A retargeting approach for mesopic vision: simulation and compensation

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Abstract

Retargeting approaches aim at providing a unified framework for image rendering in which both the intended scene luminance and the actual luminance of the display are taken into account. At the core of any color retargeting method, a color vision model and its inverse are employed. Such a color appearance model should be invertible and cover the entire luminance range of the human visual system. There are not many available models which meet these two conditions. Moreover, most of these models are developed based on psychophysical experiments over color patches, and many have never been used for complex images due to their complexity. In this research, a color retargeting approach based on the mesopic model of Shin et al. [1] is developed to work with complex images. We propose an inverse model for complex images to compensate for color appearance changes on dimmed displays viewed in dark environment. Our experimental results using both quantitative and qualitative evaluations show a discriminative improvement in the perceived color quality for mesopic vision. The proposed method can be incorporated into image retargeting techniques and display rendering mechanisms.

Keywords: Color Retargeting Algorithm, Display Rendering Algorithm,Color Appearance Models, Low Light Levels, Mesopic Vision, Simulation and Compensation

1. Introduction

With emerging new technologies such as quantum dots and organic light emitting diodes (OLEDs), the display technology has been advancing quickly giving users broader color perception experience. OLED displays have a bigger gamut area compared to the conventional CRT and LCD displays, therefore they have great potential for high quality images with low power consumption [2]. Due to their emissive pixel structure, OLED displays exhibit high contrast ratio, and a high and constant color gamut at all gray levels.

In today's world, every individual spends a lot of time in front of displays in various

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applications such as consumer electronic devices (e.g. smart phones, tablets and laptops), automotive industry [3], and virtual reality interfaces (e.g. head-mounted displays). Working with bright displays raises power consumption and eye strain issues which affect customer satisfaction. For example, it has shown that using e-Readers with backlighting interferes with the human circadian rhythm [4]. Moreover, watching TV or any bright display in dark conditions brings about negative impacts such as eye strain and reduces the lifetime of the display. Dimming the display is a trivial solution to the issues, however, it reduces the visual clarity, and especially the perceived quality of colors in images. Hence, a compensation algorithm should be employed to preserve the color appearance quality of a dimmed display [5].

Shin et al. [1] propose a fully adjustable color appearance model built upon psychophysical experiments performed on color patches in mesopic vision. The model adjusts the perceptual attributes such as white preference, color saturation, and rod contributions to difference luminance levels. In this paper, we propose a color retargeting algorithm based on Shin's model. To the best of our knowledge, this model yet has not been employed in any real image rendering algorithm. Additionally, we develop the inverse model of Shin's and our result clearly indicates the improvement in color appearance using this nonlinear model. The main contributions of this paper are as follows:

I- applying the Shin CAM to a real world image,

II- developing the inverse of Shin's model,

III- developing a color retargeting approach based on Shin's model,

IV- perceptual rendering of dark images and compensating color deviations imposed by the human visual system while viewing a dimmed display in the dark.

We make the following assumptions and limitations in the proposed algorithm: first, the display should be viewed with a dark surround and the influence of the surround is not considered in the model; second, the model does not take the size of stimuli into account; third, spatial and temporal properties of the human visual system are not addressed in the Shin model (i.e. pixels are treated as independent in the image). Hence, the proposed framework can be combined with image retargeting methods [5] to model our visual mechanisms more thoroughly. The proposed method is examined quantitatively and qualitatively; and the results are promising and show that our method performs well in both simulation and compensation modes.

2. Background

The ultimate goal in display manufacturing is to produce perceptual displays that create natural images for viewers [6]. To achieve this goal, visual system mechanisms such as contrast, luminance and color perception have to be taken into account in display rendering units [7, 8]. To have perceptual displays, it is vital to know human color perception mechanisms and be able to model them thoroughly. The model should be comprehensive enough to take into account all aspects of human color vision in all visual conditions such as different light levels [9].

The human visual system works in three different modes called photopic, mesopic and scotopic vision. Photopic vision refers to our vision at day light situations (high light levels) at which only cones are responsible for our vision. As the light level falls off to a luminance of 10 cd/m^2 [10], the visual system smoothly goes from photopic vision to mesopic vision, in which both cones and rods contribute to visual perception. In the so-called scotopic situations, the light level is lower than the absolute threshold of cone photoreceptors and the human vision is only me-

diated by rods. The photopic condition has been the main focus of most color research, and the mesopic and scotopic conditions have received much less attention [11, 12, 13].

Color appearance models (CAMs) aim at reproducing colors and color perceptual attributes of a simple stimulus as the human visual system perceives. The output of an ideal CAM should match human color perception in all viewing conditions. There are many CAMs available in the literature such as Lab, CIECAM97 [14], and CIECAM02 [15]. However, none of them is even close to the ideal model. Most color appearance models: first, do not take spatial and temporal properties of the human visual system into account; second, model appearance of simple stimuli such as color patches [16]; third, are developed for photopic conditions [17, 18]; fourth, assume pixels are independent from each other [19].

Image color appearance models (iCAMs) are proposed to fill this gap by incorporating the spatial and temporal vision to model the appearance of complex stimuli [20]. But even these models do not work well in mesopic range. A case in point is the iCAM06 model proposed by Kuang et al [20], in which the rod contributions are added to the cone responses uniformly. However, recent studies show that the rod contributions to different channels are not the same [21, 22]. Hence, the model used for mesopic vision in image appearance models should be improved. Moreover, the existing iCAMs and CAMs are only able to *simulate* (i.e. predicting appearance of the original scene as a human observer perceives) the appearance of stimuli. In other words, they are not designed for *compensating* (i.e. reproducing colors on a rendering medium with a specific viewing condition to match the original scene colors.) appearance changes of stimuli rendered on different mediums with different viewing conditions. For example, when a bright scene is reproduced on a dark display, the contrast degradation and the hue and saturation shift due to mesopic vision will affect the visual appearance of the image content completely. In this case, a compensation algorithm should be employed to retrieve the original image appearance.

An *image retargeting* technique intends to provide a unified framework for the both simulation and compensation algorithms and it can be thought of as a bidirectional image color appearance model. Wanat and Mantiuk proposed a retargeting method which consists of a global and local contrast retargeting units together with a color retargeting block [5]. The focus of our work is on the color retargeting method, which is an inseparable part of image retargeting algorithms. Every color retargeting method requires a color vision model (responsible for predicting the color of the original scene) for simulation purposes and its inverse for compensation purposes.

