Brightness Preserving Dynamic Fuzzy Histogram Equalization

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Abstract — *This paper proposes a novel modification of the brightness preserving dynamic histogram equalization technique to improve its brightness preserving and contrast enhancement abilities while reducing its computational complexity. The modified technique, called Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE[1]), uses fuzzy statistics of digital images for their representation and processing. Representation and processing of images in the fuzzy domain enables the technique to handle the inexactness of gray level values in a better way, resulting in improved performance. Execution time is dependent on image size and nature of the histogram, however experimental results show it to be faster as compared to the techniques compared here. The performance analysis of the BPDFHE along with that for BPDHE has been given for comparative evaluation.*

Index Terms — Fuzzy sets, image enhancement, image processing, video signal processing.

I. Introduction

Subjective contrast enhancement of an image is an important challenge in the field of digital image processing. Contrast enhancement produces an image that subjectively looks better than the original image by changing the pixel intensities. These techniques find application in areas ranging from consumer electronics, medical image processing to radar and sonar image processing.

Of the many techniques available for image contrast enhancement, the techniques that use first order statistics of digital images (image histogram) are very popular. Global Histogram Equalization (GHE) [1] is one such widely used technique. GHE is employed for its simplicity and good performance over variety of images. However, GHE introduces major changes in the image gray level when the spread of the histogram is not significant and cannot preserve the mean image-brightness which is critical to consumer electronics applications. To overcome this limitation, several brightness preserving histogram modification approaches, such as bi-histogram equalization (BBHE [2], MMBEBHE [3]), multi-histogram equalization (DHE [4], BPDHE [5]) and histogram specification (BPHEME [6]) have been proposed in literature.

Dynamic Histogram Equalization (DHE) [4] method, proposed by Abdullah-Al-Wadud, et al., partitions the global image histogram into multiple segments based positions of local minima, and then independently equalizes them. This technique claims of preserving the mean image brightness by this approach. However, this method has the limitation of remapping the peaks which leads to perceivable changes in mean image brightness. To avoid peak remapping, Ibrahim and Kong, in their Brightness Preserving Dynamic Histogram Equalization (BPDHE) [5] technique, use the concept of smoothing a global image histogram using Gaussian kernel followed by its segmentation of valley regions for their dynamic equalization.

These techniques process the crisp histograms of images to enhance contrast. The crisp statistics of digital images suffers from the inherent limitation that it does not take into account the inexactness of gray-values. Additionally, crisp histograms need smoothing to achieve useful partitioning for equalization.

Here we introduce a modification to BPDHE [5] technique with the use of *fuzzy statistics of digital images* (fuzzy histogram) [7]. Besides, the imprecision in gray levels is handled well by fuzzy statistics, fuzzy histogram, when computed with appropriate fuzzy membership function, does not have random fluctuations or missing intensity levels and is essentially smooth. This helps in obtaining its meaningful partitioning required for brightness preserving equalization. Experiments reveal that the use of fuzzy statistics has indeed improved performance of the algorithm.

Henceforth this modified technique is referred to as Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) technique. Section II discusses the BPDFHE technique in detail. Application of this technique to color images/video is discussed in the Section III. Experiments, conducted to evaluate qualitative performance, and computational requirement of the algorithm, and their results are discussed respectively in section IV.

II. Brightness Preserving Dynamic Fuzzy Histogram Equalization

In GHE the remapping of the histogram peaks (local maxima) takes place which leads to the introduction of undesirable artifacts and large change in mean image-brightness. The BPDFHE technique manipulates the image histogram in such a way that no remapping of the histogram peaks takes place, while only redistribution of the gray-level values in the valley portions between two consecutive peaks

This work is supported in part by Texas Instruments (I) Pvt. Ltd., Bangalore, INDIA.

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Contributed Paper
Manuscript received 09/01/10
Current version published 12/23/10
Electronic version published 12/30/10.

takes place. The BPDFHE technique consists of following operational stages:

A). Fuzzy Histogram Computation.
B). Partitioning of the Histogram.
C). Dynamic Histogram Equalization of the Partitions.
D). Normalization of the image brightness.

