Meet iCAM: A Next-Generation Color Appearance Model

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Abstract

For over 20 years, color appearance models have evolved to the point of international standardization. These models are capable of predicting the appearance of spatially-simple color stimuli under a wide variety viewing conditions and have been applied to images by treating each pixel as an independent stimulus. It has been more recently recognized that revolutionary advances in color appearance modeling would require more rigorous treatment of spatial (and perhaps temporal) appearance phenomena. In addition, color appearance models are often more complex than warranted by the available visual data and limitations in the accuracy and precision of practical viewing conditions. Lastly, issues of color difference measurement are typically treated separate from color appearance. Thus, the stage has been set for a new generation of color appearance models. This paper presents one such model called iCAM, for image color appearance model. The objectives in formulating iCAM were to simultaneously provide traditional color appearance capabilities, spatial vision attributes, and color difference metrics, in a model simple enough for practical applications. The framework and initial implementation of the model are presented along with examples that illustrate its performance for chromatic adaptation, appearance scales, color difference, crispening, spreading, high-dynamic-range tone mapping, and image quality measurement. It is expected that the implementation of this model framework will be refined in the coming years as new data become available.

Introduction

The specification of color appearance has a rich history that can be considered to predate the establishment of CIE colorimetry itself. Perhaps it is noteworthy that 2002 represents the 100th anniversary of von Kries' seminal paper on chromatic adaptation.[1] To this day, von Kries' simple hypothesis remains the fundamental building block of color appearance models. von Kries strived to extend Grassmann's laws of additive color mixture to changes in viewing conditions and thus allow the prediction of corresponding colors — one component of color appearance models. At about the same time Munsell was developing a concept of the other key component of color appearance models, a representation of appearance scales (*e.g.*, lightness, chroma, and hue).[2] These two components together form the main building blocks of all color appearance models, a chromatic adaptation transform and a color space. That early work evolved through many stages eventually culminating with the recommendation of the CIELAB color space in 1976.[3]

While CIELAB represents an approximate color appearance model, its main purpose continues to be as the basis of color difference formulas. Shortly after the adoption of CIELAB, work began on the development of more accurate and comprehensive color appearance models.[4] Work in this area accelerated rapidly through the late 1980's and early 1990's due to increased interest and practical applications requiring appearance models. A significant result from this time period was the formulation and adoption of CIECAM97s in 1997.[5]

CIECAM97s has proven successful in focusing color appearance research on improvement of a single model and providing guidance to those attempting to implement color appearance modeling in practical applications such as cross-media image reproduction. However, it was quickly realized that CIECAM97s had some weaknesses and several revisions and improvements have been proposed.[6] This work has been ongoing in CIE TC8-01 and appears to be converging to a new recommendation of a revised color appearance model tentatively called CIECAM02.[7] CIECAM02 represents a significant improvement over CIECAM97s in both performance and usability. However, it is more similar to CIECAM97s than different and does not represent a new type of color appearance model. Instead it is a significant evolution of the same type of model.

It has been recognized that there are significant aspects of color appearance phenomena that are not described well, if at all, by models such as CIECAM97s or CIECAM02. These aspects include accurate metrics of color differences, spatial aspects of vision and adaptation, temporal appearance phenomena, image quality assessment (or differences in appearance of complex stimuli), and image processing requirements. These aspects have been addressed individually in a variety of ways, some examples of which are briefly mentioned below.

A very comprehensive model of spatial vision and chromatic adaptation has been described by Pattanaik *et al.*[8,9] This multiscale model is capable of predicting many phenomena of spatial vision and color appearance and can be used for useful image transformations such as tone-scale mapping. It can also provide the basis for an image difference metric for image quality assessment.[10] While this multiscale model suggests some of the desired attributes of a next-generation color appearance model, it is not complete and its complexity has prevented widespread application in practical imaging applications.

Color difference measurement has been treated separately from color appearance modeling through the formulation of complex color difference equations such as CIE94[11] and CIEDE2000[12] built upon the foundation of CIELAB. These equations represent significant improvement in color tolerance prediction relative to the Euclidean ΔE^*_{ab} metric, but might be more complex than warranted by available data or useful in practical situations (in the case of CIEDE2000). A next generation color difference formula will almost certainly be based on fundamental improvements in the color space itself and that provides an opportunity to bring together the color appearance and color difference models and formulas.

