Perceptually Optimized Image Enhancement for OLED Displays in Power-constrained Conditions

Hsuan-Chi Huang[1], Pei-Li Sun[1]

[1] National Taiwan University of Science and Technology, Taipei 10607, Taiwan
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ABSTRACT

A psycho-visual experiment was conducted to optimize the parameters of an image enhancement model for OLED displays to maintain image quality in power-constrained conditions.

1 INTRODUCTION

A general phenomenon in OLED displays can be observed especially in middle to large size is that the luminance of the displays decreases significantly while the APL (Average Pixel Level) of the input image is high. Because OLED uses self-emissive organic materials, power consumption of the display must be limited to prevent overheating and to save power. The power saving is done by darkening the displayed image. The luminance reduction often leads to unsatisfied visual appearance. Therefore, the displayed images have to be optimized perceptually in the power-constrained conditions.

2 RELATED WORKS

2.1 APL and ARL

According to Kelley [1], Average Pixel Level (APL, historical term as Average Picture Level) refers to the average of pre-gamma input signals, while Average Relative Level (ARL) refers to the average of luminance, that is, ARL means the linear-light measure of an image. It means that if the APL of a sRGB image (gamma = 2.2) is 50%, the corresponding ARL is approximately 20%.

Dong [2] indicated that the power consumption of an OLED display is linear to the input linear RGB level (equivalent to ARL). Therefore, when we calculate power consumption of an input image, we must apply gamma correction (linearization) to the RGB signals of the input image.

2.2 OLED Display Model

Although the characteristics of OLED displays vary from manufacturer to manufacturer and from model to model, we can build a model to describe the relationship between input signals and relative output luminance based on previous studies [1][3].

According to Kelley's [1] and Sun's [3] analysis, the peak luminance (white point) level of the OLED displays they tested remains unchanged (100%) when the APL of input signal is less than 20%; but when the APL is higher than 20%, the peak luminance (white point) level decreases linearly with the rise of the APL. Eventually, when the APL reaches 100%, the peak luminance level decreases approximately 50%.

Based on the observations, we build a model to simulate the characteristics of a typical middle-size OLED display. **Fig. 1** shows the curved APL-based scaling function. This function was applied in Validation Testing (to be introduced in Section 4.3) for image simulation.

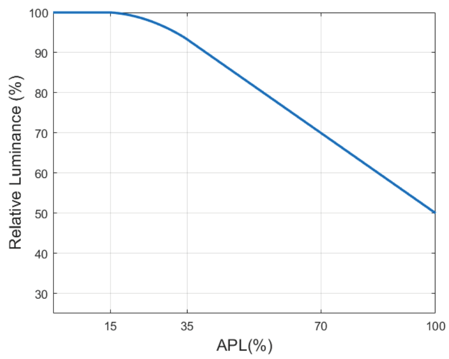


Fig. 1 APL-based scaling function

2.3 Contrast Enhancement in Power-constrained Conditions

To enhance the image contrast of power-constrained conditions, Lee [4][5] used log-based histogram equalization whereas Huang [6] generated look-up-tables for tone transformation based on image statistic and current limit for OLED displays. However, they didn't perform visual experiments to verify and to optimize the proposed models.

Moreover, these researches didn't consider the phenomenon that the luminance of the OLED displays might decrease with the increase of APL.

2.4 HDR Tone Mapping Method

We regard the luminance reduction is a problem similar to HDR to SDR tone mapping. Therefore, we refer to the concept of Durand's HDR tone mapping method [7] to compress the tone while preserving its image details.

The method decomposes an image into a base layer and a detail layer using a bilateral filter. Afterward, reduce the contrast of the base layer, thereby the details of the image are preserved.

Durand's method can effectively retain the details. However, the tone mapping could reduce image fidelity, therefore we enhance the image through Gamma and

Weight of CLAHE (Contrast Limited Adaptive Histogram Equalization) [8].

2.5 Gamma Compensation and Weighted CLAHE

Contrast reduction is the primary negative effect caused by power constrain. Human vision is very sensitive to the luminance reduction of the bright portion of an image, but it is not necessarily noticed in dark regions.

Subjective evaluation of inverse tone mapping operator [9][10] shows that simple global model could effectively restore the contrast of an image. Thus, we use gamma compensation to enhance the tone-compressed image.

