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Spectrum Modeling Using only RGB Values

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Abstract. The most effective approach to achieving color consistency lies in accurate spectrum modeling, and the key to recover a faded spectrum is to recall the chromogenic metamer. In this paper, a spectral modeling mechanism is designed utilizing three primary colors as its core. Spectral recovering has been completed for all of the 1269 Munsell colors with corresponding RGB parameters. With both maximum entropy (ME) and least mean square error (LS) objectives, the mechanism works well with a result of 0.0046 as the average mean square error in the whole Munsell color space. The contribution of our approach not only lies in the accurate conversion from RGB to spectrum, but also in developing a set of color metamers for chromogenic methods of color calibration.

Keywords. Spectrum Modeling, chromogenic metamer, maximum entropy, color constancy

1. Introduction

Color constancy plays a vital role in image recognition for intelligent machines. Without color constancy algorithm, mobile robots may misjudge out the color of substances, especially due to the illuminant changing. As a matter of fact, when a color is captured by a color camera in RGB format, its spectral information decreases or is lost largely [1]. On the other hand, the color-matching functions can't be precisely identical to a variety of visual-system sensitivities. With RGB color-matching functions as the foundation of metamerism, matching lights in color are so different spectrally. That is the main reason why dynamic calibration is difficult in changing illumination. Visual sensing of intelligent machines is enhanced when surface properties (including color) of objects can be reliably estimated, despite changes in the ambient lighting conditions. Therefore, the best way of color constancy lies in efficient spectrum estimation, while the key to recovering a faded spectrum is to recall the chromogenic metamer—color genes as can be called. As a physical property of a color material, chromogenic spectrum is its real identification (ID).

In fact, spectral representation of color is a popular topic of investigation [2-5], and many methods have been developed for color constancy. One of the most popular constancy algorithms is the linear model proposed by Maloney and Wandell [2]. They described a computational method for estimating surface spectral reflectance to represent

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spectra with a linearly weighted sum of spectral basis functions, but without accuracy given. Ho, Funt, and Drew [3] separated surface and illuminant spectra using linear model representations from the color signals. D'Zmura and Iverson [4,5] also used a linear model for surface and illuminant spectra. Finlayson, Hordley and Morovic proposed a chromogenic filter method for spectral estimation [6], they showed that the choice of filter does have a significant effect on algorithm performance [7]. Parkkinen et al. analysed Munsell colors and computed characteristic vectors of the correlation matrix of its sample set. They showed that as many as eight characteristic spectra are need to achieve good representation for all spectra, but did not research the reconstruction of color spectra [8]. Clark, J.J. and Skaff, S. investigated the use of a maximum entropy spectral model for surface spectra from photoreceptor measurements [9]. It is shown that the maximum entropy models have similar performance to linear PCA-based models, even though they require no priori information [9]. Artificial neural networks are biologically inspired non-linear methods that are usually treated as black boxes. The performance of neural networks depends heavily on high-quality big data usually for pattern identification [10]. The main drawbacks are their high dimensionality and no mathematic formula representation of color spectra.

In this paper, we show the feasibility of spectrum modeling based on the three primary color spectra associated with three RGB parameters. In order to get spectral models for color calibration, spectra modeling for 1269 Munsell color patches [11] have been completed utilizing three primary colors [12,13], with maximal entropy (ME) as well as least mean square error (LS) objectives.

2. Principles of color representation and spectrum modeling

Figure 1 represents a color experiment system. Munsell color patches are taken as testing samples. A camera of high quality is used as the receptor. The selection of light source for illumination depends on different measurement systems which will be introduced later.

