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REDUCTION OF POWERCONSUMPTION IN EMISSIVE DEVICES BASED ON POWER CONSTRAINT CONTRAST ENHANCEMENT

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Abstract— In this paper we are consuming the total power required to display the image. For this we use the histogram of that image. The histogram is modified as log based histograms that reduce overstretching articrafts of the conventional histogram equalization technique. Then we develp a model called power constrained contrast enhancement for consuming the power. The objective function in PCCE consists of power term and histogram equalization term. Moreover, we extend the proposed algorithm to enhance video sequences, as well as still images. Simulation results demonstrate that the proposed algorithm can reduce power consumption significantly while improving image contrast and perceptual quality.

Index Terms—Contrast enhancement, emissive displays, histogram equalization (HE), histogram modification (HM), image enhancement, low-power image processing.

Due to the rapid development of imaging technology has made it easier to take and process digital photographs. However, we often acquire low-quality photographs since lighting conditions and imaging systems are not ideal. High contrast is an important quality factor for providing better experience of image perception to viewers. Histogram equalization (HE) is widely used to enhance low-contrast images. Notice that, in addition to contrast enhancement, power saving is also an important issue in various multimedia devices, such as mobile phones and televisions. A large portion of power is consumed by display panels in these devices [2], [3], and this trend is expected to continue as display sizes are getting larger.

To design such a power-constrained contrast-enhancement (PCCE) algorithm, different characteristics of display panels should be taken into account. Display panels can be divided into emissive displays and non emissive displays [4]. Cathode-ray tubes, plasma display panels (PDPs), organic light-emitting diode (OLED), and field emissive displays(FED) are emissive displays that do not require external light sources, whereas the thin-film transistor liquid crystal display (TFT-LCD) is a non emissive one. . Emissive displays have several advantages over non emissive ones, including high contrast and low-power consumption. In an emissive display, each pixel can be independently driven, and the power consumption of a pixel is proportional to its intensity level. Thus, an emissive display generally consumes less power than a nonemissive one. Due to these advantages, the OLED and the FED are considered as promising candidates for the next-generation display. Although the OLED is now used mainly for small panels in mobile devices,

its mass-production technology is being rapidly developed, and larger OLED panels will be soon adopted in a wider range of devices. We propose a PCCE algorithm for emissive displays based on HE. First, we develop a histogram modification (HM) scheme, which reduces large histogram values to alleviate the contrast overstretching of the conventional HE technique.

Then, we make a power-consumption model for emissive displays and formulate an objective function, consisting of the histogram-equalizing term and the power term. To minimize the objective function, we employ convex optimization techniques. Furthermore, we extend the proposed PCCE algorithm to enhance video sequences. Simulation results shows the required output *i.e* image with high image contrast and good perceptual quality and reduced power consumption.

HE TECHNIQUE

Many contrast-enhancement techniques have been developed. HE is one of the most widely adopted approaches to enhance low-contrast images, which makes the histogram of light intensities of pixels within an image as uniform as possible. The main objective of this paper is to develop a power-constrained image enhancement framework, rather than to propose a sophisticated contrast-enhancement scheme. Thus, the proposed PCCE algorithm adopts the HE approach for its simplicity and effectiveness. Here, we first review conventional HE and HM techniques and then develop an LHM scheme, on which the proposed PCCE algorithm is based.

HISTOGRAM EQUALIZATION

In HE, we first obtain the histogram of pixel intensities in an input image. We represent the histogram with a column vector ***h*** , whose ***kth*** element ***hk*** denotes the number of pixels with intensity ***k*** . Then, the probability mass function ***pk*** of intensity is calculated by dividing by the total number of pixels in the image. In other words

$$p_k = \frac{h_k}{1^t h} \qquad (1)$$

where 1 denotes the column vector, all elements of which are 1.The cumulative distribution function (CDF) ***ck*** of intensity ***k*** is then given by

$$c_k = \sum_{i=0}^{k} p_i \qquad (2)$$

Let ***xk*** denote the transformation function, which maps intensity in the input image to intensity. ***xk*** in the output image. In HE, the transformation function is obtained by multiplying the CDF by ***ck*** the maximum intensity of the output image. For a b-bit image, there are 2^b=L different intensity levels, and the transformation function is given by

$$Xk = [(L-1)ck+0.5] \qquad (3)$$

where[a] is the floor operator, which returns the largest integer smaller than or equal to . Thus, in (3), is rounded off to the nearest integer since output intensities should be integers. Note that b=8 andL-1=255,

when an 8-bit image is considered. If we ignore the rounding-off operation in (3), we can combine (2) and (3) into a recurrence equation, i.e.,

$$Xk\text{-}xk\text{-}1 = (L-1)pk \text{ for } 1 \le k \le L-1. \qquad (4)$$

With the initial condition ***x0***=(L-1)pα. This can be rewritten in vector notations as

$$Dx = \overline{\mathbf{h}} . \qquad (5)$$

Where D $\in$ R^{LXL} is the differential matrix, i.e.,

$$D = \begin{bmatrix} 1 & 0 & 0 & \cdots & 0 & 0 \\ -1 & 1 & 0 & \cdots & 0 & 0 \\ 0 & -1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & 0 & \cdots & 1 & 0 \\ 0 & 0 & 0 & \cdots & -1 & 1 \end{bmatrix} \quad (6)$$

and $\bar{h}$ is the normalized column vector of , given by

$$\bar{h} = \frac{L-1}{1^t h} \quad (7)$$

Histogram Modification

The conventional HE algorithm has several drawbacks. First, when a histogram bin has a very large value, the transformation function gets an extreme slope. This can cause contrast overstretching, mood alteration, or contour artifacts in the output image. Second, particularly for dark images, HE transforms very low intensities to brighter intensities, which may boost noise components as well, degrading the resulting image quality. Third, the level of contrast enhancement cannot be controlled since the conventional HE is a fully automatic algorithm without any parameter. To overcome these drawbacks, many techniques have been proposed. One of those is HM

