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ADAPTIVE IMAGE ENHANCEMENT APPROACH BASED ON DOUBLE-PLATEAUS HISTOGRAM

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ABSTRACT

An adaptive contrast enhancement approach is formalized in this work. The approach is relied on double-Plateaus histogram enhancement. It is composed of three stages. In first stage, the image histogram is clipping relied on self-adaptive double-plateaus procedure. The second stage uses the contrast factor parameter in automatic classification approach to split the clipped image into overexposed and underexposed sub image. The contrast enhancement approach based on statistical operations and neighborhood processing is applied on each sub image. The contrast is enhanced without losing the original histogram characteristics. In addition, this approach doesn't require a threshold parameter in its operation. The results show that this approach is successful in increasing image enhancement, with other state-of-the-art approaches being outperformed in term of visual performance and quantitative tests.

Keywords: *Image contrast, Image enhancement, Double-plateau histogram, Image histogram*

1. INTRODUCTION

Improvement of images is an imperative step in a production of digital image processing. However, it is still the main challenge in image processing area. It allows enhancing the appearance to human viewers or to another systems performance. The image is enhanced via modifying its contrast and/or dynamic range. There exit several methods that have proposed for increasing image contrast [1-20] [27-29]. Image enhancement Histogram Equalization (HE) is an effective approach [1]. By (HE) the gray level distribution of an image is uniformed. Unfortunately, image enhanced by the HE is suffered from visual artifacts, loss of details and saturation-shifting brightness distortion. Some methods based on separating the histogram to several parts and equalizing them to enhance (HE) separately [2]. Such as, (BBHE) [3], (DSIHE) [4] (MMBEBHE) [5]. BBHE and DSIHE employ the median in addition to mean values as a separating point, respectively. Furthermore, RMSHE [7] is to extend BBHE technique which recurrently maintain the brightness by performing image decomposition. Sim et al. [8] suggested a technique of Recursive Sub image HE (RSIHE) that each partition should have the same number of pixels by divining the histogram relied on an average value. The histogram is separated into r partitions, where r is the recursive level. Outcome the ideal value of r is hard. No enhancement with the high value of r will occur in spite of adequate fulfillment of the brightness preservation property [9]. The brightness saturation in homogeneous area is caused by the global histogram equalization with histogram of many peaks. This problem is processed by MPHEBP [10].

The clipped or plateau (HE) is important in histogram equalization approach. Clipped histogram equalization helps to maintain the brightness and to monitor the rate of enhancement. Several approaches based on clipped (HE) such as (BUBOHE) [11], (WTHE) [12], (GC-CHE) [13], (SAPHE) [14] and (MSAPHE) [15]

Double-plateau histogram equalization [16] is proposed based on lower and upper threshold values. The noise is constrained based on the upper threshold. Protect and enhance the image is

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relied on a lower threshold. Determine the upper and lower threshold is main critical of double-plateau histogram equalization. Empirically, the maximum value is being put at 20-30% for the complete number *p*. Nonparametric modified histogram equalization [18] (NMHE) was achieved by several steps. (1) Eliminate spikes from input of histogram. (2) Clip the outcome and normalize it. (3) Calculate the summary deviation from the standardized histogram of this intermediate altered histogram. (4) Using it as a weighing factor to construct a final modified histogram that is a weighted mean of the modified histogram.

Experimental results have shown that this technique generates outcomes superior to several p revious algorithms to contrast improvement [18]. In addition, statistical operations and neighborhood processing play an important role to increase contrast enhancement by getting the desired result such as manipulation of brightness and contrast [19]. Further, Singh and Kapoor introduced an exposure relied on subimage histogram equalization (ESIHE) [20], which uses an exposure-related threshold to bisect the input histogram and mean brightness as a threshold to clip the histogram.
In this work, an adaptive and automatic approach relied on double-Plateaus histogram enhancement is proposed. First, the histogram is clipped by the histogram enhancement algorithm of Self-adaptive double-plateaus. Then, the modified image is spilt to overexposed and underexposed sub images by automatic contrast factor parameter. Finally, the contrast enhancement approach is provided to every sub image separately.
The algorithm suggested prevents important chang es in brightness and image details. In addition, the washed-out appearance is disallowed, and the artlessness of the improved image is preserved. It doesn't require any parameter regulation and executed in short computational time. The paper is planned as next; in Section 2 the projected approach is introduced. The implementation result, and comparison are specified in Section 3. At end, conclusion is explored in Section 4.

