Grey Level Image Contrast Enhancement using Barnacles Mating Optimizer

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April 28, 2020

of distorted or degraded images ??

Abstract

Image contrast enhancement is a very important phase for processing of digital images. The main goal of image contrast enhancement is to improve the visual quality by improving the contrast level of images which otherwise distorted or degraded due to casual acquisition of images. The most popular method to perform ~~the said~~ task is Histogram Equalization (HE). However, the exhaustive approach taken during HE is an algorithmically complex task. In this paper, we have considered image contrast enhancement as an optimization problem and a new meta-heuristic algorithm, called Barnacles Mating Optimizer (BMO), is used to find the optimal solution for this optimization problem. A grey level mapping technique is used here to convert an image to a solution of the optimization problem. The algorithm has been evaluated on standard Kodak, MIT-Adobe FiveK images, H-DIBCO 2016 and H-DIBCO 2018. The obtained results clearly display the effectiveness of the proposed method. The results are compared for Kodak images only with other nine state-of-the-art methods present in the literature and the comparison proves the superiority of the proposed method. To test the applicability of BMO in solving real world problems, we have applied it as a pre-processing step in binarization of H-DIBCO 2016 and H-DIBCO 2018 datasets.

Sentence ?

this

Benchmark data sets

Results...

1 Introduction

medical image processing, optical character recognition,

biometric applications...

Image processing is a very popular and active area of research in the field of computing as it has various real-life applications, like medicine, industry and transportation to name a few. However, it consists of all the operations applied on digital images which aim at changing the structural characteristics of the images. Contrast enhancement is a process that is applied on images to increase their dynamic range. The main goal of image enhancement is to increase the readability and interpretability of the information present therein. Whenever we talk about an enhancement algorithm, we simply mean that the algorithm in discussion produces better-quality image to be used for some particular application. It is generally achieved by suppressing the noisy pixels or increasing the contrast [1, 2].

contrast?

Now, a question arises, why is there even a need of image enhancement? The answer is quite obvious. Quality of digital image suffers due to several factors, like contrast, illumination and noise during the image acquisition process. So, what is image enhancement? In simpler terms, it is defined as the separation factor between the brightest spot and the darkest spot in images [3]. This factor indicates high contrast or low contrast depending on its value. In spatial domain, Histogram Equalization (HE) is a most commonly used method, and its modification is proposed in ~~the work reported in~~ [4]. It scales the magnitudes of the probability density function of the original input image before applying HE. The scaling factor is altered in an adaptive way depending on the average image intensity values of an image.

Image enhancement changes the photo-metric characteristics of an image to make it better than before for automatic processing of image through computing devices. In general terms, there are two different methods which are used to enhance the image attributes: filtering techniques and contrast enhancement. Filtering techniques substitute every pixel of the input image by a value which is calculated from the original value of that pixel and the neighboring pixel values. Whereas, contrast enhancement, a mapping is brought into action between the grey level values of the input image and a new set of grey level values in order to get a more homogeneous distribution of the corresponding foreground and background pixels [5, 6]. In other words, we can say that contrast enhancement allows histogram of grey levels to become flatter. One of the simplest ways to achieve contrast enhancement is *global intensity transformation*. This method uses

the method called

the

histograms

the proposed approach needs a NAME + ACRONYM

of... What type? name for this

lookup tables, then the intensity levels of an image are mapped into a set of new grey levels. This method performs intensity transformation on all grey levels of the image. The main goal is to obtain a lookup table or transfer function which produces an output image with improved parameters. ?? Unlike global techniques, local techniques either apply different functions on pixels of the input image or different areas of the image, or they use different parameters in the same function [7, 8] to bring differences.

Recently, ~~some~~ methods have been proposed for image quality measures and used for grey level image enhancement. Probably the most powerful measure out of those is combining the number of edge pixels, intensities of these pixels and the entropy of the whole image. These measures have been applied for image enhancement ~~by using~~ in Particle Swarm Optimization (PSO) [7], Cuckoo Search (CS) ~~algorithm~~ [8] and Differential Evolution (DE) [9] by considering the image enhancement problem as an optimization problem.