In this recent approach to HM, the first step can be expressed by a vector-converting operation **m=f(h)** where m = $[m0,m1,\ldots,mL-1]^t$ denotes the modified histogram .Then, the desired transformation function $X= [x_0, x_1,\ldots\ldots x_{L-1}]^t$ can be obtained by solving $Dx=\bar{m}$ (8)

which is the same HE procedure as in (5), except that $\bar{m}$ is used instead of where is the normalized column vector of m i.e.,

$$\bar{m} = \frac{L-1}{1^t m} m \quad (9)$$

C. LHM

We develop an HM scheme using a logarithm function, which is monotonically increasing and can reduce large values effectively. In [20], Drago *et al.* demonstrated that a logarithm function can successfully reduce the dynamic ranges of high-dynamic-range images while preserving the details. We exploit this property and apply a logarithm function to our HM scheme, which is called LHM. We use the following logarithm function to convert the input histogram value to a modified histogram value m_k

$$m_k = \frac{\log(h_k . h_{max} . 10^{-\mu} + 1)}{\log(h_{max}^2 . 10^{-\mu} + 1)} \qquad (10)$$

Where mk denotes the maximum element within the input histogram h and μ is the parameter that controls the level of HM. As μ gets larger, $hk.hmax.10^{-\mu}$ in (10) becomes a smaller number. Therefore, a large μ makes mk almost linearly proportional to hk. Thus, the histogram is less strongly modified. On the other hand, as μ gets smaller $hmax.10^{-\mu}$, becomes dominant and

$$\log(h_k . h_{max} . 10^{-\mu} + 1) \backsimeq \log(h_k) + \log(h_{max} . 10^{-\mu})$$

$$\backsimeq \log(h_{max} . 10^{-\mu}) \qquad (11)$$

Consequently m_k, becomes a constant regardless of h_k, making the modified histogram uniform. In this way, a smaller results μ in stronger HM. Fig. 1(a) illustrates how the proposed LHM scheme modifies an input histogram according to parameter μ , and Fig. 1(b) plots the corresponding transformation functions, which are obtained by solving (8). In this test, the "Door" image in Fig. 1(c) is used as the input image.