2. PROPOSED APPROACH

The proposed approach includes three main processes. They are Self-adaptive double-plateaus histogram enhancement, automatic image separation, which based on contrast factor parameter, and use of statistical operation and neighborhood processing to enhance contrast [19]. The projected approach is described in figure. 1

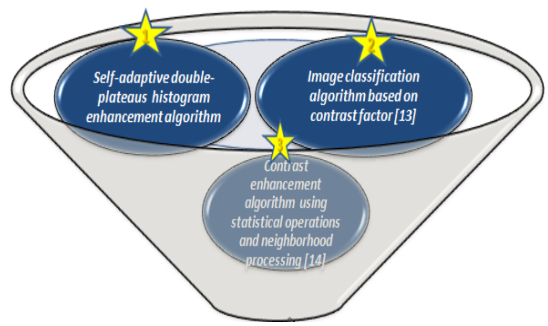

Figure 1: Our proposed approach

2.1 Self-adaptive double-plateaus histogram enhancement

The first process of improving the Self-adaptive dual-plateau histogram is to enhance images of low contrast. It has the ability to overcome the drawback of (HE). In addition, the threshold value of Double-plateaus is to self-adaptively adjust the numerous types of images. Using the higher threshold value set, this process can record noise and the background. At the same time, by setting a lower threshold value, the process will optimize grim targets and clear image. The image histogram is adjusted using the self-adaptive setting of two appropriate T_{up} and T_{down} plateau thresholds in relation to Eq. 1.

$$P_m(k) = \begin{cases} T_{up} & (P(k) \geq T_{up}) \\ P(k) & T_{down} \leq P(k) \leq T_{up} \\ T_{down} & 0 \geq P(k) \leq T_{down} \end{cases} \quad (1)$$

where $P_m(k)$ refers to plateau histogram, and $P(k)$ is to image histogram, T_{up} as well T_{down} represent the thresholds of upper-clipping and lower-clipping limits plateau, respectively. In addition, k marks a gray level, such that $0 \leq k \leq 255$.
The upper-clipping limit plateau threshold is computed using (Eq. 2) [17];

$$T_{up} = PEAKs_{avg} \quad (2)$$

where "PEAKs" represents a set of local maximums (maxima) for a histogram of zero statistics uninvolved. The lower-clipping limit plateau threshold is computed as in Eq. 3.

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$$T_{down} = \frac{\min\{N_{total}, T_{up} \times L\}}{M} \quad (3)$$

where N_{total} is to pixels number in source image, T_{up} represents an upper- clipping limit plateau threshold value, L refers to the total numbers of non-zero gray level and M signifies the total number of original gray level [17]. After estimating, in addition to updating the two thresholds of double-plateau of histogram enhancement, the histogram of original image is pared and adapted.

2.2 Image Classification Relied on Contrast Factor

The neighborhood pixels are similar to the least dynamic range available when an image appears dark and are well thought of as an underexposed image. The neighborhood pixels reside in the highest usable dynamic range for a clearer image, and the image is considered an over-exposed image. Nonetheless, we rarely find a strictly over-exposed (bright) image or a purely underexposed (dark) image. Under-exposed, over-exposed or variations of the two regions found in one image are various in most of the recorded images. The parameter of "contrast factor" splits the image into overexposed and underexposed regions [21]. This parameter is calculated to retain information in the image relied on luminance (intensity) variance with an average luminance of local neighborhood. The factor of contrast is estimated by Eq. 4;

$$CF = \frac{\sum_{(i,j)\in W_{i,j}} (I_{i,j} - \bar{I}_{W_{i,j}})^2}{\sum_{i,j\in W_{i,j}} \sigma^2 I_{W_{i,j}}} \quad (4)$$

where $I_{i,j}$ is to gray-level values (i.e., intensities) of the image, $\bar{I}_{W_{i,j}}$ refers to the local average gray level value in $W_{i,j}$ window. Furthermore, $\sigma^2_{I_{W_{i,j}}}$ acts a local standard deviation for $W_{i,j}$ window. The contrast factor value is in-between [0, 1]. The image here is well-considered to be a mixed-type image. Therefore, several attempts were made to divide the image by using a new threshold T into underexposed and overexposed regions. This threshold is to split an image into two regions where the enhancement is performed separately with respect to their respective regions (Eq. 5).

$$T = L\ (1 - CF) \quad (5)$$

where L is the number of gray degrees. Here, the threshold divides gray rates into two sections. The dark (i.e. underexposed) region within the $[0, T-1]$ range and the bright (i.e. overexposed) area within the $[T, L-1]$ range.

