High Dynamic Range Image Reproduction Using a Visual Contrast Mapping Model

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Abstract

A model for high dynamic range (HDR) image reproduction is proposed in this research. The main concept behind this model is to perform image reproduction based on the equivalence of perceived visual contrast for every pixel. A relative perceived visual contrast (RPVC) function is derived in this research from paper published by Burkhardt et al. to provide the base for visual matching between the HDR scene and the reproduced image in low dynamic range (LDR) medium. The adapting background luminance and physical contrast are the control parameters for this function. Many crucial features (for example bilateral type filter and IPT color spacing) found in prior HDR models (like iCAM06 etc.) are also incorporated in this model. Psychophysical experiment was performed in a specially configured setting to compare a real HDR scene with reproduction images on LDR monitor. The reproduced LDR images by six other HDR models were compared by pair comparison method. The results indicate that while iCAM06 has better performance in overall and bright region, this RPVC model has better performance in the dark region.

Introduction

High dynamic range (HDR) image reproduction has been explored by both the computer graphics community and the imaging science community for some time. One early HDR publication from the computer graphics community was presented by Miller and colleagues in 1984 at SIGGRAPH [1]. Consequent works are referred to as tone mapping operators (TMO) which include computing algorithms for processing graphical data.

In the imaging science community, Land and McCann proposed the Retinex theory way back in 1967 with the concept of center/surround spatially opponent operation [2]. Recently, the Retinex theory has been applied in several HDR image reproduction models [3, 4]. On the other hand, after CIE recommended both CIELAB and CIELUV as uniform color spaces in 1976, color appearance models have been an actively researched area, resulting the recommendation of CIECAM97 and consequently CIECAM02 color appearance models. However, it was known that these models only handle the solid color patch type stimulus. Meanwhile, S-CIELAB was proposed to include the consideration of spatial property for image color difference by incorporating spatial filtering [5]. Fairchild proposed a concept of image appearance model handling the spatial functionality for the stimuli in pictorial image [6, 7]. As a result, iCAM and the enhanced model, iCAM06 were proposed and applied in HDR image reproduction with all the color appearance functionalities carried on from the long-researched CIE color appearance models [8]. Most references to these prior HDR image processing models and their characteristics can be found in [9] as listed in Table 1.

Table 1: List of the prior HDR image processing models [9].

Time	Authors	Characteristics
1984	Miller	Mapping by constant brightness ratio
1993	Tumblin-Rushmeier	Mapping brightness value in suprathreshold level
1993	Chiu	First spatially-varying operator
1994	Ward	Match contrast sensitivity in photopic threshold
1996	Ferwerda	Match contrast sensitivity in scotopic visibility
1997	Ward Larson	Histogram mapping
1998	Pattanik	Multiscale for threshold and suprathreshold vision
2002	Ashikhmin	Mapping by local contrast equivalence
2002	Durand-Dorsey	Fast bilateral filter
2002	Fairchild	iCAM image appearance
2002	Fattal	Attenuating large gradient for compression
2002	Kotera	Adaptive scale-gain MSR Retinex
2002	Reinhard	Photographic tone mapping
2005	Reinhard-Devlin	Photoreceptor model
2007	Wang	Integrated surround Retinex
2007	Kuang	iCAM06 image appearance

There have been many publications regarding the evaluation of HDR image reproduction models [10, 11, 12, 13, 8, 14, 15]. The iCAM06 model consistently showed better performance than other models after its modifications from the previous iCAM model. These modifications include a bilateral filter, photoreceptor response function and luminance dependent local contrast enhancement [8]. In the mean time, both Ledda [11] and Yoshida [13] indicated that when conducting psychophysical experiments to compare these models, subjects behaved differently with and without referencing image. Furthermore, when a real scene is present as a reference, the fast bilateral filtering method seems to generate higher contrast and more detail visibility than in the reference images [11, 13]. It is also noted that iCAM model reproduced the image with less local contrast and colorfulness compared with original scenes [8]. Contrast attribute seems to be the area that deserves further deliberation.