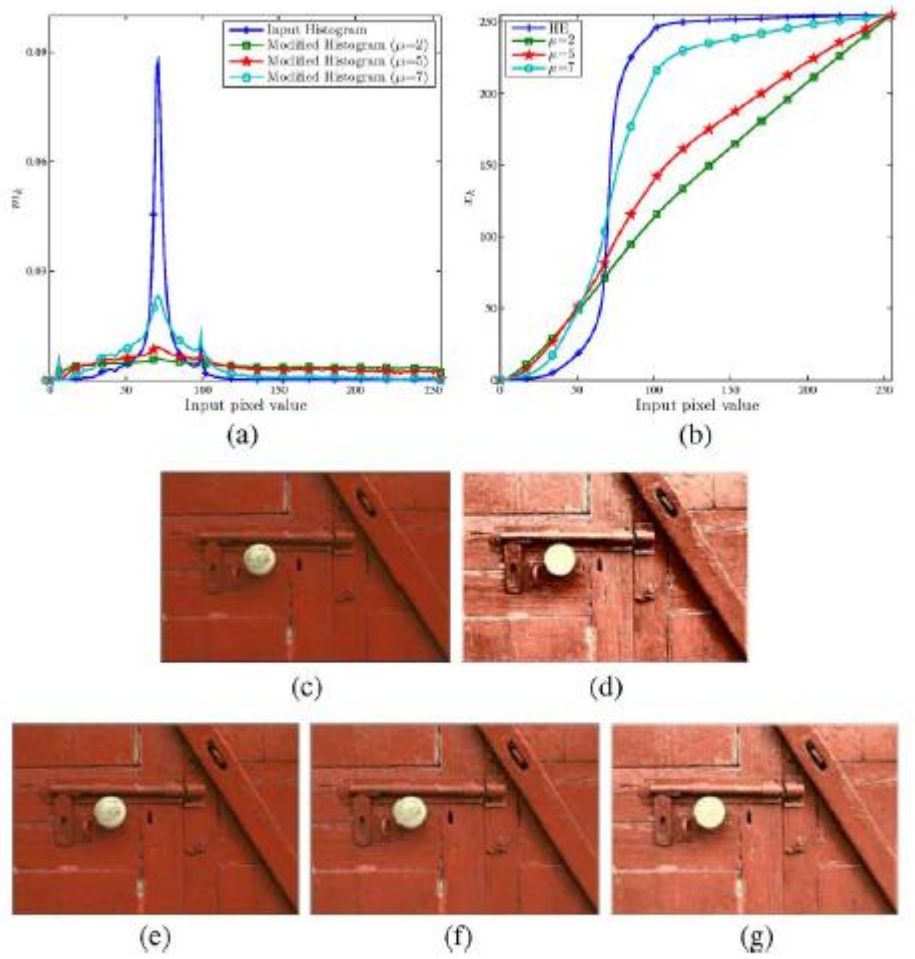

Fig. 1. Illustration of LHM: (a) The input and modified histograms of the test image in (c), in which each histogram is normalized so that the sum of all elements is 1. (b) The corresponding transformation functions. [(d)–(g)] The output images. (a) Histograms. (b) Transformation functions. (c) Input image. (d) HE. (e) $\mu = 2$. (f) $\mu = 5$. (g) $\mu = 7$.

In the above Fig. 1(d)-(g) compare the output images of the conventional HE algorithm and the proposed LHM scheme. On the other hand, the proposed algorithm with μ=5 yields less artifacts on the door knob while enhancing the details on the background region. . Therefore, by controlling the single parameter μ , LHM can obtain the transformation function, which varies between the identity function and the conventional HE result.

PCCE algorithm

Here, we propose the PCCE algorithm. Fig. 2 shows an overview of the proposed algorithm. We first gather the histogram information h from an input image and apply the LHM scheme h to obtain the modified histogram m. Without power constraint, we can solve equation Dx=$\bar{m}$ in (8) to get the transformation function. However, we design an objective function, which consists of power-constraint and contrast-enhancement terms. We then express the objective function in terms of variable y = Dx.

Based on the convex optimization theory, we find the optimal y that minimizes the objective function. Finally, we construct the transformation function x from y via $x=D^{-1}y$ and use x to transform the input image to the output image.

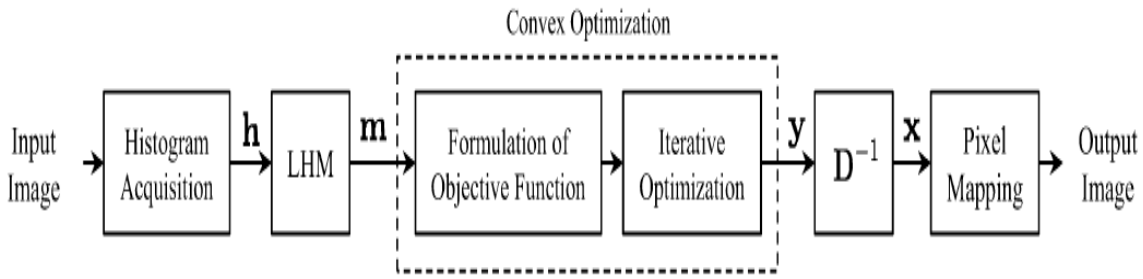

Fig. 2. Flow diagram of the proposed PCCE algorithm.

We model the power consumption in an emissive display panel that is required to display an image. A pixel-level power model for an OLED module. According to their experimental results, power P to display a single-color pixel can be modeled by

$$P = w_0 + w_r R^\gamma + w_g G^\gamma + w_b B^\gamma \qquad (12)$$

where, R,G and B are the red, green, and blue values of the pixel. Exponent γ is due to the gamma correction of the color values in the sRGB format. A typical is γ 2.2. , *w*0 accounts for static power consumption, which is independent of pixel values, and, *wr*,*wg* and *wb* are weighting coefficients that express the different characteristics of red, green, and blue sub-pixels. we ignore parameter for static power consumption.

Then, we model the total dissipated power (TDP) for displaying a color image by

$$\text{TDP}=\sum_{i=0}^{N-1}(w_r R_i^\gamma + w_g G_i^\gamma + w_b B_i^\gamma) \qquad (13)$$

where N denotes the number of pixels in the image and (Ri,Gi,Bi) denotes the RGB color vector of the pixel. The weighting coefficients, wr ,wg and wb, and are inversely proportional to the sub-pixel efficiencies, For example, in a particular OLED panel in a mobile phone, the weighting ratios are about *w*r : *w*g : *w*b= 70 : 15 : 154 . However, we note that different display panels have different weighting coefficients.

For a grayscale image, the TDP is similarly modeled by

$$\text{TDP}=\sum_{i=0}^{N-1} Y_i^\gamma \qquad (14)$$

Where *Yi* is the gray level of the *i*th pixel. . Therefore, the TDP in (14) can be compactly written in vector notations

TDP=$\sum_{i=0}^{L-1} h_k x_k^{\gamma} = h^t \emptyset^{\gamma}(x)$ (15)

as where $\emptyset^{\gamma}(x) = [x_0^{\gamma}, x_1^{\gamma}, \ldots\ldots, x_{L-1}^{\gamma}]^t$ and h is the histogram vector whose *k*th element is hk.

