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Contrast Improvement on Various Gray Scale Images Together With Gaussian Filter and Histogram Equalization

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Abstract
This paper proposes a new contrast enhancement technique Modified Weighted Sub Range Histogram Equalization (MWSRHE) that applies smoothing and modified weighing technique on Histogram Equalization (HE). The core idea of this method is, first smoothens the input histogram using Gaussian filter for removing noises. Next, it partitions the input image in spatial domain into several sub-histograms based on the smoothed intensity values. Then, it modifies these sub histograms by means of a weighing process. Finally, HE process is applied independently to these sub histograms. The output transformation function is based on the intensity value of the surrounding pixels. This will improve the contrast within the objects of an image. Our results from various test images show that this method outperforms existing methods. MWSRHE preserves the original brightness, produces images with better contrast enhancement and sharpens the edges of an image.

Keywords
Histogram Equalization, Contrast Enhancement, Brightness Preservation, Histogram Weighing.

I. Introduction

HE based contrast enhancement is achieved through the redistribution of intensity values. The resultant contrast enhanced image provides feature extraction in computer vision system. Histogram modification based techniques are the most popular techniques to achieve better contrast enhancement [1].

HE is one of the commonly used algorithms for image enhancement due to its simplicity and effectiveness. It remaps the gray levels based on the probability distribution of the input gray levels. It flattens and stretches the dynamic range of the images histogram and resulting in overall contrast improvement. HE has been applied in various fields such as medical image processing, speech recognition and satellite image processing [2-3].

But, HE is not being recommended to be used in consumer electronics such as TV because it may significantly change the brightness of an input image and cause undesirable artifacts such as saturation artifact and washed out appearance. This is not a desirable property in some applications where brightness preservation is necessary. Kim [4] has proposed a method known as Brightness Preserving Bi Histogram Equalization (BBHE) to overcome the above mentioned problems. BBHE separates the input image's histogram into two based on its mean value. These sub histograms are then equalized independently. This technique is capable to preserve the original brightness to a certain extent. Y. Wan et al. [5] proposed a method called equal area Dualistic Sub Image Histogram Equalization (DSIHE) which is an extension of BBHE. DSIHE differs from BBHE only in the segmentation process. The input image is segmented into two, based on median rather than mean. S.D. Chen et al. [6] proposed a method called Recursive Mean Separate Histogram Equalization (RMSHE) in which histogram of the given image is partitioned based on mean recursively.

S.D.Chen and A.R.Ramli [7] proposed a method called Minimum Mean Brightness Error Bi Histogram Equalization (MMBEBHE) is an extension of BBHE which performs the separation based on the threshold level, which would yield minimum difference between input and output mean called Absolute Mean Brightness Error (AMBE). It is also not free from side effects. K.S. Sim et al. [8] generalized DSIHE into Recursive Sub Image Histogram Equalization (RSIHE). Median based histogram segmentation takes place only once in DSIHE but occurs many times in RSIHE.

In Weighted Thresholded Histogram Equalization (WTHE) [9], the probability distribution function (histogram) of an image is modified by weighing and thresholding before the HE is performed. Kim and M.G.Chung [10] proposed a method known as Recursively Separated and Weighted Histogram Equalization (RSWHE). RSWHE consists of image segmentation module, histogram weighing module and HE module. But this method fails to preserve the spatial relationship among the pixels and it is difficult to find the optimal value of recursion level 'r'. Haidi Ibrahim and N.S.P. Kong [11] proposed a method called Image Sharpening using Sub Regions Histogram Equalization in which a Gaussian filter is used to smoothen the image pixel intensity values.

In this paper, we proposed a novel HE based method known as MWSRHE to enhance the image contrast and sharpen the edges of an image. At the same time, this method preserves the original brightness of the image. Specifically, MWSRHE consists of four modules: First, it smoothens the intensity values of the input histogram using Gaussian filter for removing noises. Secondly, it partitions the input image, in spatial domain, into several sub-images, based on the smoothened intensity values. By doing this, spatial relationship among the pixels is taken into consideration for the transformation. Third, Histogram weighing module changes the intensity values of sub histograms through a weighing process. Finally, HE module equalizes the weighted sub-histograms independently.

In Section II, the traditional HE and recently proposed HE based methods are analyzed. Section III presents the proposed method MWSRHE. The experimental results are discussed in Section IV and conclusion is given in Section V.

II. Review of HE Methods

This section covers the details regarding HE and it is basically a reprint of [4-6] and [8].

