Spectral Adaptation: A Reason to Use the Wavenumber Scale

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Abstract

Chromatic adaptation refers to the ability of the human visual system to adjust to the color of the illumination, or other prevailing stimuli, such that perceived object colors vary far less with changes in illumination than would be expected from simple radiometry or colorimetry. Models of chromatic adaptation are generally formulated as extensions of the von Kries hypothesis of some sort of independent gain control mechanisms operating on the three types of cone signals. This paper introduces a new way to model the phenomenon with no requirement for the first stage chromatic processing. This model is referred to as a spectral adaptation model since it acts upon spectra rather than chromatic signals such as tristimulus values. The spectral adaptation model was compared with other models of adaptation both computationally and through limited psychophysical data. It is shown to have reasonable, and flexible, performance and could be of practical value in applications such as spectral image reproduction. A limiting case of the spectral model, a model of perfect color constancy, is also described and compared with traditional chromatic adaptation models.

Introduction

Von Kries hypothesized that chromatic adaptation could "be conceived in the sense that the individual components present in the organ of vision are completely independent of one another and each is fatigued or adapted exclusively according to its own function."[1] He also went on to say in reference to his own ideas that "people will perhaps recall with pitying smiles the efforts of previous decades which undertook to seek an understanding ... by such lengthy detours". The intervening decades have witnessed even more distorted routes of scientific investigation eventually leading back to ideas very similar to those proposed over a century ago by von Kries. A current waypoint on this journey is represented by the CAT02 chromatic adaptation transform embedded in the CIECAM02 color appearance model.[2] CAT02 returns to a simple, linear von Kries scaling ("adapted exclusively according to its own function"), but does not use cone responsivities ("individual components present in the organ of vision"). Instead, CAT02 uses an optimized linear transformation from CIE XYZ tristimulus values to RGB responses that accurately model the overall chromatic adaptation response of human observers when combined with linear von Kries scaling.

Von Kries was exploring what remains to this day as one of the most important visual phenomena impacting the appearance of colors in various viewing environments, chromatic adaptation. Chromatic adaptation refers to the ability of the human visual system to automatically (as in sub-consciously) compensate for changes in illumination color (and intensity through light/dark adaptation) to produce object color perceptions that are more stable than the simple tristimulus values (or cone responses) predict. The relative stability of object color perceptions is so strong that the resulting perception is sometimes referred to as color constancy. However, careful observation of object color appearance across illumination changes and the phenomenon of illuminant metamerism show that color constancy is an overstatement of actual human performance. If color constancy existed perfectly, then there would be no need for chromatic adaptation models since basic colorimetry would be reduced to the integration of spectral reflectances weighted by color matching functions with no need to include an illuminant or source. This concept will be revisited through one of the adaptation models explored in this paper.

While there is certainly a rich history of psychophysical experimentation on, and mathematical modeling of, chromatic adaptation,[3] there are also many other types of adaptation observed in the human perceptual systems. One example is pattern, or spatial frequency, adaptation. The phenomena and modeling of spatial frequency adaptation are often described using chromatic adaptation as an analogy. For example, after exposure to a high-spatial-frequency pattern (fine grating), a slightly-lower-spatial-frequency pattern will appear to have an even lower frequency. This is similar to how a yellow stimulus might appear slightly greenish after adaptation to a red field. Spatial frequency adaptation is typically modeled using a small number (5-6) of band-pass spatial frequency channels (analogous to the three cone types sampling the light spectrum) that are subject to gain control (analogous to von Kries scaling of the cone responses).