2.3 Enhancing Contrast base on Statistical Operations and Neighborhood Processing

After splitting the image into under exposed and over exposed sub images using contrast factor parameter, the contrast enhancement algorithm is carried out to every separate sub image independently [19]. Consider the input sub images I_1, I_2 of dimensions $M1\times N1$, $M2\times N2$, respectively. Consequently, the histogram equalization is functional for every sub image I_1, I_2 to obtain the equalized images IEqualized1, IEqualized2. So, this algorithm can be summarized as next;

1. Pad every input sub images I_1, I_2 using two columns and rows.
2. Estimate the maximum and minimum intensity of every sub images vianext equation;

$$X_1 = \frac{MAX(I_1) - MIN(I_1)}{2} \qquad X_2 = \frac{MAX(I_2) - MIN(I_2)}{2} \quad (6)$$

3. Compute the mean value for each sub image I_1, I_2.

$$mean_1 = \sum_{i=1}^{M1}\sum_{j=1}^{N1} \frac{I_1(i,j)}{M1\times N1} \qquad mean_2 = \sum_{i=1}^{M2}\sum_{j=1}^{N2} \frac{I_2(i,j)}{M2\times N2} \quad (7)$$

4. Compute the threshold using next equation;

$$Threshold_1 = abs(X_1 - mean_1) \qquad Threshold_2 = abs(X_2 - mean_2) \quad (8)$$

5. For every separate sub image I_1, I_2, choice the first processed pixel $I_1(i,j)$ and $I_2(i,j)$ using a window size of 3×3, and then use its eight neighborhood to compute the Local Standard Deviation $\sigma_{I_{1(i,j)}}, \sigma_{I_{2(i,j)}}$. then, estimate the difference as next;

$$diff_{I_1(i,j)} = (I_1(i,j) - \sigma_{I_1(i,j)}) \qquad diff_{I_2(i,j)} = (I_2(i,j) - \sigma_{I_2(i,j)}) \quad (9)$$

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6. Test if the difference is less or greater than the threshold with respect to the next criteria;
   a. In under exposed sub image, when $diff_{I_1(i,j)}$ is greater than Threshold1then exchange the processed $pixel_1(i,j)$ using an equalized one $I_{Equalized1}(i,j)$.
   b. For over exposed sub image, if $diff_{I_2(i,j)}$ is larger than Threshold2then exchange processed pixel $I_2(i,j)$ using equalized sub image $I_{Equalized2}(i,j)$.
   c. Else, the treated pixel in each sub image is right-hand as it is.

7. The window slides to succeeding pixel for every sub image. Steps 6 to 8 are repetitive until the last pixel of everyone is mapped.

8. Test if all pixels in every sub image have been remapped with respect to the equalized value.

9. Merge the sub images into one image to get a resultant image. This algorithm is illustrated in Figure 2.

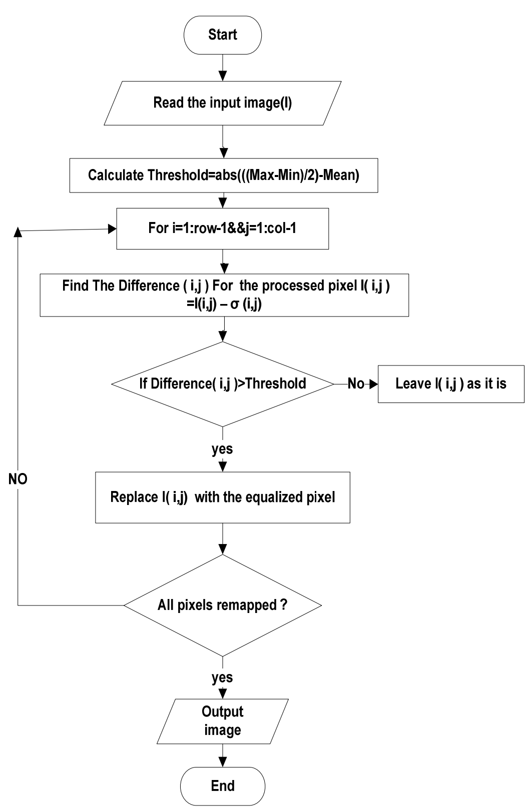

Figure 2: Flowchart for the algorithm of contrast enhancement

The following steps are considered in order to implement the proposed approach;

Step 1: Insert an image.

Step 2: Clip the histogram of the image consuming self-adaptive double-plateaus histogram enhancement algorithm.

Step 3: Split the clipped image through the parameter of the contrast factor into the under-exposed and over-exposed sub-images.

Step 4: In every isolated sub image, for each pixel, compute the threshold using Eq. 8 and find the difference via Eq. 9. When the difference of processed pixel is greater than threshold, then exchange it using the equalized pixel, else it right-hand as it is. This step is repeated until the final pixel is mapped.

Step 5: The resultant image is obtained by combine these sub images into one image.

Figure 3 displays the flowchart of our proposed solution.