B. Constrained Optimization Problem

We save the power in an emissive display by incorporating the power model in (15) into the HE procedure. We have two contradictory goals, i.e., we attempt to enhance the image contrast by equalizing the histogram, but we also try to decrease the power consumption by reducing the histogram values for large intensities. These goals can be stated as a constrained optimization problem, i.e.,

Minimize $\|Dx - \bar{m}\|^2 + \propto h^t \emptyset^{\gamma}(x)$

Subject to $x_0 = 0$

$x_{L-1} = L - 1,$

Dx≥0. (16)

The objective function has two terms$\|Dx - \bar{m}\|^2 + \propto h^t \emptyset^{\gamma}(x)$, i.e., is $\|Dx - \bar{m}\|^2$ the histogram-equalizing term in (8) and $h^t Ø^{\gamma}(x)$ is the power term in (15). By minimizing the sum of these two terms, we attempt to improve the image contrast and reduce the power consumption simultaneously. There are three constraints in our optimization problem in (16). The two equality constraints X0 = 0 and XL-1 = L-1state that the minimum and maximum intensities should be maintained without changes. The inequality constraint Dx≥0 indicates that the transformation function should be monotonic, i.e, xk≥xk-1 for every k. Note that a≥0 denotes that all elements in vector a are greater than or equal to 0.

- **Solution to the Optimization Problem:**

Exponent γ in the power term $h^t Ø^{\gamma}(x)$ is due to the gamma correction, and a typical γ is 2.2. For generality, let us assume that γ is any number greater than or equal to 1. Then, the power term $x= h^t Ø^{\gamma}(x)$ is a convex function of x, and the problem in (16) becomes a convex optimization problem [21]. Based on the convex optimization theory, we develop the PCCE algorithm to yield the optimal solution to the problem. According to the minimum-value constraint in (16) x0, is fixed to 0 and is not treated as a variable. Thus, the transformation function can be rewritten as $X= [x_0, x_1, \ldots\ldots x_{L-1}]^t$ after removing x0 from the original x . Similarly, the dimensions of, $\overline{\mathbf{m}}$, h and $Ø^{\gamma}(x)$ are reduced to by removing the first elements,

By substituting variable and expressing the maximum- value constraint in terms of, (16) can be reformulated as respectively, D and has a reduced size (L-1)X(L-1) by removing the first row and the first column. Then, we reformulate the optimization problem by the change of variable y=Dx . Each element

in the new variable is the difference between two output-pixel intensities, i.e. yk = xk-xk-1. Thus, y is called the differential vector. Then, x = D^{-1}y

, where

$$\mathbf{D}^{-1} = \begin{bmatrix} 1 & 0 & \cdots & 0 & 0 \\ 1 & 1 & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 1 & \cdots & 1 & 0 \\ 1 & 1 & \cdots & 1 & 1 \end{bmatrix} \in \mathbb{R}^{(L-1)\times(L-1)}. \qquad (17)$$

By substituting variable and expressing the maximum-value constraint in terms of , (16) can be reformulated as x = D^{-1}y

Minimize $\|y - \bar{m}\|^2 + \propto h^t \emptyset^\gamma (D^{-1}y)$

Subject to $1^t y = L - 1,$

y≥0. (18)

$J(y,v,\lambda) = \|y - \bar{m}\|^2 + \propto h^t \emptyset^\gamma (D^{-1}y) + v\left(1^t y - (L-1)\right) - \lambda^t y$ (19)

To solve the optimization problem, we define the Lagrangian cost function, i.e.,

$v \epsilon R \; and \; \lambda = [\lambda_0, \lambda_1, \ldots\ldots \lambda_{L-1}] \; \epsilon \; R^{L-1}$

Are Lagrangian multipliers for the constraints. Then, the optimal can be obtained by solving the Karsh–Kuhn–Tucker conditions

$1^t y = L - 1$ (20)

y≥0 (21)

λ≥0 (22)

Λy=0 (23)

$2(y-\bar{m}) + \alpha\gamma D^{-t} H \emptyset^{\gamma-1}(D^{-1}y) + v1 - \lambda = 0$ (24)

Where

Λ = diag(λ) and H= diag(h)

We first expand the vector notations in (24) to obtain a system of equations and subtract the the equation from the (i+1) one to eliminate *v* . Then, we have a recursive system, i.e.,

$y_{i+1} = y_i + \bar{m}_{i+1} - \bar{m}_i + \frac{\alpha\gamma}{2} h_i \left(\sum_{k=1}^{i} y_k\right)^{\gamma-1} + \frac{\lambda_{i+1} - \lambda_i}{2}$ for $1 \le i \le L-2$ (25)

In the Appendix, we show that all values can be eliminated from the recursion in (25) using (21)–(23) and that all yi values can be expressed in terms of a single variable Z. More specifically,

Each yi is a monotonically increasing function of Z, given by. Then, the remaining step is to determine that satisfies the maximum-value constraint in (20). To this end, we form a function, i.e.,

$$f(z) = 1^t y-(L-1)=\sum_{i=1}^{L-1} gi(z)-(L-1) \quad (26)$$

And find a solution to f(Z)=0. Since f(Z) is monotonically increasing, there exists a unique solution to f(Z)=0 . In this paper, we employ the secant method to find the unique solution iteratively. Let$z^{(n)}$ denote the value of at the the iteration. By applying the secant formula, i.e.,

$$z^{(n)} = z^{(n-1)} - \frac{z^{(n-1)}-z^{(n-2)}}{f(z^{(n-1)}-f(z^{(n-2)})} f(z^{(n-1)}), \quad n=2,3,\ldots. \quad (27)$$

