Master's Thesis

Perceptual Color Enhancement for OLED Display

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Abstract

Perceptual Color Enhancement for OLED Display

Self-emitting displays such as organic light emitting diodes (OLED) dominate power consumption in embedded systems, and their power efficiency became one of the crucial factors in improving usability of mobile systems. A simple luminance reduction trades energy efficiency off the visibility of visual objects. This paper presents a perception-based enhancement method that enhances the visibilities of visual objects in self-emitting displays, under dynamic luminance changes for less power consumption. Given the power savings, our system tries to maintain the least perceptual difference from a source image through the adaptive control of image luminance. Our enhancement method is based on the contrast sensitivity function (CSF), and we modeled a scale factor using the saliency map of source image with a weight factor to increase degree of contrast enhancement in regions of high human interest. This enhancement causes changes of power consumptions in OLED display, because power consumption of OLED is dependent on the contents to be displayed. We apply power-adaptive darkening for prevent increasing power consumptions, which is computed with power difference between uniformly darkened image and contrast enhanced image.

Results show that our method achieves high enhancement of a visual quality of image in condition of maintaining power consumptions of OLED display comparison to simple darkening. Additionally, we conducted user experiments to investigate effects of our method, and found that our method better maintains the visibility of visual objects under reduced luminance.

Keywords: OLED display, perception-based contrast enhancement, power consumptions, luminance management, color space

1. Introduction

Since self-emitting displays such as organic light emitting diodes (OLEDs) dominate power consumption in embedded systems, their power efficiency is becoming an important factor in improving the usability of mobile systems. Unlike other electronic parts of mobile devices, the display has larger possibilities of controlling its power consumption, which can be achieved by adapting its color or luminance levels to lighting environments.

While liquid crystal displays (LCDs)—another mainstream of displays for embedded systems—consume nearly constant power regardless of colors to be displayed due to its back-lighting mechanism, the power consumption of OLEDs relies heavily on the colors of content to be shown, resulting from its self-emissive electroluminescent layer. For an instance, a solid white image consumes much more power than a solid black image. The content of the higher luminance requires device to consume the more energy. A common way of reducing the power consumption is simple reduction of luminance levels (Fig. 1). In Fig. 1, we present results of luminance scaling with darkening ratio, which range is from 1.0 to 0.5. This can be simply achieved by scaling RGB channels of image with darkening ratio. However, such a simple strategy trades energy efficiency off the visibility of visual objects, significantly degrading perceived visual quality.

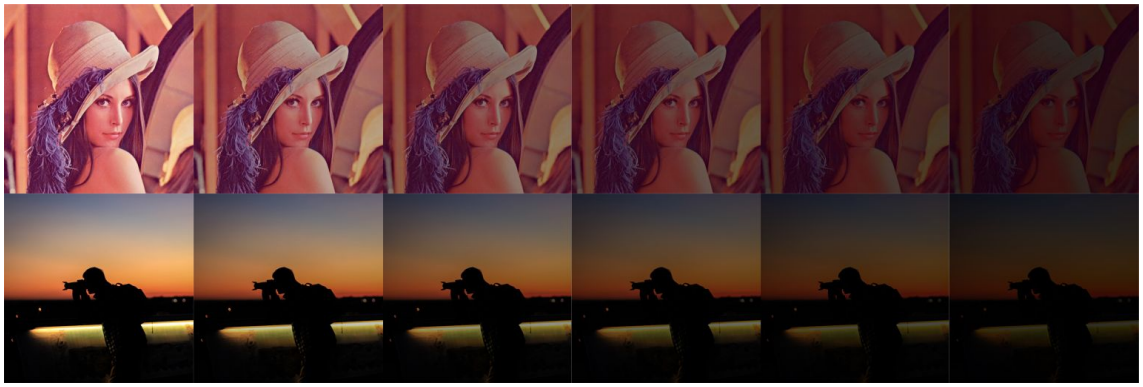

Fig. 1. Examples of simple reduction of luminance levels.

The study of Dong et al. [1], [2] is one of the successful attempts that dynamically control the color of OLEDs for power efficiency. The colors of GUI components were optimized with energy-efficient color transformation. Their result shows considerable improvement in efficiency of energy consumption. However, their work is limited only in GUI components, which is only applicable discrete set of colors. Also, the significant changes of the chromaticity may not match well the user preference. These limitations motivated us to explore a better approach that can save power with less perceptual degradation and be used in natural images as well as discrete GUI components.

In this paper, we present a technique to improve visual quality over the straightforward approach. We pursued to make an energy-saving method, which is adaptable to not only GUI but also other contents. More precisely, we present how to enhance/match the contrast of images in the condition of maintaining equivalent power consumptions to uniformly darkened image.

Basically, our method is based on the contrast sensitivity function (CSF), which is served as a basis for perception-based enhancement or sampling for many research areas [3-6]. The changes are compensated by the global and local contrast enhancement, so that the resulting outputs match the perceptual intensity of the source images.

2. Related Work

The study referring low power consumption of display in hardware technology is highly progressed, while contents based approach is rarely commanded. In this section, we describe previous studies about power consuming model of OLED and color metrics for computations of perceptual distance.

2.1 Power Model of OLED Display

Dong et. al. introduced the color−power model of OLED display [7], [8]. In according to their study, power consumption of a pixel is modeled with linear combination of R, G, and B values, represented with the formula (1).

$$\mathrm{P(R,G,B)} = C_0 + C_R \times R + C_G \times G + C_B \times B, \quad (1)$$

where $\mathrm{P(R,G,B)}$ is power of a pixel, $\mathrm{C_R, C_G, C_B}$ are measured values for R,G,B values, and $\mathrm{C_0}$ is device dependent constant, which is power consumption for displaying the black screen. Dong et. al. presented the experimental result of $\mathrm{C_R}$, $\mathrm{C_G}$, $\mathrm{C_B}$ values as 1.033254 μW, $1.916862 μW, and 2.444181 μW for Galaxy S mobile device [7]. The power model of image $\mathrm{P_{image}}$ is summation of power consumption of each pixel and it can be represented as the formula (2).

$$\mathrm{P_{image}} = \sum_{p\in\{1,\ldots,W\}\times\{1,\ldots,H\}} P_p(R,G,B), \quad (2)$$

where the resolution of image is $\mathrm{W} \times \mathrm{H}$, and $\mathrm{P_p(R,G,B)}$ is power of a pixel.

2.2 Perceptual Color Spaces

In order to reflect perception of human visual system (HVS) on computations in color space, many perception-based color metrics are suggested. The CIE76 metric based on CIE Lab space is a common choice, which has perceptual uniformity. The CIE Lab space is composed with (L^*, a^*, b^*), where L^* is lightness and a^*, b^* are related to chromaticity [9]. In the CIE Lab space, the Euclidean distance is proportioned to perceived color difference of HVS. The perceptual color distance $\Delta\varepsilon_{76}$ in CIE Lab between two color values is computed as the formula (3).

$$\Delta\varepsilon_{76} = \sqrt{(\Delta L^*)^2 + (\Delta a^*)^2 + (\Delta b^*)^2} \tag{3}$$

A related color space, the Hunter Lab space is often used instead of CIE Lab space. The difference of Hunter Lab space from CIE Lab is that Hunter space measures blues more than yellows, and shows lower sensitivity on dark colors [10]. Additionally, Hunter Lab space coordinates are based on a square root function, while the CIE Lab coordinates is based on a cube root function.

Similarly with CIE Lab space, CIE Luv space is widely used. CIE Luv is consisted with three components, (L^*, u^*, v^*). L^* is identical value with L^* of CIE Lab, lightness. u^*, v^* are related to correlates of chroma and hue. In many cases, CIE Luv space shows comparable performance to CIE Lab space e.g., image enhancement [11].

