

Contrast Enhancement Using Bi-Histogram Equalization With Brightness Preservation

¹Gowthami Rajagopal, ²K.Santhi

¹PG Student, Department of Electronics and Communication
K S Rangasamy College Of Technology, TN, India

²Assistant Professor, Department of Electronics and Communication
K S Rangasamy College Of Technology, TN, India

Abstract— Contrast enhancement is an important factor in the image preprocessing step. One of the widely accepted contrast enhancement method is the histogram equalization. Although histogram equalization achieves comparatively better performance on almost all types of image, global histogram equalization sometimes produces excessive visual deterioration. A new extension of bi-histogram equalization called Bi-Histogram Equalization with Neighborhood Metric (BHENM). First, large histogram bins that cause washout artifacts are divided into sub-bins using neighborhood metrics, the same intensities of the original image are arranged by neighboring information. Then the histogram of the original image is separated into two sub-histogram based on the mean of the histogram of the original image; the sub-histogram are equalized independently using refined histogram equalization, which produces flatter histogram. BHENM simultaneously preserved the brightness and enhanced the local contrast of the original image. Simulation result shows better brightness preservation.

Keywords – Bi-Histogram Equalization, Contrast enhancement, Flat Histogram, Brightness Preservation.

I.INTRODUCTION

Contrast enhancement plays a crucial role in image processing applications, such as digital photography, medical image analysis, remote sensing, LCD display processing, and scientific visualization. There are several reasons for an image/video to have poor contrast: the poor quality of the used imaging device, lack of expertise of the operator and the adverse external conditions at the time of

acquisition. These effects result in under-utilization of the offered dynamic range. As a result, such images and videos may not reveal all the details in the captured scene and may have a washed-out and unnatural look. Contrast enhancement targets to eliminate these problems, thereby to obtain a more visually-pleasing or informative image or both.

Histogram equalization is a well-known contrast enhancement technique due to its performance on almost all types of image. Generally, histogram equalization can be categorized into two main processes: global histogram equalization (GHE) and local histogram equalization (LHE). In GHE, the histogram of the whole input image is used to compute a histogram transformation function. As a result, the dynamic range of the image histogram is flattened and stretched and the overall contrast is improved. The computational complexity of GHE is comparatively low, making GHE an attractive tool in many contrast-enhancement applications. The major drawbacks of GHE are that it cannot adapt the local information of the image and preserve the brightness of the original image. In contrast, LHE uses a sliding window method, in which local histograms are computed from the windowed neighborhood to produce a local intensities remapping for each pixel. The intensity of the pixel at the center of the neighborhood is changed according to the local intensity remapping for that pixel. LHE is capable of producing great contrast results but is sometimes thought to over-enhance images. It also requires more computation than other methods because a local histogram must be built and processed for every image pixel [1].

Brightness Preserving Bi-Histogram Equalization [2] (BBHE) method divides the image histogram into two parts. In this method, the separation intensity is represented by the input mean brightness value, which is the average

intensity of all pixels that construct the input image. After this separation process, these two histograms are independently equalized. So the mean brightness of the resultant image will lie between the input mean and the middle gray level. The basic ideas used by the BBHE method of decomposing the original image into two sub-images and then equalize the histograms of the sub-images separately, so called equal area dualistic sub-image HE (DSIHE) method [3]. Instead of decomposing the image based on its mean gray level, the DSIHE method decomposes the images aiming at the maximization of the Shannon's entropy of the output image. For that, the input image is decomposed into two sub-images, being one dark and one bright, respecting the equal area property. DSIHE method [4] does not present a significant shift in relation to the brightness of the input image, especially for the large area of the image with the same gray-levels. Minimum Mean Brightness Error Bi-Histogram Equalization [5] (MMBHE) method, partition the histogram of the original image into sub histograms and then independently equalize each sub histogram with GHE.MMBEBHE first tests all possible separating point values from image intensity range. The difference between the mean value of the original image's histogram and the mean values of the sub-histograms are calculated for every separating point. The separating point is then chosen to minimize the difference between the input and output means. Recursive sub-image histogram equalization [6] (RSIHE) chooses to separate the histogram based on gray level with cumulative probability density equal to 0.5. This method yields better image compensation and provide improving image quality. Brightness Preserving Weight Cluster Histogram Equalization assigns each nonzero bin of the original image's histogram to a separate cluster, and computes each cluster's weight. Then three criteria are used to merge pairs of neighboring clusters. The clusters acquire the same partitions as the resultant image histogram. The sub-histograms are then equalized independently. In doing so, they equalize some of the sub- images in their ranges toward the mean and others away from the mean, depending on their respective histograms. Thus the resulting equalized sub-images preserve the overall mean brightness. The main drawback of these methods is that they do not improve the local contrast of the image[7].