It is the primary focus of this study to further contemplate the human visual contrast processing capability into existing HDR models to make the appearance of the reproduced LDR image closer to the real HDR scene. Contrast mapping function and necessary features found in the prior HDR models (especially iCAM06) are incorporated together to make a less complicated

HDR model that also handles contrast attribute better for HDR image reproduction.

Relative Perceived Visual Contrast

The luminance that we encounter daily ranges from 100,000 cd/m^2 for bright sunlight, to 100 cd/m^2 for indoors or to 0.001 cd/m^2 under dark starlight [16, 17]. This is a very wide range of luminance, and the human eyes are capable to adapt to it. However, such wide dynamic range is generally beyond the signal range that current photographic material nor digital camera's sensor can record at one time. The ability for human visual system to cope with such high dynamic range of luminance is well explained by Wandell [18]:

"The most important information represented by the visual pathways is the image contrast, not the absolute light level. The image contrast is the ratio of the local intensity and the average image intensity. To represent the image contrast, neurons in the visual pathway change their sensitivity to compensate for changes in the mean illumination level. This process, call visual adaptation…"

Burkhardt et al. [19] published a paper in 1984 studying the symmetry and constancy in the perception of negative and positive luminance contrast at the suprathreshold level. The perceived difference between a rectangular bar and its background was defined as the perceived contrast. The results show a nearly symmetrical relation between the perception of negative and positive contrast that is largely invariant for background luminance levels from 0.017 to 200 cd/m^2. Crucial information is also revealed in the paper – the data describes the relation between physical contrast (PC) and corresponding perceived visual contrast (VC) for rectangular bars viewed with varying background luminance, which shows a full feature of the perceived visual contrast at suprathreshold level. Unfortunately, only one curve (luminance at 200 cd/m^2) in the original figure was based on fitted data points, the rest of the curves were drawn by eye in the original paper. However, these data imply the human visual contrast response for those luminance levels, which can serve as the mapping function between physical contrast and perceived visual contrast when proper numerical function can be derived.

As listed in Table 2, the regression results from the estimated data points in Burkhardt's paper, the relation between the physical contrast (PC) and the visual contrast (VC) are explained well for different levels of background luminance in a general form as:

$$VC = offset + scalar * Log(PC) \quad (1)$$

Table 2: Regression results between physical contrast and visual contrast at different levels of background luminance for estimated data from Burkhardt's paper.

Background Luminance (cd/m^2)	Offset	Scalar	R^2
0.017	0.56584	0.42340	0.994
0.170	0.60598	0.46576	0.998
1.550	0.68856	0.55212	0.982
17.000	0.77979	0.64606	0.959
200.000	0.87780	0.74729	0.932

A very important commonality between the findings of Van Nes [20] and Burkhardt [19] is that the human contrast perception is influenced by the background luminance levels, which trigger the thought to further model the values in the terms of offset and scalar in Table 2 as two separate functions of the background luminance values. The results for the two separate regressions of the offset term (R^2= 0.984) and the scalar term (R^2= 0.985) are:

$$\text{Predicted Offset} = 0.68495 + 0.078793 * Log(Luminance) \quad (2)$$

$$\text{Predicted Scalar} = 0.54758 + 0.081779 * Log(Luminance) \quad (3)$$

A relative perceived visual contrast (RPVC) function can be therefore summarized in one single equation with two control parameters -- input physical contrast (PC) and background luminance (L_B) as:

$$VC=(0.68495+0.07879*Log(L_B))+(0.54758+0.08177*Log(L_B))*Log(PC) \quad (4)$$

Burkhardt's original paper sets the output perceived visual contrast at 1.0 for the input physical contrast at 1.0 for background luminance at 200 cd/m^2 which is too limited for a real-life HDR image. Assuming the maximum luminance to be 1,000,000 cd/m^2 and the minimum luminance at 0.001 d/m^2 (for a range of 9 log units), the maximum physical contrast can be 0.99999 [19]. With some constrain and clipping on the extended boundary condition, a new concept of Relative Perceived Visual Contrast (RPVC) based on Burkhardt's data set is proposed as the following equation:

$$RPVC(x, y) = (0.68495 + 0.078793 * Log(L_B(x, y))) + (0.54758 + 0.081779 * Log(L_B(x, y))) * Log((Lmax(x, y)-Lmin(x, y))/(Lmax(x, y)+Lmin(x, y))) – 0.15770 \quad (5)$$

Where $L_B(x, y)$ is the adapting background luminance, Lmax and Lmin are the central and background luminance respectively whichever are larger and smaller. The estimated values of the RPVC function are shown as Fig. 1. Therefore given physical contrast ※(X-axis) under certain adaptation luminance level, a corresponding relative perceived visual contrast value can be found (on Y-axis). When mapping it back from Y-axis to X-axis, the same perceived visual contrast value can be found under different levels of adaptation luminance at different physical contrast values respectively. In a way, to keep the perceived visual contrast consistent when mapping from higher to lower adapting luminance, the physical contrast has to be increased which will compensate the not-enough-visual-contrast issue commonly seen when mapping very high luminance area down to lower luminance area. Therefore, this RPVC function can simulate the Stevens effect – increase in perceived image contrast with luminance. When mapping up from extremely low adapting luminance to moderate low luminance while keeping the perceived visual contrast consistent, the physical contrast has to be decreased which would solve the too-much-visual-contrast issue commonly seen in reproducing the darker region.

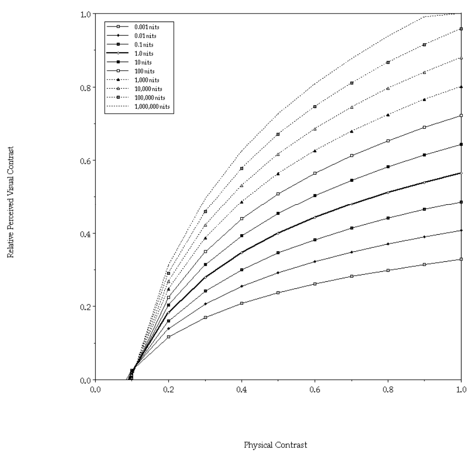

***Figure 1**. Estimated relative perceived visual contrast curves (vs. physical contrast) for luminance levels ranged from 0.001 cd/m^2 to 1,000,000 cd/m^2*

HDR with RPVC Function

Prior psychophysical experiments have demonstrated that for simple configurations, "cone contrast" (the ratios of within-type cone excitation) between a target surface (center) and its immediate area (background) largely determines the color appearance. [21, 22, 23]. Based on the concept of "constancy of cone contrast" Hurlbert and Wolf [23] point out the observation that equal cone contrasts have approximately equal appearance. This matches with an earlier finding by Chichilnisky and Wandell [22] that equal cone (additive) increments against different backgrounds have equal appearance, subject to a background-dependent gain. In other words, even though the center-background ratios are not the same at different background luminance levels, the appearances can be still equal due to the adjustment role introduced by the different gain values. This is the main concept in this visual contrast mapping model that using the RPVC function to perform the tone mapping between HDR and LDR scene. Therefore for each pixel within a HDR image, the central stimulus $S_C(x, y)$ and its background stimulus $S_B(x, y)$ as well as the adapting background luminance $L_B(x, y)$ are sufficient to determine its RPVC(x, y) value. When mapping to a known LDR reproduction medium, after a linear mapping on its background stimulus $S'_B(x, y)$and adapting background luminance $L'_B(x, y)$, the reverse mapping through the RPVC function can back calculate the LDR central stimulus $S'_C(x, y)$ which is the reproduced image on the LDR medium.