A related topic is the measurement of image differences and image quality in which both spatial vision modeling and color difference modeling are required. Examples of this work include the combination of CIELAB-based color difference metrics with spatial filtering of images to predict the visibility of differences in complex stimuli.[13] Johnson and Fairchild presented a modular framework for such a model that could be used as the basis of next-generation models capable of being applied to various tasks.[14]

A final aspect to consider is the utility of a model in practical applications. For example, in gamut mapping it is often desired to manipulate image pixels by changing lightness and/or chroma along lines of constant perceived hue. In many color spaces, such as CIELAB and CIECAM97s, lines of constant hue angle do not represent lines of constant perceived hue to the degree required for gamut mapping and corrections to the spaces must be made.[15] Ebner *et al*., described a color space, IPT, for image processing applications in which constant hue lines represent perceived constant hue to a high degree of accuracy.[16] Such a space does not solve all problems of color appearance, but does address one issue of practical importance and has found use in a variety of applications requiring significant gamut mapping.

It is clear that many ideas for improved types of color appearance models have been outlined and that the time might be appropriate for a revolutionary change in the way color appearance models for cross-media image reproduction are formulated. The requirements for such a model include simple implementation for images, spatially localized adaptation and tone mapping for high-dynamic-range images and other spatial phenomena, accurate color appearance scales for gamut mapping and other image editing procedures, spatial filtering for visibility of artifacts, and color difference metrics for image quality assessment. While various models or algorithms are available to address each of these aspects individually, none exist with all of these capabilities simultaneously. Such a model might well represent the next logical progression in color appearance modeling. The framework and implementation of a model of this type, called iCAM, is described in this paper. It is hoped that iCAM will provide the foundation for further model improvements over the coming years with the ultimate goal of providing a general purpose color model for cross-media image reproduction, image manipulations, image difference and quality measurements, and high-dynamic-range imaging.

Framework of iCAM

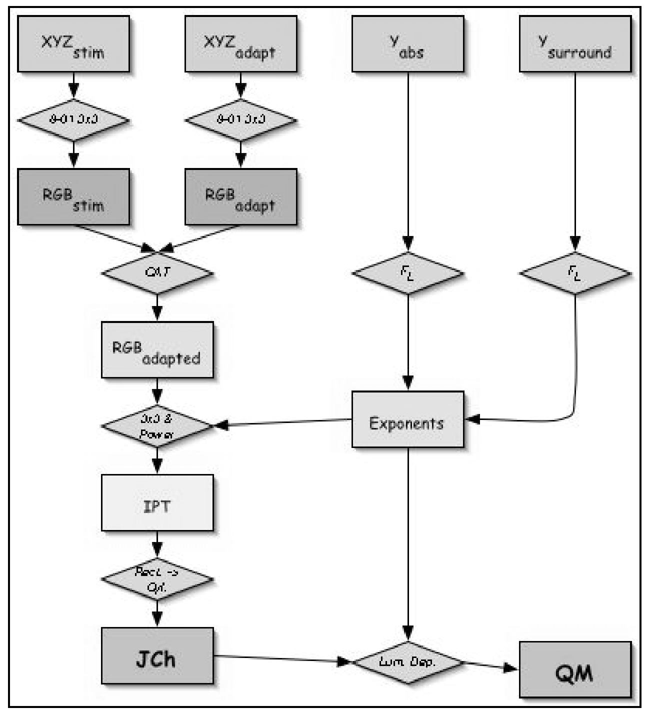

Figure 1. Flow chart of iCAM for simple stimuli (or a single pixel).

Figure 1 provides a flowchart of the iCAM model framework as applied to single stimuli. This represents the traditional appearance modeling approach of treating each pixel as a stimulus in a point-wise fashion. The process is to start with tristimulus values for the stimulus and adapting point (often the white point) and luminance values for the adapting level and surround. The tristumulus values are transformed to RGB values that are utilized in a linear, von Kries adaptation transform identical to the one proposed for CIECAM02. The adapted signals are then transformed into the IPT color space to take advantage of its accurate constant hue contours and lightness and chroma dimensions similar to CIELAB. The adapting and surround luminance levels are used to modulate the nonlinearity in the IPT transform to allow for the prediction of various appearance phenomena. A rectangular-to-cylindrical transformation is performed on the IPT coordinates to derive lightness, chroma, and hue predictors and the adapting luminance information is then used to convert these to brightness and colorfulness predictors. Saturation can be easily derived from these. Color difference metrics are then built upon the appearance correlates.

