A Power Constrained Contrast Enhancement For Emissive Displays Based On Histogram Equalization

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Abstract:

A power-constrained contrast-enhancement algorithm for emissive displays based on histogram equalization (HE) is proposed in this paper. We first propose a log-based histogram modification scheme to reduce overstretching artifacts of the conventional HE technique. Then, we develop a power-consumption model for emissive displays and formulate an objective function that consists of the histogram-equalizing term and the power term. By minimizing the objective function based on the convex optimization theory, the proposed algorithm achieves contrast enhancement and power saving simultaneously. 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 scontrast and perceptual quality.

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

1. INTRODUCTION:

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. Much effort has been made to enhance images by improving several factors, such as sharpness, noise level, color accuracy, and contrast. Among them, high contrast is an important quality factor for providing better experience of image perception to viewers. Various contrast-enhancement techniques have been developed. For example, histogram equalization (HE) is widely used to enhance low-contrast images .Whereas a variety of contrast-enhancement techniques have been proposed to improve the qualities of general images, relatively little effort has been made to adapt the enhancement process to the characteristics of display devicesimage contrast. To design such a power-constrained contrast-enhancement (PCCE) algorithm, different characteristics of display panels should be taken into account. Modern display panels can be divided into emissive displays and non-emissive displays.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. Extensive simulation results show that the proposed algorithm provides high image contrast and good perceptual quality while reducing power consumption significantly.

2. HE TECHNIQUES:

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. It can increase the dynamic range of an image by deriving a transformation function adaptively. A variety of HE techniques have been proposed .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.

HE:

In Histogram Equalization pixel intensity is obtained from the input image. Column vector of the histogram is given as h, whose k th element is given as $h_k$denotes the number of pixel with intensity k. The probability mass function p_k of intensity k is estimated by dividing h_k by the total number of pixels in the image. It can be given as

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

where 1 denotes the column vector in which all elements are 1. The cumulative distribution function (CDF) c_k of intensity k is then given as

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

Let x_k denotes the transformation functions, which maps intensity k in the input images to intensity x_k in the output image. HE, the transformation function is obtained by multiplying the CDF c_k by 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

$$x_k = \lfloor (L-1)c_k + 0.5 \rfloor \quad (3)$$

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

Histogram Modification:

Image contrast enhancement plays a vital role in digital image processing especially in biomedical applications and secures digital image transmission. The objective of any image enhancement technique is to improve the characteristics or quality of an image, such that the resulting image is better than the original image. To improve the image contrast, numerous enhancement techniques have been proposed. One of the conventional methods adopted is the Histogram Equalization (HE) technique. Histogram Equalization (HE) has proved to be a simple and effective image contrast enhancement technique. However, it tends to change the mean brightness of the image to the middle level of the gray-level range, which is not desirable in many applications. Thus, HE has limitations since preserving the input brightness of the image is required to avoid the generation of non-existing artifacts in the output image.

When a histogram bin has a large value, the transformation function gets an extreme slope. From (4) that the transformation function has sharp transition between x_{k-1} and x_k when h_k or equivalently, $p_k$is large. This cause contrast overstretching, mood alteration, or contour artifacts in the output image. Second particularly for dark images, HE transform from low intensities to brighter intensities, which boost noise components as well, degrading the resulting image quality. Third level of contrast enhancement cannot be controlled because the conventional HE is a fully automatic algorithm without parameter.

To overcome this drawback, many techniques have been proposed. One of those is HM. HM is the technique that employs the histogram information in an input image to be obtain the transformation function. HE can be regarded as the special case of the HM. In modified the input histogram before the HE procedure to reduce slopes in the transformation function, instead of the direct control of the histogram.