Several important features learned from the prior published HDR image processing models, especially iCAM06 model are integrated into this current model. The initial dynamic range compression is done in density (log) domain. Bilateral-type filter is also used to generate the background stimulus for the HDR scene since it is needed to preserve the edge detail and in the mean time create the averaged scene background. A very special feature in this model is to perfrom the RPVC mapping in LMS space, not the regular XYZ space, since LMS is closer to the cone contrast situation. There is also surround luminannce dependence correction in IPT space to account for Bartleson-Breneman and Hunt effects. The complete process flow is summarized as:

1. Read in the absolute colorimetric values from an HDR file as the original scene image.
2. A logarithmic transformation is taken on the input image's absolute XYZ values to establish the reference scene image. Histogram analysis is applied on the reference scene image to locate the maximum and minimum bounds of the scene dynamic range. They are taken from 99.8% and 0.2% accumulated percentile to avoid noise.
3. A scaling factor (sf) is computed by the ratio of the dynamic ranges of luminance (Y) between the scene(S) and the reproduced display medium (D) in log space. A linear mapping in log space is performed for the image from the scene range to the range of the reproduction medium. A white point mapping is also included by setting the maximum values as the base for scaling and adding back the medium white point as offset.
4. Transform the original scene image (CIE XYZ values) to the LMS space to generate the central stimulus (Sc) of the scene.
5. Process the original scene image signals in the LMS space with the bilateral (range-domain) filter [14] to generate the spatially adapted background stimulus (S_B) of the scene.
6. Compute the adapting background luminance (L_B) of the scene by converting the spatially adapted background stimulus (S_B) of the scene back to absolute luminance unit.
7. Transform the projected medium value (in log XYZ space) back to 10 base value to generate the projected adapting background luminance (L'_B) on the reproduction medium.
8. Transform back the projected medium value from XYZ back to the LMS space to form the background stimulus (S'_B) on the reproduced medium.
9. With the pre-calculated values for 1. adapting background luminance of the scene (L_B), 2. adapted background stimulus of the scene (S_B), 3. central stimulus of the scene (S_C), 4. projected adapting background luminance on the reproduction medium (L'_B), and 5. projected background stimulus on the reproduction medium (S'_B), the RPVC function can be used to calculate the central stimulus (S'_C) of the reproduced LDR image in the LMS space as:

$$RPVC_i\,((L_B(x, y), S_{iB}(x, y), S_{iC}(x, y)) = RPVC_i\,((L'_B(x, y), S'_{iB}(x, y), S'_{iC}(x, y)) \quad (6)$$

10. Compensate S'_c (x, y) for the surround luminance influence in the IPT space.
11. Convert from IPT space to LMS and to XYZ colorimetric space. Convert the reproduced LDR image to the device-dependent signals of the output medium for display.

Experimental

A special configuration was used to create high dynamic range condition for exact visual match between real scene and reproduced LDR display images. Two cool-white florescent light sets in different illumination levels were used aside (similar to 45/0 viewing geometry) separately to generate bright and dark sides for high dynamic range scene. A black board was inserted between the two sides and parallel to the observer's viewing direction to reduce the light leaking from the bright side. A Minolta CS-1000 was used to measure the luminance. The luminance reading on the brightest patch of a Kodak Q-13 gray scale was 317.8 cd/m^2 on the bright side. On the dark side, the luminance reading on the brightest patch of a Kodak Q-13 gray scale was 3.458 cd/m^2. Part of the lighting configuration is shown in Fig. 2.

***Figure 2**. The lighting configuration used in this experiment. The cool-white florescent light set on the left side provides much higher illumination than the one on the far right side (not seen on the right).*

A Canon 5D digital camera with a Canon EF 50mm/2.8 macro lens was used. Three pictures in 1/12, 1/3 and 1.3 seconds exposures at f8.0 were taken at ISO 100. Adobe Photoshop CS3 was used to generate the .hdr file to be processed by a MATLAB program. These original images are shown in Fig 3. An Eizo ColorEdge CG21 21-inch LCD monitor at D65 white point and Gamma 2.2 setting was used to display the test images.