CIE94 metric is extended version of CIE76, because perceptually saturated region is found in CIE76. The components of coordinates are not changed, (L^*, a^*, b^*), but the L^* is computed from (L^*, c^*, h^*) space. CIE94 is improved in a perceptual uniformity in comparison to CIE76. The color distance $\Delta\varepsilon_{94}$ between (L_1^*, a_1^*, b_1^*) and (L_2^*, a_2^*, b_2^*) is defined as follows:

$$\Delta\varepsilon_{94} = \sqrt{(\frac{\Delta L*}{k_L S_L})^2 + (\frac{\Delta C_{ab}^*}{k_C S_C})^2 + (\frac{\Delta H_{ab}^*}{k_H S_H})^2} \tag{3}$$

where

$$\Delta C_{ab}^* = \Delta\sqrt{(a^*)^2 + (b^*)^2}, \quad \Delta H_{ab}^* = \sqrt{\Delta a^{*2} + \Delta b^{*2} - \Delta C_{ab}^{*\,2}}$$

$$S_C = 1 + K_1 C_1^*, \quad S_H = 1 + K_2 C_1^* \tag{4}$$

S_L, k_C, and k_H are generally unity. k_L, K_1, and K_2 are weighting factors and C_1^* is square root sum of a_1^* and b_1^*.

CIEDE2000 is advanced metric from CIE94, because perceptual non-uniformity still is a problem, especially blue region. For this reason, the definition of color distance is renewed. More precisely hue rotation term is added and four values are compensated; neutral colors, lightness S_L, chroma S_C, hue S_H. The color distance $\Delta\varepsilon_{00}$ is defined as follows:

$$\Delta\varepsilon_{00} = \sqrt{(\frac{\Delta L'}{k_L S_L})^2 + (\frac{\Delta C'}{k_C S_C})^2 + (\frac{\Delta H'}{k_H S_H})^2 + R_T \frac{\Delta C'}{k_C S_C}\frac{\Delta H'}{k_H S_H}} \tag{5}$$

where

$$\Delta L' = L_2^* - L_1^*, \quad \bar{L} = \frac{L_1^* + L_2^*}{2}, \quad \bar{C} = \frac{C_1^* + C_2^*}{2}$$
$$a_1' = a_1^* + \frac{a_1^*}{2}(1 - \sqrt{\frac{\bar{C}^7}{\bar{C}^7 + 25^7}}), \quad a_2' = a_2^* + \frac{a_2^*}{2}(1 - \sqrt{\frac{\bar{C}^7}{\bar{C}^7 + 25^7}})$$
$$C' = \frac{C_1' + C_2'}{2}, \quad C_1' = \sqrt{{a_1'}^2 + b_1^{*2}}, \quad C_2' = \sqrt{{a_2'}^2 + b_2^{*2}} \tag{6}$$

R_T is computed from $\overline{H'}$ and $\overline{C'}$. $\overline{H'}$ is derived by using C' and h' values. h' is inverse tangent function of a' and b^*. However, CIEDE2000 is difficult to use for modeling an optimization, because it only guarantees C0−continuity [12]. For this reason and simplicity of CIE Lab space, we select CIE Lab space for managing luminance in our approach.

2.3 Power-Aware Color Transform

Dong et. al. introduced the pixel-level power model of OLED and practical method to measure power consumptions of image-level power model [1]. The pixel-level power model is derived from measuring power consumptions of QVGA OLED module. The practical method measures the power consumptions of image to be displayed based on the deterministic sampling [1], [8].

Based on these power models of OLED, Dong et. al. suggest methods to find near-optimal color mapping of GUIs based on the power model of OLED [2]. It finds new color mapping of GUIs by generating color histogram and traverse all possible combinations. In considering user acceptance with CIE $L^*a^*b^*$ space, they pursued to reduce power consumptions of OLED while maintaining usability. The main difference of this research from our approach is that their method can applied on only discrete color image, because it finds a combination of colors to mapping them on GUI. In addition, they introduced automated framework of their research: Chameleon, which transforms colors of web pages to reduce power consumption of OLED displays in embedded systems [7]. The user study shows good results in preference on their results with reducing power consumptions from 41 percentages to 64 percentages. They also describe about benefits of the chameleon with user study about usage of web browser. This user study shows us that lifetime of battery is highly improved.

2.4 Image Quality Evaluation

In the CIE Lab color space, the Euclidean distance between two colors is proportional to perceptual difference. For instance, in case of that chromaticity of two colors is changed with maintaining color distance, the perceptual difference between two colors is assumed to be preserved.

Dong et. al. suggested perception-based metric to measure variations of usability, which is modeled with color distance in CIE Lab [2]. Because this metric can only measure usability of GUI based on the perceptual difference of components of GUI, it cannot be applied on measuring an enhancement degree of image quality.

In order to evaluate the degree of image enhancement, Majumder et. al. used Weber law based contrast-enhancement. Basically, increase of contrast is assumed as enhancement of image, because it enables us to distinguish an object visually in a scene. Their method makes contrasts increased by scaling local contrast with parameter, which has a higher value than Weber ratio [16]. In our research, we followed this assumption, and approximated this method for enhancing of image globally.

2.4 Contrast Sensitivity Function

The contrast sensitivity function (CSF) has been serving as a basis for perception-based enhancement or sampling for many research areas. The CSF presents sensitivity on brightness between adjacent areas. The contrast sensitivity is usually measured by the reciprocal of brightness difference that is a minimum requirement to separately recognize a lattice. The sensitivity to the stimulus of lattice is expressed with spatial frequency.

The intensity of image is generally defined with computing a mean value for all pixel intensity or a distribution of image level. The distribution is computed with color histogram. In this color histogram, horizontal axis represents the intensity of image and vertical axis is the number of pixels corresponding to the value of horizontal axis.

A contrast of image is defined with difference between the maximum value of intensity and the minimum. More simply, Michelson contrast $(L_{max} - L_{min})/(L_{max} + L_{min})$ is a common choice, where L_{max} and L_{min} represent the peak and minimum luminance levels [13], [14].

2.5 Perception-Based Contrast Enhancement

Elementary techniques of enhancing contrast for images can be one of the following three strategies [15]. Intensity transform translates pixel intensities using the predefined look-table or transfer functions. Contrast stretch is another standard technique, which converts outer end trails of pixel intensities to the minimum and maximum values in valid ranges and intermediate values are linearly stretched. Majumder and Irani [16] applied the principle of contrast sensitivity to the contrast enhancement of images. Unlike the work focusing on the threshold that makes a certain region visible, their work focused on improving contrast in suprathreshold (i.e., visible) regions. The contrast was approximated to scale with local gradients at pixels, and they reformulated the contrast enhancement problem as the scaling of hillrocks." Their iterative greedy algorithm provided an effective solution to contrast enhancement of gray-scale images as well as color images.

Ke et. al. [17] introduced an image enhancement framework with combining a bilateral tone adjustment (BiTA) and saliency-weighted contrast enhancement (SWCE). They applied the BiTA for stretching the luminance contrast of mid-tone regions. They also use saliency map as a weight to the simple method of contrast enhancement. More precisely, it adds the difference between an original luminance value of pixel and mean of luminance to the original with multiplying the value of saliency.

3. Approximated CIE Lab

In our framework, additional computations are operated to improve a visual quality of source image, e.g. luminance management in perceptual color space, generation of saliency map, which includes several conversion of color space. These procedures require display device to charge additional workloads, which are computation time and power consumptions. In the case of improving a video input, workloads can increase drastically and generate frame drops.

