ORIGINAL ARTICLE

Grey Level Image Contrast Enhancement using Grasshopper Optimization Algorithm

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The objective of image contrast enhancement is to improve the contrast of digital images which might have been degraded during acquisition. This problem is considered as an optimization problem, and in this paper Grasshopper Optimization Algorithm (GOA) is used to solve this. The proposed method includes a novel fitness function to judge the quality of the generated image. A mean intensity band pass function component is used in the fitness function, which helps in preventing the deviation of the mean intensity of the enhanced image from that of the low contrast image. This ensures that only the contrast of the image gets enhanced, leaving the brightness unaffected. Besides, this paper uses a parametric image transformation function to create the enhanced image, the parameters of which are found from the movement of the search agents of GOA in the search space. This is in contrast to the idea of searching for intensity values in the whole image intensity search space. Exhaustive experiments are performed by executing the proposed method on the standard test image datasets. Comparison shows that the proposed method outperforms many existing image contrast enhancement methods.

KEYWORDS
Grasshopper Optimization, GOA, Image Processing, Contrast Enhancement

1 | INTRODUCTION

Digital images often lose their desired contrast level due to various factors during image acquisition. The process of image contrast enhancement aims to improve the contrast which is formally defined as the difference between the brightest and darkest pixels in the image. The development of such image enhancement methods has numerous applications like in digital photography, medical and satellite image processing, consumer electronics and in many other areas. For example, photographers can safely use relatively inferior camera equipment and rely on the enhancement techniques to improve the contrast later.

There are many algorithms for image contrast enhancement. The most popular is histogram equalization which maps the gray levels of the image based on the probability distribution of the input image gray levels. This stretches and flattens the dynamic range of the histogram. The method, though simple and popular, has some inherent problems like unnatural enhancement and changing brightness of the image because of shifting of the mean intensity of the image pixels. Many applications require only the contrast to be enhanced keeping the other parameters unchanged. Some modified histogram equalization like adaptively modified histogram equalization (Santhi and Banu, 2015), and (Kim et al., 2006) are more effective than traditional histogram equalization. These methods suggest scaling of the magnitudes of the probability density function of the original image before equalization, the scaling factor being determined adaptively based on the average brightness of the original image. Methods like (Poddar et al., 2013) propose a non-parametric based histogram equalization which uses image statistics to compute a spike free modified histogram.

Another approach towards solving the problem of image contrast enhancement is the use of evolutionary algorithms. In (Hashemi et al., 2010) a genetic algorithm (GA) based image contrast enhancement method is proposed. They use a simple chromosome structure and map each gray level of the input image to another gray level to produce an output image with more contrast. Some recent works propose the use of swarm intelligence algorithms like Particle Swarm Optimization (PSO). In (Qinqing et al., 2011) a parameterized transformation function based on global and local properties of the image has been used. Improved version of PSO has been used to achieve the best transformation function. The authors (Chen et al., 2017), (Draa and Bouziz, 2014) and (Joshi and Prakash, 2015) have used Artificial Bee Colony (ABC) algorithm for image contrast enhancement. In (Draa and Bouziz, 2014) ABC algorithm has been used as an optimizer to search for a new set of gray levels to replace the gray levels of the input image. In (Joshi and Prakash, 2015), the authors have included the direction cosines in the ABC algorithm so that better solutions can be achieved by enabling the artificial bees to move in the direction of better solutions. Also they have used an improved objective function by including contrast based quality estimation, which makes use of a local band limited contrast. The work reported in (Chen et al., 2017) has made use of a parametric image transformation function, the Incomplete Beta function (Tubbs, 1987), for generating output image and has used the ABC algorithm for searching the optimal parameters of the transformation function. They have also proposed a new image contrast fitness function by including a new image contrast measure. In (Su et al., 2013), quantum-behaved PSO (QPSO) has been used for image contrast enhancement. They have also used the Incomplete Beta function (Tubbs, 1987) as the transformation function and have also proposed a novel objective function. They have improved the QPSO with an adaptive parameter control strategy. Nature inspired algorithms like the Cuckoo Search algorithm has also been used for image contrast enhancement applications (Agrawal and Panda, 2012).

In recent years, a new swarm intelligence algorithm called the Grasshopper Optimization Algorithm (GOA) (Saremi et al., 2017) has been introduced. It mimics the behavior of grasshopper swarms in nature for solving optimization problems. It has been used in recent times by researchers for solving optimization problems regarding various image processing applications, mainly in image segmentation. (Bhandari and Rahul, 2019) has used GOA for color image multilevel thresholding by using it for maximizing the fuzzy entropy function. In (Jia et al., 2019) GOA has been merged with self adaptive Differential Evolution to produce a hybrid GOA and used for multilevel satellite image segmentation. (Liang et al., 2019) has used a modified version of GOA for color image segmentation by using the Levy flight algorithm for balancing exploration and exploitation in GOA.

The recent use of GOA in image processing applications have inspired us to use GOA for parametric image contrast enhancement. The ability of GOA algorithm to balance between exploration and exploitation and hence not getting stuck in local optima, along with its ability to improve the average fitness of the population has motivated us to use this algorithm. We have used the Incomplete Beta function proposed by Tubbs (Tubbs, 1987) as the transformation function and proposed a novel fitness function. GOA has been used to search for values of parameters of the transformation function, which when used to transform the image, produces an enhanced image with high fitness.

The paper has been divided into the following sections: Section 2 contains an overview of the GOA. Section 3 describes in detail our proposed approach and describes the transformation function [subsection 3.1] and the fitness function [subsection 3.2.] used in the proposed method. Section 4 contains the experimental results and is divided into two parts:- subsection 4.1 and subsection 4.2. Subsection 4.1 lists all the parameter values used in the experiment and subsection 4.2 reports the results on various standard images. Section 5 compares our method with some state-of-the-art image contrast enhancement methods. Section 6 concludes our method by giving a summary of our results we have achieved and suggests future scope of improvements.

2 | GRASSHOPPER OPTIMIZATION ALGORITHM: AN OVERVIEW

GOA is a nature-inspired algorithm proposed by (Saremi et al., 2017). It mimics the behavior of a swarm of grasshoppers in nature. The swarming behavior is found in grasshoppers in both nymph and adulthood. The main characteristics of grasshopper swarms are:

1. Slow movement with small steps in larval grasshoppers.
2. Long range with abrupt movement in adult grasshoppers.
3. Food source seeking by dividing the search process to ensure both exploration and exploitation in the search space.

