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Image Contrast Enhancement by using Histogram Clipping and 2-D Histogram

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Abstract

Several factors affect images' contrast and eliminate details in images. Therefore, contrast enhancement is a critical process for any visual machine algorithms. To achieve this purpose, in this paper, a novel algorithm based on 2-D histogram and clipped histogram is introduced. To improve the performance of the algorithm, the histogram is divided into three sub-histograms based on mean and standard deviation. For each sub-histogram image, the clipped histogram is calculated, separately. The threshold for clipping of histogram is obtained based on the median of a 2-D histogram of an image. Based on the previous research we know that the desired distribution for a 2-D histogram is Gaussian distribution. Hence, we introduce a novel iterative algorithm for transforming the available histogram to the desired histogram. In other words, our method modifies the image histogram to improve its contrast. Our proposed method is based on Skewness, where the algorithm attempts to minimize the absolute value of Skewness. The performance of the algorithm is compared by several algorithms based on different factors. Simulation results indicate the proposed algorithm has the best performance than other algorithms.

Keywords: Visual Machine Algorithm, Contrast Enhancement, 2-D Histogram, Clipped Histogram, Gaussian Distribution, Skewness.

1. INTRODUCTION

Contrast is defined as a difference between luminance in gray or color images. Extracting features and details is too difficult in low-contrast images. The contrast of images is affected by several factors such as defects in camera or transmission systems, and environment effects such as shadow, light, etc. Contrast is a vital factor in images and it is so important for any machine vision system. Visual image quality is actively

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enriched using contrast enhancement approaches, which are increasingly essential for the design of consumer electronic devices and digital multimedia systems. Image contrast enhancement is an important process to improve the dynamic intensity range of pixels. In this process, the intensity of images is changed to increase the contrast of the image[1].

Conventional contrast enhancement such as the histogram equalization (HE) method is used widely in many practical applications. These methods usually increase image contrast at peak values and may cause noisy effects on images[2]. In previous papers, researchers introduced some methods. Such as, Brightness preserving bi-histogram equalization (BBHE)[3], Dominant Orientation-based Texture Histogram Equalization (DOTHE) [4]exposure based sub-image HE algorithm (ESIHE) [5]to overcome these challenges. Whole above algorithms divide the image histogram into several partitions and use

HE algorithm is for processing subhistograms. The main disadvantage of these methods still is intensity saturation at some of the subhistograms. In some recent papers, researchers use histogram clipping methods such as CLAHE [6] to prevent intensity saturation. The clipped histogram equalization technique is a novel version of HE methods that control undesired increasing of contrast and avoiding image saturation [7]. In [8], the histogram is clipped based on the median of the histogram. This median is named threshold and calculated adaptively for any images. In both papers, if the value of the histogram is more than the threshold value, the histogram is clipped. In [9], histogram of the image is divided into several sub-histogram based on the mean and variance of the histogram. In [10] authors used adaptive gamma correction to improve image contrast. Gamma correction is a nonlinear method for enhancing luminance and contrast in images. Another method for improving image contrast is a method based on discrete cosine transform (DCT). This method is introduced in[11], where the method operates in the DCT domain and is computationally efficient, which makes it suitable for real-time imaging systems.

Due to the importance of contrast improvement, in addition to the above research, contrast improvement has also been considered by scientists. For instance, in[12], researchers used the Fuzzy logic method for improving image contrast which an adaptive fuzzy inferencing system determines the pixel value of the output based on the contrast measure of the input image. In [13], authors introduced a method based on adaptive non-linear contrast stretching. Contrast stretching improves the contrast in an image by stretching the range of intensity values. Optimization algorithms are still used by researchers for this purpose. For instance, in [14], Artificial Bee Colony Algorithm is used for introducing adaptive image contrast enhancement. This research investigates the system performance based on different metrics such as peak signal-to-noise ratio (PSNR), SSIM (Structural Similarity Index), SNR (Signal to Noise Ratio), MSE (Mean Squared Error). Wavelet transform can be used for image contrast enhancement. In [15], researchers introduced an algorithm in the wavelet domain. In that paper, a contrast sensitivity function is obtained for each sub-band which is applied to weigh the wavelet coefficients in the sub-band.

