A Win-Win Camera: Quality-Enhanced Power-Saving Images on Mobile OLED Displays

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***Abstract*—Mobile systems will increasingly feature emerging OLED displays, whose power consumption is highly dependent on the image content. Existing OLED power-saving techniques change users' visual experience or degrade images' visual quality in exchange for power reduction, or seek a chance to also enhance image quality by employing a compound objective function. This paper presents a win-win scheme that always enhances image quality and reduces power consumption simultaneously. We define metrics to assess the profit and the cost for potential image enhancement and power reduction. Then, we propose algorithms that ensure the transformation of images into their quality-enhanced power-saving versions. Finally, the proposed scheme is realized as a practical camera application on mobile devices. The results of experiments conducted on a commercial tablet with a popular image database are very encouraging and provide valuable insights for future research and practices.**

***Index Terms*—OLED displays, power saving, image enhancement, mobile devices**

I. Introduction

Organic light-emitting diode (OLED) technology is deemed one of the most promising alternatives to *liquid crystal displays* (LCDs), which are currently used in a wide range of daily applications. OLED displays provide brighter colors, wider viewing angles, and faster response times than traditional LCD displays [13]. However, unlike LCD displays whose power consumption is dominated by external light sources, the power consumption of an OLED display comes primarily from a large number of self-emissive diodes which comprise the display panel. Although OLED displays consume nearly zero power to show a black image, they may consume more than twice the power consumed by LCD displays when a white image is shown [7]. In other words, OLED power consumption depends highly on the content of the displayed image. The latest mobile devices increasingly feature the emerging OLED displays, and the design of OLED power-saving techniques has recently generated much research interest.

An intuitive approach to reduce OLED power, referred to as *partial display dimming* [4], is to darken the portions of the displayed content that are relatively unimportant to the user. Based on the observation that a user usually focuses on just half of the screen for most (but not all) interactive applications, Tan et al. [14] exploited the partial dimming technique to dim the display's top or bottom portions. Since different colors require drastically different amounts of power, Dong et al. proposed the *color remapping* technique [6], which changes the original colors into colors that consume less power, and applied the technique to web page rendering on mobile devices [7]. These techniques are not applicable to natural images because they change users' visual experience.

To retain the original visual experience, Shin et al. [13] developed the *OLED dynamic voltage scaling* technique, which reduces the supply voltage of each pixel's circuit while maintaining the pixel's brightness value sufficiently. Based on the hardware-assisted technique, Chen et al. [5] designed an algorithm that divides an OLED display into multiple rectangular regions and optimizes the voltage of each region under a given quality requirement. Motivated by the observation that the regions of an image receive varying degrees of visual attention, Lin et al. [10] introduced a technique called *image pixel scaling*, which allows the pixel values of different-shaped regions to be scaled down by different magnitudes according to human visual attention. They also proposed an algorithm to optimize the power required to display an image while limiting the distortion of the displayed image. Essentially, the above techniques strive to retain images' visual quality.

There is a demand for image quality enhancement because mobile users are often lack of photographic expertise or lighting conditions are not always ideal at the time of acquisition [3]. An image's quality can be enhanced by improving its sharpness, noise level, color accuracy, and contrast; particularly, high contrast is a decisive factor for providing better experience of image perception [9]. A simultaneous improvement in image quality and power efficiency has recently attracted some attention. Lee et al. [9] modeled *power-constrained contrast enhancement* as an optimization problem, with an objective function comprising a contrast term and a power term. However, obtaining solutions based on the convex optimization theory [9] or multiscale retinex [12] is considered of high computational complexity for mobile devices. Importantly, optimizing a *compound* objective function cannot ensure that a simultaneous improvement in both terms is always achievable.

In this paper, we develop a win-win camera that allows users to take quality-enhanced power-saving pictures on their OLED mobile devices. First, we define metrics to efficiently estimate the contrast and the OLED power of an image, as well as a compound index to assess the magnitude of change in contrast and power for potential image transformation. Then, we present algorithms to derive the maximum achievable contrast and reducible power of an image. When the target contrast or power does not exceed the maximum limit, we ensure its being transformed into a quality-enhanced power-saving version. Next, based on the scheme, we implement an image camera that enables a picture (after taken) to be converted instantly into various win-win versions on OLED mobile devices. Finally, we conduct extensive experiments on the Samsung tablet with the Kodak database. To evaluate the capabilities in both aspects, we compare our win-win scheme with two *pure* approaches, HMA [3] and CURA [10], which aim to enhance image quality and reduce power consumption respectively. The results show that our scheme can enhance the quality of an image by 3.4 times while reducing its OLED power consumption by 27% on average; and the improvements are 88% of the quality enhanced by HMA and 73% of the power reduced by CURA, respectively.

