Image Contrast Enhancement By Using Modified Histogram Equalization Techniques

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***Abstract*—Image contrast-enhancement algorithm for emissive displays based on histogram equalization (HE) is proposed in this paper. A log-based histogram modification scheme to reduce overstretching artifacts of the conventional HE technique is first proposed. A power-consumption model is developed 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, the proposed algorithm is extended 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.**

Keywords: **Contrast enhancement, emissive displays, histogram equalization (HE), histogram modification (HM), image enhancement, low-power image processing techniques.**

I. INTRODUCTION

The development of imaging technology has made it easier to capture and process digital photographs. Then the 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 devices. 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. Therefore, it is essential to develop an image processing algorithm, which is capable of saving power in display panels, as well as enhancing image 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 [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. First, an emissive display can turn off individual pixels to express complete darkness and achieve a high contrast ratio. Second, 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 non-emissive one, which should turn on a backlight regardless of pixel intensities. Due to these advantages, the OLED and the FED are considered as promising candidates for the next-generation display, although the TFT-LCD has been the first successful flat-panel display in the commercial market. In particular, the OLED is regarded as the most efficient emissive device in terms of power consumption. 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, including televisions and computer monitors [6], [7].

II. HE TECHNIQUES

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, first review conventional HE and HM techniques and then develop an LHM scheme, on which the proposed PCCE algorithm is based.

1. Histogram Equalization (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

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

Where 1 denotes the column vector ,all elements of which are 1. The cumulative distribution function (CDF) $\mathbf{c_k}$ of intensity $\boldsymbol{k}$ is then given by

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

2. Histogram Modification (HM)

The 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 very large value, the transformation function gets an extreme slope. In other words, note that the transformation function has sharp transition between and when or, equivalently, is large. 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 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 $m = [m_0, m_1, \ldots, m_{L-1}]^t$ denotes the modified histogram. Transformation function $x = [x_0, x_1, \ldots, x_{L-1}]^t$can be obtained by solving.

$$Dx = \bar{m} \quad (3)$$

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.,

$$\bar{m} = \frac{L-1}{1^t m} m \quad (4)$$

(a)

(b)

Figure:1. (a) Original image (b) Enhanced output image using HE

3. Log based Histogram Modification (LHM)

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

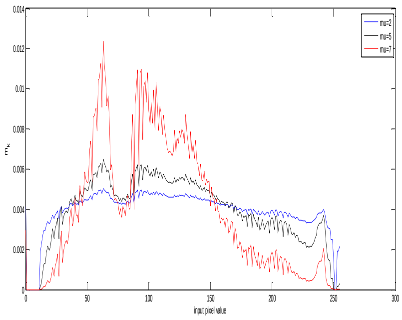
Logarithm function is to convert the input histogram value h_k to a modified histogram value m_k:

$$m_k = \frac{\log\,(h_k.\,h_{max}.\,10^{-\mu}+1)}{\log\,(h_{max}^2.\,10^{-\mu}+1)} \qquad (5)$$

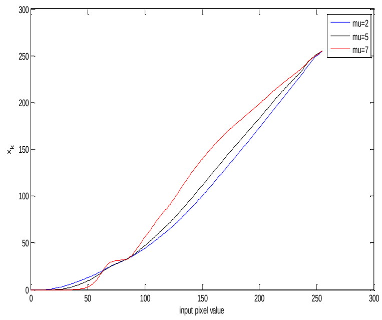
where h_{max} denotes the maximum element within the input histogram h and μ is the parameter that controls the levels of HM. μ gets larger, $h_k.\,h_{max}.\,10^{-\mu}$ in (10) becomes the smaller number. Large value of the μ makes m_k almost linearly proportional to h_k since $\log\,(1+x) \simeq x$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

$$\begin{aligned}&\log(h_k.\,h_{max}.\,10^{-\mu}+1)\\ &\quad\simeq \log(h_k)+\log(h_{max}.\,10^{-\mu})\\ &\simeq \log(h_{max}.\,10^{-\mu})\end{aligned} \qquad (6)$$

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



(a)



(b)

(c)

(d) (e)

Figure: 2. LHM scheme modifies for test images, (a)The input and modified histogram of the test image, (b)Transformation functions,(c) μ = 2, (d) μ = 5, (e) μ = 7.

III. PROPOSED TECHNIQUE

In PCCE algorithm first gather all histogram information h form the input image. Apply the LHM scheme h to obtain the modified histogram m. Equation (3) $Dx = \bar{m}$ 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], then 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.

