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MULTI HISTOGRAM EQUALIZATION BASED CONTRAST ENHANCEMENT FOR IMAGES

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ABSTRACT

The fundamental and important pre-processing stage in image processing is the image contrast enhancement technique. Histogram equalization is an effective contrast enhancement technique and thus in this paper, a histogram equalization based technique called Quadrant Dynamic with Automatic Plateau Limit Histogram Equalization (QDAPLHE) is introduced. In this method, a hybrid of dynamic and clipped histogram equalization methods are used to increase the brightness preservation and to reduce the over enhancement. Initially, the proposed QDAPLHE algorithm passes the input image through a Decision based modified median filter (DBMMF) to remove the noises present in the image. Then the histogram of the filtered image is divided into four sub histograms while maintaining second separated point as the mean brightness. Next, the clipping process is implemented by calculating automatically the plateau limit as the clipped level. The clipped portion of the histogram is modified to reduce the loss of image intensity value. Finally, the clipped portion is redistributed uniformly to the entire dynamic range and the conventional histogram equalization is executed in each sub-histogram independently. Hence, the contrast enhancement is improved and the noise amplifying artifacts are reduced. Based on the qualitative and the quantitative analysis, the QDAPLHE method outperforms compared to some existing methods in literature.

Keywords: histogram equalization, image contrast enhancement, dynamic histogram equalization, clipped histogram equalization, median filter, decision based modified median filter.

INTRODUCTION

An important challenge in the field of digital image processing is contrast enhancement. Compared to the original image, contrast enhancement produces better image by changing the pixel intensities. Of the many techniques available for image contrast enhancement, Histogram equalization (HE) is a widely used technique. The fundamental idea of histogram equalization is to flatten the histogram and stretch the dynamic range of the gray levels by using the cumulative density function of the image. Nowadays, histogram equalization is applied in various applications such as medical image processing and radar image processing [1]. In histogram equalization, the brightness of an input image is significantly changed and causes undesirable artifacts. This is not suitable for some applications where brightness preservation is necessary. To overcome the aforementioned problem, several brightness preserving methods have been proposed [2]-[6]. Generally, these enhancement methods can be classified into two types: Partitioned histogram equalization (PHE) and Dynamic partitioned histogram equalization (DPHE).

In these methods, the original histogram is divided into several sub histograms based on the histogram statistical information. The difference between the PHE and DPHE is that, in the DPHE each sub histogram is assigned to a new enhanced dynamic range instead of using the original dynamic range. One of the popular PHE based method is Mean brightness preserving Bi-Histogram equalization (BBHE). BBHE segments the original histogram into two portions by the mean of the input histogram. BBHE has been analyzed both experimentally and mathematically that this technique is capable to achieve the brightness preservation [1]. Later, Dualistic Sub -Image Histogram Equalization (DSIHE) has been proposed. This algorithm separates the input image's histogram into two sub histograms based on median of the input image [2]. This technique has been claimed to outperform BBHE both in term of brightness preservation and also entropy (image content) preservation. BBHE and DSIHE methods can preserve the mean brightness of original image in some extent. In order to provide scalable brightness preservation, Recursive Mean-Separate Histogram Equalization (RMSHE) and Minimum Mean Brightness Error Bi-Histogram Equalization (MMBEBHE) has been proposed [3].

In RMSHE algorithm, the original image is recursively segmented into some sub-images based on their mean brightness and equalized them separately. The better mean brightness will be preserved when the recursive degrees have been increased. If the recursive levels tend to infinity, the output image will be equal to input image.

For DPHE, there are two methods existing in literature: Dynamic histogram Equalization (DHE) [7] and Brightness preserving Dynamic Histogram Equalization (BPDHE) [8]. The DHE partitions the histogram of input image based on local minimal and assigns a new dynamic range for each sub-histogram. To ensure many dominating portions, the DHE further segments the large sub-histogram. To ensure many dominating portions, the DHE further segments the large sub-histogram through a repartitioning test. As the DHE does not consider the mean brightness preservation, it neglects the mean brightness preserving and tends to intensity saturation artifact.