Since, in theory, the scene and rendering device luminance can be in any of the three photopic, mesopic, or scotopic ranges, the color vision model should be viable for all luminance levels too. However, the number of models considering mesopic and scotopic range and rod contributions is not many [23, 18]. Hunt proposed a color appearance model which considers rod responses [24]. Kwak et al. introduced a lightness predictor for mesopic vision to address the stimulus size effect in their model [25]. The other presented mesopic models are not CAMs since they do not model the viewing condition into account. We refer to them as *mesopic color vision models*. Hence, color vision models covers a greater number of models, which can be less general -in terms of considering the visual appearance phenomena- and might have more limiting assumptions as compared with CAMs. Shin et al. introduced a mesopic model based on psychophysical experiments on color patches [1]. Cao et al. proposed another mesopic vision model [21], which was

employed in Kirk's perceptual tone mapping operator for low light conditions [26] and in the color retargeting approach proposed by Wanat and Mantiuk [5]. Rezagholizadeh and Clark proposed a maximum entropy-based spectral color vision model for mesopic conditions [23]. A comparison of four algorithms which can realistically simulate the appearance of night scenes on a standard display is presented in [27].

We have only a handful of color retargeting methods and none of them performs very well in simulating and compensating images at dark conditions. Our method concerns introducing a color retargeting approach of Shin et al. based on the available mesopic model. An eligible color vision model for color retargeting algorithms should possess two main features: first, the model must be applicable to the entire luminance range of the human visual system (photopic, mesopic and scotopic vision); and second, the model must be invertible. We can add a third condition to be computationally inexpensive, if the algorithm is going to be used in real time. Taking the three conditions into account, only the Cao and Shin model would be qualified to be deployed in a color retargeting framework. The Cao model, however, has shown a poor performance on reproducing colors at low light levels over both color patches [23] and complex stimuli [5]. This is mainly due to the assumption made in Cao's model between the color and the illuminance, which oversimplifies the color mechanisms of human visual system. Therefore, we study the Shin model to investigate its performance as a color retargeting method.

3. Method

3.1. Shin's Color Appearance Model for Mesopic Vision

Shin et al. proposed a modified version of the Boynton two-stage model with fitting parameters to account for the rod intrusion in mesopic vision [1]. The goal of the model is to find the matching colors in photopic range for the input colors in mesopic range. The parameters of the model are obtained as a function of luminance based on the asymmetric color matching experimental data. In their experiment, the observer is presented with a Munsell color chip under the mesopic condition and is asked to match the appearance of that patch with the simulated image reproduced by this model in the CRT display under photopic condition. The model is as follows:

1. The XYZ image (i.e. the RGB image which is transformed to the XYZ color space) is input to the model and is converted to the LMS space in the first step.

$$\begin{aligned} &[X\ Y\ Z]^t = M_{rgb2xyz} \cdot [R\ G\ B]^t \\ &LMS = [L_p\ M_p\ S_p]^t = M_{xyz2LMS} \cdot XYZ \end{aligned} \tag{1}$$

2. The LMS signals are substituted into the opponent channel equations of the Boynton two stage model:

$$\begin{aligned} A(E) &= \alpha(E)K_w((L_p + M_p)/(L_{pw} + M_{pw})) \\ &\quad + \beta(E)K'_w(Y'/Y'_w)^\gamma \\ r/g(E) &= l(E)(L_p - 2M_p) + a(E)Y' \\ b/y(E) &= m(E)(L_p + M_p - S_p) + b(E)Y' \end{aligned} \tag{2}$$

where E represents the scene photopic luminance, $A(E), r/g(E),$ and $b/y(E)$ are achromatic, red/green and blue/yellow opponent responses respectively; indices p and w indicate "photopic" and "white point" respectively; Y' represents the scotopic luminance; $\alpha(E), \beta(E), l(E), a(E), m(E),$ and $b(E)$ are the fitting functions indicating the relative contribution of the rod's response to the opponent channels; and K_w and K'_w are the maximum responses of the luminance channel at photopic and scotopic conditions.

3. Then, opponent responses, $A(E), r/g(E),$

and $b/y(E)$, are transformed back to the XYZ space and then to the RGB space.

$$[X_m\ Y_m\ Z_m]^t = \\ M_{opp2xyz} \cdot [A(E)\ \ r/g(E)\ \ b/y(E)]^t \tag{3}$$

where X_m, Y_m, and Z_m represent the mesopic XYZ values as they can be seen in photopic conditions. The parameters of the Shin model are selected according to Table 1. Functions ($\alpha(E)$, $\beta(E)$, $l(E)$, $a(E)$, $m(E)$, $b(E)$) are evaluated based on interpolation over the given points in Table 1. of [1]. The transformation matrices used in the model are listed in Table 2.

Table 1: Parameters of the Shin model

Parameter	value
K_w	1
K'_w	78.4
γ	0.77

Table 2: Transformation matrices used in the Shin Model

Parameter	value
$M_{rgb2xyz}$, [28]	$\begin{bmatrix} 0.4124 & 0.3576 & 0.1805 \\ 0.2126 & 0.7152 & 0.0722 \\ 0.0193 & 0.1192 & 0.9505 \end{bmatrix}$
$M_{xyz2LMS}$, [1]	$\begin{bmatrix} 0.155 & 0.543 & -0.033 \\ -0.155 & 0.457 & 0.033 \\ 0 & 0 & 1 \end{bmatrix}$
$M_{opp2xyz}$ [1]	$\begin{bmatrix} 1.008 & 2.149 & -0.212 \\ 1 & 0 & 0 \\ 1 & 0 & -1 \end{bmatrix}$

3.2. Developing inverse of Shin's model for compensation

As mentioned earlier, perceptual rendering necessitates involving both a color vision model and its reverse. Given the intended luminance of the original image, the forward color appearance model - the Shin model in our case- predicts the color perceptual attributes for a standard human observer. The goal of the inverse model is to take the output of the forward model (perceived original image at the intended luminance based on the Shin model) and predict the RGB values of the compensated image such that the color appearance of this image rendered on a display with a specific luminance value resembles the perceived original image. Hence, in order to develop the inverse model, we feed the color perceptual attributes of the forward model into the inverse model (i.e. inverse Shin's model) along with the luminance of the target display and obtain the compensated image to be rendered on the display. The schematic of this perceptual model is shown in Fig.1.

