Image Contrast Enhancement for Brightness Preservation Based on Dynamic Stretching

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Abstract

Histogram equalization is an efficient process often employed in consumer electronic systems for image contrast enhancement. In addition to an increase in contrast, it is also required to preserve the mean brightness of an image in order to convey the true scene information to the viewer. A conventional approach is to separate the image into sub-images and then process independently by histogram equalization towards a modified profile. However, due to the variations in image contents, the histogram separation threshold greatly influences the level of shift in mean brightness with respect to the uniform histogram in the equalization process. Therefore, the choice of a proper threshold, to separate the input image into sub-images, is very critical in order to preserve the mean brightness of the output image. In this research work, a dynamic range stretching approach is adopted to reduce the shift in output image mean brightness. Moreover, the computationally efficient golden section search algorithm is applied to obtain a proper separation into sub-images to preserve the mean brightness. Experiments were carried out on a large number of color images of natural scenes. Results, as compared to current available approaches, showed that the proposed method performed satisfactorily in terms of mean brightness preservation and enhancement in image contrast.

Keywords: Image Contrast Enhancement, Histogram Equalization, Brightness Preservation, Golden Section Search.

1. INTRODUCTION

Image processing techniques have been applied in a wide range of engineering applications such as consumer electronic devices [1], robotics [2], machine condition monitoring [3], and remote sensing [4]. In order to obtain satisfactory performance in these image based applications, the enhancement of image contrast is a fundamental requirement. Moreover, it is necessary to preserve the mean brightness of the processed image by which a better perception of the scene can be delivered to the viewer. To this end, the histogram equalization technique is an attractive candidate approach for contrast improvement because of its implementation tractability and simplicity.

Histogram equalization (HE) based image contrast enhancement is able to provide contrast improvements; however, the method tends to shift the output image brightness to the middle of the permitted intensity range [5]. The need to preserve the mean brightness of an image had thus motivated a large number of research works. A class of methods had been developed which were based on separating the image into high and low intensity sub-images and then apply equalization to each component independently. An early work had initiated schemes dividing the input image with the mean brightness in the bi-histogram equalization method (BBHE) [6]. This idea was later modified to incorporate the median value as the divider threshold in the process called dualistic sub-image histogram equalization (DSIHE) [7]. However, due to the fact that HE does not have control on the enhancement level, the output image might suffer from over-enhancement, especially if the input image contains significantly brighter or darker regions than other parts of the image. As the sub-images are processed using histogram equalization, these algorithms cannot ensure the mitigation of over-enhancement or an exact match of the input and output mean brightness values.

In order to overcome such limitation, an alternative approach of clipping the peaks of each sub-image histogram is employed to match the target histogram for achieving equalization. A pioneer example is the bi-histogram equalization with plateau level (BHEPL) where the image was separated by the mean brightness value and each histogram of a sub-image was clipped using the mean of the sub-image histogram [8]. This approach was later modified to utilize the median of sub-image histogram for clipping (BHEPLD) [9]. A recent work, adopting the bi-histogram equalization principle, adaptive image enhancement based on bi-histogram equalization with a clipping limit (AIEBHE), was reported in [10]. The clipping limit imposed on each sub-image histogram depends on the minimum of the mean and median values obtained from the histogram. These variations had resulted in the mitigation of over-enhancements, but the preservation of mean brightness in the output image was not purposefully considered. On the other hand, the authors in [11] adopted an exhaustive search approach to find a separation threshold. However, with the histogram equalization on sub-images, an exact match of input and output mean brightness still cannot be guaranteed.

In addition to dividing the input image into two sub-images to process them independently, researchers also suggested dividing the image into multiple sub-images. For instance, the dynamic quadrants histogram equalization plateau limit (DQHEPL) method had divided the image into four sub-images [9]. The clipping limits were obtained from the mean values of each sub-image histograms. The concept of using quadratic sub-images was further carried forward in the process called median-mean based sub-image clipped histogram equalization (MMSICHE) [12]. Specifically, the input image was first separated by the mean brightness. Each sub-image was further divided according to the mean brightness of the corresponding sub-image. The peaks of the sub-image histograms were clipped with the median values. The implementation of these algorithms were made more complicated, however, there was no assurance that the mean brightness of the output image can be preserved.