The remainder of this paper is organized as follows. Section II provides background information and describes the case study. In Section III, we define some basic metrics and present the fundamental algorithms of our win-win scheme. Section IV describes the implementation of the camera. The experiment results are reported in Section V. Section VI contains some concluding remarks.

II. Background and Motivation

A. OLED Image Display

An image consists of a matrix of pixels. In the RGB color space, each pixel is defined by three values that represent the intensities of the red, green, and blue additive primaries, whose combinations can create various colors. Similarly, an OLED display comprises a matrix of pixels, each of which contains three diodes that emit red, green, and blue light respectively. The light intensity of a diode depends on the electric current that flows through the diode, and the current is determined by the diode's pixel value and color [8]. Consequently, the power required to present an image on an OLED display depends highly on the image content. As modeled in [5, 8], the required power is the sum of the power consumed by all the pixels, and the power consumed by each pixel is the sum of the power consumed by its RGB diodes. Figure 1 shows the power model measured based on a Samsung Galaxy Tab 7.7, where the power increases dramatically with the pixel value in the range 0 and 255.

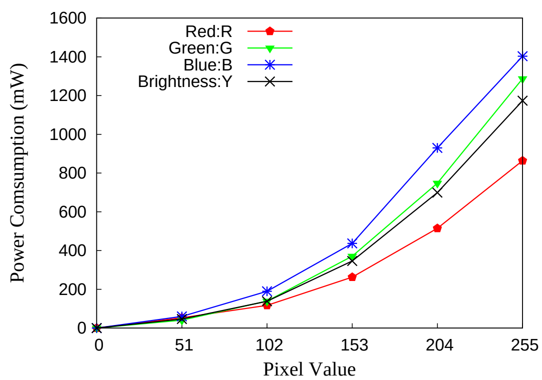
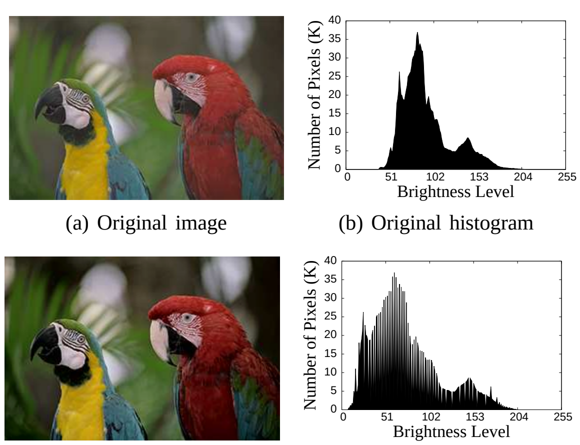


Fig. 1. An OLED power model

Since the human visual system is much more sensitive to variations in brightness than color, many image-processing algorithms fetch the brightness information from a color image and deal with the image based on its *brightness histogram* [3, 15]. A pixel's brightness can easily be derived by converting its RGB values to the YC_bC_r coordinate space with standard conversion functions, and vice versa, where Y is the brightness component. The brightness histogram of an image shows the number of pixels at each level of brightness over an intensity range. Figure 2 shows two images and their respective brightness histograms with an intensity range between 0 and 255. The enhanced histogram is produced based on the original histogram via a *transformation function* $y = f(x)$, which transforms each brightness level x into a brightness level y, with the objective of enhancing the image's visual quality.



(a) Original image (b) Original histogram

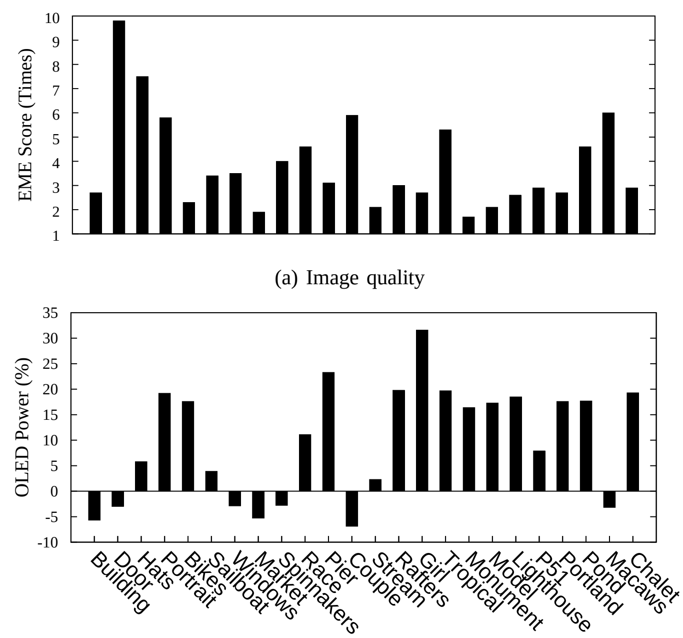
(c) Enhanced image (d) Enhanced histogram