In this recent approach to HM, the first step can be expressed by a vector-converting operation$m = f(h)$. Where $m = [m_0, m_1, \dots, m_{L-1}]^t$ denotes the modified histogram. Transformation function $x = [x_0, x_1, \dots, x_{L-1}]^t$can be obtained by solving.

$$Dx = \bar{m} \quad (8)$$

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

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

Fig1: (a) original image (b) Enhanced image by using HE (c) Enhanced image using HM

Log based Histogram modification:

HM scheme using logarithm function is developed monotonically increased and can be reduced to large value effectively. Drago et al establish the logarithm function can successfully decreases the dynamic ranges of high-dynamic–range images while preserving the details. We apply this algorithm to the HM scheme which is called LHM.

Logarithm function is to convert the input histogram value h_k to a modified histogram value m_k:

$$m_k = \frac{\log(h_k.h_{max}.10^{-\mu}+1)}{\log(h_{max}^2.10^{-\mu}+1)} \quad (10)$$

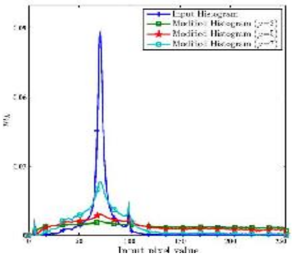
where h_{max} denotes the maximum element within the input histogram h and μ is the parameter that controls the levels of HM. μ gets larger, $h_k.h_{max}.10^{-\mu}$ in (10) becomes the smaller number. Large value of the μ makes m_k almost linearly proportional to h_k since $\log(1+x) \simeq x$ for a small x. Histogram is less strongly modified. On the other hand, as the value of the μ gets smaller, $h_{max}.10^{-\mu}$ becomes dominant.

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

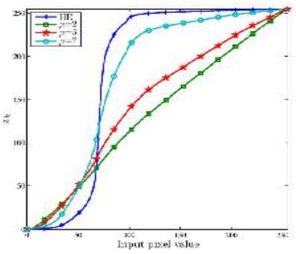
$$\simeq \log(h_{max}.10^{-\mu}) \quad (11)$$

m_k becomes a constant regardless of h_k making the modified histogram uniform. In this way smaller μ result in the stronger HM.

Figure 7(a) shows how to present the LHM scheme modifies an input histogram. According to parameter μ and Figure. 7(b) plots the corresponding transformation functions, which are obtained by solving (8). In this test, the "Door" image in Figure.7(c) is used as the input image. LHM reduced the reduced the large peak of the input histogram around the pixel values of 70 and thus relaxes the steep slope



(a)



(b)


(c)


(d)

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


(e)


(f)


(g)

ssin the transformation function of the conventional HE algorithm. Figure.7(d)-(g) compare the output images of the conventional HE algorithm and the proposed LHM method because of the steep slope, the conventional HE overstretches the contrast of the background, and it maps the input range [100,255] to the narrow output range only. Our proposed algorithm with $\mu = 5$ have less artifacts on the other hand while enhancing the details on the background region. From Figure.7(a) that LHM modifies the histogram more strongly as μ gets smaller. When$\mu = -\infty$, the modified histogram will be uniformly distributed. In extreme case when $= \infty$, the histogram is not modified at all. By controlling the single parameterμ, transfer function of LHM is obtained which varies between the identity function and the conventional HE result.

3. Proposed algorithm PCCE:

In PCCE algorithm first we gather all histogram information h form the input image. Apply the LHM scheme h to obtain the modified histogram m. Equation (8) $Dx = \bar{m}$can be solved without the usage of the power constraint. To get the transformation function x. Objective function in term of variable $y = Dx$ is designed which consist of the power constraint and contrast-enhancement terms. Based on the convex optimization theory [21], we calculate the optimal y that minimizes the objective function. The transformation function x from y via $x = D^{-1}y$ is constructed to use x to transform the input image to the output image.