The rest of the paper is organized as follows; Section II the related work and Section III proposed methodology is discussed. Section IV presents the results and discussion for the proposed work and followed by conclusion.

II RELATED WORK

A. Histogram Equalization

Histogram Equalization is a technique that generates a gray map which changes the histogram of an image and redistributing all pixels values to be as close as possible to a user –specified desired histogram. HE allows for areas of lower local contrast to gain a higher contrast. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram. Histogram equalization is a method in image processing of contrast adjustment using the image histogram. This method usually increases the global contrast of many images, especially when the usable data of the image is represented by close contrast values. Through this adjustment, the intensities can be better distributed on the histogram. Histogram equalization accomplishes this by effectively spreading out the most frequent intensity values. Histogram equalization automatically determines a transformation function seeking to produce an output image with a uniform Histogram.

Let $X=\{X(i,j)\}$ denotes a image composed of L discrete gray levels denotes as

$$X = \{X_0, X_1, \dots, \dots, X_{L-1}\}$$

For a given Image X , the probability density function $p(X_K)$

$$p(X_K) = \frac{n^k}{n} \quad (1)$$

where $K=0,1,\dots,L-1$, n^k represents the number of times that the level X_K appeA in the input image X , 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 the probability density function, the cumulative density function is defined as

$$c(x) = \sum_{j=0}^k p(X_j) \quad (2)$$

where $X_K = x$ for $k=0,1,\dots,L-1$ and $c(X_{L-1}) = 1$ by definition.

HE is a scheme that maps the input image into the entire dynamic range (X_0, X_{L-1}) by using the cumulative density function as a transform function. A transform function $f(x)$ based on the cumulative density function defined as

$$f(x) = X_0 + (X_{L-1} - X_0)c(x) \quad (3)$$

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

$$Y = f(x)$$

$$= f\{X(i, j) / \forall X(i, j) \in X\} \quad (4)$$

Based on information theory, entropy of message source will get the maximum value when the message has uniform distribution property.

III PROPOSED METHODOLOGY

A. Bi-histogram equalization

In bi-histogram equalization the histogram of the original image is separated into two sub histograms based on the mean of the histogram of the original image, the sub-histograms are equalized independently using refined histogram equalization, which produces flatter histogram.

Let I_m be the mean of the image f and assume that $I_m \in \{0, L - 1\}$. Based on I_m , the image separated into two sub-images f_i and f_j as

$$f = f_i \cup f_j$$

$$f_i = \{f(x, y) | f(x, y) \leq I_m, \forall f(x, y) \in f\} \quad (5)$$

$$f_j = \{f(x, y) | f(x, y) > I_m, \forall f(x, y) \in f\} \quad (6)$$

The probability density function of sub-images f_i and f_j is defined as

$$p_i(I_k) = \frac{n_i^k}{n_i} \quad (7)$$

$$p_j(I_k) = \frac{n_j^k}{n_j} \quad (8)$$

in which n_i^k and n_j^k represent the respective values of I_k in the two sub-images f_i and f_j and n_i and n_j are the total values of f_i and f_j respectively. Here $n_i = \sum_{k=I_0}^{I_m} n_i^k$, $n_j = \sum_{k=I_{m+1}}^{I_{m-1}} n_j^k$ and $n = n_i + n_j$.