To minimizing workloads caused by computation of adaptive luminance management, we approximate formula of conversion color space between CIE $L^*a^*b^*$ space and RGB space. The conversion from RGB to CIE $L^*a^*b^*$ includes a step of conversion to XYZ space. The conversion from CIE $L^*a^*b^*$ to XYZ color space is formulated as follows:

$$\begin{aligned} Y &= Y_n \cdot f\left(\frac{1}{116}(L^* + 16)\right), \\ X &= X_n \cdot f\left(\frac{1}{116}(L^* + 16) + \frac{1}{500}a^*\right), \\ Z &= Z_n \cdot f\left(\frac{1}{116}(L^* + 16) - \frac{1}{200}b^*\right), \end{aligned} \tag{7}$$

where, the function f is defined as follows:

$$f(t) = \begin{cases} t^3 & if\ t > \frac{6}{29} \\ 3\left(\frac{6}{29}\right)^2 (t - \frac{4}{29}) & otherwise. \end{cases} \tag{8}$$

We use an approximated CIE $L^*a^*b^*$ model, which is coined as aLab. In the conversion from CIE $L^*a^*b^*$ to XYZ color space, we approximate the function $f(t)$. The approximated $f(t)$ is as follows:

$$f(t) = t^3. \tag{9}$$

To confirm the validity of this approximation, we perform an experimental comparison between CIE $L^*a^*b^*$ and approximated CIE $L^*a^*b^*$ in measure of color difference model. This approximation causes computational differences in dark regions, we measure color difference model with reducing the luminance both CIE $L^*a^*b^*$ and aLab. Fig. 2 is set of images, which is used for aLab precision test.

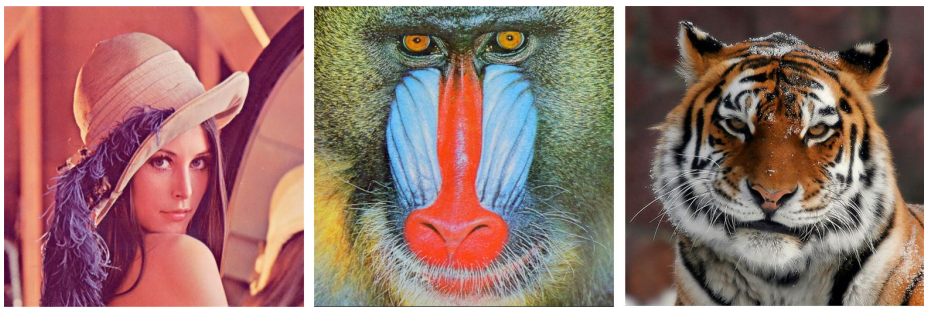

Fig. 2. Images for aLab precision test (Lena, baboon, and tiger).

Fig. 3 shows us that there are minute differences between CIE $L^*a^*b^*$ and the approximated model. In Fig. 3, the luminance scale is scaling factor for

reducing luminance of source images, e.g., when L is 0.1, the luminance of source image is reduced by ninety percentages.

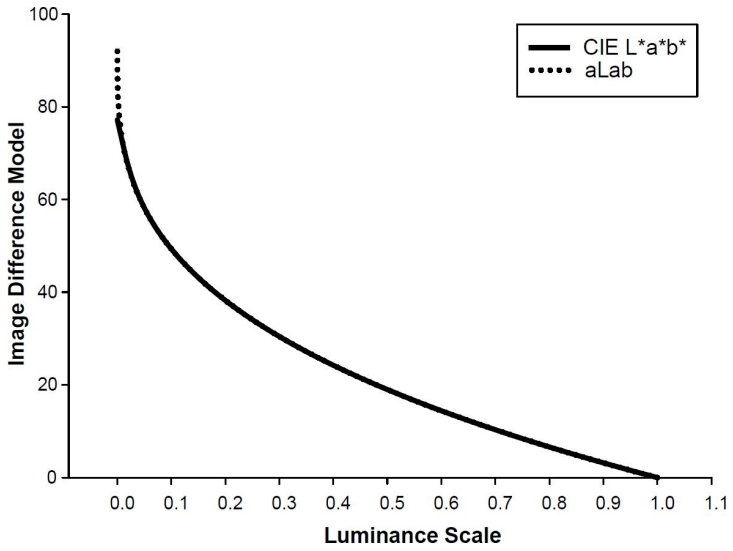

Fig. 3. Results of aLab precision tests in Lena image.

4. Algorithms

The goal of our framework is improving a visual quality of image in condition of maintaining power consumptions of OLED display. In this section, we provide a description of our framework. Fig. 4 is the overview of proposed framework.

We use a perceptual color space CIE Lab for managing luminance of image, which is defined with L in CIE Lab space. As we allude to, in order to minimize workloads in a conversion of color space, we use aLab space for conversion to CIE Lab space.

The framework is consisted with two technique based on previous research [8], [16]. In the first step, we generate uniformly darkened image, saliency map, and Weber Law-based contrast map from an input image. Next, the saliency-based global contrast enhancement is applied to a uniformly darkened image. Due to alterations of luminance in contents to be displayed, power consumption of OLED is also changed. In order to maintain power consumptions of display comparison to simple darkening, we compute ratio of power to be reduced via computing difference of power consumptions between uniformly darkened image and contrast enhanced image. With this ratio, we darken contrast image to make it has equivalent power consumptions.

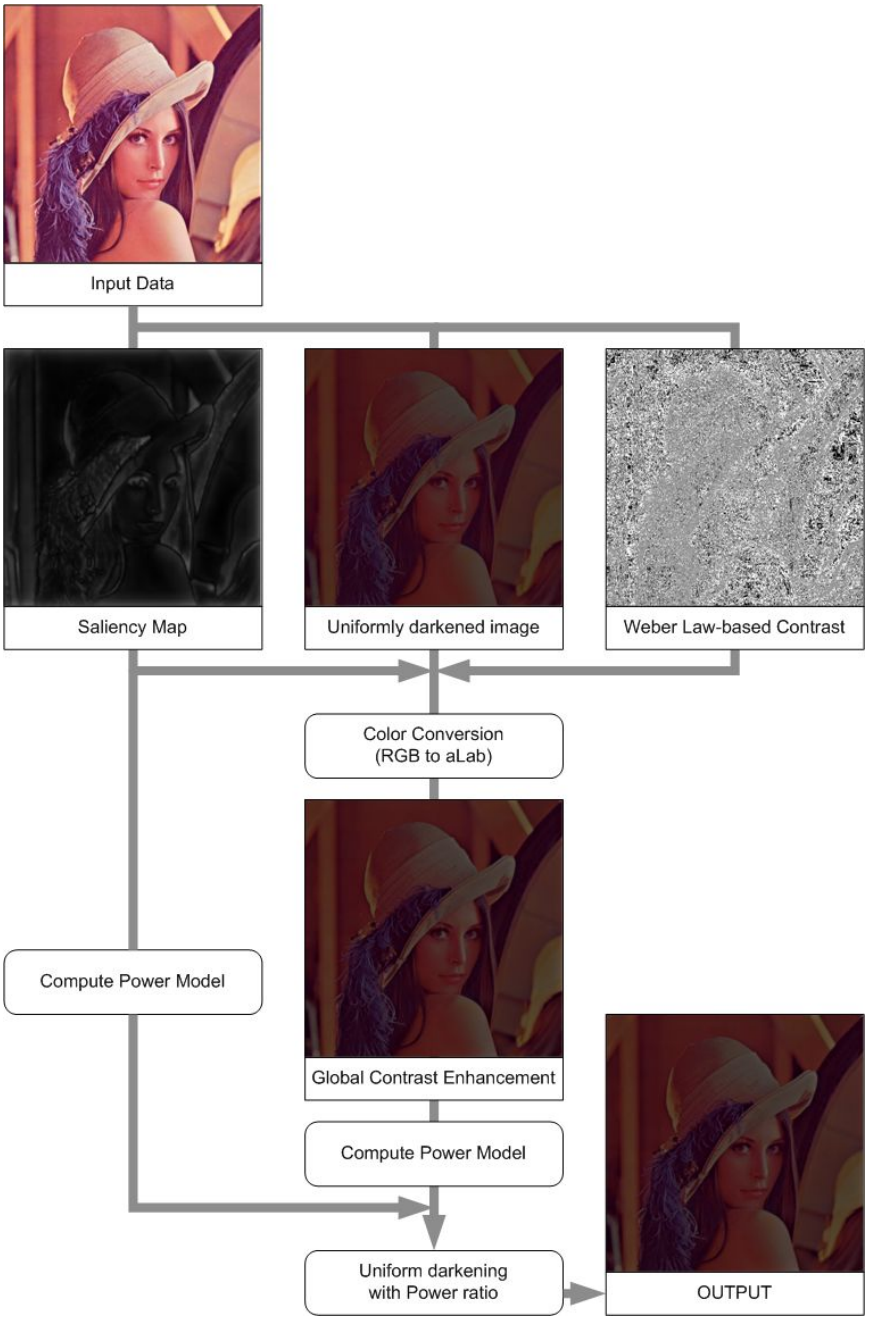

Fig. 4. Overview of our framework.

