GOOD LOOKING GREEN IMAGES

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ABSTRACT

In this paper we present a novel perceptually-based algorithm for color quantization that produces images that consume less energy than conventionally quantized images when displayed on energy-adaptive displays. To evaluate the performance of the proposed algorithm, we performed a subjective study on a standard Kodak color image database. Experimental results indicate that the proposed algorithm is able to reduce the energy consumption by 4.25% on average, while achieving the same or better subjective image quality as conventional color quantization.

***Index Terms*—** Color quantization, green computing, display energy, human visual system

1. INTRODUCTION

Displays are known as the main consumers of electrical energy in computers and mobile devices, using up to 38% of the total power in desktop computers and up to 50% of the total power in mobile devices [1]. Conventional thin film transistor liquid crystal displays (TFT LCDs) use a single uniform backlight system, which consumes a large amount of energy, much of which is wasted due to LCD modulation and low transmissivity. By contrast, emerging display technologies, such as organic light-emitting diode (OLED) and dual-layer high dynamic range (HDR) displays (e.g., Dolby's Pro-monitors with backlight modulation), consume energy in a more controllable and efficient manner [1]. In such displays, the conventional backlight is replaced by an array of individually controllable LEDs that can be left in a low or off state when they are illuminating dark regions of the image. This feature enables the design of various energy-aware display applications.

Recently, a design technique was proposed in [1] for generating energy-aware color sets with the purpose of lowering the energy consumption of energy-adaptive displays. Two variations of this technique were proposed based on a screen space-variant energy model. The first one is based on a set of discrete user-defined colors, while the second variation is based on a constrained continuous optimization of color energy in the perceptually uniform CIELAB [2] color space. In both cases, the result is a set of iso-lightness colors that are useful for various visualization purposes.

In this paper, we present a novel method to generate *good looking green images*, i.e., images that consume less energy than conventionally color-quantized (CQ) images when displayed on an energy-adaptive display, yet have the same or better perceptual quality. Starting with a conventional CQ image, colors are first converted to the CIELAB color space, where all colors within a sphere of a suitably chosen radius can be considered as perceptually indistinguishable. Just-noticeable-difference (JND) model [3] is used to find the radii of such spheres, which are then subject to search for an alternative color that consumes less energy, and is at the same time perceptually indistinguishable from the original color. This process is repeated for all pixels to obtain the "green" version of the input CQ image. Experimental results indicate that such "green" images often have better contrast and better subjective quality than the original CQ images. What distinguishes our work from that in [1] is the use of a JND model incorporating luminance and texture masking effects, as well as extensive subjective evaluation of the resulting images.

The paper is organized as follows. In Section 2, we review the background information. The proposed method is presented in Section 3. The experimental results are given in Section 4 followed by conclusions in Section 5.

2. PRELIMINARIES

2.1. Display energy consumption

The consumed energy in energy-adaptive displays is proportional to the number of 'on' pixels, and the brightness of their R, G, and B components [1]. Different colors require different amounts of energy. As proposed in [1], the sum of linear (non-gamma-corrected) RGB components can be used as a simple measure of the energy consumption of a pixel in an OLED display. Hence, if $\mathbf{C} = (R, G, B)$ is the color of a particular pixel, the corresponding display energy is

$$\mathbb{E}(\mathbf{C}) = R + G + B. \quad (1)$$

Please refer to [1] for other possible energy measures. Note that various hardware techniques, such as ambient-based backlight modulation combined with histogram analysis, and

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LCD compensation with backlight reduction, can also be used to achieve energy savings [4]. However, in this paper we will focus on the pixel-level energy consumption.

2.2. Color and Human Visual Perception

Human Visual System (HVS) cannot sense changes below the just-noticeable-difference (JND) threshold. In the literature, a variety of methods have been proposed to estimate spatial and temporal JND thresholds [3], [5], [6]. In this paper, we employ the spatial luminance JND estimator in the pixel domain for the YCbCr color space as proposed in [5]. This approach considers two dominant masking effects - background luminance masking and texture masking - as follows:

$$\begin{aligned} JND_Y(x,y) &= T_l(x,y) + T_{t,Y}(x,y) \\ &\quad - C_{l,t}\ min\{T_l(x,y), T_{t,Y}(x,y)\}, \end{aligned} \tag{2}$$

where $JND_Y(x,y)$ is the spatial luminance JND value of pixel at location (x,y), $T_l(x,y)$ and $T_{t,Y}(x,y)$ are the visibility thresholds for the background luminance masking and texture masking, respectively, and $C_{l,t}(0 < C_{l,t} < 1)$ is a weighting factor that controls the overlapping effect in masking, since the two aforementioned masking factors usually coexist in most images [5].

