Improving Brightness using Dynamic Fuzzy Histogram Equalization using Gaussion Membership Function

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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 (BPDFHE1), 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. In this paper algorithm is proposed BPDHE using Gaussion Membership Function . This algorithm enhances image contrast as well as preserves the brightness very effectively. Some images are not available to good quality, so proposed Fuzzy algorithm can be used for image enhancement to improve the quality of the image.
Index Terms
Fuzzy sets, image enhancement, image processing, histogram equalization

1. 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. Discusses the BPDFHE technique in detail. Application of this technique to color images.

2. 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[5] technique manipulates the

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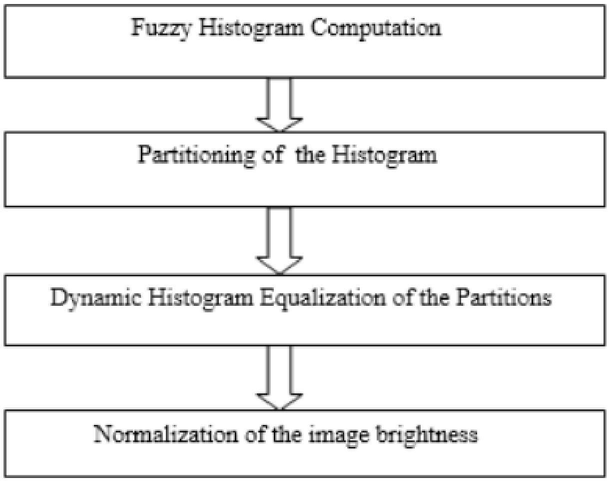
image histogram in such a way that no remapping of the histogram peaks takes place, while only redistribution of the gray-level values in the valley portions between two consecutive peak takes place. The BPDFHE [5] technique consists of following operational stages:



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

2.1. Fuzzy Histogram Computation

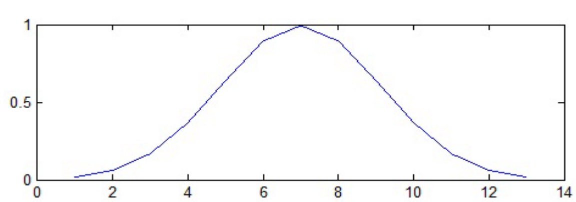
Fuzzy statistics is able to handle the inexactness of gray value and produces a smooth histogram. Fuzzy histogram[10] is a sequence of real numbers h(i), i Є {0,1,…,l-1} where h(i) is the frequency of occurrence of gray levels that are around i. By considering the gray values I(x,y) as a fuzzy number the fuzzy histogram $\tilde{I}(x,y)$ can be computed as

$$h(i) \leftarrow h(i) + \sum_{x}\sum_{y} \mu_{\tilde{I}(x,y)i} \ , k \in [a, b]$$

Where $\mu_{\tilde{I}(x,y)i}$ a fuzzy membership function. In paper used Gaussion membership function. Gaussion membership function defined as following equation

$$Gaussian(x\,;m,\sigma) = e^{-\left(\frac{(x-m)^2}{2\sigma^2}\right)}$$

Where m = mean , σ = standard deviation.



Gaussion parameter used (6,3)

For Gaussian MF if parameter is [6 3] then base spread is of 1 to 13 i.e. 2*6+1 but over the spread of width 3 i.e. 6 to 9 (center part) the peak remains high then it decreases exponentially fast.

2.2. Partitioning of the histogram

Partitioning of histogram is done to get sub-histograms[11] based on local maxima. The partition is every Valley region between two consecutive local maxima. Then dynamic equalization of these partitions is performed which not only preserves the image brightness without the remapping of histogram peaks but also image contrast is increased. To partition the image histogram first we have to detect local maxima.