In addition, histogram equalization can further enhance the contrast of an image, and based on our pilot study, we believe that the performance of weighted CLAHE is good enough.

3 EXPERIMENT

A psycho-visual experiment was carried out to optimize the parameters of Gamma and Weight of CLAHE at the 75%, 50%, 25% sRGB reduction levels respectively. The experimental setup will be introduced next.

3.1 Test Images

Referring to Bist's [10] research, 5 image types based on the APL and contrast (standard deviation of Y) were classified:

1. **Bright:** Images in this type have high APL and high contrast, which is usually the case for high dynamic range images.
2. **High-Key:** Images in this type have high APL but low contrast, which usually occurs in overexposed images or to express a light mood.
3. **Low-Key:** Images in this type have low APL but high contrast, which can often be seen in film noir or a night street view image.
4. **Dark:** Images in this type have low APL and low contrast, which usually occurs in underexposed images or deliberately produced dim images.
5. **Normal:** Images in this type have average APL and contrast, and most normal images fall into this category.

We selected two images for each of the five image types, and a total of ten images were used in the visual experiment. (**Fig. 2**)

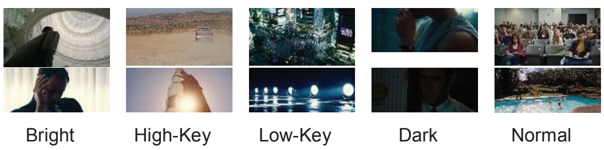


Fig. 2 Test images

3.2 Image-enhancement in Low-power Condition

First, we take the intensity Y of the input image in YCbCr space, then applied Fast Bilateral Filter on the Y plane to get the base layer. Next, subtract the base layer from the original intensity plane to get the detail layer. Afterward, apply CLAHE on the base layer and apply **Weight** and **Gamma** to the base layer. After rescale the base layer to N%, then add the detail layer back to generate Y'. The Y' plane is used to scale RGB planes.

The ARL of this output image is then rescaled to match the ARL of the image which is made by N% linear reduction of the original in non-linear sRGB space. In other words, both of them had the same power consumption.

3.3 Psychophysical Experiment

The experiment was performed in a uniform D50 dim surround condition (desk illuminance: 180 lux) and stimuli were shown on a Gigabyte AERO 15 laptop in full HD mode. The display of the laptop was characterized and certified by X-Rite Pantone to meet sRGB standard, and its peak luminance was close to 300 cd/m^2. The reason of using a LCD (IPS type) instead of an OLED display is to ensure the simulation is not affected by the complex luminance reduction phenomenon.

12 color normal observers (age 23 to 26) participated in the psychophysical experiment (4 females and 8 males). They were well instructed in the concept of "contrast and tone" before the experiment.

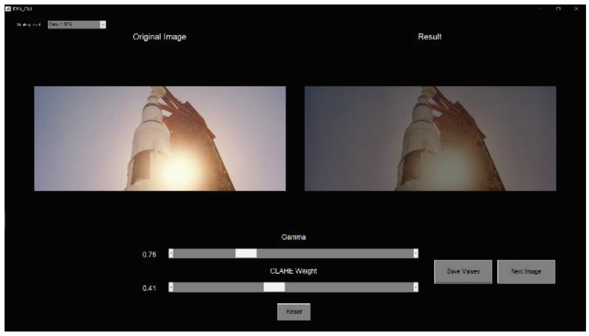


Fig. 3 GUI of the psycho-visual experiment

The 10 test images were used in the psychophysical experiment. These 10 images were randomly displayed at 75%, 50%, 25% sRGB reduction levels (N%= 75%, 50%, 25%) respectively. The participants were asked to use an interactive tool (a GUI in **Fig. 3**) to focus on the contrast of the test image to fine-tune the **Weight** between the base layer which was applied CLAHE and the original base layer, and the **Gamma** value of base layer, to make the image generated by the proposed method (right image of the GUI) as close as possible to the original one (left image of the GUI).

Once the subject considered that the results of the right image had been optimized by the tuning, the subject had to press the "Save Value" button to save the optimal Weight and Gamma values, then click "Next Image" button to display next pair of images on the screen.

For each observer, after one sRGB reduction level is completed, next sRGB reduction level will be tested. Each observer did 30 adjustments (=10 (images) × 3 (sRGB reduction levels)).

