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Image contrast enhancement for preserving entropy and image visual features

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ABSTRACT

Histogram equalization is essential for low-contrast enhancement in image processing. Several methods have been proposed; however, one of the most critical problems encountered by existing methods is their ability to preserve information in the enhanced image as the original. This research proposes an image enhancement method based on a histogram equalization approach that preserves the entropy and fine details similar to those of the original image. This is achieved through proposed probability density functions (PDFs) that preserve the small gray values of the usual PDF. The method consists of several steps. First, occurrences and clipped histograms are extracted according to the proposed thresholding. Then, they are equalized and used by a proposed transferring function to calculate the new pixel values in the enhanced image. The proposed method is compared with widely used methods such as Clahe, CS, HE, and GTSHE. Experiments using benchmark datasets and entropy, contrast, PSNR, and SSIM measurements are conducted to evaluate the performance. The results show that the proposed method is the only one that preserves the entropy of the enhanced image of the original image. In addition, it is efficient and reliable in enhancing image quality. This method preserves fine details and improves image quality, supporting computer vision and pattern recognition fields.

1. Introduction

Many image-capturing conditions cause low-quality images, noise, blurring, as well as incorrect contrast and brightness levels [1]–[4]. Therefore, considerable research interest exists for improving the quality of images to their advantage. Image enhancement techniques seek to improve the quality of the visual appearance of images to increase their effectiveness for human vision, or for image processing, pattern recognition, and computer vision applications [2], [4]–[10].

Contrast enhancement is an essential branch of image enhancement. It aims to improve the quality of the visual appearance of a low-contrast image [2], [11]–[15]. Contrast enhancement may be categorized into genetic algorithms, fuzzy set algorithms, or histogram equalization (HE) algorithms [15]–[20]. One of the most widespread techniques for low contrast enhancement is the HE [5], [15]–[19]. Several works claimed that the most widespread technique for low contrast enhancement is HE because of its simplicity and easy implementation, as well as its efficiency with most kinds of images [21]–[23]. In general, all methods that adopted the HE principle enhance the poor contrast by remapping the cumulative distribution histogram of the pixels' density values to the full range according to their probabilities [21]–[23]. The methods in this category are important preprocessing stages in many computer vision applications [6], [20], [24]–[26].

HE methods can effectively overcome the problem of low contrast low brightness. However, several approaches have been proposed for a specific type of images, and these methods fail to generalize for wide types of different images [27]–[29]. Moreover, numerous problems occurred, such as over-enhancement, noises, poor brightness, and the loss of original information and fidelity state from enhanced images [27]–[29]. These techniques also overlook the important point of preserving the original information and details in enhanced images for computer vision applications. It's important to note show that the principle of HE allows the gray levels that have high probability density values to devour the associated gray values with a small probability. This situation causes the loss of some gray levels of the original information. By contrast, the local approach of HE methods generates extra gray values, a feature that leads to additional unwanted information in the enhanced images. The optimal methods are those that produce an optimum enhanced image with similar information content as those in the original images. State-of-the-art techniques are mainly concerned with enhancing the visual appearance rather than preserving the original information content [27]–[29].

In the literature, several HE methods were proposed to overcome the challenges of low contrast enhancement [14], [20], [30]–[34]. The method is the basic and the most common approach that uses a probability density function (pdf) and different cumulative distribution functions (cdf) to transform gray values into new distributions [35]. This approach is the foundation of many subsequently developed methods. However, it produces unwanted side effects with a wide type of images. The HE results improve by applying preprocessing steps on the original image and then applying HE [36]. This technique gives better results than the basic HE [35], but many problems still appear.

Many methods tried to improve the HE performance by using the local approach which based on dividing the histogram to many parts and equalizing each part individually. In Yoon *et al.* [37], the histogram is divided into sub-histograms according to brightness and then each individual sub-histogram is equalized by extending it to its range limits. This method overcomes the over-enhancement or under-enhancement issues. However, its results are not satisfactory with wide types of images. The dualistic sub-image histogram equalization (DSIHE) method [38] improves the contrast and keeps the image details. Initially, the median of the gray-values is used as the threshold to divide the histogram into two sub-histograms and remap each part independently. This approach preserves the information and brightness of the result as comparable to those of the original images. However, this method suffers from the over-enhancement problem and produces noises.

Two methods were presented by the same researchers [39], [40] called the minimum mean brightness error bi-histogram equalization method (MMBEBHE) and the recursive mean-separate histogram equalization (RMSHE), respectively. Both methods divide the image into two parts according to the minimum mean brightness error and then enhances each part individually. The results enhanced the contrast and maintained the optimal brightness of the original images. However, both methods lose information from the original images. The MMBEBHE method is also slow, and the RMSHE is complex to develop. An improvement of the RMSHE called the (recursive sub-image histogram equalization (RSIHE) [41] used the mean value of gray levels to divides the image into two sub-histograms. In addition to unwanted side effects, the RSIHE is time consuming.

The exposure-based sub-image histogram equalization (ESIHE) [42] aims to preserve the brightness after enhancement processes. In the ESIHE method, the histogram is divided into two parts by using a proposed threshold technique. Then, each part is separately enhanced by applying HE. This approach preserves the image brightness but suffers from over-enhancement and under-enhancement problems. The dynamic histogram specification (DHS) proposed [40] has no side effects but does not achieve satisfactory enhancement with many images.