2.2.1. Detection of local maxima

This is done by using first and second derivatives of Fuzzy histogram. To find the discrete derivative as the fuzzy histogram [9] is a discrete data sequence the central differential operator is used

$$h'(i) = \frac{dh(i)}{di} \triangleq \frac{h(i+1)-h(i-1)}{2}$$

Where $h'(i)$ is first order derivative of fuzzy Histogram h (i) corresponding to ith intensity level.

2.2.2. Fuzzy histogram with marked local maxima

To minimize the approximation errors which occurs if computed from first order derivative, second order derivative is computed directly from fuzzy histogram [9] using second order central difference operator

$$h''(i) = \frac{d^2h(i)}{di^2} \triangleq h(i+1) - 2h(i) + h(i-1)$$

Where h’’(i) is the second order derivative of fuzzy histogram h(I) corresponding to ith intensity level. For the values of intensity levels where zero crossings of first order derivative are detected along with a negative value of the second order derivative, the local maxima points are indicated.

$$i_{max} = i \quad \forall \ \{h'(i+1)h'(i-1) < 0, \ \ h''(i) < 0\}$$

As perfect zero crossings do not at occur at integral values of intensity levels, points of ambiguity arise .In such cases to neighboring pairs are detected as points of maxima. To solve the problem of ambiguity the point with highest count among the neighboring pair of maxima is preserved.

2.2.3. Creating partitions

Detected local maxima points are used to form partitions in the fuzzy histogram. Suppose(n+1) intensity levels corresponds to local maxima are denoted by{ m0, m1, … , mn }. If the fuzzy histogram is defined in the range of [Imin, Imax],then after partitioning (n+1) sub-histograms[11] are obtained. They will spread in the range given {[Imin , m0], [m0+ 1, m1], ….. [mn+ 1, Imax].

2.3. Dynamic histogram equalization of sub-histogram

Each sub-histogram is equalized by using a spanning based on total number of pixels in the partition. DHE of each sub-histogram involves two operations-mapping partitions to a dynamic range and histogram equalization.

2.3.1. Mapping partition to a dynamic range

The parameters that are useful in dynamic equalization[12] process can be given by the equations

$$span_i = high_i - low_i$$

Where highi and lowi are highest and lowest intensity values contained in ith input sub histogram

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

Mi is the total number of pixels contained in sub-histogram. $span_i$ is the dynamic range of input sub histogram

If rangei. is the dynamic range of output sub histogram, it can be given as

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

Then the dynamic range for ith output sub-histogram is obtained as

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

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

The exceptions are present at the two extremities where [start1, stop1] = [0,range1] and

$$[start_{n+1}, stop_{n+1}] = [\sum_{k=1}^{n+1} range_k \,,\ L-1]$$

2.3.2. Equalizing each sub-histogram

Global HE method is used to equalize[10] each sub-histogram[11]. The remapped values are obtained for the ith sub histogram as

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

Where y(j) is the new intensity level corresponding to jth intensity level on the original image.h(k) is the histogram value at kth intensity level on the fuzzy histogram $M_i = \sum_{k=start_i}^{stop_i} h(k)$ is the total population count in the ith sub-histogram of fuzzy histogram.

2.4. Normalization of image brightness

After DHE of each sub-histogram the image obtained has the mean brightness[8] slightly different than input image. To overcome this normalization of output image is done. If g is output image of BPDFHE technique then the grey level value at pixel location (x,y) for image g is given by

$$g(x,y) = \frac{m_i}{m_0} f(x,y)$$

Where mi and m0 are mean brightness levels of the input image (f) obtained after DHE. This ensures that the mean intensity of the output image of BPDFHE is same as the input image.

3. RESULT

In this section, we present some experimental results of our proposed method, together with GHE, UHE, CLAHE, BPDHE [5] for comparison have been used for the tests. Hence the algorithm performance should be evaluated and compared on the basis of these three parameters. Here we use error in mean brightness, comparison of mean brightness and the PSNR value, computed from Fuzzy Gray Level [9] Testing of our image enhancement method is performed on 3 different images. we are used gaussion membership function and parameter used 6,3 in BPDHE. The results are shown in the form of images along with there histogram in comparison with the original mage and its histogram. The quantative analysis is performed by calculating the mean brightness of images before and after enhancement, difference in mean brightness and the PSNR of enhanced and original images. We have used 3 different histogram equalization techniques to demonstrate the performance of our brightness preserving enhancement algorithm. The methods we have used are written below: Generalized histogram equalization (GHE) Uniform histogram [11] equalization (UHE) Adaptive histogram equalization (CLAHE).

