Colors as Seen by Humans and Machines

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Abstract

The human visual system often correctly interprets a color cast in the scene as being caused by the illuminant. This awareness typically allows us to discount the illuminant when judging the color of an object. In photofinishing and camcorder applications, machines are expected to perform the same type of discounting of the illuminant. The computational issues involved turn out to be very difficult. This paper will examine the assumptions behind current color constancy models and review some of the current automatic color balance algorithms for photographic printers and camcorders.

Introduction

Studies related to human color constancy can be traced back more than one hundred years.[1] Several models have been proposed to explain how it might work, but none has produced satisfactory results for complex images. Recent work on computer vision offers additional algorithms for very limited lighting and reflection surfaces. In photofinishing applications, a similar problem is known as color exposure control, and in electronic imaging it is known as white balance control. More than 50 years of research on these consumer products has produced fairly respectable results. Amazingly, all this industrial achievement is accomplished with only a very small number of insightful ideas. In this paper we will attempt to briefly summarize the major models and ideas that have been developed so far.

Color Constancy by Humans

Although it may not be agreed to by all experts, we will tentatively propose that there are two major mechanisms that are known to maintain approximate color constancy across different illuminations: chromatic adaptation and computational normalization. The chromatic adaptation refers to the gain control of the neurons that process the color signals, while the computational normalization refers to the parallel comparison and computation on all the elements in the visual field to derive the perceptual correlates of the final perceived colors in our mind. This simple description has some obvious difficulties. For example, we do not know all the neurons that process color signals and how they adjust their gains. Also, one could say that the computational normalization is part of the neural gain control. However, experimental evidences suggest that the two mechanisms can be differentiated at least by their speed of action. Although certain visual threshold adjustment[2] takes place in less than 50 ms, chromatic adaptation requires several seconds to come to a stable color appearance.[3] On the other hand, the computational normalization is accomplished in "a flash of light".[4] Brill and West thus propose chromatic adaptation and color constancy as a possible dichotomy.[5] However, we consider that both chromatic adaptation and computational normaliza-tion work together to achieve the stable perception of colors.

If we view an indoor scene under one illuminant (say, a fluorescent light) for a long time, and then the illuminant is suddenly changed to a tungsten light, our perception of the object colors is temporarily unstable but they do not become unrecognizable. Gradually, color appearance becomes stable, although the object colors do not look exactly the same as before. Even though color constancy is only approximate,[6,7] object colors are generally recognizable.[8] We also have a clear sense of the qualitative change in the illuminant color. This sense allows us to discount the chromatic bias imposed by the illuminant.[6,8] This raises the important distinction between the "sensation" and the "perception" of color, the latter being the illuminant-discounted results of the former. Roughly speaking, the sensation is affected by the chromatic adaptation and the perception is mainly determined by the computational normalization.

Aspects of Color Constancy

Although the major focus of color constancy research has been on the "constancy" of perceived surface colors under change of illumination (either at different times or in different eyes), there are other related issues that need closer examination within the framework of color constancy. First, an extended object almost always receives different illumination on different parts of its surface, and yet this subtle variation of surface color is rarely noticed if it is noticeable at all. The perception of a constant color (mostly hue and saturation) across a homogeneous object surface is in itself a manifestation of color constancy in the spatial domain. For example, a curved surface under the sun will receive proportionally more direct sunlight on the part that faces the sun than the part that faces away from the sun. In the extreme case, with a careful examination, one can see that the more "sunny" part is indeed more yellowish that the less sunny part. The fact that it takes very careful examination to see the color variation across a surface means that the subtle change in color is suppressed by cognition, i.e., the color perception is dominated by the object and form perception. The fact that it is observable means that the color sensation is not normalized out completely. Secondly, as we move around an object and look at it from different angles, the perceived color of the object remains stable although the spectrum of the light coming into the eyes has undoubtedly changed because of local variation in illumination and mutual reflection from the surrounding surfaces. This temporal stability is another manifestation of color constancy in the temporal domain when no major change in the main light source has occurred.