The radiance indicator-based histogram equalization for retinal vessel enhancement method is proposed for retinal images [43]. The histogram is divided into sub-histograms according to multi-threshold levels. Then, each sub-histogram is equalized separately. The results of this method for medical images were satisfactory, but the technique failed to produce acceptable results with other types of images. For the proposed mean and variance-based sub-image histogram equalization (MVSIHE) [44], the histogram is divided into four sub-histograms that are equalized individually. This approach has high accuracy, but the images lost some details in some image cases.

The approach of bi-histogram equalization using modified histogram bins [45] was proposed to enhance contrast for narrow range brightness images. However, it produces low-quality contrast encasement. The adaptive histogram equalization algorithm (AHEA) is proposed by using the entropy to organize the gaps between the gray levels to identify the histogram [37]. The AHEA method affected image enhancement but produced over-enhancement or under-enhancement in some images.

The exposure region-based multi-histogram equalization method was proposed to enhance images with uneven illumination [23]. First, histograms were divided by using a region-based thresholding method. Then, the entropy of the gray level was used to reshape the new sub-histograms. This method suitably enhanced images while maintaining their original appearance. However, its results are unsatisfactory for many brightness cases. The global two stages histogram equalization (GTSHE) [46] depends on several steps. In the beginning, the clipped histogram must equalize according to the occurrences of pixel values. Then, equalizing processes are conducted according to the available and missing pixel level occurrences. The results of this method show high performance in terms of information and details preservation. However, its accuracy needs to be better with many cases of images.

Kandhway *et al.* [20] proposed the method that aims to find the optimal contrast of the magnetic resonance imaging. In this method, the minimum, maximum, mean, and median of the histogram are used to clip its values. Then, several methods are applied to reset the levels in the new histograms. This approach achieves excellent performance for medical images. However, the technique is complex to apply and is dependent on the accuracy of the methods employed in its development. Moreover, experimenting with other exciting methods shows a better result than this technique. A set of filters for enhancement, a binary tree structure to remap the grayscale, and suppressing artifacts have been proposed in Xiong *et al.* [19]. The resulting approach is simple and easy to implement. However, it requires modifying a parameter to obtain the required results, and its outcome for a wide range of images is unsatisfactory. The krill herd (KH) [20] method aims to enhance medical images based on two proposed functions; the Plateau limit function to clip the histogram and fitness function to improved different characteristic information of the anatomical images. This method improves the visual appearance of images effectively. However, it is failed to generalize for other types of images, and it didn't preserve the original entropy.

Several methods have been proposed to overcome the problem of poor contrast. Only the DSIHE method [38] explored the entropy conservation in the processed images, but its results are not satisfactory. Moreover, many of these methods have been proposed for specific purposes such as [4], [6], [9], [12], [29]. These methods fail to generalize to a wide variety of different images as claimed [23]. The proposed methods suffer from over-enhancement, under-enhancement, noise, and uneven brightness problems, as well as loss of original information from the enhanced images. These methods also ignore the point of preserving the original information, entropy, and fine details in the enhanced images.

Accordingly, the motivation of this study is to propose an adaptive HE method for gray images that enhances the poor contrast and preserves the original information (entropy) effectively. This is achieved by using the equal probability of occurrences to preserve the gray values of small values in the probability density function (pdf). The proposed approach extracts the occurrences and histogram of the gray values in the original image. Next, the histogram is clipped according to suggested thresholding method that depends on the histogram and occurrence values. Then, the occurrences and clipped histogram are equalized and used by a proposed transferring function to calculate the new gray values for enhanced images. The performance of the proposed method is compared against popular and recent contrast enhancement methods including the adaptive histogram equalization (Clahe) [47], CS [29], HE [35][28], and GTSHE [46] methods. Experiments were conducted using different benchmark datasets. The entropy measurement was used to evaluate the amount of information in the image. In addition to the contrast ratio, the peak signal-to-noise ratio (PSNR) and the structural similarity index (SSIM) measurements were employed to evaluate the quality of the enhanced images. The method is simple to implement for any type of image.

The contributions of this work are summarized as follows:

- To propose an HE method that takes equal effects for each pixel value present instead of different effects based on the percentage of each pixel value in the enhancement process.
- To propose an enhancement method that preserves fine detail and entropy in images.
- To propose an image enhancement method that can improve the quality of visual detail better than existing methods.

The remainder of this paper is organized as follows: Section 2 explores the proposed method, Section 3 presents the experiments and results, and Section 4 provides a discussion of the results. Finally, Section 5 provides the conclusion of this work.

2. Method

In this section, the proposed method is explained in detail. The flowchart of the steps of proposed method is presented in Fig. 1, and the description is presented below.