The respective CDFs are then defined as

$$P_i(I_k) = \sum_{k=0}^{I_m} p_i(I_k) \quad (9)$$

$$P_j(I_k) = \sum_{k=I_{m+1}}^{I_{m-1}} p_j(I_k) \quad (10)$$

where $P_i(I_k) = 1$ and $P_j(I_k) = 1$ by definition.

The transformation functions exploiting the CDFs

$$T_i(I_k) = I_0 + (I_m - I_0) \cdot P_i(I_k) \quad (11)$$

$$T_j(I_k) = I_{m+1} + (I_{L+1} - I_{m-1}) \cdot P_j(I_k) \quad (12)$$

Then the resultant image of the histogram can be expressed as

$$g(x, y) = T(f(x, y)) \quad (13)$$

B. Neighborhood Metrics

Neighborhood Metrics including the voting metric, inverted average metric, average metric and contrast difference metric[8]. The two new neighborhood metrics are contrast difference metric and distinction metric. Distinction metric is used to improve image local contrast and histogram flatness.

Distinction metric not only preserves the main ideas of the voting and contrast difference metrics but can divide one bin of a histogram into more sub-bins than those methods. When using the voting metric, one bin of a histogram divided into nine sub-bins. The contrast difference metric can divide one bin of a histogram into 27 sub-bins. But distinction metric can divide one bin into 2040 bins. Separating the bins into many bins will result in flat histogram in the resultant image[9].

Let γ be the function that extends an image function surrounded by a background of zero intensity in which an image is N pixels by M pixels in size and $g(x, y)$ is the intensity of an image pixel (x, y) .

$$\gamma(x, y) = \begin{cases} g(x, y), & (x, y) \in [0, N - 1] \times [0, M - 1] \\ 0, & \text{otherwise} \end{cases} \quad (14)$$

The distinction metric is expressed by the following formula

$$d_m(x, y) = \sum_{(x', y') \in R_m(x, y)} t(x, y, x', y') \quad (15)$$

which requires the following distinction function

$$t(x, y, x', y') = \begin{cases} \gamma(x, y) - \gamma(x', y'), & \gamma(x, y) > \gamma(x', y') \\ 0, & \text{otherwise} \end{cases} \quad (16)$$

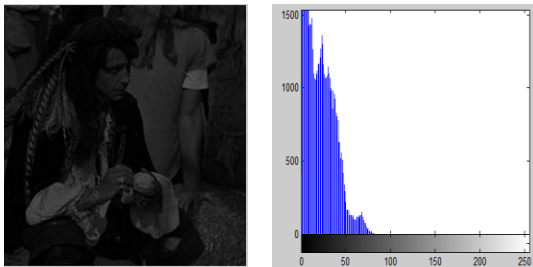
in which the distinction metric d_m is defined by $R_m(x, y)$ the set of pixels forming a square in the m by m square neighborhood centered on (x, y) and m is the positive odd integer.

The distinction metric which preserves the principle of the voting metric which uses only neighborhood pixels with intensities that is smaller than that of the current pixel. Contrast difference metric evaluates the difference in contrast between the current pixel and its neighborhood pixels. Hence it is easily to compute the minimum and maximum value, if the intensities of the current pixel and neighborhood pixels are equal to zero, the minimum value is zero and the maximum value is 2040.