Spatial frequency adaptation also extends to more complex stimuli. For example, Webster[4] has explored adaptation to image blur. After viewing a blurry image, other images appear sharper and vice versa. That work was recently extended by Fairchild and Johnson[5,6] to the examination of adaptation to noise in images. Both blur and noise can be considered particular patterns of spatial frequencies and it is reasonable to assume that similar spatial-frequency-adaptation models would apply to each situation. Interestingly, Fairchild and Johnson[5,6] were able to model pattern adaptation to noise in images without the need for spatial frequency channels. Instead, they took the Fourier transform of the adaptation pattern and blurred it to simulate the effect that spatial frequency adaptation occurs over bands of spatial frequency and not completely independently for each frequency. This blurred frequency image was then used to scale the perceived magnitude of each spatial frequency in the images being viewed (von Kries normalization in spatial frequency space). The success of that model led the author to ponder application of a similar concept to the phenomenon of chromatic adaptation. Could chromatic adaptation be modeled as multiplicative normalization to a blurred adaptation spectrum, rather than independent gain control in a limited number of channels? Is a channel-free chromatic adaptation model feasible? These were the questions that motivated the current research. Since such a model does not require that the spectral data ever be expressed in colorimetric (or any trichromatic) coordinates, it is not proper to refer to it as a *chromatic adaptation* model. Instead, the new term, *spectral adaptation* model, is used in this paper.

Since the physiology of color vision is understood well enough to know that three (in general) channels sample the visible spectrum in the retina and all further visual processing arises from these initial signals, what could be the possible advantages of a spectral adaptation model? There are situations in which it could be helpful to both express data in terms of spectra, rather than colorimetric coordinates, and have access to mathematical models allowing transformations representative of appearance in various viewing conditions. One such application is the growing field of spectral imaging.[7] Spectral imaging systems are often used to express spectral radiance or reflectance data for each pixel in a scene or imaged object. Such data are useful for accurate color reproduction, minimizing metamerism in reproduction, analysis of object properties, and conservation/restoration of valuable artifacts. A spectral adaptation model might become a functional and useful part of a spectral imaging chain, allowing appearance-like transformations without ever reducing the dimensionality of the image data or requiring estimations to return from color descriptors to required spectral output information.

Model Formulation

Figure 1 is a flow chart of the spectral adaptation model. The process begins with the spectral power distribution of the light source, Φ(λ), and the spectral reflectance factor of the stimulus, R(λ), expressed in the typical method as functions of wavelength (nm). These spectra are then initially converted to the wavenumber scale. The conversion between wavelength, λ, in nm, and wavenumber, ν, in cm^{-1} is given by Eq. 1.

$$\nu = \frac{1}{\lambda \cdot 10^{-7}} \tag{1}$$

The stimulus spectral power distribution, S(ν), is then computed by multiplying the source spectral power distribution by the spectral reflectance factor as shown in Eq. 2.

$$S(\nu) = \Phi(\nu)R(\nu) \tag{2}$$

The next step is to define a spectral blurring function with which to blur the light source spectral power distribution prior to using it as a denominator in a von Kries-like normalization of spectra. This is the step in which the conversion from the wavelength scale to the wavenumber scale comes into play. As described in the classic work of Dartnall,[8] the spectral responsivities of the human cone photoreceptors can be well represented by functions of more nearly constant shape and width on the wavenumber scale. Since the blurring of the source spectral power distribution for adaptation is designed to simulate the spectral low-pass filtering of the cone photoreceptors, this can be accomplished through convolution with a single, stationary, symmetric function of wavenumber. While a non-symmetric function might more closely model human photopigment absorption, for the purposes of this initial formulation and testing of a spectral adaptation model, a Gaussian function with a standard deviation of 1500 cm^{-1}, as defined by Eq. 3, was used. This results in a distribution where plus-and-minus two standard deviations is equivalent to approximately 44% of the visible spectrum. The precise definition of the width and shape of this blurring function is one place that the spectral adaptation model could be fine-tuned given sufficient visual data.

$$Bl(\nu) = \left(\frac{1}{\sqrt{2\pi 1500}}\right) e^{\left(\frac{-\nu^2}{2 \cdot 1500}\right)} \tag{3}$$

The spectral power distribution of the light source is then converted to an adapting stimulus through a blurring convolution with the Gaussian blurring function as given in Eq. 4.