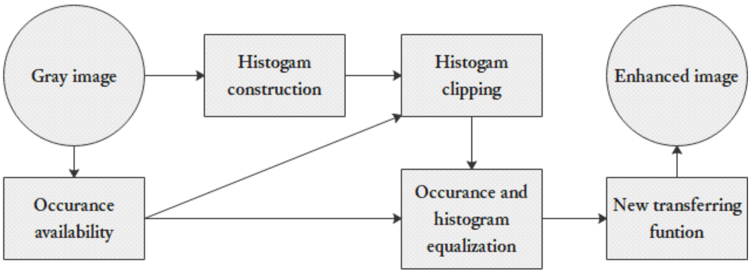

Fig. 1. The flowchart of the proposed method

2.1. Occurrence availability

In this step, the occurrence values are extracted from the input original image (l_o). Each value in the gray-scale range will be checked if it is existing in the original image or not, and the new gray values are detected. This aspect will play a major role in preserving the entropy and the image details in the subsequent enhancement steps. Thus, Equation (1) extracts the occurrences in the original image:

$$Occ(l) = \begin{cases} 1: & l \text{ is in } l_o \\ 0: & l \text{ is not in } l_o \end{cases} : for\ each\ Pixel\ in\ l_o \quad (1)$$

where the $Occ(l)$ is an occurrence array, and its size is in the maximum gray-level value (here, its size is 255). The variable l denotes each gray value in the image (0 to 255). Thus, each cell in the array Occ will be coded as 1 if the value is available in the original image and 0 if otherwise.

2.2. Histogram construction

Parallel to the occurrence availability extraction, the frequency of each gray value of the input image is extracted. That represented by constructing the histogram of the gray-values which normally range in (0 – 255). Thus, let His is the accumulator histogram of each gray level value in the image. The accumulator histogram is extracted according to Equation (2).

$$His(l) = His(l) + 1: \ for\ each\ l\ in\ l_o, \quad (2)$$

2.3. Histogram clipping

Usually, frequency variance occurs between gray values in images. This situation leads to huge variance between the accumulator values of the histogram, thereby causes many challenges in the contrast enhancement process. To overcome these challenges, the extreme affection of high values in the histogram is minimized to reduce their over affection and obtain a neutral appearance of the enhanced images. Accordingly, the histogram itself must be clipped [35], [19] so as to reduce the large values in suitable form to other accumulator values in the histogram.

Thresholding is the most popular process in state-of-the-art methods to solve this problem [1]. Several techniques have been employed to calculate the clipping thresholds. In this work, a new thresholding method is proposed to calculate a more optimal clipping threshold. Equation (3) presents the proposed thresholding method which based on the histogram values and available occurrences of the image. The suggested approach is effective and consumes less time [19],[35],[36].

$$T = \frac{1}{\#Occ} \sum_{l=0}^{L} His(l), \tag{3}$$

$$H_c(l) = T : \ for \ His(l) > T, \tag{4}$$

where T is the clipping threshold value, $\#Occ$ is the number of non-zero occurrences in the image, and H_c is the clipped histogram. The clipped histogram has fewer values relative to the original image. The high histogram values were reduced, and the low histogram values are preserved.

2.4. Equalization process

Next, the clipped histogram and occurrence matrix are equalized to produce affected new values and show the new values of pixels in the enhanced images. For effective equalization, we proposed a new equalization process that considers the state of available occurrence of gray-level values in addition to the pixel values and their frequency, unlike previous methods that consider only the pixel values and the probability of their frequency.

Accordingly, the corresponding pdf of the clipping histogram Pdf_c was computed as follows:

$$Pdf_c(l) = \frac{H_c(l)}{\sum H_c(l)}. \tag{5}$$

To add the advantage of equal probability for each available value in the image (which will be used later to increase the probability of small frequent gray-value), the corresponding probability density of occurrences is used to preserve the small accumulate histogram values from merging by associated large accumulate. The corresponding pdf of occurrences in the original image Pdf_{Occ} was computed as follows:

$$Pdf_{occ}(l) = \frac{Occ(l)}{\#Occ} \tag{6}$$

Next, two cumulative distribution functions (cdf) of both the corresponding pdf of the clipping histogram Pdf_c and the occurrences of each gray-value in the original image Pdf_{Occ} are calculated as follows:

$$Cdf_{Hc}(l) = \sum_{l=0}^{l=255} Pdf_c(l). \tag{7}$$

$$Cdf_{Occ}(l) = \sum_{l=0}^{l=255} Pdf_{Occ}(l). \tag{8}$$

The results of the each of previous equations are an array in size 255. Each array has a cumulative distribution function value ranging from 0 to 1.

2.5. Transferring function

In this method, a new transferring function is proposed to identify the optimal new gray values by using each $Cdf_{Hc}(l)$ and $Cdf_{Occ}(l)$ to combine their advantages. The proposed cumulative distribution function for the available gray values improves their small values of a traditional pdf and preserves them from disappearing by the large ones. That aim is achieved by adding the probability of each available pixel value in $Cdf_{Hc}(l)$ and $Cdf_{Occ}(l)$. The results generate a probability value from 0 to 2. To arrive the final transferred pixel value in the range of 0 to 255, we multiply each probability value in (127.5). The results include new pixel values of the enhanced image in the range of 0 to 255.

$$Image_E = (Cdf_{Occ}(l) + Cdf_{Hc}(l)) \times 127.5. \quad (9)$$

Finally, the gray values of the enhanced image pixels are integrated and presented. All the pixels values will be represented again in the enhanced images. The enhanced images will contain neither fewer nor additional occurrences. Algorithm 1 presents all the steps of the proposed method (Fig. 2).