In this paper, a global optimization technique for image contrast enhancement is used. It utilizes the idea of mapping ~~of~~ grey levels of input images into a new set of grey level values. Barnacles Mating Optimizer (BMO) [10], a new meta-heuristic algorithm, is used to perform ~~the mentioned~~ this task. To the best of our knowledge, this is the first time, BMO is used for image contrast enhancement. In a nutshell, the main contributions of this work are as follows:

- BMO, a recently proposed meta-heuristic algorithm, is applied for the purpose of image contrast enhancement.
- The proposed method is evaluated on images taken from ~~standard~~ Benchmark datasets - Kodak [11] and MIT-Adobe FiveK [12].
- It is compared with ~~9~~ nine other methods ~~consisting of~~ including HE, improved versions of HE and different optimization algorithms. names!
- To check the robustness of the proposed method, we have applied the proposed contrast enhancement method as a preprocessing step of binarizing the images of H-DIBCO 2016 and H-DIBCO 2018 datasets.

The rest of the paper is organized as follows: Section 2 presents brief idea of some of the methods proposed in the field of image enhancement. Section 3 provides an overview of BMO algorithm. In Section 4, we have discussed the proposed method in detail along with agent representation, fitness function and the procedure of implementing BMO in image contrast enhancement. Then in Section 5, the input, output and ground truth images along with their corresponding histograms are given, and also a detailed analysis of the proposed method is given by testing it on the Kodak [11] ~~dataset~~, H-DIBCO 2016 [13] and H-DIBCO 2018 [14] Benchmark datasets. For comparison purpose, we have considered Kodak [11] images only. Finally, Section 6 provides conclusive remarks and an idea of the future scope of this work as well.

Why? Reviewer will ask!!

2 Literature Survey

In the field of image contrast enhancement, several methods are proposed. Histogram Equalization (HE) is one of the most popular method. It performs contrast enhancement by effectively spreading out the most frequent intensity values, *i.e.*, stretching out the intensity range of the image. This method usually increases the global contrast of images when its usable data is represented by close contrast values. This allows for areas of lower local contrast to gain a higher contrast. Although, HE has some limitations, *i.e.*, the local contrast of an image can not be equally enhanced, over-enhancement of noise and artifacts can be easily found in the local histogram equalization enhanced images Here, we have discussed some of the approaches related to HE which tries to overcome the limitation. reference!

Adjacent-block-based modification for local histogram equalization algorithm (ABMHE) [15] proposes a technique which overcomes the limitation of HE by segmenting the image into three kinds of overlapped sub-blocks using the gradients. To overcome the over-enhancement effect, the histograms of these sub-blocks are then modified by adjacent sub-blocks. An optimal adaptive thresholding based sub-histogram equalization for brightness preserving image contrast enhancement [16] puts forward an adaptive thresholding based sub-histogram equalization (ATSHE) scheme for contrast enhancement and brightness preservation with retention of basic image features. The histogram of the input image is divided into several subhistograms using adaptive thresholding intensity values. The number of threshold values or sub-histograms of the image depends on the peak signal-to-noise ratio (PSNR) of the thresholded image. Histogram clipping is also used in this work to control the undesired enhancement of resultant image to avoid over-enhancement. This work [17] investigates a contrast enhancement algorithm which utilizes grey level S-curve transformation, locally in medical images obtained from various modalities. This is an extended gray level transformation technique that forms sigmoid alike curve through a pixel to pixel transformation. The main objective of this transformtaion to increase the difference between minimum and maximum gray values and the image gradient, locally.

Recently, optimization algorithms have become popular among the research communities. These algorithms have proved their superiority in different fields. Many such optimization algorithms have been used for image enhancement and established their superiority over the traditional approaches like HE. Here, we have briefed few of the meta-heuristic based image contrast enhancement methods found in the literature.