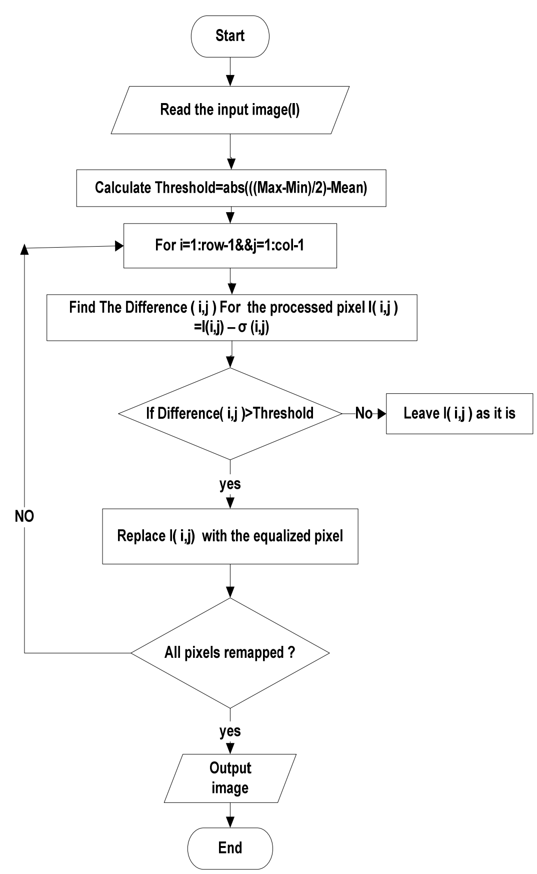

Figure 3: Flowchart for proposed approach

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3. EXPERIMENT SIMULATION AND RESULT ANALYSIS

An image enhancement measuring is not an easy task. So, some objective measures have been proposed for this determination. However, they provide partial information for the enhancement on that image. Principally, to estimate the performance of our proposed approach, Six measures are employed as (PSNR), Entropy [22], (AMBE) [23], (UIQI) [24], (SSIM) [25] and (LD)[26] .

It is being noted that, these metrics complement each other, because they measure various aspects of the image, in particular UIQI and SSIM considered a distinction between the original and the altered picture in terms of luminance, contrast and structural similarities. It is required to balance the objective assessment with a subjective one, to precisely evaluate the algorithms. For the objective and subjective performance evaluation, the proposed approach was tested using standard images with respect to the widely used USC-SIPI database. It is also important to note that the tests were performed on gray-scale images with dimension 256×256 HE [1] was achieved with the standard MATLAB *histeq* function.

3.1 Objective Assessment

The metrics is used to enumerate an image as tracks;

1. Peak Signal-to-Noise Ratio (PSNR):

Assume that $X(i, j)$ represents a source image of M by N pixels, and $Y(i, j)$ denotes a reconstructed image. Errors are measured in PSNR only on a signal of luminance. Therefore, the $X(i, j)$ pixel values take black (0) to white (255) values. Initially, the processed image (MSE) is calculated using Eq. 10.

$$MSE = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}[X_{i,j} - Y_{i,j}]^2}{M \times N} \tag{10}$$

Root means square error (RMSE) from MSE root is determined. So, Eq. 11 measures the PSNR in decibels (dB). The using of a good enhancement technique have the ability to increase the image brightness with no enhancing existing noise for input image. PSNR's broad value means good image quality.

$$PSNR = 20\log_{10}[\frac{MAX(Y_{i,j})}{RMSE}] \tag{11}$$

2. Entropy

The entropy [22] is to be used to calculate the information about the contented image and is specified by Eq. 12;

$$Entropy = -\sum_{k=0}^{255} P(k)\log(P(K)) \tag{12}$$

where $P(k)$ is to a function of probability distribution. Large entropy means the details are more visible in the image.

3. Absolute Mean Brightness Error (AMBE)

AMBE [23] is simply a measure of the difference between the generated image mean μ_p and the input image mean μ_i.

$$\text{AMBE}=|\mu_p - \mu_i| \tag{13}$$

Here, the value of AMBE gives the sense of how the image's overall appearance may have shifted in terms of preference for smaller values.

4. Universal Image Quality Index (UIQI)

In 2002, Wang and Bovik implemented a UIQI measure [24] which interfered with three comparisons of the original and distorted image; luminance, contrast, and structural comparisons as in Eq.14, Eq. 15 and Eq. 16.

$$l(x,y) = \frac{2\mu_x\mu_y}{\mu_x^2 + \mu_y^2} \tag{14}$$

$$c(x,y) = \frac{2\sigma_x\sigma_y}{\sigma_x^2 + \sigma_y^2} \tag{15}$$

$$s(x,y) = \frac{2\sigma_{xy}}{\sigma_x + \sigma_y} \tag{16}$$

Such that, μ_x, μ_y refer to mean values of source and distorted image, respectively. σ_x, σ_y refer to the standard deviation of source and distorted image, respectively. σ_{xy} represents the covariance to both images. According to the three comparisons, UIQI is specified by Eq. 17.