Algorithm 1: The proposed method

Step 1: // Deduct the occurrences of the gray values that availabile in the input image
$Occ(l) = \begin{cases} 1: & l \text{ is in } I_o \\ 0: & l \text{ is not in } I_o \end{cases} : for\ each\ Pixel\ in\ I_o, (l = 0\ to\ 255)$

Step 2: // compute the histogram of the input image
$His(l) = His(l) + 1:\ for\ each\ Pixel\ in\ image,\ (l = 0\ to\ 255)$

Step 3: // compute the clipping threshold
$T = \frac{1}{\#Occ} \sum_{l=0}^{L} His(l)$

Step 4: // compute the clipped histogram
$H_c(l) = T :\ for\ His(l) > T$

Step 5: // compute the *pdf* of the clipping histogram
$Pdf_c(l) = \frac{H_c(l)}{\sum H_c(l)}$

Step 6: // compute the *pdf* of the occurrences of each gray-values
$Pdf_{occ}(l) = \frac{Occ(l)}{\#Occ}$

Step 7: // compute the *cdf* of the $Pdf_c(l)$:
$Cdf_{Hc}(l) = \sum_{l=0}^{l=255} Pdf_c(l)$

Step 8: // compute the *cdf* of the $Pdf_{occ}(l)$:
$Cdf_{Occ}(l) = \sum_{l=0}^{l=255} Pdf_{Occ}(l)$

Step 9: // compute the new gray values of the final enhanced image
$Image_E = (Cdf_{Occ}(l) + Cdf_{Hc}(l)) \times 127.5$

Fig. 2. Proposed algorithm

3. Results and Discussion

After the proposed method is developed, several experiments were conducted to evaluate its performance. The evaluation process according to a comparison of the performance of the proposed and popular benchmark histogram equalization methods. According to the state- of- the art knowledge, the original HE method [35] is the basic principle of the histogram equalization technique and most of the next methods are improvements on it. The contrast stretching and Clahe methods [47] are popular and high-performance techniques that are prevalent in computer vision libraries. GTSHE [46], [36] is a recent method that shows a high performance relative to several state-of-the-art methods such as the MVSIHE [15], AHEA [37], ESIHE [35] techniques. These methods outperformed many well-known approaches such as the HE [35], DSIHE [31], RMSHE [32], MMBEBHE [33], RSIHE [34] methods. Accordingly, the HE [35], contrast stretching, Clahe [47], and GTSHE [46], [36] techniques were selected to evaluate the performance of the proposed method.

To obtain meaningful results that show the real performance of each of the methods, experiments were conducted on several benchmark images. The used images include 46 aerial images, 39 miscellaneous images of the database of the University of Southern California, and 100 images from the CG-1050 dataset. In total, approximately 185 different images that cover many types of shapes, object, sizes, and contrast qualities were used in the evaluation experiments.

3.1. Visual experiments

Visual experiments were conducted for a clear assessment of the methods. Fig. 3 to Fig. 7 show some of the outputs visually. These experiments were conducted on selected images to demonstrate the ability of each method to improve the appearance by optimizing the contrast.

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The visual results in Fig. 3 to Fig. 7 indicate that each method shows various forms of contrast enhancements. The first image (Fig. 3) suffers from the low contrast problem. The proposed method and GTSHE technique show balanced performance. HE and contrast stretching tends to present darkness that removes some details from the image. The Clahe did not show any enhancement.

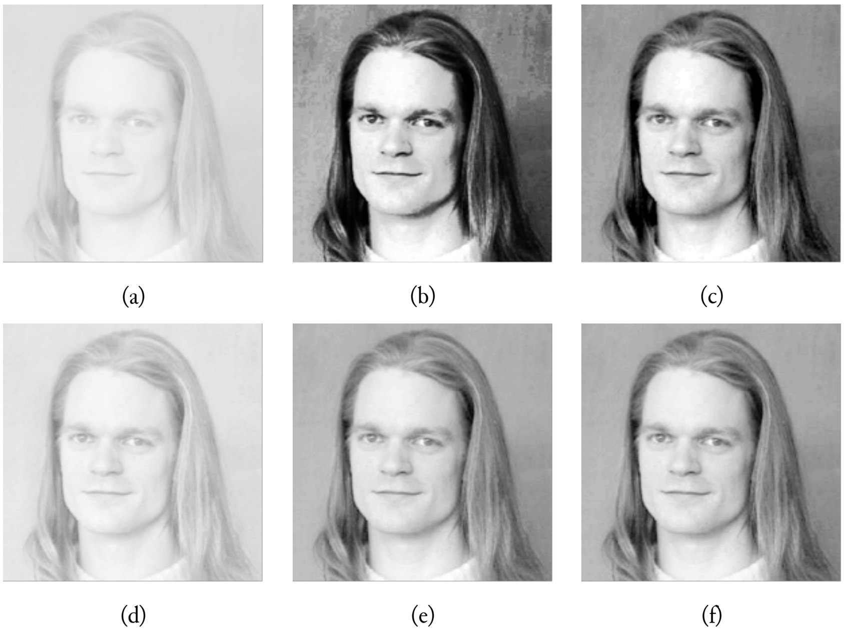


Fig. 3. (a) Original image, a fighter jet image (source: NumPy / SciPy Recipes for Image Processing: Intensity Normalization and Histogram Equalization), (b) HE, (c) Contrast stretching, (d) Clahe, (e) GTSHE, and (f) the proposed methods.

