Brightness Preserving Dynamic Fuzzy Histogram Equalization For Image Contrast Enhancement

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Abstract -- **Histogram equalization (HE) is one of the common methods used for improving contrast in digital images. However, this technique is not very well suited to be implemented in consumer electronics, such as television, because the method tends to introduce unnecessary visual deterioration such as the saturation effect. One of the solutions to overcome this weakness is by preserving the mean brightness of the input image inside the output image .**

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In this paper, we proposed a method . called Brightness Preserving Dynamic Fuzzy Histogram Equalization(BPDFHE) , which is an extension to HE that 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.

***Index Terms*— Image contrast enhancement, histogram equalization, brightness preserving enhancement, histogram partition , image processing, Fuzzy sets .**

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] 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.

with the use of fuzzy statistics of digital images (fuzzy histogram) [6]. 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.

this modified technique is referred to as Brightness Preserving Dynamic Fuzzy Histogram Equalization (BPDFHE) technique. Section II discusses the HE techniques in detail. Application of BPDFHE technique is discussed in the Section III. Experiments, conducted to evaluate qualitative performance, , and the results are discussed in section IV.

II. Histogram Equalization Techniques

In this section, we review some of the existing HE approaches in brief. Here we discuss about GHE, LHE, DHS and some methods based on histogram partitioning.

A. Global Histogram Equalization (GHE)

Suppose input image f(x, y) composed of discrete gray levels in the dynamic range of [0, L-1]. The transformation function C(rk) is defined as :

$$s_k = C(r_k) = \sum_{i=0}^{k} P(r_i) = \sum_{i=0}^{k} \frac{n_i}{n}$$

where $0 \leq s_k \leq 1$ and $k = 0, 1, 2, \ldots, L\text{-}1$.

Fig.1.

In (Fig 1), n_i represents the number of pixels having gray level r_i, n is the total number of pixels in the input image, and $P(r_i)$ represents as the Probability Density Function (PDF) of the input gray level r_i. Based on the PDF, the Cumulative Density Function(CDF) is defined as $C(r_k)$. This mapping in (1) is called Global Histogram Equalization (GHE) or Histogram Linearization. Here s_k can easily be mapped to the dynamic range of [0, L-1] multiplying it by (L-1).

GHE provides a significant improvement in image contrast, but along with some artifacts and undesirable side effects such as washed out appearance in the gray levels of the flower. In (Fig 1), larger values of n_k cause the respective gray levels to be mapped apart from each other forcing the mappings of the smaller n_k values to be condensed in a small range with the possibility of duplications. This is the main source of such side effects and loss of image details.

B. Local Histogram Equalization (LHE)

While GHE takes into account the global information and cannot adopt to local light condition, Local Histogram Equalization (LHE) performs block-overlapped histogram equalization [6], [10]. LHE defines a sub-block and retrieves its histogram information. Then, histogram equalization is applied for the center pixel using the CDF of that sub-block. Next, the sub-block is moved by one pixel and sub-block histogram equalization is repeated until the end of the input image is reached.

Though LHE cannot adapt well to partial light information [17], still it over-enhances some portions depending on its mask size. Actually, using a perfect block size that enhances all part of an image is not an easy and smooth task to perform

C. Dynamic Histogram Specification (DHS)

This approach selects some critical points (CP) from the image histogram. Then based on these CPs and other components of the histogram, it creates a specified histogram. Then HS is applied on the image based on this specified histogram. DHS (Dynamic Histogram Specification) enhances the image keeping some histogram characteristics since the specified histogram is created from the input image histogram. However, as it does not change the dynamic range, the overall contrast of the image is not much enhanced. Moreover, sometimes it causes some artifacts in the images.