The other issue regarding color constancy is the question of what aspects of the surface colors are "perceived as constant" under different illuminants. One can argue that the spectral reflectances are independent of the illumination, and the computational problem of color constancy is to recover or estimate the surface spectral reflectances.[9] Alternatively, one can assume a fixed canonical light and the problem of color constancy is to compute the transformation from the tristimulus values (r, g, b) under one illuminant to the tristimulus values (r_c, g_c, b_c) under the canonical light.[10] This view is similar to the working assumption in the exposure control algorithm for photographic printers[11, 12] that the printer corrects the image so that it will be printed as if it were taken under a standard illuminant, say D55. Still another view of color constancy maintains that the goal is to recover three reflectance factors[13] (the surface reflectance relative to that of a perfect white diffuser under the same lighting and imaging geometry).

In order to account for human color constancy, all the models still have to explain how the computed quantities, the spectral reflectances, the transformed tristimulus values, or the reflectance factors, can be mapped to the perceived colors.

The von Kries Coefficient Law

Almost all our sensory mechanisms adapt to the prevailing level of stimulus and change their operating range accordingly. The L, M, and S cones in the human retina adjust their gains or operating range according to the overall intensity of the incident light. Adjustment of sensory response can take the form of subtractive or multiplicative operations. After considering the relevant data, von Kries proposed that to a first-order approximation, chromatic adaptation works as a multiplicative gain control. If the sensor response to a diffuse white target under illuminant A is w_A and that under illuminant B, w_B, then any sensor response under B, r_B, is related to that under A, r_A, by:

$$r_B = (\frac{w_B}{w_A})r_A.$$

This type of adaptation is called the complete von Kries adaptation, because the sensor responses to the same white object under two different illuminants are adjusted to be identical. Experimental results show that our chromatic adaptation is neither complete,[14] nor sensor independent, nor entirely multiplicative.[1]

As our knowledge on the neural processing increases, it becomes clear that along the visual pathway from cones, bipolar cells, ganglion cells, LGN, V1, V2, and V4, and to higher cortical areas,[15,16] there are many other sites in which gain control is likely to happen (e.g., see Ref. 17). It is not surprising that von Kries simple law can not describe the whole picture. In fact, it is surprising that the law accounts for the major effect in most cases. One of the CIE recommended color spaces, CIELAB, uses the coefficient law to account for the chromatic adaptation. Variations of von Kries law have been described very well in Refs. 1 and 18-20. Other types of chromatic adaptation models can be found in Refs. 21 and 22.

The Retinex Theory

In 1971, Land and McCann[13] proposed a retinex theory of how colors are computed in the human visual system. The theory contains three major steps: (1) the signal is independently processed for each of the three receptor types to remove the illumination gradient and recover the correct ratio of reflectances; (2) the individual maximum in each receptor band is used to normalize all other reflectances in the band; and (3) the triplet of the normalized reflectances is used to determine the perceived color. Land has since modified the details of the theory several times.[23] Based on his many interesting experiments,[24] McCann still considers the major concept that all the reflectances in a wavelength band (as defined by a photoreceptor type) are normalized by the maximum in that band to be valid, although there has been some disagreement from other experiments.[10,25]

Color Appearance Model

Recently, Hunt[26] and Natayani, et al.[20] proposed two very comprehensive models for predicting color appearance under various illuminations. In particular, Hunt's model has been tested very extensively (see Ref. 27 and the references therein), and it has since been revised to better match the experimental data for widely different viewing conditions and display media.

Computational Models for Color Constancy

In the models discussed so far, the illuminants are assumed to be known. The models then attempt to explain how the colors under different illuminants can be calculated. But, how can the human visual system know the illuminant if it is not directly visible in the scene? This is, in fact, the key problem in the consumer product applications.

The first concrete idea was proposed by Evans[12] in 1946 for photographic printer application. He proposed that the color from the entire image should integrate to gray. This is called the gray world assumption. The same idea is later proposed again by Buchsbaum[28] for object color perception. The gray world assumption is intuitively odd because an image of an object in front of a large green grass field will more likely integrate to green rather than gray. Its main appeal is its statistical property of being not too wrong most of the time. It turns out that after long years of modifications and statistical optimization, the modified gray world model has become the best color balance algorithm for printers and cam-corders. This will be discussed further in the next section.