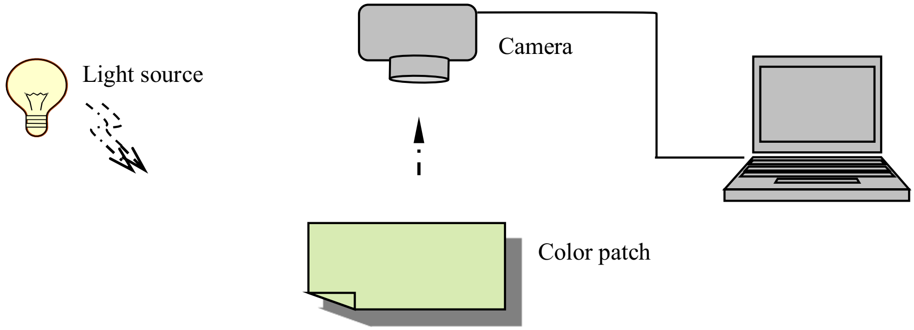


Figure 1. Diagram of color experiment system.

Colors can be expressed as RGB compositions, and in terms of spectrum, image formation of Lambertian surfaces can be written as:

$$p_k = \int_{\omega} q_k(\lambda) f(\lambda) r_s(\lambda) e(\lambda) d\lambda \tag{1}$$

where p stands for the intensity of a channel; the subscript k indicates the *R, G, or B* channel; the integral is evaluated over the visible spectrum band ω; $f(\lambda)$ is the function of a filter in front of the camera; $e(\lambda)$, $r_s(\lambda)$ and $q_k(\lambda)$ denote spectra of illuminant light, reflectance of surface, and k-channel sensitivity of sensor respectively. In the actual discrete algorithm, formula (1) can be written as follows:

$$p_k = \sum_{\lambda=1}^{M} q_k(\lambda) f(\lambda) r_s(\lambda) e(\lambda) \tag{2}$$

where $\mathrm{M} = 61$ for wavelength ranging from 400nm to 700nm, in increments of 5nm. In array form,

$$\mathrm{P} = \mathrm{Q} \cdot \mathrm{F} \cdot \mathrm{RS} \cdot \mathrm{E} \tag{3}$$

The reflectance spectra of 1269 matt Munsell color chips are measured with Perkin-Elmer lambda 9 UV/VIS/NIR spectrophotometer. Wavelength ranges from 380 nm to 800 nm and the wavelength resolution equals to 1 nm. There are 1269 different colors measured and every single color contains values of 421 channels from 380 nm to 800 nm with one nanometer step. In the 421x1269 munsell matrix, each column is one 421 component spectrum. The color coordinates (RGB) are calculated by using D65 light source and they are stored in the column vectors [14]. Another group of color data was measured by Sandra [9], with Tunsten light as the illuminate source; WV-CP410 model camera was used as the receptor; Munsell color patches as the testing samples. For every color we sampled 61 spectral points according to wavelength from 400nm to 700nm with an interval of 5nm

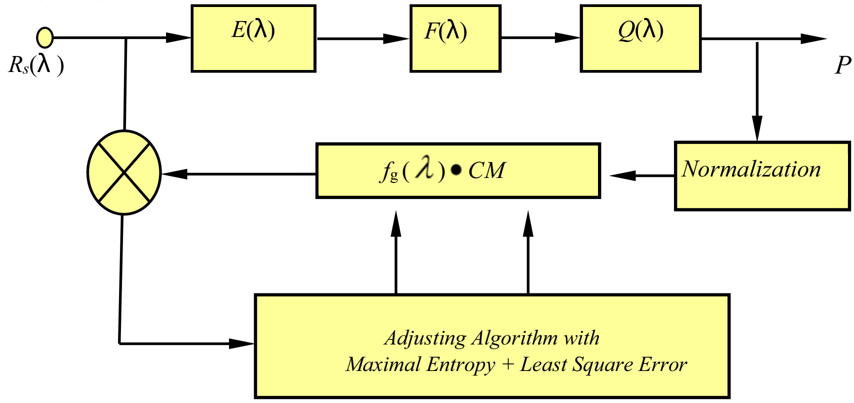


Figure 2. Mechanism diagram of spectral modeling system.