To develop the inverse of this nonlinear color vision model we carry out the following steps. First, the opponent responses of the forward model ($A(E)$, $r/g(E)$, $b/y(E)$) are fed to the inverse model. We assume that the compensated image based on the display luminance, $\overline{E}$, produces the same opponent responses as the opponent responses of the forward model to make a perfect match to the perceived image at the intended luminance, E. Second, the functions: $\alpha(\overline{E}), \beta(\overline{E}), l(\overline{E}), a(\overline{E}), m(\overline{E}),$ and $b(\overline{E})$ are evaluated for the average display luminance, $\overline{E}$. Third, the computed functions and opponent responses are substituted in the forward model (Eq. 2) and $\overline{LMS}$ values of the compensated image can be obtained as follows:

$$\begin{aligned} \overline{L_p} + \overline{M_p} &= ((L_{pw} + M_{pw})/(\alpha(\overline{E})K_w)) \times \\ &\quad (A(E) - \beta(\overline{E})K'_w(Y'/Y'_w)^\gamma) \\ \overline{L_p} - 2\overline{M_p} &= \frac{(r/g(E) - a(\overline{E}) \times Y')}{l(\overline{E})} \\ \overline{L_p} + \overline{M_p} - \overline{S_p} &= \frac{(b/y(E) - b(\overline{E}) \times Y')}{m(\overline{E})}. \end{aligned} \tag{4}$$

Fourth, the left hand side variables of Eq. 4 are transformed to $\overline{L_p}$, $\overline{M_p}$, and $\overline{S_p}$ using a

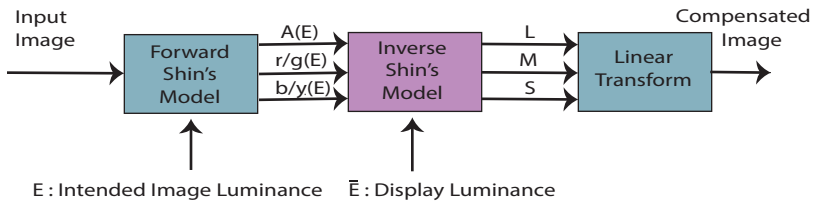


Figure 1: Schematic of the Shin color retargeting method

simple linear transformation.

$$\begin{bmatrix} \overline{L_p} \\ \overline{M_p} \\ \overline{S_p} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 \\ 1 & -2 & 0 \\ 1 & 1 & -1 \end{bmatrix}^{-1} \times \begin{bmatrix} \overline{L_p} + \overline{M_p} \\ \overline{L_p} - 2\overline{M_p} \\ \overline{L_p} + \overline{M_p} - \overline{S_p} \end{bmatrix} \quad (5)$$

And finally, a linear transformation is applied to convert the $\overline{LMS}$ values to XYZ and subsequently to RGB values.

4. Experiments and Results

In this section, the proposed algorithm is evaluated using quantitative and qualitative experiments.

4.1. Quantitative Evaluation

In the quantitative experiment, the human subject is replaced by the Shin mesopic model, to predict the human observer color perception at low light levels. The evaluation procedure of our experiment is depicted in Fig. 2. The forward Shin model is employed to simulate the perceived image at different luminance levels. This model takes in an image, the reference white and the light level under which the image is viewed. The output of the model is the simulated perceived image at photopic conditions in the the XYZ space. To derive the corresponding color perceptual attributes, the XYZ values and the reference white can be given to the LAB space.

This experiment is conducted on 4 images: {Multi-object Scene, Car, Walk Stones, Red Room} where the images are viewed in a dark surround and the results are shown in Figs. 3-6. Each of the figures shows: (a) simulated perceived original image on a bright display ($L_{src} = 250cd/m^2$), (b) simulated perceived unprocessed image on a dark display ($L_{dest} = 2cd/m^2$), (c) simulated perceived compensated image the dark display with the same brightness level, (d) compensated image, (e) simulated perceived gamut of the image shown in (a), (f) simulated perceived gamut of the unprocessed image on a dark display, (g) simulated perceived gamut of the compensated image viewed on a dark display, and (h) comparison of the three simulated perceived gamuts depicted in (e), (f), and (g). It is worth mentioning that the gamut of each image is shown in the LAB space, which is approximately a perceptually uniform color space.

The results of Figs. 3-6 show that the compensated image has a larger simulated perceived gamut and a better simulated color appearance at dark conditions compared to the unprocessed image viewed at the same condition. For example, in the *Multi-object Scene* image in Fig. 3, you may compare the checker board colors in Fig. 3-(b) and 3-(c) to see the colors in the simulated perceived compensated image more resemble the colors in Fig. 3-(a); or in the *Car* image, the blue color of sky and the car is maintained better as compared with the unprocessed image on the dark display. The simulated perceived unprocessed *Walk Stone* image shows washed out colors while in the simulated perceived

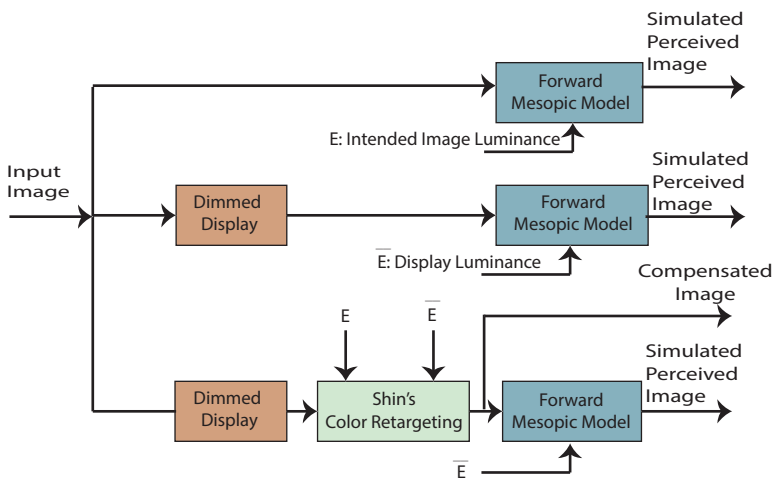


Figure 2: The procedure for evaluating the proposed Shin color retargeting method: the simulated perceived image at the intended scene luminance, E, is compared to the simulated perceived image viewed on a dimmed display with the luminance $\overline{E}$ when no processing is done to the image and the simulated perceived image processed by our color retargeting method viewed on the same display.

compensated image, the blue sky, green grass and brown stones are visible more clearly. Figure 5-(h) demonstrates that the simulated perceived gamut of the unprocessed image at dark condition is shrunk to the center of the *ab*-chromaticity diagram (achromatic region) and the simulated perceived gamut of the compensated image brings back a fairly large portion of the lost simulated perceived color gamut. In Fig. 6, the red color of the wall, carpet and the vase, the color of the cushions and the picture hung on the wall are more vivid in the dark compensated image compared to the unprocessed image.