A. Traditional HE

Consider the input image X with a total number of 'n' pixels in the gray level range $[Y_o, Y_{L-1}]$. The probability density function $P(X_k)$ for the level 'X_k' is defined as

$$P(X_k) = n_k / n \quad (1)$$

where 'n_k' represents the number of times that the level 'X_k' appears in the input image X and 'n' is the total number of samples in the input image. $P(X_k)$ is associated with the histogram of the input image which represents the number of pixels that have a specific intensity 'X_k'. Based on (1), the cumulative density function is calculated as

$$c(X) = \sum_{j=0}^{k} P(X_j) \tag{2}$$

HE maps the input image into the entire dynamic range, (Y_0, Y_{L-1}) by using the cumulative density function as a transform function. The transformation function f(X) based on the cumulative density function is defined as

$$f(X) = X_0 + (X_{L-1} - X_0)\, c(X) \tag{3}$$

Then the output image of the HE, Y= {Y (i, j)}, can be expressed as

$$Y = f(X) \tag{4}$$

$$= \{f(X(i,j)) \mid \forall X(i,j) \in X\} \tag{5}$$

The high performance of the HE in enhancing the contrast of an image is a consequence of the dynamic range expansion. HE also flattens a histogram. HE can introduce a significant change in brightness of an image, which is not suitable for the direct application of HE technique in consumer electronics.

B. BBHE

BBHE first decomposes the input histogram H(X) into two sub-histograms HL (X) and H_U (X) by using the input mean X_m, where H_L (X) is associated with the gray levels $\{X_0, X_1, \cdots, X_m\}$ and H_U (X) is associated with the gray levels $\{X_{m+1}, X_{m+2}, \cdots, X_{L-1}\}$. Then it performs conventional HE on HL(X) and HU(X) independently.

C. DSIHE

DSIHE is similar to BBHE, except that the threshold for histogram segmentation is the median X_D of the input image. That is, the input histogram H(X) is partitioned into two sub-histograms H_L (X) and H_U (X) not by the input mean X_m, but by the input median X_D. Each of H_L (X) and H_U (X) is then equalized independently as in BBHE.

D. RMSHE

RMSHE is a recursive version of BBHE. Unlike BBHE which decomposes the input histogram only once, RMSHE decomposes it recursively up to a recursion level 'r', generating '2^r' sub histograms. The resultant sub histograms are then equalized individually. When r=0, no decomposition occurs. This is equivalent to conventional H_E. When r = 1, the input histogram H(X) is decomposed into two sub-histograms $H_L(X)$ and $H_U(X)$ based on the input mean Xm .This case is the same as BBHE. When r = 2, H_L (X) is divided further into $H_{LL}(X)$ and $H_{LU}(X)$ based on a new mean X_{ml}, and $H_U(X)$ is also divided further into H_{UL} (X) and H_{UU} (X) based on another new mean X_{mu}. Here, X_{ml} is the mean of the sub-histogram $H_L(X)$, whereas X_{mu} is the mean of the sub-histogram $H_U(X)$. Similar procedures can be carried out when 'r' is greater than 2. The recursion level 'r' increases, the mean of the output image come nearer to the input mean Xm.

E. RSIHE

RSIHE is having same characteristics as RMSHE in equalizing an input image, except that RSIHE chooses to separate the histogram based on gray level with cumulative probability density equal to 0.5, whereas RMSHE uses mean separation approach. This method is proved to have slight upper hand when compared with RMSHE. But, the fact is that as the recursion level increases, the computational complexity is also increasing and the result is very similar to that of the original image. Finding an optimal recursion level with respect to images is a difficult task for all such methods.

III. MWSRHE (Modified Weighted Sub Range Histogram Equalization)

This section gives a detailed description of our proposed method MWSRHE. The existing HE based methods do not modify an input histogram at all. But, MWSRHE changes the input histogram before running into the equalization procedure. This is the fundamental difference between the previous methods and the proposed method. MWSRHE consists of four modules namely preprocessing module, segmentation module, histogram weighing module and a HE module.

The importance of the Histogram Weighing module is described below. The transformation function f(X) in (3) computes an output gray level for a given input gray level Xk. If some gray levels are observed in the image with high probabilities, large dynamic range is allocated to those gray levels. Hence, the gray levels with high probabilities are over enhanced whereas the image with low probabilities are less enhanced, which results in losing important information contained in the image. To overcome the above limitations in existing HE based methods, MWSRHE introduces Histogram Weighing module in which original PDF values are modified with weighted PDF before running into the Histogram Equalization module. The detailed description of four modules is given below.