To overcome the drawbacks of the DHE, brightness preserving dynamic histogram equalization (BPDHE) has been introduced [8]. The BPDHE uses the local maximal as the separating point rather than the local minimal. For this reason, Ibrahim and Kong [8] claim that the local maximals are better for mean brightness preservation. Finally in BPDHE, histogram equalization is implemented after assigning a new dynamic range for each sub histogram. In order to maintain the mean brightness, brightness normalization is applied to ensure that the enhanced image has similar mean brightness of the input image.

Research by Praveen *et al*. [9] has done comparison between original image and image enhanced by Histogram Equalization and Contrast Limited Adaptive Histogram Equalization (CLAHE) for bone fracture crack detection using pixel value measurement. They concluded that CLAHE is better than Histogram Equalization. CLAHE had been claimed also to improve the contrast better in the application of automated segmentation of blood vessels in retinal images when compared to Histogram Equalization [10].

Kentaro Kokufuta *et al*. [11] described an approach for real time processing of the contrast limited adaptive histogram equalization (CLAHE) using an FPGA. In this approach, a histogram is generated for each pixel in an image for remapping the pixel, and each histogram is speculatively distributed without iterations by feeding back the distribution result of its previous pixel. But the computational complexity of this approach is very high [9, 15].

Ooi and Kong *et al.* [12] proposed a bi-histogram equalization Plateau limit (BHEPL) as the hybrid of the BBHE and clipped histogram equalization. BHEPL divides the histogram of input image by the value of mean brightness of the input image. Both the sub histograms are clipped by each mean of histograms of the occupied intensity respectively. At last, conventional histogram equalization methods are able to control the enhancement rate. In addition, these methods can avoid over amplification of noise in the image.

Recently, Wayalun, Pichet *et al*., [13] presented an enhancement algorithm for chromosome images based on histogram equalization (HE). Underwater imaging is quite a challenging in the area of photography especially for low resolution and ordinary digital camera. Mean values of the stretched histogram are used to improve the contrast of the image [14]. An advance multiband satellite colour contrast improvement technique of a poor-contrast satellite images is proposed based on Discrete Cosine Transform (DCT) in [15]. The retinal images are pre-processed using Adaptive Histogram Equalization (AHE) and the blood vessels are enhanced by applying Top-hat and Bottom-hat transforms in [16]. Based on the inspiration of the local contrast range transform, a new general form of fast dynamic range compression with a local-contrast-preservation (FDRCLCP) algorithm is developed to resolve image enhancement problems directly in the spatial domain [17]. Although these methods perform well for image enhancement, the enhancement process requires high computational costs with a large memory requirement, usually leading to an inefficient algorithm and requiring hardware acceleration.

In this paper, a novel method is proposed as the extension of the BHEPL and RMSHE, called Quadrant Dynamic with Automatic Plateau Limit Histogram Equalization (QDAPLHE). First, the input image is passed through a Decision based modified median filter (DBMMF) to remove the noises present in the image. Then the proposed method divides the histogram of the filtered image into four sub-histograms while maintaining second separated point as the mean brightness. Then the clipping process is implemented by automatically calculating the plateau limit as the clipped level. The clipped portion of the histogram is modified to reduce the loss of image intensity value. Finally, the clipped portion is redistributed uniformly to the entire dynamic range and the conventional histogram equalization is executed in each sub-histogram independently. Hence, the contrast enhancement is improved and the noise amplifying artifacts are reduced. The rest of this paper is organized as follows. In preceding chapter, the methodology of the proposed Quadrant Dynamic with Automatic Plateau Limit Histogram Equalization (QDAPLHE) is discussed in detail. Then, next chapter presents the qualitative and quantitative analysis of existing and proposed image enhancement methods. The Final chapter serves as the conclusion of this work.

QUADRANT DYNAMIC WITH AUTOMATIC PLATEAU LIMIT HISTOGRAM EQUALIZATION (QDAPLHE)

The proposed QDAPLHE method uses the fundamental idea of the RMSHE. In RMSHE the number of decomposed sub-histograms increases in powers of two. Although it will produce better brightness preservation, it declines the effectiveness of the histogram equalization and yields an output image without a good enhancement i.e., the output will be same as the input. Thus in this work, the input histogram is divided into four sub-histograms. The proposed QDAPLHE consists of four processes, namely filtering process, Histogram partitioning process, clipping process, redistribution process and histogram equalization.

