

**IMAGE CONTRAST ENHANCEMENT USING HISTOGRAM
EQUALIZATION**Vaibhav A. Bhise¹, Asst. Prof Swapna M. Patil²¹Electronics and Telecommunication Department, Government College of Engineering, Jalgaon,²Electronics and Telecommunication Department, Government College of Engineering, Jalgaon, ,

Abstract — Now a days everyone is facing the problem of low contrast photographs due to lightning condition and imaging system and power consumption problem in various multimedia devices. To overcome this drawback a contrast enhancement as well as power saving algorithm for emissive display is proposed in this paper. The conventional histogram equalization (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 this drawback here we develop a log based histogram modification (LHM) technique, which reduce the contrast overstretching of the conventional H.E technique. Then we design the contrast enhancement power saving algorithm for emissive display and added it into the LHM to achieve the optimal tradeoff between contrast enhancement and power saving. The proposed algorithm can reduce the power consumption significantly while improving the image contrast and perceptual quality.

Keywords- Contrast enhancement, histogram equalization, power saving, emissive display.

I. INTRODUCTION

Now a days everyone is using handheld devices such as mobile phones, laptops, tablets etc for their work and the todays world is a digital world. Everyone requires a good quality of photographs from their imaging devices but some times we do not get a good quality of photograph due to lighting conditions and even imaging systems are not ideal. The question comes in our mind why we get the dark image from the imaging device ? The answer is if the dynamic range of the sensor on which we are imaging is very small then we get the dark image. The dynamic range is defined as the capacity of the sensor to record maximum and minimum intensity value. Much effort has been made to enhance images by improving various factors, that can be noise level, sharpness, contrast, and colour accuracy. High contrast is an important quality factor for providing better experience of image quality to viewers. Different contrast-enhancement techniques have been developed. For example, histogram equalization (HE) is widely used to enhance low-contrast images [2].

It is important to enhance the contrast of low contrast images for better image quality in addition to this power saving is also an important issue in various multimedia devices, such as mobile phones and television etc. The display panel of these devices consumed a large portion of power [1], [4] and this is expected to continue as display sizes are getting larger. Thus, it is important to develop an algorithm, that can save power in display panels, as well as enhancing image contrast.

If we want to enhance the image contrast as well to keep the power within the bound limit we must have to know the different characteristics of the display panels and we have to consider it. Modern display panels can be divided into emissive displays and nonemissive displays [3]. Plasma display panels (PDPs), Organiclight-emitting diode (OLED), Cathode-ray tubes, 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 nonemissive one. Emissive displays have several advantages over nonemissive 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 nonemissive 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 [6]. Although the OLED is now used mainly for small panels in mobile devices, the large-production technology of mobile devices is being rapidly developed, and larger OLED panels will be soon adopted in a wider range of devices, including televisions and computer monitors [5], [8].

The proposed paper is organized as follows: Section II describe the previous related work done. Section III describes the conventional HE and HM techniques. Section IV describes the proposed LHM algorithm. Section V describes the power consumption model for emissive displays and proposes the power saving contrast enhancement algorithm. Section VI describes the Experimental Result and Section VII describes the Conclusion.

II. RELATED WORKS

Several image processing techniques for power saving in display panels have been proposed very recently. Various proposed image processing techniques focus on reducing backlight intensities for TFT-LCDs while preserving the same level of perceived quality. Choi *et al.* [7] increased pixel values to compensate for the brightness losses caused by a reduced backlight intensity. To compensate for the degraded contrast, Cheng *et al.* [1] truncated both ends of an image histogram and then stretched intensities of pixels, and afterwards Iranli *et al.* [10] used HE. Tsai *et al.* [4] decomposed an image into high- and low-frequency components and applied brightness compensation and contrast enhancement to these subband images. His techniques, however, have been devised for TFT-LCDs only and cannot be employed for emissive displays, in which the power consumption is affected by pixel values directly, instead of a backlight intensity.