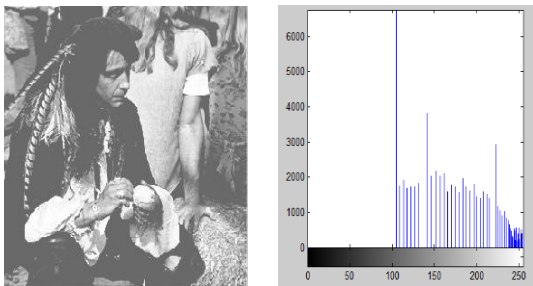
IV RESULT AND DISCUSSION

Input Image is a grayscale image and low contrast image. For the input image, Global Histogram Equalization (GHE) and Bi-Histogram Equalization with Neighborhood Metrics (BHENM) is performed. Then for the output image histogram flatness, contrast-per-pixel and mean brightness error is calculated. Experimental output for the following images as follows,

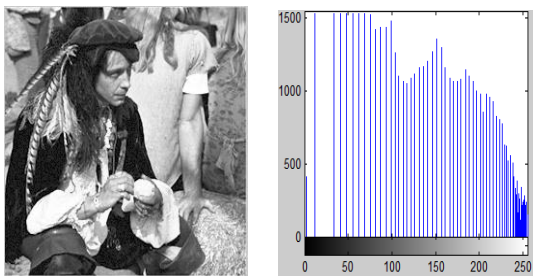
MAN IMAGE



(a) MAN image and its histogram



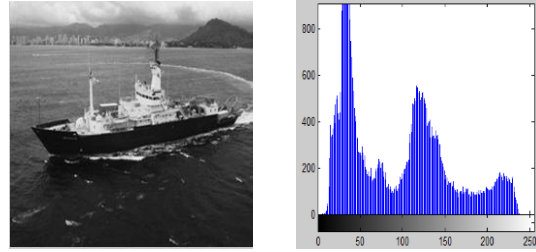
(b) Resultant image of GHE and its histogram



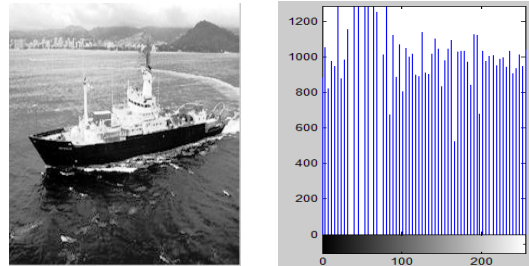
(c) Resultant image of BHENM and its histogram

Fig.1. Result of MAN Image: (a) original image and its histogram (b) Resultant image of GHE and its histogram (c) Resultant image of BHENM and its histogram.

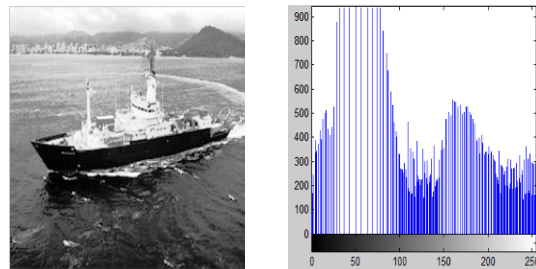
BOAT IMAGE



(a) original image and its histogram



(b) Resultant image of GHE and its histogram



(c) Resultant image of BHENM and its histogram

Fig.2. Result of BOAT Image: (a)original image and its histogram (b)Resultant image of GHE and its histogram (c)Resultant image of BHENM and its histogram.

V PARAMETER CALCULATION

A. Histogram Flatness

To measure the flatness σ of a histogram, we compute the variance of the bin sizes

$$\sigma = \frac{\sum_0^{D-1} (|h_i| - \mu_h)^2}{D} \tag{17}$$

where $|h_i|$ is the size of the i -th bin of the image histogram, μ_h is the mean histogram of the bin size and D is the number of image intensities.