4 RESULTS

4.1 Data Fitting

Fig. 4 respectively show the mean and standard deviation of the Gamma and Weight values collected from the participants for the 5 types of images at three different sRGB reduction levels. As can be seen, the optimal Gamma values are proportional to the standard deviations (contrast) of the images. It suggests that if the contrast of the original is high, the subjects tended to adjust Gamma to compensate for the loss of contrast caused by the sRGB reduction; if the contrast of the original image is low, the subjects tended to raise the brightness of the dark portion to match the level of the original to compensate for the loss of shadow detail caused by sRGB reduction and over-stretching of CLAHE.

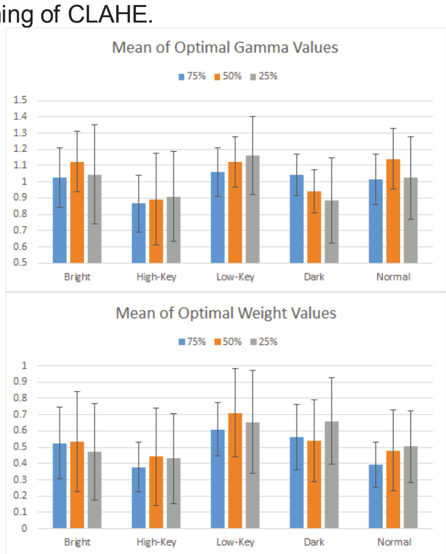


Fig. 4 Optimal Gamma and Weight values from the participants

Weight value is related to both APL and contrast of the input image. Although the correlation of the Weight value and the image statistics is not as high as that of the Gamma value, it still shows a significant trend.

We approximated the optimal Gamma and Weight values by means of polynomial regression and the results for three sRGB reduction levels are listed as follows:

75% sRGB reduction (N%=75%)

$$Gamma_{75} = 1.49 \times Y_{std}^2 - 0.32 \times APL + 1.04$$

$$Weight_{75} = 1.14 \times Y_{std}^2 + 0.03 \times APL \times Y_{std} - 0.34 \times APL + 0.56$$

50% sRGB reduction (N%=50%)

$$Gamma_{50} = -0.24 \times APL^2 + 1.08 \times Y_{std} + 0.86$$

$$Weight_{50} = 5.04 \times Y_{std}^2 - 3.46 \times APL \times Y_{std} + 0.18 \times APL + 0.5$$

25% sRGB reduction (N%=25%)

$$Gamma_{25} = -4.05 \times Y_{std}^2 + 2.5 \times Y_{std} + 0.7$$

$$Weight_{25} = 10.66 \times Y_{std}^2 - 3.78 \times APL \times Y_{std} - 2.6 \times Y_{std} + 0.84$$

where APL is the mean value of all pixels of the image in [0 1] range, Y_{std} is the standard deviation of the intensity Y(in [0 1] range also). The accuracy of the polynomial fitting is shown in **Fig. 5**.

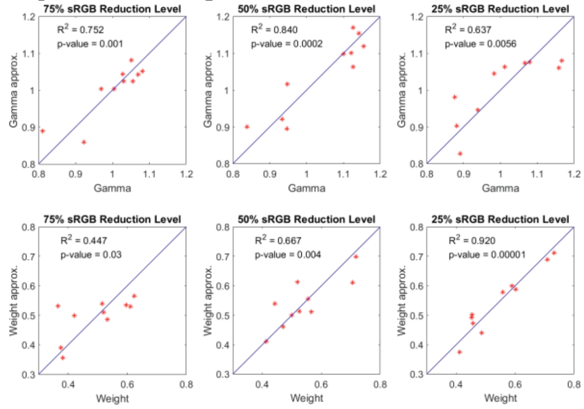


Fig. 5 Accuracy of model fitting

4.2 Different sRGB Reduction Levels

The above functions predict the optimal Weight and Gamma values at 25%, 50%, 75% sRGB reduction levels respectively. If we want to obtain the optimal Weight and Gamma value at other sRGB reduction level, we can use a quadratic polynomial to fit Weight and Gamma values respectively. In this way, according to the two quadratic polynomials, the optimal Weight and Gamma values at 0-100% sRGB reduction level could be obtained. **Fig. 6** is an example of the corresponding curves of optimal Weight and Gamma at 0-100% sRGB reduction level respectively after a certain image has been calculated.