Relying on statistical properties is not the only way to solve the illuminant color estimation problem. We can also look for the regularity in the physical process of reflection. For example, we can take advantage of the fact that the reflection component at the air-material interface of most inhomogeneous materials is usually nonselective (i.e., all visible wavelengths are reflected more or less equally). The light reflected from such a surface is an additive mixture of the unmodified illuminant spectrum and the spectrum modified by the pigments or dyes in the object. The chromaticity loci of the reflected light from different parts of the surface will be a straight line segment pointing to the illuminant chromaticity. With more than one surface in the image, it is possible to estimate the chromaticity of the scene illuminant from the intersection point of all the line segments in the chromaticity diagram.[29] It should be pointed out that a visible specular reflection is not required because the usual presence of the interface reflection component in object surfaces will create a converging "star" pattern in the chromaticity histogram. However, the interface reflection information does not seem to be used very effectively by the human visual system.[30]

Another idea[9] that has attracted a lot of attention is based on the observation that most illuminant spectra and reflectance spectra can be well approximated by a small number of basis vectors.[31-33] With sufficient sensor classes or other constraints, both the illuminant and the surface spectra can be estimated.[9,10,34] However, the assumption that a small number (2-3) of basis vectors is sufficient and the goal that the visual system should recover the spectral information of the light and surface are probably not very realistic as a model of the human color constancy.[10]

Color Constancy by Machines

Among the major applications that require machine color constancy algorithms are photofinishing printing and video camcorders. A 1993 market survey showed that about 16 billion film exposures were made in the year and about 3 billion square-feet of photographic paper were used to print images. Because a print is only a small part of the visual field and color constancy mechanisms are mostly controlled by the print viewing surrounds, the color balance error by the printer algorithm is more noticeable for the reflection prints than for the transparencies. Therefore, automatic color balance and exposure control algorithms for photofinishing printers have been the subject of intense studies for a long time mainly because of the very practical need of high speed printing for consumer images.

In addition to the basic color constancy problem of the human visual system, a photographic color printer has to deal with many other unknown causes of color variations not related to the scene illuminants. Among them are the scanner/printer calibration, the film manufacturing/processing variability, the film stock keeping, the latent image keeping, and camera filtering. It should be recognized that these factors are considered in the algorithm designs. For example, it is important to decouple the front-end and back-end calibration issues from the true color balance issues. For ease of calibration, it is also important to make sure that the scanner measures the film "printing density" with the same spectral response as the printer lamp, the color filters, and the paper combined. However, because the printing density is only indirectly related to the physical quantities in the scene, algorithms that work in the printing density domain are not working directly on the relevant quantities.

Another factor worth pointing out is that almost all color balance algorithms now in consumer products rely on statistical properties of natural images. Statistical optimization also means that algorithmic learning is a desirable feature. As the season and the region vary, the statistical parameters also ought to change.[35] An ideal commercial algorithm should be adaptive to the changes in the statistical property of the input image population. Automatic learning is a feature not yet fully explored in the existing algorithms.

The Integration-to-Gray Algorithm

In 1946, R. M. Evans filed a patent application, teaching a method for automatic exposure control (color and density balance) in photographic printers for color negative or positive transparency films. The color correction is achieved by "adjusting the intensity of the printing light so that when integrally passed through said transparency, it has the same printing characteristics as light which prints substantially as gray" (Ref. 12, lines 32-36, column 4). Realizing that if there is a dominant color in the image, the integration to gray method will result in too much correction, he further said in the patent: "It may not always be desirable to effect a correction to an exact neutral gray, but sometimes the correction need only be carried toward the neutral point, or in the direction of gray." (Ref. 12, lines 15-19, column 4).