Fig. 2. Brightness histograms of images

B. Visual Quality vs. Power Consumption

Contrast is central to images' visual quality because the human visual system perceives much more of contrast than the absolute intensity [11]. Therefore, one common and effective way to enhance an image's visual quality is to increase its contrast. The contrast is closely related to the distribution of pixels in the brightness histogram, and it can be increased by redistributing pixels' brightness levels to better use the full intensity range. Figure 2 shows an example, where the pixels' brightness levels are more evenly distributed in the enhanced histogram than in the original one, and the contrast in the enhanced image is essentially increased. Intuitively, the original and enhanced images are likely to consume different amounts of power on OLED displays; however, it is difficult to tell which of the images will consume more. This raises an interesting question: is there a win-win scheme that *always* enhances image quality and reduces power consumption simultaneously?

To answer the question and obtain design inspiration, we conducted a real-world case study. In the study, we chose the Kodak image database [1], which is popularly used in the research field of image processing [3, 16]. The database contains 24 color images, each of which is 2048×3072 in size; although the database is small, it covers a variety of themes and lighting conditions. We used a standard conversion function, called rgb2ycbcr, provided in MATLAB to convert each RGB image into its YC_bC_r format and derive its brightness histogram. To improve the images' visual quality, we applied the *histogram modification algorithm*, denoted as HMA, proposed in [3] to every image's histogram, with all tunable parameters set at their default values in [3]. The visual quality of each image was scored by EME[1] [2], which is the most frequently-used metric for image quality assessment [3, 12]. Each of the images was then displayed on the Samsung Galaxy Tab 7.7, equipped with a 1280×800 AMOLED display, for the measurement of its power consumption.



(a) Image quality

(b) Power consumption

Fig. 3. Visual quality and power consumption increased by HMA for 24 different images

Figure 3 shows the comparisons of visual quality and power consumption between each original image and its enhanced version. As expected, the visual quality (which is assessed by the EME score) of all the 24 images is enhanced by HMA for 1.7 to 9.8 times. Surprisingly, the power consumption of seven among the 24 images is reduced (not significantly though) even if HMA does not take

[1]We adopted EME, instead of SSIM used in previous related studies [5, 10], because SSIM is designed for assessing the "similarity" between two images, not for assessing the "quality" of an image.

OLED power into account. To gain further insights, we observed the process of image enhancement. In HMA, to increase the image contrast, the most frequent levels are normally spread out over the intensity range. Moreover, the OLED power will be increased and decreased if the levels are transformed toward the bright end (right) or dark end (left), respectively. Thus, to develop a win-win scheme, we shall define some metrics to assess the profit and the cost of transforming a brightness level into another, and then exploit the metrics to perform histogram redistribution.

III. Quality-Enhanced OLED Power Saving: A Win-Win Scheme

In an image enhancement technique, the transformation function plays a key role to process an image so that the resultant image is deemed *better* than the original image for a *specific* purpose. Thus, the underlying objective of our win-win scheme is to determine a transformation function $f(x)$, $0 \leq x \leq 255$, which seeks to enhance the given image's visual quality while reducing its power consumption.

A. Contrast and Power Metrics

To establish an appropriate function f, some metrics are required to effectively determine the most *preferable* enhancement operations, as well as estimate the contrast and the OLED power of the image enhanced by each operation. In addition, the metrics should be efficiently computable so that the win-win scheme is applicable to online scenarios. We detail the metrics below.

Contrast Metric. Contrast is the difference in brightness that makes some pixels distinguishable from the others. In general, the larger the difference, the more distinguishable the pixels. Let $\delta(x)$ denote the *brightness distance*[2] between level x and its preceding level that contains pixels. Moreover, the *probability density function*, PDF(x), indicates the probability of the pixels of level x in the image. Thus, the contrast contributed by the pixels of level x is estimated by PDF$(x)\times\delta(x)$; and the total contrast in histogram H is thus estimated by $C(H) = \sum_{i=0}^{255}$ PDF$(i) \times \delta(i)$. Note that the minimum contrast in a histogram is 1 and occurs when $\delta(x) = 1$ if PDF$(x) \neq 0$, $\forall\ 0 \leq x \leq 255$.

Power Metric. As mentioned previously, the power consumed by a pixel is the sum of the power required by its RGB diodes. It is time consuming to calculate the accurate power consumption by summing up the power used by all the pixels. Hence, we employ an efficient metric to approximate the power consumption of an image. Let $e(x)$ be the estimated power required for an image whose pixels' brightness levels are all x. For example, $e(x)$ can be the Y curve in Figure 1, where the Y curve is derived based on the RGB curves with the function, rgb2ycbcr, used to convert the RGB space to the $\mathrm{YC_bC_r}$ space. The probability of the pixels of level x in an image is indicated by PDF(x). Thus, the power consumed by the pixels of level x is estimated by PDF$(x) \times e(x)$; and the total power required for histogram H is estimated by $P(H) = \sum_{i=0}^{255}$ PDF$(i) \times e(i)$.

