Modeling Multiplicative Adaptation and Sumulteneous Contrast for HDR Image Display

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***Abstract* — we seek to draw inspirations from known physiological phenomena of the human visual system (HVS) to develop engineering systems for image processing. Combining multiplicative adaptation and simultaneous contrast mechanisms of the HVS in a simplified computational model, we have developed a practically implementable system that processes images in the spirit of some aspects of multiplicative adaptation and simultaneous contrast. We show that the model adapts to local background luminance levels, preserves and enhances local details, and is potentially a useful model for rendering image for high quality display.**

I. Introduction

Perception is an extremely complex multi-level process. Scientists have always been fascinated by the amazing capability of the human visual system (HVS) and there have been much research to uncover the mystery of vision. Although we still know very little about many aspects of the HVS, well established evidence about some of the vision phenomena exist. For example, in colour vision, trichromacy and colour-opponency are well understood physiological mechanisms that operate at different stages in the visual pathway. Trichromacy – any colour can be matched by appropriately mixing the three primaries, is understood to be a consequence of having three cones rather than two or four in the VHS. Colour-oponency - the three types of cones in the HVS overlap in the wavelengths of light to which they respond, it is therefore more efficient for the visual system to record differences between the responses of cones rather than each type of cone's individual response. This theory suggests that there are three opponent channels: red versus green, blue versus yellow, and black versus white.

Interestingly, both the trichromacy and the opponency models have found their engineering counterparts in modern electronic imaging systems. For example, image acquisition devices (cameras) have three types of filters responding to different wavelength ranges of the light spectrum to produce the well known Red (R), Green (G) and blue (B) pixels in an image. These three types of filters can be thought of as analogue to the three types of cones in the HVS. Similarly, in colour television/video, light-dark (achromatic, also known as the luminance, or Y) signal, and two opponent signals, I and Q in the YIQ model, or Cb and Cr in the YCbCr model, are recorded or transmitted. This is rather similar to the colour opponency signals in the HVS. Although it is not the purpose of this paper to make any direct link between the HVS and any engineering aspects of a modern digital imaging system, the fact is that scientists and engineers have been seeking inspirations from the HVS to solve real world problems. The examples of trichromacy and opponency and their similarity to the camera and signal models of today's imaging systems demonstrate that it is logical and worthwhile to seek ideas from the HVS to develop engineering solutions to imaging problems.

In this paper, we attempt to develop a simple computational model to mimic aspects of brightness perception of the HVS. It is worth stating at this juncture that we are not trying to build a model that accurately reflects the HVS (in fact this is impossible as there are still so much unknown about the HVS), rather, we seek "engineering interpretation" of some known phenomena of the HVS and to develop engineering solutions. The particular aspects of the HVS that this paper tries to study are brightness adaptation and simultaneous contrast. Through building a computational model for the brightness adaptation phenomenon, we establish that brightness adaptation and simultaneous contrast are in fact closely related and that simultaneous contrast could be interpreted as a consequence or a byproduct of brightness adaptation. We believe this is a useful insight. Although we are not sure how this insight maybe used to gain further understanding of the HVS, we were able to use this insight to construct an elegant image processing model for rendering images for high quality display.

II. Multiplicative Adaptation

Human eyes can adapt to a wide range of light intensity from moon light to direct sunlight. However, the physiology of the retinal does not maintain such wide dynamic range all the time, but rather its operating range is much narrower at any given time instant. The eyes maintain such a wide operating range through a mechanism known as adaptation. Adaptation processes dynamically adjust the retinal's response functions to best operate on the available light. Physiologically, pupil change, pigment depletion, subtractive and other multiplicative mechanisms are all responsible for maintaining the sensitivity of the system [5].

The multiplicative light adaptation can often be modelled by the Naka-Rushton formula [4]

$$R(I) = \frac{I^n}{I^n + \sigma^n} \tag{1}$$

where R is retinal response ($0 < R < 1$), semi-saturation constant σ is the I value that causes the half-maximum response, and n is a sensitivity control similar to gamma for video, film, and CRTs. Naka and Rushton used this hyperbolic function to model psychophysical adaptation and saturation in rods and cones. Changing σ with varying illumination level can be used to model the multiplicative adaptation mechanism of the HVS [4]. Figure 1 shows how the retinal response changes with different adaptation levels. This Figure illustrates how the retinal adapts its response to different ambient light level to maintain a sensitive response to the change of light for the given adaptation level.

