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Low Image Distortion Constrained Power Saving for OLED Displays

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Abstract

Organic Light Emitting Diode (OLED) displays have matured into current smartphones. How to prolong the lifetime of displays while preserving the display quality becomes a primary issue. In this paper, we propose a low image distortion constrained power-saving approach for OLED displays based on gamma correction and saturation scaling. We first investigate the impact of gamma correction and saturation scaling on the power of emissive displays. The results show that changing the gamma and saturation value can obtain lower display power consumption when original image color maps to another one. Thus, we integrate the gamma correction and the saturation scaling into a new low-power approach for OLED displays. However, low gamma and high saturation lead to distortion on displaying. To guarantee user experience in this paper, the CIEDE2000 color difference formula and the Mean Structural Similarity Index (MSSIM) are used to evaluate the effectiveness of our approach. The results show that our approach saves up significant display power with high image quality.

Keywords: *Color model, gamma correction, organic light emitting diode, power saving, saturation scaling*

1. Introduction

Modern mobile devices can be viewed as collections of heterogeneous components, such as CPU, Display, Graphics, Wi-Fi NIC, Cellular, Bluetooth, GPS, Audio, *etc.* It is generally acknowledged that CPU, Display and Wireless Network Interface are the most power hungry components [1]. The displays are commonly divided into two types: emissive and non-emissive. OLED display is a kind of emissive device which is first proposed in 1978 with the publication by Tang and VanSlyke. Now, OLED displays are widely applied to high resolution laptop displays, televisions, ultra-large signboards and mobile devices which have higher power efficiency than non-emissive devices, such as Liquid Crystal Displays (LCDs) [2]. Unlike LCDs, OLED displays do not use back light and front light, and each pixel can be driven independently. While an image is displaying, black OLED pixels can be turned off using Dynamic Power Management (DPM) technique, however, the backlights of LCDs must be fully turned on. This helps OLED displays to save a significant power over LCDs. Therefore, in order to reduce the power consumption of OLED displays, there is a chance to dim the screen luminance and scale down the strength of each pixel in the frame buffer.

Each pixel on OLED displays is composed of tiny sub-pixels which themselves emit three basic colors: red (R), green (G) and blue (B). Therefore, the color of a pixel is

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determined by the color directly emitted from the sub-pixels. Different color of a pixel results in different power consumption, as measured in [3]. Compared to traditional LCDs, AMOLED displays make the image look more vivid because the pixel array uses the PenTile Matrix structure. In our target smartphone with a 480×800 Super AMOLED display, the blue pixel consumes more power than the green and the red pixel, and gray consumes more power than the other pure color with the same strength.

Gamma correction is a flexible approach to the tone mapping, which is used in image processing to map one set of colors to another [4-5]. When decreasing gamma value, brightness of display content becomes dark. Although we reduce energy consumption by darkening the content, the readability of the content is seriously impacted.

To obtain the impact of screen luminance, gamma and saturation on display power consumption, we adjust the three values. In Section 3, we will present this process and show how we exploit an image metric to obtain minimum gamma value and saturation level, which can be used to retain the image quality at an acceptable level.

In this paper, we propose a power-saving policy for OLED displays based on gamma correction and saturation scaling, and then deeply investigate the power consumption of ten color images ("Dormer", "Skifield", "Sea", "Lion", "Building", "Bird", "Flower", "Land", "Swan" and "Fish") on our platform. Our contributions mainly include three aspects:

1) We present an approach to reducing the power consumption of OLED displays by integrating gamma correction and saturation scaling.

2) The gamma correction and saturation scaling integration results in high distortion of display content when the gamma value or the saturation level exceeds a certain threshold. In this paper, CIEDE2000 and MSSIM are used to evaluate the amount of image distortion.

3) We observe that a higher saturation image consumes less power without changing hue- and value-dimension in the Hue, Saturation, and Value (HSV) color model. Furthermore, when a higher gamma value is used, saturation scaling affects the power consumption of OLED displays much more obviously because the image with higher brightness starts to be washed out.

The rest of the paper is organized as follows: In Section 2, we describe several works that are most related to our work. Section 3 proposes our approach that saves power for emissive displays while preserving image quality. Then, in Section 4, we present experiment results and evaluate our power-saving approach. Finally, this paper draws the conclusion and talks about the future work in Section 5.