A. Preprocessing Module

This module smoothens the input histogram using Gaussian filter for removing noises. Gaussian filter is a low-pass filter and it is used to smooth the input image through a two dimension (2D) convolution operator. So, the high frequency components of the image are reduced. Coefficients for a (2D) Gaussian filter are calculated by using the following equation:

$$G(i,j) = \frac{1}{\sqrt{2\pi\sigma}} \exp\left(-\frac{i^2 + j^2}{2\sigma^2}\right) \tag{6}$$

where (i,j) are the coordinates relative to the center of the filter and sigma is the standard deviation. After all the coefficients of the Gaussian filter have been calculated, these values need to be normalized such that the sum of the coefficients must be equal to one.

B. Segmentation Module

In this module, the input image is divided into several sub images based on the smoothened intensity values obtained from the convolution with Gaussian filter. As a low-pass filter, Gaussian filter reduces the high frequency components of the image, leaving the low frequency components, which are normally the base of the objects in the image. Thus, by grouping the pixels based on this smoothened value is analogous to group the pixels into their corresponding objects. Because of this, the intra object contrasts could be increased. If the input image has 'L' gray levels, then it is divided into 'L' sub images.

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C. Histogram Weighing Module

This module modifies the probability distribution function of the sub images as follows:

1. Compute both highest probability P_u and the lowest probability P_l by using (7) and (8).

$P_u = \max_{0 \le k \le L-1} P(k)$ (7)

$P_l = \min_{0 \le k \le L-1} P(k)$ (8)

2. For each sub histogram, compute an accumulative probability value α_i by using (9). Note that the sum of all α_i's equal to 1.

$$\alpha_i = \sum_{k=l_i}^{u_i} p(k) \quad (9)$$

3. For each sub histogram, change the original PDF P(k) into weighted PDF $P_w(k)$ by using pre computed values of (10)

$$P_w(k) = \begin{cases} P_u & \text{if } P(k) > P_u \\ \left(\dfrac{P(k) - P_l}{P_u - P_l}\right)^r * P_u & \text{if } P_l \le P(k) \le P_u \\ 0 & \text{if } P(K) < P_l \end{cases} \quad (10)$$

The modified PDF values $P_w(k)$ need to be normalized since the sum of all weighted PDF values $P_w(k)$ from k=0 to L-1 is no longer one. The normalization procedure is done by using (11). The resultant weighted and normalized PDF, called $P_{wn}(k)$, is then forwarded to HE module.

$$P_w(k) = P_w(k) \Big/ \sum_{j=0}^{L-1} P_w(j) \quad (11)$$

D. Histogram Equalization Module

This module separately equalizes each of all sub histograms using (1), (2) and (3). The combination of all resultant sub images now becomes the final output image.

The proposed algorithm for MWSRHE is given below.

1. Input the image, X(i, j) with a total number of 'n' pixels in the gray level range $[Y_0, Y_{L-1}]$
2. In the preprocessing module, apply Gaussian filter to smoothen the given input image using (6)
3. In the Segmentation module, the input image is divided into several sub images based on the smoothened intensity values obtained from the convolution with Gaussian filter.
4. In the histogram weighing module,
(a) Compute the Probability Density Function P(k) for the individual pixels of the sub image using (1).
(b) Compute the maximum probability 'P_u' and minimum probability 'P_l' using (7) and (8)
(c) Modify the PDF value P(k) into weighted PDF $P_w(k)$ using (10)
(d) Modified PDF needs to be normalized using (11)
5. In the HE module,
(a). Compute cumulative density function C(X) using (2).
(b). Map the input gray level to the output gray level (level mapping) using transformation function defined in (3).

IV. Experimental Results

The performance of the newly developed method, MWSRHE was tested on standard images cameraman, blood1, and rice. All of these images are with size of 512 X 512 pixels. To compare the performance of MWSRHE, the same images are enhanced with the contemporary enhancement techniques GHE, RSIHE and RSWHE. For all these methods, the performance is measured qualitatively in terms of human visual perception and quantitatively by using the two widely used metrics such as Peak Signal-to-Noise Ratio (PSNR) and Absolute Mean Brightness Error (AMBE). AMBE provides a sense of how the image global appearance has been changed. Lower the AMBE values gives better enhancement. If the output image is found to have higher PSNR value, then the image is said to have improved contrast after the application of enhancement procedure.