Figure 2 presents the diagram of spectral modeling system designed. Representing a physical property, $R_s(\lambda)$ is the surface reflectance spectrum group of the color patch samples, $E(\lambda)$, $F(\lambda)$, $Q(\lambda)$ are the spectra of illuminant, filter and photoreceptor respectively. $f_g(\lambda)$ is a soft filter designed for correcting the error of linear representation as well as illuminant, which will be further described later.

As the core of the whole modeling system, the color basis function CM was constructed by incorporating the photoreceptor's sensibilities and the acknowledged three color primaries. It can be expressed as follows:

$$CM = CM_1 + g \cdot CM_0 \tag{4}$$

where CM_1 is a typical characteristic selected as the standard sensitivity triplets; CM_0 are the three color primaries; g is a coefficient automatically adjusted during system optimization. It depends on the photoreceptor or camera used. Tunable color triplets are formed so as to be applicable to a variety of photoreceptors (cameras) and color data measured in later unknown conditions.

A filter was defined to be chromogenic if the relationship between filtered and unfiltered RGBs varies with and depends strongly on illumination [7]. Here, the color spectra correspondingly matched with RGBs can be called as the chromogenic metamer. With the basis function as the core of estimation formula adjusted by a soft filter on the first level, this modeling mechanism operates using maximum entropy (*ME*) [9] as well as *LS* objectives.

$$u = f_g(\lambda) \cdot (CM \cdot P) \tag{5}$$

where CM is the color basis function of this algorithm formula, *P* are the RGB values of color measured. $f_g(\lambda)$ is the soft filter which is different from a common digital filter for smoothing curves. It has been proven that it is sensitive to the changing of the illuminant. There are two ME engines in the modeling mechanism: finding optimal weights of three basis spectra with maximal entropy and minimum modeling error in whole color space.

$$\alpha_{\max en} = \arg\min\left\{\sum_{j=1}^{M} m(j)\log[m(j)]\right\} \tag{6}$$

$$m(j) = \frac{\exp\left[\sum_{i=1}^{3} \alpha_i CM_i(j)\right]}{\sum_{j=1}^{M} \exp\left[\sum_{i=1}^{3} \alpha_i CM_i(j)\right]}$$

Here, finding the minimum to get maximal entropy is due to negative logarithm values.

$$f_g(\lambda)_{\max en} = \arg\min\left\{\sum_{k=1}^{N} v(k)\log(v(k))\right\} \tag{7}$$

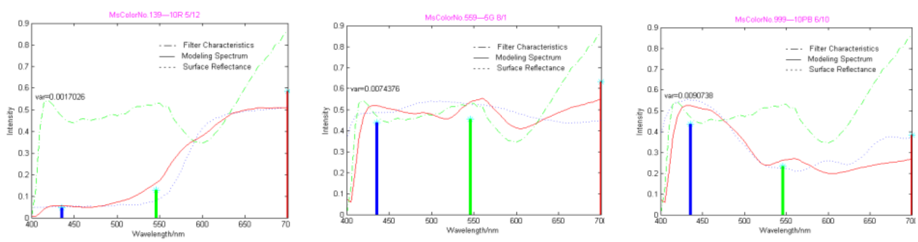
$$v = \sum_{j=1}^{M} \left[u(j) - s(j)\right]^2$$

It is convenient to complete optimization above with the help of MATLAB tools.

3. Performance and results

In Figure 3, the solid curve (red) is the modeled spectrum with experimental data. The dashed curve (blue) is the reflectance spectrum of Munsell color patch. The dash dot curve (green) is the characteristic spectrum of the filter. The upright posts (blue at 435.8nm, green at 546.1nm, red at 700nm) stand for the three color values, supporting their corresponding spectrum. The modeling curves above are only three typical performance of this modeling system. Practically, all the 1269 Munsell colors have been processed and tested as one group. In addition, another group of Munsell color data with unknown experimental conditions has also been test with an inferior result. Note that the filter characteristic curve remains the same for all colors in the whole Munsell space.

One of the two groups of data is without illumination spectrum, which is not a shortage of this modeling approach, but just another advantage considering its flexibility to different illuminants as the data used are from experiments and associated with illuminants.