2. Related Work

Power-saving technologies on components of mobile devices have been extensively studied. Some literatures [6-7] proposed reducing and conserving power consumption of mobile devices on aspect of CPU. Other studies [8-10] primarily focus on the wireless network interface. In addition, some literatures [11-17] provide the techniques to reduce the power consumption of display components.

Cheng *et. al.*, presents a chromaticity and luminance scaling algorithm for minimizing power consumption of backlight TFT-LCD monitors, which reduces power consumption by scaling the luminous intensity of the red, green and blue LED backlights independently according to the image histograms of each color channel [11]. Chang *et. al.*, presents an approach to Dynamic backlight Luminance Scaling (DLS) with appropriate image compensation, which keeps the perceived intensity or contrast of the image as close as possible to the original while achieving significant power reduction [12]. Cheng *et. al.*, propose a Concurrent Brightness and Contrast Scaling (CBCS) technique for TFT-LCD display, which can conserve power by reducing the backlight illumination while retaining the image fidelity through preservation of the image contrast.

They formulated and optimally solved the CBCS optimization problem with the objective of minimizing the fidelity and power metrics [13].

Dong *et. al.*, introduce a color adaptive web browser, called Chameleon, which renders web pages with power optimized color schemes under user-supplied constraints [14]. Anand *et. al.*, propose a dynamic adaptation technique that saves LCD display energy while playing fast-paced real-time 3D games, such as Quake III and Planeshift. Furthermore, the authors use the Mean Square Error (MSE), the Peak Signal to Noise Ratio (PSNR) and the MSSIM as quality metrics to evaluate their solution that exploits the gamma function provided by those games to dim the LCD backlight and save display power [15]. Lee *et. al.*, propose a Power Constrained Contrast Enhancement (PCCE) algorithm for emissive displays based on histogram equalization, which can enhance image contrast and reduce power consumption. Specifically, the authors state the power-constrained image enhancement as a convex optimization problem and use the convex optimization theory to minimizing the objective function. Thus, the proposed algorithm achieves contrast enhancement and power saving simultaneously [16]. Wee *et. al.*, proposed a technology to save OLED displays power by gradually dimming the non-interesting regions of the display for game players [17]. These techniques mainly devised for LCDs and cannot be applied to OLED displays. Although, literatures [16-17] proposed the power-saving schemas for emissive displays, to our knowledge, no attempt has been made to integrate the gamma correction and the saturation scaling into a low-power technique for OLED displays.

3. Proposed Approach

In this section, we firstly describe the power consumption model of OLED displays. Then, we present the relationship of screen luminance and display power on different gamma values. To guarantee the display quality with low distortion, we adopt two image metrics to evaluate our approach. Finally, we investigate the power consumption of display content when our approach is applied.

3.1. OLED Display Power Model

The power consumption of OLED displays can be measured accurately by diverse power meters. But these measurement tools are very professional. In order to measure the power consumption of OLED displays without using any assistant tools, literatures [16-18] present a pixel-level power model for display content of OLED displays as follows:

$$P_{content} = \sum_{i=1}^{n} P^{i}_{pixel} = \sum_{i=1}^{n} (w_0 + w_1 \cdot R_i^{\gamma} + w_2 \cdot G_i^{\gamma} + w_3 \cdot B_i^{\gamma}) \tag{1}$$

Where n is the pixel number of display content. R_i, G_i and B_i are three color values of the *ith* pixel in the display content. The exponent γ is the gamma value of display content in the standard RGB (sRGB) color space. Let w_0 be the static power consumption, which is not affected by the pixel value. Meanwhile, the constants w_1, w_2 and w_3 are the efficiency coefficients of red, green and blue respectively. The values of the three coefficients are inversely proportional to the power efficiency values of the corresponding color. For example, on our platform, the coefficient ratios are about $w_1 : w_2 : w_3 = 24 : 35 : 50$. That is, the blue pixels have lower power efficiency than the red and green because the coefficient w_3 is larger than the other two coefficients. However, the aging process of display component results in different color power efficiency, as well as different OLED displays have distinct power characteristic. Therefore, the three coefficients are not always constant and need to be recalibrated over the lifetime of the device [14-19].