Table 1. PSNR Values of Different HE Methods

	Cameraman	Rice	Blood1
HE	19.2229	15.8968	18.4925
RSIHE	18.2849	18.3510	17.4524
RSWHE	34.3825	26.2449	31.5820
MWSRHE	35.2143	28.8961	34.4483

Table 2. AMBE Values of Different HE Methods

	Cameraman	Rice	Blood1
HE	8.7349	18.7677	2.4138
RSIHE	13.5336	9.1875	27.6832
RSWHE	3.7731	7.0133	5.3022
MWSRHE	2.9765	6.5461	2.0127

The original Rice image and its histogram are given in fig. 1(a). The enhanced images of the same by GHE, RSIHE and RSWHE are shown in fig. 1(b) to 1(d) respectively. It is evident from the visual comparison that RSIHE exhibits better performance than GHE due to its partition based enhancement. Moreover, it is apparent from fig. 1(c) and 1(d) that RSIHE and RSWHE introduce unwanted artifacts in the enhanced image. It is noted that MWSRHE shows better results in terms of visual perception, PSNR and AMBE values when compared to those of GHE, RSIHE and RSWHE. The contrast of the enhanced image is found to increase progressively. It is noted that the subsequent increase in the contrast has not introduced any artifacts in the enhanced image. In addition, a clear distinction is noted when we compare the histogram pattern of existing methods with MWSRHE. Similarly, MWSRHE is found to produce better results for other images such as cameraman in terms of visual perception, compared to other methods as shown in fig. 2(a) to 2(e). The PSNR values obtained for these images are given in Table 1 and the AMBE values are furnished in Table 2.