D. Histogram Partitioning Approaches

As we know , BBHE tries to preserve the average brightness of the image by separating the input image histogram into two parts based on input mean and then equalizing each of the parts independently. DSIHE partitions the image based on entropy. RMSHE proposes to partition the histogram recursively more than once. A common drawback of most of the existing histogram partitioning approaches is that they cannot expand much, while the outside region expands so much that creates the unwanted artifacts since they keep the partitioning point fixed through the entire process.

III. BRIGHTNESS PRESERVING DYNAMIC FUZZY HISTOGRAM EQUALIZATION

As mentioned earlier, 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 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) 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 $\tilde{I}$ (x, y) , the fuzzy histogram is computed as:

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

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

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

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

$$\mathring{h}(i)=\frac{dh(i)}{di}\underset{=}{\Delta}\frac{h(i+1)-h(i-1)}{2} \qquad (3)$$

where, h_i represents the first order derivative of the fuzzy histogram h_i corresponding to the i_{th} intensity level.

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.

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

where, 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).

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

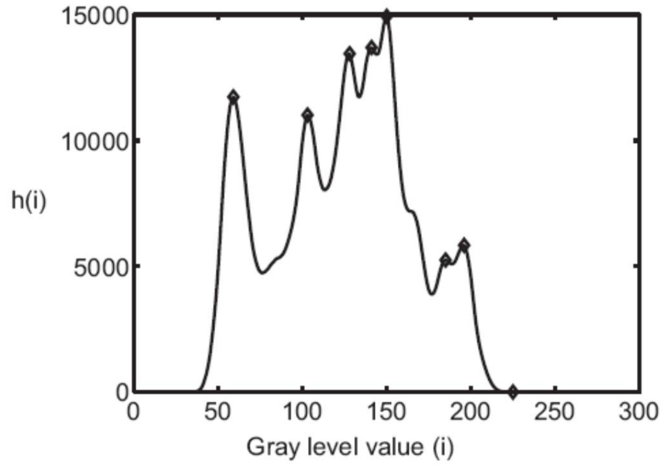

Fig.2.Fuzzy histogram with marked local maxima.

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.

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.

$$span_i = high_i - low_i \qquad (6)$$

$$factor_i = span_i \times \log_{10} M_i \qquad (7)$$

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

where i high and i low are the highest and lowest intensity values contained in the i_{th} input sub-histogram, i M 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:

$$start_i = \sum_{k=1}^{i-1} range_k + 1 \qquad (9)$$

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

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

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

IV. Experimental Results

In this section, we present some experimental results of our proposed method, together with GHE, BPDHE for comparison. 4 images have been used for the tests. The orginal images, together with the results based on GHE, BPDHE and BPDFHE, are shown in Figs. 3, 4, 5 and 6.

Enhancing image 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.

Our BPDFHE uses 3 fuzzy membership options :

1) Gaussian :

uses a gaussian membership function , Width of support and spread factor of 'gaussian'. Suggested is [5,2] for uint8

2) Triangular :

uses a triangular membership function , Width of support of 'triangular'. Suggested is 5 for uint8

3) Custom :

uses the user defined membership values , User defined membership values of 'custom'. Suggested is [1 2 3 4 5 4 3 2 1]

Now let's take a look at the results :

a) We applied BPDFHE choosing the Gaussian membership with parameters [4 , 6]:

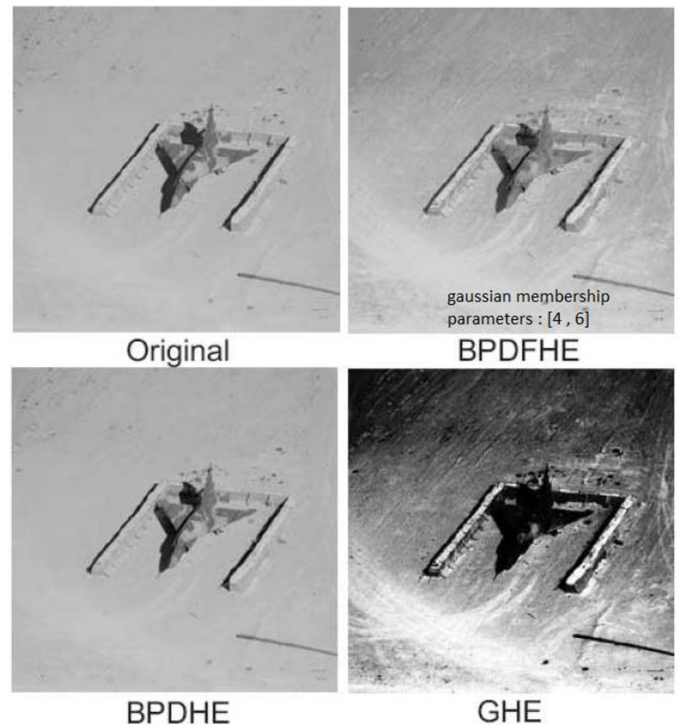

Fig.3.

b) We applied BPDFHE choosing the triangular membership with parameters [5]:

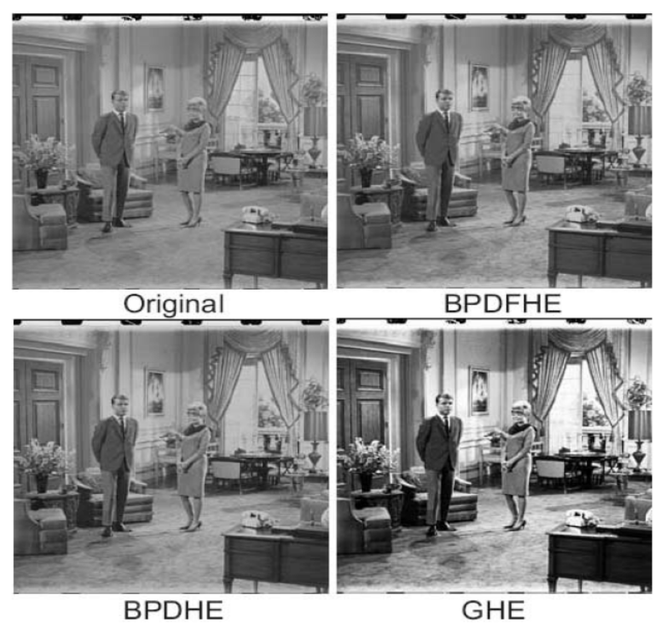

Fig.4.

c) We chose a medical photo of brain and applied the mentioned method and got some interesting result , we applied the three option of BPDFHE and observed that non of them couldn’t enhance the picture as good as BPDHE but we can get the important information from BPDFHE .
Here is the results:

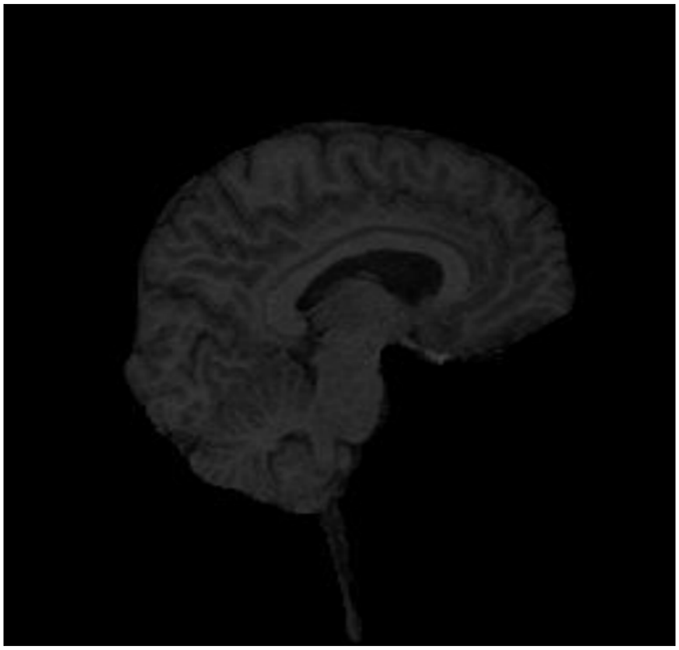

Fig.5.a. orginal

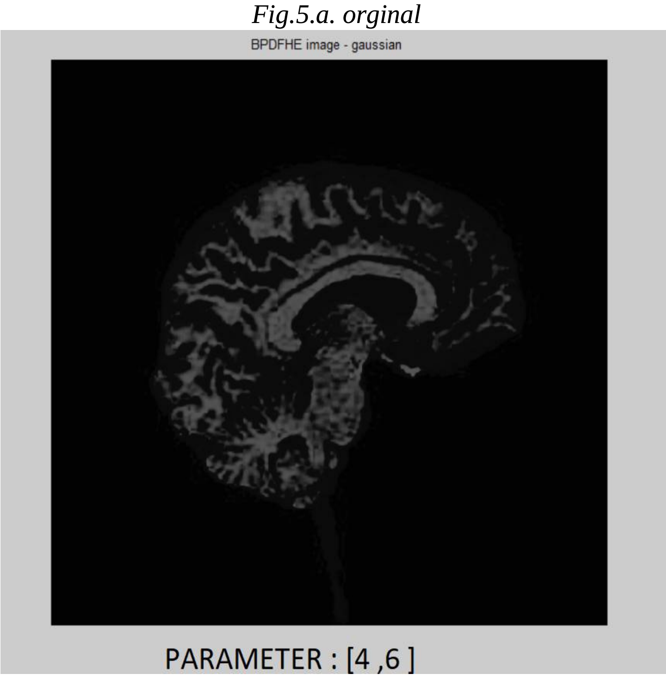

Fig.5..b. BPDFHE_gaussian

Fig.5.c. BPDFHE_tringular

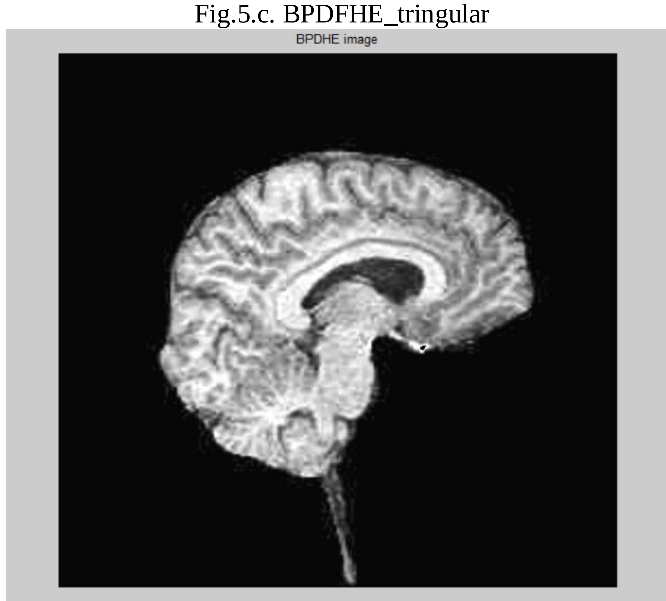

Fig.5.d. BPDHE

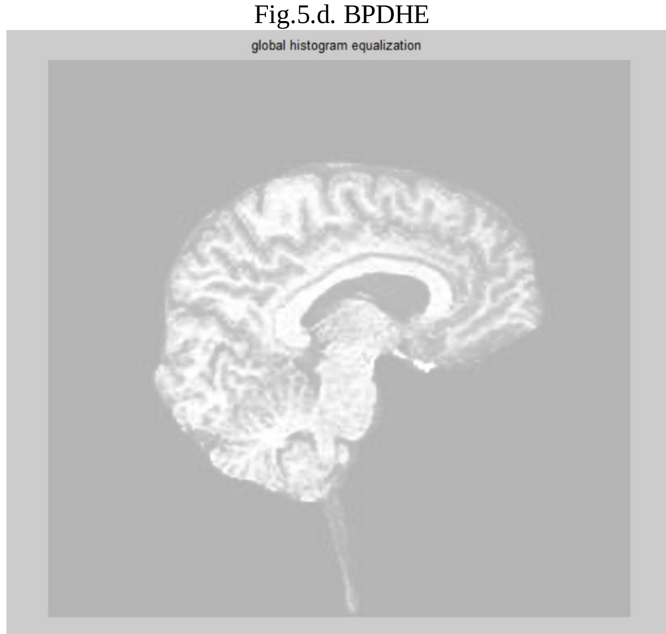

Fig5.e. GHE

d) We have tried another experiment . this time we applied it on a noisy picture , again BPDHE was better than our method , and could preserve the brightness of photo among the noises .