To evaluate the color appearance quality of images quantitatively, a color difference metric can be employed. A particular application of the quantitative assessment techniques is to replace a human subject in evaluating the quality of images, and accordingly, gives rise to a less expensive, more effective, more repeatable and consistent, and more time efficient approach. The metric used for this purpose should be based on a comprehensive color appearance model. There are several color difference measures in the literature such as ΔE_{xy}, ΔE_{ab}, ΔE_{94}, and ΔE_{00}; however, none of them gives an ideal perceptual measure to be used with complex images. In spite of the reported limitations and deficiencies of these measures, they are the only available metrics for quantitative color quality assessment and have been used in the literature extensively. Hence, the quantitative evaluation of our method is done as following. A qualitative assessment will be performed in the next subsection to verify the results of the quantitative evaluation.

The chromaticity difference measure, ΔE^c_{94}, is derived from the well-known color difference metric, ΔE_{94} by removing the lightness component from the ΔE_{94} formula. ΔE^c_{94} is used to evaluate the chromaticity deviation of simulated perceived uncompensated and compensated images on the dimmed display compared to the perceived colors of the original scene.

$$\Delta E^c_{94} = \sqrt{(\frac{\Delta C^*_{ab}}{k_C S_C})^2 + (\frac{\Delta H^*_{ab}}{k_H S_H})^2} \qquad (6)$$

where

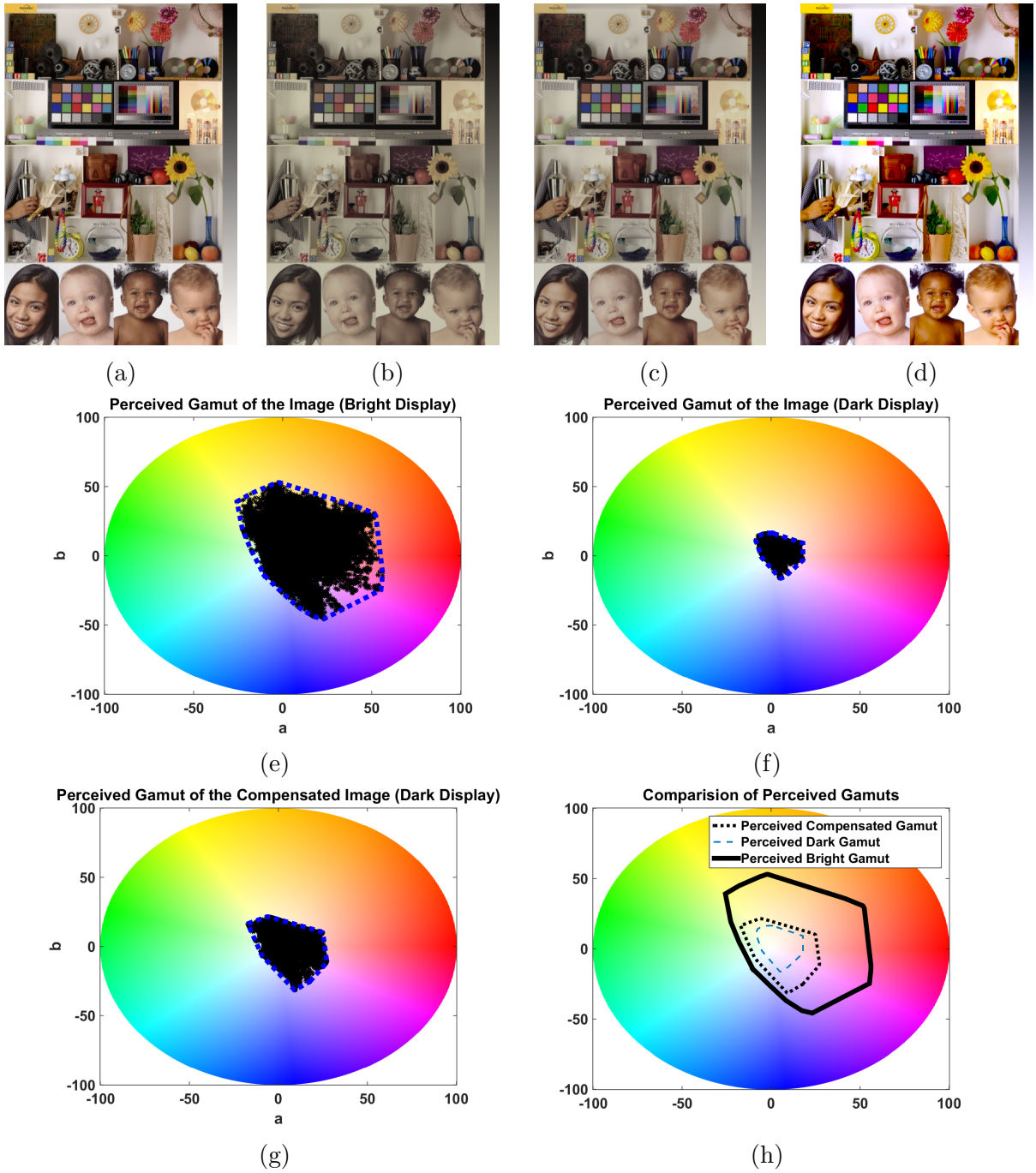


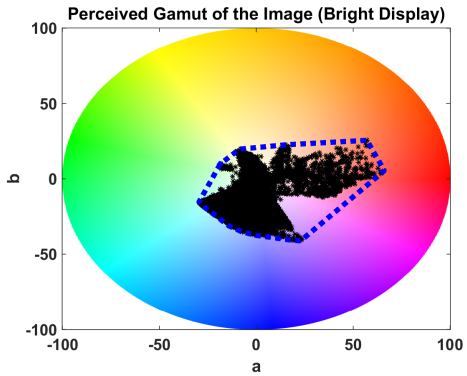
Figure 3: The reverse Shin model is put to test based on the evaluation schematic shown in Fig. 2. (a) Perceived colors in the Original Scene ($L_{source} = 250cd/m^2$) (b) Perceived colors on a Dimmed Display ($L_{dest} = 2cd/m^2$) (c) Perceived colors of Compensated Image ($L_{dest} = 2cd/m^2$) (d) Compensated image (rendered on the display) ($L_{dest} = 2cd/m^2$) (e) Gamut of the original scene (f) Gamut of simulated perceived image on a dimmed display (g) Simulated perceived gamut of compensated image (h) Comparison of simulated perceived gamuts