The power consumption of OLED displays is determined by the strength of screen luminance and the power consumption of display content [20], which defined as follows:

$$P_{display} = L \cdot P_{content} + P_{base} \tag{2}$$

Where L is the screen luminance, which can be scaled from 0 to 255. And P_{base} is the base display power, which represents the intrinsic power consumed for keeping the OLED displays on.

3.2. Gamma Correction

The output light intensity of display devices is proportional to the input signal raised to a power denoted by γ. The following formula represents the relationship between the input signal and the output intensity:

$$L_d = L_{\max} \cdot L_n^{\gamma} \tag{3}$$

Where L_{max} is the maximum luminance of pixels, L_n is the normalized pixel value and L_d is the resulting luminance. The gamma correction is called gamma compensation or tone mapping operator, which is widely investigated in graphics implementations. To compensate for the non-linearity of the display components, a power of the reciprocal of the gamma value can be used so that the overall system γ is approximately 1 [15-21]. The mathematical definition of gamma correction is as following:

$$L_d = L_{\max} \cdot L_n^{1/\gamma} \tag{4}$$

Gamma correction directly affects the luminance of each pixel in display content via a Look Up Table (LUT). Scaling up the gamma value can brighten the image, which makes the dark area more clear. Scaling down the gamma value can darken the image, which makes the bright area more distinct. As shown in Figure 1, we apply five gamma values to two original images ("Dormer" and "Skifield"), and observe that the luminance of image increases along with the addition of gamma value.

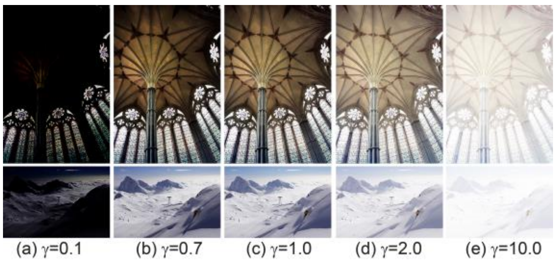


Figure 1. The Images Luminance Varies with γ

A low gamma value can save significant display power. However, dark region becomes dark and hard to distinct and high distortion is hard to maintain user experience. Although the MSE and the PSNR are widely used to evaluate image quality among image processing community, they do not account for human perception. To measure the impact of power-saving approaches on image quality, CIEDE2000 and MSSIM are used as two quality metrics. The CIEDE2000 color different equation is able to accurately predict the perceived differences between two color images, which was described in [22] and derived based on CIELAB equation as shown in the follow generic formula:

$$\Delta E = \sqrt{\left(\frac{\Delta L'}{K_L S_L}\right)^2 + \left(\frac{\Delta C'}{K_C S_C}\right)^2 + \left(\frac{\Delta H'}{K_H S_H}\right)^2 + R_T\left(\frac{\Delta C'}{K_C S_C}\right)\left(\frac{\Delta H'}{K_H S_H}\right)} \tag{5}$$

Where $\Delta L^{'}$, $\Delta C^{'}$, and $\Delta H^{'}$ represent the CIELAB metric lightness, chroma, and hue difference respectively, as well as the S_L, S_C and S_H stand for the weight functions of lightness, chroma, and hue, respectively. The function R_T is used to improve the color difference in the blue region. The K_L, K_C, and K_H are the parametric factors that affect the color feeling.

As well as the CIEDE2000 formula is sophisticated and designed for measuring the visual difference, the MSSIM is also adopted to account for the human visual perception [23], which divides the original image and the output image into several windows and compares the luminance, the contrast and the structural similarity with the other windows. The average value of all windows comparative results is the MSSIM value between the two images. The MSSIM quality metric is expressed with the following equation.

$$MSSIM(x,y) = \frac{1}{n}\sum_{i=1}^{n}\frac{(2\cdot\mu_{x_i}\cdot\mu_{y_i}+c_1)\cdot(2\cdot\sigma_{x_i y_i}+c_2)}{(\mu_{x_i}^2+\mu_{y_i}^2+c_1)\cdot(\sigma_{x_i}^2+\sigma_{y_i}^2+c_2)} \tag{6}$$

Where n is the number of windows. μ, σ^2 and σ stand for expectation, variance and covariance, respectively. We let x_i denote the *ith* window of original image and y_i be the *ith* window of output image. The constants C_1 and C_2 are used to avoid divisor being very close to zero.