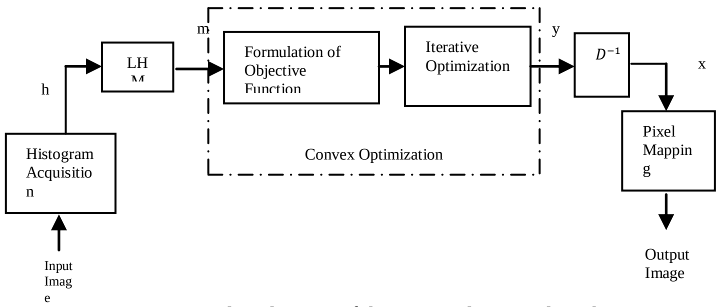


Figure: 3.Flow diagram of the proposed PCCE algorithm

1. Power Model for Emissive Displays

Power consumption in an emissive display panel is modeled which is required to display an image. Dong et al proposed a pixel-level power model for an OLED module. Experimental results shows that the power P to display a single-color pixel can be modeled by

$$P = \omega_0 + \omega_r R^\gamma + \omega_g G^\gamma + \omega_b B^\gamma \quad (7)$$

where R,G and B are the red, green and blue values of the pixel. γ Exponent is due to the gamma correction of the color value. After transforming the color values into luminous intensities in the linear RGB format the linear relation between the power and luminous intensities. w_0 is a static power consumption, which is independent of pixel values, and $w_r, w_g and w_b$ are weighting coefficients that express the different characteristics of red, green, and blue sub-pixels.

In this method, pixel values are changed to save power in a display panel and ignore the parameter w_0 for static power consumption. Then total dissipated power (TDP) for displaying a color image by

$$TDP = \sum_{i=0}^{N-1} (w_r R_i^\gamma + w_g G_i^\gamma + w_b B_i^\gamma) \quad (8)$$

where N denotes the number of the pixels in the images. (R_i, G_i, B_i) Denotes the RGB color vector of the ith pixels. $\omega_r, \omega_g\ and \omega_b$ are weighting coefficient inversely proportional to the sub pixel coefficients ,which depends on the physical characteristics of the specific display panel. For example OLED panel in the mobile phone have a weighting coefficient ratios about $\omega_r : \omega_g : \omega_b = 70:115:154$. Different display panel have a different weighting coefficients.

For grayscale image, the TDP model is given as

$$TDP = \sum_{i=0}^{N-1} Y_i^\gamma \quad (9)$$

where Y_i is the gray level of the ith pixel. There are h_k pixels with gray level k in the input image, and these pixels are assigned gray level x_k in the output image by the transformation function. TDP in (14) can be compactly written in the vector notation as.

where $\phi^\gamma(x) = [x_0^\gamma, x_1^\gamma, \ldots, x_{L-1}^\gamma]^t$ and h is the histogram vector whose kth element is h_k.

2. Constrained Optimization Problem

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.,

$$\begin{aligned} &\text{Minimize } \|D_x - \bar{m}\|^2 + \alpha h^t \phi^\gamma(x) \\ &\text{Subject to } x_0 = 0, \\ &x_{L-1} = L - 1, \\ &D_x \succcurlyeq 0 \end{aligned} \quad (10)$$

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 $k\ a \succcurlyeq 0$ 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.

3. Solution to 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 $X = [x_1, x_2, \ldots, x_{L-1}]^t$ after removing x_0 from the original x. The dimensions of $\bar{m}h$ 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.

The optimization problem is reformulated by changing the 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

$$D^{-1} = \begin{bmatrix} 1 & 0 & 0 & \ldots & 0 \\ 1 & 1 & 0 & \ldots & 0 \\ 1 & 1 & 1 & \ldots & 0 \\ 1 & 1 & 1 & \ldots & 1 \end{bmatrix} \in R^{(L-1)\times(L-1)} \quad (11)$$

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

$$\begin{aligned} &\text{Minimize } \|y_x - \bar{m}\|^2 + \alpha h^t \phi^\gamma(D^{-1}y) \\ &\text{Subject to } 1^t y = L - 1, \\ &y \succcurlyeq 0 \end{aligned} \quad (12)$$

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

$$J(y, \mathrm{v}, \lambda) = \|y - \bar{m}\|^2 + \alpha h^t \phi^\gamma(D^{-1}y) + \mathrm{v}\left(1^t y - (L-1)\right) - \lambda^t y \quad (13)$$

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

$$1^t y = L - 1 \quad (14)$$

$$y \succcurlyeq 0 \quad (15)$$

$$\lambda \succcurlyeq 0 \quad (16)$$

$$\wedge\, y = 0 \quad (17)$$

$$2(y - \overline{m}) + \alpha\gamma D^{-t} H \phi^{\gamma-1}(D^{-1}y) + v1 - \lambda = 0 \quad (18)$$