All previous papers are based on one-dimensional (1-D) histogram modification for contrast enhancement. In some recent papers, authors use 2-D histogram. The main advantage of the 2-D histogram is that it can count the pairs of adjacent pixels with gray levels and represent the gray level difference between the pixels of an input image and their neighbors [16]. As a comparison, a 1-D histogram is nothing more than counting how many voxels with a particular intensity occur in the image. The intensity range of the image is divided into bins. A voxel then belongs to the bin if its intensity is included within the range the bin represents. Therefore, we use a 2-D histogram in our paper. In addition, we use a clipped histogram equalization technique to avoid any undesired increasing pixel intensity. We use three-level thresholds for clipping histograms. Three-level thresholds eliminates outlier values and increase the image contrast algorithm. As mentioned above, for a 2-D histogram, the desired distribution is Gaussian distribution. For ideal Gaussian distribution, the amount of Skewness is equal to zero. Therefore, in our proposed algorithm, we attempt to minimize the value of Skewness for the 2-D histogram of an image. Hence, the algorithm is an iterative algorithm that improves image quality, adaptively.

The rest of this paper is organized as follows; in section 2, we introduce our proposed algorithm, mathematically. In section 3, simulation results are presented and discussed, conclusion is explained in section 4.

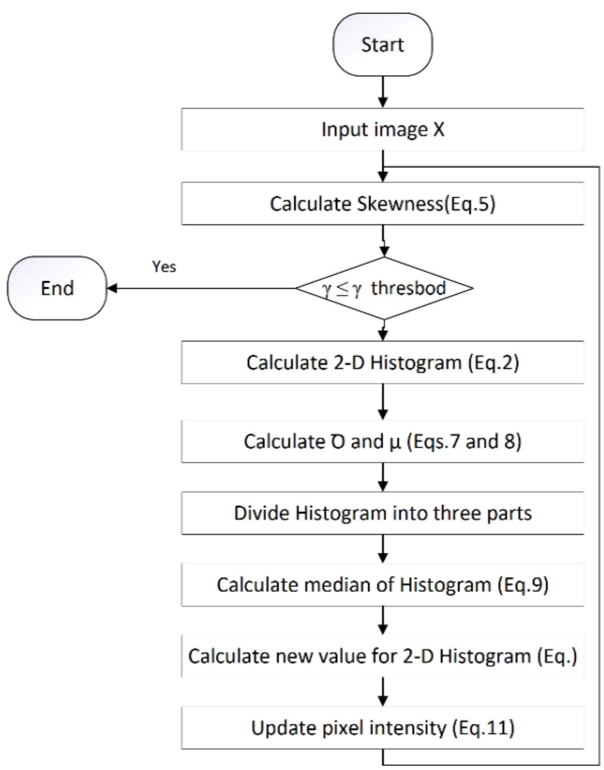

Fig. 1. Flowchart of the proposed algorithm.