The idea must not have been very convincing to the examiner, because it took more than five years before the patent was issued. However, the idea was very simple to implement and apparently relatively effective. According to a recent study, the method produces a "satisfactory" print about 70% of the time.[36] The integration to gray method was known in the trade as the large area transmission density (LATD) method. It quickly became the backbone of almost all of the color balance algorithms used in printers and camcorders. Bartleson[11] provided a very detailed review on the development and refinement of the LATD method before 1956. He also elaborated on the optimal correction level that Evans referred to in his patent.

The complexity of the early algorithms was limited by the then available sensors, electronic components, and analog computing machinery. The two major problems of the LATD algorithm were quickly recognized: (1) it fails when the image contains large areas of some saturated color (in the US, this is called subject failure; in Europe, it is called dominant color); and (2) it is biased toward low density areas (or underexposed areas). For example, in the negative of a flash picture, the dark background is weighted more heavily than the main subjects in the foreground.

Various solutions have been proposed to reduce the error magnitudes when the above two problems occur. The error in the dominant color (or subject failure) problem is reduced by: (a) using different correction levels: "If the LATD of a negative is only slightly different from typical it is assumed that the difference is caused by some unwanted film variability, and it is given a high-percentage correction. In contrast to this, if the LATD color of the negative is significantly different from typical, it is declared to be an atypical negative.... and they are printed at low correction, allowing the color to remain in the print." (Ref. 37, page 4.17); (b) excluding saturated colors[38] (also when they are outside of the middle range of the luminance signals[39]); (c) sampling along edges in the image[40-41] or using weighted average according to spatial contrast[42]; (d) using averages from multiple frames[43]; (e) using between-frame similarity[44,45]; (f) using color space classification[46]; (g) changing color balance as a function of over- or under- exposures[37,47]; and (h) using a priori knowledge of the light source distribution.[48,49] The error in the low-density bias problem is reduced by: (a) throwing away under-exposed regions[43]; and (b) using geometric weighting (the center portion of the image is more likely to contain the main subjects of interest) and other heuristic rules.[37,50]

In addition to the average density, other simple features such as the minimum density, the maximum density, and other various combinations are used in the regression optimization of the algorithm performance.[51-54] An interesting variation is the histogram normalization method proposed by Alkofer,[40] which assumes that randomly sampled image densities have a normal distribution and at every percentile of the red, green, and blue distribution the densities should be printed neutral.

Scene Classification and Object Recognition

As memory devices become cheaper and the computing processors become more and more powerful, algorithms are designed to be more intelligent in an attempt to recognize objects and scene types in the images and adjust color balance accordingly. For example, detecting faces and skins[55,56] in the images can be used to help produce a pleasing skin tone. Detection of sky, backlit, flash, snow, or beach scenes will allow the color and density balance algorithm to adjust its estimated correction, depending on the scene types. Computer vision and image understanding research will play a major role in this effort.

Discussion

There are comparisons of human and machine color constancy that are quite interesting to make: (1) the incomplete von Kries adaptation is similar to the correction level concept in the printer algorithms; and (2) human color constancy works better along the yellow-blue illuminant direction,[57] while the printer color balance algorithms are also designed the same way. This is because errors occur less frequently and are less noticeable along that direction, and, therefore, we can afford to correct them more aggressively.

