Low-Contrast Image Enhancement Histogram method using Grey Wolf Optimization search algorithm

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Abstract- This paper brings out a novel optimized histogram equalization based brightness preserving impendent to improve the contrast of low-contrast and to conserve the brightness using grey wolf optimization (GWO) search algorithm. In traditional histogram equalization algorithms produce fatigued appearance of the resultant image because of excessive brightness variation, which degenerate the quality. To alter histogram of the image,the proposed method employs grey wolf hunting procedure and plateau limits. In this method, luminance and chrominance components are separated and based on the average value of the luminance component, histogram is separated into two. The lower and upper histogram are modified and equalized with respect to the computed plateau limits prevailed by grey wolf optimization search technique. The proposed method is compared with various histogram processing techniques to show the potency of it. The performance of this algorithm is evaluated using subjective quality measures such as PSNR, AMBE etc.

Keywords –Grey wolf optimization algorithm, Histogram, Plateau limit and Low-contrast images.

I. INTRODUCTION

In the area of image processing, image enhancement is an one of essential domain. The pictorial version of the image is mended for machine interpretation and human perception. Due to several reasons and procedure of image acquisition, the images are often corrupted by noise and distortion. Therefore, to enhance the quality of the image, image contrast enhancement is required.

In image enhancement domain, contrast enhancement is one of the proficiency which heightens the overall quality of an image [1]. Direct enhancement methods [2][3][4] and indirect enhancement method [5][6] are the two major classes in the domain of contrast enhancement technique. In the former one, some performance metrics are used to represent quantitatively the contrast of the image. To mend these metrics, algorithms are developed for quality bettermentof the image. In the latterone the range of the image histogram is ameliorated by probability distribution function (PDF) of input image.

There are many algorithms developed with alteration of histogram, due to advantages of the histogram based techniques [7]. Processing of the histogram imply various techniques say histogram equalization (HE), histogram modification and histogram matching. HE [8] is utilized extensively in the process of contrast enhancement as easy to implement. But for images with low contrast, HE can produce unnatural image and artifacts because it doesn't consider mean brightness of an image. Therefore, diverse versions of traditional HE techniques are discussed here.

II.LITERATURE SURVEY

In literature, some suggests to conserve mean brightness of an image, division of thehistogram into respective regions based on some of the statistical parameters or by restricting the histogram value in a region using threshold value. Kim et.al [9] proposed Bi-Histogram equalization (BBHE). In this scheme by using average value of input image, the histogram is divided into two histograms. Then HE is applied independently to each histogram. This scheme preserves the mean brightness but suffers from the problems: Firstly, mean value is not depending on whether image is dark/bright and not suitable for many applications. Secondly it becomes more complicated for H/W implementation.

Wan,Y,chen et.al [10] proposed dualistic sub-image histogram equalization method (DSIHE). DSIHE scheme is like as BBHE but here histogram is divided based on the median value. Then apply HE separately and compiled into one image. But this method is also not significant for preserving the brightness. Soong-Der Chen et.al[11] is proposed *MMBEBHE*to solve washed-out appearance in the image. This approach is alike to BBHE except the average value is the AMBE for each of the threshold level. But it requires considerable amount of computation when the large range of gray level.

Rahman Ramli et al. [12] proposed RMSHE, is like as BBHE except the division of the histogram into n number of times. As number of recursion increasing more brightness preservation can be accomplished. But in RMSHE method difficult to know optimum number of division for effective contrast enhancement and increases the computational complexity.Kuldeep Singh, Rajiv Kapoor et al. [13] proposed ESIHE method. In this method first clipped the histogram bin based on threshold computed. Latter segment the histogram and apply HE. WahidaBanu et al. [14] proposed ACMHE algorithm. Here they did the clipping process based on average difference metrics.