$$\Phi_{adapt}(\nu) = \Phi(\nu) * Bl(\nu) \tag{4}$$

The computations in this paper were completed under the assumption of full adaptation to the adapting stimulus computed in Eq. 4. However, incomplete adaptation (or incomplete discounting-the-illuminant) as implemented in the CIECAM02 color appearance model can also be implemented in a similar fashion in a spectral model. At this stage, a degree of adaptation factor, D, would have to be selected in the range between 0.0 (no adaptation) and 1.0 (complete adaptation, used in this paper). Incomplete adaptation is implemented by adjusting the adapting spectral power distribution through a weighted (by D) average of the blurred source spectral power distribution (Eq. 4) and the equal-energy illuminant, E(ν) scaled to the same absolute luminance level as shown in Eq. 5.

$$\Phi'_{adapt}(\nu) = (D)\Phi_{adapt}(\nu) + (1 - D)E(\nu) \tag{5}$$

The spectral adaptation transformation is accomplished through a multiplicative gain control (von Kries-type normalization) of the stimulus spectral power distribution, S(ν), by the adapting spectral distribution, Φ'adapt(ν), as described in Eq. 6.

$$S_{adapted}(\nu) = \frac{S(\nu)}{\Phi'_{adapt}(\nu)} \tag{6}$$

The adapted stimulus function is essentially a reflectance factor function since the light source (or at least a blurred version thereof) has been removed and the units are restored to those of the reflectance factor ratio. The adapted stimulus can then be converted to a normal reflectance factor function by the simple wavenumber to wavelength conversion (inverse of Eq. 1) as defined in Eq. 7.

$$R_{adapted}(\lambda) \equiv S_{adapted}(\nu) \tag{7}$$

The adapted reflectance factor function can then be used to compute appearance correlates (e.g., CIELAB lightness, chroma, hue) through normal tristimulus integration using the equal-energy illuminant (or no illuminant at all). As described, the spectral adaptation model functions to compute corresponding colors for the equal-energy illuminant, or in the terms of the CIECAM02 color appearance model, the equal-energy illuminant represents the reference viewing condition.

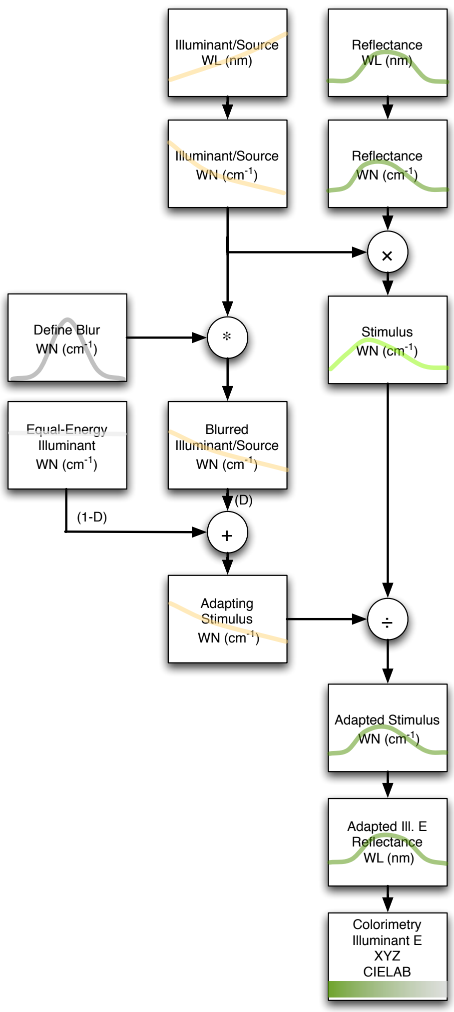

Figure 1. Flow chart of the spectral adaptation model beginning with the object reflectance and source spectral power distribution and ending with the corresponding colorimetry under the equal-energy illuminant.