The grasshoppers move abruptly during exploration and move locally during exploitation. The mathematical model to simulate this behavior is as follows:

$$X_i = S_i + G_i + A_i \tag{1}$$

where X_i is the position of the ith grasshopper, S_i is the social interaction between the ith grasshopper and other grasshoppers of the swarm, G_i represents gravitational attraction of earth for the ith grasshopper, and A_i represents the wind advection. The components in Equation 1 are calculated as follows:

$$S_i = \sum_{j=1, j\neq i}^{N} s(d_{ij})\hat{d}_{ij} \tag{2}$$

where $d_{ij} = \mid x_j - x_i \mid$ is the distance between ith and jth grasshoppers, $\hat{d}_{ij} = \frac{(x_j - x_i)}{d_{ij}}$ is the unit vector from ith to jth grasshoppers, N is the number of grasshoppers, and $s(r)$ is the social interaction function (Figure 1) used to define the strength and nature of interaction forces between two grasshoppers. It is calculated as :

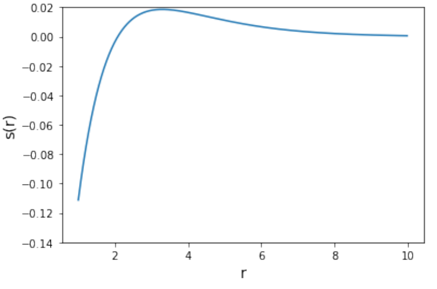
$$s(r) = f e^{-\frac{r}{l}} - e^{-r} \tag{3}$$

where f and l indicate the strength of attraction and attractive length scale respectively. These values are chosen as f=0.5 and l=1.5 following the work reported in (Saremi et al., 2017). Also, as $s(r)$ tends to 0 for higher values of r, the distances between the grasshoppers are mapped in the interval [1,4].

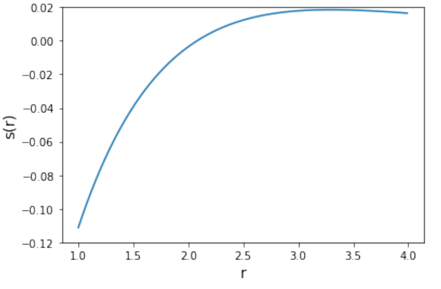
G_i is defined as:

$$G_i = -g\hat{e}_g \tag{4}$$

where g is the gravitational constant and $\hat{e}_g$ is unit vector towards the center of the earth.



(a)



(b)

FIGURE 1 (1a) Social Interaction Function and (1b) Social Interaction Function for r in range [1,4]

A_i is defined as:

$$A_i = u\hat{e}_w \tag{5}$$

where u is a constant drift due to wind, and $\hat{e}_w$ is a unit vector in the direction of wind. By substituting S_i, A_i and G_i in Equation 1 we get:

$$X_i = \sum_{j=1, j\neq i}^{N} s(\mid x_j - x_i \mid) \frac{(x_j - x_i)}{d_{ij}} - g\hat{e}_g + u\hat{e}_w \tag{6}$$

However, Equation 6 is not directly used for solving optimization problems as due to this mathematical model the grasshoppers quickly reach to their comfort zone and also do not converge to a specific target (Saremi et al., 2017). Therefore for solving optimization problems, a modified version of Equation 6 is used as follows:

$$X^d{}_i = c\left(\sum_{j=1, j\neq i}^{N} c\frac{ub_d - lb_d}{2} s(\mid x_j^d - x_i^d \mid) \frac{(x_j - x_i)}{d_{ij}}\right) + \hat{T}_d \tag{7}$$

where ub_d and lb_d are the upper and lower bounds in the Dth dimension respectively, $\hat{T}_d$ represents the Dth dimension of the target, $s()$ is the social interaction function and c is a coefficient which is linearly decreased with the number of iterations and is calculated as:

$$c = c_{max} - l(\frac{c_{max} - c_{min}}{L}) \tag{8}$$

where l is the current iteration, L is the total number of iterations, c_{max} and c_{min} are the maximum and minimum values of c respectively and are chosen as $c_{max} = 1$ and $c_{min} = 0.00001$.

In Equation 7 the inner c decreases the comfort zone, attraction zone and repulsion zone between the grasshoppers as iteration increases. The outer c reduces the movement of the grasshoppers around the target or solution, thereby balancing exploration and exploitation and making the grasshoppers converge at the target.

In optimization problems, there is no target $\hat{T}_d$ like that in Equation 7 as we do not know the solution of the problem. Therefore the grasshopper with the best fitness value is considered as the target for the grasshoppers, thus ensuring the proper areas of the search space get explored and exploited for the solution.

The flowchart for the Grasshopper Optimization Algorithm is given in Figure 2.

3 | PROPOSED APPROACH

GOA is used here to solve the problem of image contrast enhancement. We use parametric image enhancement method i.e. we use a transformation function to transform the image pixel intensities to new intensity values. The food source for the grasshoppers or search agents is a pair of parameters of the transformation function, which is used for formulating the transformation function. This transformation function, when used to transform the whole image, produces an image of high fitness. The fitness of the image is measured with the help of the fitness function. Thus, to formulate the problem of image contrast enhancement as an optimization problem, we need to design a transformation function and a fitness or objective function, which evaluates the quality of image produced by using the set of parameters for the transformation function. The following sections describe in detail the transformation function and the fitness function used in the proposed approach.

3.1 | Transformation Function

Images with low contrast can be enhanced by histogram stretching or grayscale re-scaling. This is achieved by a re-scaling transform of the form

$$I^{'}(x,y) = T(I(x,y)) \tag{9}$$

where $I(x,y)$ is the gray scale intensity value of the pixel at (x,y) position of input image, $I^{'}(x,y)$ is the gray scale intensity value of the pixel at (x,y) position of the output image and T is the transformation function. The transformation function can be linear or non-linear. Piece-wise linear transformation functions can however produce negative or greater than 255 intensity values at points of subsection (Chen et al., 2017). Thus a continuous non-linear curve is a comparatively better transform function. Four standard non-linear continuous transformation functions are shown in Figure 3. But for real life applications since the nature of the image is not known, the type of transformation function that can be applied to enhance a particular image is not fixed. So (Tubbs, 1987) proposed the Incomplete Beta

