Tone Reproduction and Color Appearance Modeling: Two Sides of the Same Coin?

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Abstract

Color appearance models and tone reproduction algorithms are currently solving different problems. These classes of algorithms are also developed and used in different communities. However, they show remarkable functional similarities. Perhaps there is reason to think that they could in fact be one and the same thing. The advantages would be that we could achieve dynamic range reduction while taking human color vision into account. Vice-versa, we could predict the appearance of color over a large range of intensities. But how to overcome the differences, and how to construct an algorithm that could be both a tone reproduction model as well as a color appearance model?

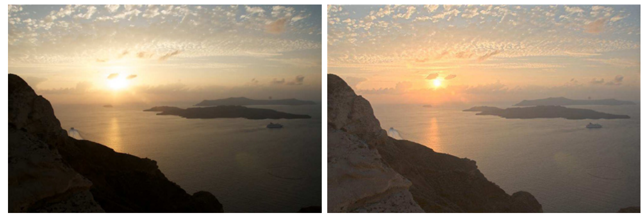

Figure 1. *This scene was captured with a single exposure (left) and high dynamic range imaging technologies (right). The image on the right was tonemapped for display/print using the photographic tone reproduction operator [3]. Photograph courtesy of Tania Pouli.*

Introduction

An imaging pipeline consists of processes to capture, store, transmit and display images and video. Traditional imaging pipelines are designed around the abilities of conventional capture and display devices, and therefore do not need dynamic range beyond what can be represented with a single byte per color channel. This situation is changing as image capture and in particular display technologies are maturing to include higher dynamic ranges [1]. High dynamic range imaging technologies produce and manipulate pixel data that conceptually consist of floating point numbers instead of 8-bit integer formats [2].

The benefit is clear: capturing data at full fidelity will lead to better imagery, even if the display device is not capable of reproducing the full dynamic range. An example is shown in Figure 1, where a single 8-bit exposure of a scene is compared with a high dynamic range (HDR) capture of the same scene. The resulting high dynamic range image was tonemapped to fit the reproduction range of paper. Note that the exposure on the left has both under- and over-exposed areas. This is not uncommon and therefore a good example of the utility of high dynamic range imaging technologies.

While representing pixels as floating point numbers rather than bytes may seem a minor change, there are many perceptual as well as technological aspects that require a reassessment. On the technological side, there are still many challenges. Perhaps the main one is that HDR image and video capture devices generate an enormous amount of data that would have to be managed. Standard compression algorithms are not directly amenable to HDR data [4, 5, 6, 7], with the implication that broadcast standards have yet to emerge.

Second, HDR movie cameras are only just becoming available, including the Red Epic[1] and the camera by Contrast Optical Engineering [8].

Third, it is not entirely clear how much dynamic range should be captured. While the range of illumination between starlight and bright sunlight over which the human visual system can adapt is around 10 orders of magnitude [9], it seems overkill to try and capture this full range at all times. The human visual system is able to simultaneously perceive around 4 orders of magnitude of illumination under a specific laboratory set-up [10], although in practice this number may be a bit higher. It would probably be good practice to design imaging pipelines around this number.

If it is assumed that HDR imagery and video will be captured with such a dynamic range, then displays should match this capability as well. Currently, only very few displays currently come even close, the Dolby prototype displays [1] and their commercial derivatives by SIM2[2] being the exception. Print technology is inherently incapable of reaching such dynamic range due to its reflective nature. Nonetheless, it may be foreseen that display devices will soon exhibit a greater variety in dynamic range than currently available.

Whether low dynamic range legacy content or high dynamic range data is sent to a display, it will need to be mapped into a format that can be handled by that given display. In particular, it will need to be tonemapped to fit the dynamic range of the display device, and should take into consideration the state of adaptation of the observers.

In recent years, much progress has been achieved in the design of algorithms that map high dynamic range images to low dynamic range display devices [2, 6]. Moreover, these algorithms have been subjected to psychophysical evaluation such as preference ratings [11, 12, 13] and similarity ratings [14, 13, 15, 16].

Although several tone reproduction operators are capable at compressing dynamic range, in this paper we argue that one weakness that persists is the lack of sensible color management. In particular, it is well-known that there exist luminance-induced appearance phenomena such as the Hunt and Stevens ef-

[1] http://www.red.com/

[2] http://www.sim2.com/

fects, the Helmholz-Kohrausch effect and the Bezold-Brücke hue shift [17, 18] which indicate that there is a complex relationship between the perception of color and the luminance level at which colors are perceived. Currently, these effects are not generally taken into consideration in tone reproduction operators, leading to images that generally look either too vivid or too dull, and are certainly unsuitable for accurate color reproduction.