Jing Rui Tang et al. [15] proposed BHEMHB by Histogram bin modification based on the median brightness value of the image. Bhandari and Maurya et al. [16] proposed a method using cuckoo search based algorithm and compared the results with the different techniques using various parameters. But in [17],compared many nature inspired algorithms and concluded that GWO is the best method. This paper claims to get better enhanced image using GWO and applying HE on the two sub-histograms.

III. METHODOLOGY

3.1 Histogram Equalization -

Histogram Equalization (HE) is a technique of contrast adjustment using histogram of the image. First compute the PDF and cumulative distribution function (CDF) for individual sub histograms. PDF is the proportion of histogram bins with respect to number of pixels of the image.

$$PDF(j) = \frac{h(j)}{R} j = 0,1,2,3,4 \ldots .255 \qquad (1)$$

where R is the sum of pixels in an image and h represents histogram of an image.
The CDF is the collection of probability distribution function.

$$CDF(j) = \sum_{x=0}^{j} PDF(x) \qquad j = 0,1,2,3,4 \ldots .255 \qquad (2)$$

The HE for individual sub-histogram is specified as

$$Z = L_{j-1} + \left(L_{\mathrm{j}} - L_{j-1}\right) \cdot CDF_j \qquad (3)$$

Where$L_j$and L_{j-1} are higher and lower dynamic range of the corresponding jth sub- histogram.

3.2 Objective Functions -

The necessity of an objective function is to depict automatically the amount of enhancement required of an image without interference of human. The several quality parameters such as PSNR, entropy are used as enhancement criterion of the objective function. The fitness function is

$$\mathbf{OFI} = \left(\mathbf{log}\left(\mathbf{log}\left(\mathbf{E}(\mathbf{z_s})\right)\right)\right)^{\frac{\mathbf{n_{\varepsilon dges}(z_s)}}{\mathbf{x \cdot y}}} \cdot \mathbf{H}(\mathbf{Z_e}) \qquad (4)$$

$$\mathbf{OF2} = \mathbf{PSNR}(\mathbf{z_e}) \qquad (5)$$

OF = (OF2 * 0.5) + (OF1 * 0.5) (6)

Where Ze is enhanced image and Zs is sobel-edge image.