On the other hand, the method, proposed in [13], emulates the image histogram using the Gaussian mixture model and separates it using the intersection points of the Gaussian components. The sub-images are then separately stretched using the estimated Gaussian parameters. Global contrast enhancement is achieved by applying this technique on both color and depth images [14]. The homomorphic filtering is applied on the modified histogram in order to preserve mean brightness in [15].

In this work, instead of employing histogram equalization as the main contrast enhancement processor, the dynamic stretching strategy is adopted. The concept of using mean or median value as the separation threshold is abandoned. Instead, the efficient golden section search approach is employed to find an optimal threshold such that the preservation of mean brightness in the output image is accomplished. Experiments were conducted on a large number of color images and statistics were collected to verify the proposed method.

The rest of this paper is organized as follows. In Section 2, related backgrounds are reviewed. The proposed brightness preservation method using dynamic stretching is described in Section 3. Experiments and results are presented in Section 4. Section 5 contains the conclusion.

2. RELATED BACKGROUND

There are classes of reported works that aim at image contrast enhancement by equalizing the image histograms of separated sub-images and the clipping of histograms. The choice of the separation threshold and the clipping limit, such as the mean or median value, has not been unified. In this section, several representative approaches are reviewed.

2.1 Conventional Histogram Equalization

This is the basis of many aforementioned image contrast enhancement algorithms. Given an intensity image, which may be converted from a color image, the pixel value or brightness can be described as

$$I(u,v) \in [0 \;\; L-1], \tag{1}$$

where (u,v) is the pixel coordinate in the image, $L-1$ is the maximum allowed intensity level. For example, if the image is represented as an 8-bit digital signal, then $L = 2^8 = 256$. In general, we have $u = 1,\ldots,U$ and $v = 1,\ldots,V$; where the image is of the size $N = U \times V$ in width-by-height.

In histogram equalizations [5], at first the statistics of the image is collected, giving the histogram

$$\mathbf{h} = [n(i)], \tag{2}$$

where i is the intensity index, $n(i)$ is the number of pixels having intensity i. The histogram is often normalized to produce the probability density $p(i)$ by diving $\mathbf{h}$ with the total number of pixels N in the image, such that

$$\sum_{i=0}^{L-1} p(i) = 1.$$

The cumulative density is then constructed from

$$\begin{gathered} c(i) = \sum_{j=0}^{i} p(j) \text{ and} \\ \max\{c(i)\} = 1. \end{gathered} \tag{3}$$

The enhanced or output image is obtained from mapping the original intensity to a desired level as

$$I_{enh}(i) = I_{\min} + (I_{\max} - I_{\min}) \times c(i), \tag{4}$$

where $I_{\min}$ and $I_{\max}$ are the desired minimum and maximum intensity levels of the enhanced image.

2.2 Sub-image Based Histogram Equalization

The conventional histogram method can be regarded as a global approach where all pixels are processed. Conversely, there are algorithms that separate the input into sub-images and manipulate the pixel intensities using different procedural settings for each sub-image.

In the bi-histogram equalization algorithm, the input image is separated into two sub-images to produce two histograms and each is processed independently [6]. First, the mean intensity or brightness of the input image is calculated from

$$\mu_m = \sum_{i=0}^{L-1} (i \times p(i)). \tag{5}$$

Two sub-images $\mathbf{I}_{hi}$ and $\mathbf{I}_{lo}$ are created, where

$$\begin{aligned} \mathbf{I}_{hi} &= \{I(i) \mid i > \mu_m\}, \\ \mathbf{I}_{lo} &= \{I(j) \mid j \le \mu_m\}. \end{aligned} \tag{6}$$