In the case of the fighter jet image (Fig. 4), the problem of tight range contrast of gray-level values is enhanced perfectly with the proposed method. The GTSHE approach generates a satisfactory result but tends exhibit over brightness. The HE and contrast stretching methods achieved low enhancement, and no enhancement is shown by Clahe. The poor-quality contrast aerials image in Fig. 5 is enhanced well with all methods except HE, but the proposed and GTSHE methods show better performance.

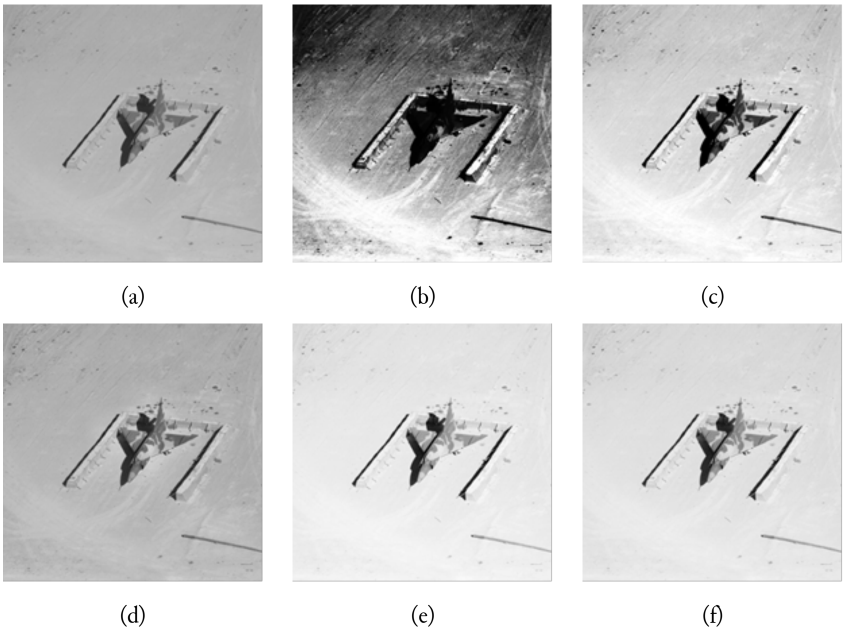


Fig. 4. (a) Original image, a fighter jet image (miscellaneous dataset, 7.1.02 image), (b) HE, (c) Contrast stretching, (d) Clahe, (e) GTSHE, and (f) the proposed methods.

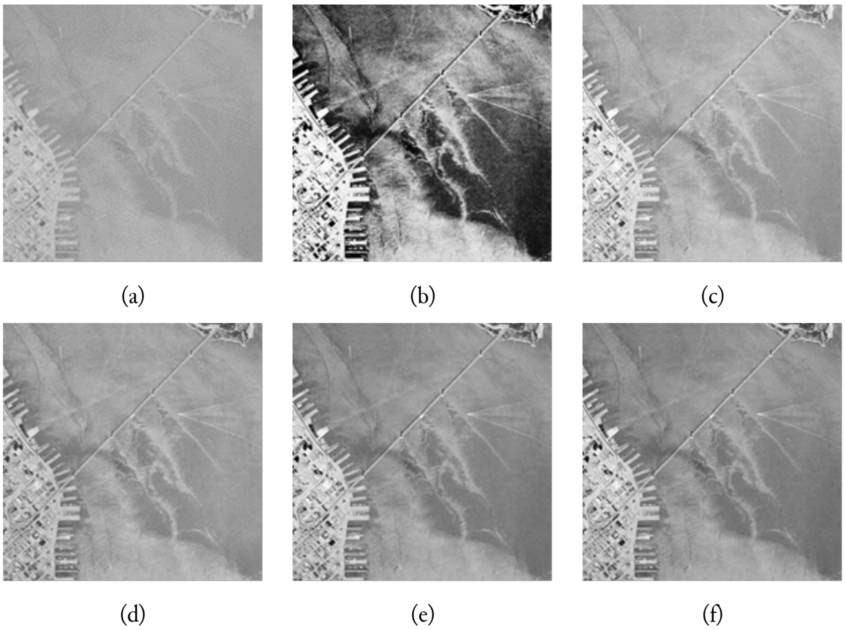


Fig. 5. (a) Original image, an aerial image (aerials dataset, 2.2.06 image), (b) HE, (c) Contrast stretching, (d) Clahe, (e) GTSHE, and (f) the proposed methods.

To show adaptivity, the focal methods were applied on an extremely large and good quality contrast image (Fig. 6). The proposed method, GTSHE, and contrast stretching show minor changes and preserved the original quality. HE and Clahe show major changes and the over-enhancement problem with fine images.