Filtering process

During the process of sampling, transmission and receiving of the data, it is necessary to smooth the noisy signals while at the same time preserving the edge information. Digital images are corrupted often by impulse noise, due to faulty sensors in the camera, transmission of images through faulty channels. Two types of impulse noises are: 1) salt and pepper noise 2) random valued impulse noise. Various non-linear filtering techniques are formulated here. Salt and pepper noise is effectively removed by Standard Median Filters (SMF) by preserving the edges but flatters at high noise densities [18]. The above drawback is eliminated by an adaptive median filter

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(AMF), but owing to its increasing the window size lead to blurring of images [19]. In recent years, some threshold based median and related impulse noise filters were proposed such as Detail preserving filter (DPF) [20], Pixel-wise MAD (PWMAD) [21] filter, Signal dependent rank order mean (SD-ROM) filter [22], Switched median filters [23], [24]. The above said filters do not have a strong decision or does not consider the local information. Hence, at heavy noise levels, they fail without preserving the original image details. To avoid the blemish, Decision based filter (DBA) [25] was proposed. This filter identifies the processed pixel as noisy, if the pixel value is either 0 or 255; else, it will be considered as not noisy. Under High noisy environment, the Decision based filter replaces the noisy pixel with neighborhood pixel. In spite of repeated replacement of neighborhood pixel results in streaks in restored image. To avoid the streaks in images, a Decision based modified median filter (DBMMF) [36] is proposed.

Algorithm of DBMMF: The Decision based modified median filter (DBMMF) initially detects impulse and corrects it subsequently. All the pixels of an image lie between the dynamic ranges [0, 255]. If the processed pixel holds minimum (0) or maximum (255), pixel is considered as noisy and processed by DBMMF else as not noisy and the pixel is unaltered. The brief illustration of the algorithm is as follows:

Step 1: Choose the window (2-D) of size 3x3. Pixels present in the current window are assumed as A_{xy}.

Step 2: Check for the condition $0 < A_{xy} < 255$, if the condition is true then consider the pixel as not noisy and left unaltered.

Step 3: If the processed pixel A_{xy} holds 0 or 255 i.e. (A_{xy}=0 or A_{xy} =255) then pixel A_{xy} is considered as corrupted pixel. Convert 2-D array into 1-D array. Sort the 1-D array which is assumed as D_{xy}.

Step 4: Initialize two counters, forward counter (FC) and reverse counter (RC) with 1 and 9 respectively. When a 0 or 255 are encountered inside the window FC is increased by 1 or RC is decremented by 1 respectively. When the pixel is noisy, there happens to be two possible cases.

Case I: If the processing pixel is noisy and the current processed window contains few 0's and 255's. So check for 0 or 255 in sorted array D_{xy}, simultaneously counters would propagate along the D_{xy} array thereby eliminating outliers retaining only the pixel that hold values other than 0 and 255. After checking all the pixels FC and RC would hold a particular value that indicates the number of outliers are eliminated on either sides. The noisy pixel is replaced by the midpoint of the sorted array.

Case II: Every pixel that exists inside the kernel is the combination of 0 or 255. Even this condition is addressed by the case I operation, thereby making the algorithm simple. When all the pixel elements hold 0 or 255 then the values are retained, assuming it as texture of the image.

Step 5: Steps 1 to 4 is repeated until all pixels of the entire image is processed.

The Quantitative performance of the DBMMF algorithm is evaluated based on Peak signal to noise ratio (PSNR) and Image Enhancement Factor (IEF) as in equations (1) to (3).

$$PSNR = 10\log_{10}(L-1)^2 / MSE \tag{1}$$

$$MSE = \frac{\sum_i \sum_j \left| X(i,j) - Y(i,j) \right|^2}{N} \tag{2}$$

$$IEF = \frac{\left(\sum_{i} \sum_{j} C(i,j) - X(i,j) \right)^2}{\left(\sum_{i} \sum_{j} Y(i,j) - X(i,j) \right)^2} \tag{3}$$

Here, $X(i,j)$ and $Y(i,j)$ are the input and output images respectively, $C(i,j)$ is the corrupted image, N is the total number of pixels in the input or output images and L is the number of intensity value.