The following sub-sections contain the details of the steps involved.

A. Fuzzy Histogram Computation

A *fuzzy histogram* is a sequence of real numbers $h(i), i \in \{0,1,\cdots,L-1\}$ where $h(i)$ is the frequency of occurrence of gray levels that are "around i". By considering the gray value $I(x,y)$ as a fuzzy number $\widetilde{I}(x,y)$, the fuzzy histogram is computed as:

$$h(i) \leftarrow h(i) + \sum_x \sum_y \mu_{\widetilde{I}(x,y)i}, k \in [a,b] \tag{1}$$

where $\mu_{\widetilde{I}(x,y)i}$ is the triangular fuzzy membership function defined as

$$\mu_{\widetilde{I}(x,y)i} = \max\left(0, 1 - \frac{|I(x,y) - i|}{4}\right) \tag{2}$$

and $[a,b]$ is the support of the membership function.

Fuzzy statistics is able to handle the inexactness of gray values in a much better way compared to classical crisp histograms thus producing a smooth histogram. Thus the use of fuzzy histogram is suitable for this particular application.

B. Partitioning of the Histogram

The local maxima based partitioning of the histogram, to obtain multiple sub-histograms, is performed in this step. This way every valley portion between two consecutive local maxima forms a partition. When the dynamic equalization of these partitions is performed the peaks of the histogram do not get remapped and this results in better preservation of the mean image-brightness while increasing the contrast.

1) Detection of Local Maxima: The local maxima in the Fuzzy Histogram are located using the first and second derivative of the Fuzzy histogram. Since the histogram is a discrete data sequence, we use the central difference operator for approximating a discrete derivative (Eq. 3)

$$\overset{\circ}{h}(i) = \frac{dh(i)}{di} \triangleq \frac{h(i+1) - h(i-1)}{2} \tag{3}$$

where, $\overset{\circ}{h}(i)$ represents the first order derivative of the fuzzy histogram $h(i)$ corresponding to the i^{th} intensity level.

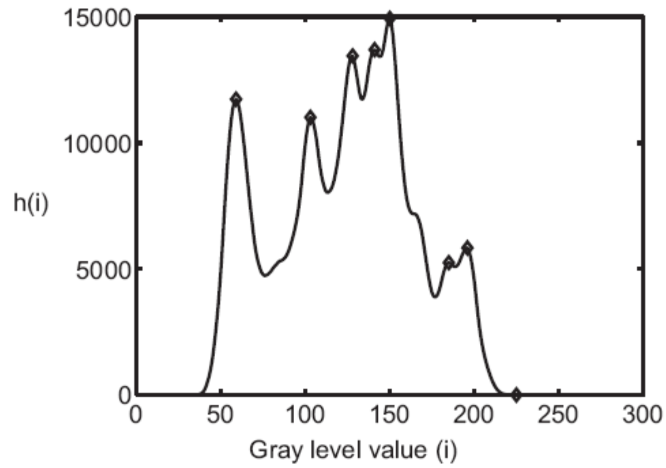

Fig. 1. Fuzzy histogram with marked local maxima.

The second order derivative is computed directly from the fuzzy histogram using the second order central difference operator (Eq. 4). This is done in order to minimize approximation errors which propagate if computed from the first order derivative.

$$\overset{\circ\circ}{h}(i) = \frac{d^2h(i)}{di^2} \triangleq h(i+1) - 2h(i) + h(i-1) \tag{4}$$

where, $\overset{\circ\circ}{h}(i)$ represents the second order derivative of the Fuzzy Histogram $h(i)$ corresponding to the i^{th} intensity level.

The local maxima points are then indicated for those values of intensity levels where zero crossings of the first order derivative are detected along with a negative value of the second order derivative (Eq. 5).

$$i_{\max} = i \forall \left\{ \overset{\circ}{h}(i+1) \times \overset{\circ}{h}(i-1) < 0, \overset{\circ\circ}{h}(i) < 0 \right\} \tag{5}$$

However, points of ambiguity arise in most situations as perfect zero crossings do not occur at integral values of intensity levels. In such situations, generally two neighboring pairs are detected as points of maxima. The ambiguity can be resolved by preserving the point with the highest count among the neighboring pair of maxima.