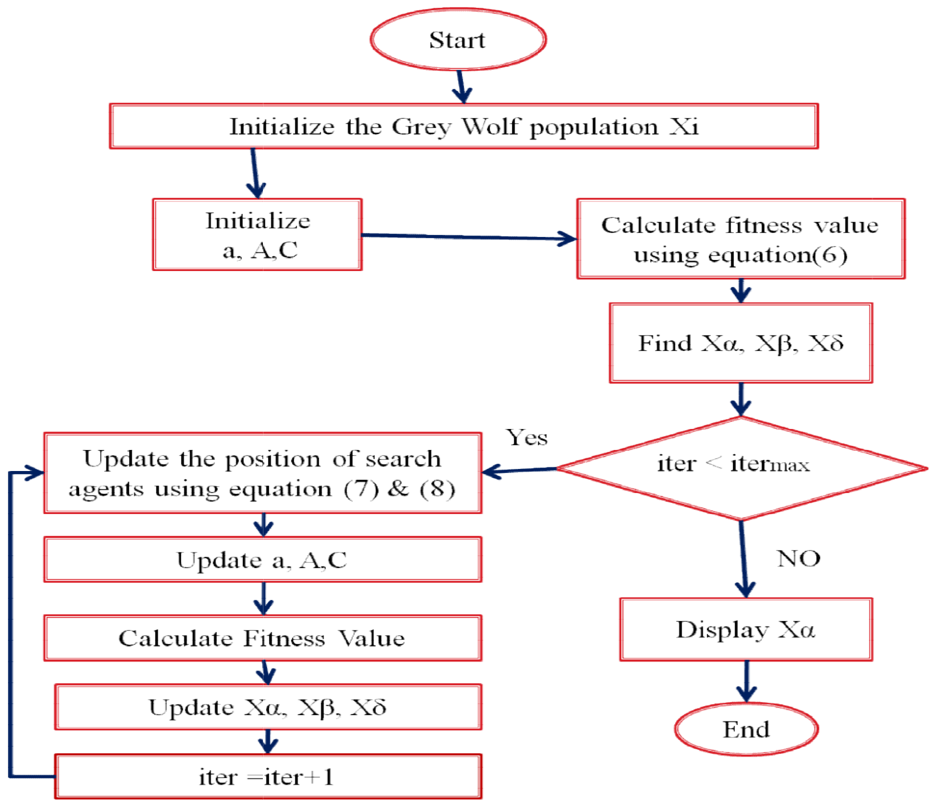
3.3 GWO –

In Mirjalali et al.[18] optimization algorithm is invigorated from attacking process of wolves. Delta(δ), omega(ω), beta(β) and alpha(α) are four parameters in this model. α is selected as first fitting solution by updating their position with respect to prey using equations (7) and (8), followed by β and δ . And omegas(ω) are considered as scapegoats in the pack.The flowchart of GWO algorithm is shown below in fig(1).

$$\vec{D} = \left|\vec{C} \cdot \vec{P}_p(n) - \vec{P}(n)\right| \qquad (7)$$

$$\vec{P}(n+1) = \vec{P}_P(\mathrm{n}) - \vec{A} \cdot \vec{D} \qquad (8)$$

Where, $\vec{P}_P$ and $\vec{P}$ are prey and wolf position vectors, respectivily.



Fig(1): Flowchart of GWO algorithm

The procedure of the GWO algorithm is explained below

i. The grey wolves population will be initialized.

ii. Initialize a, A, C.

The vector $\vec{a}$ is linearly decreased from 2 to 0, to give emphasis to explorations. When $|A| > 1$ solutions tends to diverge and $|A| < 1$ avoid stagnation in local solutions. The components of A and C are the combination controlling parameter a and random numbers as r_1 and r_2.

$$\vec{A} = 2a\vec{r_1} - a \quad \text{and} \quad \vec{C} = 2\vec{r_2}$$

iii. Determine the fitness value of each search agents α, β and δ, is estimating approximate possible position of prey. $\vec{D}_\alpha$, $\vec{D}_\beta$ and $\vec{D}_\delta$ are three coefficients of optimization and given in equations (7) and (8).

iv. Find best search agents X_α, X_β and X_δ

v. while (n < maximum number of iterations)