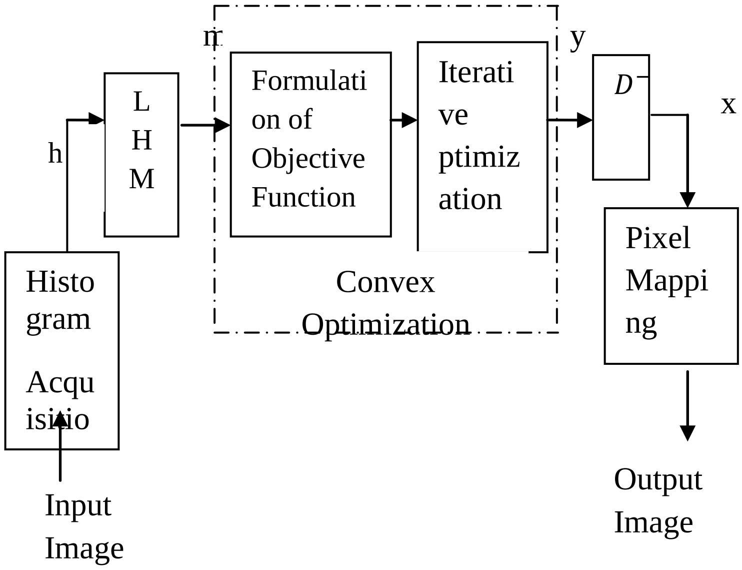


Figure.3. Flow diagram of the proposed PCCE algorithm

Constrained Optimization Problems

Power in an emissive display is saved by incorporating the power model in (15) into the HE procedure. Image contrast is enhanced by equalizing the histogram and power consumption is decreased by reducing the histogram values for large intensities. These can be stated as a constrained optimization problem, i.e.,

$$\text{Minimize } \|D_x - \bar{m}\|^2 + \alpha h^t \phi^\gamma(x)$$

$$\text{Subject to } x_0 = 0,$$

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

$$D_x \succcurlyeq 0 \qquad (16)$$

The objective function $\|Dx - \bar{m}\|^2 + \alpha h^t \phi^\gamma(x)$ has two terms, i.e, $\|Dx - \bar{m}\|^2$ is the histogram-equalization term in (8) and $h^t \phi^\gamma(x)$ is the power term in (15) Image contrast and power consumption is reduced by the minimizing the sum of two terms. α is the user-controllable parameter, which estimate the balance between two terms. Three constraints in our optimization problem (16). The two equality constraints $x_0 = 0$ and $x_{L-1} = L-1$ state that the minimum and maximun intensities should be maintained without changes. If display express L different intensity levels, the output range of the transformation function should also be $[0, L-1]$ to exploit the full dynamic range. Inequality constraint $Dx \succcurlyeq 0$ indicates the transformation function x should be monotonic, i.e..$x_k \geq x_{k-1}$for every $ka \succcurlyeq 0$ denotes that all element in the vector a are greater than or equal to 0. The solution to optimize problem may yield a transformation function, which reverse the intensity ordering of pixel and visually annoying artifacts in the output image.

A. *Solution of the optimization problem*Exponent γ in the power term $h^t\phi^\gamma(x)$ is due to the gamma correction, and a typical γ is 2.2. Let us assume γ any number greater than or equal to the 1. The power term $h^t\phi^\gamma(x)$ is a convex function of x and the problem (16) becomes the convex optimization problem [21]. PCCE algorithm is developed based on the convex optimization to yield the optimal solution to the problem. Minimum-value constraint in (16),x_0 is fixed to 0 and is not treated as a variable. Thus, the transformation function can be rewritten as $X = [x_1, x_2, \dots, x_{L-1}]^t$ after removing x_0 from the original x. The dimensions of $\overline{m}h$ and $\phi^\gamma(x)$ are reduced to $L-1$by removing the first elements. D has a reduced size $(L-1)\times(L-1)$ by removing the first row and the first column.