Genetic Algorithm (GA) [18] for image contrast enhancement is proposed in [5]. This work uses GA to find the optimal mapping of the grey levels of the input images with new grey levels which produces better contrast for the image and as a result the dynamic range of the image increases, which is the reason behind better quality of the image. Artificial Bee Colony (ABC) [19] algorithm for image enhancement is proposed in the work reported in [20]. The image contrast enhancement optimization problem is regarded as a foraging process of bee colony. The position of a food source denotes a possible solution of this image contrast enhancement problem. The fitness value of a food source represents the quality of the associated solution. Cuckoo Search (CS) [21] algorithm for image contrast enhancement is reported in [8].The CS algorithm is based on the parasitic breeding behavior of the cuckoo bird. The cuckoo bird depends on other host bird's nest for laying its eggs. The host bird nurtures the egg assuming it as its own. The basic objective of cuckoo search algorithm is to find the best nest where the probability of hatching of an egg is maximum. A generation is represented by set of host nests. The best nest which carries the egg is the solution. The best nests in each generation are carried over to next generation. A transformation function is used which contains four parameters, namely, a, b, c and d. CS is used to find the best set of these parameters. CS is also used for maximizing the fitness function. Particle Swarm Optimization (PSO) [22] for image enhancement is proposed by the authors of [7]. PSO algorithm is a multi-agent based search strategy modeled on the social behavior of organisms such as bird flocking and fish schooling. It uses a transformation function, which incorporates both local and global information of the input images. This transformation function contains four parameters namely, a, b, c and k to produce large variation in the processed image.

~~Now, a thought comes in our mind, what is the necessity of new optimization algorithm?~~ There are several such algorithms for image contrast enhancement. *No Free Lunch* theorem [23] states that a single optimization algorithm can not solve every type of optimization problem. Some are better fit for some particular problem but maybe does not produce expected result in other problems. This motivates the researchers to propose new optimization algorithm which is better than the past proposed methods. As image contrast enhancement is a very important pre-processing step, it's result have a fair amount of weightage in image processing. Every method which is already proposed in this domain produces better result than the previous. This inspired us to come up with a new method which produces even better results than the rest.

BMO is a recently proposed meta-heuristic optimization algorithm which has been previously applied to optimize 23 benchmark functions and optimal reactive power dispatch problem [10]. In this work, we have used BMO to enhance the contrast of degraded images.

3 Barnacles Mating Optimizer: An Overview

BMO [10] is an evolutionary algorithm inspired from micro-organisms called barnacles, which exist since Jurassic times. Most of the barnacles have both male and female reproductions.

In BMO, a solution is represented by a barnacle, which is analogous to a chromosomes in GA and particles in PSO. The initial population of BMO is generated randomly and sorted in order of their fitness values with the best Barnacle on the top of the population.

Two barnacles are chosen randomly as parents - father (brn_F) and mother (brn_M). If the distance between brn_F and brn_M is less than equal to the penis length pl of brn_F, mating occurs between brn_F and brn_M, and an offspring is produced by .

$$B^i_{new} = \alpha \times brn^i_F + \beta \times brn^i_M \qquad i = 1, \dots, d \tag{1}$$

$brn^i_F \in \mathbb{R} / [0,1]$??

Typical dimension d ?

mean = ? σ^2 = ? of the normal (Gaussian) distribution

How is the distance computed?

where α is a normally distributed pseudo-random numbers between $[0, 1]$, $\beta = 1-\alpha$, brn_F^i and brn_M^i represent the i^{th} dimension of the variables corresponding to the father and mother respectively. Basically α and β represent the percentage of characteristic of Father and Mother that are embedded in the generation of new offspring. The offspring inherits the behavior of the Father and Mother based on probability of random number in $[0, 1]$.