Since our goal is to eventually perform color quantization, we need a measure of the difference between colors. To this end, we employ the CIELAB color space [2], and in particular, we compute the difference between two colors in CIELAB using the CIEDE2000 color distance [2], which we label D_{00}. This distance possesses desirable perceptual uniformity properties, meaning that the distance between two colors approximately corresponds to their perceptual difference. For large uniform color patches, $D_{00} = 2.3$ is usually considered as color JND [2]. However, JND in natural images is affected by visual masking and is not the same for all pixels. As explained in Section 3, the interplay between the JND threshold in (2), which incorporates masking effects, and D_{00} in CIELAB, forms the core of the proposed method.

3. THE PROPOSED METHOD

Consider a color image $\mathbf{I}$ of size $W \times H$ pixels. Let $\mathbf{r} = (x,y)$ denote the pixel location within $\mathbf{I}$, and $\mathbf{C}(\mathbf{r})$ be the color of the pixel at location $\mathbf{r}$. The image will first be color quantized (CQ) using a well-known CQ method [7]. Let $\tilde{\mathbf{I}}$ be the CQ version of $\mathbf{I}$, $\{\mathbf{C}_1, \mathbf{C}_2, ..., \mathbf{C}_N\}$ be the set of N distinct colors in $\tilde{\mathbf{I}}$, and $P_i = \{\mathbf{r} \in \tilde{\mathbf{I}} : \mathbf{C}(\mathbf{r}) = \mathbf{C}_i\}$ be the set of all pixels in $\tilde{\mathbf{I}}$ with color $\mathbf{C}_i$, $i = 1, 2, ..., N$. Our goal is to replace each color $\mathbf{C}_i$ with another color, such that the total energy consumption of the image is reduced, while the perceptual quality of the new image is not decreased compared to the original CQ image. To achieve this goal, we will first cast this problem as an optimization problem, and then solve it via a general optimization method.

Let $\mathbf{C} = (Y, Cb, Cr)$ be the YCbCr color of a given pixel in $\tilde{\mathbf{I}}$. Let JND_Y be the spatial luminance JND of this pixel, computed as in (2) from the luminance (Y) component of $\tilde{\mathbf{I}}$. Given JND_Y, two new colors $\mathbf{C}^+$ and $\mathbf{C}^-$ are generated from $\mathbf{C}$ by adding and subtracting JND_Y to or from the luminance component of $\mathbf{C}$ as follows

$$\begin{aligned} \mathbf{C}^+ &= (Y + JND_Y, Cb, Cr), \\ \mathbf{C}^- &= (Y - JND_Y, Cb, Cr). \end{aligned} \tag{3}$$

These two new colors can be considered perceptually indistinguishable from $\mathbf{C}$, since their chroma components are the same as those of $\mathbf{C}$, and the difference between their luminance components and the luminance component of $\mathbf{C}$ does not exceed the JND threshold. The three colors $(\mathbf{C}, \mathbf{C}^+, \mathbf{C}^-)$ are then transformed to CIELAB, and the CIEDE2000 distances between them are calculated:

$$\begin{aligned} R^+ &= D_{00}(\mathbf{C}, \mathbf{C}^+), \\ R^- &= D_{00}(\mathbf{C}, \mathbf{C}^-). \end{aligned} \tag{4}$$

Note that due to the nonlinear transformation from YCbCr to CIELAB, R^+ may be different from R^-. We set $R = \min\{R^+, R^-\}$. Now, all colors in CIELAB whose distance D_{00} from $\mathbf{C}$ does not exceed R should be perceptually indistinguishable from $\mathbf{C}$. These colors form a sphere (with respect to D_{00}) in the CIELAB space. The desired new color is a color within the sphere whose energy $\mathbb{E}$ is minimal.

