise} \end{cases}$$

3. EXPERIMENTS AND RESULTS

Our implementation of the color matching function was compared to the band selection method using two well known HSIs, the HYDICE urban image, and the ROSIS Pavia University image. The urban HSI is composed of 162 spectral bands and has the size 307×307 pixels. The Pavia University image has 103 spectral bands and contains 610×340 pixels. Thresholding and gamma-correction were used for both methods so that they only differ in color channels. Fig. 5 shows the results from the CMF and band selection method on the two datasets. The histograms of the red, green, and blue channels are compared in Figures 3 and 4.

There is not a stark visual difference between the color matching function and the band selection method. The images from both methods are realistic. However both images using band selection result in overly saturated green colors of the grass. This is also the case when their histograms are compared. The band selected histograms have the same form as the CMF, though they are not as smooth as the CMF histograms.

The CMF gives consistent, realistic results, does not need prior training, and only requires the specific spectral band
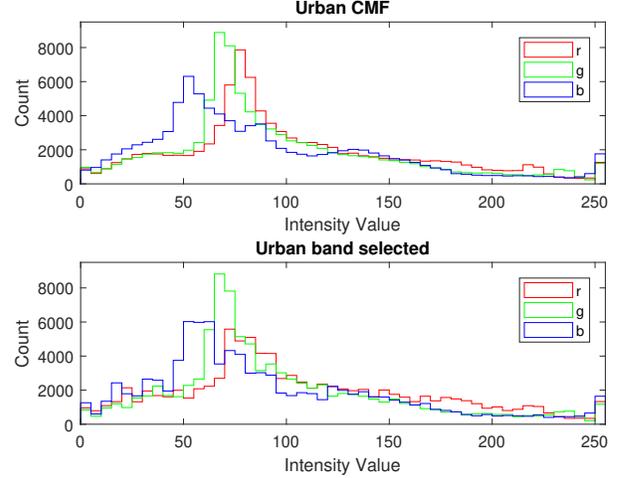
Fig. 3: Histogram of the RGB channels of the Urban dataset, band selected (above) and color matched (below).
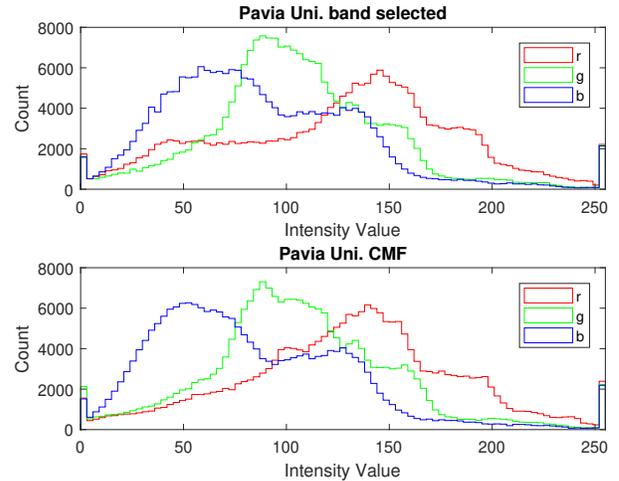
Fig. 4: Histogram of the RGB channels of the Pavia university dataset, band selected (above) and color matched (below).

names to process a hyperspectral image. The processing time was 0.29 sec for the urban image, and 1.21 sec for the Pavia university image. The processing time increases as the images grow larger, it is still fast and gives an accurate color image immediately.

4. CONCLUSION

We have a CMF for HSI to create realistic RGB color images. The method transforms the visible spectral bands of hyperspectral images, to the three-channel XYZ color space, and then maps the XYZ colors to the sRGB color space. The method is fast and provides a standardised way of visualising hyperspectral images in realistic colors.

Fig. 5: A comparison between the CMF (column 1 and 2) and the band selection method (column 3 and 4) on the urban dataset (top row), and the Pavia university dataset (bottom row).

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