$$UIQI(x,y) = l(x,y).c(x,y).s(x,y) = \frac{4\mu_x\mu_y\mu_{xy}}{(\mu_x^2+\mu_y^2)(\sigma_x^2+\sigma_y^2)} \quad (17)$$

5. Structural Similarity Index (SSIM):

Wang et. al. [25] implemented the Structural Similarity Index as an UIQI enhancement. The mean structural similarity index is calculated as follows; the original and distorted images are divided into 8 x 8 parts, first. The blocks will be transformed into vectors after that. Second, the photos predict two mean μ_x, μ_y, two normal derivatives and one covariance meaning σ_{xy}. Finally, measurements of luminance, contrast and structure are determined based on statistical values, as in UIQI. Eq. 18 measures the index of structural similarity between the images *x* and *y*.

$$SSIM(x,y) = \frac{(2\mu_x\mu_y+c_1)(2\sigma_{xy}+c_2)}{(\mu_x^2+\mu_y^2+c_1)(\sigma_x^2+\sigma_y^2+c_2)} \quad (18)$$

where c_1 and c_2 represent constants. SSIM is carried out locally, as in UIQI, using a B x B sliding window, which travels pixel by pixel vertically as well horizontally cover every image columns and rows top-left corner.

6. Luminance Distortion (LD)

Let LD is the luminance mean correlation between the enhanced and the original images [26]. Eq.19 determines the LD.

$$\text{LD} = \frac{2\bar{X}(\bar{Y})}{(\bar{X})^2+(\bar{Y})^2} \quad \bar{X} = \frac{1}{L}\sum_{i=1}^{L} x_i \quad \bar{Y} = \frac{1}{L}\sum_{i=1}^{L} y_i \quad (19)$$

such that X_i and Y_i refer to the values of the original and processed image, respectively. LD id in-between 0 and 1. Furthermore, the mean luminance of a processed image is closed to source image when LD pending ‘1’. Thus, the brightness is preserved.

We simulated various images with (HE)[1], contrast enhancement algorithm [19], ESIHE [20] and NMHE[18] to show the efficiency of the suggested approach, The experimental results based on PSNR, Entropy, AMBE ,UIQI, SSIM and LD measuring are illustrated in Table 1.

Table 1 explores the result to 10 standard gray-scale images with dimension 256×256. Our proposed approach preserves image details, as specified using high entropy. Lower entropy implies the proposed approach's higher ability to mitigate the problems of intensity saturation and reserve image information. The proposed approach improves the image whereas preserves the brightness as respect to highest LD value and the lowest AMBE. Here, as defined by the maximum PSNR value between different methods, it does not improve existing noise. It has values of UIQI similar to 1. UIQI's sense should be closer to unity in order to preserve the natural appearance well. It also discusses the substantial preservation of structural material as a higher SSIM benefit in enhanced image. It shows more retaining structural details, which accompanies an increase in the edge content of the image. In certain cases, therefore, it has provided photographs with higher results.

The proposed approach can be carried out with brief computational time. The average of processing time is 13.3825 seconds. It is being noted that the proposed approach affords better results as compared to previously reported.

3.2 Subjective Assessment

Fig. 4, Fig. 5 and Fig. 6 explore visual results with respect to the implementation and completing of numerous enhancement techniques on three standard gray-scale images (pout, tiffany and Girl). Here, the original image is not obvious. It has a poor local contrast like the objects in the image, which are not simply perceivable. Histogram Equalization was used to increase an initial image's contrast, but the white region's specifics are improved, and the image becomes worse. In Fig. 4, the image pout has low contrast and overall high brightness. HE's results, contrast enhancement algorithm [19] show that a significant change in brightness does not dissuade the image's washed-out look. ESIHE's output image has dark areas via light, and NMHE's output image shows that the overall brightness remains high, and the details are very blurred. The results indicate that the recommended solution successfully maintains the naturalness of the picture and, owing to the significant change in brightness, avoids the side effect. To determine the efficiency of an image, we use tiffany (Fig.5), whose intensities are concentrated with a low intensity value considering a dark area. The product of HE (Fig. 5(b)) and the algorithm for contrast enhancement [19] (Fig. 5(c)) reveals that some high lights in her face are blurred.

Table 1. Comparison of various algorithms with respect to 10 standard images.