Now, if the distance between brn_F and brn_M is greater than pl of brn_F, sperm casting occurs. This sperm casting process is expressed as Equation 2.

$$B_{new}^i = random(0,1) \times brn_M^i \tag{2}$$

Which type of distribution? Uniform?

It is to be noted that the new offspring is generated from the Mother barnacle in this sperm casting process. This is because it receives the sperm from the water that has been released by the other barnacles elsewhere and there is no information about the Father barnacle.

The value of pl plays an important role in this algorithm. Larger pl implies greater exploration and smaller pl implies greater exploitation. If exploration is not considered properly, the algorithm may get stuck in local optima. Whereas if exploitation is not properly taken care of, the algorithm may show slow convergence or in worst case, may not even converge. As per recommendation in [10], we have set $pl = 0.6 \times N$, where N is the size of the barnacle population. In Algorithm 1, the pseudocode of BMO is described. Why? optimized

Algorithm 1 Pseudocode of BMO

Input: $popSize, maxIter$
Output: Best barnacle (solution) $B_{best} = (b_1, b_2, ..., b_D)$

Randomly generate initial population $B(0)$
Calculate $fitness(B_i) \forall i \in [1, popSize]$
Sort B_is according to fitness value
$pl = 0.6 \times popSize$
while $t < maxIter$ **do**
  Select brn_F and brn_M randomly
  if $distance(brn_F, brn_M) \leq pl$ **then**
    Generate offspring using Equation 1
  else
    Generate offspring using Equation 2
  end if
  Sort and update population B
  $t = t + 1$
end while
return $B[0]$ (the best Barnacle)

fitness criterion

Euclidean distance ??

give equ (1)

give equ (2)

Give typical settings popSize, maxIter, D, N, α, $\beta = \frac{1}{2}$?

4 Proposed Image Contrast Enhancement Approach

As we have already mentioned, the present work is related to image contrast enhancement using BMO, where we map the grey levels of an input image into a new set of grey levels to produce better quality image. This technique at the end yields more homogeneity to the image histogram. We have used this meta-heuristic algorithm for the said task, as an exhaustive search technique of better mapping is very time consuming.

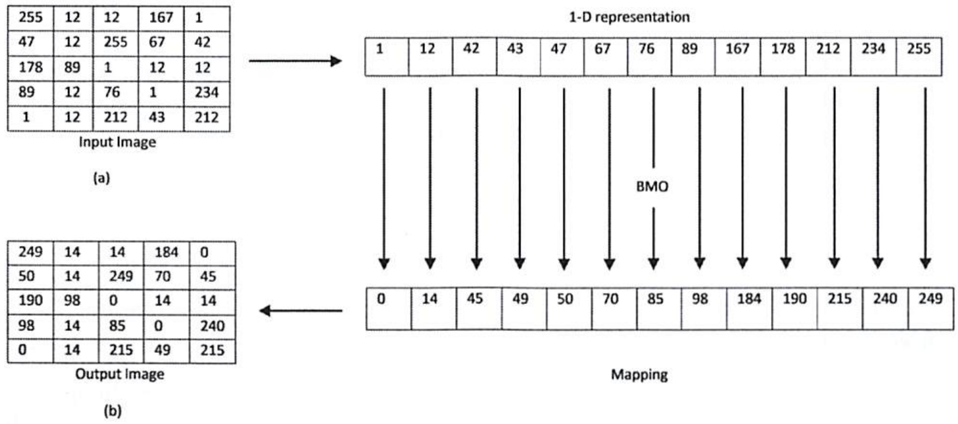
As we have considered image enhancement as optimization problem, it gives rise to the necessity of defining two important features of the algorithm: the representation of solution and the objective or fitness function. Here, we have defined and explained these two aspects, then the use of BMO to accomplish the task of getting optimal result in image enhancement is presented.

There must be a geometrical relation between

N, D, the range of $\{b_i\}_{i=1}^{D}$, pl.

I can not imagine that $pl = 0.6\,N$ is a good choice in general.