Furthermore, two histograms $\mathbf{h}_{hi}$ and $\mathbf{h}_{lo}$ are formed and cumulative densities are computed. Finally, each sub-image is equalized using intensity ranges $[0 \;\; \mu_m]$ and $[\mu_{m+1} \;\; L-1]$, giving two enhanced sub-images $\mathbf{I}_{enh,hi}$ and $\mathbf{I}_{enh,lo}$. The final enhanced image is the aggregation of these sub-images, computed as,

$$\mathbf{I}_{enh} = \mathbf{I}_{enh,hi} \cup \mathbf{I}_{enh,lo} . \tag{7}$$

When the histogram equalization processes are carried out using a uniform target histogram, the mean brightness values of the enhanced sub-images are shifted to the middle of the corresponding ranges, that is

$$\mu_{enh,hi} = 0.5 \times (\mu_m + L), \;\; \mu_{enh,lo} = 0.5 \times \mu_m . \tag{8}$$

The output image mean brightness, $\mu_{enh,m}$ is the sum of these two mean intensities weighted by the respective number of pixel used from original image. We have

$$\mu_{enh,m} = w_{hi} \times \mu_{enh,hi} + w_{lo} \times \mu_{enh,lo} , \tag{9}$$

where $w_{hi} = n(i)/N$, $i = 0, \ldots, \mu_m$; and $w_{lo} = n(j)/N$, $j = \mu_{m+1}, \ldots, L-1$. It can be observed that the output image mean brightness depends on the features of the image. The limitation of this method is that only when the two sub-images have the same number of pixels or when two weights are at $w_{hi} = w_{lo} = 0.5$ and $\mu_m = L/2$, the brightness preservation could be accomplished.

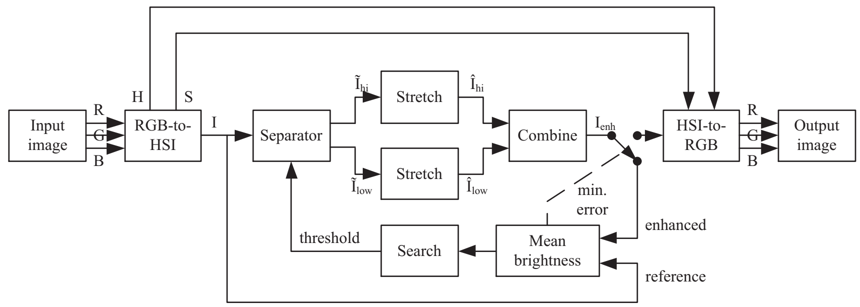

FIGURE 1: Block diagram of the proposed brightness preserving dynamic stretching approach.

2.3 Clipped Histogram Equalization

In addition to the shift in mean intensity, the conventional histogram equalization method also suffers from the generation of artifacts where abrupt intensity changes appear in the output image. This drawback arises where pixel intensities tend to concentrate in a narrow range giving rises to peaks in the histogram. In order to mitigate this problem, the histogram peaks are clipped prior to the calculation of the cumulative density [8]. Similar initial procedures in bi-histogram equalization are adopted where two sub-images are obtained and two histograms are constructed. Then two clipping limits are computed from

$$\begin{aligned} T_{hi} &= \sum_{i=0}^{\mu_m} \left(i \times p(i) \right) \\ T_{lo} &= \sum_{j=\mu_m+1}^{L-1} \left(j \times p(j) \right), \end{aligned} \tag{10}$$

which are effectively the mean values of the individual sub-histograms. The histograms are clipped such that

$$\begin{aligned} \mathbf{h}_{hi} &= \begin{cases} h_{hi}(i), & h_{hi}(i) < T_{hi} \\ T_{hi}, & \text{otherwise} \end{cases} \\ \mathbf{h}_{lo} &= \begin{cases} h_{lo}(i), & h_{lo}(i) < T_{lo} \\ T_{lo}, & \text{otherwise}. \end{cases} \end{aligned} \tag{11}$$

The subsequent processes follow the conventional histogram equalization procedure where each sub-image is manipulated independently as found in the bi-histogram equalization algorithm.