Image	Quality measures	Original image	HE	Algorithm [19]	ESIHE	NMHE	Proposed approach
Lena	PSNR	-	19.1239	19.2854	22.1190	17.7819	41.7569
	Entropy	7.4429	5.9735	6.1433	7.4135	7.0495	7.4391
	AMBE	-	0.0136	0.0155	0.0018	0.1142	4.1540e-004
	UIQI	-	0.8269	0.8239	0.9063	0.9270	0.9978
	SSIM	-	0.8573	0.8588	0.9201	0.9469	0.9987
	LD	-	0.9996	0.9995	1.0000	0.9782	1.0000
couple	PSNR	-	15.9077	15.9794	21.2214	16.1486	51.7687
	Entropy	7.1720	5.9594	6.0543	7.0768	6.9571	7.1453
	AMBE	-	0.0171	0.0169	6.2148e-004	0.0434	0.0017
	UIQI	-	0.6472	0.6458	0.8443	0.6853	0.9995
	SSIM	-	0.6753	0.6754	0.8660	0.7148	0.9997
	LD	-	0.9994	0.9994	1.0000	0.9963	1.0000
Moon	PSNR	-	9.3927	18.8814	26.4919	32.6695	60.7933
	Entropy	5.4294	4.2796	4.5983	5.3331	5.1393	5.4281
	AMBE	-	0.2903	0.0545	0.0040	0.0046	2.1243e-004
	UIQI	-	0.2322	0.9032	0.5920	0.9334	0.9999
	SSIM	-	0.2792	0.9349	0.7049	0.9827	0.9999
	LD	-	0.7103	0.9734	0.9998	0.9997	1.0000
cameraman	PSNR	-	19.0970	19.2343	19.7900	15.2974	50.6195
	Entropy	7.0097	5.9106	6.1921	6.8893	6.7732	7.0099
	AMBE	-	0.0341	0.0321	0.0487	0.1427	0.0022
	UIQI	-	0.6892	0.6896	0.8360	0.8636	0.9984
	SSIM	-	0.8069	0.8107	0.9103	0.8780	0.9994
	LD	-	0.9975	0.9978	0.9951	0.9653	1.0000
pout	PSNR	-	13.2866	13.3468	14.6802	9.2262	29.6910
	Entropy	6.1875	5.7211	5.8203	6.1744	5.2307	6.2101
	AMBE	-	0.0665	0.0679	0.1446	0.3377	0.0033
	UIQI	-	0.4516	0.4497	0.5781	0.6551	0.9432
	SSIM	-	0.5642	0.5642	0.6513	0.7637	0.9765
	LD	-	0.9896	0.9895	0.9226	0.8539	1.0000
Girl (Tiffany)	PSNR	-	16.8101	16.9843	17.9986	13.0651	38.1085
	Entropy	7.1412	5.9546	6.1494	7.0702	6.5685	7.1365
	AMBE	-	0.0293	0.0252	0.0465	0.2127	0.0023
	UIQI	-	0.7397	0.6951	0.8305	0.6892	0.9973
	SSIM	-	0.6990	0.7419	0.8634	0.7154	0.9953
	LD	-	0.9984	0.9988	0.9965	0.8814	1.0000
Airplane (F-16)	PSNR	-	11.7268	12.1029	22.5786	17.8941	42.0515
	Entropy	6.7297	5.7377	6.0634	6.6850	6.3812	6.7216
	AMBE	-	0.2034	0.1842	0.0598	0.1148	8.1661e-004
	UIQI	-	0.4813	0.4538	0.9319	0.8522	0.9933
	SSIM	-	0.5617	0.5412	0.9673	0.9072	0.9981
	LD	-	0.9443	0.9555	0.9967	0.9843	1.0000
Girl	PSNR	-	13.0035	13.0642	18.2151	10.8150	47.7979
	Entropy	5.5939	4.6755	4.8047	5.5242	5.2771	5.5957
	AMBE	-	0.0478	0.0464	0.0981	0.2744	0.0014
	UIQI	-	0.2348	0.2337	0.7578	0.8261	0.9847
	SSIM	-	0.3018	0.3023	0.9080	0.8694	0.9987
	LD	-	0.9958	0.9961	0.9866	0.9229	1.0000
Einstein	PSNR	-	14.9793	15.0160	20.9206	16.2159	35.9993
	Entropy	6.8936	5.9462	5.9936	6.8682	6.5764	6.8909
	AMBE	-	0.0777	0.0774	0.0481	0.0017	0.0114
	UIQI	-	0.6250	0.6238	0.8263	0.6234	0.9942
	SSIM	-	0.6659	0.6660	0.8486	0.6559	0.9969
	LD	-	0.9859	0.9860	0.9928	1.0000	0.9996
Aerial	PSNR	-	11.2949	11.5501	25.7367	14.2820	51.2938
	Entropy	6.9277	5.8954	6.1622	6.8379	6.6880	6.9252
	AMBE	-	0.2078	0.1931	0.0077	0.1189	0.0017
	UIQI	-	0.5754	0.5541	0.9310	0.6827	0.9998
	SSIM	-	0.5737	0.5544	0.9384	0.6879	0.9998
	LD	-	0.9426	0.9514	0.9999	0.9833	1.0000

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ESIHE test (Fig.5(d)) and NMHE((Fig.5(e)) display no wash-out presence. Nevertheless, her overall lighting is still particularly dark NMHE and she is not physically satisfied with the skin tone of her face. The results show that the proposed solution avoids the significant change in brightness and image information, prevents the wash-out appearance and maintains the image's naturalness.