I do not see a need for this "flatten" transformation because all BMO operations can be done on a matrix!



?

Figure 1: Agent representation and reconstruction of image from an agent produced by BMO

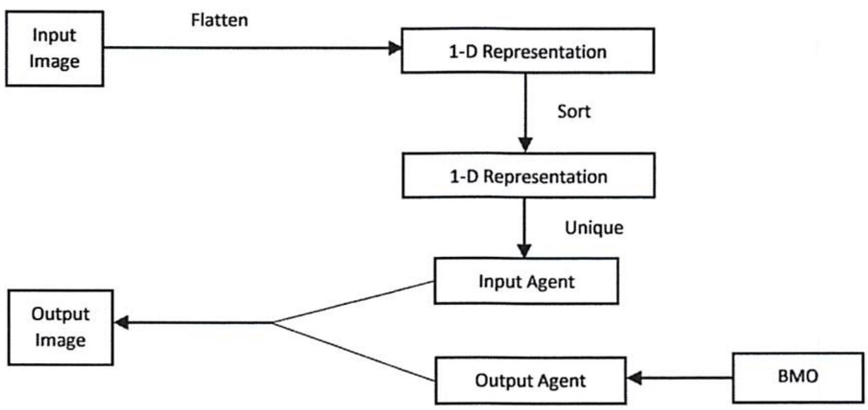


Figure 2: Conversion of an input image to output image using BMO

4.1 Agent Representation

To apply BMO to solve the image contrast enhancement problem, we need to convert the image to a vector (1-D array) [5], which is used as an agent, rather a Barnacle in present work. This image to agent conversion must be done in a way such that the agent representing the input image, reserves all its characteristics and image can be reconstructed from a given agent.

Here, the solution to the problem is an ordered vector of $\mathcal{D}$ integers in the interval [0, 255] representing a possible mapping of the grey levels of the input image, $\mathcal{D}$ denotes the number of grey levels in the input image as well as the dimension of the problem. To convert the input image to its corresponding agent, the following steps are followed:

- Flatten the input image $(n \times m)$ to an 1-D array $(1 \times (n * m))$
- Sort the 1-D array in increasing order. by what
- Remove duplicates from the 1-D array.
- Now, the generated 1-D array $(1 \times \mathcal{D})$ represents the input image.

After, BMO generates the best agent (Barnacle), we need to reconstruct the image corresponding to this agent. To do this, we need to replace the pixel values in the image with their corresponding values of the newly generated agent. This is described in Figure 1.

4.2 Fitness function

Please draw an image and explain these numbers!

Now, to evaluate the quality of the solutions (agents) in the BMO algorithm, we use a formula which utilizes the number of edge pixels, the intensity of edge pixels and the entropy of the whole image. This formula is given in Equation 3, which is used in [8, 7, 9, 24, 25].

$$F(Z) = \log(\log(E(I(Z)))) \cdot \frac{n(I(Z))}{(H \times V)} \cdot H(I(Z)) \tag{3}$$

Now, let's discuss the components of this fitness function.

use $ $

- F(Z) represents the quality of the output image obtained by using the mapping represented by the solution vector Z on input image I.
- E(I(Z)) represents the sum of edge intensities of the image. The enhanced image is desired to have larger value than the original low-contrast image. It can be obtained by first applying the image edge detector (here we consider Canny edge detector [26]), followed by calculating the summation of intensities of edge pixels.
- n(I(Z)) represents the number of edge pixels of the enhanced image. The enhanced image should be sharper, which means it has more edge pixels than the original low-contrast image. It can be calculated by counting the number of pixels whose intensity value is above a particular threshold value in the Canny edge image.
- H(I(Z)) represents the entropy of enhanced image. It is calculated by Equation 4.

$$H(I(Z)) = \begin{cases} -\sum_{i=0}^{255} h_i \log_2(h_i) & \text{if } h_i \neq 0 \\ 0 & \text{otherwise} \end{cases} \tag{4}$$

  where, h_i is the probability of occurrence of the i-th intensity value of the image.
- $H \times V$ represents the size of the image.