The problem associated with this clipping action is that the resultant image mean brightness does not normally have a closed-form solution. This is due to the variations in image contents and the difficulties in choosing proper clipping limits.

3. DYNAMIC STRETCHING BASED BRIGHTNESS PRESERVATION

In order to enhance the image contrast and to preserve the output image mean brightness, an approach based on dynamic range stretching is proposed and coined as the dynamic stretching based brightness preservation (DSBP) method. The method adopts the sub-image separation principle; in addition, the separation threshold is obtained from the efficient golden section search approach [16].

The system block diagram is shown in Fig. 1. Given a color image in the red-green-blue format, it is first converted to the hue-saturation-intensity (HSI) space where the intensity is extracted by adopting the method described in [5]. This signal is often called the gray-level image. The I-channel is then separated into the low and high groups, $\mathbf{I}_{hi}$ and $\mathbf{I}_{lo}$, by the threshold to be determined with golden section search method. These two groups are stretched to occupy their corresponding complete intensity range and combined again to produce the enhanced image. The overall mean intensity or brightness of this image is calculated and compared with the input image mean brightness. The difference, namely brightness error, is used to drive the search for an optimal threshold. The separation, stretching and brightness error calculation processes are iterated until a threshold is found that minimizes the brightness error. Finally, when the iteration terminates, the enhanced intensity component is combined with the original hue and saturation to give the output image through the HSI to RGB conversion.

To start the Golden Section search process, a trial threshold $\tilde{I}_m \in [0 \;\; L-1]$ is determined to separate the image into two sub-images $\tilde{\mathbf{I}}_{hi}$ and $\tilde{\mathbf{I}}_{lo}$, where

$$\begin{aligned} \tilde{\mathbf{I}}_{hi} &= \{I(i) \mid i > \tilde{I}_m\}, \\ \tilde{\mathbf{I}}_{lo} &= \{I(j) \mid j \le \tilde{I}_m\}. \end{aligned} \tag{12}$$

The dynamic range of each sub-image is then stretched up to the permitted intensities. That is

$$\hat{\mathbf{I}}_{hi} = \tilde{I}_{m+1} + \frac{\tilde{\mathbf{I}}_{hi} - \min\{\tilde{\mathbf{I}}_{hi}\}}{\max\{\tilde{\mathbf{I}}_{hi}\} - \min\{\tilde{\mathbf{I}}_{hi}\}} \times \left(L - 1 - \tilde{I}_{m+1}\right) \tag{13}$$

$$\hat{\mathbf{I}}_{lo} = \frac{\tilde{\mathbf{I}}_{lo} - \min\{\tilde{\mathbf{I}}_{lo}\}}{\max\{\tilde{\mathbf{I}}_{lo}\} - \min\{\tilde{\mathbf{I}}_{lo}\}} \times \tilde{I}_m\,. \tag{14}$$

The two stretched sub-images are aggregated according to Eq. 7 and the mean brightness is calculated with Eq. 5.

Furthermore, a second trial threshold is selected to obtain another mean intensity. Hence, for these two thresholds $\tilde{I}_{m,1}$ and $\tilde{I}_{m,2}$, we have mean brightness $\hat{\mu}_1$ and $\hat{\mu}_2$. When the trial threshold cannot produce the desired mean brightness preservation, a search procedure is invoked to find a proper threshold by using the efficient golden search algorithm. A search ratio $\rho = (\sqrt{5}-1)/2$ as well as a threshold range $\Delta_m = \tilde{I}_{m,2} - \tilde{I}_{m,1}$ is defined; assuming $\tilde{I}_{m,2} > \tilde{I}_{m,1}$. For this work, $\tilde{I}_{m,1}$ and $\tilde{I}_{m,2}$ are set to the allowed intensity limit, that is, $\tilde{I}_{m,1} = 0$ and $\tilde{I}_{m,2} = L-1$. The function that is used for the golden section search is

$$f(\mu) = \mid \mu - \mu_m \mid, \tag{15}$$

which reaches the minima when the mean brightness of the enhanced image μ is equal to the mean brightness of the input image μ_m, hence make the function unimodal which is a requirement of the golden section search algorithm. The proposed process then proceeds as given in Algorithm 1 below.