Contrast-to-Power Index. Basically, *histogram redistribution* based on function f is to adjust the brightness distance $\delta(x)$, for each level x, such that $\sum_{i=0}^{255}\delta(i) \leq 256$ still holds after adjustment. Intuitively, increasing a level's brightness distance will increase the contrast contributed by the level but the total power consumption as well; and the case is exactly the opposite if the level's distance is decreased. Thus, we need some index to determine which levels' distances should be increased and decreased, respectively. We make some observations based on a level x selected to adjust. The amount of contrast increased or decreased is proportional to its PDF(x). On the other hand, the magnitude of change in power is *inversely* proportional to the number of the pixels whose levels are smaller than or equal to x, i.e., its *cumulative probability function* CDF(x). It implies that, when some level's distance is to be increased, a level with large PDF and CDF values is always preferable. Accordingly, we define an index, CPI(x)=PDF(x)$\times$CDF(x), to assess the *preferability* of increasing level x's distance.

[2]For ease of presentation, we assume that the brightness distance of the first level that contains pixels is 1 and will never change.

B. Fundamental Algorithms

Based on the proposed metrics, we present an algorithms to derive the minimum power, P_{min}, required by a histogram such that its contrast is not smaller than that in the original histogram H. Then, given the target power P_{tar} in the range $[P_{\mathrm{min}}, P(H)]$, we describe an algorithm that *must* produce a win-win histogram whose contrast is not smaller than $C(H)$ and power is not larger than $P(H)$. The algorithms, with some minor modifications, can also be used to derive the maximum achievable contrast C_{max} and deal with the target contrast C_{tar} in the range $[C(H), C_{\mathrm{max}}]$.

Algorithm 1

Input: A histogram H and a power function e
Output: The minimum power P_{min}
1: Compute PDF(x), CDF(x), CPI(x), $\forall x$, based on H
2: Build $\rho(x)$ based on PDF(x), $\forall x$, by WTHE
3: $\delta(x) \leftarrow 0$ if PDF(x) = 0, and 1 otherwise, $\forall x$
4: Build $\hat{H}$ based on H and δ
5: **while** $C(\hat{H}) < C(H)$ **do**
6: $\quad\delta(x)\leftarrow\max(\lfloor\rho(x)\times255\rfloor, 1)$ for x with the largest CPI(x)
7: $\quad$CPI(x) $\leftarrow -1$
8: $\quad$Update $\hat{H}$ based on δ
9: **return** $P_{\mathrm{min}} \leftarrow P(\hat{H})$

Given an image's histogram H and an estimated power function e, Algorithm 1 determines the minimum power P_{min} required to retain the contrast. Initially, PDF(x), CDF(x), and CPI(x) of each level x, where $0 \leq x \leq 255$, are computed based on H, and they will not change thereafter (Line 1). To avoid the *histogram spike problem*, where brightness levels with high (resp. low) probabilities get over (resp. less) enhanced in the resultant image, we adopt a low-complexity method called WTHE[3] [15] to build a new probability function ρ that redistributes the original probabilities among the levels (Line 2). Then, throughout the algorithm, we maintain a function $\delta(x)$, $\forall x$. To derive P_{min}, we set $\delta(x)$ at 0 if PDF(x)$=0$ in H, and 1 otherwise (Line 3), and then build a new histogram $\hat{H}$ based on H and δ (Line 4). Actually, $\hat{H}$ is H with all levels x whose PDF(x)$\neq 0$ concentrated on the dark end. Note that $\hat{H}$ requires power less than any histogram, in which brightness levels having pixels are not merged (thus retaining all details) and the order of levels is preserved (thus preventing the creation of intensity artifacts). Moreover, the contrast in $\hat{H}$ is currently the minimum because its contrast is 1.