Our target is to find the mapping for which the fitness value is maximum, as the expected output image should have more number of edges with higher intensity, and a higher contrast.

5 Result and Discussion

This section presents the experimental results and their analysis over different degraded images. The quantitative measure have been made with nine well-known state-of-the-art algorithms to ensure the applicability of BMO in enhancement of image contrast.

5.1 Experimental Setup

To show the effectiveness on ICE, the proposed method has been tested on Kodak dataset [11], released by Eastman Kodak Company for unrestricted usage. The dataset contains 24 lossless, true color (24 bits per pixel) images having 756x512 resolution and the image are available in PNG format. This dataset is widely used for testing in image processing and image compression techniques. The image samples were converted to their corresponding gray scale images, which serve the purpose of ground truth (GT) in our experiments. The contrast of the GT images are then reduced to 10% which serve as the inputs of our method.

The proposed approach is compared with nine state-of-the-art contrast enhancement methods. These are (i) conventional histogram-based image contrast enhancement approaches [4, 27, 28]; (ii) GA-based image contrast enhancement approach [5]; (iii) CS-based image contrast enhancement [8]; (iv) PSO-based image contrast enhancement [29]; (v) ABC-based image contrast enhancement approaches [20, 30, 31]. The performance evaluation is conducted using three criteria: (i) Peak Signal-to-Noise Ration (PSNR); (ii) Structural Similarity Index Measure (SSIM) [32]; (iii) Visual Information Fidelity (VIF) [33].

explain

In BMO, we have used population size as 10 and maximum number of iterations as 20 , pl as 0.6 × population size for further experiments. These parameters are used keeping in mind the trade off between computational cost and obtained result.

Formula or explain by example image!

equations

Image	PSNR	SSIM ~~[32]~~	VIF ~~[33]~~
Kodim01	33.0932	0.969219	0.736279
Kodim02	32.8514	0.955238	0.780909
Kodim03	29.7155	0.942627	0.76344
Kodim04	30.1293	0.935176	0.723372
Kodim05	34.1767	0.97849	0.776128
Kodim06	31.0041	0.95843	0.765921
Kodim07	34.3892	0.969426	0.76427
Kodim08	33.8793	0.975515	0.750455
Kodim09	33.3231	0.960089	0.737187
Kodim10	36.0557	0.963063	0.72306
Kodim11	32.4534	0.952485	0.754335
Kodim12	34.6411	0.957733	0.707737
Kodim13	30.4764	0.964795	0.752268
Kodim14	33.0717	0.977675	0.773587
Kodim15	34.9965	0.969789	0.767793
Kodim16	29.0946	0.935201	0.721723
Kodim17	33.9388	0.951498	0.721842
Kodim18	34.2307	0.96884	0.764037
Kodim19	31.727	0.972959	0.719807
Kodim20	35.6647	0.963018	0.767657
Kodim21	33.3846	0.950026	0.754884
Kodim22	34.2667	0.956401	0.758852
Kodim23	32.379	0.9645	0.77333
Kodim24	37.6243	0.972536	0.76163
Average	33.095	0.961	0.751

What is the meaning of this table? Are these numbers for comparision or PSNB = 33.095 good or bad? ??

Table 1: PSNR, SSIM and VIF values of test images enhanced with BMO

5.2 Performance Evaluation

5.2.1 Performance on Kodak dataset

This section presents the performance on Kodak dataset [11] by our proposed method. The obtained PSNR, SSIM and VIF values for all the enhanced 24 kodak images are tabulated in Table 1. It is noticed that, the obtained PSNR, SSIM and VIF values are quite significant and thus, their mean values outperforms the sate-of-the-art methods, stated in [20].