Algorithm 1 Dynamic Stretching based Brightness Preservation Algorithm

Input: $\rho, \Delta_m, \mu_m, \tilde{I}_{m,1}, \tilde{I}_{m,2}, \hat{\mu}_1, \hat{\mu}_2$

Output: enhanced image $\mathbf{I}_{enh}$

Define convergence tolerance $\tau < 1/L, \Delta_m$

while $\Delta_m > \tau$

set $\Delta\tilde{I}_{m,1} = |\hat{\mu}_1 - \mu_m|, \Delta\tilde{I}_{m,2} = |\hat{\mu}_2 - \mu_m|$

if $\Delta\tilde{I}_{m,1} > \Delta\tilde{I}_{m,2}$ **then**

set $\tilde{I}_{m,1} \leftarrow \tilde{I}_{m,1} + \Delta_m \times \rho$

else

set $\tilde{I}_{m,2} \leftarrow \tilde{I}_{m,1} + \Delta_m \times (1-\rho)$

end if

Do image separating and stretching using $\tilde{I}_{m,1}$ and $\tilde{I}_{m,2}$ to obtain $\hat{\mu}_1$ and $\hat{\mu}_2$

Calculate $\Delta_m = \tilde{I}_{m,2} - \tilde{I}_{m,1}$

end while

Aggregate stretched sub-images to give $\mathbf{I}_{enh}$

4. EXPERIMENTS

A collection of 220 color images, including 20 publicly available standard test images from http://r0k.us/graphics/ko-dak/, captured in natural environment such as clear day, night time and poor conditions with overcast weather, were used in the experiment to verify the performance of the proposed method. The image sizes are 400×300 pixels width-by-height and are stored in 24-bit RGB colored JPG format. The qualities of the enhanced image are assessed and compared in terms of metrics including brightness error, contrast, entropy, and gradient as defined below. The statistics of the metrics for all the images are plotted in box plots for further comparison of the proposed dynamic stretching based brightness preservation (DSBP) method to other available methods namely, conventional uniform histogram equalization (UNFHE), BBHE, DSIHE, BHEPL, BHEPLD, AIEBHE, and MMSICHE.

Brightness Error:

The deviation in mean brightness while approximating the enhanced image in comparison to that of the input image is referred as the brightness error [6] and expressed as following

$$\mu_{err} = \mu_{enh} - \mu_m \, . \tag{16}$$

From Eq. 16, it is clear that if the average brightness is preserved in the output image, the error will be as minimum as zero.

Contrast:

The contrast depends not only on the average intensity but also on the dispersion around a central pixel [10], as expressed as,

$$e = \frac{1}{N}\sum I_{enh}^2(x,y) - \left(\frac{1}{N} I_{enh}(x,y)\right)^2 , \tag{17}$$

where (x, y) refers to the pixel location. A higher value of e denotes better contrast.

Entropy:
It is a measure of the information content of the image and defined as

$$\mathbf{H} = -\sum_{i=0}^{L-1} p(i)\log_2 p(i), \tag{18}$$

where a higher value is desirable.

Gradient:
According to [5], the gradient is defined as

$$\mathcal{G} = \frac{1}{N}\sum_{x,y}\left(\Delta x^2 + \Delta y^2\right), \tag{19}$$

where, $\Delta x = I_{enh}(x, y) - I_{enh}(x+1, y)$ and $\Delta y = I_{enh}(x, y) - I_{enh}(x, y+1)$. The larger the gradient value is, the sharper the image is perceived by a viewer.

4.1 Qualitative Evaluation
For the visual assessment, two sample images and their outputs from different approaches are shown in Fig. 2 and Fig. 3.