References

1. C. J. Bartleson, A review of chromatic adaptation, in *Color 77,* F. W. Billmeyer and G. Wyszecki, Eds., Adam Hilger, Bristol, 1977, pp. 63-96.
2. M. M. Hayhoe, N. I. Benimoff, and D. C. Hood, The time-course of multiplicative and subtractive adaptation process, *Vis. Res.* **27**: 1981-1996 (1987).
3. M. D. Fairchild and P. Lennie, Chromatic adaptation to natural and incandescent illuminants, *Vis. Res.* **32**:2077-2085 (1992).
4. E. H. Land and N. W. Daw, Colors seen in a flash of light, *Proc. Nat. Acad. Sci., U.S.A.,* **48**:10001008 (1962).
5. M. H. Brill and G. West, Chromatic adaptation and color constancy: a possible dichotomy, *Color Res. Appl.* **11**(3):196-204 (1986).
6. L. Arend and A. Reeves, Simultaneous color color constancy, *J. Opt. Soc. Am., A,* **3**:1743-1751 (1986).
7. J. Walraven, T. L. Benzschawel, and B. E. Rogowitz, Color constancy interpretation of chromatic induction, *Die Farbe,* **37**:67-68 (1989).
8. B. J. Craven and D. H. Foster, An operational approach to colour constancy, *Vis. Res.,* **32**(7):13591366 (1992) .
9. L. T. Maloney and B. A. Wandell, Color constancy: a method for recovering surface spectral reflectances, *J. Opt. Soc. of Am., A.* **3**:29-33 (1986).
10. D. A. Forsyth, A novel algorithm for color constancy, *Int. J. Comput. Vis.* **5**(1):5-36 (1990).
11. C. J. Bartleson and R. W. Huboi, Exposure determination methods for color printing: the concept of optimum correction level, *J. SMPTE* **65**:205-215 (1956).
12. R. M. Evans, Method for correcting photographic color prints, US Patent 2,571,697 (1951). (The patent application was filed on June 20, 1946.)
13. E. H. Land and J. J. McCann, Lightness and retinex theory, *J. Opt. Soc. Am.* **61**:1-11 (1971).
14. E. J. Breneman, Corresponding chromaticities for different states of adaptation to complex visual fields, *J. Opt. Soc. Am., A,* **4**:1115-1129 (1987).
15. R. L. De Valois and K. K. De Valois, A multi-stage color model, *Vis. Res.* **33**(8):1053-1065 (1993).
16. M. D'Zmura and P. Lennie, Mechanism of color constancy, *J. Opt. Soc. of Am., A,* **3**:1662-1672 (1986).
17. S. J. Ahn and D. I. A. MacLeod, Link-specific adaptation in the luminance and chromatic channels, *Vis. Res.* **33**:2271-2286 (1993).
18. M. D. Fairchild, Formulation and testing of an incomplete-chromatic-adaptation model, *Color Res. Appl.* **16**(4):243-250 (1991) .
19. R. W. G. Hunt, A model of colour vision for predicting colour appearance in various viewing conditions, *Color Res. Appl.* **12**(6):297-314(1987).
20. Y. Nayatani, K. Takahama, H. Sobagaki, and K. Hashimoto, Color-appearance model and chromaticadaptation, *Color Res. Appl.* **15**:210-221 (1990).
21. H. Helson, *Adaptation-Level Theory,* Harper & Row, New York, 1964.
22. D. B. Judd, Hue, saturation, and lightness of surface colors with chromatic illumination, *J. Opt. Soc. Am.* **30**:2-32 (1940).
23. E. H. Land, Recent advances in retinex theory, *Vis. Res.* **26**:7-21 (1986).
24. J. J. McCann, Color constancy: small overall and large local changes, *SPIE Proc.* **1666**:310-320 (1992).
25. D. H. Brainard and B. A. Wandell, Analysis of the retinex theory, *J. Opt. Soc. Am., A,* **3**:1651-1661 (1986).
26. R. W. G. Hunt, Revised colour-appearance model for related and unrelated colours, *Color Res. Appl.* **16**(3):146-165 (1991).
27. M. R. Luo, X. W. Gao, P. A. Rhodes, H. J. Xin, A. A. Clarke, and S. A. R. Scrivener, Quantifying colour appearance. Part IV. transmissive media, *Color Res. Appl.* **16**(3):191-209 (1993).
28. G. Buchsbaum:1980, A spatial processor model for object color perception, *J. Franklin Institute,* **310**:126 (1980).
29. H. -C. Lee, Method for computing the scene-illuminant chromaticity from specular highlights, *J. Opt. Soc. Am. A,* **3**(10): 1694-1699 (1986).
30. A. C. Hurlbert, H. -C. Lee, and H. H. Bulthoff, Cues to the color of the illuminant, *Supplement to Investigative Ophthalmology and Visual Science,* **30**(3):221 (1989).
31. J. Cohen, Dependency of the spectral reflectance curves of the Munsell color chips, *Psychonom. Sci.* **1**:369370 (1964)
32. D. B. Judd, D. L. MacAdam, G. W. Wyszecki, Spectral distribution of typical daylight as a function of correlated color temperature, *J. Opt. Soc. Am.* **54**:1031-1040 (1964).
33. J. P. S. Parkkinen, J. Hallikainen, and T. Jaaskelainen, Characteristic spectra of Munsell colors, *J. Opt. Soc. Am., A,* **6**(2): 318-322 (1989).
34. M. D'Zmura and G. Iverson, Color constancy. I. Basic theory of two-stage linear recovery of spectral descriptions for lights and surfaces, and Color constancy. II. Results for two-stage linear recovery of spectral descriptions for lights and surfaces, *J. Opt. Soc. Am., A,* **10**(10):2148-2165 and 2166-2180 (1993).
35. R. M. Goodwin and J. A. Manico, *Adjusting photographic printer color exposure determination algorithms*, US Patent 4,962,403 (1990).
36. T. Terashita, *Photographic Printer*, US Patent 4,707,119 (1987).
37. Eastman Kodak Company, *Advanced Color Printing Technology for Photofinishers and Professional Finishers,* Eastman Kodak Company, Rochester, N.Y. (1979).
38. B. Fergg, W. Zahn, and W. Knapp, *Automatic color printing apparatus*, US Patent 4,101,217 (1978).
39. D. Schmidt and P. Bachmann, *Circuit apparatus for automatic correction of TV color balance*, US Patent 5,040,054 (1991) .
40. J. S. Alkofer, *Tone value sample selection in digital image processing method employing histogram normalization*, US