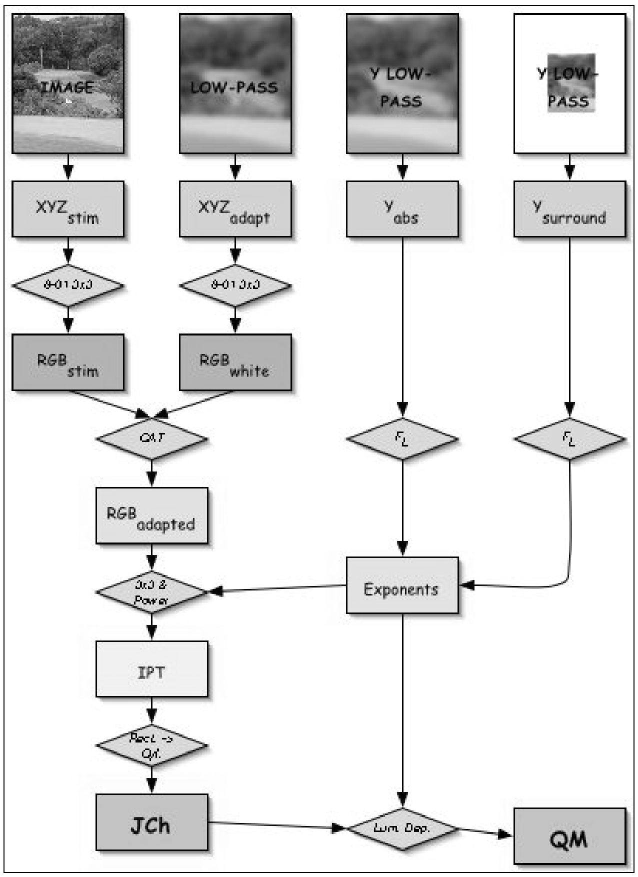

Figure 2. Flow chart of iCAM for spatially-complex stimuli.

Figure 2 is a similar flow chart that illustrates the more complete version of iCAM for spatially complex stimuli. This is the formulation that extends color appearance modeling to a new level. The stimulus is replaced with an image and the adapting stimulus becomes a spatially (and temporally if temporal aspects are considered) low-pass image. The adapting luminance is also derived from a low-pass image of the luminance channel and the surround luminance is derived from another low-pass image derived from a larger spatial extent. The processing is the same as described in Fig. 1. However, the spatial derivation of the viewing conditions information allows for significantly more complex appearance predictions to be made on an automated basis (*e.g.*, spatial appearance phenomena, tone mapping of high-dynamic range images, image difference metrics, *etc.*). Spatial filtering of the stimulus image is performed using appropriate contrast sensitivity functions to enable image difference and image quality specifications. Further, the various low-pass images can be used to identify various image types as necessary for image-dependent appearance and preference transformations.

An Implementation of iCAM

The previous section outlined the framework of iCAM and provided some guidance as to how the various stages would be computed. At this point, there is no intention to lay out a single, fixed procedure for the implementation of this model. This is necessary since the required visual data to set all of the parameters simply has not been acquired yet. However, it is certainly possible to create an initial implementation of iCAM based on current practices and reasonable estimates of the interactions between features. Such an implementation has been completed for the purposes of this paper. It is fully expected that each component of iCAM will be tested and refined through new visual experiments over the coming decades.

There is not enough space in a short paper to detail all of the equations and computations necessary for an iCAM implementation. However, all of the necessary equations have already been published and they will be described below with appropriate references. In addition, Mathematica notebooks with the full iCAM implementation described here and several example computations are posted on the internet at <www.cis.rit.edu/mcsl/iCAM/>. The Mathematica notebooks not only include the equations and examples, but also explanations of each step in the process for those interested in customizing any part. Other forms of code will also be made available.

