

A Novel Power Saving Framework for Emissive Displays Using Contrast Enhancement Based On Histogram Equalization

Geetha Manikya Prasad R, S Srividya

¹(PG Scholar) Department of ECE, Chaitanya Institute Of Science and Technology, JNTU (K)

geethamanikyadav@gmail.com

²Associate Professor, Department of ECE, Chaitanya Institute Of Science and Technology, JNTU (K)

srividycist@gmail.com

Abstract — This paper proposes a novel power-constrained contrast-enhancement framework for emissive displays based on histogram equalization (HE). To deduce the impact of the overstretching artifacts of the old HE log-based histogram is applied. Power-consumption model is developed for emissive displays and formulate an objective function that contain power term and histogram-equalizing term. The Proposed Framework provides contrast improve and power saving. Proposed algorithm is extend to improve the video sequences, as well as still images contrast and perceptual quality assessment..

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

INTRODUCTION

Due to the very fast development in the Digital imaging technology has made easier to take and process digital photographs in all scenarios. We often need only low contrast image only when the conditions are not in our favor such as bad lightning condition and when imaging

systems are not ideal. Digital Image is enhanced by improving many factors such as sharpness, noise level, color accuracy, and contrast. High contrast is an important quality factor for provides better experience of image perception to viewer. Various contrast enhancement techniques have been developed. For example, histogram equalization (HE) is widely used to enhance low-contrast images [1].

Contrast-enhancement techniques have been introduced to improve the qualities of

general images, relatively little efforts has been made to adapt the enhancement, process to the characteristics of display devices. In contrast enhancement power saving is also an important issue in various multimedia devices, such as mobile phones and television but displays consume more power in such devices [2],[3].

PCCE algorithm is proposed for the emissive displays based on the HE. Histogram value is reduced in the histogram modification (HM) scheme to alleviate the contrast overstretching of the conventional HE technique. Power consumption model for emissive displays and formulate an objective function, consisting of the histogram –equalizing term and the power term. Convex optimization techniques are employed to decrease the objective function. Simulation result shoes that the proposed algorithm provides a high image contrast and better perceptual quality while reducing power consumption.

II. HE TECHNIQUES

HE is one of the most adopted approaches to enhance low-contrast images, which makes the histogram of the light intensities of pixels within an image as uniform as possible [1]. It enhances the dynamic range of an image by deriving a transformation function adaptively. A variety of HE techniques have been presented in [10]-[17]. The proposed PCCE algorithm adopts the HE for its simplicity and effectiveness. Here, we describe conventional HE and HM techniques and then develop an LHM scheme, on which the proposed algorithm is based.

A. 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 in which all elements are 1. The cumulative distribution function (CDF) c_k of intensity k is then given as

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

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 [1], [17]. For a b -bit image, there are $2^b = L$ different intensity levels, and the transformation function is given by

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

where $\lfloor a \rfloor$ is the floor operator, which provides the largest integer smaller than or equal to a . Thus, in (3), $(L-1)c_k$ is rounded off to the nearest integer since output intensities should be integers. Note that $b = 8$ and $L - 1 = 255$, when an 8-bit image is considered.

If rounding-off operation in (3) is ignored, than we combine (2) and (3) into a recurrence equation, i.e.,

$$x_k - x_{k-1} = (L - 1)p_k \text{ for } 1 \leq k \leq L - 1 \quad (4)$$

with an initial condition $x_0 = (L - 1)p_0$. In vector notation it can be given as

$$Dx = \bar{h} \quad (5)$$

where $D \in R^{L \times L}$ is the differential matrix i.e.

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

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

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

B. HM

The conventional HE algorithm has several drawbacks. 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 [18], [19]. HE can be regarded as the special case of the HM. In

[16],[17] 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.,

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

C. LHM

HM scheme using logarithm function is developed monotonically increased and can be reduced to large value effectively. Drago et al in [20] 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 :

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

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, $h_k \cdot h_{max} \cdot 10^{-\mu}$ in (10) becomes the smaller number. Large value of the μ makes m_k almost linearly proportional to h_k since $\log(1+x) \approx x$ for a small x . Histogram is less strongly modified. On the other hand, as the value of the μ gets smaller, $h_{max} \cdot 10^{-\mu}$ becomes dominant.

$$\begin{aligned} & \log(h_k \cdot h_{max} \cdot 10^{-\mu} + 1) \\ & \approx \log(h_k) \\ & + \log(h_{max} \cdot 10^{-\mu}) \\ & \approx \log(h_{max} \cdot 10^{-\mu}) \quad (11) \end{aligned}$$

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 1(a) shows how to present the LHM scheme modifies an input histogram. According to parameter μ and Figure. 1(b) plots the corresponding transformation functions, which are obtained by solving (8). In this test, the "Door" image in Figure.1(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

III.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 transformation function x from y via $x = D^{-1}y$ is constructed to

use x to transform the input image to the output image.