Table-1. PSNR for CT Chest image at different noise densities

Noise in %	PSNR in DB				
	SMF	AMF	DPF	DBA	DBMMF
10 %	38.2	45.1	37.9	43.7	46.4
20 %	34.5	42.7	31.2	40.1	43.1
30 %	27.9	40.0	27.1	38.4	41.5
40 %	23.4	35.4	23.5	36.7	40.7
50 %	19.7	29.3	20.9	34.9	38.6
60%	15.1	24.7	18.4	37.3	36.2
70 %	13.0	20.6	17.8	35.1	34.9
80 %	11.4	16.8	15.4	33.7	33.6
90 %	9.8	12.4	11.4	31.3	31.7

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Table-2. IEF for CT Chest image at different noise densities.

Noise in %	IEF				
	SMF	**AMF**	**DPF**	**DBA**	**DBMMF**
10 %	93.7	257.2	75.1	246.2	540.3
20 %	76.2	268.3	36.7	265.4	519.4
30 %	62.3	235.3	19.6	279.1	465.8
40 %	43.1	189.7	15.3	221.4	460.3
50 %	25.8	93.1	13.4	203.4	435.7
60%	14.5	39.0	10.7	182.3	402.9
70 %	5.3	15.4	8.6	146.5	359.4
80 %	3.9	9.3	7.3	119.2	295.7
90 %	2.7	6.4	6.9	66.8	184.1

From the Tables 1 and 2, it can be readily observed that the DBMMF algorithm has high PSNR and IEF when compared to other algorithms. The DBMMF algorithm gives excellent noise suppression capabilities in gray scale images corrupted by salt and pepper noise for high noise densities and also fairs well in preserving the global edge of the high detail images and outclasses other classical and existing recent algorithms.

Histogram partitioning process

Each image has different histogram, which depends on the brightness and darkness of the image (intensity value), and this histogram is partitioned to enhance the image. The proposed QDAPLHE method divides the histogram into four sub histograms based on mean value. The mean-based partition approach tends to segment the number of pixels equally in each sub histogram. Hence, each separating point can be calculated using the following equations:

$$s_1 = .25 \times \{I_w \times I_h\} \tag{4}$$

$$s_2 = .5 \times \{I_w \times I_h\} \tag{5}$$

$$s_3 = .75 \times \{I_w \times I_h\} \tag{6}$$

Where s_1, s_2 and s_3 are intensities set to 0.25, 0.50 and 0.75, respectively, for the total number of pixels in the histogram of the input image. I_w and I_h represent the width and height of the input image, respectively.

Clipping process

Histogram equalization stretches the high contrast region of the histogram, and compresses the low contrast region of the histogram [27]. As a consequence, when the object of interest in an image occupies only a small portion of the image, then the object will not be successfully enhanced by histogram equalization. Histogram equalization method causes level saturation effects as it extremely pushes the intensities towards the right or the left side of the histogram.

A clipped histogram equalization method tends to overcome these problems by restricting the enhancement rate. It is known that the enhancement from histogram equalization is heavily dependent on the cumulative density function [c(x)]. Therefore, the enhancement rate is proportional to the rate of c(x). The rate of c(x) is given by the following equation

$$\frac{d}{dx} c(x) = p(x) \tag{7}$$

The probability density function $p(x)$ is given by

$$p(x) = \frac{h(x)}{N} \tag{8}$$

where $h(x)$ is the histogram for intensity value '*x*' and 'N' is the total number of pixels in the image. The enhancement rate is limited by limiting the value of p(x), or h(x) [28].

Therefore, the clipped histogram equalization modifies the shape of input histogram by decreasing or increasing the value in the histogram's bins based on a threshold limit before the equalization takes place. This threshold limit is also known as the clipping limit, or clipping threshold (T_c) or the plateau level of the histogram and based on this threshold value, the histograms will be clipped.

To avoid the intensity saturation and over enhancement problem, the proposed QDAPLHE method adopts the Clipped Histogram Equalization (CHE) to control the enhancement rate by defining a plateau limits automatically to each sub histogram. Here, the plateau limit (or T_c) is determined automatically by calculating the average occupied intensity in each sub- histogram.
Each plateau limit is identified as

$$P_i = \frac{1}{s_i - s_{i-1}} \times \sum_{k=m_{i-1}}^{m_i} h(X_k) \tag{9}$$

where $h(X_k)$ is the histogram at the intensity level 'k'.