On the other hand, color appearance modelling is an active area of research that has led to several models that predict the perception of color under different illumination conditions [17]. With the tristimulus values of a patch of color given, as well as a description of the environment in which it is observed, such models predict the perception of color in terms of appearance correlates, which include lightness, brightness, hue, saturation, colorfulness and chroma [19, 17, 18].

Few color appearance models are designed with high dynamic range imaging in mind, although notable exceptions exist [20, 21, 22, 23]. In particular, the models proposed by Kim et al. [22] are based on a psychophysical dataset that spans a much higher dynamic range than the psychophysical dataset that lies at the heart of most color appearance models [24].

The purpose of this paper is to argue that although tone reproduction and color appearance modelling may be addressing different problems, their aims partially overlap. Moreover, their functional similarity is unmistakable, albeit also with significant differences. This is especially the case for tone reproduction operators that model aspects of human vision.

This paper catalogs the similarities and differences in order to show where the opportunities lie to construct a combined tone reproduction and color appearance model that could serve as the basis for predictive color management under a wide range of illumination conditions. It is thought that such an algorithm would benefit both fields of high dynamic range imaging as well as color imaging.

To this end, the remainder of the paper begins by briefly describing the aforementioned luminance-induced appearance phenomena. Then, the structure of tone reproduction operators is outlined, insofar based on neurophysiology. These models are functionally closest to color appearance models, which are discussed next. A discussion of attempts to bring tone reproduction and color appearance modelling closer together then precedes the conclusions.

Luminance Induced Appearance Phenomena

The overall amount of light under which colors are observed may change the appearance of these colors. For instance, on a bright sunny day colors tend to appear more colorful than on an overcast day [18]. Several different observations have been made that relate to the relationship between illumination and color appearance.

First, the Hunt effect states that as the luminance of a given color increases, so does its perceived colorfulness [25]. Further, perceived brightness contrast also changes with luminance, which is known as the Stevens effect [26]. Brightness itself is not only a function of luminance, but also depends on the saturation of the stimulus. This is described by the Helmholtz-Kohlrausch effect, although this effect depends on hue angle as well [27]. Finally, the perception of the hue of monochromatic light sources depends on luminance level, which is described by the Bezold-Brücke hue shift [17].

Figure 2. *The image on the left was tonemapped with the photographic operator [3], which compresses the luminance channel of the Yxy color space. It therefore does not take luminance induced appearance phenomena into account. The image on the right was tonemapped using the color appearance model by Kim et al. [22].*

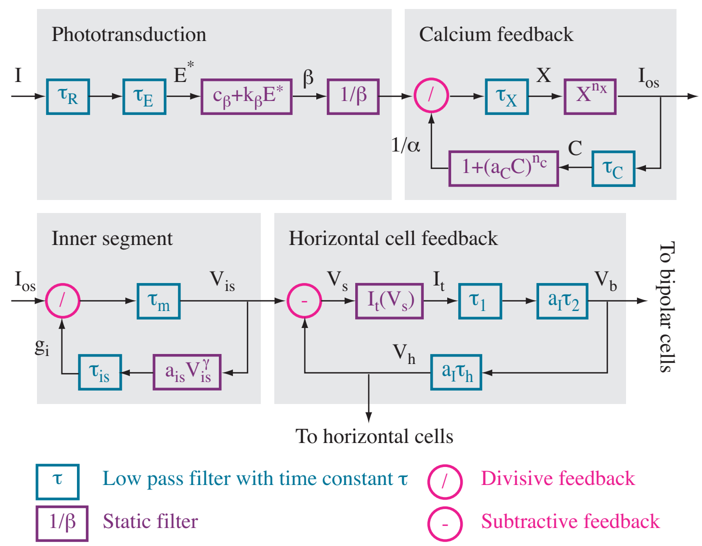

Figure 3. *A recent model of photoreceptor behavior (after [28]).*

The implication for high dynamic range imaging algorithms, and in particular tone reproduction, is that if an image of a scene is displayed at much lower luminance levels than were present in the scene itself, a tone reproduction operator should take these effects into account to ensure that the image is perceived in the same way as the original scene, despite the differences in luminance levels. An example demonstrating the difference between tone reproduction with and without color management is given in Figure 2.