We reformulate the optimization problem by the change of variable$y = Dx$. Each element y_k in the new variable y is the difference between two outputs –pixel intensities. i.e., $y_k = x_k - x_{k-1}$.y is called as the differential vector. Then $x = D^{-1}y$. where

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

$$\text{Minimize } \|y_x - \overline{m}\|^2 + \alpha h^t \phi^\gamma(D^{-1}y)$$

$$\text{Subject to } 1^t y = L-1,$$

$$y \succcurlyeq 0 \qquad (18)$$

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

$$J(y, \text{v}, \lambda) = \|y - \overline{m}\|^2 + \alpha h^t \phi^\gamma(D^{-1}y) + \text{v}\left(1^t y - (L-1)\right) - \lambda^t y \quad (19)$$

where$\text{v} \in R$ and $\lambda = [\lambda_1, \lambda_2, \dots, \lambda_{L-1}] \in R^{L-1}$ are Lagrangian multipliers for the constraints. The optimal y can be obtained by solving the Karush-Kuhn-Tucker conditions [21], i.e.,

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

$$y \succcurlyeq 0 \quad (21)$$

$$\lambda \succcurlyeq 0 \quad (22)$$

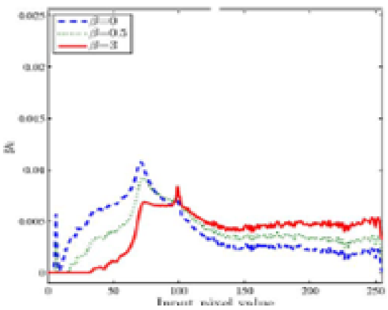
$$\wedge y = 0 \quad (23)$$

$$2(y - \overline{m}) + \alpha\gamma D^{-t} H \phi^{\gamma-1}(D^{-1}y) + \text{v}1 - \lambda = 0 \quad (24)$$

find a solution to $f(z) = 0. f(Z)$ is monotonically increasing, there exists a unique solution to $f(z) = 0$. We employ the secant method to find the unique solution iteratively. Let $z^{(n)}$ denotes the value of z at the n th iteration. by applying the secant formula, i.e.,

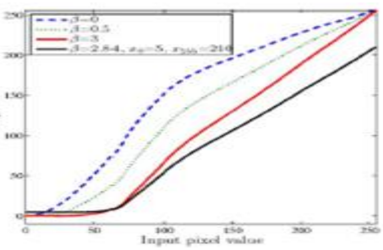
$$z^{(n)} = z^{(n-1)} - \frac{z^{(n-1)} - z^{(n-2)}}{f\left(z^{(n-1)}\right) - f\left(z^{(n-2)}\right)} f\left(z^{(n-1)}\right), n = 2,3 \ldots \quad (27)$$

For example Figure 9 shows the results of the proposed PCCE algorithm at various β values. In this test, the "Door" image in the Figure.1(c) is used as the input image, the LHM parameter μ is set to 5, and γ is set to 2.2. In Figure 9(a), when $\beta = 0$, the power term is not considered in (18). We get a differential vector $y = \bar{m}$. As α Decreases, the element y_k for low pixel values k decreases, whereas the $y_k$values for high k values increases. In Figure 9(b), changes in y lower the transformation function, reducing the power consumption. Larger the value of the β power consumption will be more. TDP value is 9028×10^9 without the power constraint. At $\beta = 0.5$ *and* 3, the proposed algorithm reduces the TDP to $3.55 \times 10^9$and 1011×10^9. In this way the proposed algorithm calculates the



(a)

(b)



(c)

(d)

(e)

(f)

Figure.4. PCCE result 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 Figure.1(f). (a) Differential vectors y (b) Transformation function x. (c) $\beta = 0$ (d) $\beta = 0.5$ (e) $\beta = 3$. (e)$\beta = 2.84$. (f)$x_0 = 5$and $x_{255} = 210$.

transformation functions that balance the requirements of the power saving and contrast enhancement. Power saving can be controlled by the single parameterβ.