The input data are simply the XYZ tristimulus values of the stimulus/image and the adapting field and the absolute luminance of the adapting field and surround. These are normally expressed in terms of the CIE 1931 Standard Colorimetric Observer. For spatially-dependent computations such as image quality measurement, the first step would be spatial filtering of the images after an appropriate opponent transformation followed by transformation back to tristimulus values.[13] The image and adapting field data would then be transformed to spectrally sharpened RGB responsivities for the chromatic adaptation transform. The currently preferred transformation is the modified Li *et al*. matrix[6] that has also been selected for use in CIECAM02 by TC8-01.[7] The chromatic adaptation transformation is a linear von Kries transformation with an incomplete adaptation factor identical to that found in CIECAM02.[6,7] The adapting field is derived from a low-pass image with the degree of blurring depending on the viewing distance, desired result, and application. In the extreme this low-pass image would simply be the mean image. When high-dynamic range tone mapping, or local adaptation, is required then some low-frequency (*e.g*. below 0.5 cycle/deg.) information would be retained. The adaptation transform is used to compute corresponding colors for a reference viewing condition chosen to be complete adaptation to a uniform illuminant D65 field to correlate with the IPT color space derivation.

Once the D65 corresponding colors are obtained, they are transformed via a set of exponential non-linearities and a linear matrix transformation to the IPT opponent color space that represents lightness, chroma, and hue information.[16] In average viewing conditions (typical luminance level and average surround), the normal IPT exponents would be used. In other cases the exponents are modified by the surround-luminance image (to predict changes in image contrast with surround luminance and extent) or the adapting field luminance image (to predict the Hunt and Stevens effects and allow for high-dynamic-range tone mapping). The application of spatially varying exponents in the IPT transform to perform local tone-mapping is inspired by the recent work of Moroney.[17] The magnitude of the influence of absolute luminance levels can be computed using the F_L factor currently used in CIECAM97s and CIECAM02.[4,5,7] The F_L factor is then used to modulate the exponents in the IPT transformation.

The IPT opponent coordinates are converted into correlates of lightness, chroma, and hue (JCh) via a normal rectanglar to cylindrical coordinate transformation. Additionally, brightness and colorfulness (QM) predictors are obtained by multiplying J and C by F_L raised to an appropriate exponent (0.25 in CIECAM02). Saturation can be determined through a ratio of either C/J or M/Q. Lastly, color differences can be calculated as Euclidean distances in the lightness-chroma or brightness-colorfulness spaces as appropriate. A more rigorous color difference equation can be derived by using the formulation of the CIE94 equation to account for changes in tolerances with chroma. A more complex equation will almost certainly not be necessary in practical applications.

Examples

Several examples of the performance of iCAM have been created and included in this section. These include descriptions of its chromatic adaptation accuracy, appearance scale accuracy, color difference metrics and computed examples of its prediction of simultaneous contrast, crispening, spreading, high-dynamic-range tone mapping, and image quality scales.

Since iCAM uses the same chromatic adaptation transform as CIECAM02, it will perform identically for situations in which only a change in state of chromatic adaptation is present (*i.e.*, change in white point only). CIE TC8-01 has worked very hard to arrive at this adaptation transform and it is clear that no other model currently exists with better performance (although there are several with equivalent performance). Thus the chromatic adaptation performance of iCAM is as good as possible at this juncture.[6,7,18]

The appearance scales of iCAM are identical to the IPT scales for the reference viewing conditions. The IPT space has the best available performance for constant hue contours and thus this feature will be retained in iCAM.[15] This feature makes accurate implementation of gamut-mapping algorithms far easier in iCAM than in other appearance spaces. In addition, the predictions of lightness and chroma in iCAM are very good and comparable with the best color appearance models in typical viewing conditions.[19] The brightness and colorfulness scales will also perform as well as any other model for typical conditions. In more extreme viewing conditions, the performance of iCAM and other models will begin to deviate. It is in these conditions that the potential strengths of iCAM will become evident. Further visual data must be collected to evaluate the model's relative performance in such situations.