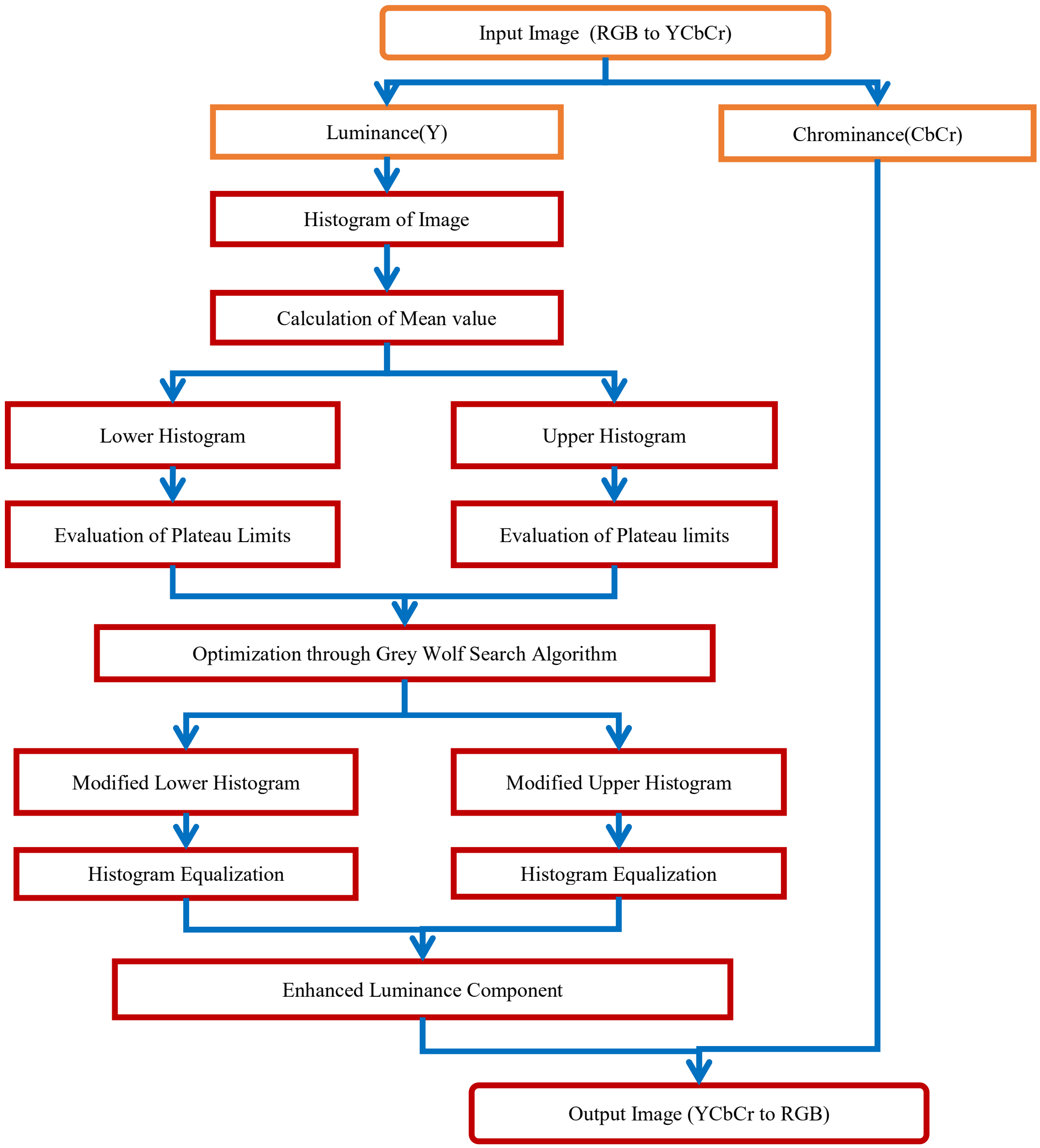
- For each of search agent
  - Current search agent position is updated.
- End for
- Values a, A, C are updated
- Update X_α, X_β and X_δ by computing fitness value of all search agents.
- n = n+1

end while

vi. Give the value of X_α.

***3.4**Detail steps of proposed algorithm–*

The proposed algorithm flowchart is as demonstrated in fig.(2)



Fig(2):The proposed algorithm flowchart

Detailed procedure of GWO based proposed method

Step 1: Low contrast input image with size may be F x G is taken for processing.
Step 2: The chrominance and luminance components of the input image are separated and luminance component is considered for further processing.
Step 3: Luminance component histogram is evaluated.
Step 4: Histogram is separated as upper and lower histogram by using equation (9)

$$m_i = \frac{\sum_{j=0}^{z-1} l_j * n_j}{M} \qquad (9)$$

where l_j is intensity of jth gray level and n_j is addition of pixels of jth level. Based on m_i , the histogram is parted into higher histogram (H_{IH}) and lower histogram (H_{IL}) with dynamic ranges from $m_i + 1$ to maximum gray level value $l_{\max}$ and minimum gray level $l_{\min}$ to m_i respectively.

Step 5: Computation of plateau limits (PL) values for H_{IH} and H_{IL}.