Where, $\wedge = diag(\lambda) and\ H = diag(h)$

Expand the vector notation in (18) to obtain a system of equations and subtract the i th equation from the $(i+1)$th one to eliminate v. recursive system can be given as

$$y_{i+1} = y_i + \overline{m}_{i+1} - \overline{m}_i + \frac{\alpha_\gamma}{2} h_i \left(\sum_{k=1}^{i} y_k\right)^{\gamma-1} + \frac{\lambda_{i+1} - \lambda_i}{2}$$

$$for\ 1 \le i \le L - 2 \quad (19)$$

All the λ_i values can be eliminated from the recursion in (19) using (15)-(17) and that all y_i values can be expressed in terms of a single variable z. y_i is monotonically increasing function of z that satisfies the maximum-value constraint in (14). form a function i.e.,

$$f(z) = 1^t y - (L-1) = \sum_{i=1}^{L-1} g_i(z) - (L-1) \quad (20)$$

and find a solution to $f(z) = 0$. $f(Z)$ is monotonically increasing, there exists a unique solution to $f(z) = 0$. It employs 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.,

$$z^{(n)} = z^{(n-1)} - \frac{z^{(n-1)} - z^{(n-2)}}{f(z^{(n-1)}) - f(z^{(n-2)})} f\left(z^{(n-1)}\right), n = 2,3 \ldots \quad (21)$$

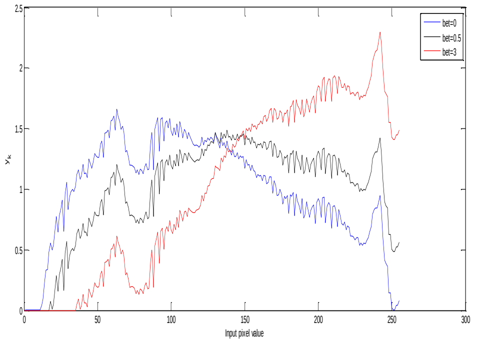
iteratively until the convergence , solution from z . From z, it can be estimated all elements in y since $y_i = g_i(z)$. Transformation function $x = D^{-1}y$ is the optimal solution to the original problem in (10), which enhances the contrast and saves the power consumption subject to the minimum-value, maximum-value and monotonic constraints.

Parameter α in the objective function in (12) estimates the relative contribution of the histogram-equalizing term $\|y - \overline{m}\|^2$ and the power term $h^t \phi^\gamma(D^{-1}y)$ .These have different order of magnitude. y and $\overline{m}$ are not affected by the resolution of the input image, histogram values depends upon the image resolution. Power terms is proportional to the resolution of the input image and it is easy to compensate the unbalance the between the two terms by dividing the power terms by the average luminance value and image resolution.

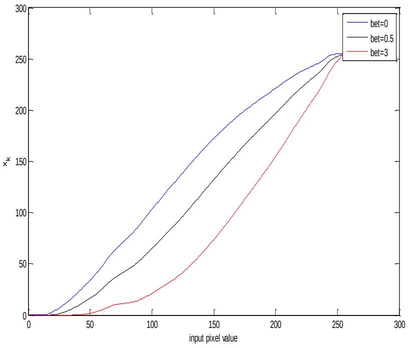
$$\beta = \alpha \times \sum_{i=0}^{N-1} Y_{input,i} \quad (22)$$

Where, $Y_{input,i}$ is the gray level of the ith in the input image. Then, it controls β instead of α.

In this test image in the Figure.2(c) is used as the input image, the LHM parameter μ is set to 2, and γ is set to 2.2.



(a)



(b)

(c) (d)

(e)

Figure: 4. (a) Differential vector y, (b) Transformation function x, (c) $\beta = 0$, (d) $\beta = 0.5$, (e) $\beta = 3$.

4.Special Case of $\gamma = 2$

In, although the value of the $\gamma = 2.2$, Then considered the value of the $\gamma = 2$ to make TDP in (15) a quadratic function, which is easier to analyze than the general convex function. when $\gamma = 2$, the objective function in (16) becomes a quadratic function, given by

$$J_q(x) = (Dx - \overline{m})^t (Dx - \overline{m}) + \alpha x^t H x \quad (23)$$

$$= x^t D^t D x - 2x^t D^t \overline{m} + \overline{m}^t \overline{m} + \alpha x^t H x \quad (24)$$

By differentiating $J_q(x)$ with respect with respect to x and setting it to 0. obtains the following transformation function:

$$x = (D^t D + \alpha H)^{-1} D^t \overline{m} \qquad (25)$$

Therefore in special case of $\gamma = 2$, the transformation function is given in a closed form, without requiring the convex optimization procedure.

IV. Results and Discussions

Evaluate the performance of the proposed algorithm on test image, i.e., “kodim”. This process only the luminance components in the experiments. More specifically, given a color image, 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 Y-component only using (14). In all experiments, is set to 2.2.