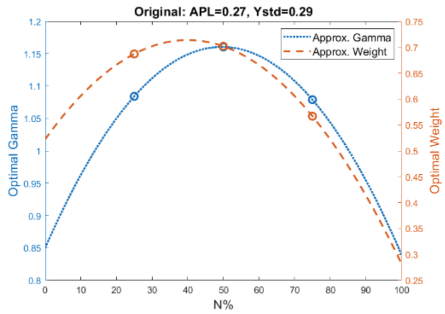
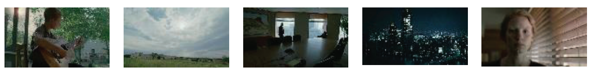


Fig. 6 An approximation of the optimal Gamma Weight

4.3 Validation Testing

To verify the optimal functions, we asked 7 subjects (3 females, 4 males) to compare images generated by linear reduction method and our proposed method side-by-side. 5 images different from **Fig. 2** were used for our validation testing. These images included elements of people, natural scenery, indoor scene, and night scene. (**Fig. 7**)



(1) (2) (3) (4) (5)

Fig. 7 Images for the validation testing

The sRGB reduction levels used in user study were

80%, 60%, 40% (N=80%, 60%, 40%), each original was presented with these three sRGB reduction levels, and displayed a pair of images simultaneously each time. This pair of images included an image with linear sRGB reduction only and an image with our proposed method, and were randomly displayed on the left or right figure. Each image was applied to the OLED APL model introduced in Section 2.2 before being displayed, simulating the condition viewed on an OLED display.

Each image was scored on a scale from 0 (bad) to 100 (excellent), while the original image with no sRGB reduction level (N=100%) represented 100 points. Participants were allowed to view the reference original whenever they desired.

All users gave the image generated by the proposed method a higher score than another image with linear sRGB reduction in every reduction level. The mean scores and standard deviations are shown in **Table 1**.

5 DISCUSSION

According to the results of the Validation Testing shown in Table 1, when the sRGB reduction level decrease, the scores of both models decrease accordingly.

Table 1 Mean opinion scores in Validation Testing

Reduction Level:	80%	60%	40%
Linear sRGB scaling (mean ± std.)	71.9 ± 17.1	58.4 ± 18	43.5 ± 17.4
Proposed model (mean ± std.)	80 ± 16.7	67.6 ± 18.6	56.4 ± 21.1

However, in the case of a reduction level of 40%, although the proposed method still has a higher score than the linear sRGB reduction, the standard deviation has also increased to 21.1, indicating that at low reduction level, the contrast enhancement is not preferred in some cases, and this phenomenon of over-stretching of contrast is mainly caused by CLAHE. How to improve the CLAHE for low reduction levels is one of our future works.

In terms of image content, we can see that the proposed method performed well to the images with higher dynamic range (Fig.7 (1), (3)). The proposed method can effectively restore the contrast of the original image in the sRGB reduction condition. Night scene (Fig.7 (4)) got the lowest score. Although we have restored the image contrast, the overall improvement is not obvious. How to enhance the visual performance for low-APL originals is another future work to do.

Original 80% 60% 40% 20%

Fig. 8 A series of images optimized by proposed model at different reduction levels.

6 CONCLUSION

To limit power consumption of OLED displays, a general phenomenon can be observed especially for middle to large size OLEDs is that the luminance of the displays decreases significantly while the APL (Average Pixel Level) of the input image is high. This makes it possible to display the same pixel level in different luminance. The luminance reduction often leads to unsatisfied visual appearance. Therefore, the displayed images have to be optimized perceptually in the power-constrained conditions.

We refer to the concept of HDR tone mapping, compressing the sRGB level of the image while retaining the details, then compensated the Gamma and Weight of CLAHE back.

A psycho-visual experiment was conducted to optimize the parameters of Gamma and Weight of CLAHE at assigned three sRGB reduction levels. We could obtain the optimal Gamma and Weight of CLAHE at any reduction level through optimization models.

We asked subjects to evaluate the model in an independent validation experiment with another three reduction levels. All subjects gave the proposed method higher scores than the images with linear reduction. It indicates the images indeed perceptually optimized by the proposed method.

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