Clipping process is applied after finding the plateau limit. The clipped portion can be determined as

$$h_{ci}(X_k) = \begin{Bmatrix} h(X_k) & h(X_k) \le P_i \\ P_i & h(X_k) > P_i \end{Bmatrix} \tag{10}$$

where $h_{ci}(X_k)$ is the clipped histogram at intensity level 'k'.

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While using the clipping process, all the values above the plateau limit (T_c) are removed, which may lead to loss on original intensity value of the image. Hence, the histogram in the clipped portion is adjusted using the equation (11).

$$h_{mci}(X_k) = \begin{cases} h_{ci}(X_k) & h_{ci}(X_k) \le P_i \\ P_i + \dfrac{h_{ci}(X_k) - P_i}{3} & h_{ci}(X_k) > P_i \end{cases} \tag{11}$$

where $h_{mci}(X_k)$ is the modified clipped histogram at intensity level 'k'.

This type of clipping process has the effect of the contrast enhancement and reduces the noise amplifying artifacts.

Redistribution process

Because of this clipping process, the sub histograms may not ensure the balance space in each sub-histogram for sufficient contrast enhancement. When the side of the sub-histogram is narrow, contrast enhancement obtained in narrow stretching space is less significant and wide stretching space introduces redundant contrast enhancement. Consequently, the processed image tends to suffer from loss of image details and intensity saturation artifact. To overcome these drawbacks, the clipped portion is redistributed over the entire dynamic range. For this, the proposed QDAPLHE method maintains the point s_2 as the brightness preserving. The separating points of s_1, s_2 and s_3 are reassigned to a new grey level represented as t_1, t_2, and t_3 respectively.

$$t_1 \cong s_2 \times \frac{s_1 - s_0}{s_2 - s_0} \tag{12}$$

$$t_2 \cong s_2 \tag{13}$$

$$t_3 \cong (L - 1 - s_2) \times \frac{s_3 - s_2}{s_4 - s_2} + s_2 \tag{14}$$

Where s_0 and s_4 are assigned to the minimum and maximum output intensity value. (ie., $s_0 = 0$ and $s_4 = L-1$ (255)). The new dynamic ranges are determined for all the quadrant sub-histograms.

Histogram equalization

The final step in the proposed QDAPLHE method is to equalize each new quadrant sub-histogram independently. The output of histogram equalization, Y(X) of this sub-histogram can be determined by using the equation (15).

$$Y(X) = t_{i-1} + (t_i - t_{i-1}) \times \frac{\sum_{k=m_{i-1}}^{m_i} h_{mci}(X_k)}{M_i} \tag{15}$$

The total of the clipped histogram at i-th sub-histogram M_i is given by

$$M_i = \sum_{k=m_{i-1}}^{m_i} h_{mci}(X_k) \tag{16}$$

EXPERIMENTAL RESULTS AND DISCUSSIONS

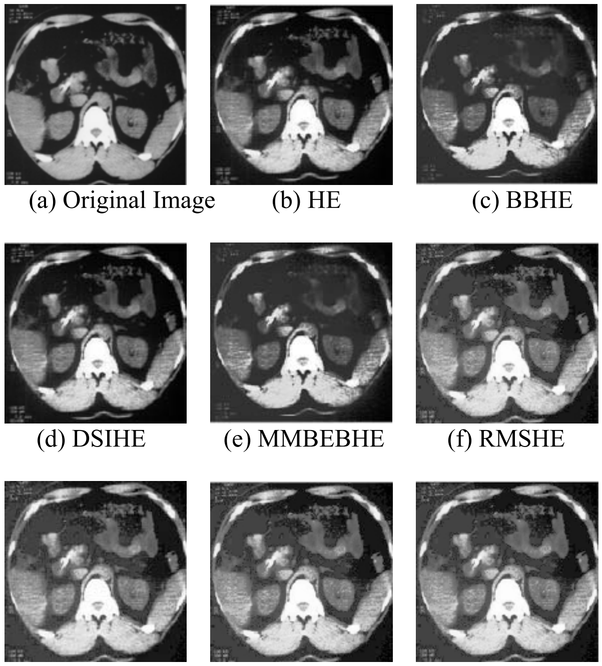
The performance of the proposed QDAPLHE method is tested on numerous images. The images like Einstein, girl, House and couple are taken from data base (http://decsai.ugr.es/cvg/dbimagenes/) and CT abdomen images were obtained from Kanyakumari Government medical college, Asaripallam, Tamil Nadu, India with the help of Dr. J. Ravindran. CT abdomen image of size 256x256 pixels is taken to evaluate the capability of the proposed method. The proposed QDAPLHE method is qualitatively and quantitatively analyzed.