Hence, the algorithm repeatedly increases the contrast (and also the power) of $\hat{H}$ until its contrast is larger than or equal to that of H (Line 5). In each iteration, a level x with the largest CPI index is selected to increase its brightness distance (Line 6). Its $\delta(x)$ is increased to the larger of $\lfloor\rho(x) \times 255\rfloor$ and 1 for two reasons: 1) the intensity range is allocated to x in proportion to the adjusted probability $\rho(x)$, instead of PDF(x), to avoid over-enhancement; and 2) if $\rho(x)$ is so small that the allocated range will be zero, $\delta(x)$ is set at 1 to avoid any loss of contrast. Moreover, CPI(x) is set at -1 to indicate that level x has been selected (Line 7), and $\hat{H}$ is updated based on δ to obtain a histogram whose contrast and power

[3]Any method developed to resolve the problem could be used instead here. In our experiments, we set the parameters of WTHE at their default values in [15].

are increased incrementally (Line 8). After the **while** loop terminates, P_{min} is set as $P(\hat{H})$ and returned. Now, given P_{tar} in the effective range, a win-win histogram can also be produced by Algorithm 1, with the **while** loop's condition in Line 5 replaced by $P(\hat{H}) \leq P_{\text{tar}}$ and the previous histogram of $\hat{H}$ that breaks the condition returned in Line 9 simply.

IV. A Win-Win Camera for OLED Mobile Devices

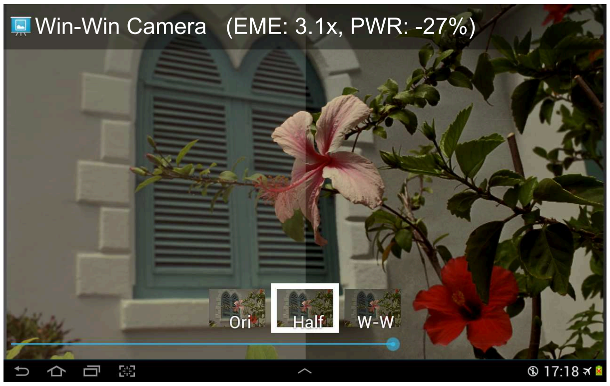


Fig. 4. A snapshot of our win-win camera

Next, we describe a win-win camera that allows users to take, view, edit, and save pictures on their OLED mobile devices. The camera provides a unique filter, which implements the proposed win-win scheme, for the conversion of an image into various quality-enhanced power-saving versions in an online fashion. We developed the camera as a stand-alone Android app and installed it on a Samsung Galaxy Tab 7.7. Figure 4 shows a snapshot of the app. The user can select one of the three thumbnails, as shown in the middle of the screen, to preview the original image, a win-win image, or a compound image. If the win-win thumbnail is selected, the user can swipe the sliding bar, whose two endpoints correspond respectively to the two versions with the maximum achievable contrast and reducible power, to generate any win-win images instantly.

Our camera app comprises three major modules: *pre-processing*, *transformation*, and *post-processing*. When a picture of any size (either taken by the user directly with the camera or retrieved from the storage) is to be displayed on the screen, it is loaded into a *Bitmap* structure and resized to fit the 1280×800 screen resolution by the Android system automatically. Then, the pre-processing module is responsible for constructing the histogram H of the resized image. On the Samsung tablet with GPU supported, the pre-processing requires approximately 22 ms. Next, the transformation module computes $P(H)$ and executes Algorithm 1, based on H and the power function e estimated for the tablet, to determine P_{min}. It takes approximately 20 ms to derive P_{min} and $P(H)$, which correspond to the two endpoints of the sliding bar respectively. Whenever the user swipes the bar to a new position, the module also takes charge of computing the corresponding P_{tar} in the range $[P_{\text{min}}, P(H)]$ and determining the win-win histogram $\hat{H}$ with respect to P_{tar}. Our algorithm takes less than 1 ms to return $\hat{H}$ (because most computations, i.e., those in Lines 1-4 of Algorithm 1, have been done when P_{min} was determined). Finally, a win-win image is constructed by the post-processing module according to $\hat{H}$ and displayed on the tablet screen. The post-processing requires approximately 13 ms. When the edited image is to be saved, the original picture is applied with the transformation function f of $\hat{H}$ (which can be done in 40 ms) and then saved to the storage for future use.

Overall, transforming a picture only takes 96 ms (and thus consumes negligible energy) on the Samsung tablet. Moreover, each subsequent image editing via the sliding bar only takes $1 + 13 = 14$ ms because H, P_{min}, and $P(H)$ need to be derived only once for each picture. Note that our win-win scheme is not restricted to nature images. In addition to this camera application, the scheme, which is very efficient in terms of the computation time and energy cost, can also be applied to other online scenarios, such as a screen power-saving mode for graphical user interfaces on OLED tablets [10].

V. Performance Evaluation

A. Experiment Setup

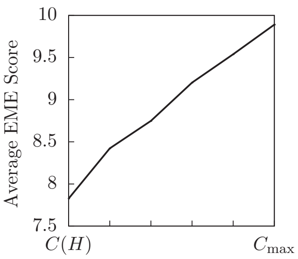
To evaluate the performance, and better understand the properties, of our win-win scheme, we conducted extensive experiments on the Kodak image database [1]. The scheme aims to improve image quality and power efficiency simultaneously; thus, its performance was evaluated in terms of the images' quality scored by EME [2] and the OLED power[4] required to display the images on a Samsung Galaxy Tab 7.7.