4.PCCE FOR VIDEO SEQUENCE

PCCE algorithm is extended for the video sequence. Using power control parameter β power is reduced in the output image. In proposed algorithm fixed value of β can be applied for each frame and a typical video sequence is composed with the fluctuating brightness levels. Experiments shows that the bright frame can be enhance with the parameter β and darker frame severely decreased if the brightness is reduced further by reducing the parameterβ. For each frame, first we set the target power consumption TDP_{out} based on the input.$TDP_{in} = \sum_{k=0}^{L-1} h_k \,.\, k^{\gamma}$and then control parameter β to achieve TDP_{out}. We set

$$TDP_{out} = k.TDP_{in} \quad (32)$$

where$k$ is the power-reduction ratio. when$k = 1$the proposed algorithm saves no power during the contrast enhancement. when$k$ is smaller, than the proposed algorithm darkness the output frame and decreases the power consumption. The Power model indicated that a brightness frame consumes more power than the dark frame. Thus more power saving ids done by the brighter frame. The power reduction ratio k in (32) can be set to a smaller value. The ratio of the dark frame should be closer to 1 since small power reduction may cause poor image quality by reducing the observation, thus we set the power ratio k as

$$k = (1 - \frac{\bar{y}}{L-1})^{p} \quad (32)$$

where$\bar{Y}$ denoted the average gray level of the input frame and p is a user-controllable parameter. For a bright input frame with high $\bar{Y}$, k is set to a small value to the achieve aggressive power saving. For a dark input frame with low $\bar{Y}$.k is set to be close to 1 to avoid the brightness reduction.The target power consumption TDP_{out} is estimated using (32) and (33). Then parameter β is calculated to achieveTDP_{out}. Since TDP_{out} is inversely proportional to β. The value of the β can be obtained by the bisection method, which is iteratively halves a candidate range of the solution into two subdivision and select the subdivision containing in the solution. In (33) equation the power-control parameter p is calculated. Note that the same $\bar{Y}$, large p provides a smaller k and saves more power.

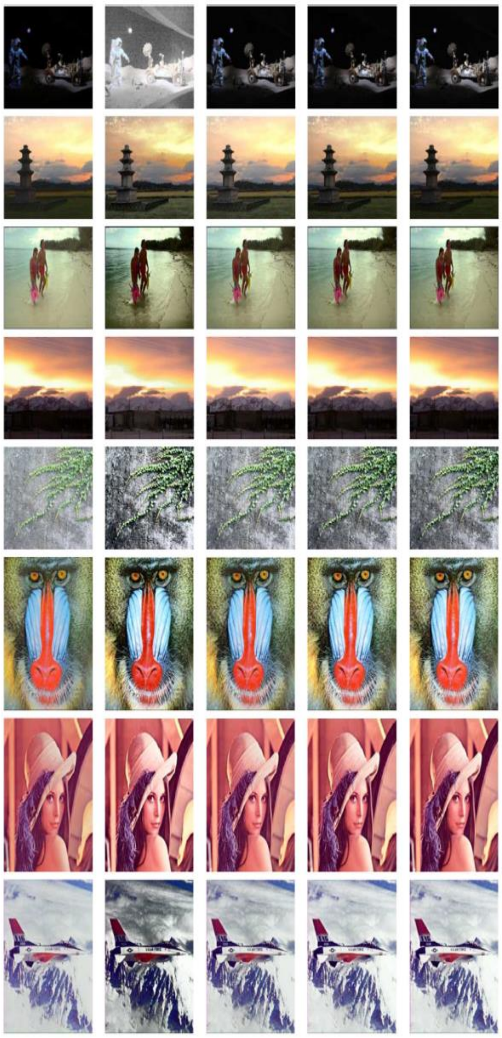


Fig. 4. Contrast enhancement results on the test images "Moon, " "Pagoda, " "Beach, " "Sunset, " "Ivy, " "Baboon, " "Lena, " and "F-16": (images, (b) the conventional HE algorithm, (c) WAHE [17], (d) PCCE with adapted μ, and (e) PCCE with $\mu = 5$. The proposed PCCE algorithm the power constraint ($\beta = 0$).