There is a special case of the spectral adaptation transformation when the blurring function (Eq. 3) is defined as a delta function and adaptation is complete (D=1.0). In this case, the spectral adaptation model reduces to a simple removal of the source's influence on the stimulus and the adapted stimulus becomes identical with its reflectance factor function. Such a transformation is another description of perfect color constancy. In a spectral model it is possible to compute perfect color constancy for any stimulus while that is not mathematically feasible for the typical trichromatic chromatic adaptation models. It is worth noting that while a color constancy model might be a computational convenience in some applications, it does not represent color appearance in general since it neglects the phenomenon of metamerism. However, there is a general interest in the comparison between the appearance predictions of perfect color constancy and those of more traditional appearance models such as CIECAM02. Since this comparison has been enabled by the derivation of the spectral adaptation model and, more importantly, the spectrally-defined visual adaptation data described below, the color constancy model is compared with the spectral adaptation, CAT02, and CIELAB adaptation models in the analyses that follow.

Experimental Model Testing

Since chromatic adaptation is generally accepted as a physiological process that occurs after absorption of light in the three classes of cone photoreceptors, it is usually modeled as a trichromatic phenomenon and psychophysical data are normally reported only in trichromatic, rather than spectral, terms. Therefore a limited psychophysical experiment was undertaken to provide a very modest amount of data, quantified spectrally, that could be used to compare the spectral adaptation model formulated in this paper with other common techniques for modeling chromatic adaptation. This experiment was not intended to provide a significant set of results for model fitting and generalization and, as such, only one observer was used. The analyses of these data should be taken only in the sense that they show the relative performance of various models and not as a meaningful metric of overall model performance.

The experiment was completed by one experienced observer (the author) who performed magnitude scaling of color appearance (lightness, chroma, and hue) of a series of stimuli under a variety of light sources. The reflective samples consisted of the 24 patches of a vintage Macbeth ColorChecker Chart. The chart was viewed in its entirety under each of five light sources in a Macbeth Spectralight III viewing booth. These sources included simulators of CIE illuminants A and D75, a TL84 narrow-band fluorescent source, horizon light (tungsten at a lower CCT than Ill. A), and a cool-white fluorescent source. The data in table I were measured with a PhotoResearch PR-650 spectroradiometer aimed at a PTFE plaque placed on the bottom-center of the viewing booth. This instrument records absolute spectral radiance from 380 nm to 780 nm in 4nm increments. Viewing distance was not strictly controlled, but each patch of the chart subtended approximately two-degrees of visual angle.

For each light source, the observer scaled perceived lightness, chroma, and hue for each of the 24 patches and then the process was repeated for the next source. Each patch-source combination was scaled only once. General repeatability for such scaling tends to be on the order of 10% for lightness, 20% for chroma, and 5% for hue based on previous experience. Lightness was scaled from zero for a perfect black to ten for a perfect white with a scaled value of five representing a middle gray. Chroma was scaled such that achromatic colors were assigned a value of zero and the scale increments were the same perceived magnitude as the lightness scale. Thus a scaled chroma of 5 should be as different from gray as a perfect white is from a middle gray. Lastly, hue was scaled similarly to hue designations in the Swedish Natural Color System

[9] with each hue being expressed as a percentage combination of no more than two unique hues.

The raw scaled data were then converted to approximate CIELAB values such that they could be compared with equal-energy appearance predictions of the various adaptation models. This conversion was accomplished by multiplying the lightness and chroma by 100 to convert them into approximate L* and C* values. Hue scales were converted using linear interpolation between the CIELAB hue angles of the unique hues as specified by Fairchild.[3,10] CIELAB a* and b* coordinates were then directly computed from C* and h.