We conducted three sets of experiments to evaluate our scheme, denoted as CPI, from different perspectives. First, we validated the efficacy of the proposed metrics by drawing their relationships with image quality and power consumption, in their effective ranges $[C(H), C_{\text{max}}]$ and $[P_{\text{min}}, P(H)]$, individually. This set of experiments also helped us understand the impacts of the two tunable parameters on the two performance objectives. Then, we investigated the maximum achievable quality and reducible power of each image under CPI by setting the target power P_{tar} at $P(H)$ and the target contrast C_{tar} at $C(H)$, respectively. The experiment set allowed us to be aware of the characteristics of the image database, as well as the potential of each image for quality enhancement and power reduction. Finally, we compared CPI with two algorithms, namely HMA [3] and CURA [10]. HMA is a contrast enhancement algorithm developed to not only improve the image contrast but also preserve the same brightness as in the original image. To this end, HMA imposes limits on histogram redistribution within a *stretching range* to preserve the average brightness, and then spreads the brightness levels over the range to enhance the contrast based on carefully designed penalty terms. Contrarily, CURA aims to minimize the power required to display an image while retaining the image's visual quality. Based on human visual attention, CURA segments an image into regions with different attention levels, and then scales down the brightness levels of pixels in each region without violating the region's tolerable distortion. In the set of experiments, the tunable parameters of HMA and CURA were set at the values suggested respectively in [3] and [10], while the target contrast C_{tar} of CPI was set at 60% of each image's C_{max} to allow a tradeoff between the enhanced contrast and the reduced power.

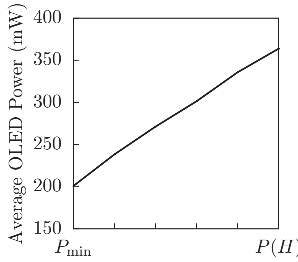
B. Efficacy of Contrast and Power Metrics

Figure 5 shows the individual impacts of the contrast and power metrics on the average EME score and the average OLED power of the 24 images produced by CPI. Actually, each image's individual result also follows a similar trend. As shown respectively in Figures 5(a) and 5(b), the EME score increases with the target contrast C_{tar}, while the OLED power increases with the target power P_{tar}. The results indicate that the two metrics can, indeed, proportionally reflect an image's visual quality and power consumption, respectively. This in turn implies that a higher-quality (resp. lower-power) image can be produced by CPI with a larger C_{tar} (resp. a smaller P_{tar}). Moreover, the EME score increases slowly with P_{tar} in Figure 5(c), while the OLED power increases quickly with C_{tar} in Figure 5(d). The results indicate that the contrast-to-power index can capture the *preferability* of each enhancement operation, and the most preferable ones are always selected by CPI first. From the figure, we also observe that the EME score and the OLED power at $C(H)$ are the same as the

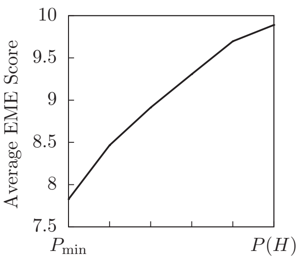
[4] An image's OLED power is derived by subtracting the power when a black image is shown on the tablet from the power measured when the image is shown.



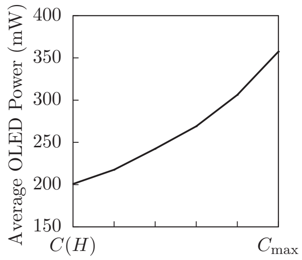
(a)



(b)



(c)

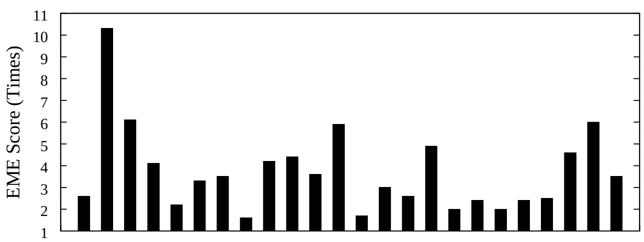


(d)

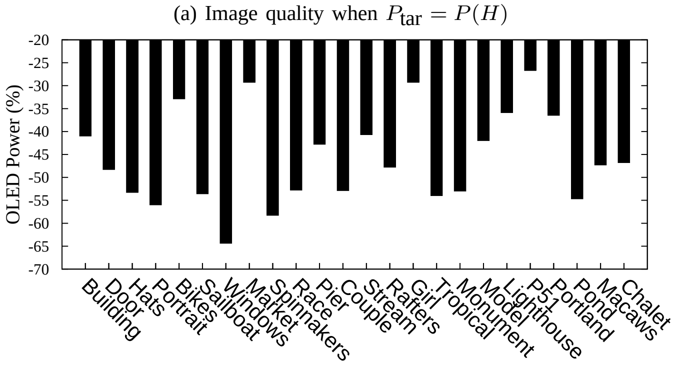
Fig. 5. The impacts of the contrast and power metrics on the average EME score and OLED power

counterparts at P_{min}. This is because the same histogram will be produced when C_{tar} is set at $C(H)$ or P_{tar} is set at P_{min}. With a similar reason, the score and power at $P(H)$ are the same as those at C_{max}. Thus, the efficacy of the two tunable parameters in terms of producing quality-enhanced power-saving images is equivalent.