The standard benchmark image, shown in Fig. 2(a), contains a natural outdoor scene under daylight. Figures 2(b), 2(c), and 2(d) are obtained from the methods UNFHE, BBHE, DSIHE respectively, which are based on image separation and equalization towards a uniform distribution. As these methods do not provide any restriction on the processed brightness, the output images from these methods are observed to be brighter than the input image. Enhancements from the implementations based on clipping of histogram peak are shown in Figures 2(e), 2(f), 2(g), 2(h), and 2(i). For these methods, though the output brightness is close to the input, significant artifacts can be observed in the homogeneous region of the sky. On the contrary, the output from the proposed method, shown in Fig. 2(j), does not suffer from such limitation. The image is enhanced with better color tone and higher contrast, thus makes it more appealing to the human viewer. Moreover, the change in brightness is not noticeable.

Figure 3 depicts another example image sampled from the dataset along with the generated outputs from all the approaches compared. The image is captured in poor weather condition; hence the color is not vivid and the contrast is low. It can be observed that results from UNFHE, BBHE, DSIHE tend to generate viewing artifacts where there is abrupt change in intensity. Moreover, they produce patches that are either too dark or too bright, such that feature details are lost in the resultant image. For the cases of BHEPL, BHEPLD, AIEBHE, and MMSICHE, the artifacts are mitigated, but the improvement in contrast is not significant; especially the output from BHEPL gives the least contrast as observed by a human viewer. On the other hand, the result from DQHEPL has such a large deviation from the original mean brightness that the sea region in the image lost the fine details. The enhanced image from the proposed method is shown in Fig. 3(j). It is evident from the image that the proposed method not only maintains the mean brightness as close to that of input image, but also increases the image contrast in order to improve the fine details of the image. With more vivid color and improved information content, the output of the proposed method achieves higher perceptual performance than the other methods in comparison.

FIGURE 2: Sample experiment result - 1. Enhancement methods: (a) input image, (b) UNFHE, (c) BBHE, (d) DSIHE, (e) BHEPL, (f) BHEPLD, (g) AIEBHE, (h) DQHEPL, (i) MMSICHE, (j) DSBP.