The MSSIM is varies from -1 to +1. A value closed to +1 means that the extracted structural information of the two images is almost similarity. On the contrary, when the value is close to -1, it shows that the output image has high distortion compared to the original image. Figure 2 shows the relationship between the MSSIM and γ. To find the math representation to represent this relationship, we use a logistic function [24] to fit the plotted data. From Figure 2, we find the fitting results are non-linear curves with high coefficient of determination (R^2). The R^2 of the fitting curves are greater than 0.999 close to 1, which indicates the curve fitting is excellent.

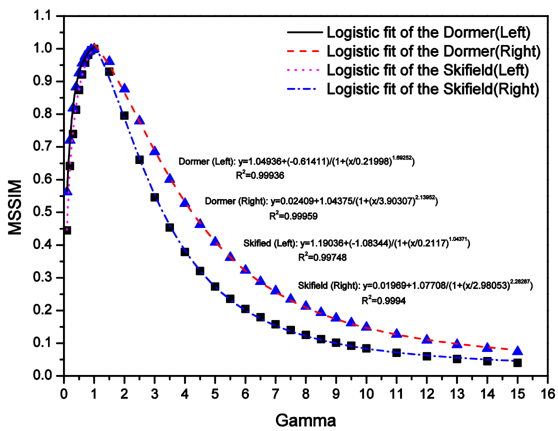


Figure 2. The MSSIM of Images Varies with γ

To account for human visual perception, we assume that M_0 is the perceptual difference threshold of MSSIM for an acceptable image quality. The image whose MSSIM value is not less than 0.99 cannot be considered, being noticed as distinct from the original image. More details about the perceptual threshold for the MSSIM metric are shown in [25] and [26]. When M_0 is substituted into the fitting equations shown in Figure 2, the ranges of gamma are obtained, which results in low image distortion. For example, M_0 is set to 0.99, then, the gamma of "Dormer" ranges from 0.82 to 1.20, as well as the gamma of "Skifield" ranges from 0.88 to 1.13.

To obtain the power consumption of the two images, we show the screen with images applied the different gamma values, vary from 0.1 to 15, enumerating the every possible screen luminance from 0 to 255. The image "Skifiled" consumes much more power than "Dormer" because the former has more bright pixels when the same gamma value and screen luminance are applied. High screen luminance improves the end user experience especially when display content is dark. However, the high screen luminance consumes much more power than the low screen luminance. For example, "Dormer" consumes 519.726mw and 305.997mw when the luminance is set to 255 and 30 respectively. On the other hand, low screen luminance makes end user hard to distinguish the display content, especially when a dark image is shown, although it reduces the display power consumption.

The impact of gamma correction indicates that a dark image consumes less power than a bright image. Therefore, power saving can be achieved when γ is less than 1. Moreover, the structural information of output image and original image is similar when the MSSIM is close to M_0. The gamma correction approach (GC) is adopted to create output image with low distortion. The pseudo code of GC is shown in Figure 3.

```
Input: original image I.
Output: output image I'.
1: m ← -1; n ← 1; γ ← 0; oldm ← -1; oldγ ← γ;
2: WHILE  m < M0 DO
3:     oldm ← m; oldγ ← γ;
4:     γ ← γ + (0.1)^n;
5:     pixel (x, y) ← get the first pixel of I;
6:     WHILE  pixel (x, y) of I  is exist DO
7:         read r, g, b of pixel (x, y);
8:         calculate r', g', b' using gamma function with γ;
9:         write r', g', b' to pixel (x, y) of I';
10:        pixel (x, y) ← get the next pixel of I;
11:    END WHILE
12:    m ← the MSSIM value between I and I';
13: END WHILE
14: IF n <= 1 THEN
15:    m ← oldm; γ ← oldγ;
16:    n ← n + 1;
17:    go to line 2;
18: END IF
```

Figure 3. The Pseudo Code of GC

In intrinsic while loop, the gamma correction selects γ starts from 0 to create an output image (lines 5-11). Next, in extrinsic while loop, the gamma correction increases γ gradually for output image until its human visual perception is satisfied (lines 2, 4 and 12). To retain two decimal places of γ, the extrinsic while loop is performed again (lines 14-18). After the process is executed, if γ is still less than 1 meaning the output image has high similarity with the least power consumption.