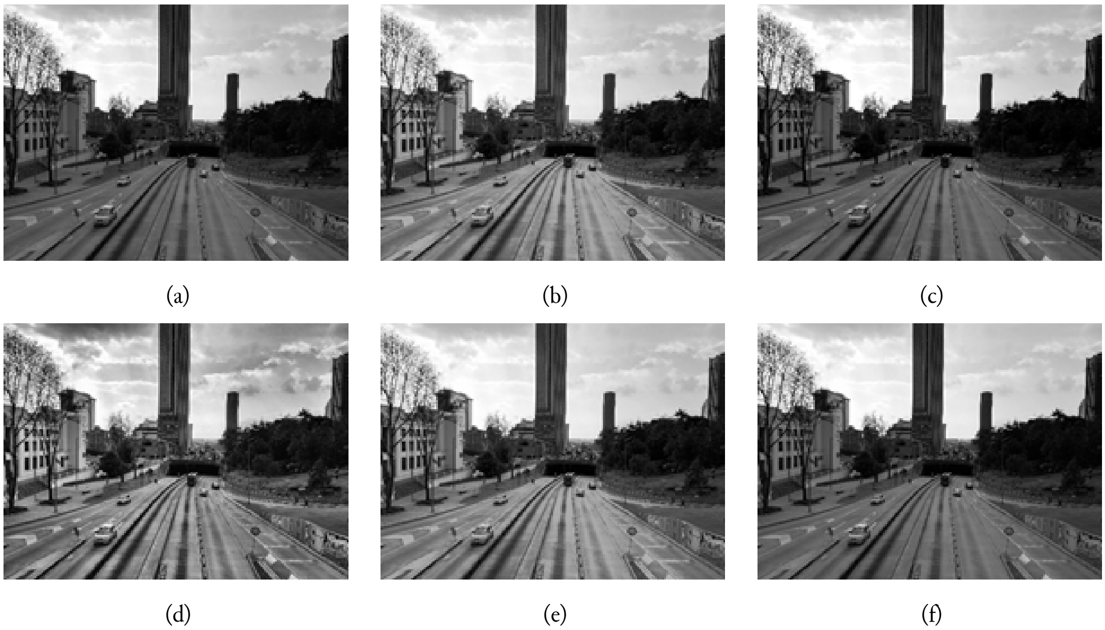


Fig. 6. (a) Original image, the Im_78 image from CG-1050 dataset, (b) HE, (c) Contrast stretching, (d) Clahe, (e) GTSHE, and (f) the proposed methods.

Applied to Lena image (Fig. 7), the HE, proposed approach, and GTSHE method show a good performance. To show the results clearly, zooming was applied. The proposed method shows more harmonic contrast than its counterparts which, in turn, reveal some rapid changes between the enhanced gray-scale levels.

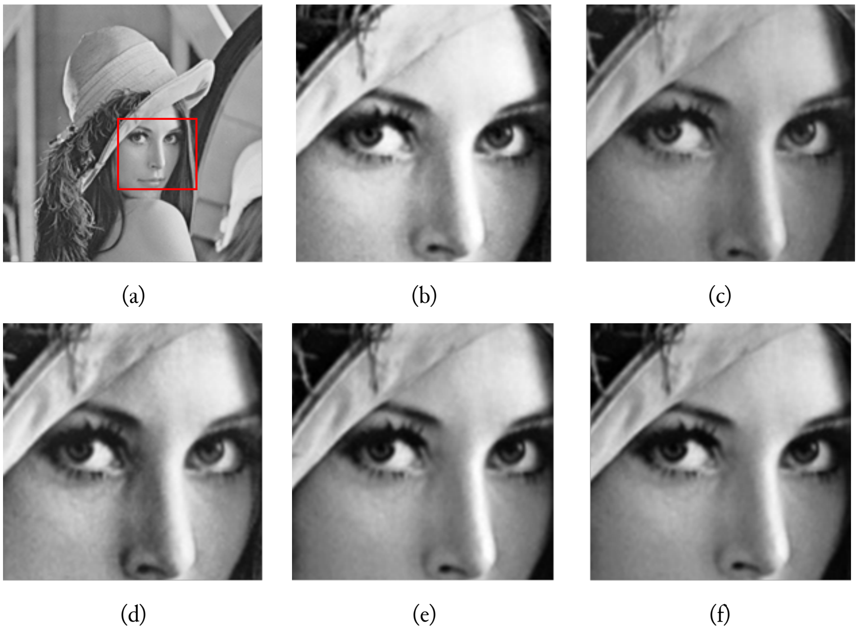


Fig. 7. (a) Original image, a focus on sub-image of Lena, (b) HE, (c) Contrast stretching, (d) Clahe, (e) GTSHE, and (f) the proposed methods.

3.2. Statistical expeiments

Visual experiences are clearly understandable to humans, but they do not constitute a scientific process for accurately and effectively evaluating the performance of the methods involved. This approach is not an analytical scientific measurement technique, and its estimation is not based on any meaningful measurements. Moreover, humans may not recognize some problems and noise. To overcome these features, this work performs an evaluation experiment using previously mentioned benchmark datasets and statistical measurements that involve the average information content (entropy), contrast, PSNR, and SSIM.

Entropy presents the average information content in an image. It is a popular measurement for evaluating the amount of information in the image. In this work the term entropy is the main measurement used to evaluate the main objective of this work. Its formula presented in an equation (10):

$$Entropy = \sum_{l=0}^{l=255} e(l) = -\sum_{l=0}^{l=255} p(l)\, log_2 p(l) \tag{10}$$

Where $p(l)$ is the probability of the gray value l in the image.