Neurophysiology-Based Tone Reproduction

A good number of tone reproduction operators resemble parts of human neurophysiology, and in particular the behavior of photoreceptors. The flow chart of a recent model of photoreceptor behavior is given in Figure 3 [28]. This is an accurate temporal model that takes adaptation into account. However, if its temporal components are integrated out, it results in a steady-state model which can be accurately modelled by the Naka-Rushton equation, which was originally used to model the response function of a certain species of fish:

$$V = \frac{L^n}{L^n + \sigma^n} \tag{1}$$

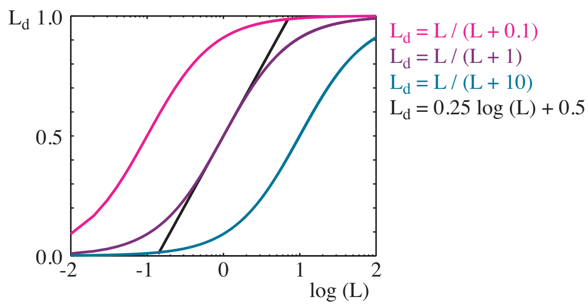

Figure 4. *The Naka-Rushton equation plotted for different semi-saturation constants (0.1, 1 and 10). Note that around the inflection point, the response is approximately logarithmic as shown by the straight line.*

Here, V is the photoreceptor response as a result of being exposed to a luminance of L. This function is plotted in Figure 4, showing that on a log-linear scale this response is sigmoidal, having a single inflection point. The constant σ is known as the semi-saturation constant, which is the value of L that produces an output of 0.5. The constant n determines the steepness of the function around the inflection point, and often ranges somewhere between 0.5 and 1.0 ($n = 0.76$ for the above model).

The Naka-Rushton equation and variants thereof are used in several tone reproduction operators [29, 30, 31, 32, 3, 33, 34], where the function is applied to all pixels identically. Thus, a display value L_d is calculated to be identical to the photoreceptor response V. The value of the semi-saturation constant can be computed from the average pixel luminance [33]. Of course there are many other ways to compress an image for display [2], although sigmoidal compression tends to be used often as it gives plausible results while being computationally inexpensive.

However, there exists one main problem with this approach, which is that most operators work on a single luminance channel, reconstructing a color image after compression. This does not take into account any form of color appearance, leading at best to a single ad-hoc parameter that can be user-adjusted, as discussed next.

Color Reconstruction

For algorithms that compress the luminance channel, the process of reconstructing a color image typically involves the extraction of a single luminance channel L from a color image (R, G, B), usually computed as a weighted average of the red, green, and blue inputs using $L = 0.2126R + 0.7152G + 0.0722B$. The luminance values L are then compressed or expanded into display values L_d using one of the many algorithms available, followed by reconstitution into a new color image (R_d,G_d,B_d). The latter is achieved by calculating [29]:

$$R_d = L_d \left(\frac{R}{L}\right)^e \tag{2a}$$

$$G_d = L_d \left(\frac{G}{L}\right)^e \tag{2b}$$

$$B_d = L_d \left(\frac{B}{L}\right)^e \tag{2c}$$

The user-specified parameter $e \in [0, 1]$ controls the amount of saturation in the display image. Values around the $e = 0.6$ mark usually offer a reasonable trade-off between under- and over-saturation. Example results of this procedure are shown in Figure 5. As shown here, in particular images with a strong color cast benefit from setting this exponent to values lower than 1.0.

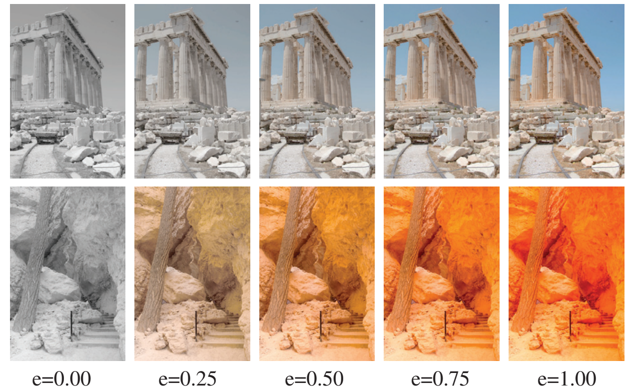

Figure 5. *After tonemapping the luminance channel of these images with Drago's tone reproduction operator [35], color images were reconstructed using Equation* (2) *for different values of* e.