J.Stark *et al.*[9] proposes a scheme for adaptive image-contrast enhancement based on a generalization of histogram equalization (HE). HE is a useful technique for improving image contrast, but it has many disadvantages. Different results can be obtained with relatively minor modifications. A precise description of adaptive HE is set carried out, and this is used in a discussion of past suggestions for variations on HE. A key feature of this formalism is a "cumulation function, which is used to generate a grey level mapping from the local histogram. Selecting alternative forms of cumulation function one can achieve various types of effects. A particular form is proposed. By changing the one or two parameters, this process can produce a range of degrees of contrast enhancement, at one point leaving the image as it is, at another yielding full adaptive equalization.

Wang *et al.*[16] proposed a novel histogram equalization technique, equal area dualistic sub image histogram equalization. First, he decomposed the image into two equal area sub-images based on its original probability density function. Then the two sub-images are equalized respectively. Finally, we obtain the results after the processed sub-images are composed into one image. The simulation results indicate that the algorithm can not only enhance the image information effectively but also preserve the original image luminance well enough to make it possible to be used in a video system directly.

Ward *et al.*[12] proposed fast and effective method for image contrast enhancement. In his proposed method, the probability distribution function (histogram) of an image is modified by weighting and thresholding before the histogram equalization (HE) is performed. He shows that his method provides a convenient and effective mechanism to control the enhancement process, and therefore adaptive to various types of images. He also explained the various application of the proposed method in video enhancement.

Kim *et al.*[15] proposed a method of novel extension of histogram equalization to overcome the drawback of histogram equalization such as the brightness of an image can be changed by applying the HE technique, due to which the histogram of an image becomes flat. The importance of the proposed algorithm is to utilize independent HE separately over two sub images obtained by decomposing the input image based on its mean with a constraint that the resulting equalized sub images are bounded by each other around the input mean. He shows mathematically his proposed algorithm preserves the mean brightness of a given image significantly well compared to typical histogram equalization while enhancing the contrast therefore, provides a natural enhancement that can be used in consumer electronic products.

Yu *et al.*[17] described a fast approach for enhancing the contrast of an image, which was based on localized contrast manipulation. His approach was not difficult to implement and has several other important properties (adaptive, multiscale, weighted localization, etc.).

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 [2]. It can increase the dynamic range of an image by deriving a transformation function adaptively. A variety of HE techniques have been proposed [9]–[12]. 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 general, HM is the technique that employs the histogram information in an input image to obtain the transformation function [14], [13]. Thus, HE can be regarded as a special case of HM. A recent approach to HM [11], [12] modifies the input histogram before the HE procedure to reduce extreme slopes in the transformation function, instead of the direct control of the output histogram. For instance, Wang and Ward [12] clamped large histogram values and then modified the resulting histogram further using the power law. Also, Arici *et al.* [11] reduced the histogram values for large smooth areas, which often correspond to background regions, and mixed the resulting histogram with the uniform histogram.

III. HE TECHNIQUES

A. HISTOGRAM

The histogram of a digital image with intensity levels in the range $[0, L-1]$ is a discrete function given by

$$h(r_k) = n_k \quad (1)$$

where r_k is the k th intensity value and n_k is the number of pixels in the image with intensity r_k . In other words the histogram of an image represents the relative frequency of occurrence of the various grey level in the image.

B. NORMALIZED HISTOGRAM

The normalized histogram gives the probability of occurrence of intensity level r_k in an image and it is given by

$$p(r_k) = n_k / MN \quad (2)$$

for $K = 0, 1, 2, \dots, L-1$. Where the product MN gives the total number of pixels in the image. The sum of all components of a normalized histogram is equal to 1.

C. NATURE OF HISTOGRAM

In the dark image the components of the histogram are concentrated on the low (dark) side of the intensity scale. Similarly, the component of the histogram of the light image are biased towards the high side of the intensity scale. An image with low contrast has a narrow histogram located typically towards the middle of the intensity scale. The components of the histogram of the high contrast image cover a wide range of the intensity scale. Thus an image whose pixels tend to occupy the entire range of the intensity levels and in addition tend to be distributed uniformly will have an appearance of high contrast and will exhibit a large variation of gray tones.

D. HISTOGRAM EQUALIZATION

Histogram equalization is the technique which is widely used to enhance low-contrast images, which makes the histogram of light intensities of pixels within an image as uniform as possible. In other word the HE is the process to spread out the grey levels in an image so that they are evenly distributed across their range.