In [19] which uses one plateau limit. In [16], based on the information available in the separated histograms, PL values are calculated. This PLs are computed on the basis of gray level criterion (GLCs) by using equations shown below

$$T_{L1} = GLC_{L1} X P_L \quad (10)$$

$$T_{L2} = GLC_{L2} X P_L \quad (11)$$

$$T_{L3} = GLC_{L3} X P_L \quad (12)$$

$$T_{H1} = GLC_{H1} X P_H \quad (13)$$

$$T_{H2} = GLC_{H2} X P_H \quad (14)$$

$$T_{H3} = GLC_{H3} X P_H \quad (15)$$

Where P_L and P_H are the highest values in H_{IH} and H_{IL} respectively. GLC_L and GLC_H are the GLC of l_{th} plateau limit in H_{IH} and H_{IL}. The GLCs values are obtainable as

$$GLC_{L1} = GLC_{L2} - D_{LH} \quad (16)$$

$$GLC_{L2} = \frac{mi-miL}{mi-lmin} \quad (17)$$

$$GLC_{L3} = GLC_{L2} + D_{LH} \quad (18)$$

$$GLC_{H1} = GLC_{H2} - D_{HH} \quad (19)$$

$$GLC_{H2} = \frac{lmax - miH}{lmax - mi} \quad (20)$$

Where m_{iH} and m_{iL} are the mean values corresponding to H_{IH} and H_{IL}. D_{HH} and D_{LH} is the GLC difference of H_{IH} and H_{IL} respectively and calculated by using equations below.

$$D_{HH} = \begin{cases} \frac{1-GLC_{H2}}{2} & if \quad GLC_{H2} > 0.5 \\ \frac{GL \quad H2}{2} & if \quad GLC_{H_2} \leq 0.5 \end{cases} \quad (22)$$

$$D_{LH} = \begin{cases} \frac{1-GLC_{L2}}{2} & \text{if} \quad GLC_{L_2} > 0.5 \\ \frac{GLC_{L2}}{2} & \text{if} \quad GLC_{L2} \leq 0.5 \end{cases} \quad (23)$$

Step 6: Find the upper and lower bound for the arguments required in Gray wolf optimization algorithm using plateau limits as shown in equations (24)–(29).

$$\frac{T_{L1}}{2} < T1L \leq \frac{T_{L1}+T_{L2}}{2} \quad (24)$$

$$\frac{T_{L1}+T_{L2}}{2} < T2L \leq \frac{T_{L2}+T_{L3}}{2} \quad (25)$$

$$\frac{T_{L2}+T_{L3}}{2} < T3L \leq \frac{T_{L3}+P_{kL}}{2} \quad (26)$$

$$\frac{T_{H1}}{2} < T1H \leq \frac{T_{H1}+T_{H2}}{2} \quad (27)$$

$$\frac{T_{H1}+T_{H2}}{2} < T2H \leq \frac{T_{H2}+T_{H3}}{2} \quad (28)$$

$$\frac{T_{H2}+T_{H3}}{2} < T3H \leq \frac{T_{H3}+P_{kH}}{2} \quad (29)$$

Step 7: Plateau limits computed using equations (10) to (15) are now further optimized using GWO algorithm with the objective functions shown in equations (6)– (8) and bounds calculated in step 6.

Step 8: Depending on this plateau limits, the histogram clipping is performed. With these plateau limits modified the segmented histograms using Eq. (30) and Eq. (31).

$$H_{IL} = \begin{cases} T1L & if\ H_{IL}(j) \leq T1L \\ T2L & if\ T1L < H_{IL}(j) \leq T3L \\ T3L & if\ H_{IL}(j) > T3L \end{cases} \qquad (30)$$

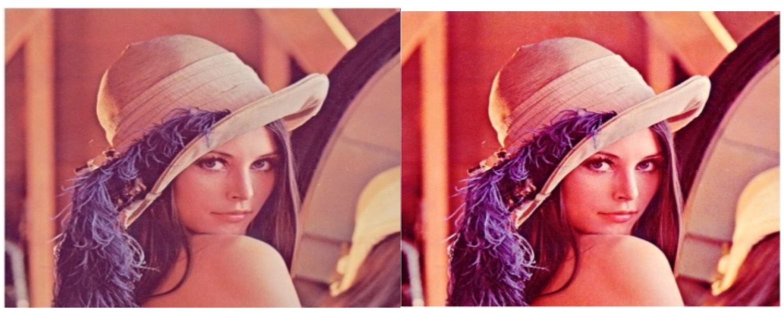
$$H_{IH} = \begin{cases} T1H & if\ H_{IH}(j) \leq T1H \\ T2H & if\ T1H < H_{IH}(j) \leq T3H \\ T3H & if\ H_{IH}(j) > T3H \end{cases} \qquad (31)$$