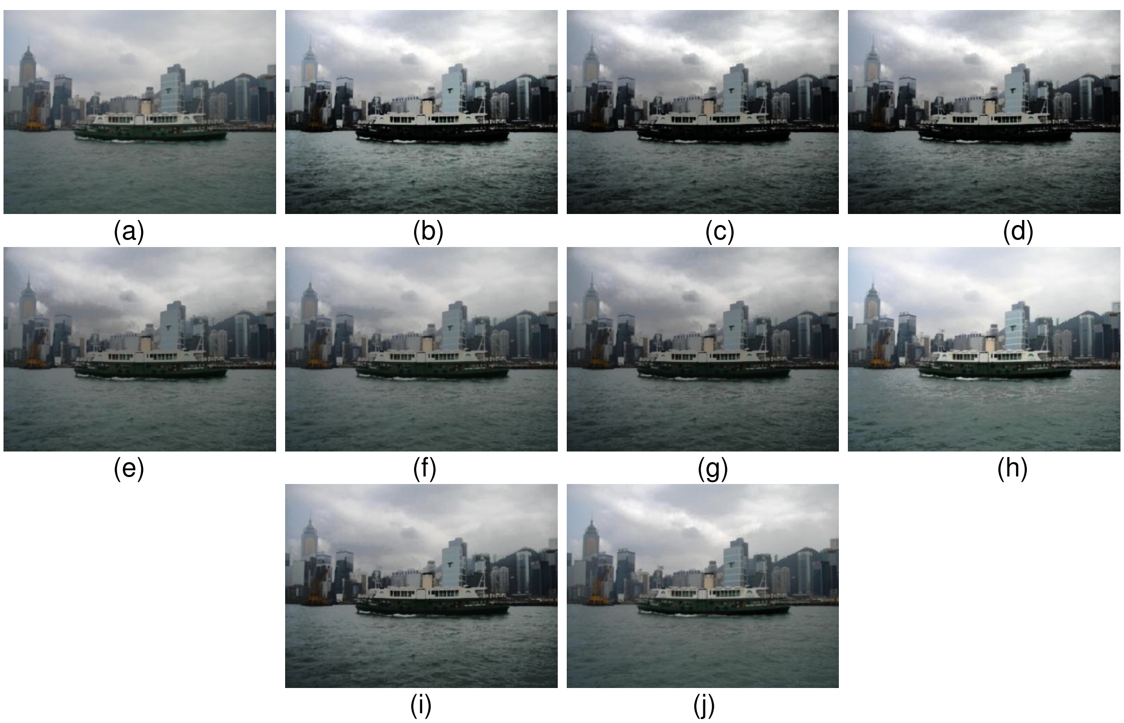

FIGURE 3: Sample experiment result - 2. Enhancement methods: (a) input image, (b) UNFHE, (c) BBHE, (d) DSIHE, (e) BHEPL, (f) BHEPLD, (g) AIEBHE, (h) DQHEPL, (i) MMSICHE, (j) DSBP.

4.2 Quantitative Evaluation

Statistics of the performance metrics were collected over the 220 test images and are displayed as box plots in Fig. 4 to illustrate the performance of the test methods.

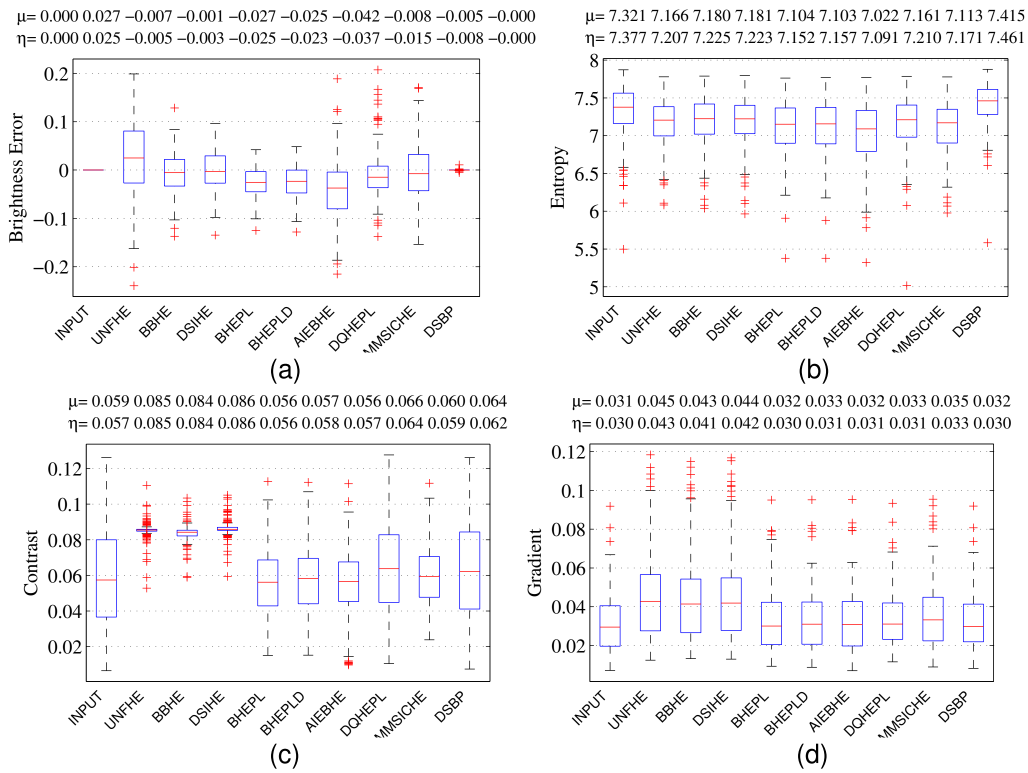

FIGURE 4: Box plots of result statistics for methods compared: (a) brightness error, (b) entropy, (c) contrast and (d) gradient[1].

Figure 4(a) shows the statistics of the brightness error between the input and the enhanced images from different methods. The input is the reference, hence has zero error, as shown in the left-most box. In the case of UNFHE method, the spread is largest as there is no mechanism to preserve the brightness. For the other methods, whether based on histogram equalization towards a uniform histogram or clipping of the histogram, there is significant brightness error with wide spreads. On the other hand, the proposed method produces the smallest spread with zero average brightness error among all the test methods.