Let we represent the histogram with a column vector $\mathbf{h}$ whose k th element h_k denotes the number of pixels with intensity k . Then the probability mass function (PMF) p_k of intensity k is given by

$$p_k = \frac{h_k}{\mathbf{1}^T \mathbf{h}} \quad (3)$$

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

$$c_k = \sum_{i=0}^k p_i \quad (4)$$

HE transforms the input pixel intensities to output pixel intensities to make the histogram of the output image as uniform as possible. Let x_k denotes the transformation function which maps the intensity k in the input image to intensity x_k in the output image. For HE the transformation function is obtain by multiplying the CDF (c_k) by the maximum intensity of the output image. For a b -bit image the maximum intensity is $(2^b - 1)$ and therefore the transformation function is given by

$$X_k = \lfloor (2^b - 1)c_k + 0.5 \rfloor \quad (5)$$

Here $2^b - 1$ is rounded of to the nearest integer since output intensities must be integer. Here we consider only 8-bit image therefore $2^b - 1 = 2^8 - 1 = 255$. We can combine equation (4) and (5) into a recurrence equation if we ignore the rounding-off operation in equation (5).

$$x_k - x_{k-1} = 255.p_k \quad \text{for } 1 \leq k \leq 255 \quad (6)$$

Considering the initial condition $x_0 = 255.p_0$. This can be written in vector notation as

$$\mathbf{D}\mathbf{x} = \bar{\mathbf{h}} \quad (7)$$

Where $\mathbf{D} \in \mathbb{R}^{256 \times 256}$ is the differential matrix.

$$\mathbf{D} = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 & 0 & 0 \\ -1 & 1 & 0 & \dots & 0 & 0 & 0 \\ 0 & -1 & 1 & \dots & 0 & 0 & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots & \vdots & \vdots \\ 0 & 0 & 0 & \dots & -1 & 1 & 0 \\ 0 & 0 & 0 & \dots & 0 & -1 & 1 \end{bmatrix} \quad (8)$$

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

$$\bar{\mathbf{h}} = \frac{255}{1^T \mathbf{h}} \mathbf{h} \quad (9)$$

E. HISTOGRAM MODIFICATION

HM is the technique which used the histogram information in an input image to obtain the transformation function [13], [14]. H.M [11], [12] modifies the input histogram before the HE procedure to reduce the extreme slopes in the transformation function. Let $\mathbf{m} = [m_0, m_1, m_2, \dots, m_{255}]^T$ represents the modified histogram. Then we perform the HE procedure with the modified histogram instead of the original histogram $\mathbf{h}$. Thus the HE in equation (8) can be performed with the modified histogram $\mathbf{m}$ as follows

$$\mathbf{D}\mathbf{x} = \bar{\mathbf{m}} \quad (10)$$

Where

$$\bar{\mathbf{m}} = \frac{255}{1^T \mathbf{m}} \mathbf{m} \quad (11)$$

IV. PROPOSED LHM ALGORITHM

The extreme slope or overstretching artifacts in the transformation function of the HE procedure can be avoided by reducing the large values of histogram bins before the HE procedure i.e the histogram must be modified before the HE procedure [22]. So to modify the histogram we proposed the logarithmic function which is monotonically increasing and has the capacity to reduce large values of histogram bin. We proposed the following logarithmic function to convert the input histogram value h_k to a histogram value m_k .

$$m_k = \frac{\log(h_k h_{\max} \cdot 10^{-\mu} + 1)}{\log(h_{\max}^2 \cdot 10^{-\mu} + 1)} \quad (12)$$

Where, $h_{\max}$ denotes the maximum element within the input histogram. The constant 1 is used here so that it prevents the logarithmic function from having a negative value. The parameter μ which is used in equation (5) controls the level of HM. When μ is large then $h_k \cdot h_{\max} \cdot 10^{-\mu}$ becomes small. Due to this large value of μ , the modified histogram m_k becomes almost linearly proportional to h_k . Since $\log(1+x) \cong x$ for small x . Thus the histogram is not strongly modified. When μ is small, then the value of $h_{\max} \cdot 10^{-\mu}$ is large then

$$\begin{aligned} \log(h_k \cdot h_{\max} \cdot 10^{-\mu} + 1) &\cong \log(h_k) + \log(h_{\max} \cdot 10^{-\mu}) \\ &\cong \log(h_{\max} \cdot 10^{-\mu}) \end{aligned} \quad (13)$$

Due to this, the modified histogram m_k becomes constant and it does not depends on h_k . Therefore the modified histogram becomes uniform. Therefore small value of μ gives strongly modified histogram which is uniform.