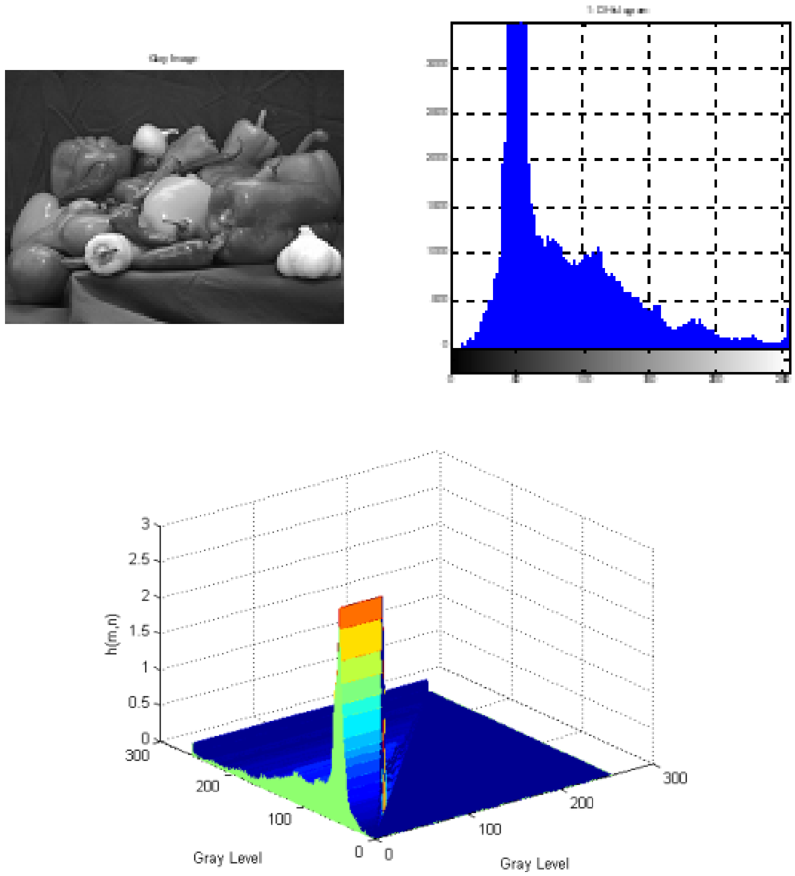

Fig. 2. Gray image, 1-D and 2-D histogram.

2. PROPOSED ALGORITHM

In this section, the proposed algorithm is described. The proposed algorithm flowchart is shown in figure 1. In the proposed algorithm the image contrast is improved based on the iterative algorithm. The Skewness of the histogram is used as a decision metric. The algorithm is repeated until the Skewness is less than a threshold value. In the first subsection, a 2-D histogram is introduced. In the second subsection, the Clipped histogram is presented mathematically and in the third subsection, the proposed algorithm is described. The proposed clipped histogram algorithm is obtained based on the standard division and mean of the image histogram.

2.1. Sub-Section Head Style

As mentioned before, a 2-D image histogram gives more information than a 1-D image histogram. Therefore, this research uses a 2-D histogram to improve image contrast. For calculating a 2-D image histogram, assume a color or gray-level image with low contrast quality. For gray images, the histogram intensity has values between zeros to 255. Color images have three channels for main colors (i. e. Blue, Green, Red), each with values between 0 to 255. Letting $X = \{x(i,j)|\, 1 \le i \le M, 1 \le j \le N\}$ as input image where M and N are the number of pixels in rows and columns, respectively. $\Omega = \{x_1, x_2, \ldots, x_k\}$ as a sorted k distinct gray level of image X. The 2-D histogram is defined mathematically as follows [16]:

$$H_x = \{h_x(m,n) | m = 1, \dots, k; \quad n = 1, \dots, k\} \quad (1)$$

where

$$h_x(m,n) = \frac{scr_w(m,n)}{\sum_{i=1}^{k}\sum_{j=1}^{k} scr_w(i,j)} \quad (2)$$

The scr in the above equation is defined as follows:

$$scr_w(m,n) = \sum_{\forall i}\sum_{\forall j}\sum_{k=-[w/2]}^{[w/2]}\sum_{\ell=-[w/2]}^{[w/2]} \phi_{m,n}(x(i,j) + k, j + \ell))(|x_m - x_n| + 1) \quad (3)$$

where w is the odd number. For each pixel a square $w \times w$ neighborhood pixels are considered, and:

$$\phi_{m,n}\big(x(i,j), x(i+k, j+k)\big) = \begin{cases} 1, & x_m = x(i,j), x_n(i+k, j+k \\ 0, & O.W \end{cases} \quad (4)$$

To understand the difference between 1-D and 2-D histograms, figure 2 indicates 1-D and 2-D histograms for a typical image. In this image, the value of the window, w, for 2-D histogram is assumed to be 3.

As mentioned in [17], the desired 2-D histogram has a Gaussian distribution. Therefore, we attempt to transfer the 2-D histogram of the input image to Gaussian distribution. Skewness indicates the degree of asymmetry in the probability distribution. If the data are symmetric to the mean, the skewness will be zero. Skewness has been normalized to the third torque. The skewness is actually a measure of the degree of symmetry of the distribution function. The Skewness is defined as follows[14]:

$$\gamma_1 = \frac{\mu_3}{\sigma^3} \quad (5)$$

Based on the above discussion, in our paper, we attempt to minimize the absolute value of Skewness. In other words, the algorithm is finished when the amount of Skewness is less than the specified value. The details of the proposed algorithm are described in the next sections.