C. Maximum Achievable Quality and Reducible Power



(a) Image quality when $P_{\text{tar}} = P(H)$



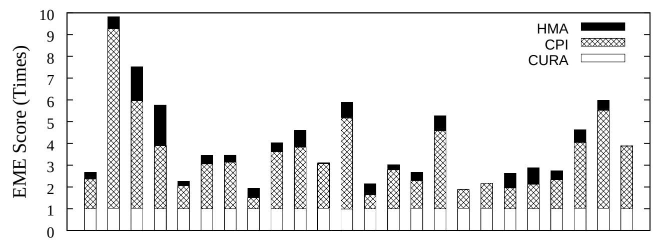
(b) Power reduction when $C_{\text{tar}} = C(H)$

Fig. 6. Maximum achievable quality and reducible power under CPI

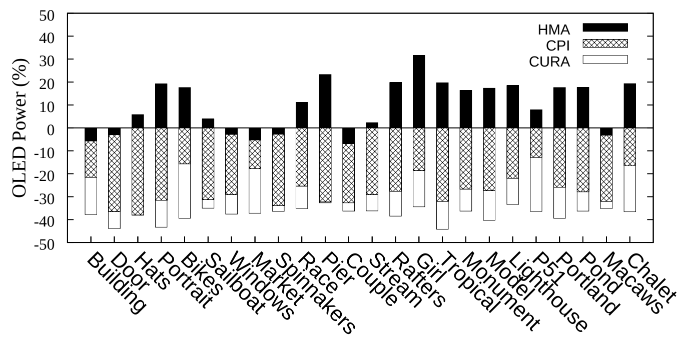
Figure 6(a) shows the maximum achievable quality of each of the 24 images under CPI, where the target power is set to be the same as the original histogram's. Clearly, the magnitude of quality enhancement varies significantly among the images. It implies that the image database covers a variety of brightness histograms and allows a comprehensive study of our win-win scheme. We observed that the maximum achievable quality depends highly on the histogram's pattern. Specifically, a narrower histogram usually allows a larger quality enhancement than a wider one. The reason is that the whole intensity range of a narrow histogram has yet to be fully utilized and thus provides a large potential for contrast enhancement. The results show that the EME score of an image can be increased to at least 1.6 times and up to 10.3 times its original score, depending on the image's histogram pattern, with the average being 6 times. Thus, the visual quality of most nature images can be further enhanced, without increasing their power consumption.

Figure 6(b) shows the maximum reducible power of each image under CPI, where the target contrast is set the same as in the original histogram. Like the maximum achievable quality, the magnitude of power reduction varies significantly as well, and the maximum reducible power also depends on the histogram's pattern. We observed that a histogram whose brightness levels are concentrated on the bright end of the intensity range usually has room for power reduction. Just the opposite is true when a histogram's levels are concentrated on the dark end. Based on the results, the OLED power required for the images can be reduced by 27% to 63%, without decreasing their contrast. The maximum reducible power is 46% on average; thus, there is potential room for nature images to reduce their OLED power consumption.