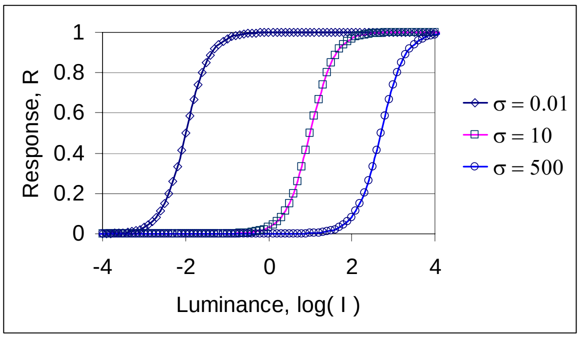

Figure 1: Multiplicative adaptation serves as a mechanism to maintain the sensitivity of the visual system. The response curve for a smaller σ represents how the retinal responses to a lower light environment whilst that of a larger σ represents a high light level case.

III. Simulteneous Contrast

The well known simultaneous contrast phenomenon [1] is illustrated in Figure 2. This phenomenon says that the same foreground intensity will be perceived as darker in a brighter background and vice versa. It is not difficult to imagine a situation where a higher intensity which is in front of a bright background will be perceived darker than a lower intensity which is in front of a dark background. In the Figure, two background squares have intensities of B1 and B2 where B2 > B1, and the two foreground squares have intensities F1 and F2 where F2 > F1. F2 is sometimes perceived darker in the (F2, B2) combination than F1 in the (F1, B1) combination even though F2 actually has a bigger intensity value.

IV. A Model of Brightness Perception

Combining the observations of multiplicative adaptation and simultaneous contrast as discussed in Sections II and III, we here present a simplified image processing model. Again, we want to stress this is an engineering solution not an accurate physiological model.

It is clear from above discussions that the perceived brightness of a pixel is a function of its intensity and its surround or background luminance level. For a pixel of intensity D against a background lamination level of BLL, the perceived brightness of D will be a function of both D and BLL:

$$Brightness(D) = F(D, BLL) \tag{2}$$

where $F()$ is the response function for converting luminance to brightness.

The function should mimic the adaptation mechanism of Figure 1 and the simultaneous contrast mechanism of Figure 2. For the same intensity, the perceived brightness will be brighter in a darker surround than in a brighter surround, and vice versa. For the different adaptation level, the response curve should shift to make the response adapt to the adaptation level. Determining the form of F is obviously difficult. Here we present a simplified model.

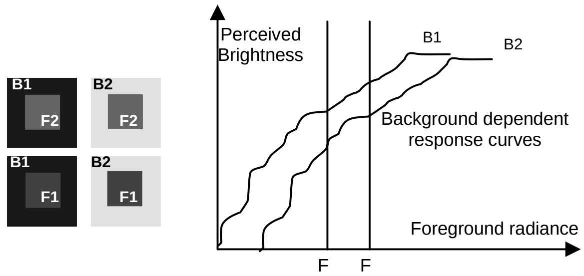

Figure 2: An illustration of perceived brightness response curves for the simultaneous contrast phenomenon. The response curve is background dependent which is analogue to Figure 1 where the response curve is adaptation level dependent. Note the illustration is not an accurate depiction of the actual response curve but rather is an illustration to aid understanding of the simultaneous contrast phenomenon.

A. *A Simplied Model*

In this much simplified model, the perceived brightness as a function of the pixel intensity and its surround lamination level is defined as

$$Brightness(D) = \begin{cases} BLL + K(D - BLL) & \\ 1 & if \quad (BLL + K(D - BLL)) > 1 \\ 0 & if \quad (BLL + K(D - BLL)) < 0 \end{cases} \tag{3}$$

where K is the parameter to control the curve slope of the response function. Clearly the response curve is a linear curve. However, it is not difficult the see that the response of Brightness (D) does fulfil some aspects of the multiplicative adaptation and simultaneous contrast mechanisms as discussed in Figure 1 and Figure 2. Figure 3 is a plot of (3) which is rather similar to Figure 1. In this figure, D1 and D2 are two pixel intensities located in three different backgrounds BLL1, BLL2 and BLL3. The red Line, green line and blur line are the response curves for different background levels. It is seen that the lower intensity pixel D1 with a darker background BLL1 is perceived as a higher brightness F(D1,BLL1) than a higher intensity pixel D2 in a bright background BLL3.