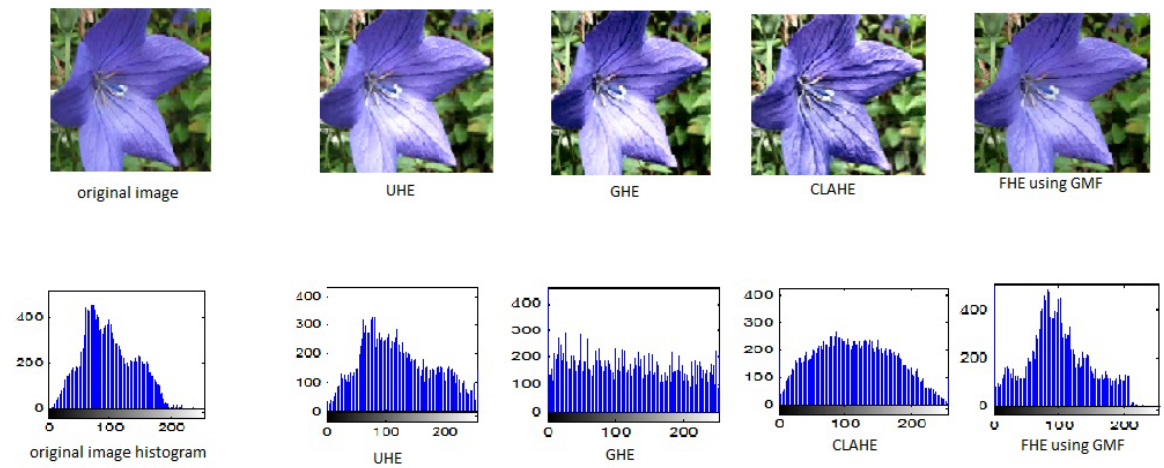


Fig.1 - ORIGINAL IMAGE (flower),UHE(Uniform histogram equalization), GHE(Generalized histogram equalization), CLAHE(adaptive histogram equalization), FHE using GMF(Guassion membership function) image enhancement (above) and histogram (below)

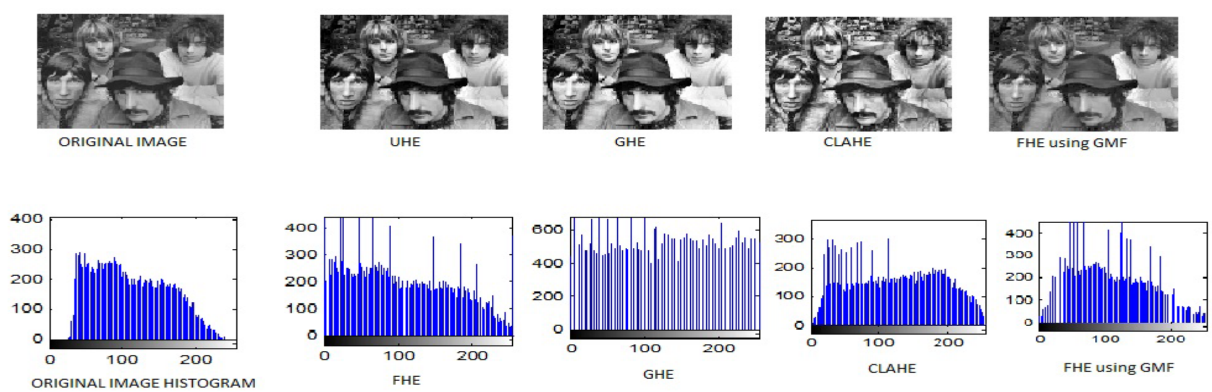


Fig.2 - ORIGINAL IMAGE (I2),UHE(Uniform histogram equalization), GHE(Generalized histogram equalization), CLAHE(adaptive histogram equalization), FHE using GMF(Guassion membership function) image enhancement (above) and histogram (below)