D. Algorithm Comparison



(a) Image quality when $C_{\text{tar}} = 60\% \times C_{\text{max}}$

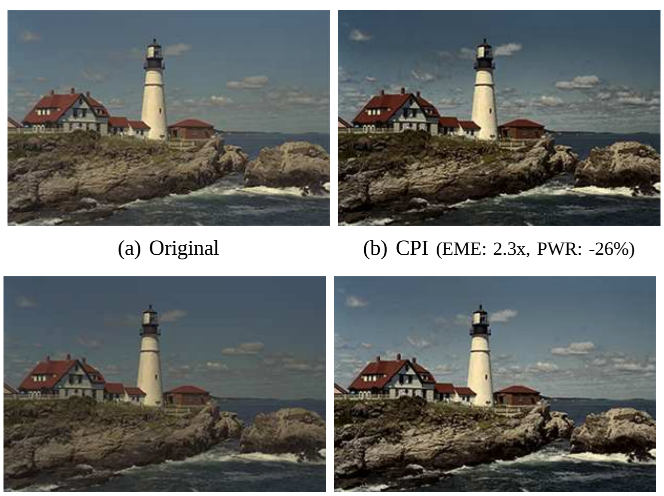


(b) Power consumption when $C_{\text{tar}} = 60\% \times C_{\text{max}}$

Fig. 7. Image quality and power consumption achieved by CPI, HMA, and CURA

Figure 7(a) shows the visual quality of each of the images produced by CPI, HMA, and CURA, respectively. HMA slightly outperforms CPI in terms of quality enhancement. The main reason is that HMA attempts to increase the contrast as far as possible by rearranging the brightness distances between all levels, while CPI only selects the most *preferable* levels to achieve the target contrast. However, the average EME scores achieved by HMA and CPI are 3.9 times and 3.4 times the original score, respectively. This result indicates that the difference between their capabilities of enhancing quality might not be so significant as expected. Interestingly, three images' scores achieved by CPI are even larger than the scores achieved by HMA. We examined the histograms of the three images (namely Monument, Macaws, and Chalet) and drew the reason as follows. In order to make the brightness similar to the original image's, HMA confines histogram redistribution to a stretching range smaller than the intensity range. When the range is so "crowded" that the available room is not sufficient for contrast enhancement, HMA will merge some levels to spare extra room and sacrifice some details as a consequence. By contrast, CPI retains any image details. Thus, CPI is superior to HMA in some cases. Unlike HMA and CPI, CURA attempts to reduce OLED power while retaining the visual quality of images. The result demonstrates that CURA is capable of retaining satisfactory visual quality because the EME scores achieved are very close to the scores of the original images.

Figure 7(b) shows the power consumption of each image produced by CPI, HMA, and CURA, respectively. The result shows that CURA can reduce the OLED power required to display each of the images by 33% to 44%, with the average being 37%. Under CPI, the power consumption can be reduced by 16% to 38%, depending highly on the images' histograms, with an average of 27%. In general, CURA outperforms CPI in terms of power reduction. This is because CURA only scales down (and never increases) the brightness levels of pixels based on human attention, and it usually reduces more power when the low-attention regions contain a larger number of bright pixels. Contrarily, CPI not only decreases some levels to reduce OLED power but also increases others to enhance the contrast. However, we noticed an exception with the Hats image. To identify the cause, we examined its histogram and found a specific pattern. There is large room available on the dark end for potential power reduction, while some levels with relatively large brightness and high probabilities (i.e., large CPI values) can be selected to increase the contrast without significantly incurring power consumption. As for HMA, it enhances the images' quality at a cost of a 2% to 32% increase in power consumption for 17 images, while it saves power by 3% to 7% for 7 images. For the 24 images, the average power increase is 10%. To conclude, when C_{tar} is set at 60% of $C_{\max}$, CPI can achieve 88% of the image quality achieved by HMA and reduce 73% of the OLED power reduced by CURA on average.



(a) Original

(b) CPI (EME: 2.3x, PWR: -26%)

(c) CURA (EME: 1x, PWR: -39%)

(d) HMA (EME: 2.7x, PWR: 18%)

Fig. 8. The Portland image and its various versions produced by CPI, CURA, and HMA respectively

Figure 8 shows the Portland image and its various versions produced by CPI, CURA, and HMA, respectively. On the whole, the image produced by CURA looks darker than the others because CURA transforms all the brightness levels toward the dark end. Contrarily, CPI and HMA transform dark levels toward the dark end while bright levels toward the bright end so as to enhance the contrast. However, the OLED power is often increased as HMA enhances the contrast, but it is not the case for CPI. The reason is that HMA tends to enlarge the brightness distances between all levels even if some of them only contribute minor contrast enhancements but require huge increases in OLED power. Interestingly, the image produced by CPI looks more vivid than the original one, although CPI lowers the average brightness (since the power is reduced). This is because those dark pixels look even darker while some bright pixels become even brighter in the resultant image; moreover, contrast is much more central, than the absolute brightness, to the image quality perceived by the human visual system [11].

VI. Concluding Remarks

We have presented a win-win OLED camera, which relies on an efficient scheme called CPI to produce quality-enhanced power-saving images on mobile devices. Our experiment results based on a Samsung Galaxy Tab 7.7 with the Kodak image database [1] show that CPI can averagely enhance 88% of the image quality enhanced by HMA [3] and reduce 73% of the OLED power reduced by CURA [10] simultaneously. The rationale behind the improvements is to redistribute brightness levels over the intensity range so as to transform the levels toward the dark end while increasing the distances between them. This also explains why the performance of CPI is more manifest when a histogram contains large room on the dark end for power reduction and, meanwhile, some levels with high occurrence probabilities on the bright end for contrast enhancement. We hope our study brings new thinking and motivates further research in this emerging topic.

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