B. Contrast-per-pixel

Contrast-per-pixel measures the average intensity difference between a pixel and its adjacent pixels. This value shows the local contrast of the image.

$$C = \frac{\sum_{i=0}^{N-1} \sum_{j=0}^{M-1} \left(\sum_{(m,n) \in R_3^{(i,j)}} |\gamma(i,j) - \gamma(m,n)| \right)}{M*N*8} \quad (18)$$

C. Average Absolute Mean Brightness Error(AAMBE)

$$AAMBE = \frac{1}{S} \sum_{n=1}^S |\tilde{X} - \tilde{Y}| \quad (19)$$

where S is the total number of sample images, \tilde{X} and \tilde{Y} are the average intensity of the original and resultant images respectively. If the resultant image preserves the original image brightness, AAMBE is low.

TABLE I

Histogram Flatness

METHOD	MAN	BOAT
ORIGINAL	5.34721	30.76589
GHE	1.03252	26.86987
BHENM	1.21321	26.90559

TABLE II

Contrast- Per- Pixel

METHOD	MAN	BOAT
ORIGINAL	18.35021	19.02569
GHE	24.62873	25.87334
BHENM	25.34236	27.32225

TABLE III

Mean Brightness Error

METHOD	MAN	BOAT
ORIGINAL	0.13050	0.10263
GHE	0.02515	0.01138
BHENM	0.00517	0.00866

VI CONCLUSION

A new method of histogram extension is Bi-Histogram Equalization with Neighborhood metrics in which image contrast and histogram flatness are simultaneously improved while the brightness of the original is preserved. Use of

distinction neighborhood metrics is to sort pixels of equal intensity into different bins to improve image local contrast and separate the histogram into sub-histogram and then equalizes them independently to preserve the image brightness.

VII REFERENCES

[1] R. C. Gonzalez, and R. E., Woods, Digital Image Processing, 2nd ed., Prentice Hall, 2002.

[2] Y.-T. Kim, "Contrast enhancement using brightness preserving bi-histogram equalization," IEEE Trans. Consum. Electron., vol. 43, no. 1, pp. 1–8, Feb. 1997.

[3] Y. Wang, Q. Chen, and B. Zhang, "Image enhancement based on equal area dualistic sub-image histogram equalization method," IEEE Trans. Consum. Electron., vol. 45, no. 1, pp. 68–75, Feb. 1999.

[4] H.Ibrahim and N.S.P Kong , " Brightness Preserving Dyanmic Histogram Equalization For Image Contrast Enhancement," IEEE Trans. Consum. Electron., vol. 53, no. 1, pp. 1752–1758, Nov. 2007.

[5] Chen and A. Ramli , "Minimum mean brightness error bi- histogram equalization in contrast enhancement," IEEE Trans. Consum.Electron., pp. 1310–1319Nov.2003.

[6] K. S. Sim, C. P. Tso, and Y. Y. Tan, "Recursive sub-image histogram equalization applied to gray scale images," Pattern Recognition Letters, vol. 28, no. 10, pp. 1209–1221,Nov. 2007.

[7] Nyamlkhagva Sengee, and Heung-Kook Choi, "Brightness Preserving Weight Clustering Histogram Equalization," IEEE Trans. Consumer Electron., vol.54, No.3, August 2008.

[8] M.Eramain and D.Mould , "Histogram Equalization using Neighborhood Metrics," Computer and Robot Vision, the 2nd Canadian Conference on,IEEE CNF, Proceedings, pp. 397-404,May.2005.

[9] Nyamlkhagva Sengee and Heung-Kook Choi, "Contrast Enhancement using Histogram Equalization with a Neighborhood Metrics," Journal Of Korean Multimedia Society, vol. 11, no. 6, pp. 737-745,Jun. 2008.

[10] Soong-Der Chen, and Abd. Rahman Ramli, "Minimum mean brightness error bi-histogram equalization in contrast enhancement", IEEE Trans.Consumer Electron., vol. 49, no. 4, pp. 1310-1319, Nov. 2003.

[11] Chao Wang and Zhongfu Ye, "Brightness preserving histogram equalization with maximum entropy: a variational perspective", IEEE Trans. Consumer Electron., vol. 51, no. 4, pp. 1326-1324, Nov. 2005.