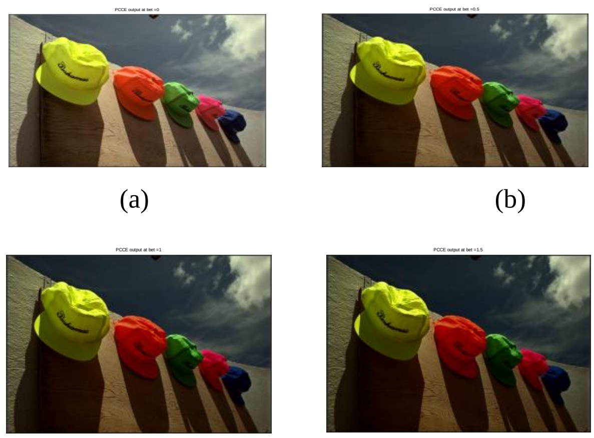
1.Contrast Enhancement without Power Constraint

First, the proposed PCCE algorithm is compared without the power constraint ($\beta = 0$) with the conventional HE and HM techniques. Then 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. In the user-controllable parameter μ for LHM in (10) is set to 2, for the test image, to achieve the best subjective quality. On the other hand, μ is fixed to 2. For the WAHE results, parameter ***g*** is adapted for each image to achieve the best subjective quality. The transformation functions, which are used to obtain the image in figure.

It can be observe from Figure that the conventional HE algorithm causes excessive contrast stretching. In the “kodim” 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. The contrast overstretching suppresses the overall brightness of the 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 the image. In general, the conventional including amplified noises, contour artifacts, detail losses, and mood alteration.

2. Contrast Enhancement with Power Constraint

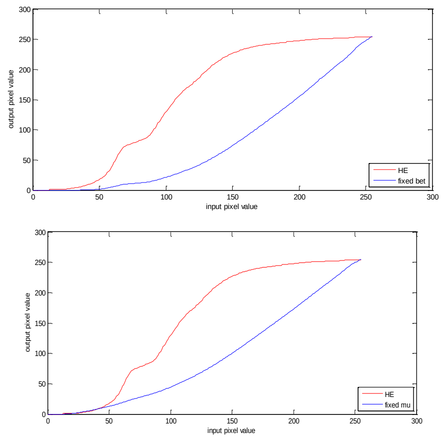
Next, evaluate the performance of the proposed PCCE algorithm with the power constraint ($\beta > 0$). The output images obtained by the proposed algorithm at different values. β. As gets larger, the overall brightness of the output images decreases, but the image contrast is relatively well preserved. 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 then the output images when β has a very high value of 15. Even in this case, the originally bright images “kodim” 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. The transformation functions vary according to β. As β gets larger, the proposed algorithm lowers the transformation functions to save more power, but it preserves the Slopes of the functions (or, equivalently, the contrast) for input pixel values with large histogram values. However, as β gets larger, the proposed algorithm inevitably reduces the contrast for infrequent input-pixel values. For example, “kodim” has low histogram values for input-pixel values around 90. Thus, at $\beta = 3$ the transformation function becomes flat near that pixel Values. Compares the TDP measurements for the images in figures. For the dark 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. However, the proposed algorithm can reduce TDPs by increasing parameter β Moreover, for brighter images, the proposed algorithm $\beta = 0.5$ can reduce the power consumption more significantly while improving the overall contrast. For instance, on the image, the proposed algorithm at $\beta = 1.5$ reduces the TDP by more than 70%, as compared with the input image, but it still improves it constant.



(a) (b) (c) (d)

Figure:5. PCCE results: (a) $\beta = 0$, (b) $\beta = 0.5$, (c) $\beta = 1.5$, (d) $\beta = 3$

The above figure compares the outputs of the proposed algorithm at $k = TDP_{out}/TDP_{in}$ 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 $xk = c.k$, where constant is set for each image in such a way that the method achieves the same as the proposed algorithm. Where as the linear mapping method provides dull output images due to the reduced dynamic ranges, the proposed algorithm provides significantly better image contrast and perceptual quality. An exception is the "kodim" image, on which the proposed algorithm sacrifices the details in the mountain region to improve the contrast in the sky region. In this test $\beta = 1.5$, the mean and the variance of the power-reduction ratios for the two test images are 0.36 and 0.009, respectively. At $\beta = 3$,the mean becomes 0.26, and the variance becomes 0.015. At $\beta = 15$,the mean is 0.14, and the variance is 0.010.



(a) (b)

Figure: 5.1.Transformation function for obtaining the PCCE results in above figure .

(a) For fixed µ (b) for fixed β

V. Conclusion

Proposed the PCCE algorithm for emissive displays, can enhance image contrast and reduce power consumption. In this paper a power-consumption model and have formulated an objective function, which consists of the histogram-equalizing term and the power term. Specifically, stated the power-constrained image enhancement as a convex optimization problem and have derived an efficient 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, the simple LHM scheme, which uses the same transformation function for all pixels in an image are employed, 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 [10] and [11], which process an input image adaptively based on local characteristics.

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