V. PROPOSED CONTRAST ENHANCEMENT POWER SAVING ALGORITHM

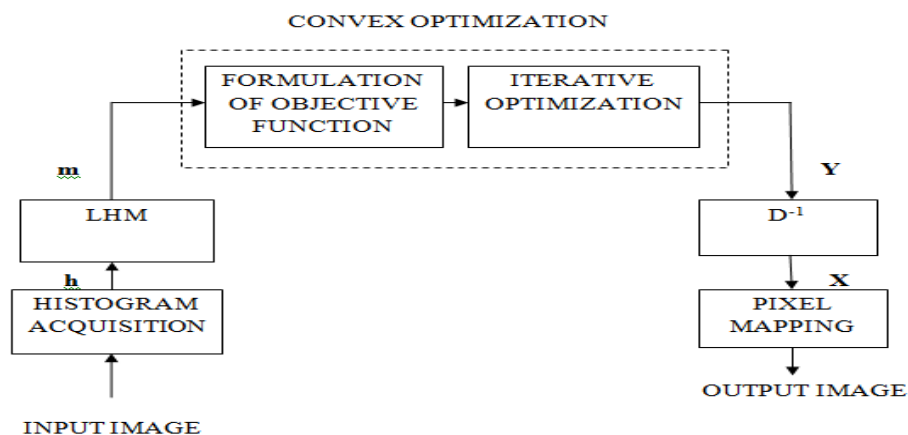


Fig. 1 Flow diagram of the proposed Algorithm

The overview of the proposed algorithm is shown in Fig. 1. As shown in Fig. 1 the first step of the proposed algorithm is acquisition of histogram information $\mathbf{h}$ from the input image and the second step is apply the LHM to $\mathbf{h}$ to obtain the modified histogram $\mathbf{m}$. Equation (8) $\mathbf{D}\mathbf{x} = \bar{\mathbf{m}}$ gives the transformation function $\mathbf{x}$ without the power constraint. So, to enhance the contrast and to save the power consumption we design the power model which consist of an objective

function. The objective function consist of the power saving term and contrast enhancement term. The objective function can be express in terms of variable $\mathbf{y} = \mathbf{D}\mathbf{x}$. We find the optimal $\mathbf{y}$ that minimizes the objective function based on the convex optimization theory [21]. Therefore we can construct the transformation $\mathbf{x}$ from $\mathbf{y}$ using $\mathbf{x} = \mathbf{D}^{-1}\mathbf{y}$ and use $\mathbf{x}$ to transform the input image to the output image.

A. PROPOSED POWER MODEL FOR EMISSIVE DISPLAY

To save the power and contrast enhancement simultaneously we proposed the power consumption model for emissive display. In [19], Dong *et al.* presented a pixel-level power model for an OLED module. They observed that power P to display a single-color pixel is modeled by

$$P = w_0 + w_r R^\gamma + w_g G^\gamma + w_b B^\gamma \quad (14)$$

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 $\gamma = 2.2$ [20]. In other words, after transforming the color values into luminous intensities in the linear RGB format, we obtain a linear relation between the power and the luminous intensities. Also w_0 , accounts for static power consumption, which is independent of pixel values, and w_r , w_g , and w_b are weighting coefficients that express the different elements of red, green, and blue subpixels.