2) Creating Partitions: The local maxima points in the fuzzy histogram can now be used to form the partitions. Let $(n+1)$ intensity levels corresponding to the local maxima, detected in the previous stage of operation, be denoted by $\{m_0, m_1, \cdots, m_n\}$. Assuming the original fuzzy histogram to have a spread in the range of $[I_{\min}, I_{\max}]$, then the $(n+1)$ sub-histograms obtained after partitioning are $\{[I_{\min}, m_0], [m_0+1, m_1], \cdots, [m_n+1, I_{\max}]\}$.

C. Dynamic Histogram Equalization of the Sub-histograms

The sub-histograms obtained are individually equalized by the DHE [5] technique. The equalization method uses a spanning function based on total number of pixels in the partition to perform equalization. It involves two stages of operation, namely, mapping partitions to a dynamic range and histogram equalization.

1) Mapping Partitions to a Dynamic Range: The following set of equations give the parameters that are useful in dynamic equalization process.

$$span_i = high_i - low_i \tag{6}$$

$$factor_i = span_i \times \log_{10} M_i \tag{7}$$

$$range_i = \frac{(L-1)\times factor_i}{\sum_{k=1}^{n+1} factor_k} \tag{8}$$

where $high_i$ and low_i are the highest and lowest intensity values contained in the i^{th} input sub-histogram, M_i is the total number of pixels contained in that partition. The dynamic range of the input sub-histogram is specified by $span_i$, while the dynamic range used in the output sub-histogram is $range_i$.

The dynamic range for the i^{th} output sub-histograms can be obtained from $range_i$ as

$$start_i = \sum_{k=1}^{i-1} range_k + 1 \tag{9}$$

$$stop_i = \sum_{k=1}^{i} range_k \tag{10}$$

The exceptions are present at the two extremities, where $[start_1, stop_1] = [0, range_1]$ and $[start_{n+1}, stop_{n+1}] = \left[\sum_{k=1}^{n+1} range_k, L-1\right]$.

2) Equalizing each Sub-histogram: The method for equalizing each partition of the histogram is similar to that used for global histogram equalization. For the i^{th} sub-histogram, the remapped values are obtained as in Eq. 11.

$$y(j) = start_i + range_i \sum_{k=start_i}^{j} \frac{h(k)}{M_i} \tag{11}$$

where $y(j)$ is the new intensity level corresponding to the j^{th} intensity level on the original image, $h(k)$ is the histogram value at the k^{th} intensity level on the fuzzy histogram, and $M_i = \sum_{k=start_i}^{stop_i} h(k)$ is the total population count in the i^{th} partition of the fuzzy histogram.

D. Normalization of Image Brightness

The image obtained after the dynamic histogram equalization of each sub histogram is has the mean brightness that is slightly different than the input image. To remove this difference the normalization process is applied on the output image.

Let m_i and m_o be the mean brightness levels of the input image and the image (f) obtained after dynamic histogram equalization stage. If g is the output image of BPDFHE technique then the gray level value at the pixel location (x, y) for the image g is given as

$$g(x,y) = \frac{m_i}{m_o} f(x,y) \tag{12}$$

This brightness preserving procedure ensures that the mean intensity of the image obtained after process is the same as that of the input.

III. CONTRAST ENHANCEMENT OF COLOR IMAGES

Most electronic equipments acquire and display color images. In this respect, the method of enhancing color images would be of better interest. Most of the classical approaches apply equalization of the red, green, and blue planes in the RGB images. However, this approach has an inherent problem of changing the hue of the output image. Thus, we perform the YCbCr color space, where we only equalize the intensity band of the image, while preserving the chromaticity of the image. This method produces better perceptible results as compared to equalizing the R, G, and B planes separately.