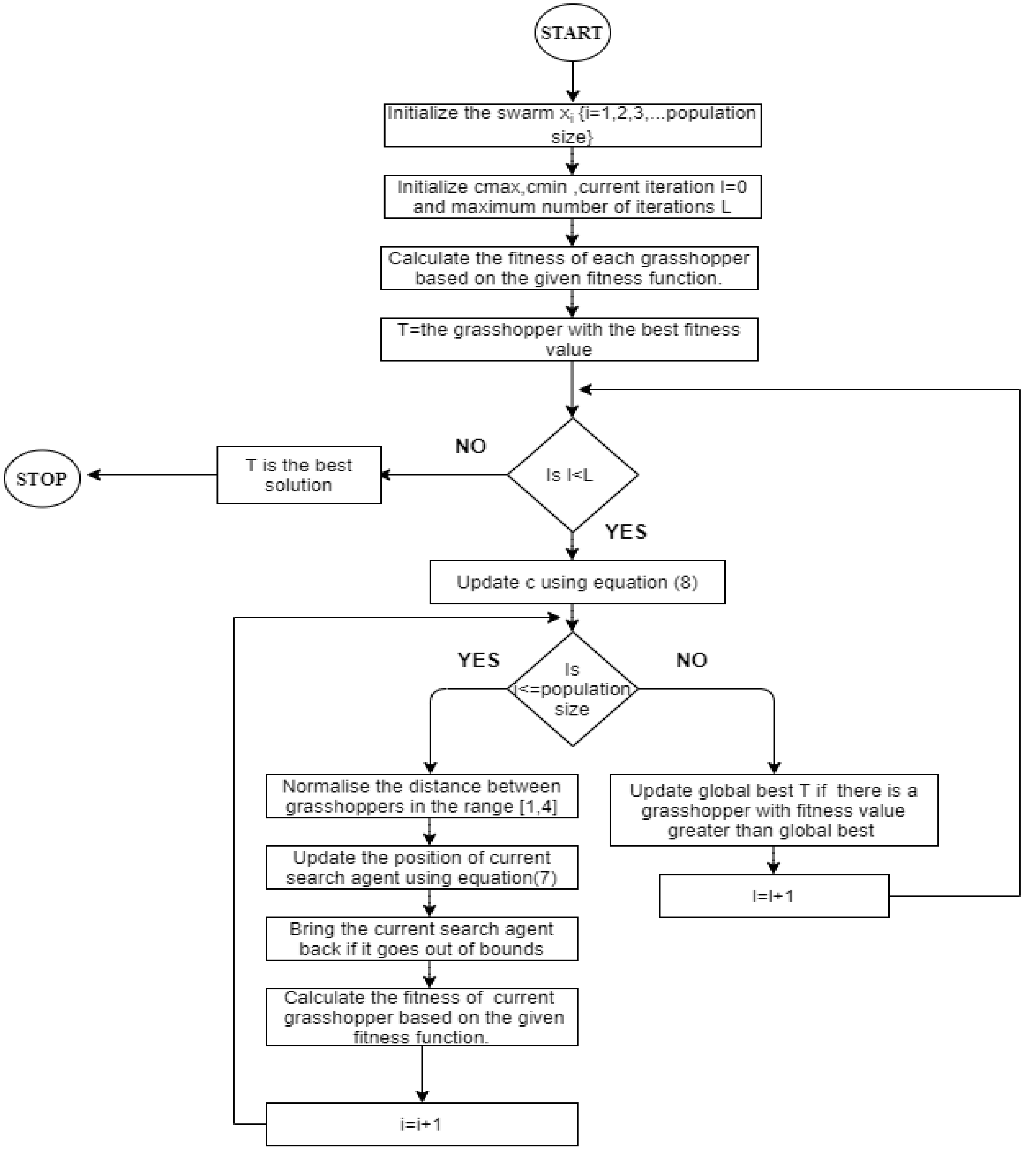
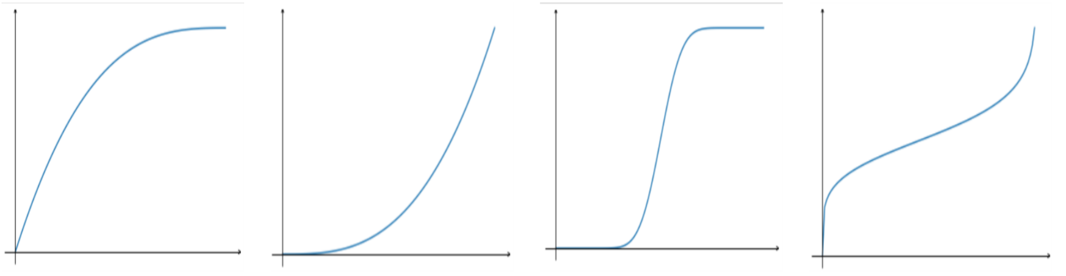


FIGURE 2 Flowchart for Grasshopper Optimization Algorithm



(a) (b) (c) (d)

FIGURE 3 *Four non-linear transform functions with horizontal and vertical axes representing intensity values of input image and output image respectively. (Figure 3a) Transform for stretching darker intensities (Figure 3b)Transform for stretching lighter intensities(Figure 3c) Transform for compressing ends and stretching middle regions (Figure 3d) Transform for stretching ends and compressing middle regions.*

function as the transformation function which is defined as

$$T(i(x,y)) = B^{-1}(\alpha,\beta) \times \int_{0}^{i(x,y)} z^{\alpha-1}(1-z)^{\beta-1}dz \tag{10}$$

where, B is the beta function defined by:

$$B(\alpha,\beta) = \int_{0}^{1} z^{\alpha-1}(1-z)^{\beta-1}dz \tag{11}$$

Here $i(x,y)$ is the intensity of the (x,y) pixel of input image normalized in the range [0,1],

$$i(x,y) = \frac{I(x,y) - i_{min}}{i_{max} - i_{min}} \tag{12}$$

i_{max} and i_{min} are maximum and minimum intensity values respectively, z is the variable of integration and α and β are parameters of the equation. The intensity of (x,y) pixel of output image $I^{'}(x,y)$ is obtained as

$$I^{'}(x,y) = (i_{max} - i_{min}) \times T(i(x,y)) + i_{min} \tag{13}$$

Here GOA is used to search for appropriate α and β values of the transformation function. Here, x and y coordinates of the grasshoppers are used as α and β values for the transformation function. Thus each grasshopper in the search space represents an unique transformation function. That transformation function is used for transforming the whole image and its fitness (calculated according to the fitness function) is associated with that particular grasshopper. Thus the grasshoppers effectively search for that pair of α and β in the search space, which when used to transform the whole image, produces the best possible enhanced image. Thus it becomes important that along with using the best possible optimization algorithm, we also carefully choose the fitness function, so that our optimization algorithm leads us to an image of best quality. The fitness function used is described in the following subsection 3.2.