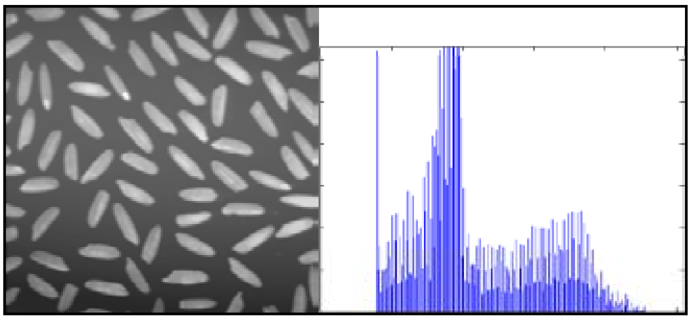

Fig. 1(a) Original Rice Image and its Histogram

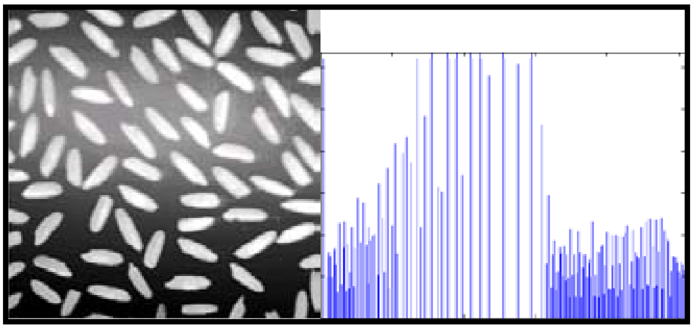

Fig. 1(b) Result of GHE & its histogram

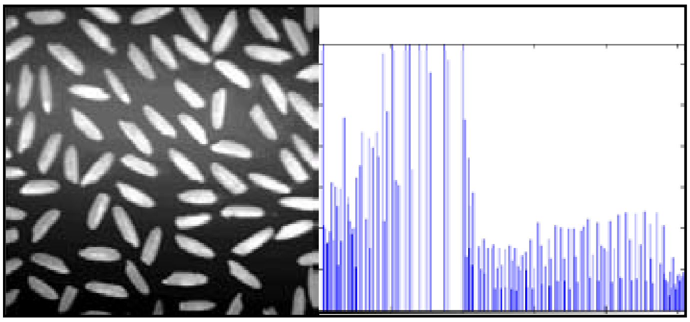

Fig.1(c) Result of RSIHE and its histogram

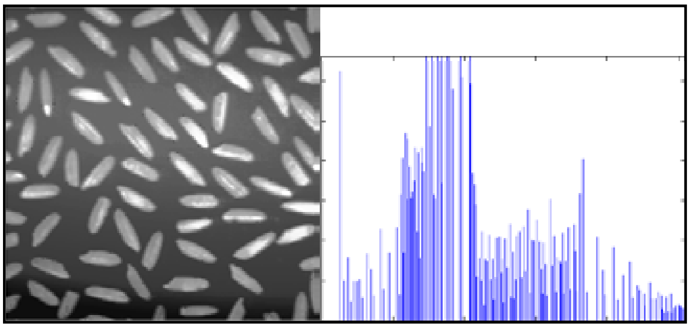

Fig. 1(d) Result of RSWHE and its histogram

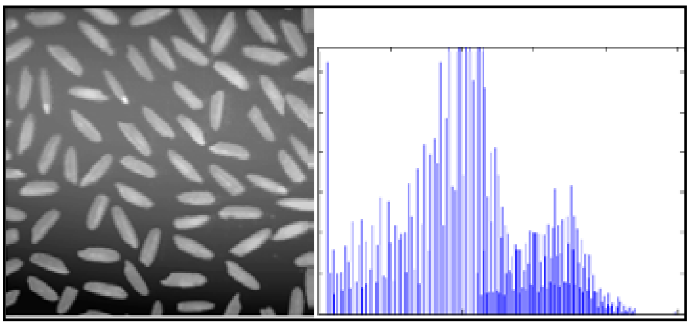

Fig. 1(e) Result of MWSRHE and its histogram

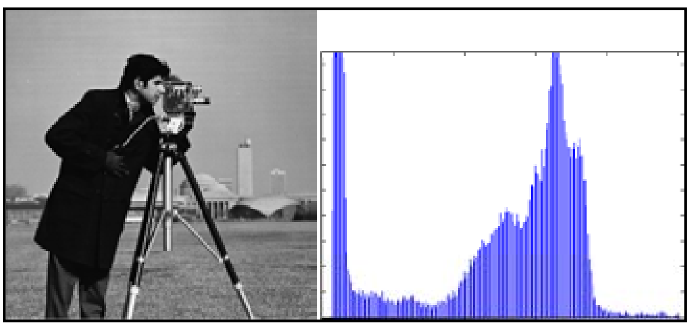

Fig. 2(a) Original cameraman Image and its Histogram

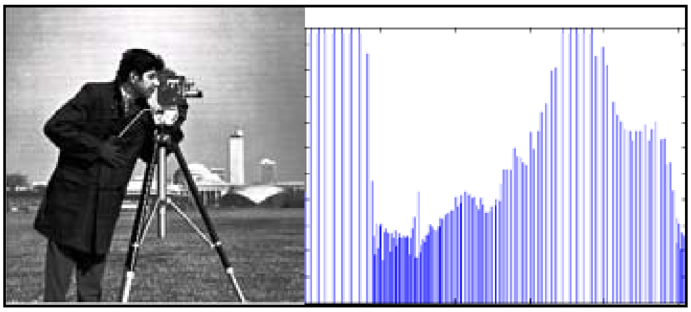

Fig. 2(b) Result of GHE & its histogram

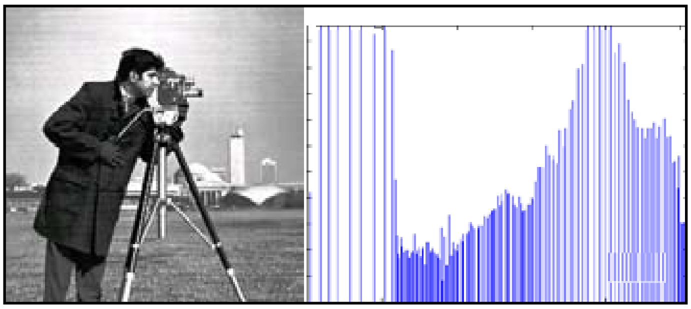

Fig2(c) Result of RSIHE and its histogram

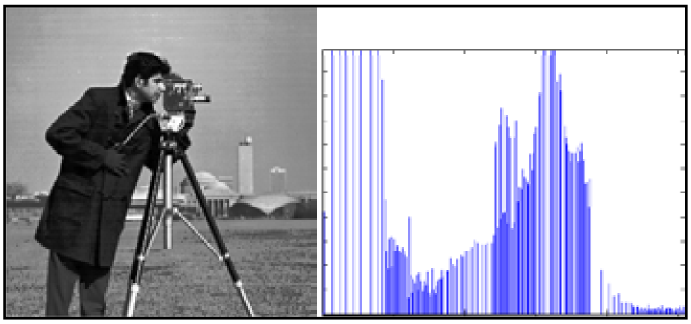

Fig. 2(d) Result of RSWHE and its histogram

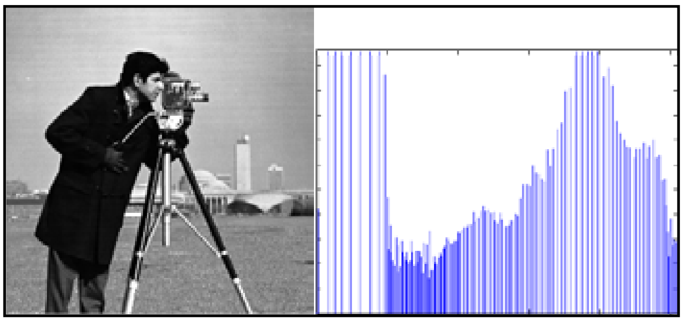

Fig. 2(e) Result of MWSRHE and its histogram

V. Conclusion

The experimental results show that the proposed method, named MWSRHE is able to achieve visually pleasant enhancement effects. The over enhancement and level saturation artifacts are eliminated. MWSRHE is designed to achieve the goals such as preserve the image brightness, enhance the image contrast and sharpen the edges of the image as well. MWSRHE is composed of four different modules: First, it smoothens the intensity values of the input histogram using Gaussian filter for removing noises. Secondly, it partitions the input image, in spatial domain, into several sub-images, based on the smoothed intensity values. By doing this, spatial relationship among the pixels is also taken into consideration for the transformation. Third, histogram weighing module changes the sub histograms through a weighing process

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based on a normalized power law function. Finally, HE module equalizes the weighted sub-histograms independently. Compared with many other global HE based enhancement methods, images enhanced using the MWSRHE method shows well enhanced contrast with very less artifacts.

In practice, the proposed MWSRHE method is computationally simple and suitable for processor based implementation.