2.1. Clipped Histogram

Figure 3 indicates the idea behind the clipped histogram. As shown in this figure, the histogram values more than the threshold value is clipped to avoid image saturation. Similar to recent research, we use the median of the histogram to calculate the threshold value. The main advantage of the median is that it cannot be affected to outlier values. Therefore, by assuming T_c as threshold level, it is defined as follows:

$$T_c = median(H_x) \quad (6)$$

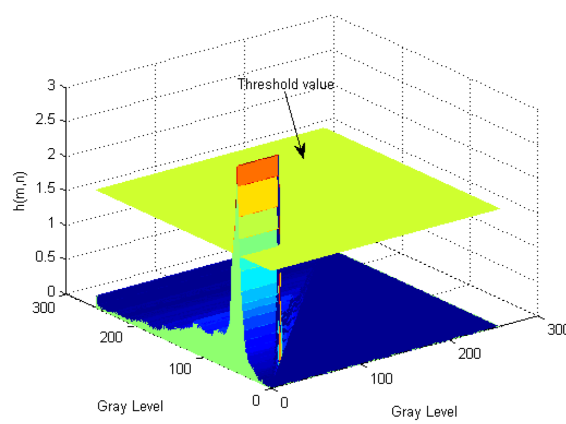

Fig. 3. Threshold level.

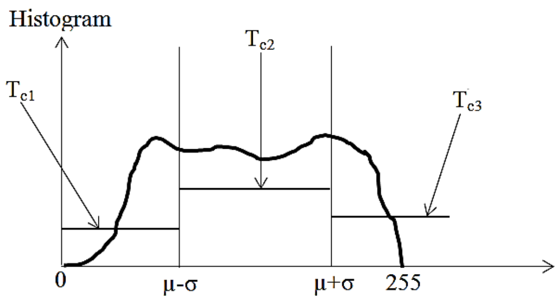

Fig. 4. Sub-histogram image.

Most papers use a single threshold for images. However, due to the Non-uniform distribution of image pixels, a single threshold does not have enough performance for image contrast enhancement. Therefore, we use three threshold levels to increase the algorithm's performance. In this method, the image histogram is divided into three parts and for any part the value of the threshold (i.e. median) is calculated separately. Figure 4 indicates the histogram that is divided into three sub-histograms. For simplicity, in this image, we show our idea in a 1-D histogram.

As shown in Figure 3, the image is divided into three partitions based on the standard deviation and mean of the histogram. Therefore, we divide the image into three parts at first. The metrics for division are standard deviation and mean of 2-D image histogram that are calculated as follows:

$$\mu = \text{mean}(H_x) \tag{7}$$

$$\sigma = \text{standard deviation}(H_x) \tag{8}$$

In the second step, for all parts, the value of the threshold is calculated as follows:

$$T_{ci} = \text{median}\Big((H_x | x \in i^{th}\, area)\Big) \quad i = 1,2,3 \tag{9}$$

In the third step, for any three areas, a new value for the histogram is updated as follows

$$h_c(m,n) = \begin{cases} T_{ci} & h_x(m,n) \geq T_{ci} \\ h_x(m,n) & h_x(m,n) \leq T_{ci} \end{cases} \tag{10}$$

Finally for any intensity value, m, and the mapping function is calculated as follows:

$$T(m) = R + (P - R) \times c(m) \tag{11}$$

where R and P are lower and upper bands of any area and c is cumulative distribution function (CDF) and for each area is calculated as follows:

$$c(m) = \sum_{i=1}^{m} \sum_{j=1}^{k} h_c(i,j) \tag{12}$$

2.2. Iterative Algorithm

As mentioned before, the desired distribution for a 2-D histogram is Gaussian distribution. In addition, for Gaussian distribution, the value of Skewness is zero. Skewness can be positive or negative. Therefore, we want to reduce the absolute value of Skewness to achieve desired 2-D histogram. In the proposed iterative algorithm, in each iteration, the values of mean, median, and standard deviation are updated. Therefore, although the number of sub-histograms is constant, their borders are changed. Unless to [9], the process is applied to all pixels in each iteration, hence, all pixels have the opportunity to receive the optimal value.

It is obvious Skewness may not be exactly zero and the algorithm gets stuck in the infinite loop. Therefore, we define a threshold for avoiding this problem as follows:

$$|\gamma_1| \leq \delta \tag{13}$$

Based on the above explanations, the proposed algorithm is presented as follows.