3.2 | Fitness Function

After GOA is applied on the input images, enhanced images are produced. To evaluate the quality of enhanced image, a suitable fitness function is required. Based on the value of fitness function, the quality of enhanced images can be judged impartially. Now, 5 performance measures and related terms have been combined to form the fitness function. By meticulous observation and based on intuition, it is can be said that high contrast desired output images will have more edge pixels compared to low contrast input images. Hence, number of edge pixels and sum of intensity of those edge pixels are needed to evaluate the quality of enhanced output images. Overall, the fitness function can be described by following equation.

$$F(I_e) = log(log(Sum(I_e))) \times E(I_e) \times S(I_e) \times BP(I_e) \times CM(I_e) \tag{14}$$

Talking about the first two terms, as sum of all edge pixels intensity ($Sum(I_e)$) can be very large, composition of two logarithm functions is applied on that large sum. Count($E(I_e)$) is also multiplied with that value. The count($E(I_e)$) and intensity sum $Sum(I_e)$ can be obtained by applying Canny edge detector((Ding and Goshtasby, 2001)) on the enhanced image.

Now, the third term $S(I_e)$ determines entropy value of enhanced image. This can be mathematically explained by following equation.

$$S(I_e) = \sum_{i=0}^{255} h_i log_2(h_i) \tag{15}$$

Here h_i gives the probability of occurrence of i-th intensity value of the image.

Now the fourth term BP (I_e) acts just like a non ideal mean intensity band-pass function.

This function helps to preserve the brightness of input image by not allowing the mean intensity of the enhanced image to deviate from mean intensity of the low contrast input image. This function gives a small bandwidth of mean intensity so that only enhanced images with mean in that bandwidth will become more fit. Thus it gives more fitness to an enhanced image with comparable brightness. This band-pass function is non ideal or realistic in nature to keep a smooth change in function's behaviour. The function can be described by Equation 16.

$$BP(I_e) = k^{-(\bar{I}_e - \bar{I}_{in})^2}, k > 1 \tag{16}$$

$\bar{I}_e$ is mean intensity of enhanced image. $\bar{I}_{in}$ is mean intensity of input image. k is a constant which can be set based on required bandwidth. k is greater than 1 and more the k gets near 1, bandwidth increases. So in order to preserve brightness of input image, bandwidth of mean intensity should not be large but again not very small too. Small bandwidth means sharply decreasing band-pass function which will reduce fitness of most of the enhanced images despite having small difference in brightness.

Here, in Figure 4 it can be seen that with k approaching to 1, BP (I_e) has very high bandwidth but for $k = e$ or $k = 1.50$ bandwidth is very small so these values are inadequate to pass-band images with high value in other three terms of fitness and brightness close to input image's brightness. So, by rigorous experimentation, the value of k used in the proposed method is chosen as $k = 1.02$.

The last term in $F(I_e)$, $CM(I_e)$ gives global contrast measure. It is evident that contrast depends on the difference between every intensity values with mean intensity value of the image. Now, to increase contrast, a contrast measure

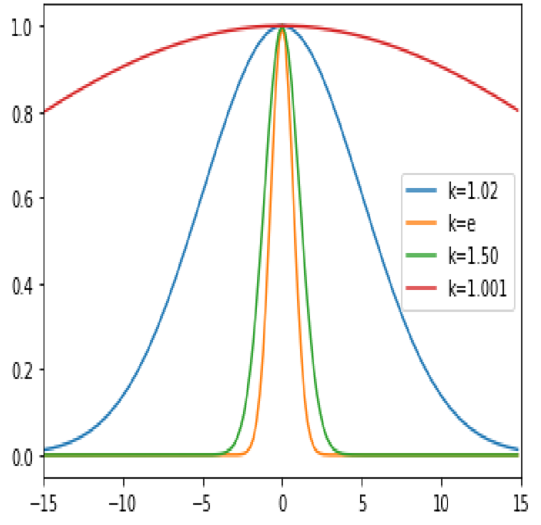


FIGURE 4 Nature of BP function for various values of k

function is designed which will find standard deviation of the enhanced image.

$$CM(I_e) = \sqrt{\frac{1}{MN}\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}(I_{eij} - \bar{I}_e)^2} \tag{17}$$

Above expression describes this contrast measure function (CM(I_e)). Here I_{eij} gives (i, j) pixel's intensity in two-dimensional image with dimension M and N (size $M \times N$). $\bar{I}_e$ is mean intensity value of the image. Optimization algorithm will try to increase this fitness value while searching in search space and increase in contrast measure will cause spreading of histogram of the image. Thus this fitness measure allows only images with high contrast measure to be more fit and thus increases contrast of the low resolution images.

4 | EXPERIMENTAL RESULTS

4.1 | Parameter Tuning

The proposed image contrast enhancement method is applied on the Kodak Lossless True Color Image Suite (Company, 2013) and selected images of MIT-Adobe FiveK Dataset (Bychkovsky et al., 2011) to evaluate its performance. The first dataset contains 24 images and number of selected images from the second dataset is 8, which are first converted into gray scale images and used as ground truth for the performance evaluation. The ImageEnhance module from the Python Imaging Library (PIL) (PIL) is used to decrease the contrast of these gray scale images. The images so generated are used as input image for applying the proposed algorithm and enhancing the contrast. These enhanced images are then compared with the ground truth images in terms of some standard performance evaluation metrics.

The performance metrics used for comparing the performance of the different image enhancement methods are (1) Peak Signal-To-Noise ratio (PSNR) (2) Structural Similarity Index Measure (SSIM) and (3) Visual Information Fidelity (VIF).

The list of parameter values for performing the experiment is given in Table 1:

TABLE 1 Parameter values of GOA used for present work

Parameter	Value
α	upper-bound=10; lower-bound=0
β	upper-bound=10; lower-bound=0
Number of Grasshoppers	20
Total number of iterations	50
c_{max} [eq: 8]	1
c_{min} [eq: 8]	0.00001
f [eq: 3]	0.5
l [eq: 3]	1.5
k [eq: 16]	1.02

4.2 | Discussion

The first experiment is conducted on the Kodak Lossless True Color Image Dataset (Company, 2013). For visual observation, the results for images 1 to 10 in dataset (Company, 2013) are given in Figures [5-14], where first image is the ground image, third image is the input image with low contrast, fifth image is the transformed image with high contrast and second, fourth and sixth images are the histograms of first, third and fifth images respectively.