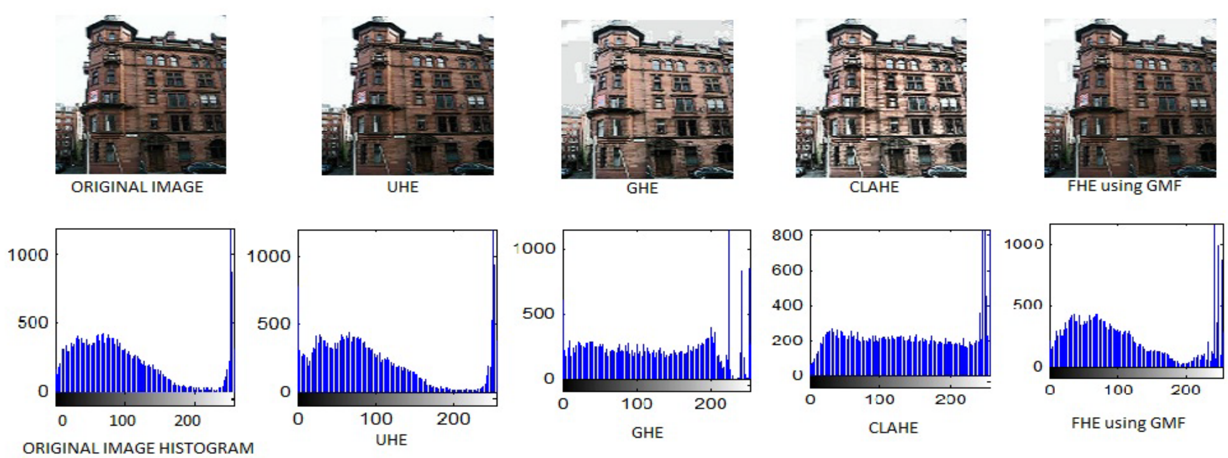


Fig.3 - ORIGINAL IMAGE (glassgow),UHE(Uniform histogram equalization), GHE(Generalized histogram equalization), CLAHE(adaptive histogram equalization), FHE using GMF(Guassion membership function) image enhancement (above) and histogram (below)