The contrast ratio presents the difference in the gray values between occurrences in the image. In low contrast states, the contrast ratio is small. It is presented by calculating the standard division value of pixels in the image.

The PSNR is a widely use measurement approach to evaluate image quality and signals in general. In this case, it provides a value about the contrast that shows the enhancement quality of the processed image by the original image. The following formula presents the of PSNR equation (11):

$$PSNR = 10\, log_{10}\left(\frac{255^2}{MSE}\right) \tag{11}$$

$$MSE = \frac{1}{(X \times Y)} \sum_{x=0}^{x=X-1} \sum_{y=0}^{y=Y-1} (Orginal_{image}(x,y) - Processed_{image}(x,y))^2 \tag{12}$$

where the size of image presented in X and Y, and the current positions of the pixel are presented by x and y.

The SSIM measured the quality of images by estimating the similarity between two images. The SSIM considers structural information changes such as contrast in the resulting image. The SSIM is computed according to different sub-images, the measure between the two sub-images x and y of image in size X×Y are presented by the following equation:

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} c_1 = (0.01 \times L)^2, c_2 = (0.03 \times L)^2 \quad (13)$$

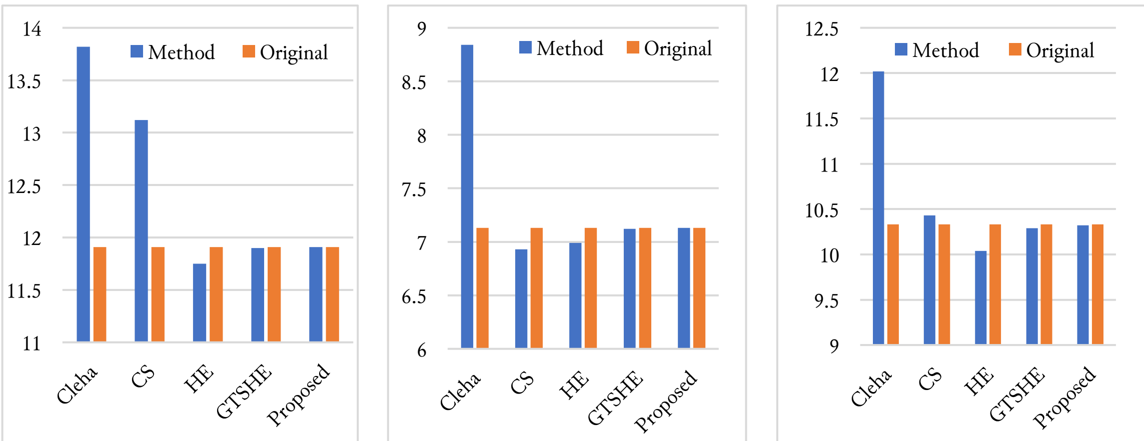
where L is the dynamic range of the pixel-values, and μ_x, μ_y are the mean of x and y. σ_x^2, σ_y^2 is the variance of x and y, σ_{xy} the covariance of x and y.

Table 1 indicates that the entropy and the absolute changes in the entropy among the methods and the original images. The proposed method is the optimal approach in preserving image information. The said method has entropy values like those of the original images and shows no difference between the original and enhanced images for all datasets.

Table 1. The entropy and absolute difference in entropy values between the original images and enhanced images of the Clahe [47], CS [29], HE [35], GTSHE [46], and proposed methods for the aerials, CG-1050 dataset, and Miscellaneous images.

	Aerials		CG-1050 dataset		Miscellaneous	
	Entropy	*abs(Difference)*	*Entropy*	*abs(Difference)*	*Entropy*	*abs(Difference)*
Original	11.91	0	7.13	0	10.33	0
Cleha[47]	13.82	1.91	8.84	1.71	12.02	1.69
CS[29]	13.12	1.21	6.93	0.2	10.43	0.1
HE [35]	11.75	0.16	6.99	0.14	10.04	0.29
GTSHE [7]	11.9	0.01	7.12	0.01	10.29	0.04
Proposed	**11.91**	**0**	**7.13**	**0**	**10.32**	**0.01**

Conversely, the other methods have lower or higher entropy values (Fig. 8). Thus, each involved method lost information of or added noises to the enhanced images. As shown in Table 1 and Fig. 8, the Clahe method performed satisfactorily in visual experiments but was worst in the case of preserving original information in processed images. GTSHE is the second-best approach but losses some information in all datasets.



(a) (b) (c)

Fig. 8. The entropy values between the original and enhanced images of the Cleha, CS, HE, GTSHE, and Proposed methods for (a) Aerials, (b) CG-1050 dataset, and (c) Miscellaneous datasets.

Table 2 shows the results of the contrast, PSNR, and SSIM measurements. These measurements cannot give a direct meaningful evaluation in low contrast encasement because they cannot distinguish between fine enhancement, over-enhancement, under-enhancement, and noises. However, analysis of all values allows us to recognize the degrees of performance of each method. The contract values show the differences between new gray-values of the enhanced images. A higher value means high contract and more visual appearance, but we should ensure that the high values do not cause the loss information and produces noises and over-enhancement. Therefore, it should be attached with high values of SSIM and PSNR.

Table 2. The Contrast, PSNR and SSIM of the Cleha, CS, HE, GTSHE, and Proposed method for Aerials, CG-1050 dataset, and Miscellaneous datasets images.