A linear relation between the power and the luminous intensities can be obtain after transforming the color values into luminous intensities in the linear RGB format. So in order to save the power it is necessary to control the pixel intensities in a display panel so in this paper we alter the pixel values to save the power in a display panel. Here we ignore the parameter w_0 for static power consumption. Thus we model the total dissipated power (TDP) for displaying a color image by

$$TDP = \sum_{i=0}^{N-1} w_r R_i^\gamma + w_g G_i^\gamma + w_b B_i^\gamma \quad (15)$$

Here N represents the number of pixels in the image and (R_i, G_i, B_i) denotes the RGB color vector of the i th pixel. We model the TDP for gray scale image which is given by

$$TDP = \sum_{i=0}^{N-1} Y_i^\gamma \quad (16)$$

Where Y_i is the gray level of the i th pixel. With gray level k there are h_k pixels in the input image, and gray level x_k will assigned to these pixels in the output image by the transformation function. Thus, the TDP in (7) can be compactly written in vector notations as

$$TDP = \sum_{i=0}^{N-1} h_k x_k^\gamma = \mathbf{h}^t \boldsymbol{\varphi}^\gamma(\mathbf{x}) \quad (17)$$

Where $\boldsymbol{\varphi}^\gamma(\mathbf{x}) = [x_0^\gamma, x_1^\gamma, \dots, x_{L-1}^\gamma]^t$ and $\mathbf{h}$ is the histogram vector whose K th element is h_k .

B. POWER CONSTRAINED LHM

We save the power by incorporating the power model in (17) in LHM method. We now have to face two contradictory goals one is to enhance the contrast by equalizing the histogram and second one is to save the power consumption by reducing the histogram values for large intensities. We consider these goals as constrained optimization problem, i.e.,

$$\begin{aligned} &\text{minimize} && \|\mathbf{D}\mathbf{x} - \bar{\mathbf{m}}\|^2 + \alpha \mathbf{h}^t \boldsymbol{\varphi}^\gamma(\mathbf{x}) \\ &\text{subject to} && x_0 = 0, \\ & && x_{L-1} = L-1, \\ & && \mathbf{D}\mathbf{x} \geq 0 \end{aligned} \quad (18)$$

Now in the objective function $\|\mathbf{D}\mathbf{x} - \bar{\mathbf{m}}\|^2 + \alpha \mathbf{h}^t \boldsymbol{\varphi}^\gamma(\mathbf{x})$ there are two terms, the first term is $\|\mathbf{D}\mathbf{x} - \bar{\mathbf{m}}\|^2$ which is the histogram equalizing term in (10) and the second one is $\mathbf{h}^t \boldsymbol{\varphi}^\gamma(\mathbf{x})$ which is the power consumption term in (17). Thus in order to improve the contrast and reduce the power consumption simultaneously we minimize the sum of that two terms. Where α is a user controllable parameter because of which we can determine the balance between these two terms.

Now we have three constraints in our optimization problem (18). The first one is two equality constraints $x_0 = 0$ and $x_{L-1} = L-1$ and which states that the minimum and maximum intensities should be maintained without changes. The second one is inequality constraint $\mathbf{D}\mathbf{x} \geq 0$ and which indicates that the transformation function $\mathbf{x}$ should be monotonic.

C. SOLUTION TO THE OPTIMIZATION PROBLEM

By assuming that γ is any number greater than or equal to 1. Then, the power term $\mathbf{h}^t \varphi^\gamma(\mathbf{x})$ is a convex function of $\mathbf{x}$ and the problem in (18) becomes a convex optimization problem [21]. Based on the convex optimization theory we develop the power saving and contrast enhancement algorithm to yield the optimal solution to the problem. From (18) x_0 is fixed to 0 and therefore it is not a variable. Thus the transformation function becomes as $\mathbf{X} = [x_1, x_2, \dots, x_{L-1}]^t$. Similarly the dimensions of $\bar{\mathbf{m}}$, $\mathbf{h}$, and $\varphi^\gamma(\mathbf{x})$ are reduced to $L-1$ by removing the first elements respectively and $\mathbf{D}$ size reduced to $(L-1)$ by $(L-1)$ after removing the first row and the first column. Therefore the optimization problem can be reformulated by changing the variable $\mathbf{y} = \mathbf{D}^{-1}\mathbf{x}$. Here the new variable $\mathbf{y}$ has the elements y_k where $y_k = x_k - x_{k-1}$. Thus $\mathbf{y}$ is called the differential vector. Then $\mathbf{x} = \mathbf{D}^{-1}\mathbf{y}$, where

$$\mathbf{D}^{-1} = \begin{bmatrix} 1 & 0 & \dots & 0 & 0 \\ 1 & 1 & & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 1 & 1 & \dots & 1 & 0 \\ 1 & 1 & & 1 & 1 \end{bmatrix} \in \mathbb{R}^{(L-1) \times (L-1)} \quad (19)$$