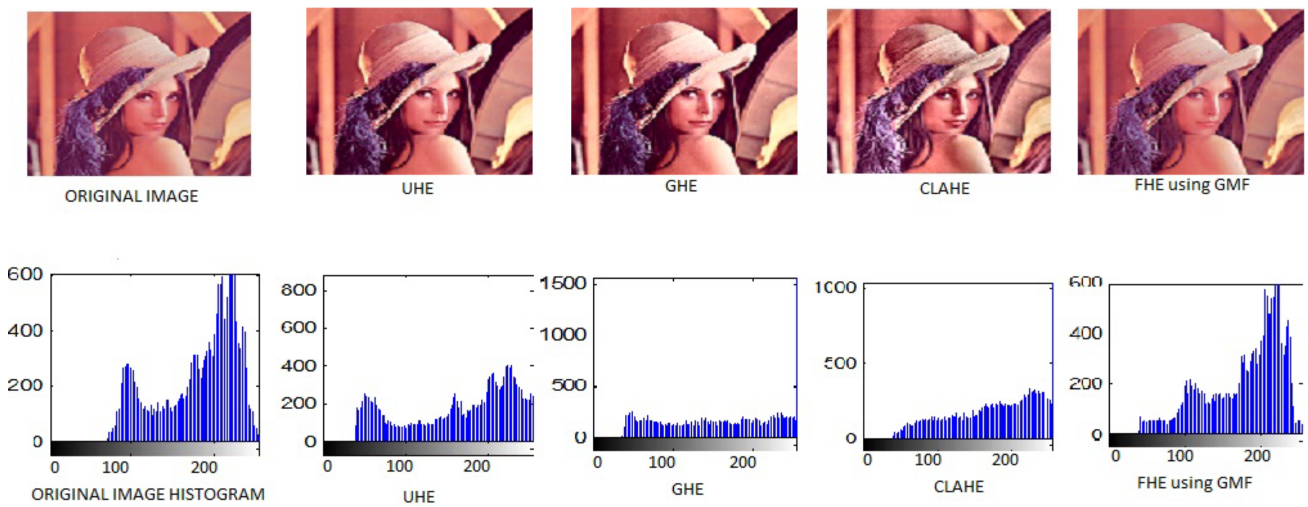


Fig.4 - ORIGINAL IMAGE (lena),UHE(Uniform histogram equalization), GHE(Generalized histogram equalization), CLAHE(adaptive histogram equalization), FHE using GMF(Guassion membership function) image enhancement (above) and histogram (below)

4. Quantitative Analysis

We have performed calculations to justify the meaning of fullness of our results in terms of numeric value. The measures that we have used are mean brightness, change in mean brightness and PSNR in between enhanced and original images.

Table.1 Comparison of mean brightness

original		GHE	UHE	CLAHE	FHE using GMF
FLOWER	112.54	126.43	131.67	128.74	113.05
PINKFLOD	112.21	122.98	108.08	124.23	112.36
GLASSGOW	104.17	122.29	102.01	137.32	103.90
LENNA	128.22	124.00	124.94	133.29	128.39

Table 1 shows the mean brightness obtained before and after enhancing the images. First column shows original image mean brightness and there after it shows mean brightness obtained by using UHE, GHE, CLAHE and FHE using GMF. Rows indicate the images names on which we have tested our enhancement results. For first image flower.jpg the original image brightness on average was 112 (approx.) but in case of UHE, GHE and CLAHE it has increased and reached to 131, 126 and 128 hence none of them were able to preserve the brightness. However, in case of FHT mean brightness is 112 and 113 hence it shows that our FHE algorithm is capable of maintaining the mean image brightness. Similar results for justifying the brightness preserving quality can be seen from other images.

Table.2 Error in mean brightness

original		GHE	UHE	CLAHE	FHE using GMF
FLOWER	0	13.89	19.13	16.20	0.517
PINKFLOD	0	10.76	4.13	12.41	0.144
GLASSGOW	0	18.11	2.16	33.15	0.274
LENNA	0	4.21	3.27	5.06	0.164

The error in mean brightness is shown in Table 2. It shows that error in brightness using FHE is not more than 0.5 but in other cases it is very large. We can even say that CLACHE is showing highest error in mean image brightness after enhancement.

Table.3 PSNR comparison of all HE techniques

original	GHE	UHE	CLAHE	FHE using GMF
FLOWER	17.43	19.68	17.09	28.54
PINKFLOD	19.78	23.26	17.32	33.88
GLASSGOW	17.76	39.74	14.28	34.25
LENNA	19.02	22.23	19.39	32.66

We have also compared the performance of our algorithm by measuring the PSNR values of our enhancement technique. PSNR measure indicates the error in between content of our image obtained by enhancement method to the original contents. Higher the SNR indicates the minimum differences or error in enhanced and original image. In brief, we can say that a technique will be considered good if it has high SNR. Hence, Table 3 is given and highest PSNR is obtained for FHE technique which is compared to other histogram equalization methods. If we compare HE using GMF then GMF based FHE is giving better PSNR.

5. CONCLUSION

This paper proposes FHE (using Gaussion membership function) 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 compared to BPDHE. From the results it is seen that BPDFHE can very efficiently preserve the mean image-brightness and PSNR than other histogram techniques as UHE, GHE, and CLAHE.

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