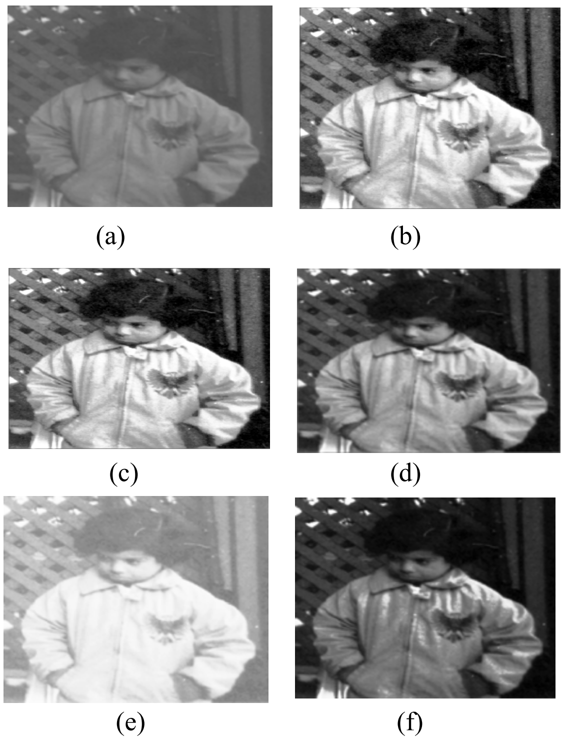

Figure 4. (a) Source 'tiffany image, (b) HE, (c) algorithm [19], (d) ESIHE, (e) NMHE, (f) the proposed algorithm

The Girl picture (Fig.6) is used for experimentation as well. The Girl image that usually has a high brightness is shown in Fig. 6. The side effects such as wash-out appearance can be clearly seen because their backdrop is dark and not easily visible, and significant change in HE brightness (Fig. 6(b)) and contrast enhancement algorithm [19] (Fig. 6(c)).

The NMHE result (Fig. 6(e)) indicates that the overall brightness remains high and the information in the face and context are blurred. The proposed technique in (Fig. 6(f)) explores that it preserves the image details effectively and prevents the change in brightness more than ESIHE (Fig. 6(d)) and other methods. In addition, Figure 7 shows the comparisons results for Lena image by PSNR, Entropy, AMBE, UIQI, SSIM, and LD.

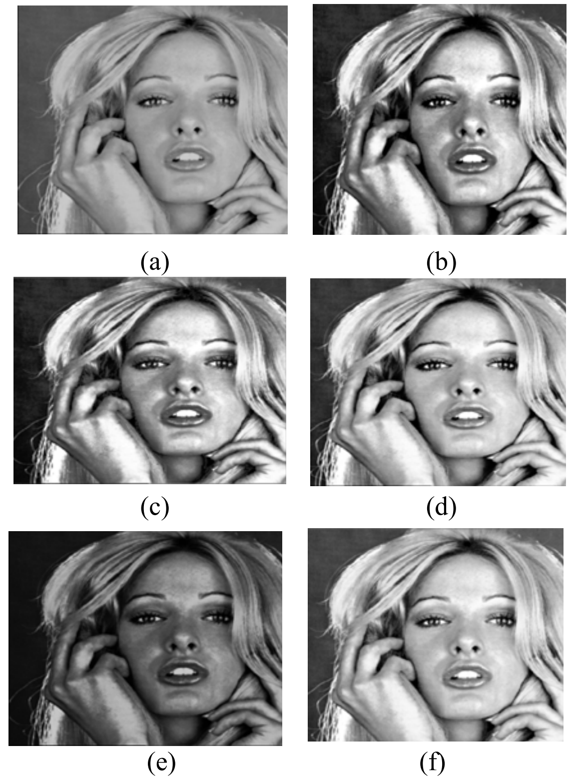

Figure 5. (a) Source 'tiffany image, (b) HE, (c) algorithm [19], (d) ESIHE, (e) NMHE, (f) our algorithm

Figure 6. (a) Source 'girl image, (b) HE, (c) algorithm [19], (d) ESIHE, ,(e) NMHE ,(f) our algorithm