The second experiment is conducted on selected images of the MIT-Adobe FiveK Dataset (Bychkovsky et al., 2011). The selected images are '0014', '0024', '0037' ,'0050', '0059', '0115', '0255' and '4889'. Here also, for visual observation, the results for the images are given in Figures [15-22], where first image is the ground image, third image is the input image with low contrast, fifth image is the transformed image with high contrast and second, fourth and sixth images are the histograms of first, third and fifth images respectively.

It can be seen that the proposed method is successfully increasing the contrast by spreading the histogram.

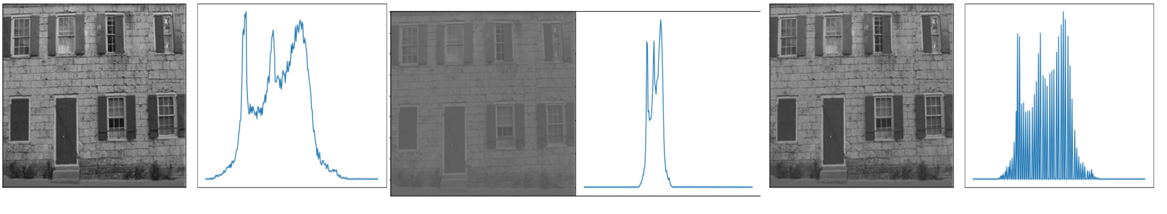


FIGURE 5 Kodim01 PSNR=31.12 SSIM=0.98 VIF=0.83

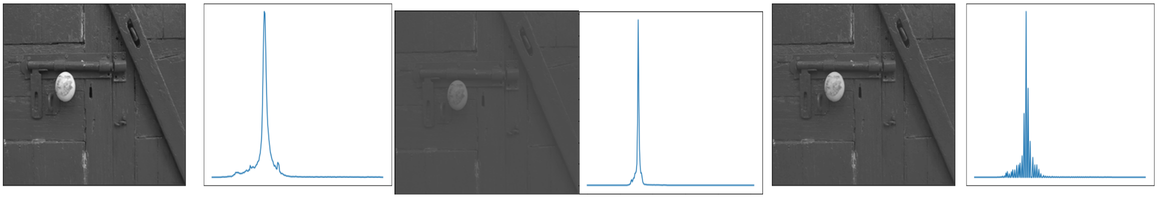


FIGURE 6 Kodim02 PSNR=34.28 SSIM=0.97 VIF=0.73

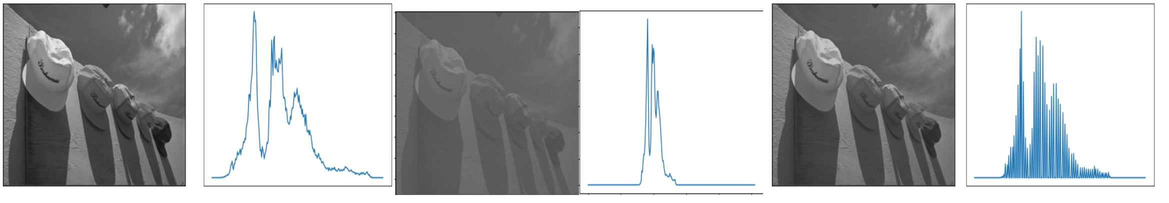


FIGURE 7 Kodim03 PSNR=29.71 SSIM=0.97 VIF=0.80

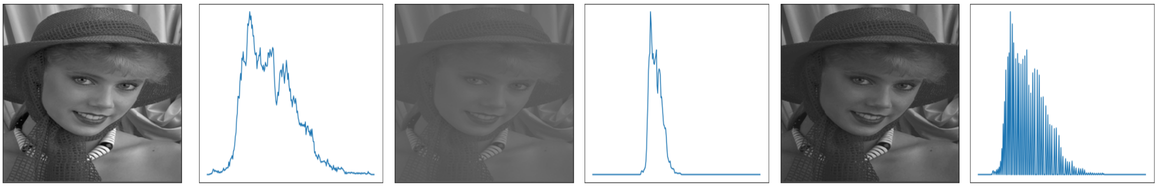


FIGURE 8 Kodim04 PSNR=30.07 SSIM=0.97 VIF=0.79

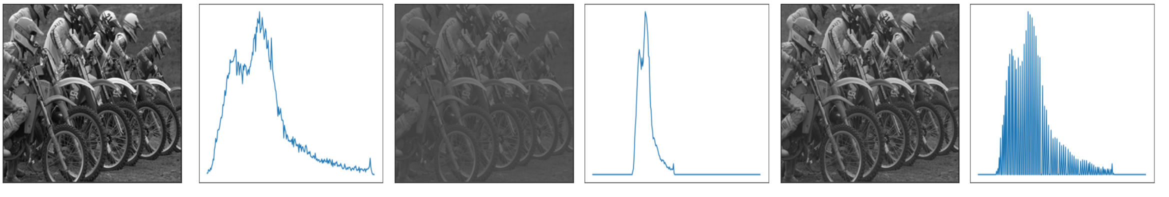


FIGURE 9 Kodim05 PSNR=26.99 SSIM=0.95 VIF=0.79

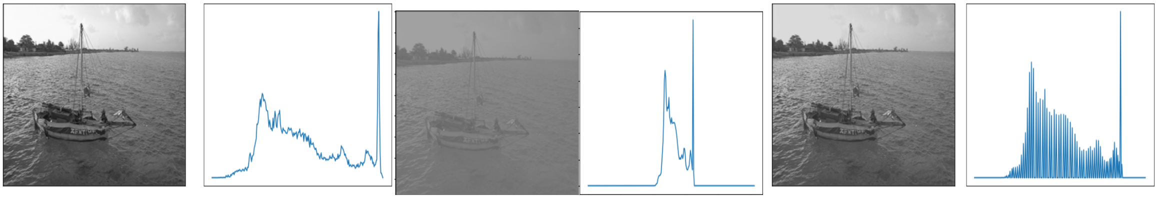


FIGURE 10 Kodim06 PSNR=26.19 SSIM=0.98 VIF=0.80

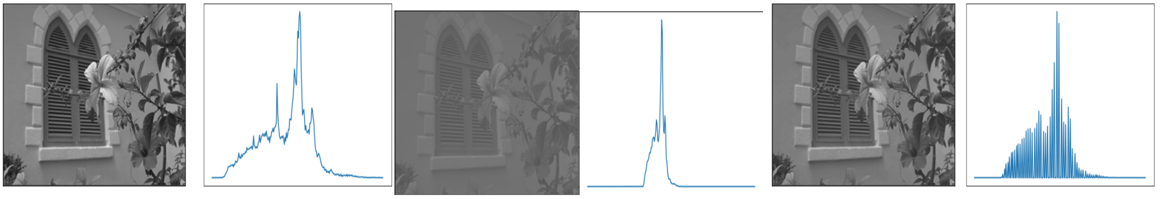


FIGURE 11 Kodim07 PSNR=30.50 SSIM=0.97 VIF=0.82

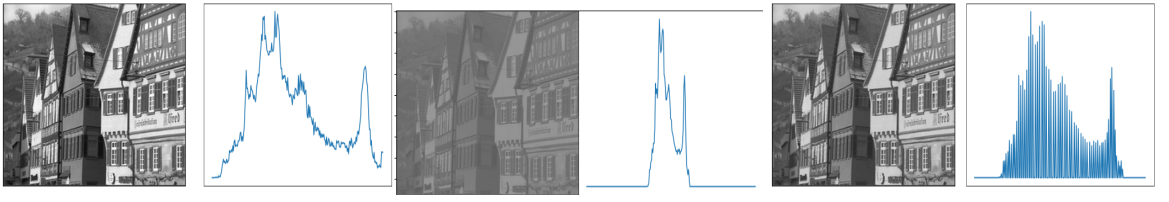


FIGURE 12 Kodim08 PSNR=26.60 SSIM=0.97 VIF=0.81

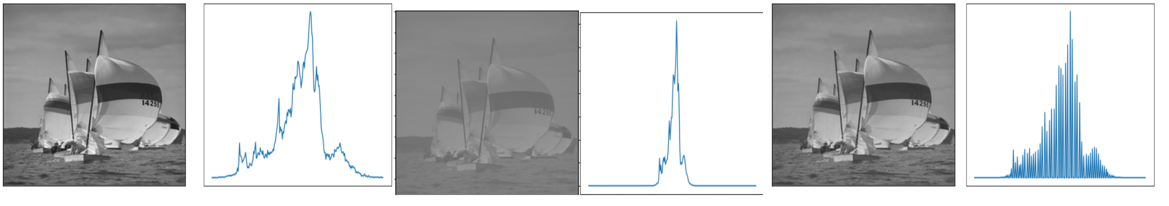


FIGURE 13 Kodim09 PSNR=31.94 SSIM=0.98 VIF=0.82

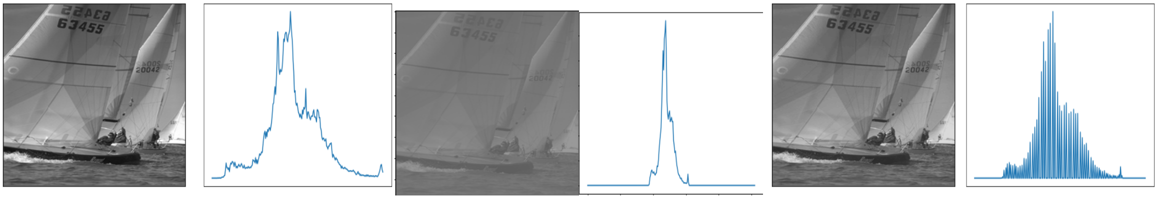


FIGURE 14 Kodim10 PSNR=30.71 SSIM=0.98 VIF=0.80