State

The quantitative comparison with ICE state-of-the-art methods are displayed on Table 2. The table provides the comparison results of the proposed method with other nine state-of-the-art methods [4, 5, 8, 20, 27, 28, 30, 29] and [31] based on PSNR, SSIM [32], VIF [33] values, on Kodak dataset [11]. For this purpose, the comparison table presents the average values of the three mentioned criteria of the 24 Kodak images. A greater value indicates better image quality.

It is very clear from Table 2 that the proposed method is superior to the other nine methods. In terms of PSNR values, we can see that the proposed method beats other methods with significant margin. [20] has produced the second best result for this criterion. The PSNR difference between this and the proposed method is 8.435 which is quite impressive. In terms of both SSIM, and VIF, proposed method has produced the best result, which proves its superiority over other methods.

/ x the

For visual comparison, we have plotted the histograms for input degraded images, corresponding resultant images as well as ground truth images. Figure 3, Figure 4 and Figure 5 show the obtained results. In these figures, the first column represents the input image, second column represents its corresponding histogram, third column represents the output image and fourth column shows its corresponding histogram, lastly, the fifth and sixth column represents the ground truth image and its corresponding histogram respectively.

;

The image histogram acts as a graphical representation of the tonal distribution of the pixels in an image. The histograms of the images show the frequency of pixels intensity values. The X-axis represents the gray

Method	PSNR	SSIM [32]	VIF [33]
Ref. [4]	16.26	0.79	0.41
Ref. [5]	18.87	0.88	0.51
Ref. [8]	15.46	0.86	0.52
Ref. [20]	24.66	0.95	0.75
Ref. [27]	19.88	0.87	0.51
Ref. [28]	17.78	0.72	0.63
Ref. [30]	13.56	0.85	0.60
Ref. [29]	19.84	0.91	0.53
Ref. [31]	13.79	0.86	0.69
Proposed method	**33.095**	**0.961**	**0.751**

Sort them by categories of Sec 5.1

Table 2: Comparison of the proposed ICE method with state-of-the-art methods based on PSNR, SSIM and VIF values

level intensities and the Y-axis shows the frequency of those intensities. For an image with good contrast, the pixel values should be well distributed within the range [0,255]. In the Ground Truth images, the pixel values are well spread in [0,255] and this is reflected in their corresponding histograms. Since we have reduced the contrast of the images before using those as input, the pixel values have narrow bandwidth *i.e.,* their histograms are concentrated at a narrow region. From the histograms of the output images, we can observe that pixel values are spread quite well within [0,255].

5.2.2 Additional testing

In addition, we have evaluated our method on two different types of datasets to prove its robustness and effectiveness. These are (i) High definition scene image dataset; MIT-Adobe FiveK dataset [12] and (ii) Document image datasets; H-DIBCO 2016 [13] and H-Dibco 2018 [14]. The MIT-Adobe FiveK dataset contains 5000 photographs which were taken by SLR cameras. These photographs cover broad range of scenes, subjects and lighting conditions. The photos are in DNG format.The original images of MIT-Adobe FiveK dataset are converted to gray level image, which serve the purpose of ground truth in our experiments. The contrast of the GT images are then reduced to 10% which serve as the inputs of our method.The table 6 displays six sample images on MIT-Adobe FiveK dataset and their enhanced forms. The first column represents the input image, second column represents the output image and the last column represents the corresponding ground truth images. From 6, it is quite evident that the proposed BMO is able to enhance the contrast of the low contrast images quite well.

Besides this, the robustness of our method has also been shown through the evaluation of document images. It is because, binarization of document images indicates the strength of the enhanced module more minutely as it needs pixel level clarity. Therefore, most of the binarization methods expect an effective pre-processing that reduces uneven illumination and background variations to enhance the picture quality. We use two standard datasets H-DIBCO 2016 [13] and H-DIBCO 2018 [14], provided by ICDAR group. These datasets provide 20 ancient handwritten images, having various types of the degradation like uneven background illumination, black patches, bleed through and fainted characters. ICDAR competition organizer also provides the GT binary images for these 10 handwritten pages.