By substituting $\mathbf{x} = \mathbf{D}^{-1}\mathbf{y}$ and expressing the maximum value constraint in terms of $\mathbf{y}$, equation (18) can be reformulated as

$$\begin{aligned} & \text{minimize } \|\mathbf{y} - \bar{\mathbf{m}}\|^2 + \alpha \mathbf{h}^t \varphi^\gamma(\mathbf{D}^{-1}\mathbf{y}) \\ & \text{subject to } 1^t \mathbf{y} = L-1, \\ & \mathbf{y} \geq 0 \end{aligned} \quad (20)$$

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

$$\mathbf{J}(\mathbf{y}, \mathbf{v}, \boldsymbol{\lambda}) = \|\mathbf{y} - \bar{\mathbf{m}}\|^2 + \alpha \mathbf{h}^t \varphi^\gamma(\mathbf{D}^{-1}\mathbf{y}) + v(1^t \mathbf{y} - (L-1)) - \boldsymbol{\lambda}^t \mathbf{y} \quad (21)$$

Where $v \in \mathbb{R}$ and $\boldsymbol{\lambda} = [\lambda_1, \lambda_2, \dots, \lambda_{L-1}] \in \mathbb{R}^{L-1}$ are lagrangian multipliers for the constraints. Thus the output $\mathbf{y}$ can be obtained by solving Karush-Kuhn-Tucker conditions [21], i.e.,

$$1^t \mathbf{y} = L-1 \quad (22)$$

$$\mathbf{y} \geq 0 \quad (23)$$

$$\boldsymbol{\lambda} \geq 0 \quad (24)$$

$$\boldsymbol{\Lambda} \mathbf{y} = 0 \quad (25)$$

$$2(\mathbf{y} - \bar{\mathbf{m}}) + \alpha \gamma \mathbf{D}^{-1} \mathbf{H} \varphi^{\gamma-1}(\mathbf{D}^{-1}\mathbf{y}) + v \mathbf{1} - \boldsymbol{\lambda} = 0 \quad (26)$$

Where $\boldsymbol{\Lambda} = \text{diag}(\boldsymbol{\lambda})$ and $\mathbf{H} = \text{diag}(\mathbf{h})$.

After the expansion of the vector notation in (26) we get a system of linear equations and by subtracting the i th equation from the $(i+1)$ th equation we can remove v . Therefore we get a recursive system i.e.,

$$y_{i+1} = y_i + \overline{m_{i+1}} - \overline{m_i} + \frac{\alpha \gamma}{2} h_i (\sum_{k=1}^i y_k)^{\gamma-1} + \frac{\lambda_{i+1} - \lambda_i}{2} \quad (27)$$

For $1 \leq i \leq L-2$

Each y_i is a monotonically increasing function of z , given by $y_i = g_i(z)$. z satisfies the maximum-value constraint in (22). Now we form a function i.e.,

$$f(z) = 1^t \mathbf{y} - (L-1) = \sum_{i=1}^{L-1} g_i(z) - (L-1) \quad (28)$$

The solution is $f(z) = 0$. Since $f(z)$ is a monotonically increasing, and therefore there exist a unique solution to $f(z) = 0$. Here we used the secant method [18] to find the unique solution iteratively. Let $z^{(n)}$ denotes the value of z at the n th iteration.