Input: image X
Output: image Y

1. Calculate Skewness based on Eq. 5
2. While γ_1 upper than threshold value do
3. Calculate 2-D histogram based on Eq. 2
4. Calculate mean and standard deviation based on Eq. 7 and Eq. 8, respectively
5. Divide histogram into three parts
6. Calculate median of histogram based on Eq. 9 for each parts
7. Calculate new value for 2-D histogram based on Eq. 10
8. For each intensity value, calculate a new value for pixels based on Eq. 11
9. Check the value γ_1 for output image
10. If condition in Eq. 13 is satisfied the algorithm is finished, otherwise return to step 1

2.3. Sub-section Head Style

To evaluate the performance of the algorithms; we need to examine our proposed algorithm's performance by different metrics. Nowadays, there are several metrics that are used by researchers for investigating their algorithms. In this research, we use five metrics including PSNR, SSIM, AMBE, Entropy, and spatial frequency. The first one is peak signal-to-noise ratio (PSNR) which is used widely in many types of research. PSNR is defined as follows [18]:

$$\text{PSNR} = 10 \log_{10}\left(\frac{255^2}{MSE}\right) \tag{14}$$

where MSE is the Minimum square error and is defined as follows:

$$\text{MSE} = \frac{1}{M \times N}\sum_{i=1}^{M}\sum_{j=1}^{N}(g(i,j) - u(i,j))^2 \tag{15}$$

A higher PSNR indicates the image has better performance. In the other words, for two algorithms, the algorithm which has a higher PSNR is a better algorithm.

The second metric is the structural similarity index (SSIM). SSIM is used for measuring the similarity between two images. The SSIM index is a full reference metric; in fact, the measurement of image quality is based on an initial uncompressed or distortion-free image as a reference that is defined as follows [13]:

$$\text{SSIM} = \frac{(2\mu_1\mu_2 + C_1)(2\sigma_{12} + C_2)}{(\mu_1^2 + \mu_2^2 + C_1)(\sigma_1^2 + \sigma_2^2 + C_2)} \tag{16}$$

where $\mu_1, \mu_2, \sigma_1, \sigma_2$ and σ_{12} are mean of the original image, mean of the improved image, the standard deviation of the original image, the standard deviation of the improved image, and the covariance of both images, respectively. In addition, C_1 and C_2 are constant values.

The third metric is absolute mean brightness error (AMBE) which indicates the change of gray levels between the input and output images. AMBE is defined as follows[19]:

$$\text{AMBE} = |\mu_1 - \mu_2| \tag{17}$$

where μ_1 and μ_2 are the means of input and output images of algorithms. For two algorithms, each algorithm has less AMBE is better and it has a higher performance.

The fourth metric that is used in this research is entropy. In information theory, entropy can be interpreted as the average level of "information", "surprise", or "uncertainty" inherent in the variable's possible outcomes. The higher entropy shows the image has more information and the algorithm has better performance. The entropy can be defined as follows [16]:

$$H = -\sum_{i=0}^{255} p_i \log(p_i) \tag{18}$$

where p_i is a probability of *i*th intensity in the histogram.

The last metric that is used by us is spatial frequency (SF). Spatial frequency is a property of any structure that is periodic across positions in space. This metric calculates sinusoidal components per unit of distance. This metric is obtained as follows:

$$\text{SF} = \frac{1}{\lambda} \tag{19}$$

where λ is wavelength. For image contrast enhancement algorithms, a higher value of SF indicates the algorithm has better performance.

3. EXPERIMENT AND RESULTS

In this section, we evaluate the performance of our proposed algorithm by employing our algorithm on different images. The images are downloaded from the Contrast Enhancement Evaluation Database (CEED2016) database [20]. Five metrics including SF, SSIM, PSNR, Entropy, and AMBE are established for comparing the performance of all algorithms. In this research, the performance of our proposed algorithm is compared with CLAHE, DCT, DOTHE, and ESIHE algorithms. Figure 5 indicates the original, low contrast, and improved images. The values of metrics are described in Table 1. It is observed the proposed algorithm has the best performance than other algorithms. The performance of other algorithms is also shown in Table 1 and Figure 5. It is observed for different metrics, different algorithms have different performances. In fact, the best algorithm should be selected based on the usage of the algorithm and its applications.