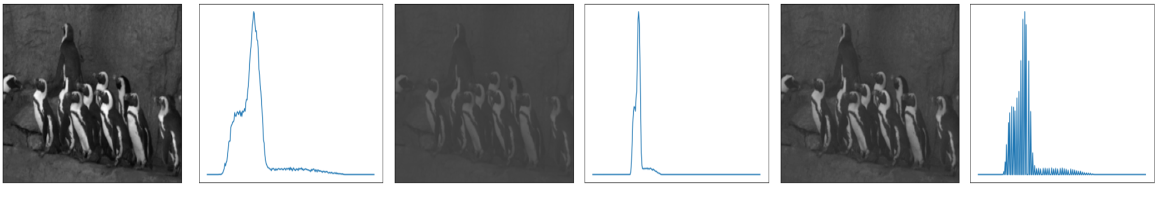


FIGURE 15 Mit 0014 PSNR=31.57 SSIM=0.97 VIF=0.77

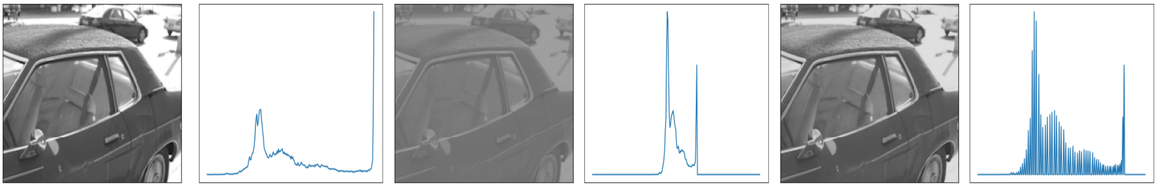


FIGURE 16 Mit 0024 PSNR=26.14 SSIM=0.97 VIF=0.80

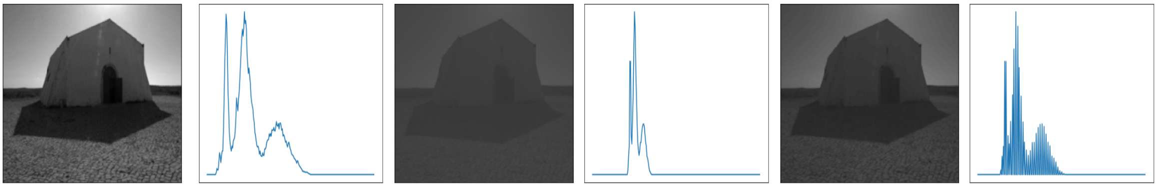


FIGURE 17 Mit 0037 PSNR=29.89 SSIM=0.96 VIF=0.71

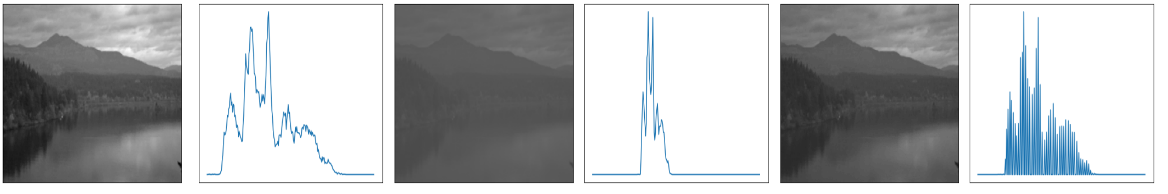


FIGURE 18 Mit 0050 PSNR=28.71 SSIM=0.97 VIF=0.71

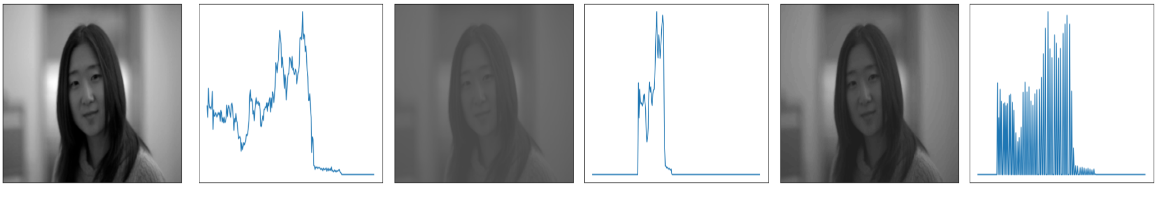


FIGURE 19 Mit 0059 PSNR=26.10 SSIM=0.91 VIF=0.75

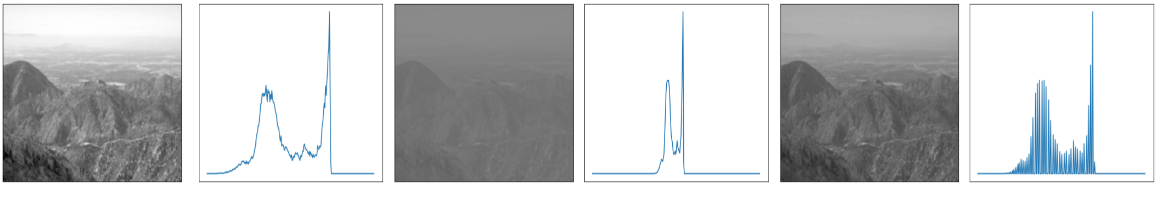


FIGURE 20 Mit 0115 PSNR=31.31 SSIM=0.98 VIF=0.78

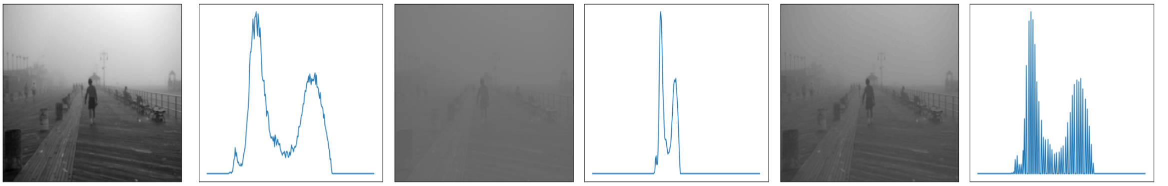


FIGURE 21 Mit 0255 PSNR=30.75 SSIM=0.98 VIF=0.70

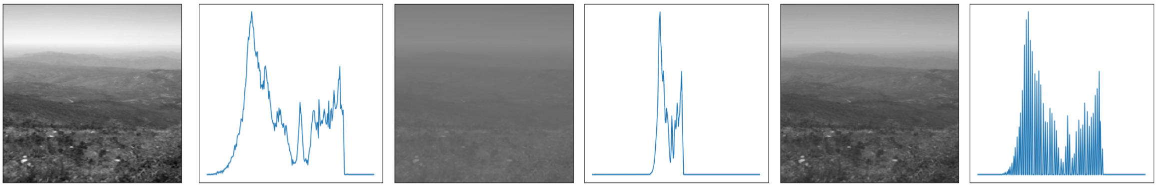


FIGURE 22 Mit 4889 PSNR=28.42 SSIM=0.97 VIF=0.76

5 | COMPARISON

The performance of the proposed method is compared with some state-of-the-art image enhancement methods with respect to standard test images.

The first comparison is done with respect to the Kodak Lossless True Color Image Suite (Company, 2013). The proposed method is compared with the following methods(Chen et al., 2017)- (Chen et al., 2017), (Santhi and Banu, 2015), (Kim et al., 2006), (Poddar et al., 2013), (Hashemi et al., 2010), (Agrawal and Panda, 2012), (Qinqing et al., 2011), (Draa and Bouziz, 2014) and (Joshi and Prakash, 2015). The values of PSNR, SSIM and VIF is averaged over the 24 images in the dataset and compared with the methods stated above and showed in Table[2].