Plots of information content, entropy, from the resultant images are illustrated in Fig. 4(b). It is shown that results from methods under comparison produce lower entropy values. This is due to the use of histogram equalization as the enhancement technique. With histogram equalization, the output image intensity may not cover all possible intensity levels, thus gives a reduction in entropy. On the other hand, the proposed DSBP approach, making use of dynamic range stretching, is able to occupy the permitted intensity levels and gives higher average entropy value of 7.415 against the input images of 7.321. Moreover, from the plot, it is clear that the first and third quartiles are close to each other, meaning that the entropy increment is consistent in the proposed method.

The performance metric in output image contrast is depicted in Fig. 4(c). The UNFHE, BBHE, DSIHE methods are expected to attain highest contrast as there is no unrealistic intensity limiting technique functioning in these methods. This often tends to produce undesirable viewing artifacts

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[1] μ and η represent mean and median respectively.

as observed in the qualitative analysis. On the other hand, the smoothing based approaches are unsuccessful in preserving the brightness, though next higher level of contrast can be achieved with these methods. The output from the proposed method gives an average contrast of 0.064 as compared to the input at 0.059 which is better than the other methods by employing a marginal trade-off between brightness preservation and mitigation of artifacts.

Figure 4(d) shows the performance measure of image gradient. Similar to the case of contrast, approaches employing histogram equalization without clipping produce high gradient measures at the expense of unwanted artifacts. The methods that adopt histogram clipping reduces artifacts by compromising gradient to a lower measure. The weakness of the smoothing based methods is the limited capability in brightness preservation, though they give higher gradient metric. On the other hand, the proposed method not only preserves the brightness but also improves artifacts reduction while ensuring the increment in gradient to 0.032 against the input at 0.031.

In addition to the boxplot analysis, hypothetical investigation was carried out to evaluate the performance of the proposed DSBP method. The T-test was performed to determine if the brightness of the enhanced image from different methods is significantly different from that of the original image. For the analysis, significance level was set at 0.05 to test the null hypothesis, which is defined as the difference of brightness between the input and enhanced image has a mean value of zero. Here, $h=1$ indicates the rejection of the null hypothesis at the mentioned significance level, whereas $h=0$ indicates the opposite. The $p-$value (or probability value) is the probability of observing the outcome given the null hypothesis is true.

Method	**Mean** (μ)	h	$p-$**value**
Input	0.000	N/A	N/A
UNFHE	0.027	1	0.000
BBHE	-0.007	0	0.316
DSIHE	-0.001	0	0.925
BHEPL	-0.027	1	0.000
BHEPLD	-0.025	1	0.001
AIBEHE	-0.042	1	0.000
DQHEPL	-0.008	0	0.336
MMSICHE	-0.005	0	0.370
DSBP	-0.000	0	0.997

TABLE 1: Comparison of brightness error.

From Table 1, it can be observed that for the UNFHE, BHEPL, BHEPLD, and AIBEHE methods, the null hypothesis is rejected, that is, the mean of the brightness error is significantly different from zero. Among the different methods that were failed to reject $h=0$, the proposed DSBP has the maximum $p-$value of 0.997. Therefore it can be concluded that, for DSBP, there is a higher chance that the brightness is preserved in the output image.

In summary, the visual assessment and numerical evaluation demonstrate that the proposed method maintains the brightness level to avoid artifacts generation while ensuring sufficient contrast improvement, thus achieves a balanced trade-off between the two conflicting objectives in image processing.

5. CONCLUSION

An effective approach for image contrast enhancement with mean brightness preservation has been presented. Based on the principle of bi-histogram equalization, the integration of dynamic range stretching and the golden search process had produced enhanced images with accurate preservation of the output image mean brightness with respect to the input. Experiments carried out had verified that the proposed method outperforms other current methods in terms of absolute brightness error, information content, contrast and gradient.

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