Here is the results:

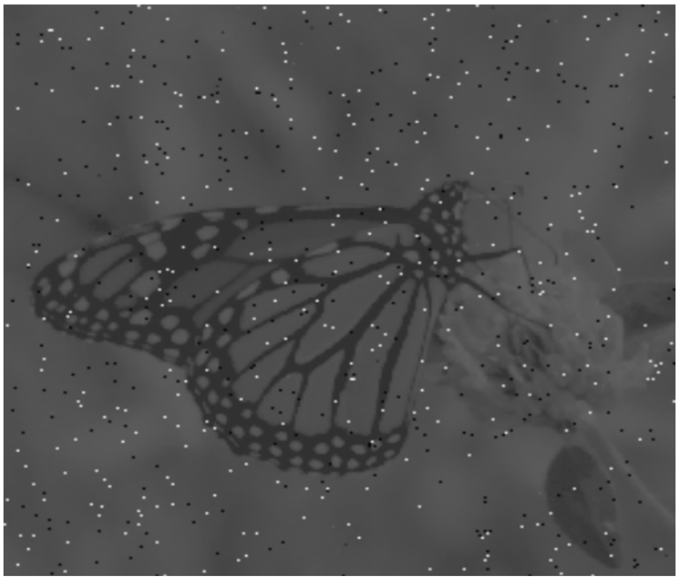

Fig.6.a. orginal

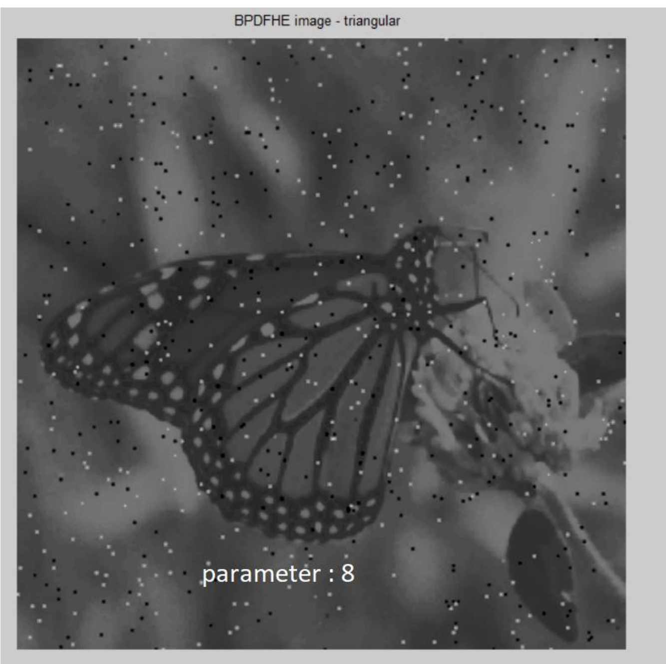

Fig.6.d. BPDFHE_tringular

Fig.6.c. BPDHE

Fig6.d. GHE

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 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.

VI. REFERENCES

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