Iteratively until the convergence, we obtain solution. From, we can compute all elements in y since yi=gi(z). Finally, the transformation function $x=D^{-1}y$ is the optimal solution to the original problem in (16), which enhances the contrast and saves the power consumption simultaneously subject to the minimum-value, maximum-value, and monotonic constraints. Parameter in the objective function in (18) determines the relative contributions of the histogram-equalizing term $\|Dx - \bar{m}\|^2$ and the power term $h^t Ø^\gamma(D^{-1}y)$. These two terms, however, have different orders of magnitude in general. Whereas y and $\bar{m}$ are not affected by the resolution of an input image, histogram values in h depend on the image resolution. Moreover, the power term is generally proportional to the average luminance value of the input image. It is convenient to compensate the unbalance between the two terms by dividing the power term by the image resolution and the average luminance value. More specifically, we change the variable by

$$\beta = \alpha \times \sum_{i=0}^{N-1} Yinput, i \quad (28)$$

where isYinput,i the gray level of the pixel in the input image. Then, we control β instead of α . For example, Fig. 3 shows the results of the proposed PCCE algorithm at various β values. In this test, the "Door" image in Fig. 1(c) is also used as the input image; the LHM μ parameter is set to 5, and is set to γ 2.2. In Fig. 3(a), when β=0 , the power term is not considered in (18), and we obtain the differential vector y=$\bar{m}$. As β gets larger, the elements yk for low pixel values k decrease, whereas yk values for high k values increase.

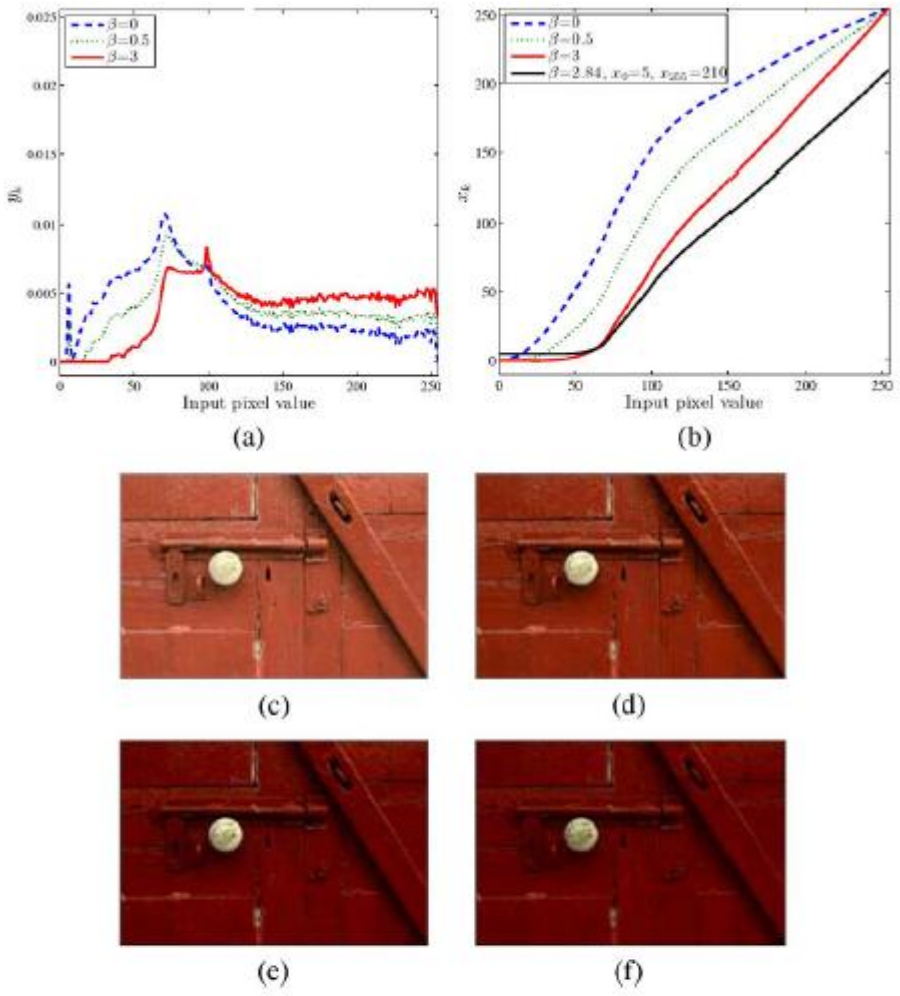

Fig. 3. PCCE results on the "Door" image at various β values. In the black curve in (b) and the corresponding output image in (f), generalized minimum- and maximum-value constraints $x_0 = 5$ and $x_{255} = 210$ are used. In the other cases, the original constraints $x_0 = 0$ and $x_{255} = 255$ are used. Note that (c) is the result without the power constraint, and thus, it is exactly the same as Fig. 1(f). (a) Differential vectors $\mathbf{y}$. (b) Transformation functions $\mathbf{x}$. (c) $\beta = 0$. (d) $\beta = 0.5$. (e) $\beta = 3$. (f) $\beta = 2.84$, $x_0 = 5$, and $x_{255} = 210$.