4.1 Weber Law−based Model of Contrast Enhancement

When images are degraded through blur or resampling, local contrast of pixels are significantly changed. Given a pixel $\mathbf{p}$, Weber's law, which CSF follows [18], describes its perceived change in contrast, ΔC_p with respect to its original contrast C_p by

$$\frac{\Delta C_p}{C_p} = \lambda_p. \tag{10}$$

when λ_p is greater than a certain threshold τ, the stimuli becomes visible. Such thresholds can be found using CSF [3−6].

While the work of Majumder et al. [16] focused on suprathreshold contrast sensitivity, we focus on reconstructing the original contrasts from the resampled images; we actually do not care whether pixels were initially visible or not.

Resampling typically results in the reduction of contrasts (visual acuity), which makes $\lambda < 1$. This leads to lower sensitivity of images, and thereby, people are likely to perceive the resampled images have lower intensities than the source images. Similarly to [16], we linearly approximate a pixel contrast as the sum of its partial derivatives against four neighbors:

$$\lambda_p \approx \frac{1}{4}\sum_{q \in N_4(p)}\left(\frac{I'_q - I'_p}{I_q - I_p}\right) \tag{11}$$

4.2 Global Contrast Enhancement

Our goal is to maintain the original contrast; this leads to $\lambda \geq 1$. A simple solution for global application is to find the average λ of all the pixels:

$$\Lambda = \frac{1}{\Omega}\sum_{q\in\Omega}\lambda_p, \tag{12}$$

where Ω is a set of all the pixels in an image, and $|\Omega|$ the cardinality of Ω. Let S be $1/\Lambda$ the reciprocal of the mean contrast reduction. As a consequence, S (≥ 1) is the global scaling factor for the pixels in an image. When $S \gg 1$, the contrast is enhanced much more than the source images. The scaling needs reference points. At first, we used the global average μ of the entire pixels in I' as:

$$J = (I' - \mu)/\Lambda + \mu, \tag{13}$$

where J is the contrast-enhanced image.

A better way to do scaling is the use of multiple channels. For instance, we find the average of luminance levels for the RGB channels, separately. Weighting by the perceptual distance (e.g., CIE76 metric) for each color, luminance averages are computed, separately. When enhancing the pixels, the reference luminance levels are computed by moving averaging the pixels.

4.3 Saliency-Based Global Contrast Enhancement

We modeled the saliency-based global contrast enhancement to enhance the visual quality according to human visual attention [19], [20]. As we alluded to, we generate the saliency map from a source image

We use the Itti et. al.'s method to generate saliency map, which is based on the model of center-surround differences [19]. The region of high visual attention represented with white color in saliency map. We use saliency map as a weight factor for higher increases of contrast in the region of high visual attentions. We provide examples of saliency map in Fig. 5. The left-side image in each pair is source image, and right-side image is the saliency map.

We use the saliency map for modeling the enhancement factor S, which is generally modeled with manual parameter in the contrast enhancement. The enhancement factor S is used as scaling factor for managing contrast variations, and it is modeled with the formula (14):

$$\mathrm{S} = 1 + \frac{\mathrm{Sal}}{\lambda}, \tag{14}$$

where Sal is a saliency value and λ is a mean of contrast between a source image and the uniformly darkened image.

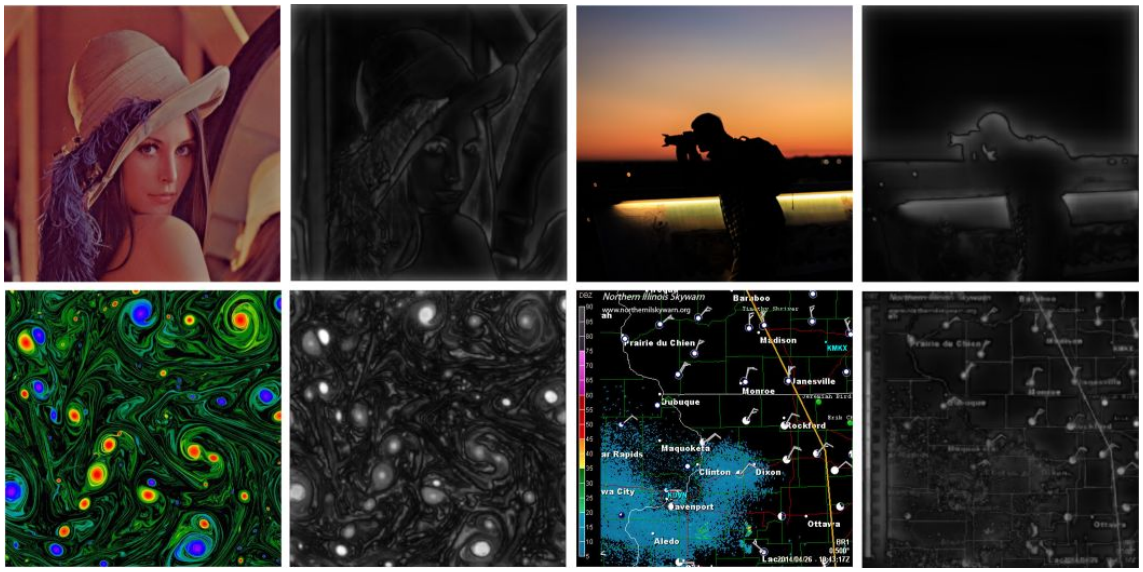

Fig. 5. Examples of generated saliency map(right) from source images(left).

Ke et. al. [16] suggested the saliency-weighted contrast enhancement (SWCE) method. The differences of our method are that Ke et. al.'s method is designed for local contrast enhancement, and it requires additional enhancement parameters, which is designated manually. With this scale factor, our saliency-based global contrast enhancement model is modeled as follows:

$$J = S(I' - \mu) + \mu, \tag{15}$$

where J is the saliency-based contrast-enhanced image, and the μ is the global average of luminance I' for the entire pixels.