IV. EXPERIMENTAL RESULTS

In this section, we present some experimental results of our proposed method, together with GHE, BPDHE for comparison. The images from the USC SIPI database [ftp://sipi.usc.edu/pub/database/misc.zip] have been used for the tests. The source images, together with the results based on GHE, BPDHE and BPDFHE, are shown in Figs. 2, 3, and 4.

Enhancing image/video contrast without altering image brightness is the restrained goal of the histogram modification technique discussed here. Hence the algorithm performance should be evaluated and compared on the basis of these two parameters. Here we use Luminance Distortion measure and the Contrast feature value, computed from Fuzzy Gray Level

Co-occurrence Matrix, to compare performance of GHE, BPDHE and our BPDFHE techniques.

Following subsections describe the two measures in detail.

A. Luminance Distortion:

Luminance Distortion (Q), a measure of how close the mean luminances of two images are [10], is used here to evaluate the brightness preserving capability of a contrast enhancement algorithm. It measures the change in the mean brightness of an image introduced by a contrast enhancement algorithm.

Let $X = \{x_i \mid i = 1,2,3,\cdots,N\}$ and $Y = \{y_i \mid i = 1,2,3,\cdots,N\}$ be the reference and test image, then the luminance distortion is defined as

$$Q = \frac{2\mu_x \mu_y}{\mu_x^2 + \mu_y^2} \tag{13}$$

where μ_x and μ_y are the mean luminance of X and Y respectively. Q takes value in the range $[0,1]$ and $Q = 1$ when the mean luminance of the two images being compared is exactly the same.

Computation of Luminance Distortion: As suggested by Wang and Bovik [8], we first calculate the luminance distortion at every image location using 7×7 neighborhood around it, and then the overall luminance distortion for the entire image is calculated.

Let $Q_{i,j}$ be the luminance distortion at location (i, j) in the image of size $M \times N$, then the luminance distortion value for the entire image is given by

$$Q_{image} = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} Q_{i,j} \tag{14}$$

The value of Q_{image} tends toward *One* as the change in mean image brightness introduced by the contrast enhancement algorithm becomes small. The luminance distortion values, introduced by the GHE, BPDHE and BPDFHE algorithms while modifying the test images, are given in Table I. It can be seen that BPDFHE can very effectively preserve the image brightness and its performance is at least as good as BPDHE and even slightly better in most of the cases.

TABLE I
LUMINANCE DISTORTION

Image Id	GHE	BPDHE	BPDFHE
5.2.08	0.9199	0.9938	0.9950
5.3.01	0.8576	0.9849	0.9553
5.3.02	0.8917	0.9937	0.9638
7.1.02	0.8097	0.9991	0.9974
7.1.09	0.9112	0.9955	0.9969

B. Contrast from Fuzzy Gray Level Co-occurrence Matrix:

The contrast feature value computed using fuzzy gray level co-occurrence matrix [7] of an image is used to evaluate and compare the contrast enhancement provided by different algorithms.

The Fuzzy co-occurrences matrix of an image I is $F = [f_{mn}]_{L \times L}$ where f_{mn} corresponds to the frequency of occurrence of a gray-value 'around m' separated from another pixel, with gray-value 'around n', by a distance d in a specific direction θ, is represented as

$$F = f(I, d, \theta) \tag{15}$$

In our experiments we use rotational invariant co-occurrence matrix (F'), obtained by averaging the four symmetrical fuzzy co-occurrence matrices computed with $\theta = 0^\circ, 45^\circ, 90^\circ, 135^\circ$ and $d = 1$, to find the contrast feature value. The pyramidal membership function $\left(\mu_{\tilde{m}I(x,y),\tilde{n}I(x,y\pm d)}\right)$ used to build these matrices is defined as

$$\mu_{\tilde{m}I(x,y),\tilde{n}I(x,y\pm d)} = \max\left(0, \max\left(0, 1 - \frac{|I(x,y) - m|}{5}\right) - \frac{|I(x, y \pm 5) - n|}{5}\right) \tag{16}$$

where membership value gives the occurrence of the gray value 'around m' separated from another pixel with gray-value 'around n' by a distance d in the specific direction θ.