By apply the secant formula, i.e.,

$$z^{(n)} = z^{(n-1)} - \frac{z^{(n-1)} - z^{(n-2)}}{f(z^{(n-1)}) - f(z^{(n-2)})} f(z^{(n-1)}) \quad (29)$$

Where $n=2,3,4,\dots$

Iteratively until the convergence, we obtain the solution z . From z we can compute all elements in $\mathbf{y}$ since $y_i = g_i(z)$. Therefore, the transformation function $\mathbf{x} = \mathbf{D}^{-1}\mathbf{y}$ is the optimal solution to the original problem in (18) and therefore it enhances the contrast and saves the power consumption simultaneously subject to the minimum- value, maximum-

value, and monotonic constraints. The average luminance value of the input image is proportional to the power term. We can compensate the unbalance between the two terms by dividing the power term by the image resolution and the average luminance value. We can change the variable by

$$\beta = \alpha \sum_{i=0}^{N-1} Y_{input,i} \quad (30)$$

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

VI EXPERIMENTAL RESULT

The modified histogram equation which is given by Equation (12) gives the following result. Fig. 2 shows the input image and Fig. 3 plots the histogram of the input image. Fig. 4 to Fig. 6 plots the modified histogram for various μ values. Here we observed that the LHM reduces large values in the input histogram when μ becomes smaller and therefore the histogram is strongly modified when μ becomes smaller. We see that LHM reduces the large peak of the input histogram and thus relaxes the steep slope in the transformation function of the conventional HE algorithm. Fig. 7 shows the equalized image. Fig. 8 to Fig. 10 shows the output image for various μ value. From Fig. 4 to Fig. 6 it is observed that LHM modifies the input histogram more strongly as μ becomes smaller. When μ becomes smaller the transformation function gets closer to the identity function. Hence, by controlling the single parameter μ the LHM can obtain the transformation function which varies between the identity function and the conventional HE transformation function.



Fig.2 Input image

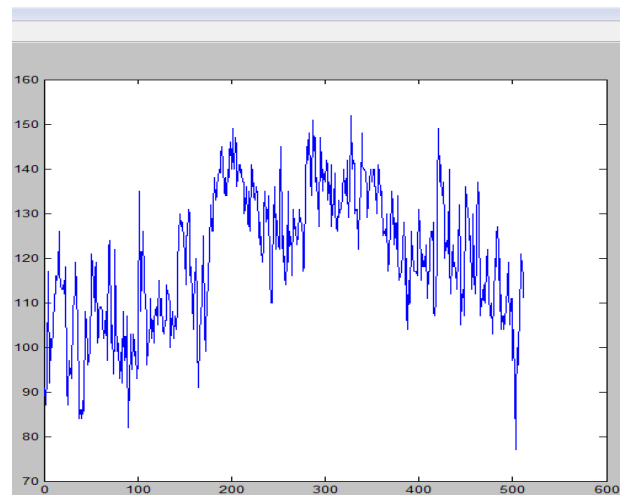


Fig.3 Histogram of the Input Image

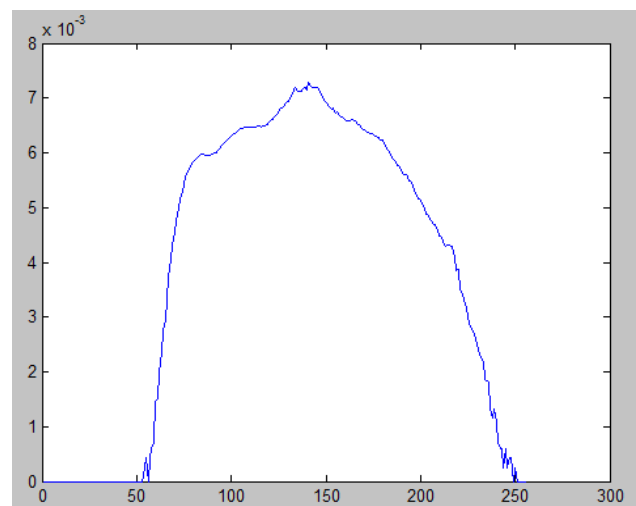
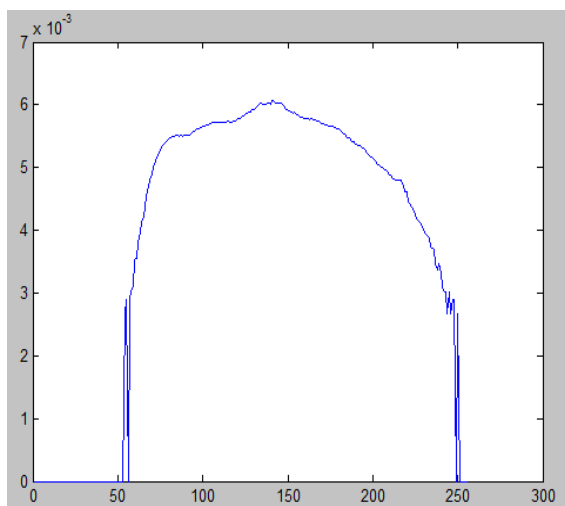