As shown in Fig. 3(b), these changes in y lower the transformation function, reducing the power consumption. A bigger β saves more power. Without the power constraint, the TDP is $9.28X10^9$. At β=5 and 3, the proposed algorithm reduces the TDP to $3.55X10^9$ and $1.11X10^9$ respectively. In this way, the proposed algorithm determines the transformation function that balances the requirements of power saving and contrast enhancement optimally. Furthermore, the amount of power saving can be controlled by the single parameter β. Specifically, instead of the minimum and maximum-value constraints in (16), we can use generalized constraints x0=lmin and xL-1=lmax to derive the transformation function, which

maps the input dynamic range [0,L-1] to the output dynamic range [lmin,lmax]. For instance, Fig. 3(b) also shows the transformation function with constraints x0=5 and x255=210. Parameter β is set to 2.84 to consume the same TDP as the red curve(x0=5, x255=210,β=5) in Fig. 3(b). Comparing the output images in Fig. 3(e) and (f), we see that the new constraints reduce the dynamic range and degrade the overall contrast. In the remainder of this paper, the original constraints are employed to exploit the full dynamic range.

- PCCE FOR VIDEO SEQUENCE

We extend the proposed PCCE algorithm to enhance video sequences. The proposed algorithm provides a power-reduced output image using the power-control parameter β. We can apply the proposed algorithm with fixed to β each frame in a video sequence. However, a typical video sequence is composed of frames with fluctuating brightness levels. Experiments in Section V-B will show that a bright frame can be enhanced with large β to save power aggressively, whereas a dark frame can be severely degraded if its overall brightness is reduced further with the same β .Therefore, we develop a scheme that determines β adaptively according to the brightness level of each frame. For each frame, we first set the target power consumption TDPout

TDPin = $\sum_{k=0}^{L-1} hk.k^{\gamma}$ TDP based on the input power consumption TDP and then control parameter TDPout to Achieve TDP. Specifically, we set

TDPout=k.TDPin (32)

Where is the power-reduction ratio $\bar{Y}$ When k=1, the proposed algorithm saves no power during the contrast enhancement. On the other hand, when K is smaller, the proposed algorithm darkens the output frame and decreases the power consumption. The power model in indicates that a bright frame consumes more power than a dark frame. Therefore, more power saving can be achieved for a brighter frame, and the power-reduction ratio K in (32) can be set to a smaller value. On the other hand, the ratio for a dark frame should be close to 1 since even a small power reduction may yield poor image quality by reducing the contrast further and erasing details. Based on these observations, we set the power-reduction ratio K by

$K=(1-\frac{\bar{y}}{L-1})^{\rho}$

Where $\bar{Y}$ denotes the average gray level of an input frame and ρ is a user-controllable parameter. For a bright input frame with high $\bar{Y}$, is set to a small value to achieve aggressive power saving. On the contrary, for a dark input frame with low

$\bar{Y}$,k is set to be close to 1 to avoid the brightness reduction. To summarize, given an input frame, we determine the target power consumption TDPout using (32) and (33). Then, we find parameter β to

achieve TDPout. Since TDPout is inversely proportional to β, we can easily obtain the desired β using the bisection method, which iteratively halves a candidate range of the solution into two subdivisions and selects the subdivision containing the solution. Thus, in the video enhancement β, is automatically determined, and the only power-control parameter is in ρ (33). Note that, for the same $\bar{Y}$, larger ρ yields smaller k and saves more power.