Qualitative analysis

The qualitative analysis involves performance comparison with existing brightness preserving methods, namely HE, BBHE, DSIHE, MMBEBHE, RMSHE, BPDHE and BHEPL. Figure-1 shows the output images produced by these HE methods for the CT abdomen image.

From the experimental results, the enhancement produced by existing methods and proposed method are shown in Figures 1(a) to 1(i) for input images. In general, the conventional histogram equalization algorithms are prone to missing luminance levels due to the mapping function calculation and this will lead to cause the lack of information in case of a gradation background. To overcome these shortcomings, clipping based method (QDAPLHE) is developed and the output result is shown in Figure-1(i).

Based on Figure-1(b), it is clear that the histogram equalization method enhances the images, but it also amplifies the noise level of the images. From the Figures 1c and 1f (BBHE, RMSHE), the drawback of these methods is obviously seen that they preserves the mean brightness of the images without emphasizing on the image details significantly, that is, the problem of intensity saturation occurs in some regions of the image even this methods improve the contrast of the image.



(a) Original Image (b) HE (c) BBHE

(d) DSIHE (e) MMBEBHE (f) RMSHE

(g) BPDHE (h) BHEPL (i) Proposed DAPLHE

Figure-1. Results for CT abdomen image.

Figure-1(i) shows that the contrast of all the tested images is enhanced successfully using the proposed QDAPLHE method. In addition, this method preserves the image details successfully. Figures 1(g) and 1(h), shows that BPDHE and BHEPL methods produces acceptable and natural enhanced images. Compared to these BPDHE and BHEPL methods, the proposed QDAPLHE method reduces the intensity saturation problem and also it can significantly improve the performance.

Quantitative analysis

To prove the robustness of the proposed methods, three kinds of quantitative comparisons tests which are the absolute mean brightness error, Standard deviation and Peak signal to noise ratio have been evaluated and tabulated in Tables 3 to 5 respectively.

Absolute mean brightness error (AMBE): The first test which is used as the performance measure is Absolute Mean Brightness error (AMBE). AMBE is used to evaluate the ability of the enhancement method to maintain the mean brightness.

$$AMBE = \left(X_m - Y_m\right) \qquad (17)$$

where, X_m is the mean of the input image and Y_m is the mean of the output image

The minimum value of AMBE results that the mean brightness of the input is successfully maintained in the output image. Table-3 shows the AMBE measure obtained for the sample images. The AMBE values calculated by the existing methods HE, BBHE, RMSHE are compared with the AMBE value of proposed method. From the Table-3, it can be readily observed that the proposed method QDAPLHE has 13.13% less AMBE average value when compared to BHEPL, the method with second minimum average value.

Standard deviation (Image Contrast): By measuring the standard deviation, the contrast of the image can be studied. Standard Deviation 'σ' is given by

$$\sigma = \sqrt{\sum_{l=0}^{L-1} (l-\mu) \times p(l)} \qquad (18)$$

where Mean, $\mu = \sum_{l=0}^{L-1} l \times p(l)$ and 'l' represents the pixel value in the image.

From the Table-4, it is clear that the standard deviation value obtained for the proposed QDAPLHE method is less compared to all the existing methods for all the images.

Peak signal to noise ratio (PSNR): Another quantitative test used to measure the richness of details and appropriateness is peak signal to noise ratio (PSNR). Based on mean squared errors (MSE), PSNR is defined as

$$PSNR = 10\log_{10}(L-1)^2 / MSE \qquad (19)$$

Table-3. Absolute Mean Brightness Error (AMPE).