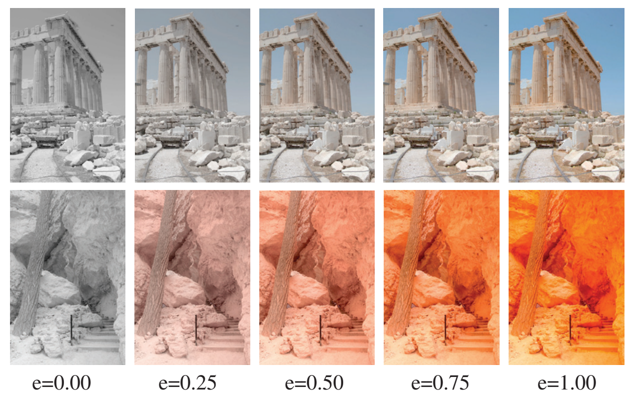

Figure 6. *Color processing using Equation* (3). *The parameters are otherwise identical to those used for Figure 5.*

An alternative function also controls saturation with an explicit parameter. In this linear formation, luminance is claimed to be affected less by the value of e [36]:

$$R_d = L_d \left(\left(\frac{R}{L} - 1\right) e + 1\right) \tag{3a}$$

$$G_d = L_d \left(\left(\frac{G}{L} - 1\right) e + 1\right) \tag{3b}$$

$$B_d = L_d \left(\left(\frac{B}{L} - 1\right) e + 1\right) \tag{3c}$$

An example of this approach is shown in Figure 6. Note that for smaller values of e especially the images in the bottom row show a marked hue shift from orange to pink.

Based on psychophysics, it was found that the parameter e in this formulation can be linked to a contrast compression factor, which indicates by how much the contrast was reduced as a result of applying a tone reproduction operator. It was found that the relation between contrast compression factor and parameter e is sigmoidal [36].

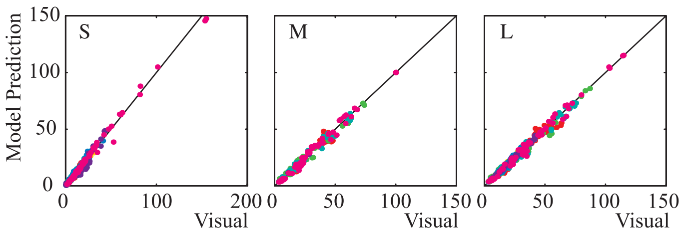

Figure 7. *The output of the combined chromatic adaptation and non-linear response compression step of [42] plotted against a set of corresponding color datasets for each of the S, M and L color channels.*

Nonetheless, these approaches are ad-hoc and used only to create images that are visually pleasing. Notably, it ignores the interrelation that exists between light levels and the perception of color. It also ignores issues related to chromatic adaptation which would have to be addressed if the image depicts a scene with a different dominant light source from the environment in which the image is observed. Thus, this level of color management is too simple and tone reproduction operators would benefit from more advanced and integrated color management. Nonetheless, in tone reproduction saturation adjustment is still the norm rather than the exception.

Color Appearance Modelling

Color appearance models are designed from the ground up to account for differences in viewing environment. They can be used to predict appearance correlates, but they can also be used to transform a patch of color to account for differences in viewing environment [17, 37, 18]. Most color appearance models consist of three separate steps. First, a chromatic adaptation transform is computed. Second, a non-linear response compression is executed. Finally, appearance correlates are computed based on the output of the response compression step. The most common color appearance models are CIECAM97 [38] and CIECAM02 [39], with the latter currently being widely adopted as the industry standard. For imaging systems, CIECAM02 has been extended to work with images rather than uniformly colored patches [20, 21, 40].

The chromatic adaptation transform is usually executed in a sharpened cone response space, followed by non-linear response compression which operates in the Hunt-Pointer-Estevez color space [37], modelling the responses of the three cone types. Crucially, in color appearance models the non-linear response compression is executed in each channel independently, albeit that the semi-saturation constant has the same value across all three channels.

As chromatic adaptation and response compression are working in different color spaces, we note that the combined result does not adhere to the von Kries hypothesis, which states that photoreceptor types work independently of each other [41]. Despite this, the chromatic adaptation transform employed in CIECAM02 matches corresponding color datasets well.