V. References

[1] Rafael C. Gonzalez and Richard E. Woods, "Digital image processing", 2nd edition, Prentice Hall, 2002.

[2] Anil K. Jain, "Fundamentals of Digital Image Processing" Englewood Cliffs, NJ, Prentice Hall, 2004

[3] J. Zimmerman, S. Pizer, E. Staab, E. Perry, W. McCartney, and B. Brenton, "Evaluation of the effectiveness of Adaptive Histogram Equalization for Contrast Enhancement," IEEE Trans. Medical Imaging, Vol. 15, issue 2 Nov. 1988 Page(s): 304 –312

[4] Y. T. Kim, "Contrast Enhancement using Brightness Preserving Bi Histogram Equalization," IEEE Trans. Consumer Electron., Volume 43, Issue 1. 1997 Page(s): 01 –08.

[5] Yu Wan, Qian Chen and Bao-Min Zhang., "Image Enhancement based on Equal Area Dualistic Sub Image Histogram Equalization Method", IEEE Trans. Consumer Electron., Volume 45, Issue 1, Feb. 1999 Page(s): 68 – 75.

[6] Soong-Der Chen, Ramli,A.R, "Contrast Enhancement using Recursive Mean Separate Histogram Equalization for Scalable Brightness Preservation" IEEE Trans. Consumer Electron., Volume 49, Issue 4, Nov. 2003 Page(s): 1301 – 1309.

[7] S. D. Chen, and A. R. Ramli, "Minimum Mean Brightness Error Bi Histogram Equalization in Contrast Enhancement " IEEE Trans. Consumer Electron., Volume 49, Issue 4, Nov. 2003 Page(s): 1310 – 1319.

[8] K. S. Sim, C. P. Tso, and Y, Y. Tan., "Recursive Sub-Image Histogram Equalization applied to gray-scale images" Pattern Recognition Letters, Volume 28, 2007 Page(s): 1209-1221

[9] Q. Wang and R. K. Ward, "Fast image/video Contrast Enhancement based on Weighted Thresholded Histogram Equalization" IEEE Trans. Consumer Electron., Volume 53, Issue 2, Nov. 2007 Page(s): 757 – 764.

[10] M. Kim and M. G. "Recursively Separated and Weighted Histogram Equalization for Brightness Preservation and Contrast Enhancement", IEEE Trans. Consumer Electron., Volume 54, Issue 3, Nov. 2008 Page(s): 1389-1397

[11] Haidi Ibrahim and N.S.P. Kong , "Image sharpening using Sub- Regions Histogram Equalization", IEEE Trans. Consumer Electron., Volume 55, Issue 2, Nov. 2009 Page(s): 891-895.