Six other HDR image reproduction models (1. iCAM06 [7, 8], 2. local contrast [24], 3. bilateral filtering [25], 4. photographic operator [26], 5. photoreceptor [27], 6. Rahman Retinex [28, 29] and this RPVC model were used to generate the test images. The MATLAB program from RIT's web site was used to process the file for iCAM06. The executable programs from the attached CD

***Figure 3**. The original images: (1) under (2) normal (3) over exposure.*

in Reinhard et al's publication [9] were used for the other five models. All the seven reproduced images are shown in Fig. 4.

***Figure 4**. The reproduced HDR images (1. iCAM06 (top left), 2. Local Contrast, 3. Bilateral Filtering, 4. Photographic Operator, 5. Photoreceptor, 6. Rahman Retinex, and 7. RPVC model).*

Forty-one observers participated in the visual assessment. Each of them was instructed to pick one of the two images on the LCD monitor for which is more resemble visually to the real scene in three separated rounds. The criteria given for all three rounds are: (1) overall reproduction, (2) reproduction in the bright region and (3) reproduction in the dark region.

Results and Discussions

The results of the pair comparison for all three rounds (overall, bright area and dark area) are shown in Table 3.

Table 3: List of the resulting Z-scores for all three tests

No.	HDR Model	Z- Scores		
		Overall	Bright area	Dark area
1	iCAM06	1.944	1.568	0.799
2	Local contrast	0.670	0.747	0.234
3	Bilateral filtering	-1.280	-1.066	-0.577
4	Photographic operator	-2.052	-1.779	-1.115
5	Photoreceptor	-0.611	-0.640	-0.015
6	Rahman Retinex	0.019	0.033	-0.377
7	RPVC	1.310	1.136	1.050