Given F', it is normalized to obtain F'_{norm} which gives the joint probability of occurrence of one pixel having gray value 'around m' with another pixel separated by a defined spatial relationship and having gray-value 'around n'. Now the contrast feature value (C) is obtained as

$$C = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} |i - j|^2 F'_{norm}(i, j) \tag{17}$$

The contrast values for the input test images and their processed output images produced by GHE, BPDHE and BPDFHE algorithms are given in Table II. It can be observed that the contrast improvement provided by the BPDFHE is credibly more than that provided by the BPDHE technique in most of the cases.

TABLE II
CONTRAST FROM FUZZY CO-OCCURRENCE MATRIX

Image Id	Original	GHE	BPDHE	BPDFHE
5.2.08	365.7	1036.8	393.0	417.9
5.3.01	182.6	309.7	196.6	194.0
5.3.02	297.8	1373.9	429.9	861.6
7.1.02	68.5	855.2	77.1	114.3
7.1.09	175.9	844.5	229.6	310.6

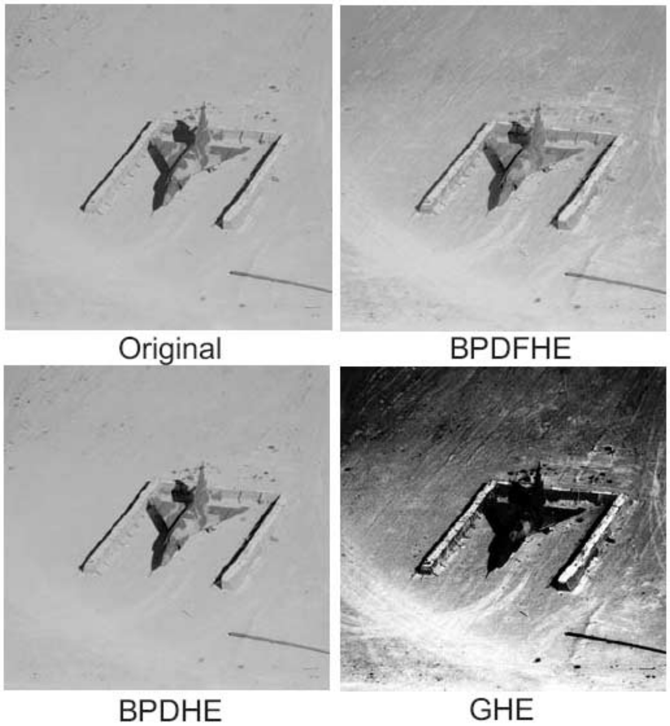

Fig. 2. Results for the image 7.1.02.

C. Analysis of Executional Requirement

The execution time changes dynamically with each image and, depend on two factors, (a) size of the image and (b) the number of peaks present in the histogram of the image. As the size of image increases, the computational resources required for histogram computation (II.A) and gray-level mapping (II.D) also increase. Whereas, an increase in the number of peaks in the image histogram increases the number of partitions in which the histogram is split, resulting in the increase of execution time for dynamic equalization (II.C). Execution times for BPDHE and BPDFHE are reported in Table III. The techniques have been tested using a mathematical simulation utility[2] with a generic x86 processor based PC[3].

TABLE III
COMPUTATIONAL REQUIREMENTS (CPU TIME CONSUMED IN SECONDS)

Image Id	BPDHE	BPDFHE
5.2.08	0.942	0.921
5.3.01	3.846	3.836
5.3.02	3.841	3.731
7.1.02	0.976	0.943
7.1.09	0.974	0.935