Each of the four adaptation models under consideration (Spectral, CAT02, CIELAB, Constancy) were used to predict equal-energy corresponding colors for each of the 24 test patches and each of the five light sources. The spectral adaptation model is that described earlier in this paper with complete adaptation. CAT02 is the von Kries adaptation model on spectral-sharpened cone responses that is incorporated in the CIECAM02 color appearance model, also with complete adaptation.[2] CIELAB[11] is the von Kries adaptation transform built into the CIELAB color space which is normalization of CIE XYZ tristimulus values rather than cone responses. Constancy refers to the special case of the spectral model described previously where the effects of the source are perfectly removed. Essentially, the constancy model represents direct computation of CIELAB coordinates for Ill. E using the stimulus reflectance factors only. Once the experimentally-scaled values and all the predicted corresponding colors were expressed as equal-energy CIELAB coordinates, color differences were computed between the predicted and observed results, summarized in Fig. 2.

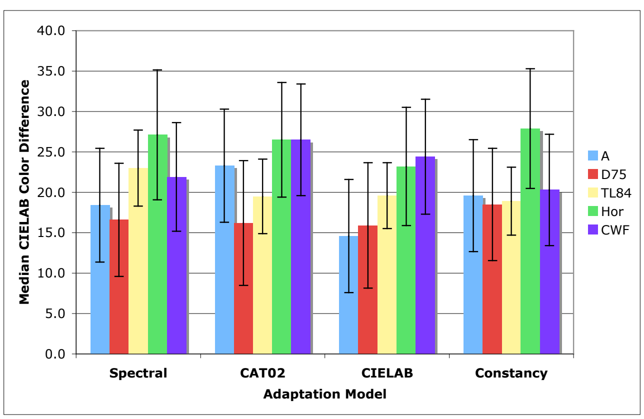

Figure 2. Median CIELAB color differences (ΔE) between visually scaled appearance and model predictions for each model and light source. Error bars represent 95% confidence intervals on the means across the 24 stimuli.*

Figure 2 includes the median color differences and differences in the various CIELAB coordinates for each model and viewing-condition combination. Error bars in Fig. 2 were computed as 95% confidence intervals on the means across the 24 patches of the ColorChecker Chart. Noteworthy in the results is a general trend for all of the models to significantly under-predict observed chroma for all of the sources except the narrow-band TL84. Overall, the differences between prediction and observation are quite large, on the order of 20 CIELAB units. However, this is about on par with the expected uncertainty in magnitude estimation for a single observer and trial. Of more importance is that there is no significant difference in the performance of the spectral model in comparison with the other models for the prediction of appearance for a single observer (and observation). This suggests that the spectral model, and indeed the color constancy model, might be viable spectral processing techniques for the preservation of appearance information.

Since it is known that mean color appearance data across numerous observers can be predicted to the level of approximately five CIELAB units and that the CAT02 model provides what is likely the best prediction of these mean results, it is also of interest to see how the other models compare with CAT02 in a more direct computational comparison. Thus to avoid the uncertainty associated with a new, and very abbreviated, psychophysical experiment, the computational comparison with CAT02 described in the next section was undertaken.

Computational Model Testing

The stimuli from the visual experiment were used, however the visual scaling results have no bearing on this computational comparison. Instead of comparing with the visually scaled results, the predictions of CAT02 were deemed the standard. Thus the predictions of each of the other three models were compared for all of the experimental conditions with the predictions of CAT02. The results are expressed in the same terms as those for the visual scaling results. The CAT02 differences (all zeros since CAT02 is the standard) are included in the tabulated and plotted results as a reminder of the computational paradigm.

The computational comparison results (median differences) are plotted in Fig. 3. Of immediate note is the significantly smaller differences for all the models. The models do agree with one another much better than they agree with the single observer and the magnitudes of these overall differences between the models are on the order of the precision of the best available color appearance data. The largest differences from CAT02 are obtained for the spectral model and the most significant of these were for the two fluorescent light sources. Perhaps it is not surprising that sources with such non-smooth spectral power distributions (the narrow-band TL84 in particular) would produce the most significant differences between a spectral and a chromatic adaptation model. It is quite likely that the spectral model could be tuned for significantly better performance by optimizing the blurring function and degree of adaptation. Particularly large differences show up in the a* differences for the two fluorescent sources. This can likely be attributed to the large mercury emission at 546.1 nm not being blurred enough in the adaptation spectral power distribution and thus causing a larger bias in the red-green directions.