Step 9: Now, using equation (3) HE is applied to modified sub-histograms individually and using the mapping function get the enhanced luminance component for brightness preserving.

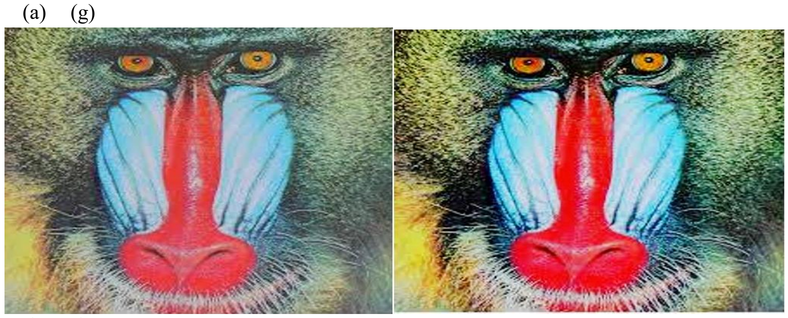
Step 10: To get a final output image, the enhanced luminance components and original chrominance are layered together.

IV. RESULTS AND DISCUSSIONS

The proposed algorithm is applied to six standard images and the experiment outcome has illustrated in fig(3). The first column depicts the low contrast input images and images obtained after proposed GWO method is shown in second column. Also the input and enhanced image histograms for image (c) and (i) is shown in fig(4).



(a) (g)



(b) (h)

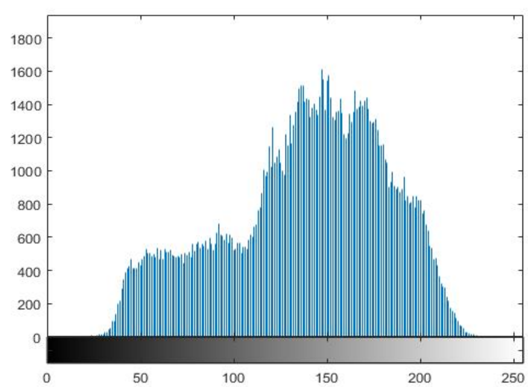
(c) (i)

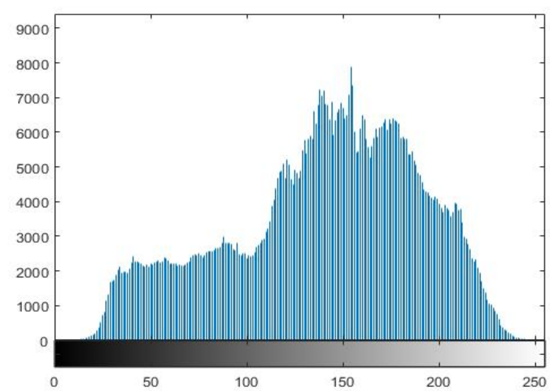
(d) (j)

(e) (k)

(f) (l)

Fig(3): Images a-f (column1) shows standard images with low contrast and images g-l(column 2) represents enhanced image.





Fig(4): Histogram of input and enhanced image.

4.1. Experimental Discussion –

The proposed algorithm efficiency is measured using parameters shown below.