Figure 6 and Table 2 indicate the results of the second image test. For this image, it is observed the performance of the proposed algorithm is better than other algorithms. It is worth noting that, it may be possible our algorithm has a worth performance than a spatial algorithm in one metric but it is better than that algorithm in other metrics. Indeed, we should consider the performance of algorithms in whole metrics.

For more investigation, we apply different images in our algorithm and other algorithms. In the following figures and tables, the results for other images are presented. It is observed for all images, our proposed algorithm has the best performance.

Fig. 6. Original, low contrast, and reconstructed images by different algorithms for the second image test.

Table 2. ***The metrics results for different algorithms for the second image test.***

	AMBE	Entropy	PSNR	SSIM	SF
Proposed algorithm	16.628	6.958	19.394	0.906	4.228
CLAHE	58.323	6.229	12.222	0.476	3.780
DCT	23.758	6.965	18.764	0.856	4.228
DOTHE	22.730	6.130	15.440	0.646	4.141
ESIHE	31.452	5.930	17.358	0.605	4.817

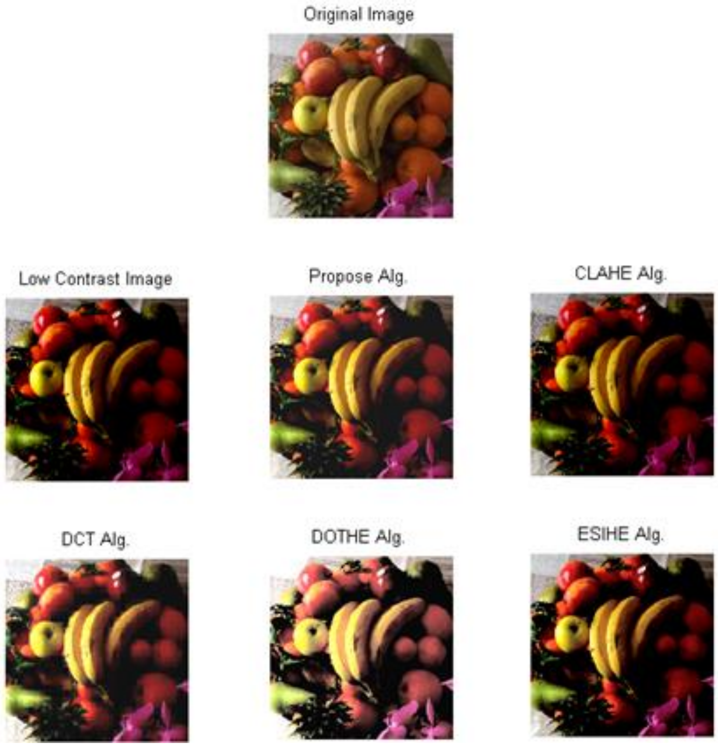

Fig. 7. Original, low contrast, and reconstructed images by different algorithms for the third image test.

Table 3. ***The metrics results for different algorithms for the third image test***

	AMBE	Entropy	PSNR	SSIM	SF
Proposed algorithm	8.098	5.947	23.393	0.851	2.303
CLAHE	44.917	5.889	14.676	0.454	1.961
DCT	4.189	6.887	21.169	0.785	2.315
DOTHE	10.666	5.816	17.004	0.692	2.127
ESIHE	31.888	5.647	16.593	0.487	1.607

Table 4. ***The metrics results for different algorithms for the fourth image test.***

	AMBE	Entropy	PSNR	SSIM	SF
Proposed algorithm	17.912	6.278	21.229	0.790	2.537
CLAHE	48.971	6.048	14.054	0.488	3.173
DCT	2.860	7.100	19.130	0.752	1.356
DOTHE	11.344	6.244	12.701	0.489	1.619
ESIHE	28.384	5.816	14.951	0.438	2.633