(a) Simulated perceived colors in the Original Scene ($L_{source} = 250cd/m^2$)

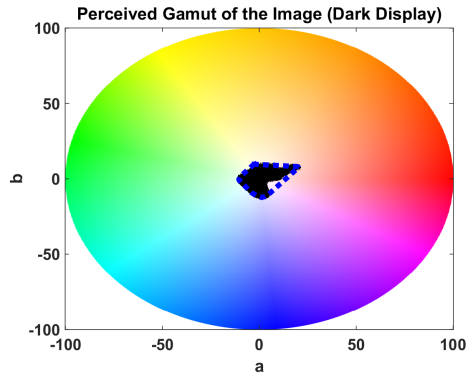
(b) Simulated perceived colors on a Dimmed Display ($L_{dest} = 2cd/m^2$)

(c) Simulated perceived colors of Compensated Image ($L_{dest} = 2cd/m^2$)

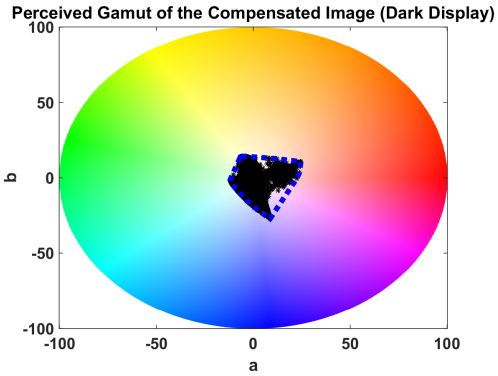
(d) Compensated image (rendered on the display) ($L_{dest} = 2cd/m^2$)



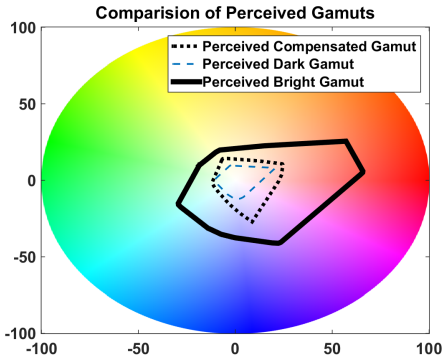
(e) Simulated perceived gamut of the original scene



(f) Gamut of simulated perceived image on a dimmed display



(g) Simulated perceived gamut of compensated image



(h) Comparison of simulated perceived gamuts

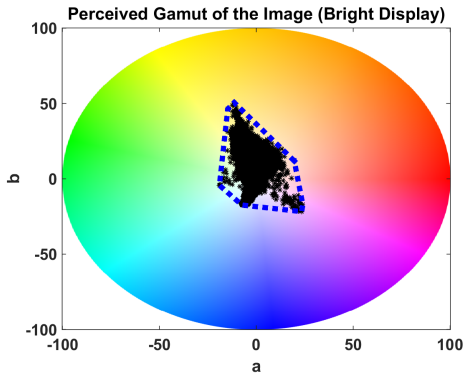
Figure 4: The reverse Shin model is put to test based on the evaluation schematic shown in Fig. 2.

(a) Simulated perceived colors in the Original Scene ($L_{source} = 250cd/m^2$)

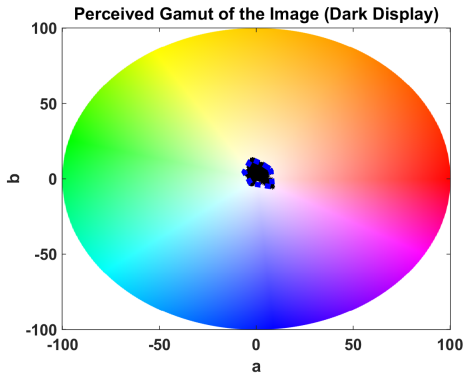
(b) Simulated perceived colors on a Dimmed Display ($L_{dest} = 2cd/m^2$)

(c) Simulated perceived colors of Compensated Image ($L_{dest} = 2cd/m^2$)

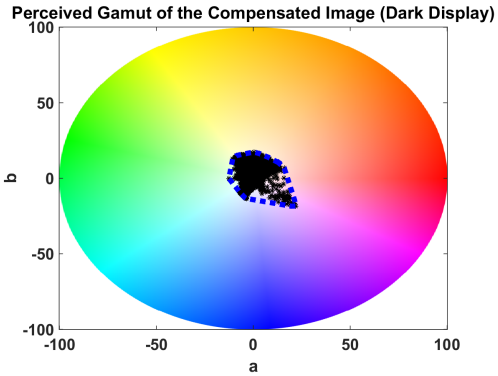
(d) Compensated image (rendered on the display) ($L_{dest} = 2cd/m^2$)



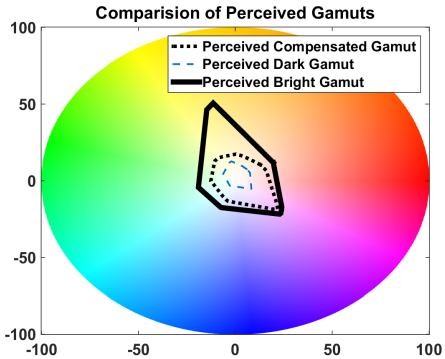
(e) Simulated perceived gamut of the original scene



(f) Gamut of simulated perceived image on a dimmed display



(g) Simulated perceived gamut of compensated image



(h) Comparison of simulated perceived gamuts

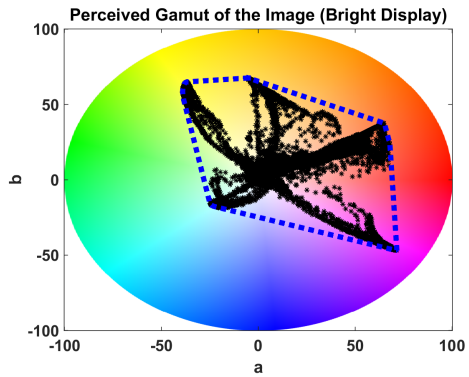
Figure 5: The reverse Shin model is put to test based on the evaluation schematic shown in Fig. 2.