The above process is repeated for each pixel $\mathbf{r} \in \tilde{\mathbf{I}}$. With $\mathbf{C}(\mathbf{r}) = \mathbf{C}_i$ denoting the original CQ color of the pixel $\mathbf{r}$, and $R(\mathbf{r})$ denoting the corresponding color distance above, we search for the new color $\mathbf{C}_{new}$ so as to

$$\begin{aligned} &\text{minimize} && \mathbb{E}(\mathbf{C}_{new}), \\ &\text{subject to} && D_{00}(\mathbf{C}_i, \mathbf{C}_{new}) \le R_i, \end{aligned} \tag{5}$$

where $R_i = \frac{1}{M}\sum_{\mathbf{r} \in P_i} R(\mathbf{r})$, and M is the cardinality of P_i. To solve this optimization problem, we used the downhill simplex method [8] with 100 iterations. The solution $\mathbf{C}_{new}$ will replace $\mathbf{C}_i$ in the new "green" image. Hence, the new image will have the same number of colors as the original CQ image, but its display energy will be reduced.

In the proposed approach, dark pixels will contribute more towards energy minimization than bright pixels, due to the background luminance masking term in (2). As shown in Fig. 3 of [3] or Fig. 1 of [5], the JND visibility threshold of dark pixels is higher than that of bright pixels. But the larger the JND threshold, the larger the term R_i will be in (5), which in turn means that the energy (and also the luminance) of dark pixels will be reduced more than that of bright pixels. Therefore, as a side effect, the contrast of the new image may be increased compared to the original CQ image. Experimental results in the next section confirm this expectation.

4. RESULTS AND DISCUSSION

The proposed method was tested on the Kodak color image database [9], with 24 lossless true color (24 bits per pixel) images of resolution 768×512 pixels. Images were first color quantized (CQ) to $N = 512$ colors using the method from [7]. The value of $C_{l,t}$ in (2) was set to 0.34 as in [5]. Fig. 1 shows an example of the CQ image and the corresponding "green" image produced by the proposed method. As seen from this figure, the perceptual quality of the produced green image is very close to the quality of the CQ image.

In our subjective experiment, a Two Alternative Forced Choice (2AFC) method [10] was used to compare subjective image quality. In 2AFC, the participant is asked to make a choice between two alternatives, in our case the original CQ image and the corresponding "green" image. This way of comparing image quality is less susceptible to measurement noise [11] than quality ratings based on scale, such as Mean Opinion Score (MOS) and Double Stimulus Continuous Quality Scale (DSCQS) [12], and is appropriate for the applications where appearance changes are not intended.

In each trial, participants were looking at two side by side images (in the same vertical position, and separated by 1 cm horizontally) on a mid-gray background. Each image pair was shown for 10 seconds. After this presentation, a mid-gray blank screen was shown for 5 seconds. During this period, participants were asked to indicate on an answer sheet, which of the two images looks better (Left or Right). They were asked to answer either Left or Right for each image pair, regardless of how certain they were of their response. Participants did not know which image was obtained by our method and which was the original CQ image. Randomly chosen half of the trials had the CQ image presented on the left side of the screen and the other half on the right side, in order to counteract side bias in the responses. This gave a total of 48 trials (duplicated to balance left and right presentation).

The experiment was run in a quiet classroom with 24 participants (all male of age between 21 and 24) at Simon Fraser University, and the study was carried out as part of a course on multimedia communications engineering. All participant had normal or corrected to normal vision. Two participants were tested in parallel, on two systems with the same display settings and hardware configuration (17-inch Dell monitor P170S, max brightness 250 Lux, with resolution 1024×768 pixels). The brightness and contrast of the monitors were set to 50%. The size of all images were reduced by a factor of 1.16 using a bicubic interpolation algorithm to fit the screen. The actual size of the displayed images on the screen were 17.5×12.3 centimeters. The illumination in the room was in the range 105-140 Lux. The distance between the monitors and the subjects was fixed at 70 cm. Each participant was familiarized with the task before the start of the expeirment via a short printed instruction sheet. The total length of the experiment for each participant was approximately 12 minutes. The results are shown in Table 1, where we indicate the number of responses that showed preference for the original CQ image and the "green" ("G") image in the second and third column, respectively.

We used the two-sided chi-square (χ^2) test [13] to examine the statistical significance of the results. The null hypothesis is that there is no preference for either the CQ or the "green" image. Under this hypothesis, the expected number of votes is 24 for both the CQ and the "green" image. The probability that the null hypothesis holds (the so-called p-value [13]) is also indicated in the table. In experimental sciences, as a rule of thumb, the null hypothesis is rejected when $p < 0.05$. When this happens in Table 1, it means that the two images (CQ and "green") cannot be considered to have the same subjective quality, since one of them has obtained a statistically significantly higher number of votes, and therefore seems to have better quality.