(a) No.139 Munsell color (b) No.559 Munsell color (c) No.999 Munsell color

Figure 3. Color spectra modeling curves.

4. Discussion and conclusions

Every chromogenic metamer of color consists of triplets supported by corresponding RGB parameters. In other words, chromogenic metamer selected consists of RGB values associated with three basis spectra. This modeling algorithm works well with a result of 0.0046 as the average mean square error. In addition, the Gamma correction error was not counted for the camera's sensitivities. If the Gamma correction error is involved in software, a much better result can be expected. Table 1 shows the comparison of this method proposed with other methods.

With a conversion from RGB to spectrum completed for the first time to our knowledge, we have demonstrated the feasibility of the idea that chromogenic metamer of color consists of extended three primary spectra associated with RGB parameters. The modeling accuracy is better than other representations before [9], with spectral estimation comparable to deep neural networks [10]. However, it is worth noting that our method is simple, efficient and less data-hungry.

Table 1. Performance comparison of modeling algorithms.

methods	minVAR	maxVAR	averageMSE
Linear	0.0133	0.1754	0.0890
PCA-based	0.0025	0.0260	0.0128
Max-Entropy+RGB	0.0017	0.0091	0.0046

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References

[1] Clark, J.J., Skaff, S. Maximum entropy models of surface reflectance spectra. Proceedings of the 22nd IEEE Instrumentation and Measurement Technology Conference, May 17-19 2005; Ottawa, ON, Canada; Vol.2. p. 1557-1560. doi: 10.1109/IMTC.2005.1604413

[2] L. T. Maloney, B. A. Wandell. Color constancy: A method for recovering surface spectral reflectance. J. Opt. Soc. Am. A. 1986; 3: 29-33. doi: 10.1016/B978-0-08-051581-6.50034-9

[3] J Ho, B.V. Funt, M.S. Drew. Separating a color signal into illuminant and surface reflectance components: Theory and applications. IEEE Transactions on Pattern Analysis and Machine Intelligence. 1990; 12(10): 966-977. doi: 10.1109/34.58869

[4] M.D.D'Zmura, G.Iverson. Color constancy III: General linear recovery of spectral descriptions for lights and surfaces. Journal of the Optical Society of America A. 1994; 11(9): 2389. doi: 10.1364/josaa.11.002389

[5] Brainard D.H., Freeman W.T. Bayesian color constancy. Journal of the Optical Society of America. A. 1997; 14(7): 1393-1411. doi: 10.1364/josaa.14.001393

[6] G. D. Finlayson et al. Color constancy using the chromogenic constraint. Proceedings of the 2005 IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'05). p.1063-6919. doi: 10.1109/CVPR.2005.101

[7] G. D. Finlayson, S. D. Hordley, P. M. Morovic,chromogenic filter design. AIC Colour 05-10th Congress of the International Colour Association.

[8] Parkkinen et al. J. Opt. Soc. Am. A. 1989 February; 6(2):318-322.

[9] Skaff, S., Clark, J.J. Maximum entropy spectral models for color constancy. Proceedings of the 15th IS&T/SID's Color Imaging Conference; 2007 Nov 5-9; Albuquerque, NM, USA. p. 100-105. doi: 10.2352/CIC.2007.15.1. art 00019

[10] Hu Chang-Hui;Yu Jian,Wu Fei, et al. Face illumination recovery for the deep learning feature under severe illumination variations [J]. Pattern Recognition. 2021; 111: 107724-107728. doi: 10.1016/j.patcog.2020.107724

[11] Munsell book of color-matte finish collection (Munsell Color, Baltimore, Md., 1976.)

[12] Stockman, A., Sharpe, L. T. Spectral sensitivities of the middle- and long-wavelength sensitive cones derived from measurements in observers of known genotype. Vision Research. 2000; 40: 1711-1737. doi: 10.1016/s0042-6989(00)00021-3

[13] David R. Bull, Fan Zhang. Intelligent image and video compression (Second Edition). 2021.

[14] http://spectral.joensuu.fi/