3.3. Gamma Correction and Saturation Scaling Integration

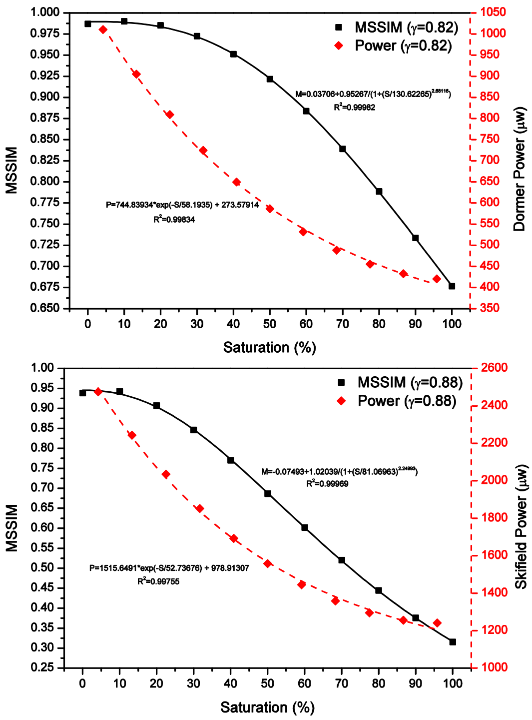
The saturation describes the dominance of hue in HSV color model. The saturation is defined as following:

$$S = \begin{cases} 0, & if \ max(R,G,B) = 0 \\ \dfrac{max(R,G,B) - min(R,G,B)}{max(R,G,B)}, & otherwise \end{cases} \tag{7}$$

Where max(R, G, B) is the largest value and min(R, G, B) is the smallest value among R, G, or B in a color. The saturation-dimension in HSV always fits into the range [0-1]. When we increase the saturation level from 0 (fully desaturated) to 1 (fully saturated), the hue we are using to describe the color dominates more and more. Similar to the gamma correction, we can obtain the range of saturation, which preserves a high similarity of output image compared to original image. For example, the saturation of "Dormer" ranges from 0 to 16%, as well as the saturation of "Skifield" ranges from 0 to 8% when M_0 is set to 0.99.

To find the main impact of saturation on image power, we measure the power consumption of display content for different saturation levels when a certain gamma value is applied with fixed hue and value. Figure 4 shows the results of this experiment for various saturation levels. As shown in Figure 4 (a) and Figure 4 (b), the power consumption of "Dormer" and "Skifield" have similar decreasing trend while saturation levels are scaling up. In addition, increasing saturation level leads to decrease power consumption. For example, the original images "Dormer" and "Skifield" save 337μw and 634μw when the saturation level increased from 20% to 60% respectively. This trend is more significant when a higher gamma value is applied.

To obtain the maximum power saving, we calculate the maximum amount of saturation of an image that is modified by gamma correction with low distortion constrained. The gamma value (0.82 for "Dormer" and 0.88 for "Skifield") can maximize the amount of power conserved, which maintains M_0 at 0.99 compared to the original image. In our experiment, we obtain MSSIM and the power consumption of output images when applying the saturation scaling from 0 to 100%. Figure 4 shows a definite trend of the MSSIM and the image power for different saturation levels. We use non-linear curve to fit the plotted data. As a result, we obtain excellent quality fits for the MSSIM and the power consumption with high R^2.



(a) Dormer (b) Skifield

Figure 4. The Comparative Results of the MSSIM and Display Content Power Consumption, while Saturation Changed from 0 to 100%

We assume that S_0 is the highest saturation level for obtaining the acceptable image quality. To calculate the power consumption of image, firstly, we substitute M = M_0 into MSSIM fitting equations shown in Figure 4 (a) and Figure 4 (b). Then, we set $S = S_0$ and substitute S to power fitting_equations shown in Figure 4 (a) and Figure 4 (b). Finally, the power consumption of image, P, is obtained. For example, we set M_0 = 0.90, then, the image "Dormer" (γ = 0.82, S_0 = 56%) consumes 557μw, which saves 229μw compared to the output image only applied gamma correction (γ = 0.82) consumed 786μw, as well as the image "Skifield" (γ = 0.88, S_0 = 21%) consumes 2001μw, which saves 280μw compared to the image only applied gamma correction (γ = 0.88) consumed 2281μw.