B. *Computing Background Luminance Level* (*BLL*)

To use (3) for converting luminance to perceived brightness, it turns out that the crucial challenge is how to calculate the background luminance level for each pixel. One obvious and simplicity way is to take some kinds of average of the surrounding pixels of a pixel to be used as its BLL. However, this naïve approach has a fatal flaw. Supposing a pixel is sitting in the vicinity of an edge, the BLL's on one side will be affected by pixels values on the other side. The consequence of this is that the BLL of the low intensity side will be raised while the BLL of the higher intensity side will be lowered. Recall that in our model which follows the simultaneous contrast principle, a lower intensity pixel in a brighter surround will be converted to brighter level, and vice versa, it is not difficult to imagine that those pixels very close to the edge will be converted to either brighter or darker, in sever cases this will create artificial edges and reverse the edge directions, this is the well-know "halo" artefacts (see left image in Figure 6).

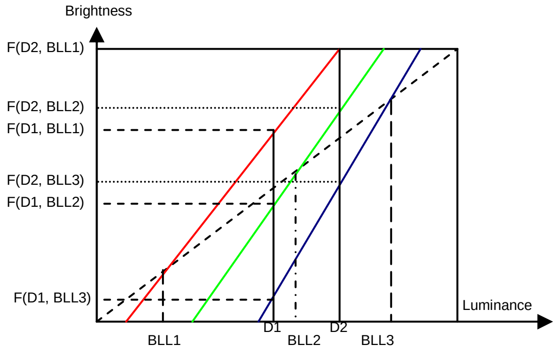

Figure 3 A simplified brightness perception model.

To overcome the aforementioned problem, we need an approach that will enable us to compute the BLL for a pixel using pixels on its own side of the edge without the influence of pixels from other side of the edge. Bilateral filtering [3] is an edge-preserving image smoothing technique which has found extensive applications in recent years. Pixels that are very different in intensity from the central pixel are weighted less even though they may be in close proximity to the central pixel. Bilateral filtering preserves sharp edges by systematically excluding pixels from the other side of the discontinuity. Its edge preserving smoothing property is illustrated in Figure 5 [3].

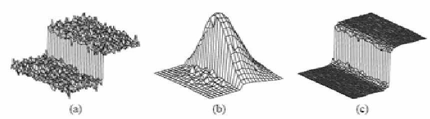

Figure 5 Illustration of bilateral filtering. (a) input signal. (b) weightings for average. (c) output signal.

Figure 6 shows a comparison of using a Gaussian smoothing and a bilateral filtering to obtain the BLL in (3). It is clearly seen that by applying bilateral filtering, we successfully avoided the halo artefacts, which appeared in the case of Gaussian smoothing.

V. Rendering Image For Display

We have developed a procedure to apply the simplified brightness perception model to render digital photographs for high quality display. Our new display algorithm consists of the following two steps:

Step 1: *Estimating minimum radiance of the scene*. During digital image acquisition, the real world luminance (radiance) is compressed by a mapping curve (the camera's response function), which is a compressive curve and can be approximated as

$$D = \frac{\log(I+1)}{\log(I_{\max}+1)} \qquad (4)$$

where D is the pixel intensity of the photograph, I is real world radiance and $I_{\max}$ is the maximum radiance received by camera. The radiance I can then be written as

$$I = e^{SD} - 1 \quad where \quad S = \log(I_{\max}+1) \qquad (5)$$

If we assume the dynamic range of the scene is 4 ~ 5 then S is 4 ~ 5.

In most cases, D would have been scaled to 0 ~ $D_{\max}$, however for most scenes, the minimum radiance of the scenes is always higher than zero. We therefore re-adjust the D value by taking into account this fact (non-zero minimum radiance)

$$D_{Adjust} = \frac{\log((I+\tau)+1)}{\log((I_{\max}+\tau)+1)} \qquad (6)$$

where τ is the estimated minimum radiance of the scene. The smaller τ is, the lower minimum radiance we estimated and the darker the scene is, and vice versa. Experience has shown that for most scenes setting τ = 1% ~ 10 % of average I worked well.