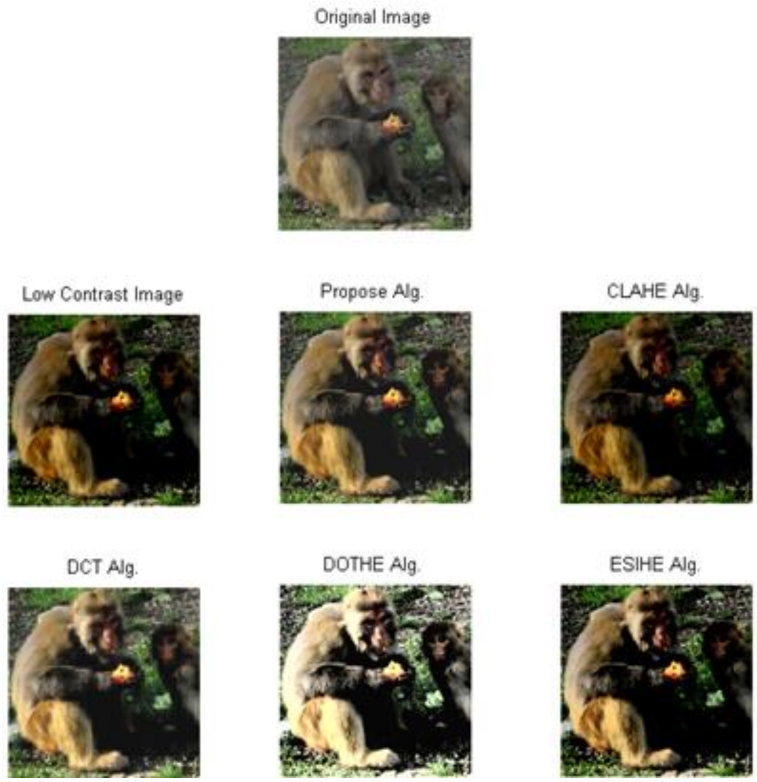

Fig. 8. Original, low contrast, and reconstructed images by different algorithms for the fourth image test.

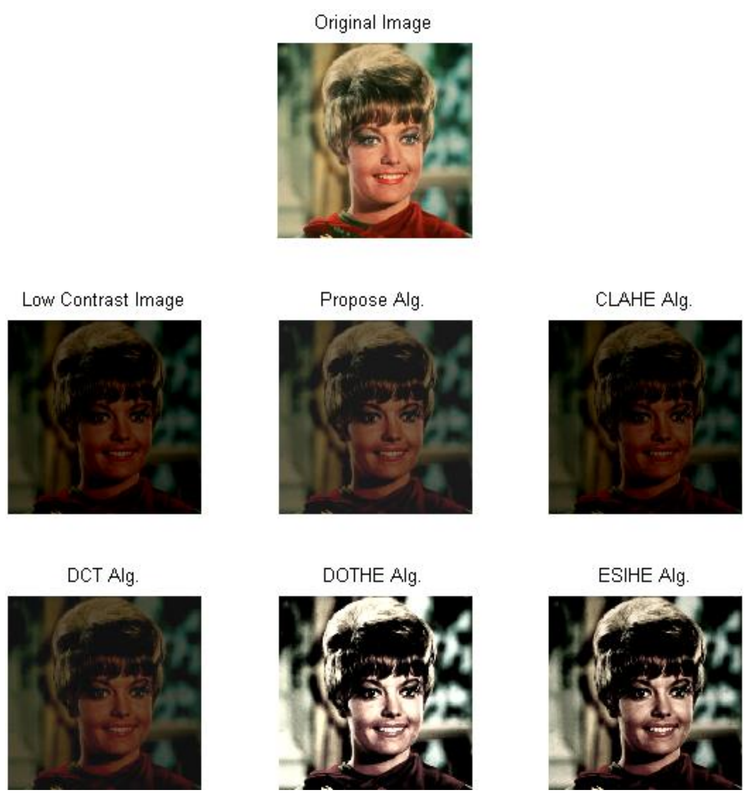

Fig. 9. Original, low contrast, and reconstructed images by different algorithms for the fifth image test.