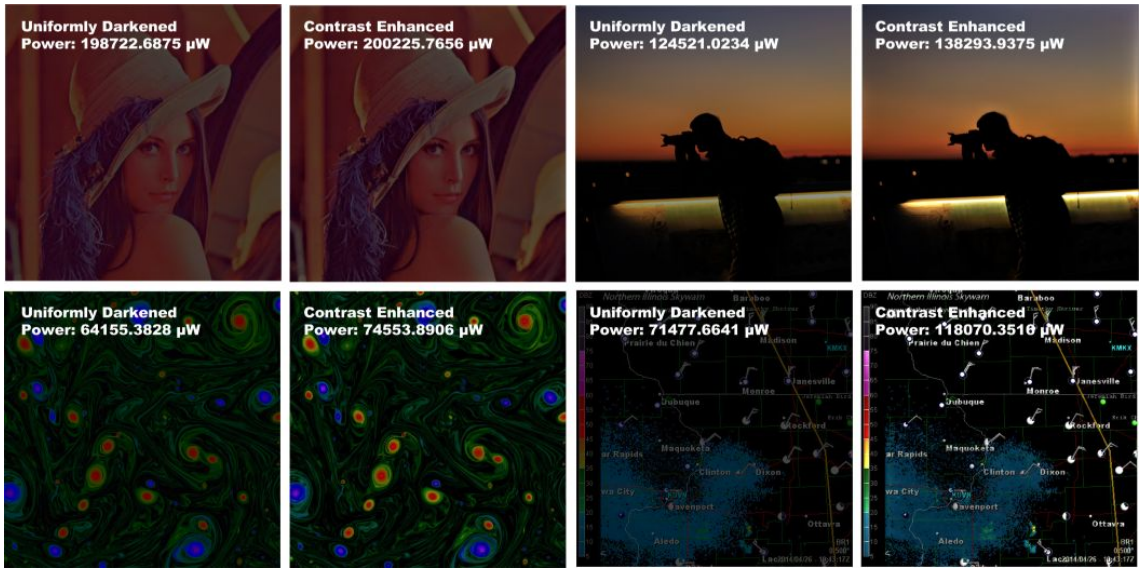

Fig. 5. Uniformly darkened images and contrast enhanced images in case of darkening with ratio 0.6.

4.4 Power-Adaptive Darkening

As provided in Fig. 5, the contrast enhancement of images causes increases in power consumptions, because power consumption of OLED display is dependent on contents to be displayed.

In order to measure consuming energy caused by color values in OLED display, we follow the pixel-based power model of OLED provided by Dong et. al.'s research [7]. The constraint of our enhancement is maintaining the power consumption while the visual quality is enhanced. In order to find a ratio of increased power consumptions, we measure power consumptions of uniformly darkened image and global contrast enhanced image. The ratio for power-adaptive darkening is computed as follows:

$$\mathrm{d} = \frac{P_u}{P_{gce}} \tag{16}$$

where $\mathrm{P_u}$ is the power consumptions of uniformly darkened image, and $\mathrm{P_{gce}}$ is the contrast enhanced image. The power consumption of OLED display is linear to RGB channels, darkening uniformly with this ratio is simple way to control power consumptions.

$$\mathrm{J_2} = \mathrm{J_1} \times \mathrm{d} \tag{17}$$

where saliency-based global contrast enhanced image is $\mathrm{J_1}$, and the power adaptive result is $\mathrm{J_2}$.

5. Results

In this section, we report the quality of images improved by the proposed method in condition of maintaining power consumptions. We provide comparison of a visual quality and power consumptions between simple darkening and our method. Four images are used with source images, which have various features, e.g. the degree of detail, the number of color, and a brightness of images. Our framework shows a better quality for dark images, which can be improved visually by increasing contrasts. Especially, the quality of image in the region of high saliency is extremely improved. We show results of our framework in Fig. 7-10. We show results of our method for four sample images, Lena, Photo, Turbulence, and Map. The Lena image has high luminance in an initial state, and it is consisted with continuous color. The photo image also has continuous color while the initial brightness is relatively dark in comparison to Lena. The turbulence and the map images are examples of discrete color image, which have difference degree of luminance each other. Our framework also has a good performance for video input, which do not cause severe frame drops and workloads.

To confirm the validity of our framework, we perform a user study for ten non-professional people about preference to result between uniformly darkened images and ours. All candidates select result of ours for preferred images.

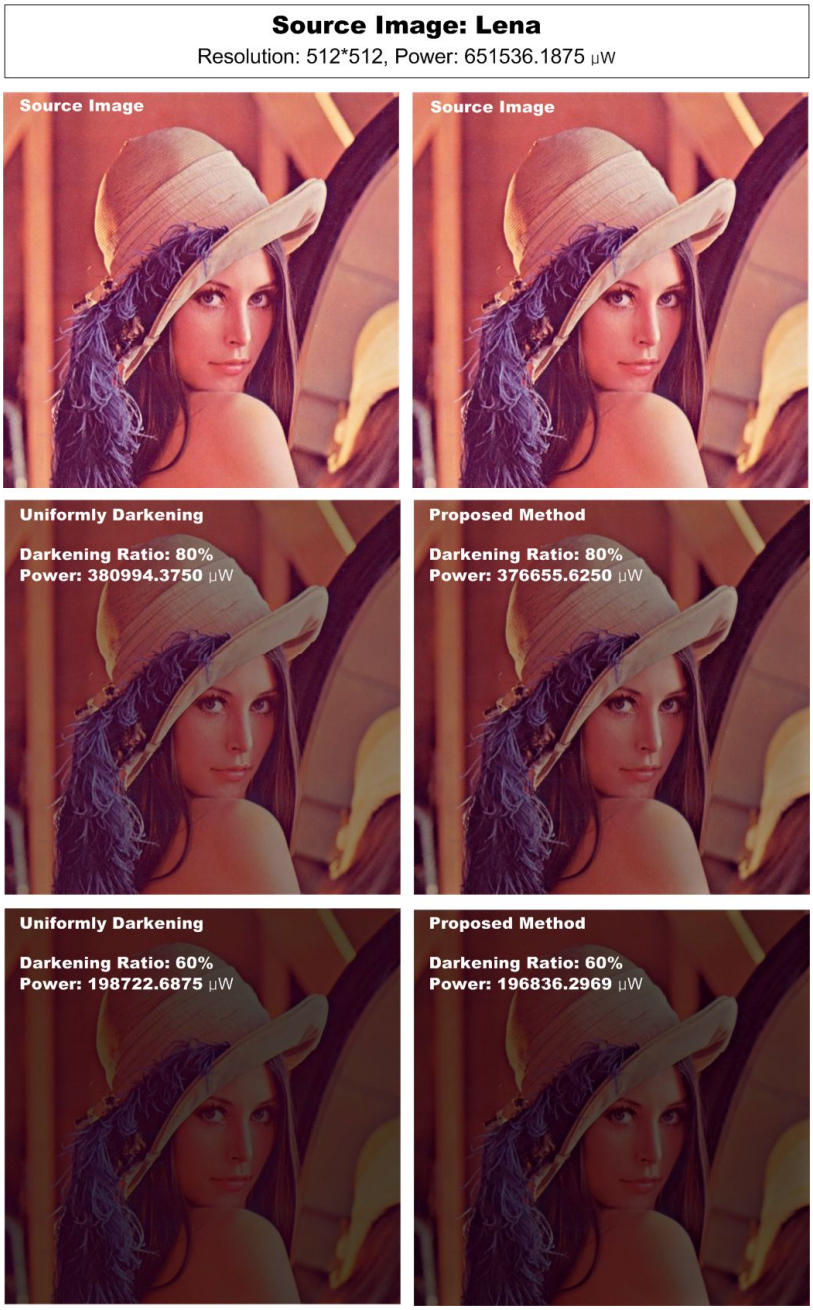

Fig. 7. Results with Lena. A comparison of results by our method (right), and uniformly darkened image (left).