There are two interesting phenomenon we make from the impact of saturation scaling on the output image. Firstly, a high saturation image consumes less power than a low saturation image. Therefore, power saving can be achieved for output image when S_0 is larger than the saturation of original image. Secondly, the structural information of output image and original image is similarity when the MSSIM value is close to M_0. Thus, the saturation scaling approach (SS) is adopted to create output image with low distortion. The pseudo code of SS is shown in Figure 5.

```
Input: original image I.
Output: output image I'.
1: m ← -1; n ← 1; s' ← 1; oldm ← -1; olds' ← 1;
2: WHILE m < M0 DO
3:    oldm ← m; olds' ← s';
4:    s' ← s' – (0.1)^n;
5:    pixel (x, y) ← get the first pixel of I;
6:    WHILE pixel (x, y) of I is exist DO
7:       read r, g, b of pixel (x, y);
8:       convert r, g, b to h, s, v;
9:       IF s' >= 0 THEN
10:         s' ← s + (1 - s) × s';
11:      ELSE IF s' < 0 THEN
12:         s' ← s × (1 + s');
13:      END IF
14:      convert h, s', v to r', g', b';
15:      write r', g', b' to pixel (x, y) of I';
16:      pixel (x, y) ← get the next pixel of I;
17:   END WHILE
18:   m ← the MSSIM value between I and I';
19: END WHILE
20: IF n <= 1 THEN
21:   m ← oldm; s' ← olds';
22:   n ← n + 1;
23:   go to line 2;
24: END IF
```

Figure 5. The Pseudo Code of SS

In intrinsic while loop, the saturation scaling selects s' starts from 1 to create an output image (lines 6-17). To change the saturation of a color image, we convert original image to HSV from sRGB color model and then process only the saturation-component without changing the hue- and value-components (lines 8 and 14). It represents that the saturation-component increased by s' on the basis of the original image's saturation when the variable s' is larger than zero as well as the saturation-component decreased by s' when s' is less than zero (lines 9-13). Next, in extrinsic while loop, saturation scaling decreases s' gradually for output image until its MSSIM value is satisfied (lines 2, 4 and 18). To retain two decimal places of saturation, the extrinsic while loop is performed again (lines 20-24). After the extrinsic while loop, if s' is larger than saturation of original image meaning the output image has high similarity with the least power consumption.

The gamma correction and saturation scaling integration approach (GS) not only decreases gamma value but also increases saturation-dimension. GS includes two steps. At first, we process original image using GC and then scale saturation using SS.

However, we observe that the three approaches, *i.e.*, GC, SS, and GS, have high time complexity that is $O(\boldsymbol{N})$ multiplication and addition operations because of the iterative way. The $\boldsymbol{N}$ represents the pixel numbers of OLED on smartphone. These algorithms, creating the low-power image from original image, consume much time and battery power when they are running on mobile devices. Fortunately, we can optimize the three processes by the following approaches:

1) If we compare two images (480×800) pixel by pixel, the while-loop in MSSIM function will run 384000 times. To obtain the MSSIM rapidly, sampled pixels are compared. In this paper, the number of sampled pixels is set to 500.
2) The ARGB (Alpha, Red, Green and Blue) values of each pixel in the frame buffer are written into a byte buffer. Then, multi-thread is used to process the tone mapping of each pixel in GC, SS and GS techniques with the parallel pattern.
3) To reduce the query time of gamma and saturation threshold, a binary search algorithm is used instead of sequential search.

The executing time of the three saving-power techniques running on our target smartphone is shown in Table 1.

Table 1. The Comparative Results of Execution Time on Samsung Galaxy Mobile Phone

Images	Before Optimization (ms)			After Optimization (ms)		
	GC	SS	GS	GC	SS	GS
dormer	10,078	21,128	25,568	139	1,164	1,576
skifield	3,818	18,514	25,995	125	482	673

The experiment results show that the execution time of the three saving-power policies on the “Dormer” image under the optimization method is 97.68%, 94.49% and 93.84% shorter than that before optimization, respectively. It gets obvious optimization effect. Furthermore, there are some other effective solutions to solve this problem:

1) The image processing can be executed on a proxy server and the mobile device only shows the output image [27].
2) The power-saving approach we proposed can be realized using specialized hardware or firmware, such as ASIC or FPGA [28].