Trend 1: Chromatic Adaptation

Based on experiments with color management in tone reproduction [34], a novel color appearance model was recently outlined that combines chromatic adaptation and non-linear response compression into a single step, operating in the Hunt-Pointer-Estevez color space [42]. The key innovation of this model is that the chromatic adaptation transform is incorporated in a per-channel semi-saturation constant, i.e. this constant is different for each channel and is specified according to the tristimulus value of the white point. This approach maintains channel independence, and is therefore a true von Kries model. Moreover, it matches corresponding color datasets equally well (the overall RMS error is 28.31 for this model and 28.57 for CIECAM02). Figure 7 shows the results of comparing the model's output against 6 corresponding color datasets [43, 44, 45, 46, 47, 48], as well as CIECAM02 [39], confirming the model's predictive power. Combining chromatic adaptation and non-linear response compression is an important step towards unifying tone reproduction and color appearance models, as it makes the two functionally more alike.

Trend 2: HDR Color Spaces

A further trend towards high dynamic range color imaging is afforded by the emergence of HDR-specific color spaces. In particular, recently the CIELAB and IPT color spaces, which both contain a compressive power function, were successfully amended to have sigmoidal compressive functions [49]. Their predictive power with respect to Munsell renotation data is similar to the conventional CIELAB and IPT spaces [50], but the non-linearity now matches those of color appearance models, tone reproduction operators, and importantly the photoreceptor response of the human visual system.

Trend 3: HDR Color Appearance Data and Models

To allow CIECAM02 to work on images rather than single colored patches, it was amended to spatially varying models, named iCAM and iCAM06 [20, 21, 40]. These models include local adaptation processes, in that a pixel's local neighborhood is taken to affect the perception of the pixel itself, thereby borrowing from spatially varying tone reproduction operators.

Recently, new data has become available to test color appearance models over an extended range of illumination [22]. The experiments underlying this data follow the same paradigm as that used to acquire the LUTCHI dataset [24], albeit that an HDR display and transparencies were used to extend the range of illumination conditions. A color appearance model fitting this new dataset was also proposed [22]. Functionally it follows existing color appearance models, although importantly it uses Equation (1) directly for its non-linear compression step. This is a simpler formulation than used in CIECAM02, although chromatic adaptation is still implemented as a separate preprocess. The model has been extended to account for the effect that edge sharpness has on the perception of colored patches [23].

Discussion

The reason that color appearance models are not yet viable tone reproduction operators is related to the manner in which they convert patches of color between viewing environments. As argued previously [51], color appearance models are run in forward and backward direction to achieve such conversion (Figure 8). In forward mode, the scene's viewing parameters are inserted, and in backward mode the target viewing environment's parameters are inserted. This works well if these two environments do not differ

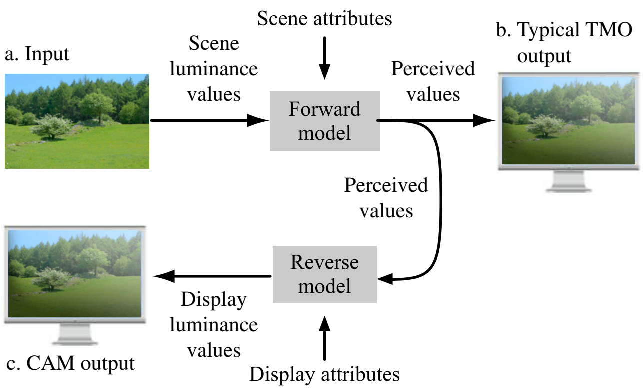

Figure 8. *A flow chart outlining typical processing paths for tone mapping operators (TMO) and color appearance models (CAM). The input is (a) is passed through the model using scene referred parameters. Many tone reproduction operators display the output directly (b), although the values represent photoreceptor output. CAMs operate the model in reverse using display referred parameters, resulting in displayable luminance values (c).*

much in overall illumination levels.

However, if there is a significant discrepancy between viewing environments, then compression will not be sufficient to produce a viable result. The reason is that dynamic range compression comes from the sigmoidal response function. Running this step in reverse largely undoes any compression, and is in fact functionally equivalent to gamma correction [51]. Unfortunately this means that color appearance models are not suitable as dynamic range reduction algorithms. Image appearance models mitigate this problem to some extent by applying spatially varying filters.

On the other hand, tone reproduction operators often omit the reverse step, and are therefore theoretically incorrect, causing the display to emit luminances that represent photoreceptor output. This means that there remains a gap between color appearance models and tone reproduction operators, each solving somewhat different problems: tone reproduction offers dynamic range reduction, while color appearance models offer accurate color management.

This problem can be solved to some extent by running a color/image appearance model on a high dynamic range image, then resetting the luminance channel to retain only chromatic adjustments and compressing the image by means of a tonemapping operator that only compresses the luminance channel [52]. Nonetheless, this is regarded as a workable intermediate solution in the absence of a more principled approach.

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