From Table 2, it can be clearly seen that proposed method outperformed all other methods that have been used to examine efficiency of proposed method for Kodak-24 image dataset(Company, 2013). Proposed method outperformed them with respect to the chosen 3 metrics which are PSNR, SSIM, VIF. Now, Method (Santhi and Banu, 2015) and Method (Poddar et al., 2013), both methods are designed based on Adaptively modified Histogram Equalization. Proposed method outperformed these two conventional contrast enhancement technique based methods for Kodak Lossless True Color Image Suite (Company, 2013). Here in Table 2 comparison, Method (Chen et al., 2017), Method (Agrawal and Panda, 2012), Method (Qinqing et al., 2011), Method (Draa and Bouziz, 2014), Method (Joshi and Prakash, 2015) have been designed for contrast enhancement using Genetic optimization algorithm. But proposed GOA algorithm based approach has been found to be more effective than all these methods mentioned earlier. Proposed method outperformed them because of two main reasons. First, GOA algorithm is effective in search and in avoiding local minima in the search space. In GOA, any search agent's position is modified based on not only global or local best agents but these are modified by all other agent's position (interaction force). The second reason is, effectiveness of objective fitness function of proposed method. Proposed method's novel objective function is more effective than objective fitness functions used by earlier mentioned methods. Method (Hashemi et al., 2010) proposed a pure GA based approach without any known optimization algorithm to enhance low contrast images. Proposed method outperformed it by significant margin.