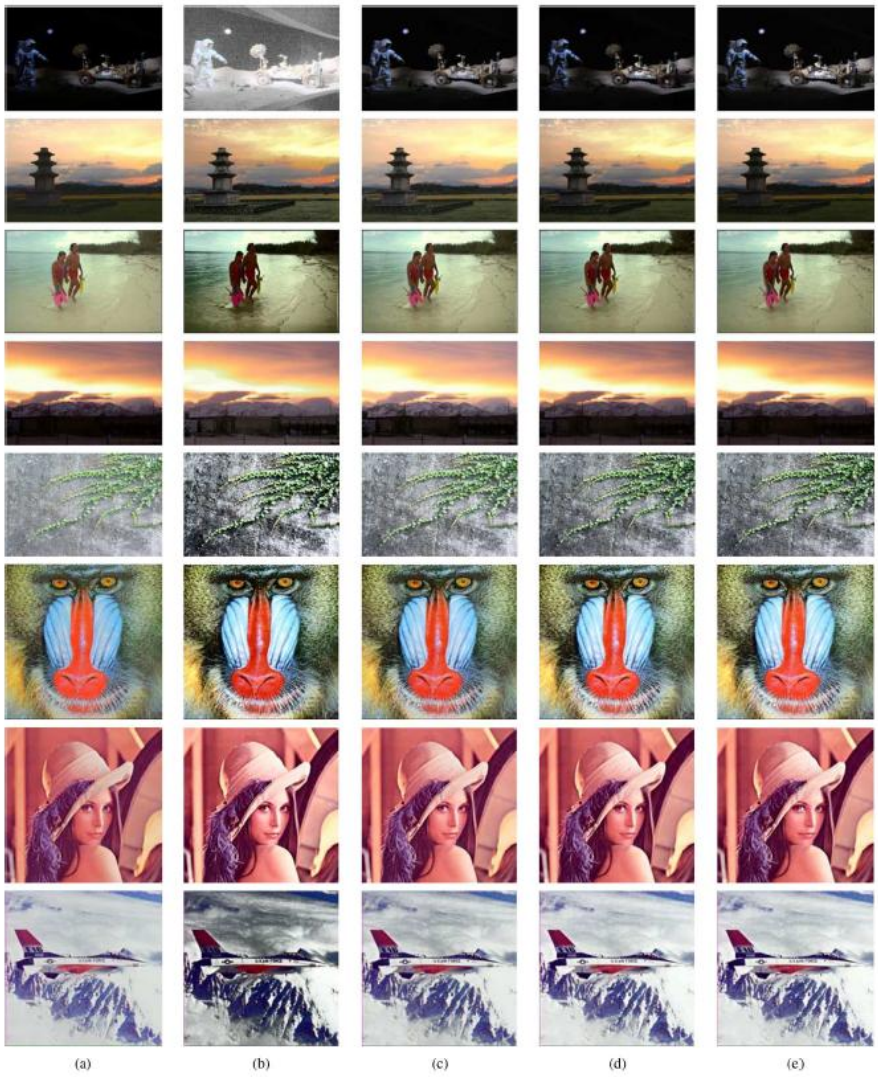

Fig. 4. Contrast enhancement results on the test images "Moon, " "Pagoda, " "Beach, " "Sunset, " "Ivy, " "Baboon, " "Lena, " and "F-16": (a) Original input images, (b) the conventional HE algorithm, (c) WAHE [17], (d) PCCE with adapted μ, and (e) PCCE with $\mu = 5$. The proposed PCCE algorithm is tested without the power constraint ($\beta = 0$).

Contrast Enhancement without Power Constraint

First, we compare the proposed PCCE algorithm without the power constraint (β=0) with the conventional HE and HM techniques. Fig. 4 shows the processed images obtained by the conventional

HE algorithm, the weighted approximated HE (WAHE) algorithm, and the proposed PCCE algorithm (β=0) the proposed algorithm is tested in two ways. In Fig. 4(d), the user-controllable parameter μ for LHM in (10) is set to 2, 6.5, 5.5, 6.5, 5, 5.5, 5, and 5 for the eight test images, respectively, to achieve the best subjective qualities. On the Other hand, in Fig. 4(e), μ is fixed to 5. For the WAHE results in Fig. 4(c), parameter g is adapted for each image to achieve the best subjective quality. Fig. 5 shows the transformation Functions which are used to obtain the images in Fig. 4. 1http://r0k.us/graphics/Kodak/ 2http://sipi.usc.edu/database/ We observe from Fig. 4(b) that the conventional HE algorithm causes excessive contrast stretching. In the "Moon" image, hidden noises become visible, degrading the image quality severely. This noise amplification is due to the steep slope of the transformation function near intensity 0, as shown in Fig. 5. The contrast overstretching suppresses the overall brightness of the "Beach" image. The transformation function reduces the input-pixel range [0, 150] to the output-pixel range [0, 50] by extending the contrast around the input-pixel intensity 170, which corresponds to the background area. Also, contour artifacts are observed in "Sunset." In general, the conventional including amplified noises, contour artifacts, detail losses, and mood alteration. Compared with the conventional HE, both WAHE and the proposed algorithm reduce artifacts by alleviating abrupt changes in the transformation functions, as shown `in Fig. 4(c) and (d). WAHE exploits spatial variance information to reduce large histogram values, based on the observation that peaks in histograms usually come from background regions. Specifically, WAHE skips repeated pixel intensities during the construction of an input histogram to focus on the contrast enhancement of textured regions. Thus, it can enhance object details, whereas it may degrade background details. For example, on the "Pagoda" image, WAHE improves the contrast of the tower but loses the details in the clouds. Similarly, since the wall in the "Ivy" image has small intensity variations, its contrast is not enhanced by WAHE significantly. The proposed PCCE algorithm provides comparable or better results than WAHE on all test images, as shown in Fig. 4(d). On the "Moon, " "Beach, " "Sunset, " "Baboon, " "Lena, " and "F-16" images, the proposed algorithm and WAHE produce similar results. However, on the "Pagoda" and "Ivy" images, the proposed algorithm yields better perceptual quality than WAHE. Notice that the proposed algorithm enhances the clouds in "Pagoda" and the patterns on the wall in "Ivy" more clearly. In Fig. 4(e), we fix the LHM parameter to 5. Except for slight differences in the "Pagoda" image, the output images with the fixed are almost indiscernible from those with the adapted values in Fig. 4(d). Experiments on various other images also confirm that μ=5 is a reliable choice. Therefore, in the following experiments, is set to 5 unless otherwise specified.