The color difference performance of iCAM will be similar to that of CIELAB since the space is very similar under the reference viewing conditions.[15,19] Thus, color difference computations will be similar to those already commonly used and the space can be easily extended to have a more accurate difference equation following the successful format of the CIE94 equations.[11] (Following the CIEDE2000 equations in iCAM is not recommended since they are extremely complex and fitted to particular discrepancies of the CIELAB space such as poor constant-hue contours.)

Simultaneous contrast (or induction) causes a stimulus to shift in appearance away from the color of the background in terms of opponent dimensions. Figure 3 illustrates a stimulus that exhibits simultaneous contrast in lightness (the gray square is physically identical on all three backgrounds) and its prediction by iCAM as represented by the iCAM lightness predictor. This prediction is facilitated by the local adaptation features of iCAM.

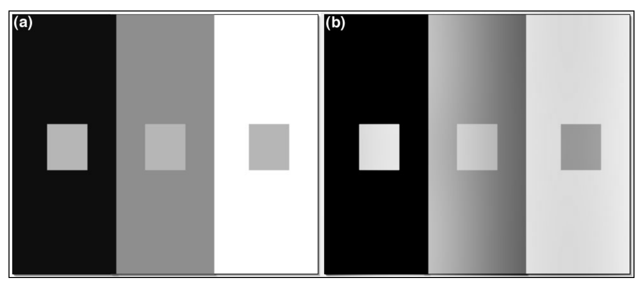

Figure 3. (a) Original stimulus and (b) iCAM lightness, J, image illustrating the prediction of simultaneous contrast.

Crispening is the phenomenon whereby the color differences between two stimuli are perceptually larger when viewed on a background that is similar to the stimuli. Figure 4 illustrates a stimulus that exhibits chroma crispening[20] and its prediction by the iCAM chroma predictor. This prediction is also facilitated by the local adaptation features of iCAM.

Spreading is a spatial color appearance phenomenon in which the apparent hue of spatially complex image areas appears to fill various spatially coherent regions. Figure 5 provides an example of spreading in which the red hue of the annular region spreads significantly from the lines to the full annulus. The iCAM prediction of spreading is illustrated through reproduction of the hue prediction. The prediction of spreading in iCAM is facilitated by spatial filtering of the stimulus image.

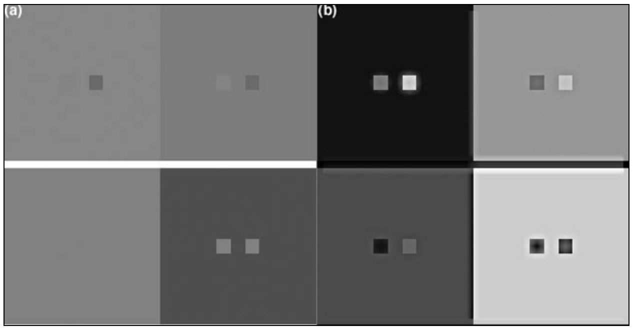

Figure 4. (a) Original stimulus and (b) iCAM chroma, C, image illustrating the prediction of chroma crispening. Original image from <www.hpl.hp.com/persona./Nathan_Moroney/>.

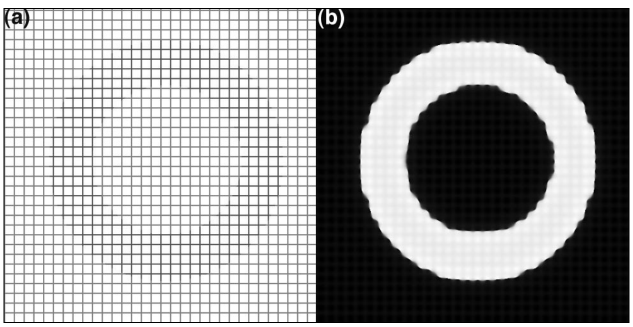

Figure 5. (a) Original stimulus and (b) iCAM hue, h, image illustrating the prediction of spreading.

High-dynamic-range images provide a unique challenge to image reproduction algorithms since they require the equivalent of dodging and burning historically performed manually in a darkroom (analog or digital). Human observation of high-dynamic-range scenes is facilitated by local adaptation that allows regions of various luminance levels to be viewed essentially simultaneously. However, images are normally reproduced on low-dynamic-range displays with a single adaptation level. Figure 6 illustrates the high-dynamic-range tone-mapping properties of iCAM by comparing an original image with a simple nonlinear tone mapping with an iCAM-processed image. The improved tone-mapping and visibility of highlight and shadow details is facilitated by the low-pass dependent modulation of the exponents in the IPT transformation.