5. EXPERIMENTAL RESULTS:-

We evaluate the performance of the proposed algorithm on eight test images, i.e., " "Moon, " "Pagoda, " "Beach, ""Sunset, " "Ivy, " "Baboon, " "Lena, " "F-16 .These test images are shown in

Figs. 4. “Beach” and “Pagoda” are from Kodak Lossless True Color Image Suite,1 “Baboon, “ “Lena, “ and “F-16” are from the USC-SIPI database,2 and the others are taken with a commercial digital camera and resized. The resolution of “Eiffel Tower” is 480x720, those of the USC-SIPI images are 512 x 512, and those of the others are720 x 480. We process only the luminance components in the experiments. More specifically, given a color image, we convert it to the YUV color space and then process only the Y-component without modifying the U- and V-components. Therefore, the TDP is also measured for the component only using (14). In all experiments, y is set to 2.2.

A. Contrast Enhancement without Power Constraint

First, we compare the proposed PCCE algorithm without the power constraint $(\beta = 0)$ 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 [17], and the proposed PCCE algorithm $(\beta = 0)$. the proposed algorithm is tested in two ways. InFig. 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 theOther 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,.

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 u=5is a reliable choice. Therefore, in the following experiments, is set to 5 unless otherwise specified.

B. 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 differenvalues.

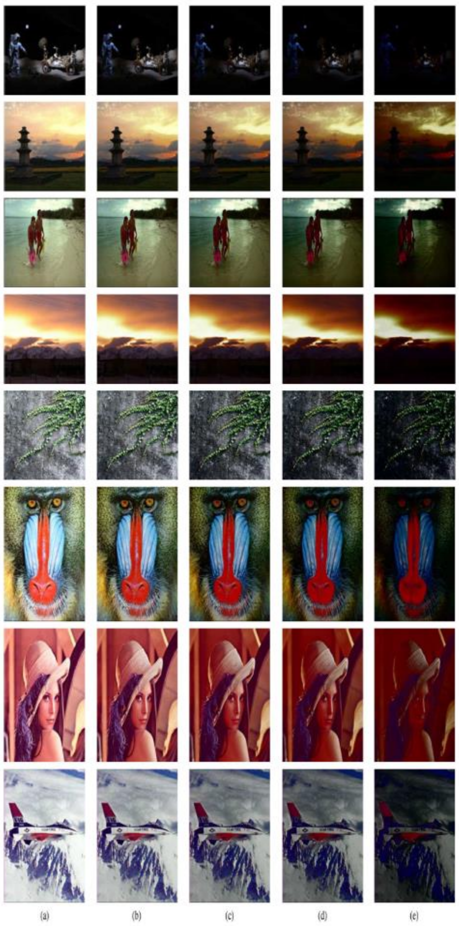


Fig. 6. PCCE results: (a) $\beta = 0$, (b) $\beta = 0.5$, (c) $\beta = 1.5$, (d) $\beta = 3$, and (e) $\beta = 15$.

Fig. 8 compares the TDP measurements for the images in Figs. 4 and 6. For the dark "Moon" image, all three contrast-enhancement methods HE, WAHE, and the proposed algorithm $(\beta = 0)$ increase pixel values to stretch the image contrast, require higher TDPs than the original input images. Fig 8 compares the outputs of the proposed algorithm at K with those of the linear mapping method. Let us recall that the power-reduction ratio is defined as TDP in (32). The linear mapping method uses a linear transformation function $x_k = c \cdot k$, , where constant is set for each image in such a way that the method achieves the same as the proposed algorithm.

6. 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, which process an input image adaptively based on local characteristics.

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