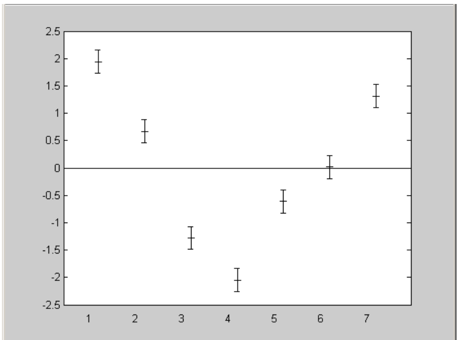

Figure 5. *Comparison results for the overall reproduction.*

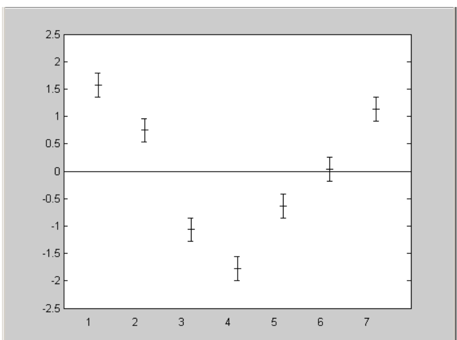

Figure 6. *Comparison results for the bright region.*

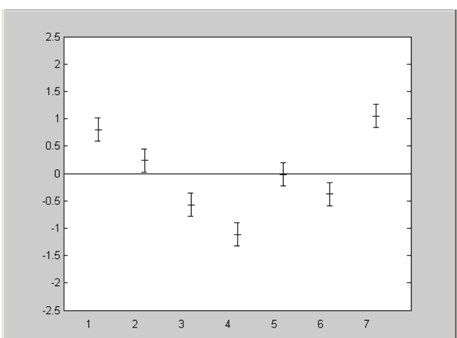

Figure 7. *Comparison results for the dark region.*

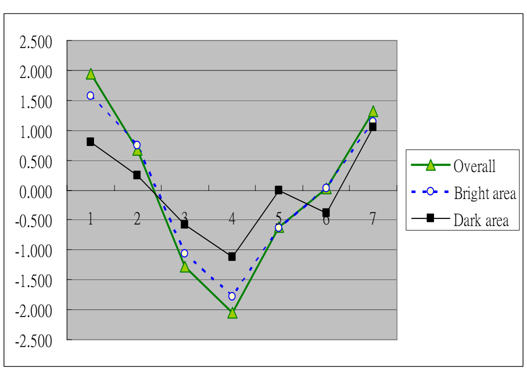

Figure 8. *Resulting Z-scores for all three rounds of tests. The HDR models used are: (1) iCAM06, (2) Local Contrast, (3) Bilateral Filtering, (4) Photographic Operator, (5) Photoreceptor, (6) Rahman Retinex and (7) RPVC.*

As shown, the first HDR model (iCAM06) has the best overall performance with the 7th model (RPVC) as the second. The performance on the bright region shows a very similar trend as the overall performance where the iCAM06 model has the best performance and the RPVC model as the second. However, when evaluating the dark region, the RPVC model has the best performance while the iCAM06 model comes second.

In the mean time, local contrast model (model No. 2) consistently has the third place on all three rounds, which re-confirms the trend that contrast attribute plays an important role in the HDR image reproduction. Moreover, the photoreceptor model (model no. 5) has better performance in dark region than in the bright region, which implies the influence of the photoreceptor's activity is also valid in the dark region. Even though in designing the RPVC model, the concerns about local contrast and photoreceptor are similarly incorporated, maybe it is the consideration of processing signals in the LMS color space or image enhancement in the IPT color space makes the difference than the earlier HDR models, like local contrast operator (model No. 2) and photoreceptor model (model No. 5).

The nonlinear tone compression functions for iCAM06 is similar to those in CIECAM02 with slightly modified user-controllable power value in a range from 0.6 to 0.85 which is still fixed at a specific value [8]. However, learning from the concept like the transducer function [20, 30], the RPVC model would change the mapping merit according to the adapting luminance levels. It may be this reason that RPVC model performs better in the dark region. Meanwhile, the iCAM06 model has more elaborate handling in the surround influence, which might contribute the reason why iCAM06 model performs better than the RPVC model in the bright region. Furthermore the original Burkhardt's data only had the background luminance level up to 200 cd/m^2, it will need further experiment to explore the model performance and possible enhancement in higher luminance levels.

Conclusions

There are two main characteristics associated with the processing of HDR image. The first is the reduction of the dynamic range between the scene and the reproduction medium. The second is the change of the visual adaptation status due to the change of the dynamic range. This model is based on the philosophy that the perceived visual contrast must be kept consistent in different visual adaptation mode so that the reproduced image can be perceived to be the same as the original scene. The visual contrast matching between the HDR scene and the reproduced LDR image is based on the relative perceived visual contrast (RPVC) function derived in this study from published paper by Burkhardt et al. in 1984, in which adapting background luminance and local physical contrast are its primary control parameters. By mapping through the RPVC function, different local physical contrast values can generate equivalent visual contrast and for every pixel the central signal of the reproduction image can be back calculated. Special processes like bilateral filter, tone compression in log space and surround compensation in IPT space learned from prior HDR image models are also incorporated in this RPVC model.

Six other HDR image reproduction models, (1) iCAM06, (2) local contrast, (3) bilateral filtering, (4) photographic operator, (5) photoreceptor and (6) Rahman Retinex were tested along with this RPVC model. A special controlled lighting environment was configured to perform the test. The iCAM06 model had the best performance for overall reproduction and reproduction in the bright region, while the RPVC model came second. However in reproduction of the dark region, the RPVC model had the best performance and the iCAM06 model came second. In the mean time, the local contrast model always came third. The results indicate that the influence of visual contrast is an important factor to be considered. The ability to compensate the perceived visual contrast through the RPVC function proposed in this study can be a vital concept for the HDR image reproduction process.

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