TABLE 2 Comparison among different image enhancement methods with the proposed method when applied over Kodak images

Method Applied	PSNR	SSIM	VIF
Method (Chen et al., 2017)	24.66	0.95	0.75
Method (Santhi and Banu, 2015)	16.26	0.79	0.41
Method (Kim et al., 2006)	19.88	0.87	0.51
Method (Poddar et al., 2013)	17.78	0.72	0.63
Method (Hashemi et al., 2010)	18.87	0.88	0.51
Method (Agrawal and Panda, 2012)	15.46	0.86	0.52
Method (Qinqing et al., 2011)	19.84	0.91	0.53
Method (Draa and Bouziz, 2014)	13.56	0.85	0.60
Method (Joshi and Prakash, 2015)	13.79	0.86	0.69
Proposed Method	28.15	0.96	0.80

The mean intensity band-pass function keeps the mean intensity or brightness of the image close to low contrast input image. So the common problem of unwanted brightness increase or decrease in histogram equalization based approaches can be avoided in proposed GOA based approach.

From Figure 5 to Figure 14, it can be clearly visible that output enhanced images are better than input images in terms of visual quality. Also, the histogram bands are longer compared to low contrast input images. That means fitness function successfully stretched the histogram of input image. From Figure 15 to Figure 22, MIT-Adobe FiveK Dataset (Bychkovsky et al., 2011) images ground truth images, input and output images with their histograms are given. Here also visual quality can be compared between input and enhanced output images. It is clearly visible that output images have better visual quality also histogram is stretched from their corresponding input images.

The second comparison is done with respect to the fitness function. Comparison has been done between the proposed fitness function and conventional fitness function. The conventional fitness function for contrast enhancement is the product of first three terms in our fitness function, that is edge intensity sum, number of edge pixels of enhanced image which can be obtained from canny edge image (transformed image formed by canny edge detector) and entropy of this image in general. The conventional fitness can be described by Equation 18.

$$F_{conv}(I_e) = log(log(sum(I_e))) \times E(I_e) \times S(I_e) \tag{18}$$

In above equation sum(I_e) gives sum of all edge pixels of enhanced images, E(I_e) gives number of edges of enhanced image and S(I_e) gives entropy of image. The fitness functions have been used and tested on the Kodak Lossless True Color Image Suite (Company, 2013). The results for both fitness are given in Table 3.

TABLE 3 Comparison among proposed fitness function and conventional fitness function when applied on Kodak Dataset(Company, 2013)

Fitness Applied	PSNR	SSIM	VIF
Proposed Fitness	28.15	0.96	0.80
Conventional Fitness	21.65	0.93	0.79

As seen from Table 3 the proposed fitness function outperforms the conventional fitness function. So proposed method's effectiveness over conventional fitness functions can be verified from Table 3. Table 4 shows the comparison of visual qualities and histograms between proposed fitness function and conventional fitness function on low contrast images. The selected images shown are 4, 5, 11, 13 and 15 of Kodak Lossless True Color Image Suite(Company, 2013). The first and third columns are the output images for proposed fitness function and conventional fitness function respectively, while second and fourth columns are their respective histograms. It can be seen that the conventional fitness function increases the contrast but along with it changes the brightness of the images also, while the proposed fitness function is able to preserve the brightness of the input images and enhance only the contrast of the images.

One important observation is, this proposed method does not increase number of intensity levels present in image. This is because a particular transformation function maps a particular intensity level to another intensity level and this is an one-to-one mapping.

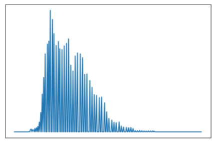
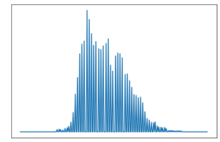
6 | CONCLUSION

A nature-inspired optimization algorithm, called GOA, has been used here for image contrast enhancement. A novel fitness function has been designed with a mean intensity band pass function to preserve brightness as much as possible. Thus the brightness of the output image is left unaltered during the enhancement process which is an important requirement of several commercial applications. The use of a parametric transformation function to create an enhanced image helps in reducing the time complexity compared to conventional transformation functions which search for probable image intensity levels. Superior performance of the approach has been proven by comparing it with many existing algorithms in terms of PSNR, SSIM and VIF. Benchmark images of Kodak Lossless True Color Image Suite (Company, 2013), and some images from MIT Adobe 5K dataset (Bychkovsky et al., 2011) have been selected to evaluate performance of the method. Future extensions of this method might include modification in the c factor which varies linearly from maximum to a minimum. Inclusion of a novel c factor variation scheme, and random walks between grasshopper can be used to get rid of local optima. Also for input images with very few intensity levels, window based parametric transformation can be used to increase number of intensity levels while enhancing those images. Robustness of the method can be confirmed by applying this not only on gray scale images but also on color images.

Conflict of Interest

None

TABLE 4 Comparison between proposed and conventional fitness function. The first and third columns are the output images for proposed fitness function and conventional fitness function respectively, while second and fourth columns are their respective histograms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	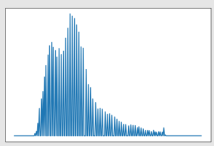		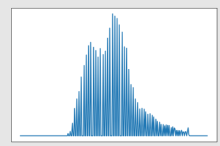
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	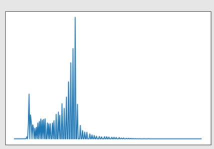		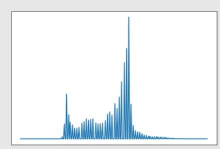
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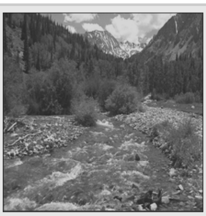	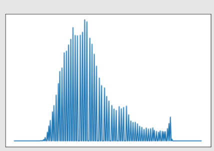	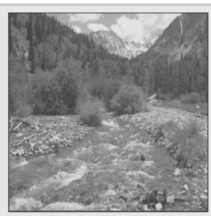	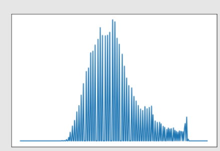
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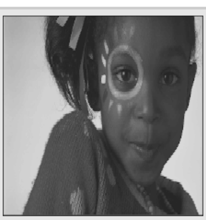	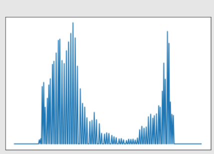	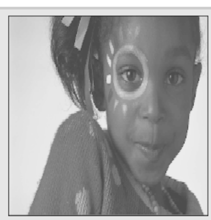	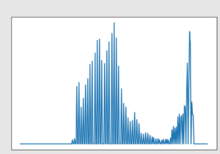
PSNR=22.21 SSIM=0.93 VIF=0.76		PSNR=14.24 SSIM=0.80 VIF=0.73	

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