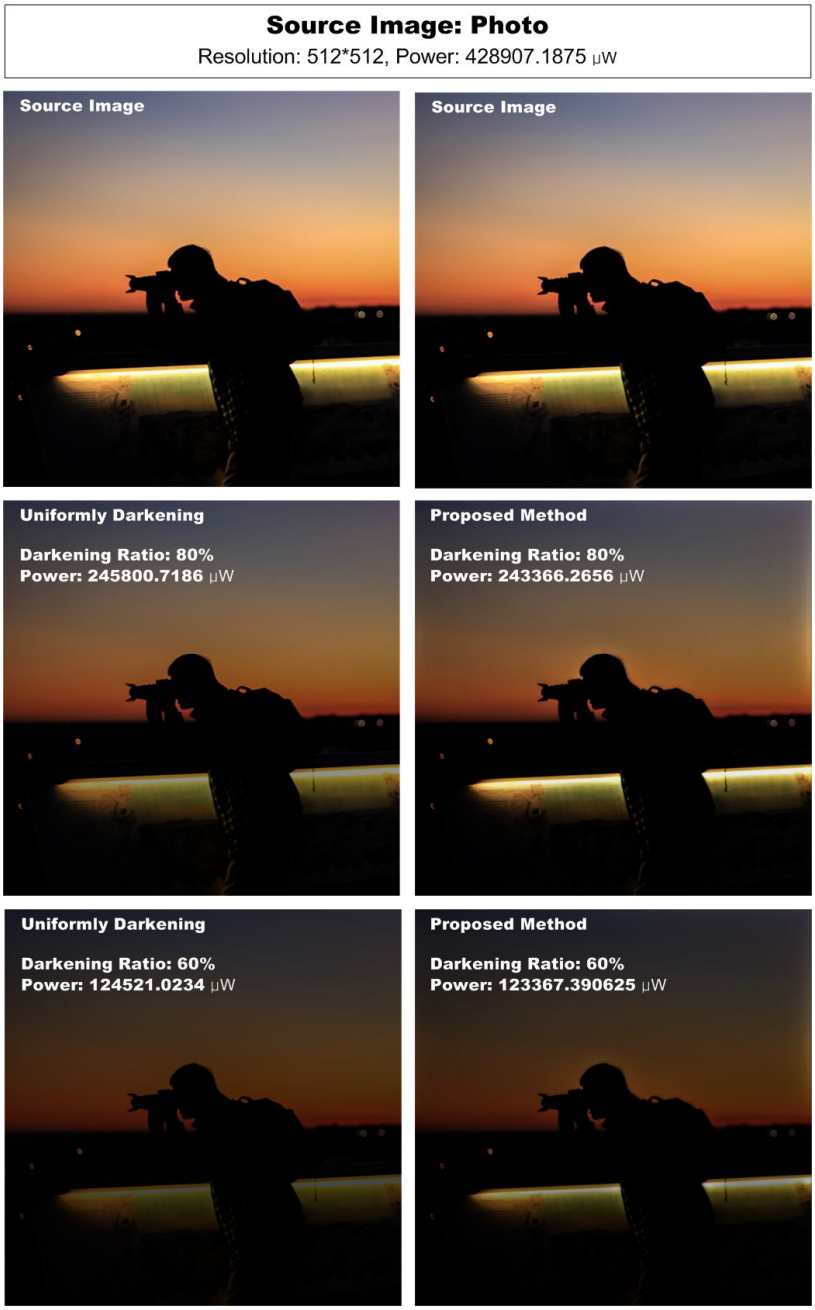

Fig. 8. Results with Photo [21]. A comparison of results by our method (right), and uniformly darkened image (left).

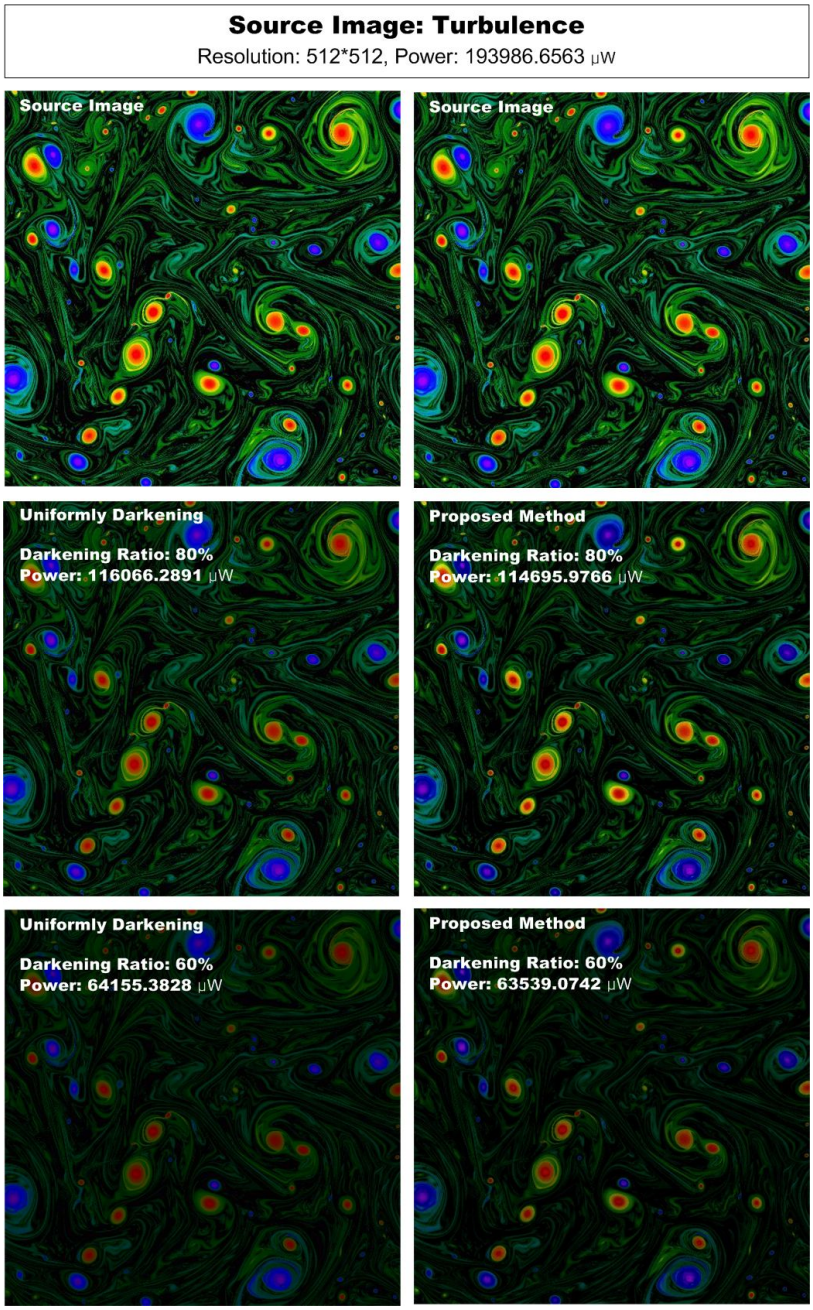

Fig. 9. Results with Turbulence [22]. A comparison of results by our method (right), and uniformly darkened image (left).