Patent 4,654,722 (1987).
41. J. Hughes and J. K. Bowker, Automatic color printing techniques, *Image Technol.* 39-43, **April/May 1969**.
42. W. Kraft and W. R. von Stein, *Exposure control process and photographic color copying apparatus*, US Patent 5,016,043 (1991).
43. S. Thurm, K. Bunge, and G. Findeis, *Method of and apparatus for determining the copying light amounts for copying from color originals*, US Patent 4,279,502 (1981).
44. T. Amano, *Method of determining exposure amounts in photographic printing*, US Patent 3,873,201 (1975).
45. T. Terashita, *Exposure control method,* US Patent 4,397,545 (1983).
46. M. Fursich and H. Treiber, B. Fergg, G. Findeis, and W. Zahn, *Method of copying color exposures*, US Patent 4,566,786 (1986).
47. T. Terashita, *Methods of setting conditions in photographic printing*, US Patent 4,603,969 (1986).
48. H. -C. Lee, *Digital color image processing method employing constrained correction of color reproduction function*, US Patent 4,663,663 (1987).
49. H. -C. Lee, A physics-based color encoding model for images of natural scenes, in *Proceedings of the Conference on Modern Engineering and Technology, Electro-Optics Session,* Taipei, Taiwan, December 6-15, 1992, pp. 25-52.
50. T. Amano and R. Andoh, *Process of and system for printing in color photography*, US Patent 3,888,580 (1975).
51. D. R. Cok, *Apparatus and accompanying methods for achieving automatic color balancing in a film to video transfer system*, US Patent 4,945,406 (1990).
52. L. A. Jones and C. N. Nelson, Control of photographic printing by measured characteristics of the negatives, *J. Opt. Soc. Am.* **32**:558-619 (1942).
53. T. Terashita, *Methods of locating abnormal originals*, US Patent 4,416,539 (1983).
54. C. M. Tuttle, Photoelectric photometry in the printing of amateur negatives, *J. Franklin Inst.* **224**:315337 (1937)
55. Y. Satoh, Y. Miyake, H. Yaguchi, and S. Shinohara, Facial pattern detection and color correction from negative color film, *J. Imag. Technol.* **16**(2):80-84 (1990).
56. K. Takahashi, T. Akimoto, and S. Watanabe, *Method of detecting flesh color in color originals*, US Patent 4,203,671 (1980) .
57. J. A. Worthey, Limitations of color constancy, *J. Opt. Soc. Am.,* **A2**:1014-1026 (1985).

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