A. Power Model for Emissive Displays

Power consumption in an emissive display panel is modeled which is required to display an image. Dong et al in [22] 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

$$P = \omega_0 + \omega_r R^\gamma + \omega_g G^\gamma + \omega_b B^\gamma \quad (12)$$

B. Power Model for Emissive Displays

Power consumption in an emissive display panel is modeled which is required to display an image. Dong et al in [22] 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

$$P = \omega_0 + \omega_r R^\gamma + \omega_g G^\gamma + \omega_b B^\gamma \quad (12)$$

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. ω_0 is a static power consumption, which is independent of pixel values, and ω_r, ω_g and ω_b are weighting coefficients that express the different characteristics of red, green, and blue sub-pixels. In this paper, we change pixel values to save power in a display panel and we ignore the parameter ω_0 for static power

consumption. Then total dissipated power (TDP) for displaying a color image by

$$TDP = \sum_{i=0}^{N-1} (\omega_r R_i^Y + \omega_g + \omega_b B_i^Y) \quad (13)$$

where N denotes the number of the pixels in the images. (R_i, G_i, B_i) denotes the RGB color vector of the i th pixels. ω_r, ω_g and ω_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

$$TDP = \sum_{i=0}^{N-1} Y_i^Y \quad (14)$$

where Y_i is the gray level of the i th 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.

$$TDP = \sum_{k=0}^{L-1} h_k x_k^Y = h^t \phi^Y(x) \quad (15)$$

where $\phi^Y(x) = [x_0^Y, x_1^Y, \dots, x_{L-1}^Y]^t$ and h is the histogram vector whose k th element is h_k . Power model in (13) or (14) is applicable only to the OLED but also other emissive displays. Rose et al. in [24] analyzed the power-consumption characteristics of several displays. Sustain power is proportional to the average picture level ω_{APL} , which is the average of luminous intensities of all pixels in an image. Average picture level ω_{APL} , which is average of the luminance intensities of all pixels in an image and it is proportional to the TDP in (14) since it is obtained by dividing the TDP by the number of pixels N. In FED the power consumption is proportional to the ω_{APL} .

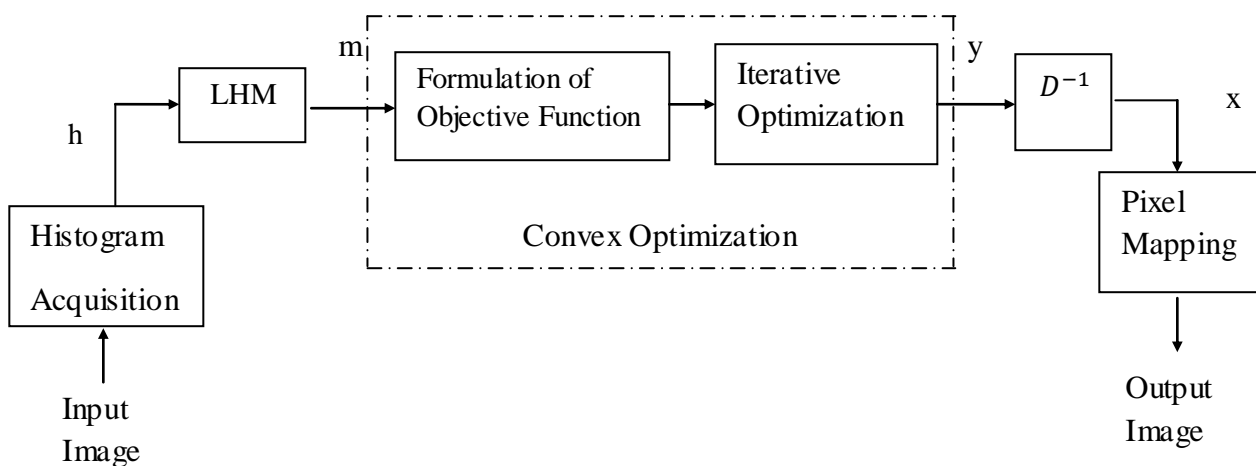


Figure.2. Flow diagram of the proposed PCCE algorithm

C. 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.,

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

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

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

$$Dx \geq 0 \quad (16)$$

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 maximum 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 $Dx \geq 0$ indicates the transformation function x should be monotonic, i.e., $x_k \geq x_{k-1}$ for every k . $a \geq 0$ 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.

D. 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 $\bar{m}h$ 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.