Images	HE	BBHE	DSIHE	MMBEBHE	RMSHE (r=2)	BPDHE	BHEPL	QDAPLHE
Einstein	17.17	19.27	12.07	14.27	10.17	3.65	3.07	1.97
girl	5.29	23.51	4.46	3.04	0.45	2.4	0.13	0.07
House	58.81	25.09	31.92	25.06	8.07	5.43	3.57	2.54
couple	96.42	33.17	43.81	18.45	10.28	3.56	2.78	1.72
CT abdomen	59.34	24.73	31.35	13.08	3.71	2.19	1.25	0.97
Average	**47.4**	**25.15**	**24.72**	**14.78**	**6.54**	**3.45**	**2.16**	**1.45**

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Table-4. Standard Deviation (STD).

Images	HE	BBHE	DSIHE	MMBEBHE	RMSHE (r=2)	BPDHE	BHEPL	QDAPLHE
Einstein	73.59	73.81	73.94	62.31	57.95	52.43	41.72	35.51
girl	75.41	70.12	75.49	68.73	37.85	35.57	27.21	28.13
House	73.65	75.13	75.51	55.43	56.79	50.72	49.27	38.54
couple	71.86	74.15	79.61	48.41	53.29	41.49	35.38	32.17
CT abdomen	82.34	76.35	79.56	69.13	50.37	48.29	45.84	29.74
Average	**75.37**	**73.91**	**67.82**	**60.80**	**51.25**	**45.7**	**39.88**	**32.82**

Table-5. Peak Signal to noise Ratio (PSNR).

Images	HE	BBHE	DSIHE	MMBEBHE	RMSHE (r=2)	BPDHE	BHEPL	QDAPLHE
Einstein	15.27	15.19	15.53	18.97	19.52	27.52	30.57	32.59
girl	13.05	13.3	13.04	14.25	27.98	33.74	34.92	35.37
House	10.81	14.26	13.92	21.45	21.32	24.63	28.64	31.49
couple	7.56	13.16	11.64	19.56	19.64	29.34	38.24	42.34
CT abdomen	16.54	23.25	18.16	23.45	31.23	32.74	33.78	37.19
Average	**12.64**	**15.83**	**14.46**	**19.54**	**23.94**	**29.54**	**33.23**	**35.79**

Where

$$MSE = \frac{\sum_i \sum_j \left| X(i,j) - Y(i,j) \right|^2}{N} \quad (20)$$

$X(i,j)$ and $Y(i,j)$ are the input and output images respectively, N is the total number of pixels in the input or output images, and L is the number of intensity values.

The PSNR values for different images are tabulated in Table-5. The PSNR values of three methods BPDHE, BHEPL and QDAPLHE are ranked the first, second and third highest values respectively. From the Table-5, it can be observed that the images processed by proposed QDAPLHE method produces the best PSNR values, as they are within the range [31 dB to 42 dB]. From these values, it can be concluded that the proposed method performs image contrast enhancement and produce images with a natural looking with less noise amplifying.

In Overall, Both Qualitative And The Quantitative Tests Favor The Proposed Method QDAPLHE As The Best Among All The Existing Methods. Thus, It Can Be Stated That The Proposed Algorithm Produces The Best Image Enhancement.

CONCLUSIONS

Although the histogram equalization is simple and effective algorithm for enhancement, it leads to over enhancement and intensity saturation problem. To overcome this effect, dynamic histogram equalization is powerful method for enhancing the low contrast images, also in some cases it leads to noise amplification and intensity saturation problems. To overcome the level saturation effects occurred in histogram equalization, clipped histogram equalization methods are developed by restricting the enhancement rate. Hence, a new method QDAPLHE is proposed as a hybrid of Dynamic histogram equalization method and Clipped histogram equalization method. The qualitative and the quantitative analysis are performed on the proposed method and the results are represented in the Figure-1 and in the Tables 3 to 5. From the experimental results, both qualitative and the quantitative tests favor the proposed method QDAPLHE as the best among all the existing methods. Also this technique is more suitable for consumer electronic products where preserving the original brightness is essential.

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