Image quality metrics can be derived from image difference metrics that are based on normal color difference formulas applied to properly spatially-filtered images. This approach has been used to successfully predict various types of image quality data.[14] Figure 7 illustrates the prediction of perceived sharpness[10] and contrast[21] differences in images through a single summary statistic (mean image difference). This performance is equivalent to, or better than, that obtained using other color spaces optimized for the task.[14]

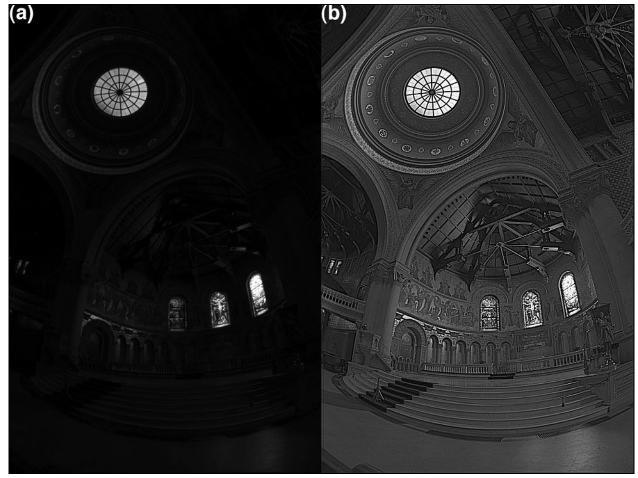

Figure 6. (a) Linear mapping of a high-dynamic-range image and (b)the same image mapped through the iCAM spatial adaptation mechanisms. (Both images are gamma corrected in an identical manner. Original HDR image from <www.debevec.org>.)

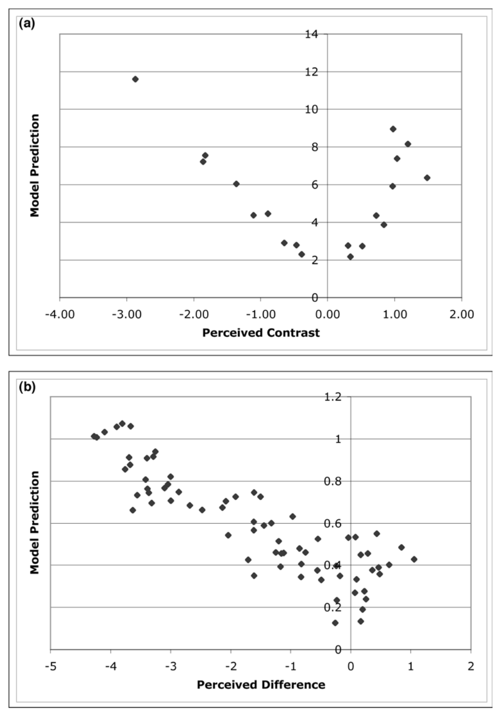

Figure 7. iCAM image differences as a function of (a) perceived image contrast and (b) perceived image sharpness for a variety of image transformations. (Note: Desired predictions are a v-shaped data distributions since the perceptual differences are signed and the calculated differences are unsigned.)

Conclusions

CIECAM02 represents a significant advance over CIECAM97s in terms of performance and simplicity. It will certainly be well received and find wide application. However, while the improvements in such traditional color appearance models might be reaching a plateau, it is becoming apparent that there are opportunities for the application of different types of models to other problems such as high-dynamic range tone mapping, gamut mapping, and image quality measurement. It is in this spirit that the iCAM model framework has been developed to supplement models such as CIECAM02.

While the iCAM framework is in place and its performance for various tasks is already quite good, there is clearly much room for improvement and enhancement through the collection and analysis of new types of visual image appearance data. The authors expect to spend many years working on the refinement and testing of this model framework and hope that others will join in the task by testing this and other models and generating new types of visual data to expand the model's capabilities. It appears that the goal of a relatively simple model capable of predicting spatial and color appearance phenomena along with measurements of image differences for image quality applications might be within reach. Of course, if that goal is reached, there will always be the addition of temporal phenomena to challenge researchers working on applications such as digital cinema.