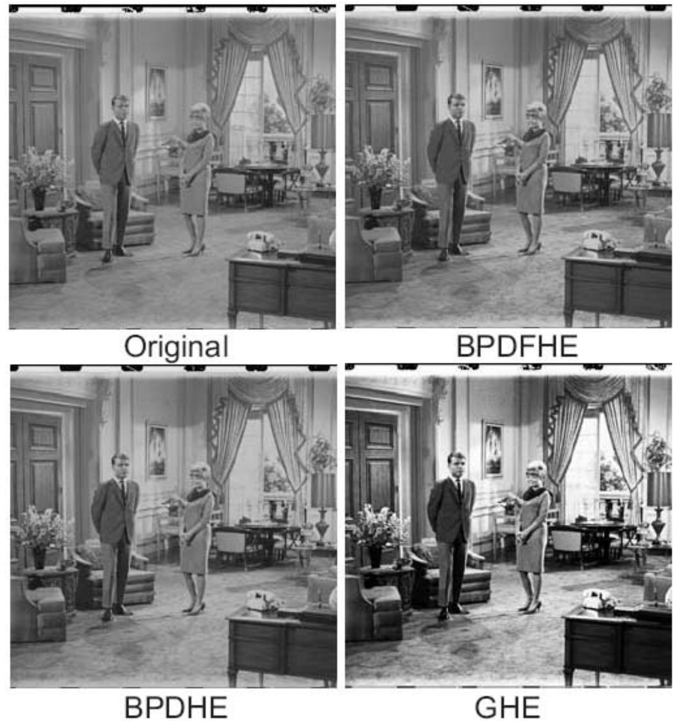

Fig. 3. Results for the image 5.2.08.

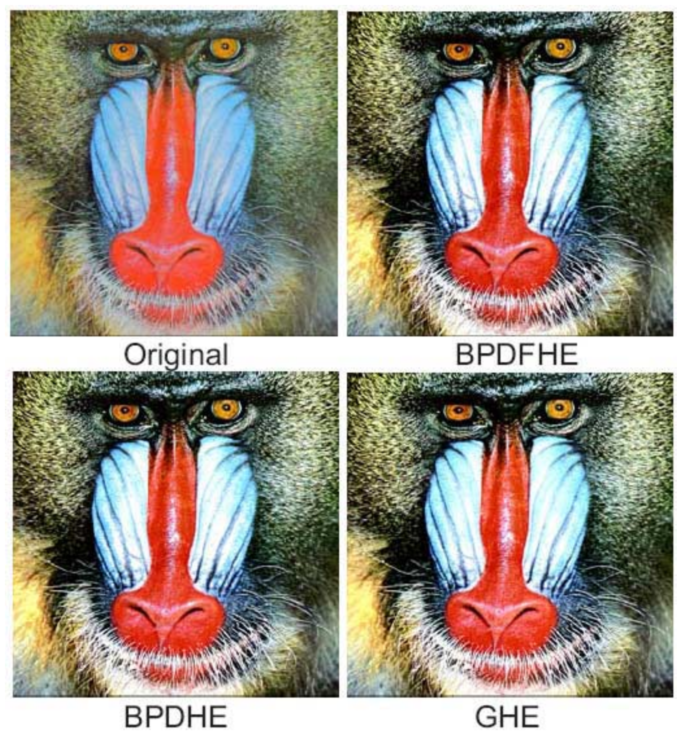

Fig. 4. Results for the image 4.2.03.

V. CONCLUSION

This paper proposes BPDFHE as a modification to BPDHE to improve its ability to enhance contrast and preserve brightness. The novelty of BPDFHE lies in the use of fuzzy statistics of digital images for representation and processing of the images. This gives it the improved ability to preserve brightness and provide better contrast enhancement as

[2] Matlab R2007a.
[3] Intel® Core™ 2 Duo CPU at 2.66 GHz with 2GB of RAM.

compared to BPDHE. From the results it is seen that BPDFHE can very efficiently preserve the mean image-brightness and its performance is at least as good as BPDHE. In most cases the contrast improvement provided by BPDFHE is credibly more than that provided by BPDHE.

ACKNOWLEDGMENT

The authors would like to thank Professor Ajoy K. Ray, Professor of Electronics and Electrical Communication Engineering at Indian Institute of Technology Kharagpur for his continual support.

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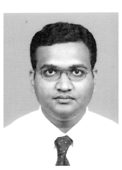
BIOGRAPHIES



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