Contrast Enhancement with Power Constraint

Next, we evaluate the performance of the proposed PCCE algorithm with the power constraint ($\beta>0$). Fig. 6 shows the output images obtained by the proposed algorithm at different values. The images in Fig. 6(a) are exactly the same as those in Fig. 4(e) β. As gets larger, the overall brightness of the output images decreases, but the image contrast is relatively well preserved. Note that the perceptual quality and the subjective contrast of the output images at $\beta = 0.5$ are almost the same as those at $\beta=0$. In particular, when these images are displayed on OLED panels, it is hard to distinguish the case without the power constraint $\beta=0$ from the case with the power constraint $\beta>0$ unless β is set to be very high. Fig. 6(e) shows the output images when β has a very high value of 15. Even in this case, the originally bright images "Ivy" and "F-16" retain visual details partly, but the other relatively dark images are severely degraded. In general β, can be set to a higher number for a brighter image to save power more aggressively. On the other hand, for a dark input image, β should be less than 2 for the proposed algorithm to yield good image quality.

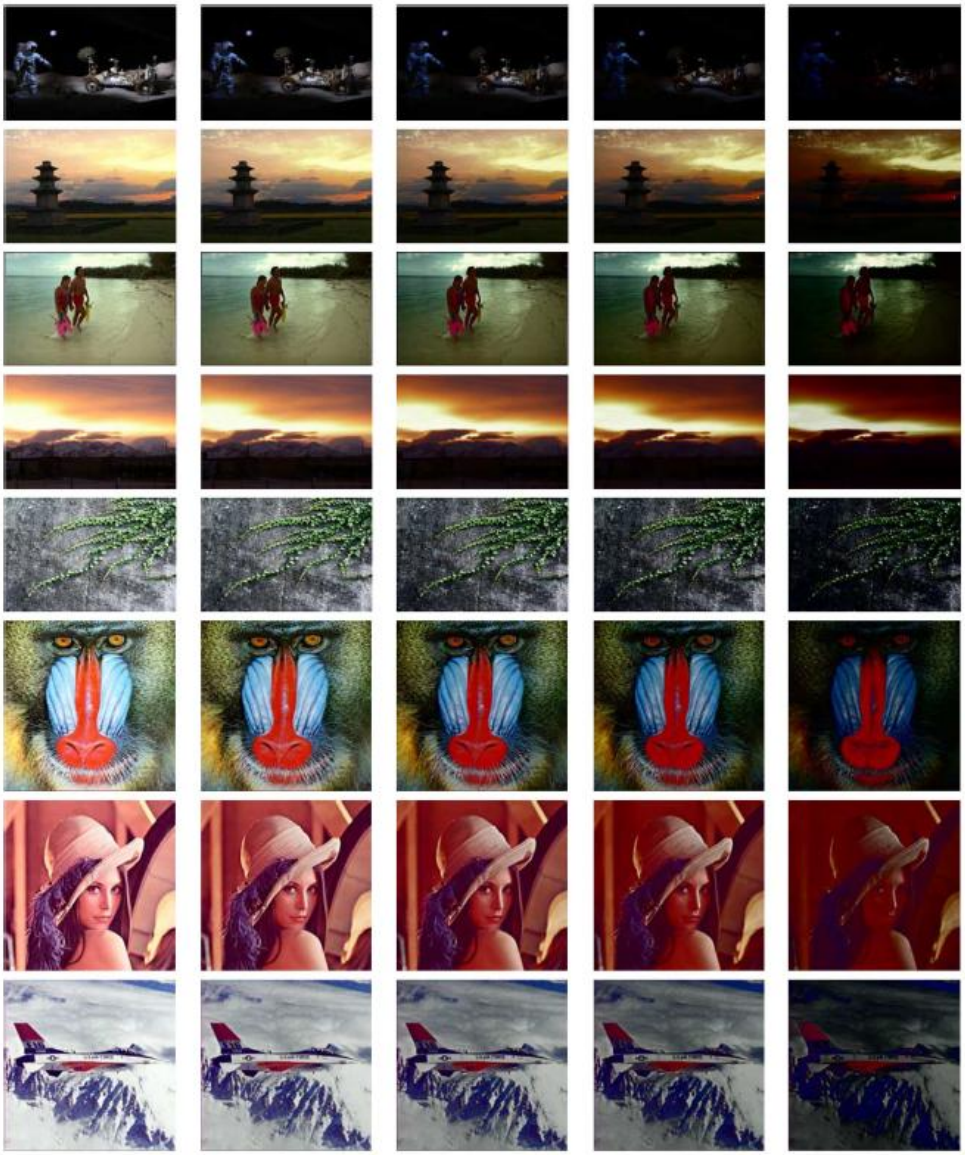

Fig. 6. PCCE results: (a) $\beta = 0$, (b) $\beta = 0.5$, (c) $\beta = 1.5$, (d) $\beta = 3$, and (e) $\beta = 15$.

Conclusion

We have proposed the PCCE algorithm for emissive displays, which can enhance image contrast and reduce power consumption. We have made a power-consumption model and have formulated an objective function, which consists of the histogram-equalizing term and the power term. Specifically, we have stated the power-constrained image enhancement as algorithm to find the optimal transformation function. Simulation results have demonstrated that the proposed

algorithm can reduce power consumption significantly while yielding satisfactory image quality. In this paper, we have employed the simple LHM scheme, which uses the same transformation function for all pixels in an image, for the purpose of the contrast enhancement. One of the future research issues is to generalize the power-constrained image enhancement framework to accommodate more sophisticated contrast-enhancement techniques, such as and, which process an input image adaptively based on local characteristics.

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