Fig.4 Modified Histogram($\mu = 1$)

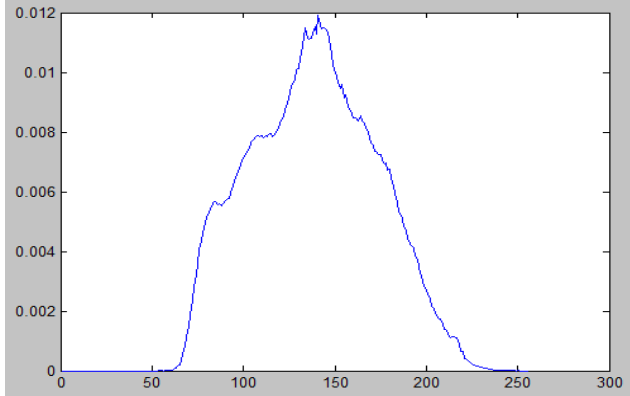


Fig.5 Modified Histogram($\mu = 5$)



Fig.6 Output Image($\mu = 8$)

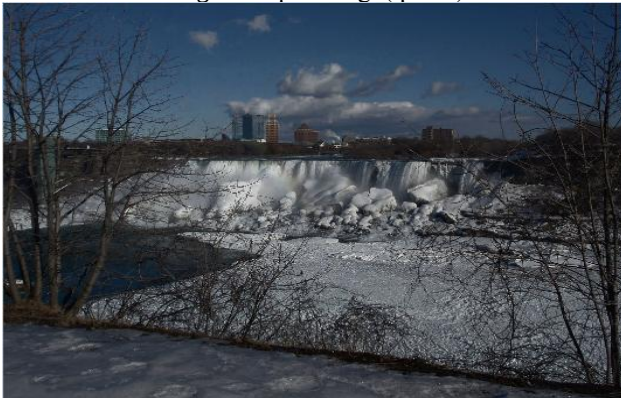


Fig.7 Equalized Image

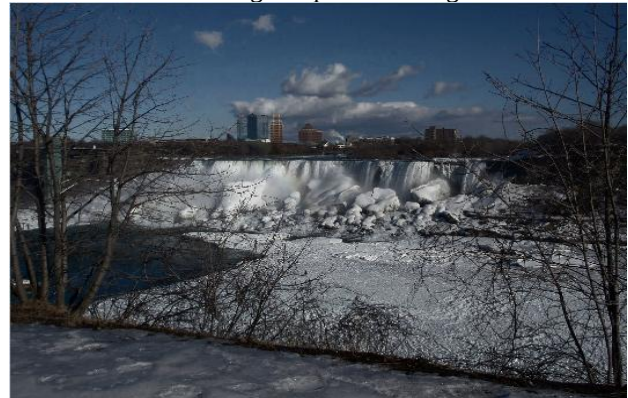


Fig.8 Output Image($\mu = 1$)



Fig.9 Output Image($\mu = 5$)

Fig.10 Output Image($\mu = 8$)

Fig. 11 to Fig. 14 shows the output of the proposed Power Saving Contrast Enhancement algorithm at various β values. Fig. 2 is taken as the input image. A bigger β saves more power. When $\beta=0$, the power term is not considered. As we increase the value of β the overall brightness of the output images decreases, but the contrast of the image is preserved. β must be high value for a brighter image to save more power. For dark image β must be less than 2 for the proposed algorithm results in a good image quality. Therefore the proposed algorithm reduces the power consumption as well as improves the overall contrast.



Fig.11 Output Image ($\beta=0$)



Fig.12 Output Image ($\beta=2$)



Fig.13 Output Image ($\beta=4$)



Fig.14 Output Image ($\beta=7$)

VII. CONCLUSION

We have proposed the Power Saving Contrast Enhancement 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 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, 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 [10] and [11], which process an input image adaptively based on local characteristics.

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