(a) Simulated perceived colors in the Original Scene ($L_{source} = 250cd/m^2$)

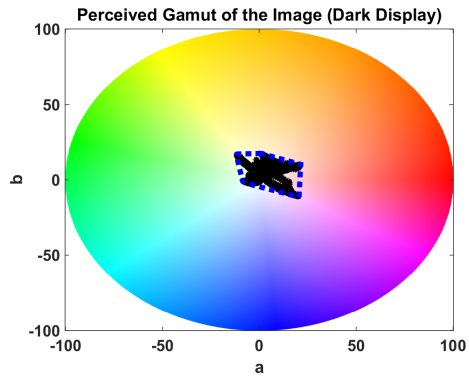
(b) Simulated perceived colors on a Dimmed Display ($L_{dest} = 2cd/m^2$)

(c) Simulated perceived colors of Compensated Image ($L_{dest} = 2cd/m^2$)

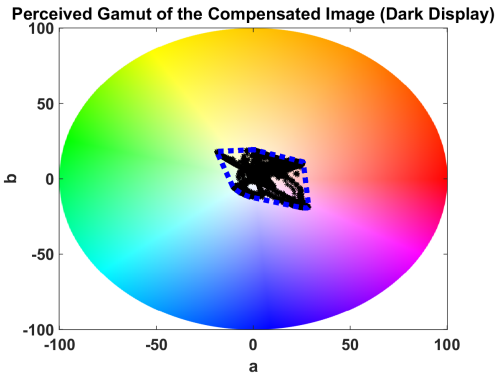
(d) Compensated image (rendered on the display) ($L_{dest} = 2cd/m^2$)



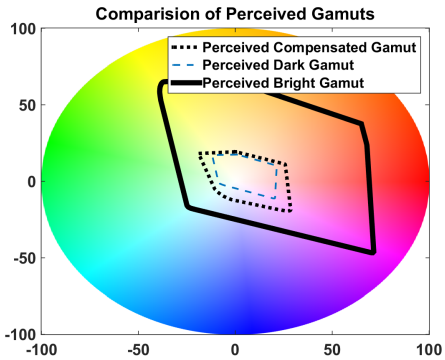
(e) Simulated perceived gamut of the original scene



(f) Gamut of simulated perceived image on a dimmed display



(g) Simulated perceived gamut of compensated image



(h) Comparison of simulated perceived gamuts

Figure 6: The reverse Shin model is put to test based on the evaluation schematic shown in Fig. 2.

$$
\begin{aligned}
&C_1^* = \sqrt{(a_1^*)^2 + (b_1^*)^2}, C_2^* = \sqrt{(a_2^*)^2 + (b_2^*)^2} \\
&\Delta C_{ab}^* = C_1^* - C_2^* \\
&\Delta a^* = a_1^* - a_2^*, \Delta b^* = b_1^* - b_2^* \\
&\Delta H_{ab}^* = \sqrt{(\Delta a^*)^2 + (\Delta b^*)^2 - (\Delta C_{ab}^*)^2} \\
&S_C = 1 + K_1 C_1^*, S_H = 1 + K_2 C_1^*
\end{aligned} \tag{7}
$$

and where (a_1^*, b_1^*) and (a_2^*, b_2^*) refer to the a^*b^* values of two CIE 1976 $L^*a^*b^*$ coordinates, K_1 is set to 0.045, $K_2 = 0.015$, and $k_C = k_H = 1$ [29].

The results of the perceptual chromaticity difference between the dark and bright image for both uncompensated and compensated approaches of Figs. 3-6 are shown in Table 3. The ΔE_{94}^c measure of compensated images is almost reduced by the factor of 2 as compared to that of the uncompensated images.

Another quantitative measure, introduced in this work, is the percentile coverage of simulated perceived gamut of images at dark relative to the simulated perceived gamut of the bright image (i.e. the proportion of the overlapping area of the simulated perceived gamut of the dark image to the simulated perceived gamut of the original bright image.) In the rest of the paper, we refer to this measure as the Effective Gamut Ratio (EGR). The EGR index is used to evaluate the performance of our proposed method on compensating the shrunk gamut area of the simulated perceived unprocessed image and the results are reported in Table 4. The EGR measure is shown to be almost two times bigger for the compensated images with our method compared to the unprocessed ones; and EGR of the *Walk Stones* image is enhanced by the factor of 4.

Figure 7 demonstrates the ΔE_{94}^c and EGR indices of the four images at different display luminance values: 1, 2, 5, and 10 cd/m^2. We may summarize the results of this figure as following: first, the perceptual difference of compensated images is smaller than unprocessed images for all examined luminance values; second, the ΔE_{94}^c measure decreases as the display luminance grows; third, our proposed method covers a greater portion of the simulated perceived gamut of the original image comparing to the unprocessed one; fourth, the EGR index has an increasing nature dependence with respect to the display luminance.

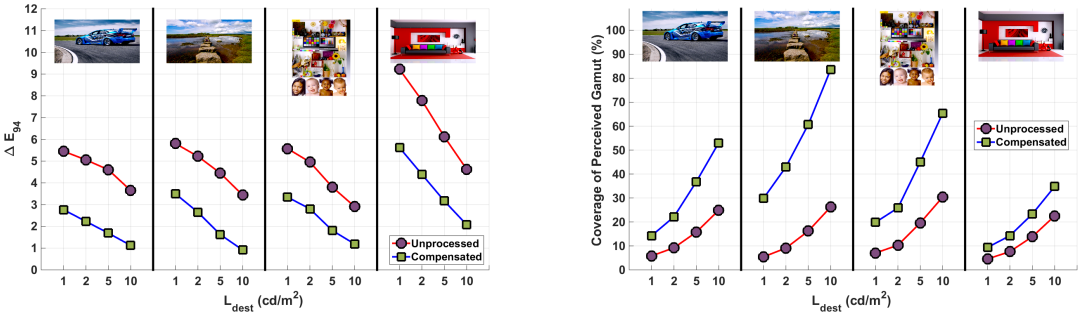
4.2. Qualitative Evaluation

A subjective experiment is conducted to evaluate the proposed compensation algorithm based on the user preference of color appearance of images shown on a dimmed display. The experiment is done on a Samsung Galaxy Tab AMOLED-based Android device. The size of the display is 10.5" with a resolution of 2560 × 1600. A set of 5 images is used for the experiment, shown in column (a) of Fig. 8. The images are selected such that they span a range of colors: red, green, blue, yellow, purple, orange, and brown. Each image has a simple context and a dominant color in order to minimize the variation of visual attention between different users and facilitate selection of their preferred choice. 8 observers with normal color vision participated in the experiment from different cultures (Indian, Chinese, Middle East, and Western), genders (4 females and 4 males), ages (in the range of [25-40] years) and educational background.

4.2.1. Experimental Methods

In the experiment, the following methods are evaluated:

Our color retargeting method: is based on the forward and inverse of the Shin mesopic model introduced in this paper as a color retargeting approach in Fig. 1.