4. Results

In this section, we evaluate our power-saving approach using the other eight color images. As shown in Figure 6, these test images are “Sea”, “Lion”, “Building”, “Bird”, “Flower”, “Land”, “Swan” and “Fish”. Except that the images “Sea”, “Land” and “Swan” are taken by our target smartphone, the rest images shown in Figure 1 and Figure 6 are from Baidu Image Library (image.baidu.com).

Figure 6 (a) shows the original images. Figure 6 (b) shows the output images only applied the gamma correction approach (GC). Pixel luminance of original images is transformed with the gamma function. We observe that the overall image luminance becomes dark compared to original images. Figure 6 (c) shows the output images when only the saturation scaling approach (SS) is applied. Pixel saturation of the whole images is scaled up, which results in an increasing color dominating. The images shown in Figure 6 (d) are applied the gamma correction and saturation scaling integration approach

(GS). Therefore, the overall images shown in Figure 6 (d) are dark and saturated compared to the original images.

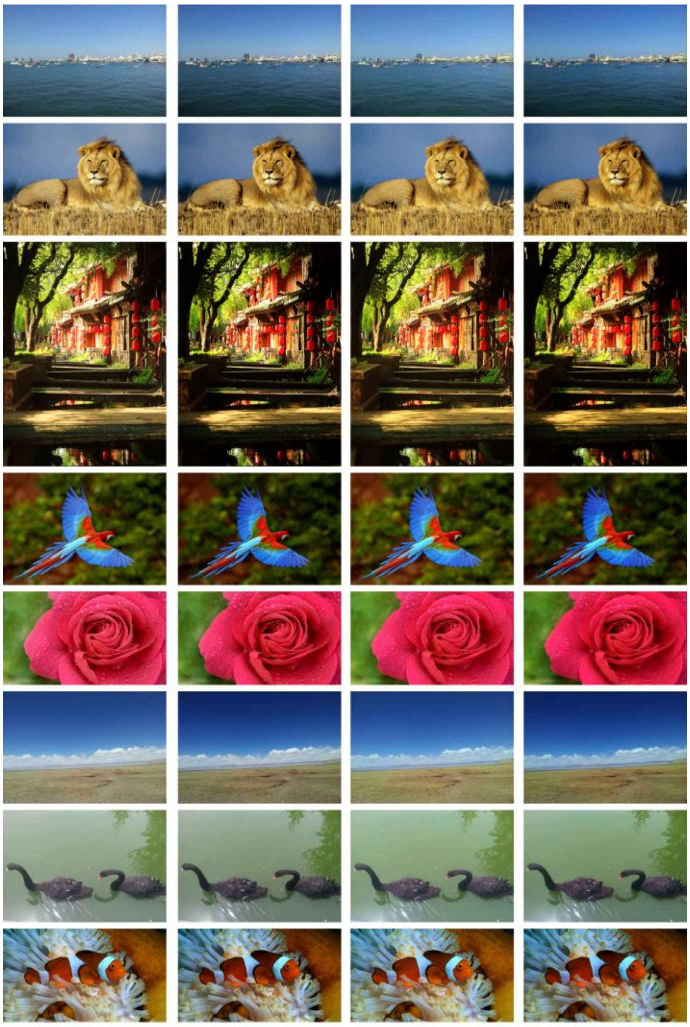


Figure 6. Low Image Distortion Constrained Power-Saving Results on the Color Images

Table 2 provides the parameters of output images shown in Figure 6. As shown in the table, MSSIM of output images are close to 0.99 and the CIEDE2000 color difference is less than 20, which indicates that these output images are close to the original images.