Also of note is how closely the color constancy model comes to replicating the CAT02 predictions. There are some systematic differences, but they do tend to be small suggesting that the color constancy approach could be a very viable spectral processing technique for appearance preservation when metamerism is not a significant concern.

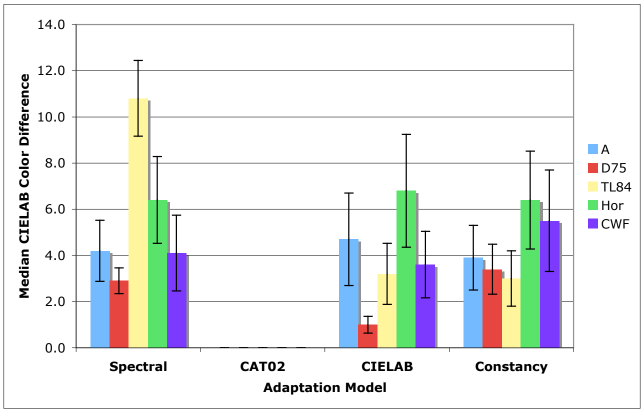

Figure 3. Median CIELAB color differences (ΔE) between CAT02 and other model predictions for each model and light source. Error bars represent 95% confidence intervals on the means across the 24 stimuli.*

Lastly, as has been observed in a variety of color appearance model tests,[3] CIELAB does perform reasonably well in comparison with CAT02. There are systematic differences in the corresponding-color predictions that are known to be meaningful when large sets of color appearance data are examined and there are known limitations (particularly constant-hue contours) in the CIELAB appearance scales, but these analyses affirm that CIELAB can be used as a good, first-order approximation of a color appearance model.

General Discussion

The spectral adaptation model and its limiting case of a color constancy model provide interesting fodder for colorimetric computations and theoretical (almost philosophical) analyses of how physical color stimuli get converted into color appearance perceptions by the human visual system as well as how to mimic these procedures computationally and in imaging systems. However, given current physiological understanding of the trichromatic nature of human color vision, should one really be contemplating such models at all? And if so, is there any utility beyond natural scientific curiosity about what might happen if color information were processed in a different way?

The answer to these questions seems to be a resounding "yes". Why? It turns out there is both the potential for physiological plausibility of such models and there are certainly practical applications in spectral imaging for spectral adaptation models.

Beginning with physiological plausibility. Since the human visual system is known to be a trichromatic detector at the retinal level, where could the spectral information come from that is required for a spectral adaptation model? In the world of spectral imaging, Imai *et al.*[12] have developed a very accurate capture system based on a trichromatic camera and the addition of one filter to allow the capture of six spectral samples through two exposures. Spectra are then estimated for each image pixel as linear combinations of six basis functions. If the visual system were able to capture spectral samples with three cone types exposed through two different types of filtration, then it is feasible for the human visual system to accomplish the same spectral imaging accuracy. There are several ways the human visual system might accomplish this feat. The most significant of which is the difference in pre-retinal filtration between the foveal and extra-foveal regions of the retina. In the fovea, the cones detect light that has first passed through the yellow filter of the macula while in the periphery there is no macula. This spectral difference is remarkably similar to the optimal filtration change derived by Imai *et al.*[12] So the human visual system need only view the same scene location with the fovea and extra-foveal retina in order to obtain the six spectral samples necessary to accomplish accurate spectral imaging, spectral adaptation, and approximate color constancy. There are other possible mechanism including differences in pre-retinal absorption in the two eyes and differences in cone spectral responsivities due to self-screening and the changes in cone shape from the fovea (long and thin) to the periphery (shorter and wider). Thus it is clear that it is at least feasible that the human visual system has some access to spectral information in a scene and is not a simple trichromatic detector. That full descriptions of color appearance require five dimensions,[3] not just three, also supports the idea that the visual system is more than trichromatic in some sense. While this discussion establishes plausibility, it by no means provides any evidence that the visual system takes advantage of this potential information.