As seen in Table 1, in only 8 out of 24 trials the p-value is greater than 0.05 - these are indicated in bold typeface. In all other cases, subjects showed a statistically significant preference for the "green" image. Looking across all trials (i.e., summing up all the votes for the two options), the results show that participants have preferred the "green" images more than CQ images (800 vs. 352 votes) with overall $p = 0.0001$, which is a very statistically significant result, because the odds of it occurring by chance are 1 in 10000.

We believe that the reason for this preference for "green" images is related to the contrast enhancement brought by the proposed energy minimization. To examine this issue further, we computed the expected context-free contrast (ECFC) measure as defined in [14] for all CQ images and their corresponding "green" images. The quantity $\Delta C = (C_2 - C_1)/C_1$ is used as a measure of contrast enhancement, where C_1 and C_2 are the ECFC's of the CQ image and the "green" image, respectively. The results are shown in the fifth column in Table 1. These results indicate that, on average, the ECFC of the "green" image is higher by about 13.25% with respect to the CQ image, which often seems to be preferred by the viewers. This phenomenon can be observed in Fig. 1, where the contrast in the hair and shoulder area of the "green" image (right) is higher than in the CQ image (left).

Finally, the energy reduction percentage for each image in the database is shown in the last column of Table 1. Here, $\Delta\mathbb{E} = (\mathbb{E}_2 - \mathbb{E}_1)/\mathbb{E}_1$, where $\mathbb{E}_1$ and $\mathbb{E}_2$ are the total energies of the CQ image and the "green" image, respectively. As seen from these results, the proposed method is able to reduce the energy by about 4.25% on average. While seemingly small, this saving can translate to many MegaWatts when all the displays around the world are taken into account. We also observed that images with a larger percentage of dark pixels or textured regions result in higher energy savings, because these kinds of pixels provide larger JND values in (2).

The average processing time of the proposed method (implemented in MATLAB without code optimization) on an In-

Table 1. Experimental results.

Image	CQ	"G"	p-value	ΔC (%)	$\Delta\mathbb{E}$ (%)
kodim1	15	33	0.0094	5.11	-3.70
kodim2	10	38	0.0001	3.19	-5.71
kodim3	13	35	0.0015	5.35	-4.00
kodim4	12	36	0.0005	5.50	-4.12
kodim5	13	35	0.0015	14.33	-6.25
kodim6	18	30	**0.0833**	16.90	-3.28
kodim7	19	29	**0.1489**	14.60	-3.67
kodim8	14	34	0.0039	9.33	-3.60
kodim9	11	37	0.0002	7.73	-2.81
kodim10	14	34	0.0039	9.85	-2.30
kodim11	14	34	0.0039	26.37	-4.70
kodim12	12	36	0.0005	10.07	-2.70
kodim13	8	40	0.0001	10.24	-4.35
kodim14	8	40	0.0001	14.14	-5.00
kodim15	13	35	0.0015	16.15	-5.20
kodim16	19	29	**0.1489**	8.90	-3.93
kodim17	18	30	**0.0833**	11.54	-6.85
kodim18	16	32	0.0209	9.70	-7.94
kodim19	25	23	**0.7728**	8.74	-3.42
kodim20	19	29	**0.1489**	51.16	-3.00
kodim21	17	31	0.0433	10.78	-3.40
kodim22	18	30	**0.0833**	17.28	-3.51
kodim23	8	40	0.0001	19.70	-3.90
kodim24	18	30	**0.0833**	11.20	-3.87
Total	352	800	0.0001		
Mean				13.25	-4.25


(a)


(b)

Fig. 1. (a) Color-quantized (CQ) image *kodim4* with 512 colors; (b) the corresponding "green" image, with $\Delta C = 5.5\%$ and $\Delta\mathbb{E} = 4.12\%$.

tel Core 2 Duo @ 3.33 GHz, with 8 GB RAM was about 23 seconds. Hence, in the current form, the proposed method would be suitable for server-side implementation, where color conversion is done once for all users. Further optimization is needed for making this method feasible for mobile users.

5. CONCLUSION

In this paper, we presented a novel perceptually-based algorithm for color quantization. The resulting "green" images consume less energy than conventionally color quantized images, yet have the same or often better perceptual quality. Experimental results indicate that the contrast of "green" images is higher than that of conventional CQ images, which often leads to better subjective quality. Compared to conventional color quantization [7], the proposed method reduces the energy by an average of 4.25%, improves the contrast by an average of 13.25%, and produces images with better subjective quality in most cases.

6. REFERENCES

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