(a) (b)

Figure 7: The ΔE^c_{94} measure and the EGR index are evaluated for the unprocessed and compensated images at different display luminance levels: 1, 2, 5, and 10 cd/m^2.

(a) Original Image (b) Wanat (c) iCAM06 (d) Our Method

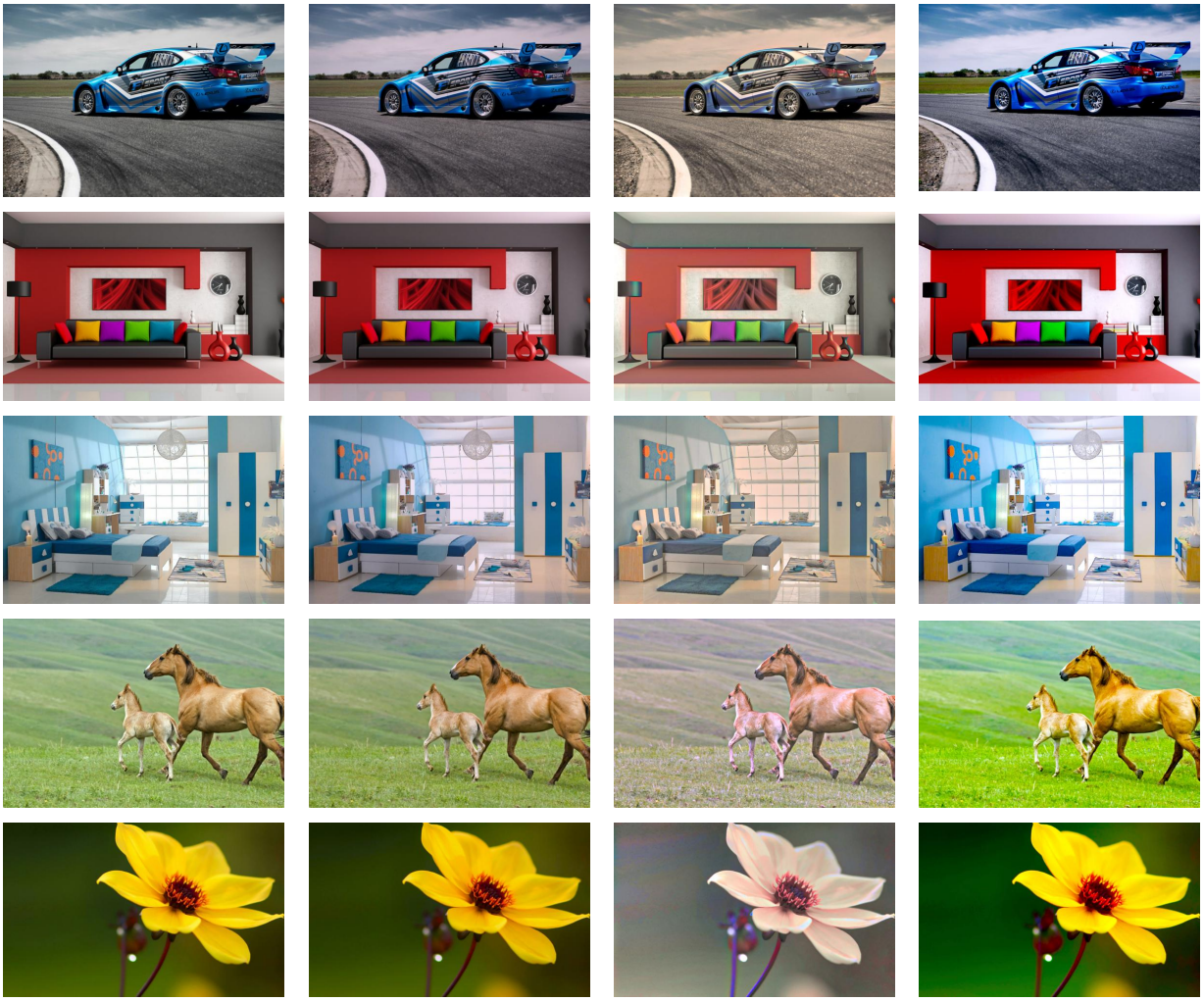


Figure 8: The original images and the results of different approaches applied to each image are shown. Images are processed for $L_{src} = 250\ cd/m^2$ and $L_{dest} = 2\ cd/m^2$.

Table 3: Mean ΔE^c_{94} measure between a test image viewed at $L_{dest} = 2\ cd/m^2$ and the perceived original image at $L_{src} = 250\ cd/m^2$

Test Image	Unprocessed	Our Method	Wanat	iCAM06
Multi-object Scene	5.0	**2.80**	4.37	5.62
Car	5.05	**2.23**	4.36	7.23
Walk Stones	5.22	**2.65**	4.54	5.74
Red Room	7.79	**4.39**	7.09	7.42
Blue Room	6.19	**3.36**	5.43	8.26
Horse	6.58	**3.45**	7.17	10.93
Flower	23.61	**21.17**	24.15	31.13

Table 4: The EGR index (the percentile coverage of perceived gamut (%)) between a test image viewed at $L_{dest} = 2\ cd/m^2$ and the perceived original image at $L_{src} = 250\ cd/m^2$

Test Image	Unprocessed	Our Method	Wanat	iCAM06
Multi-object Scene	10.3	**25.9**	12.0	9.9
Car	9.2	**22.1**	10.2	10.0
Walk Stones	9.1	**43.0**	14.8	20.5
Red Room	7.6	**14.3**	7.7	9.9
Blue Room	13.5	**36.3**	14.8	17.7
Horse	9.7	**25.8**	9.92	14.2
Flower	7.2	**15.8**	7.6	15.3

The Wanat color retargeting approach [5] is proposed by Wanat and Mantiuk. In this algorithm, the Cao algebraic model and its inverse is employed in the retargeting method. This algorithm is implemented and used for processing images as explained in [5].

iCAM06 is one of the most well-known image appearance methods in the literature [20]. The input parameters of this model are set as: maximum luminance, $max_L = 2\ (cd/m^2)$; overall contrast, p = 0.7; surround adjustment, $gamma_{value}$=1.

Figure 8 shows the output of the different models. Column (b), (c), (d), and (e) shows the result of applying no processing, the Wanat color retargeting model, iCAM06, and our method respectively.