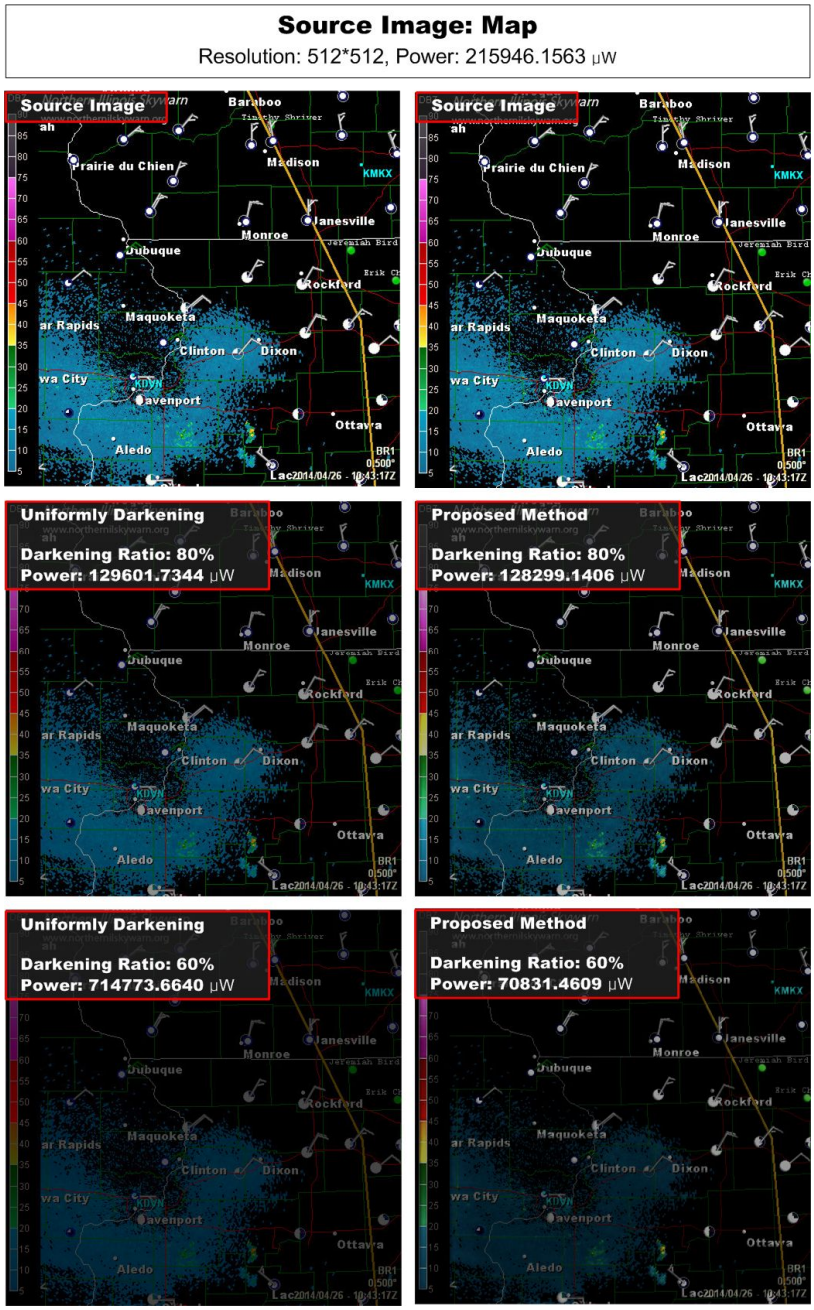

Fig. 10. Results with Map [23]. A comparison of results by our method (right), and uniformly darkened image (left).

6. Discussion and Limitations

The goal of our work can be modeled with an optimization problem, e.g., constrained optimization. In order to model with a constrained optimization, error metric for measuring a visual quality of image is necessary. There is a similar approach for measuring a visual difference between two images in previous work of Dong et. al. [2], which is modeled with square sum of Euclidean distance in perceptual color space, but it cannot measure degree of improvement in a visual quality [21], [22].

The main limitation of our algorithm is that additional computation workloads caused by the proposed method. Our framework includes generating three images, saliency map, contrast map, and uniformly darkened image. This requires us to measure power consumptions of OLED hardware. Currently, we only consider the pixel-based power model based on Dong et. al.'s study, which enables us to estimate power consumption of images.

We made an effort to reduce predictable workloads in many ways. We make use of mipmap for twice computing of power consumptions both uniformly darkened image and contrast enhanced image in power-adaptive darkening. Additionally, we approximate CIE Lab color space for minimizing workloads for luminance management. Although we provide experimental results to demonstrate the validity of this approximation, a benefit of this

approximation in power consumptions is not measured by using OLED display device.

The user study and the experiment for demonstrating an improvement of visual quality are required. Currently, we perform a brute-force user survey for ten non-professional people about preference. This user study can be more persuasive with increasing the number of candidates and designing a method to measure an effectiveness of proposed method.

7. Conclusions and Future Work

We suggest an effective framework for better visual quality in case of reducing luminance of display with maintaining power consumptions. This framework consists with the saliency-based contrast enhancement method and a power adjustment method. The saliency-based contrast enhancement method is based on the CSF function [16], and the model of power consumptions in OLED displays is followed by Dong et. al.'s work [8]. The result shows us highly improved visual quality comparison to simply darkened image.

We used approximated CIE $L^*a^*b^*$ space for minimizing workloads of our framework. This approximation is also useful for future work, e.g., optimization. The constrained optimization can be used for achieving this goal, which includes error metric for measuring a visual quality and constraint for maintaining power consumptions. In our approach, improvement parameter is not required. This can strengthen robustness of algorithm, but this parameter can be used for optimizing with the constrained optimization.

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Appendix: Additional Examples of Result

We provide additional results of proposed method in Fig. 11−14. Fig. 11−12 show good enhancement in a visual quality, while examples of Fig. 13−14 are selected with low improved images. We defined the enhancement factor S in the formula (14) instead of simple scaling factor, which is generally designated with a manual parameter. In the case of using a manual parameter on our method, Fig. 13−14 shows a better enhancement of a visual quality. In order to apply a manual parameter α on our method, the formula (15) is represented as follows:

$$J = \alpha \cdot S \cdot (I' - \mu) + \mu, \tag{18}$$

where, J is the saliency−based contrast−enhanced image, and the μ is the global average of luminance I' for the entire pixels.

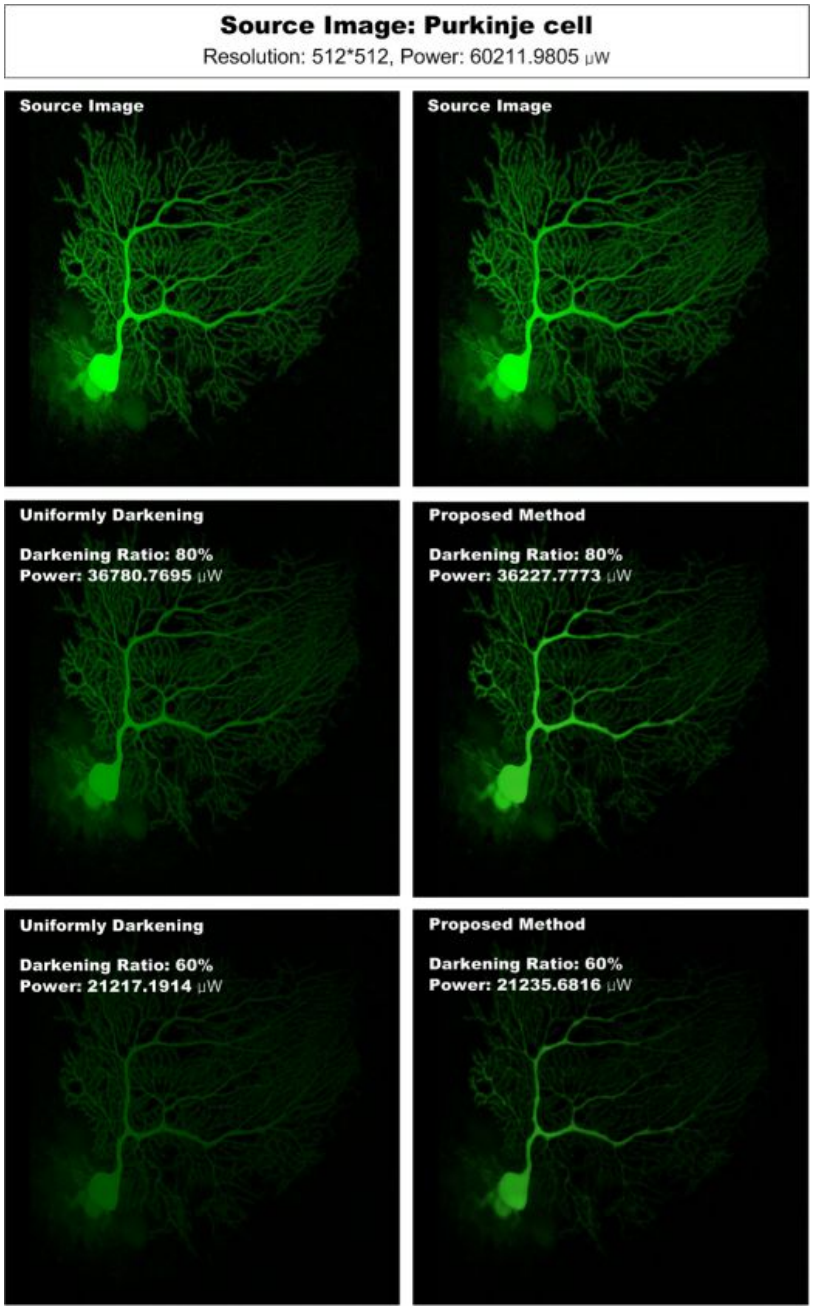

Fig. 11. Results with Purkinje Cell. A comparison of results by our method (right), and uniformly darkened image (left).