1) Peak signal to noise ratio (PSNR)

   Output image quality is assesses by PSNR and is evaluated using equation (32).

$$PSNR = 20.\log_{10}(\mathrm{MAX1}) - (10)\log_{10}(\mathrm{MSE}) \quad (32)$$

$(MAX1)$ is maximal pixel value and mean square error (MSE) is

$$MSE = \frac{1}{FG}\sum_{c=0}^{F-1}\sum_{d=0}^{G-1}[O(c,d) - P(c,d)]^2 \qquad (33)$$

where O(c,d) and P(c,d) is the pixel value of enhanced and original image at position (c,d) and F and G represents dimension .

2) Structural Similarity Index (SSIM)

Higher SSIM value represents the performance is better and is calculated as

$$SSIM(e,f) = \frac{(2\mu_e\mu_f + C_1)(2\sigma_{ef} + C_2)}{(\mu_e^2 + \mu_f^2 + C_1)(\sigma_e^2 + \sigma_f^2 + C_2)} \qquad (34)$$

3) Absolute Mean Brightness Error (AMBE)

AMBE represents the difference of average intensity values of enhanced and input image.

$$AMBE = \left| m_{\tilde{i}} - m_i \right| \qquad (35)$$

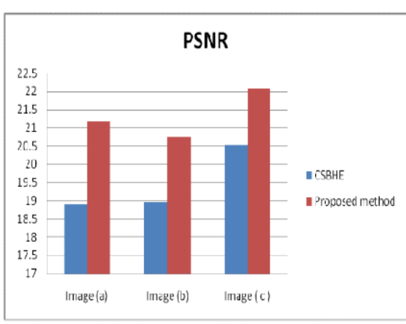
AMBE is smaller indicates the more in effect for preservation of intensity of an input image.

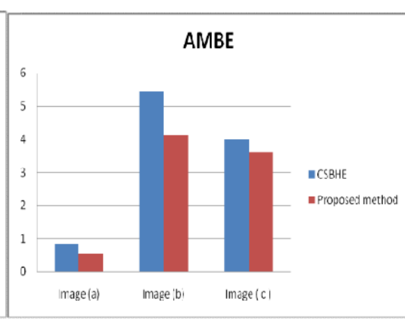
4.2. Comparision and Analysis –

The proposed algorithm is applied on six standard low contrast input images (a) to (f). Theaim of the proposed algorithm is preserving the mean brightness and low contrast image enhancement of an image. This is measured by using PSNR, SSIM and AMBE value as depicted in table 1. The results is compared with the technique CSBHE [16] for images (a), (b) and (c) as shown in fig (5), fig(6) and fig(7).

Table 1. Results in terms of PSNR, SSIM, AMBE.

Image Number	PSNR	SSIM	AMBE
Image (a)	21.1491	0.92055	0.055429
Image (b)	20.7491	0.91461	4.1212
Image (c)	22.0745	0.87782	3.6063
Image (d)	25.6419	0.95948	5.4897
Image (e)	19.7469	0.87344	8.1872
Image (f)	19.0835	0.90483	9.6015





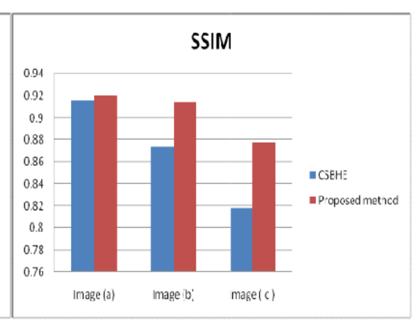


Fig (5): Comparison graph of PSNR value.Fig (6): Comparison graph of AMBE value.Fig (7): Comparison graph of SSIM value.

V.CONCLUSION

With the objective of brightnessand feature preservation, a novel grey-wolf search and hunt based approach has been purported for image contrast enhancement. Initially the histogram is partitioned as 2 sub histograms. Later three plateau limits aredetermined and optimized by grey-wolf search algorithm to each one histogram. Then image is modified based on these limits followed by histogram equalization. Results shows that the proposed algorithm produced highest PSNR, SSIM etc and concluded that proposed technique enhances low contrast images with brightness preservation.

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