Table 5. ***The metrics results for different algorithms for the fifth image test.***

	AMBE	Entropy	PSNR	SSIM	SF
Proposed algorithm	9.851	5.239	11.499	0.612	2.284
CLAHE	93.149	5.129	8.243	0.213	1.988
DCT	73.519	5.527	10.114	0.475	2.083
DOTHE	62.025	5.291	13.991	0.496	1.743
ESIHE	39.358	5.118	13.999	0.481	1.750

4. CONCLUSION

We proposed a novel method for contrast enhancement in this research. The proposed algorithm uses 2-D histogram and divides it into three parts based on the statistical parameters. In addition, the clipping histogram method is used in this algorithm. The clipping method is a procedure to avoid image saturation. The main idea behind this research is to use Skewness to transform histogram distribution into Gaussian distribution. An iterative method is designed in this paper to minimize the Skewness of the histogram. In the end, the performance of the proposed algorithm is compared with different algorithms based on different metrics and it is observed the proposed algorithm has a better performance than other investigated algorithms.

REFERENCES

[1] T. Gonzalez R. C. and Woods R. E., “Digital Image Processing”, 2nd ed. Englewood Cliffs, NJ: Prentice- Hall, 2002

[2] Mousania, Younes, Salman Karimi, and Ali Farmani. "Optical remote sensing, brightness preserving and contrast enhancement of medical images using histogram equalization with minimum cross-entropy-Otsu algorithm." *Optical and Quantum Electronics* 55.2 (2023): 105

[3] Abin, Deepa, et al. "Brain Tumor Image Enhancement Using Blending of Contrast Enhancement Techniques." *International Conference on Image Processing and Capsule Networks*. Cham: Springer International Publishing, 2022

[4] Singh N, Kaur L, Singh K, Histogram equalization techniques for enhancement of low radiance retinal images for early detection of diabetic retinopathy, Engineering Science and Technology, an International Journal 2019; 22: 736-745

[5] Chaudhary, Suneeta, Anuj Bhardwaj, and Puneet Rana."Image enhancement by linear regression algorithm and sub-histogram equalization."*Multimedia Tools and Applications* 81.21 (2022): 29919-29938

[6] Sonali, et. Al., An approach for de-noising and contrast enhancement of retinal fundus image using CLAHE, Optics & Laser Technology 2019; 110: 87-98

[7] Fu X, Cao X, Underwater image

enhancement with global–local networks and compressed-histogram equalization, Signal Processing: Image Communication, 2020: 86

[8] Kandhway P, Bhandari A. K., An optimal adaptive thresholding based sub-histogram equalization for brightness preserving image contrast enhancement, Multidimensional Systems and Signal Processing 2019; 66

[9] Guo,Jiawei, et al. "A survey on image enhancement for Low-light images." *Heliyon* (2023)

[10] Veluchamy M, Subramani B, Image contrast and color enhancement using adaptive gamma correction and histogram equalization, Optik, 2019; 183: 329-337

[11] Parihar A. S, Histogram modification and DCT based contrast enhancement, 2nd International Conference on Inventive Systems and Control (ICISC), 2018.

[12] Fernandes S., Shetty A., Vashi H., Kelkar V., Adaptive Contrast Enhancement using Fuzzy Logic, International Conference on Advances in Computing, Communication and Control (ICAC3), 2019.

[13] Yelmanov S., Romanyshyn Y., A New Image Enhancement Technique Based on Adaptive Non-linear Contrast Stretching. IEEE 2nd UkraineConference on Electrical and Computer Engineering (UKRCON), 2019.

[14] Keerthanaa K., Radhakrishnan A., Performance Enhancement of Adaptive Image Contrast Approach by using Artificial Bee Colony Algorithm, Fourth International Conference on Computing Methodologies and Communication (ICCMC), 2020.

[15] Bin X, et. Al., Brightness and contrast controllable image enhancement based on histogram specification, Neuro computing 2018; 275: 2798-2809

[16] Mittal H, Saraswat M, An optimum multi-level image thresholding segmentation using non-local means 2D histogram and exponential Kbest gravitational search algorithm, Engineering Applications of Artificial Intelligence 2018; 71: 226-235

[17] King K.M, Kim D. S, McCabe C. j, Random responses inflate statistical estimates in heavily skewed addictions data, Drug and Alcohol Dependence 2018; 183: 102-110

[18] Borda, Monica, Fundamentals in Information Theory and Coding. Springer. 2011.

[19] Ponticorvo A, et. al., Spatial Frequency Domain Imaging (SFDI) of clinical burns: A case report, Burns Open 2020; 4: 67-71

[20] https://data.mendeley.com/datasets/3hfzp6vwkm/3