Figure 6 Left: Application of (3) using Gaussian filtering to obtain BLL. Right: Applying (3) using bilateral filtering to obtain BLL. It is clearly seen in the edges between the sky and the buildings, the left image has clearly visible halo (ghost) edges whilst the image on the right did not have such problems.

Step 2: *Applying equation* (*3*). The new adjusted pixel values in (6) are then passed through equation (3). For the bilateral implementation, we used the fast bilateral filtering of [3]. Defining that local contrast as the difference between intensity and its background, local contrast can be enhanced if $K > 1$. We set the K value to 2 to 3 in the experiments.

Step 1 can be regarded as a global operation which is designed to set the display to the correct overall brightness level. This is correct the photograph recording process in which the minimum radiance of the scene has been set to zero. Step 2 is a local process in which the model maintains a sensitive operating range according to the local radiance level.

A. Results

The image display procedure has been applied to many images and shows good results. Figures 7 & 8 show some images rendered by histogram equalization, gamma correction, gradient domain processing [2] and our technique. Although the image by histogram equalization provides higher contrast than the original one, some artefacts and distortion also appeared. Gamma correction can improve the contrast in the darker regions; however, the bright areas appear "washed-out". Our method overcomes the drawbacks of gamma correction and histogram equalization, and provides higher visual quality. Compared with the gradient domain method, our method preserves more local details. Figure 9 presents examples showing our model can adapt to the local luminance while preserving/enhancing details. Unfortunately, only subjective evaluation is available for this kind of work and for this we provide more examples for the readers to view online at http://www.cs.nott.ac.uk/~qiu/modelBP

Figure 7 From top to bottom, left to right: The original image, the processed image by histogram equalization, the processed image by gamma correction and the processed image by our method. The original and the gamma corrected images are courtesy of Raanan Fattal [2].

Figure 8 From top to bottom, left to right: The original image, the processed image image by gamma correction, the processed image by our method and the processed image the gradient domain method [2]. The original the gamma corrected images and the processed image by Fattel's method are courtesy of Raanan Fattal [2].

VI. CONCLUDING REMARKS

In this paper, we have sought to draw inspirations from physiological phenomena of the HVS to develop engineering models for image processing. We have presented a simplified model of brightness perception and have successfully applied it to render images for high quality display. From the results we have obtained, the model has show promises

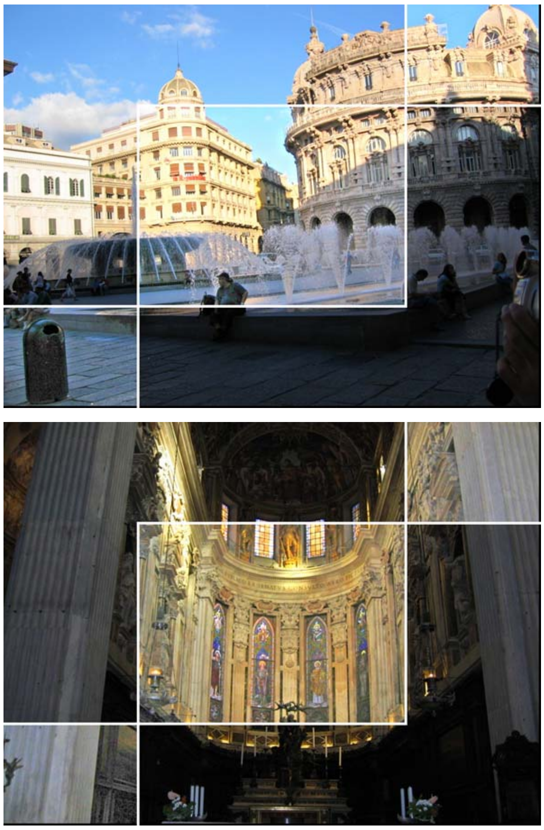

Figure 9 Examples showing our brightness perception model adapts to the local luminance and preserves/enhances local details. Pixels inside the three diagonal rectangles have been processed using our model. By utilizing the full dynamic range available at a local adaptation level, the model greatly enhances the visibility of features while at the same time preserves and enhances local details. This is in spirit similar to the multiplicative adaptation and simultaneous contrast mechanism of the HVS.

ACKNOWLEDGEMENTS

This project Sponsored by National Natural Science Foundation of China (Grant No. 60903128) and Sponsored by the Scientific Research Foundation for the Returned Overseas Chinese Scholars, State Education Ministry.

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