	Aerials			CG-1050 dataset			Miscellaneous		
	Contrast	PSNR	SSIM	Contrast	PSNR	SSIM	Contrast	PSNR	SSIM
Original	27.71	Inf.	1	42.72	Inf.	1	43.12	Inf.	1
Cleha	46.54	19.51	0.77	47.86	27.71	0.74	52.27	23.04	0.85
CS	40.78	20.77	0.89	66.13	20.4	0.81	63.82	19.19	0.87
HE	73.56	13.76	0.57	75.11	16.18	0.61	74.89	15.6	0.65
GTSHE	49.12	18.9	0.83	54.06	25.91	0.76	56.2	20.36	0.91
Proposed	**46.37**	**20.61**	**0.86**	**54.43**	**24.21**	**0.73**	**54.46**	**21.84**	**0.93**

According to the previous explanation and the results in Table 2, the proposed method, followed by the GTSHE show the best performances. With the aerial dataset images, the proposed method produces higher contrast (46.37) than that of the original images (27.71), accompanied by the high values of SSIM and PSNR (0.86 and 20.61, respectively). The CS have high values of SSIM and PSNR (0.89 and 20.77, respectively) but scored the lowest contrast results (40.78) than all methods. The HE method produces high contrast values at 73.56 but has low SSIM and PSNR results (0.57 and 13.76). in case of the CG-1050 dataset, the proposed and GTSHE methods achieve an almost similar performance. Clahe presented high PSNR and SSIM values but had low contrast values (47.86). By comparison, HE has high contrast by (75.11) but scored the worst PSNR and SSIM values. With the Miscellaneous dataset, the proposed method scored a high contrast value (54.46) comparing with the original images (43.12) and achieved high SSIM and PSNR values (0.93 and 21.84, respectively).

In summary, the entropy measurement shows that the proposed method is the only approach that preserves the information and details in enhanced images as in the original images. Moreover, the visual evaluation shows that the proposed method satisfactorily improves the low contrast and the image quality. The results of the contrast, PSNR, and SSIM measurements indicate a high performance of the proposed method relative to the other techniques with all datasets.

3.3. Discussion

The previous experiments aim to evaluate each method's ability to improve image quality by improving low contrast levels in images by preserving the details, information, and features of processed images in the same original images. According to the literature review, Clahe [47], CS, HE [35], GTSHE [46][7] methods are popular histogram equalization methods that address many challenges of the low contrast problem. Therefore, high performance is expected from using these techniques to maintain the images' information as similar to the original. According to the results, the following conclusions were reached:

HE method [35] is a simple and popular method for enhancing the contrast of a histogram. The approach is suitable for improving the low contrast in a wide range of images. However, it highlights unnecessary information in several types of images. That feature led to undesirable effects and deterioration in the visual features which is reflected in the loss of information. CS [29] is also a simple and popular method to improve low contrast by stretching the histogram to its range values. It is an acceptable method to improve the contrast in a wide range of images. However, CS may produce a slight improvement in several types of images and some noise effect. This outcome degrades unwanted effects or generates noise that distorts the original features of the images, thereby resulting in missing information or adding unwanted information to the processed image. Clahe [47] is one of the recent and popular contrast enhancement methods. It deals perfectly with the usual challenges in degraded images. In many cases, however, Clahe fails to perform efficiently. It may cause over-enhancement or under-enhancement. In addition, the main problem of this method is that it does not preserve the entropy. Clahe has worst entropy preservation among the involved methods. GTSHE [46] [7] enhances the low contrast and the visual appearance more effectively than previous methods. However, it shows extra brightness in many cases. In addition, the GTSHE outperforms other methods in the case of entropy, but it fails to preserve the entropy perfectly and in the same of original images.

The proposed method enhances the low contract and the visual properties of images. The approach also enhances the visual appearance of images efficiently. Moreover, the experiments indicate that the proposed methods perfectly preserve the entropy and image contents as comparable to the original images. Its results' entropy meets with all original images' entropy of involved datasets in the experiments.

Based on the above outcomes, the methods were effective on many images but presented some disparities. They reveal some weakness in their performances in the case of special images. In addition, they did not retain the original information of the images. Nevertheless, the results prove that the proposed method is the best in terms of preserving the original information details. The suggested approach improves contrast quality in all images without producing side effects, over-enhancement, and under-enhancement under all image states.

4. Conclusion

This research proposes a contrast enhancement method based on a histogram equalization approach that preserves the entropy of the enhanced image like that of the original image. The proposed method extracts the occurrences and histogram of the gray values in the original image. Then, the occurrences and the clipped histogram are equalized. Finally, the new pixel values are calculated by a proposed transferring function. To validate the performance of the proposed method, it compared with widely use benchmark methods such as Clahe, CS, HE, and GTSHE. Experiments using benchmark datasets and entropy, contrast, PSNR, and SSIM measurements are conducted to evaluate the performance. The results show that the proposed method is the only approach that preserves the information and details in enhanced images as in the original images. In addition, the results of the contrast, PSNR, and SSIM measurements indicate a high performance of the proposed method relative to the other techniques with all datasets. The proposed method satisfactorily improves the low contrast and the image quality without producing side effects.

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