Further support comes from the need for more than one set of average color matching functions. The CIE 1931 (2°) and 1964 (10°) standard colorimetric observers provide some measure of mean color matching responses. To the degree that these responses are present in each observer and that they are not linear transformations of one another, they provide another way to quantify the differences between foveal and extra-foveal chromatic responses and provide the six samples necessary for good spectral reconstruction. Recent experimental results from Liu *et al.*[13] provide direct measurements of the accessibility of spectral information to observers and the requirements for spatially varying color matching functions. In their experiments, observers matched small central stimuli (a display) with large peripheral stimuli (the surrounding room illumination). Observers could easily make matches when they fixated the display (or the surround), but those matches would break down as soon as eye movements were allowed. Essentially these highly metameric (LCD display, LED room illumination) matches cannot be preserved across even small changes in the viewing configurations. Therefore, even when a match is made for one viewing configuration, a few eye movements allow the observers to distinguish the two types of stimuli. This is a case of trichromatic matching not being robust across eye movements and therefore illustrates the ability of human observers to detect metamers which is an indication that they are in some way accessing spectral information (if only subconciously).

Spectral imaging systems[7] are rapidly developing to the point where they might soon see practical application in a variety of areas. In some cases these systems are designed strictly to provide physical metrics of spectral distributions, but in others the objective is accurate color reproduction and it is not unreasonable to think that end-to-end spectral imaging systems might be implemented that never require a reduced-dimensionality (e.g., trichromatic) image representation. In such cases a spectral adaptation model might be very useful.

In cases where spectral reflectance information for each pixel is available (e.g., images of flat objects) and for which metamerism is not a significant concern, the color constancy model appears to be a very feasible method for approximate appearance processing. Essentially this model suggests that appearance is defined by the spectral reflectance distribution alone and the illuminant or source is irrelevant.

In other cases, such as images of 3D scenes where nonuniform illumination and inter-reflections make it difficult to obtain a reflectance image, spectral radiance information could be usefully processed with the spectral adaptation model outlined in this paper. This will require some technique to estimate the effective adaptation spectral power distribution for each area in the image, a topic well beyond the scope of the present work. However, this does suggest the locus for a fruitful combination of recent work on image appearance models and spatial adaptation models[14] and the proposed spectral adaptation model. Regardless, the spectral adaptation model at least provides a hint on how to implement cross-media color appearance reproduction within the domain of end-to-end spectral imaging.

Conclusions

A new approach to the modeling of the visual phenomenon of chromatic adaptation, a spectral adaptation model, was derived and evaluated in comparison with CAT02 and other adaptation models. While such a model seems physiologically implausible at first blush, it is not entirely impossible that higher levels of the visual system have some access to spectral information, or at least band-limited (blurred) spectral information. If this is the case, then a spectral adaptation model might end up being more accurate than trichromatic-based models. Substantially more visual data, with full spectral information for the test and adapting stimuli, will be required to allow the precision necessary to differentiate between spectral and chromatic adaptation models. Perhaps future experiments will provide such data. In the interim, the spectral model and its limiting case, the color constancy model, provide frameworks by which spectral information can be processed with an eye toward preservation of color appearance without the need to reduce the dimensionality of the spectral information and then later attempt to reconstruct it. Quickly developing spectral imaging technologies in a variety of application areas from fine art printing, to biomedical imaging, to digital cinema might benefit from such a processing framework.

The reviewers of this paper pointed out that Funt and Ciurea[15] might have earlier suggested a spectral adaptation model. While they did address the potential advantage of using spectral information, they used that information to optimize more traditional trichromatic chromatic adaptation models. As this paper was going to press, a paper by Mizokami et al.[16] appeared in which appearance scaling (constant hue) was related to spectral, rather than colorimetric, information. That work might represent another instance of the potential use of spectral information for color appearance. Lastly, a more detailed treatement of this work has been accepted for publication.[17]

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