4.2.2. Experimental Procedure

A pairwise comparison experiment is carried out in a dark room. We developed an Android application (see Fig. 9) which shows two side-by-side images (i.e. a single image which is processed by two different approaches) to the user. Each participant compares each two method combinations (combinations of picking two out of four methods) for all five images. The observer task is to choose his/her preferred image, displayed on the Samsung tablet, in terms of color appearance at each trial. The display brightness is set to 2 cd/m^2. During the experiment, observers were able to control their viewing angle and distance from the display.

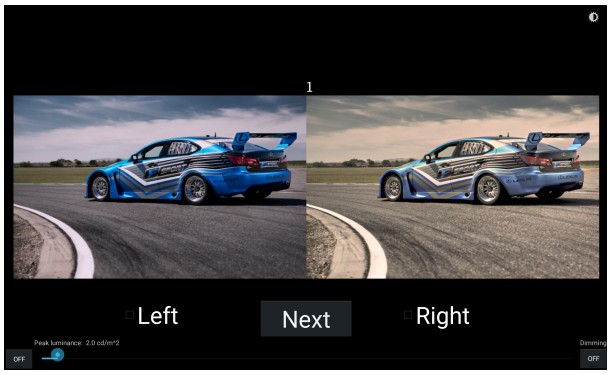


Figure 9: A snapshot of the application used for the pairwise comparison experiment.

4.2.3. Discussion of the Experiment Results

To analyse the results of the pairwise comparison experiment, the scores of each method are transformed to the just-noticeable-difference (JND) units, as defined in [30]. The difference of 1 JND unit represents that one option is selected by 75% of observers over another option. The absolute JND values are not meaningful and only the relative JND difference can be used for discriminating different choices. A method with a higher JND is preferred over methods with smaller JND values. The results of our pairwise comparison experiment scales in the JND unit are shown in Fig. 10, which indicates the greater performance of our proposed algorithm. The average JND of our method over the five images shown in Fig. 8 is 6.04 while the second best method (i.e. Unprocessed) has an average JND of 4.69. The JND score of our algorithm is significantly greater than other methods over all the images except the Flower image, in which our method is the best but its difference with the Wanat and Unprocessed algorithms is not significant. In the Flower image, the three approaches: Wanat's, Unprocessed and our method all have similar performances. This similarity may be due to the dominant yellow color of this image. As explained in [31], the yellow hues appear less saturated than other monochromatic colors. Hence, in dark conditions, yellow is more subject to losing its colorfulness. Moreover, the comparison of perceived gamuts in the quantitative results of Figs. 3-6 shows that the compensated gamut is not extended towards the yellowish region of the chromaticity diagram very much. It is worth mentioning the observation that in the unprocessed-Wanat pair comparison, some observers reported difficulty in choosing between the two. Furthermore, the results show that iCAM06 underperformed other algorithms because iCAM06 is not designed for compensation purposes and only is able to predict the appearance of the image for an intended luminance.

It is worth comparing the quantitative performance of the methods on different images based on the ΔE^c_{94} and EGR indices with the results of the qualitative experiment. Table 3 and Table 4 summarizes the quantitative results of the methods for all the images considered in this section. The two tables show the superiority of our proposed method over the other discussed techniques. Table 4 shows that the gamut coverage of our method varies over the images, since the performance of our model is content dependent and the images in our database span different chromaticities. It is evident that the quantitative measures do not completely match the qualitative experiment results, which shows that the quantitative measures still need to be improved. Moreover, it implies that the ΔE^c_{94} measure has a better correlation with the qualitative results than the EGR index, which is because in contrast to EGR, ΔE^c_{94} is a perceptual measure. If we sort the images used in the qualitative evaluation based on the Table 3 and compare the result with that of the qualitative experiment, we can infer that chromaticity difference of less than one unit is not reliable for judging the color appearance of images.

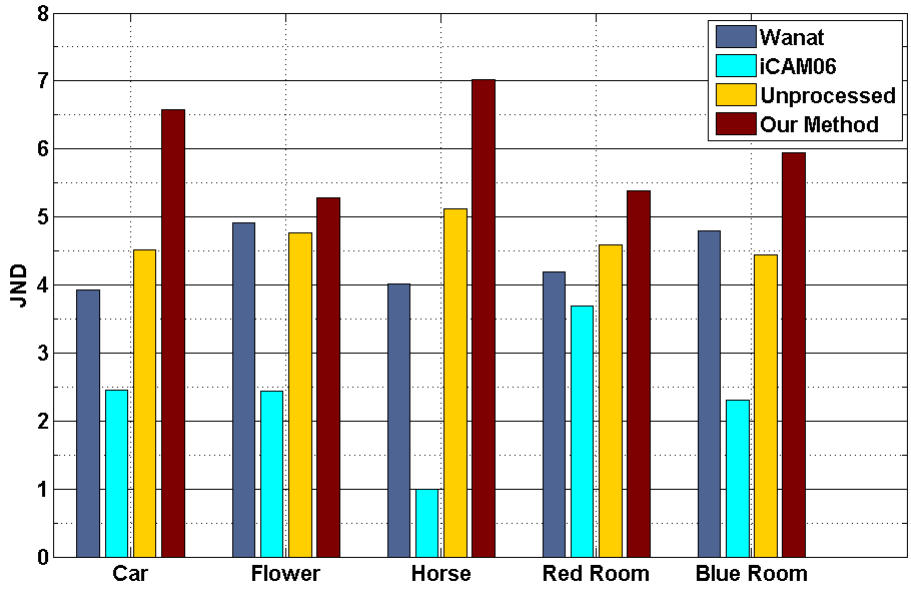


Figure 10: The result of the pairwise comparison experiment is shown in JND units. The images are shown in Fig. 8

5. Conclusion

In this paper, a color retargeting technique based on the Shin mesopic model is implemented. In this regard, the inverse of the Shin model is developed to compensate for color deviations on dimmed displays or dark rendering mediums. The proposed method is applied to real images (as opposed to the conventional model). In other words, we proposed a practical approach to perceptually render dark images and compensate for color deviations imposed by the human visual system while viewing a dimmed display. The introduced framework is evaluated using both quantitative and qualitative evaluations. In the quantitative evaluation, our method is able to roughly reduce the ΔE^c_{94} measure and expand the gamut area of simulated perceived images by the factor of two, compared with the unprocessed images. Moreover, the results of the qualitative evaluation demonstrate the promising performance of our algorithm. Plans for future extensions of the work include: first, to incorporate the proposed framework into the existing image retargeting techniques such as [5]; second, evaluating our method in an experiment and comparing it with a bigger set of existing methods; third, addressing limitations of this model by taking into account the chromatic adaptation and surround effect.

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