References

1. J. von Kries, "Chromatic Adaptation," Festchrift der Albrect-Ludwig-Universitat (Fribourg) (1902). [Translation: D.L. MacAdam, Sources of Color Science, MIT Press, Cambridge, Mass. (1970).].
2. D. Nickerson, "History of the Munsell Color System and its Scientific Application," *J. Opt. Soc. Am.* **30**, 575-586 (1940).
3. A. R. Robertson, "The CIE 1976 Color-Difference Formulae," *Color Res. Appl.* **2**, 7-11 (1977).
4. M. D. Fairchild, *Color Appearance Models*, Addison-Wesley, Reading (1998).
5. CIE, "The CIE 1997 Interim Colour Appearance Model (Simple Version), CIECAM97s," CIE Pub. 131 (1998).
6. M.D. Fairchild, "A Revision of CIECAM97s for Practical Applications," *Color Res. Appl.* **26**, 418-427 (2001).
7. N. Moroney, M. D. Fairchild, R.W.G. Hunt, C.J. Li, M. R. Luo, and T. Newman, "The CIECAM02 Color Apperance Model," *IS&T/SID 10th Color Imaging Conference, Scottsdale*, pp. 23-27 (2002).
8. S. N. Pattanaik, J. A. Ferwerda, M. D. Fairchild, and D.P. Greenberg, "A Multiscale Model of Adaptation and Spatial Vision for Image Display," *Proceedings of SIGGRAPH 98*, 287-298 (1998).
9. S. N. Pattanaik, M. D. Fairchild, J. A. Ferwerda, and D. P. Greenberg, "Multiscale Model of Adaptation, Spatial Vision, and Color Appearance," *IS&T/SID 6th Color Imaging Conference*, Scottsdale, 2-7 (1998).
10. G. M. Johnson and M. D. Fairchild, "Sharpness Rules," *IS&T/SID 8th Color Imaging Conference*, Scottsdale, 24-30 (2000).
11. CIE, Industrial Colour-Difference Evaluation, *CIE Tech. Rept*. 116, Vienna (1995).
12. M. R. Luo, G. Cui, and B. Rigg, "The Development of the CIE 2000 Colour Difference Formula: CIEDE2000," *Color Res. Appl.*, **26**, 340-350 (2001).
13. G. M. Johnson and M. D. Fairchild, "A Top Down Description of S-CIELAB and CIEDE2000," *Color Res. Appl*. **27**, in press (2002).
14. G. M. Johnson and M. D. Fairchild, "Darwinism of Color Image Difference Metrics," *IS&T/SID 9th Color Imaging Conference*, Scottsdale, 108-112 (2001).
15. G. J. Braun, F. Ebner, and M. D. Fairchild, "Color Gamut Mapping in a Hue-Linearized CIELAB Color Space," *IS&T/SID 6th Color Imaging Conference*, Scottsdale, 163-168 (1998).
16. F. Ebner, and M. D. Fairchild, "Development and Testing of a Color Space (IPT) with Improved Hue Uniformity," IS*&T/SID 6th Color Imaging Conference*, Scottsdale, 8-13 (1998).
17. N. Moroney, "Local Color Correction Using Non-Linear Masking," *IS&T/SID 8th Color Imaging Conference*, Scottsdale, 108-111 (2000).
18. C. J. Li, M. R. Luo, R.W.G. Hunt, N. Moroney, M. D. Fairchild, and T. Newman, "The Performance of CIECAM02," *IS&T/SID 10th Color Imaging Conference*, Scottsdale, pp. 28-32 (2002).
19. D. R. Wyble and M.D. Fairchild, "Prediction of Munsell Appearance Scales using Various Color Appearance Models," *Color Res. Appl.* **25**, 132-144 (2000).
20. N. Moroney, "Chroma Scaling and Crispening," *IS&T/SID 9th Color Imaging Conference*, Scottsdale, 97-101 (2001).
21. A. Calabria and M.D. Fairchild, "Compare and Contrast: Perceived Contrast of Color Images," *IS&T/SID 10th Color Imaging Conference*, Scottsdale, pp. 17-22 (2002).

Biography

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