Fig. 12. Results with Mobile. A comparison of results by our method (right), and uniformly darkened image (left).

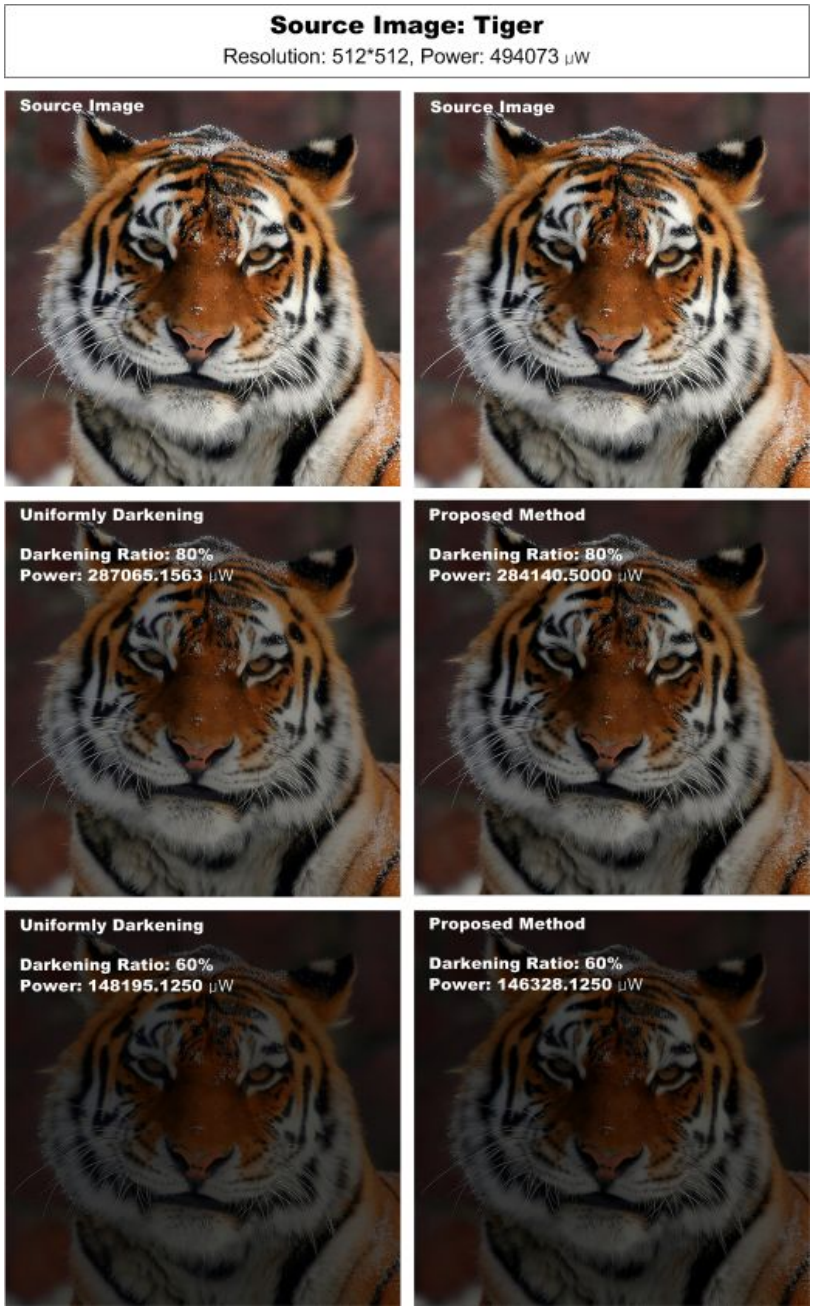

Fig. 13. Results with Tiger. A comparison of results by our method (right), and uniformly darkened image (left).

Fig. 14. Results with Castle Lichtenstein. A comparison of results by our method (right), and uniformly darkened image (left).

논문요약

OLED 디스플레이를 위한 지각기반 색 향상 기법

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임베디드 시스템에서 디스플레이에 소비되는 전력은 전체 소비전력에서 큰 비중을 차지한다. 전력 소비의 효율은 배터리의 지속시간과 직접적인 연관이 있고, 이는 모바일 디바이스의 사용성을 결정하는 중요한 요소이다. 현대의 모바일 디바이스에는 기존의 LCD와 비교해서 보다 선명하고 나은 품질의 영상을 제공하는 OLED 디스플레이가 보편적으로 사용된다.

OLED 디스플레이는 백 라이트 장치(back-lighting mechanism)를 지니는 LCD 디스플레이와는 다르게 디스플레이 될 컨텐츠의 색과 밝기에 따라 소비전력이 결정된다. 그로 인해, 디스플레이의 밝기를 줄이는 것은 디스플레이의 소비 전력을 줄이기 위한 효율적인 방법이 될 수 있다. 예로, 일부 소프트웨어에서는 디스플레이에 대한 전력 효율을 높이기 위해, 남은 전력량이 적을 경우는 디스플레이 밝기를 어둡게 해주는 기능과 주변환경 밝기를 광 센서로 감지하여 적응적으로 밝기를 변화시키는 기능을 제공한다. 하지만 밝기를 조절하는 것은 단순히 RGB 채널의 밝기를 단순히 줄이는 방법이 사용되고, 이는 디스플레이 되는 컨텐츠의 시각적 품질을 크게 저하시킨다. 특히, 어두운 이미지/영상의 경우 밝기를 줄이면 컨텐츠를 구성하는 객체간의 구분이 더욱 어려워져, 이러한 문제는 더욱 심화된다.

본 논문에서는 OLED 디스플레이의 전력 효율을 높이기 위해 컨텐츠의 밝기를

감소시키는 경우, 이미지의 밝기 대비 향상 및 사람의 시각적 관심도에 기반하여 이미지/영상 컨텐츠의 시각적인 품질을 향상시키는 프레임워크를 제안한다. 시각적으로 향상된 이미지/영상은 단순히 밝기를 줄이는 방법에 기준하여 같은 전력을 소비하도록 디자인되었다.

본 방법에서 시각적 품질을 향상시키는 것은 이미지의 밝기 대비를 증가시키는 CSF 방법에 saliency map를 가중치로 적용하여 시각적 관심이 높은 영역에 대해서 보다 밝기 대비를 증가시킨다. 이러한 경우 색 대비의 증가는 OLED 디스플레이의 소비전력을 변화시키기 때문에, OLED 디스플레이의 전력소비를 측정하여 변화된 소비전력의 비율을 계산하여, 단순히 밝기를 줄이는 경우와 같은 전력을 소비하는 결과를 얻는다.

시각적 품질이 향상된 이미지 예제들을 결과로 보이며, 단순히 밝기를 줄인 경우와의 비교를 함께 제시한다. 결과에 사용된 이미지 예제들은 연속적인 색이 사용된 경우와 이산적인 색이 사용된 이미지, 전체 이미지가 어두운 경우 및 밝은 경우를 고려하여 선택되었다. 본 방법이 적용된 이미지는 단순히 밝기를 줄인 경우와 비교하여 적은 전력 소비를 요구하면서도, 시각적으로 향상된 결과를 보인다. 특히 어두운 이미지에 대해서는 시각적 품질의 향상을 쉽게 확인할 수 있다.

주제어: OLED 디스플레이, 지각기반 대비 향상, 전력 소비, 밝기 제어, 색 공간

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