Table 2. The Properties of Eight Images Applied Three Different Approaches, *i.e.,* GC, SS and GS

Images	MSSIM	ΔE	γ	Saturation	Power (μw)
Sea (Original)	1	0	-	-	1566
Sea (GC)	0.99	9.25	0.78	-	1242
Sea (SS)	0.99	1.86	-	0.13	1489
Sea (GS)	0.97	10.14	0.78	0.13	1188
Lion (Original)	1	0	-	-	1305
Lion (GC)	0.99	3.49	0.82	-	1042
Lion (SS)	0.99	2.98	-	0.14	1223
Lion (GS)	0.97	9.77	0.82	0.14	986
Building (Original)	1	0	-	-	634
Building (GC)	0.99	15.41	0.73	-	493
Building (SS)	0.99	2.71	-	0.23	566
Building (GS)	0.99	17.67	0.73	0.23	448
Bird (Original)	1	0	-	-	445
Bird (GC)	0.99	6.45	0.78	-	332
Bird (SS)	0.99	0.19	-	0.19	433
Bird (GS)	0.98	6.45	0.78	0.19	325
Flower (Original)	1	0	-	-	914
Flower (GC)	0.99	3.77	0.85	-	780
Flower (SS)	0.99	3.83	-	0.26	846
Flower (GS)	0.99	6.80	0.85	0.26	737
Land (Original)	1	0	-	-	1427
Land (GC)	0.99	5.87	0.76	-	1058
Land (SS)	0.99	4.13	-	0.14	1342
Land (GS)	0.98	7.97	0.76	0.14	1003
Swan (Original)	1	0	-	-	1471
Swan (GC)	0.99	3.64	0.82	-	1165
Swan (SS)	0.99	5.81	-	0.09	1343
Swan (GS)	0.98	7.30	0.82	0.09	1066
Fish (Original)	1	0	-	-	1221
Fish (GC)	0.99	3.62	0.82	-	1000
Fish (SS)	0.99	0.74	-	0.09	1163
Fish (GS)	0.98	3.91	0.82	0.09	955

Figure 7 shows the power consumption of all the images in Figure 6. Although, all of the GC, SS, and GS can reduce power consumption for each image, the GS has better energy efficiency than GC and SS. For example, the color image "Swan" applied GS approach saves 108μw and 716μw compared to the output images applied GC and SS, respectively. From the figure, we also find that the blue color dominant images ("Sea", "Swan", "Land" and "Lion") consumed more power than the red color dominant images ("Flower", "Building", "Bird" and "Fish") because the blue color is less efficient than the red color on our OLED-based smartphone.

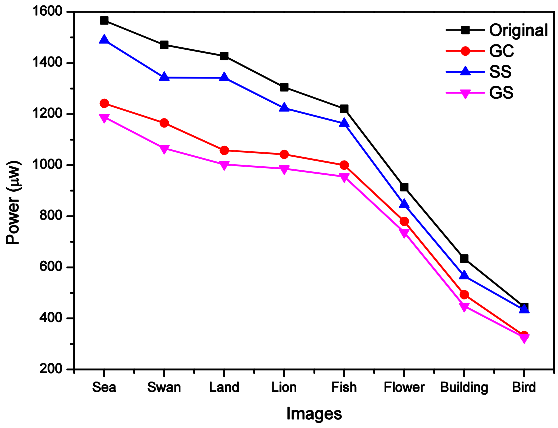


Figure 7. The Comparative Results of Images Power Consumption

5. Conclusion and Future Work

A gamma correction and saturation scaling integration approach is proposed, which reduces the power consumption of OLED displays with low distortion constrained. We present a power model for emissive displays and suggest two image quality metrics to evaluate our power-saving approach. Specifically, we investigate the impact of the gamma correction and the saturation scaling on the power consumption of OLED displays. Furthermore, we have applied three power-saving methodologies to ten color images and find the gamma saturation integration can save much more power than the other two approaches because the gamma saturation integration not only decreases the brightness but also increases the saturation. The experiment results indicate that our approach achieves significant power saving while losing an acceptable amount of image quality. As future work, we plan to improve user experience by enhancing image contrast and apply our power-saving approach to video sequences on the OLED-based mobile devices.

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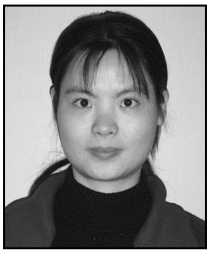

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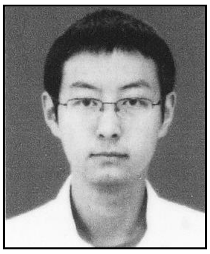

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