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

$$D^{-1} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix} \in R^{(L-1) \times (L-1)} \quad (17)$$

By substituting variable $x = D^{-1}y$ and expressing the maximum-value constraint in terms of y , (16) can be written as Minimize $\|y_x - m2 + \alpha h^t \phi^\gamma(D^{-1}y)$

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

$$y \geq 0 \quad (18)$$

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

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

Where $v \in R$ 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.,

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

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

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

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

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

where $\Lambda = \text{diag}(\lambda)$ and $H = \text{diag}(h)$

Expand the vector notation in (24) 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 $y_{i+1} = y_i + \bar{m}_{i+1} - \bar{m}_i + \frac{\alpha \gamma}{2} h_i (\sum_{k=1}^i y_k)^{y-1} + \frac{\lambda_{i+1} - \lambda_i}{2}$

$$\text{for } 1 \leq i \leq L - 2 \quad (25)$$

All the λ_i values can be eliminated from the recursion in (25) using (21)-(23) 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 (20). we form a function i.e.,

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

and 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 [25] 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.,

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

iteratively until the convergence, solution from z . From z , we can estimate 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 (16), 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 (18) estimates the relative contribution of the histogram-equalizing term $\|y - \bar{m}\|^2$ and the power term $h^t \phi^y (D^{-1}y)$. These have different order of magnitude. y and \bar{m} are not affected by the resolution of the input image, histogram values depends upon the image resolution. Power term is proportional to the resolution of the input image and it is easy to compensate the unbalance between the two terms by dividing the power terms by the average luminance value and image resolution.

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

where $Y_{input,i}$ is the gray level of the i th in the input image. Then, we control β instead of α .

IV. PCCE FOR VIDEO SEQUENCE

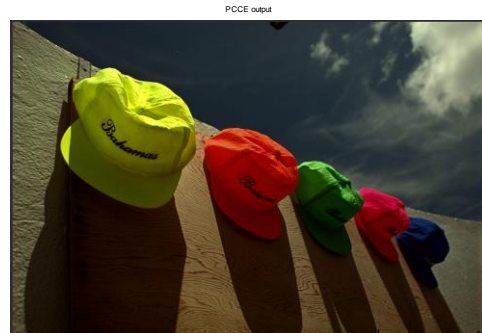
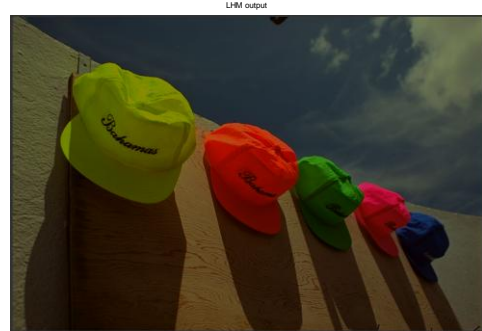
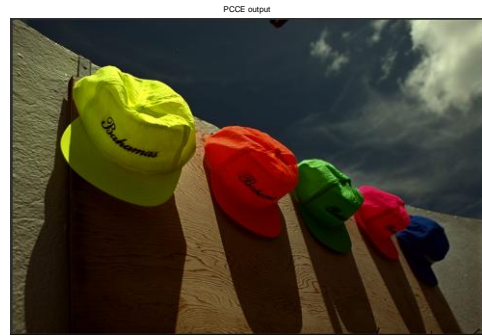
PCCE framework is extended for the video sequence. Using power control parameter β power is deduced in the output image. In proposed framework fixed value of β can be applied for each individual frame and a typical video sequence is composed with the varying brightness levels. Experimental results shows that the bright frame can be increased with the parameter β and darker frame severely decreased if the brightness is decreased further by reducing the parameter β .

For each frame, first we set the target power consumption TDP_{out} based on the input. $TDP_{in} = \sum_{k=0}^{L-1} h_k \cdot k^\gamma$ and then parameter β is controlled to achieve TDP_{out} . we set

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

where k is the power-reduction ratio. When $k = 1$ the proposed framework during the contrast enhancement no power is saved. When k is smaller, than the proposed framework darkness the output frame and significantly decreases the power consumption.

RESULTS:



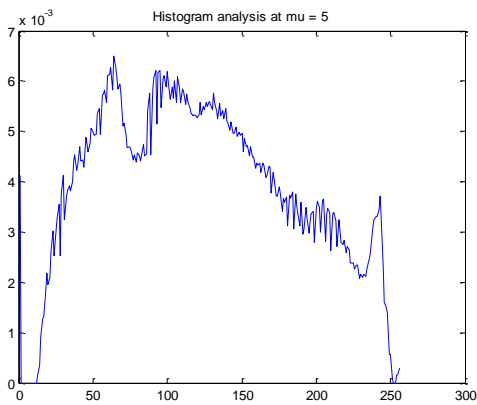
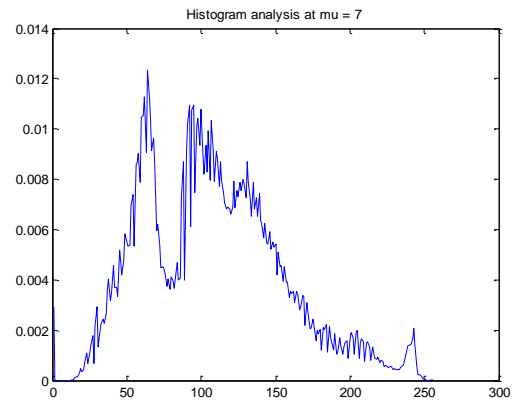
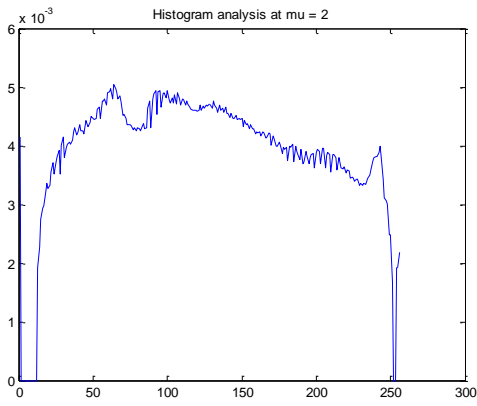


Fig: PCCE output at beta =2.84

CONCLUSION:

For emissive displays, to enhance image contrast and to reduce power consumption we are proposing new algorithm that is PCCE. We have created a power-consumption model associated have developed an objective perform, that consists of the histogram-equalizing term and therefore the power term. Specifically, we've expressed the power-constrained image improvement as a biconvex improvement downside associated have derived an economical rule to search out the optimum transformation perform. Simulation results have incontestable that the projected rule will cut back power consumption considerably whereas yielding satisfactory image quality. During this paper, we've utilized the straightforward LHM theme that uses identical transformation perform for all pixels in a picture, for the aim of the distinction improvement. one in every of the longer term analysis problems is to generalize the power-constrained image improvement framework to accommodate additional subtle contrast-enhancement techniques, like [10] and [11], that method associate input image adaptively supported native characteristics.

REFERENCES

- [1] R. C. Gonzalez and R. E. Woods, *Digital Image Processing*, 3rd ed. Upper Saddle River, NJ: Prentice-Hall, 2007.
- [2] W.-C. Cheng, Y. Hou, and M. Pedram, "Power minimization in a backlit TFT-LCD display by concurrent brightness and contrast scaling," *IEEE Trans. Consum. Electron.*, vol. 50, no. 1, pp. 25–32, Feb. 2004.
- [3] P.-S. Tsai, C.-K. Liang, T.-H. Huang, and H. H. Chen, "Image enhancement for backlight-scaled TFT-LCD displays," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 19, no. 4, pp. 574–583, Apr. 2009.
- [4] W. Den Boer, *Active Matrix Liquid Crystal Displays*. Amsterdam, The Netherlands: Newnes, 2005.
- [5] S. R. Forest, "The road to high efficiency organic light emitting devices," *Org. Electron.*, vol. 4, no. 2/3, pp. 45–48, Sep. 2003.
- [6] B. Young, "OLEDs—Promises, myths, and TVs," *Inf. Display*, vol. 25, no. 9, pp. 14–17, Sep. 2009.
- [7] H. D. Kim, H.-J. Chung, B. H. Berkeley, and S. S. Kim, "Emerging technologies for the commercialization of AMOLED TVs," *Inf. Display*, vol. 25, no. 9, pp. 18–22, Sep. 2009.
- [8] I. Choi, H. Shim, and N. Chang, "Low-power color TFT LCD display for hand-held embedded systems," in *Proc. Int. Symp. Low Power Electron. Des.*, 2002, pp. 112–117.
- [9] A. Iranli, H. Fatemi, and M. Pedram, "HEBS: Histogram equalization for backlight scaling," in *Proc. Des. Autom. Test Eur.*, Mar. 2005, pp. 346–351.
- [10] J. Stark, "Adaptive image contrast enhancement using generalizations of histogram equalization," *IEEE Trans. Image Process.*, vol. 9, no. 5, pp. 889–896, May 2000.
- [11] J.-Y. Kim, L.-S. Kim, and S.-H. Hwang, "An advanced contrast enhancement using partially overlapped sub-block histogram equalization," *IEEE Trans. Circuits Syst. Video Technol.*, vol. 11, no. 4, pp. 475–484, Apr. 2001.
- [12] Z. Yu and C. Bajaj, "A fast and adaptive method for image contrast enhancement," in *Proc. IEEE ICIP*, Oct. 2004, vol. 2, pp. 1001–1004.
- [13] T. K. Kim, J. K. Paik, and B. S. Kang, "Contrast enhancement system using spatially adaptive histogram equalization with temporal filtering," *IEEE Trans. Consum. Electron.*, vol. 44, no. 1, pp. 82–87, Feb. 1998.