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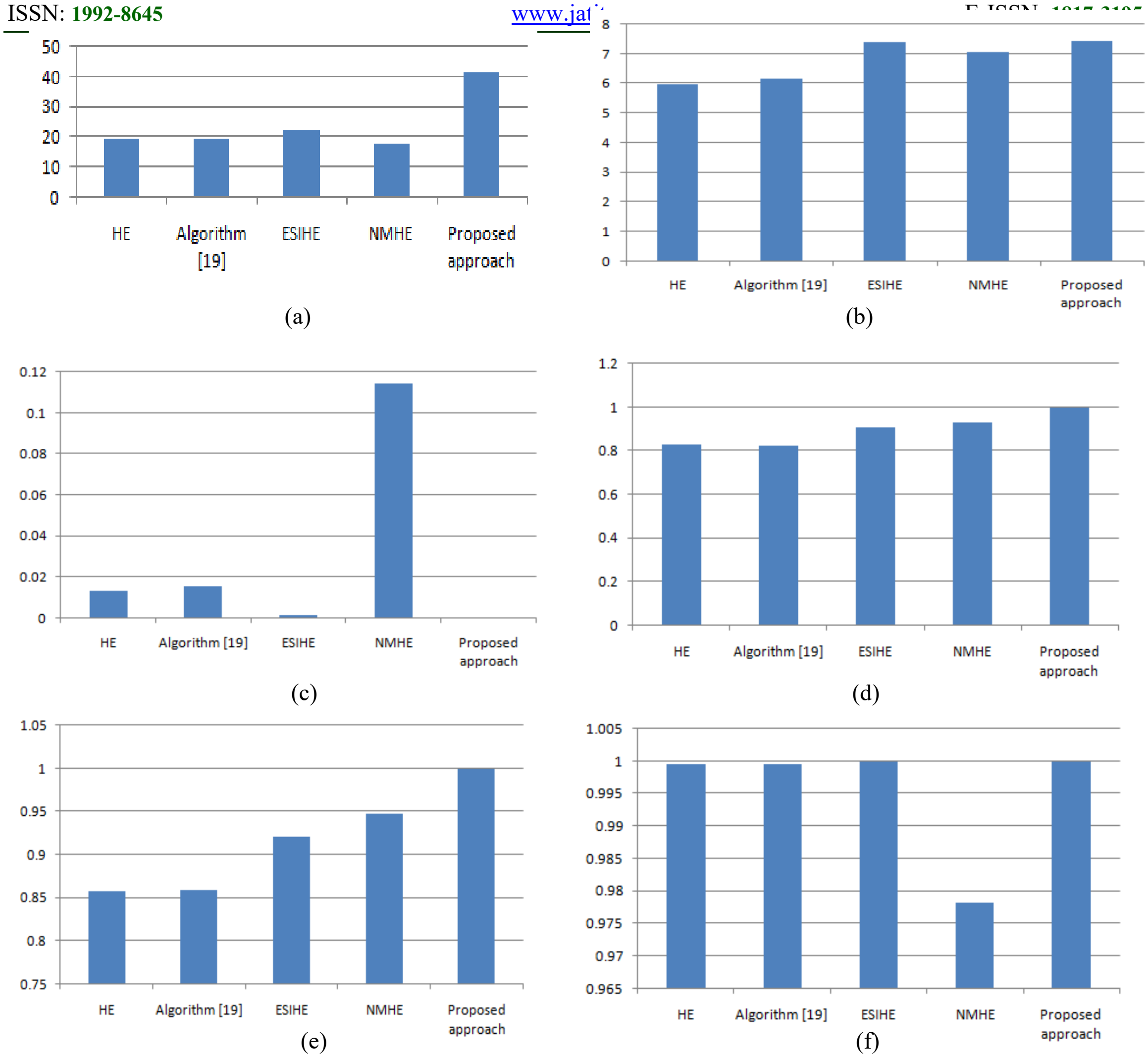

Figure 7. Comparisons results to Lena image by (a) PSNR, (b) Entropy, (C) AMBE, (d) UIQI, (e) SSIM, and (f) LD

4. CONCLUSION

An adaptive approach to improve image enhancement of low contrast based on double-plateaus histogram enhancement is presented in this paper. The proposed approach can be carried out with no parameter tuning and it executed in low computational time. The results of our experimental explored that the suggested method produces high-quality processed images and, in comparison, prevents unnecessary enhancement. Also, it avoids the brightness variation and keeps details of the image. In addition, it prevents the washed-out appearance and preserves the naturalness of the enhanced image. Additionally, it carried out to a widespread range of image types and then adapted the local information for the image. The experimental results have been demonstrated using qualitative and quantitative evaluations and they compared to other previously reported in the same area.

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