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# A Comparative Study of Evolutionary Based Optimization Algorithms on Image Quality Enhancement

**D. Yugandhar**
Assoc.Prof,
Department of Electronics and Communication Engineering,
Aditya Institute of Technology and Management, Tekakli,
Srikakulam District, Andhra Pradesh, India
yugndasari@gmail.com

**S.K. Nayak**
Professor,
Department of Electronic Science,
Berhampur University, Berhampur,
Odisha, India
sknayakbu@rediffmail.com

Abstract- In this paper presents the image enhancement and contrast enhancement to improve the interpretability of the information present in images for human viewers. Here, the Second Derivative like Measurement of Enhancement (SDME) has been proposed as fitness function and the adaptive algorithms used incomplete beta function as the transformation function in order to enhance contrast of the grayscale images. The parameters of the beta functions are estimated with the help of Artificial Bee Colony Algorithm (ABC), Teaching and Learning based optimization (TLBO) algorithm and Elitist TLBO algorithm on grayscale images. Simulation results show that the Elitist TLBO performs better results than the other two optimization algorithms.

Keywords: Image enhancement, Second Derivative like Measurement (SDME), Artificial Bee Colony Algorithm (ABC), Teaching-Learning-based optimization (TLBO), Elitist Teaching-Learning-based optimization.

## Introduction

The principal objective of enhancement is to process the images so that the result is more suitable than the original image for a specific application. Image enhancement techniques are designed to improve the quality of an image as perceived by a human being by improving the contrast of the images in many important areas such as remote sensing, autonomous navigation, and biomedical image analysis [1]. Image enhancement can be done in both spatial domain and transform domain. The spatial domain method operates directly on pixel gray level value, where as the transform domain method modifies the Fourier spectrum of an image. Elementary spatial enhancement techniques are histogram based because they are simple and fast. Histogram manipulations basically modify the histogram of an input image so that the visual quality of the image has been improved. Histogram equalization, a spatial domain technique is a very popular technique for enhancing the contrast of an image [2]. Histogram equalization has "mean-shift" problem, and it shifts the mean intensity value to the middle gray level of the intensity range. So this technique is not useful where brightness preservation is required.

Yeong-Taeg Kim [3] proposed a method to solve this problem by dividing the input image histogram into two parts based on the mean value. Then histogram equalization is applied to the both separated parts with the new intensity range, first minimum gray level to the mean value and for second mean value to the maximum gray level. It helps in specifying the shape of the histogram, which we desired. Images captured during dim light with poor contrast and they enhanced by stretching the dynamic range of the grayscale histogram by linearly or nonlinearly transforming the input gray levels [4].

Tubbs [5] optimized the image enhancement problem using regularized incomplete Beta function. Population based optimization algorithms are generated from the natural phenomenon of birds [6-8]. The classical evolutionary computation algorithms have been for image enhancement of poor quality images. Xiaoping Su, et al. [9], proposed the fitness function, which is formed by combining the AC power measure and the Brenner's measure[9] and the proposed fitness function is implemented using genetic algorithm (GA), particle swarm optimization (PSO), quantum behaved particle swarm optimization (QPSO) and adaptive quantum behaved particle swarm optimization (AQPSO) algorithms.

Zhiwei Ye et al. [10], proposed a fitness function based upon the combination of three parameters threshold, entropy and gray-level probability density of the image. Hence, in our work, we have been implementing the ABC, TLBO and Elitist TLBO algorithm by taking SDME as the fitness function.

## Artificial Bee Colony Algorithm (ABC)

Artificial Bee Colony algorithm [11] was elegantly launched by Karaboga for optimizing a statistical problem. The innovative technique replicates the smart foraging conduct of honey bee swarms. In ABC algorithm, the search in each cycle consists of three steps:

i. Sending employed bees onto their food sources and evaluating their nectar amounts
ii. After sharing the nectar information of food sources, the selection of food source regions by the onlooker and evaluating the nectar amount of the food sources.
iii. Determining the scout bees and then sending them randomly onto possible new food sources.

***Pseudo code for ABC Algorithm***

1. Generation of training samples
2. Initialization of initial population $x_i$ , $i = 1,2,3,....SN$
3. Evaluation of function the fitness of the population
4. Iteration = $1,2,3,\ldots MCN$
5. FOR each employed bee
   {
   Generate new solution $g_i$
   Calculate value $t_i$
   Perform greedy process
   }
6. Calculate probability values $v_i$ for the solution $x_i$
7. FOR each onlooker bee
   **{**
   Produce a new solution $u_i$ from the solution $x_i$ , depending on $v_i$ and evaluate them
   Perform greedy process
   }
8. If abandoned solution exists in scout, replace them with new solution
9. Memorize the best solution

## Elitist TLBO Algorithm [15]

Population based optimization algorithms have been developed to find near optimal solutions by carefully converting natural phenomenon into algorithmic format. The TLBO [12-14] algorithm based upon two phases like teacher phase and learners phase.

*A. Teacher Phase*

During this phase a teacher tries to increase the mean result of the class in the subject taught by him or her depending on his or her capability. Let $M_j$ be the mean and $T_i$ be the teacher at any iteration $i$ . Now teacher $T_i$ will try to improve existing mean $M_j$ toward it so that the new mean will be designated as $M_{new}$ and the difference between the existing mean and new mean is given by

$$Difference\_Mean_i = r_i(M_{new} - T_F M_j) \quad (1)$$

Where, $T_F$ is the teaching factor which decides the value of mean to be changed, and $r_i$ is the random number lies in the range 0 and 1. Value of $T_F$ can be either 1 or 2.

$$T_F = round[1 + rand(0,1)\{2-1\}] \quad (2)$$

$$X_{new,i} = X_{old,i} + Differenc\_Mean_i \quad (3)$$

where $X_{new,i}$ is the updated value of $X_{old,i}$ and $T_F = rand(0,1)$ represents a uniformly distributed random value that ranges from zero to one. Accept $X_{new,i}$ if it gives better function value. All the accepted function values at the end of the teacher phase are maintained and these values become the input to the learner phase. The learner phase depends upon the teacher phase.

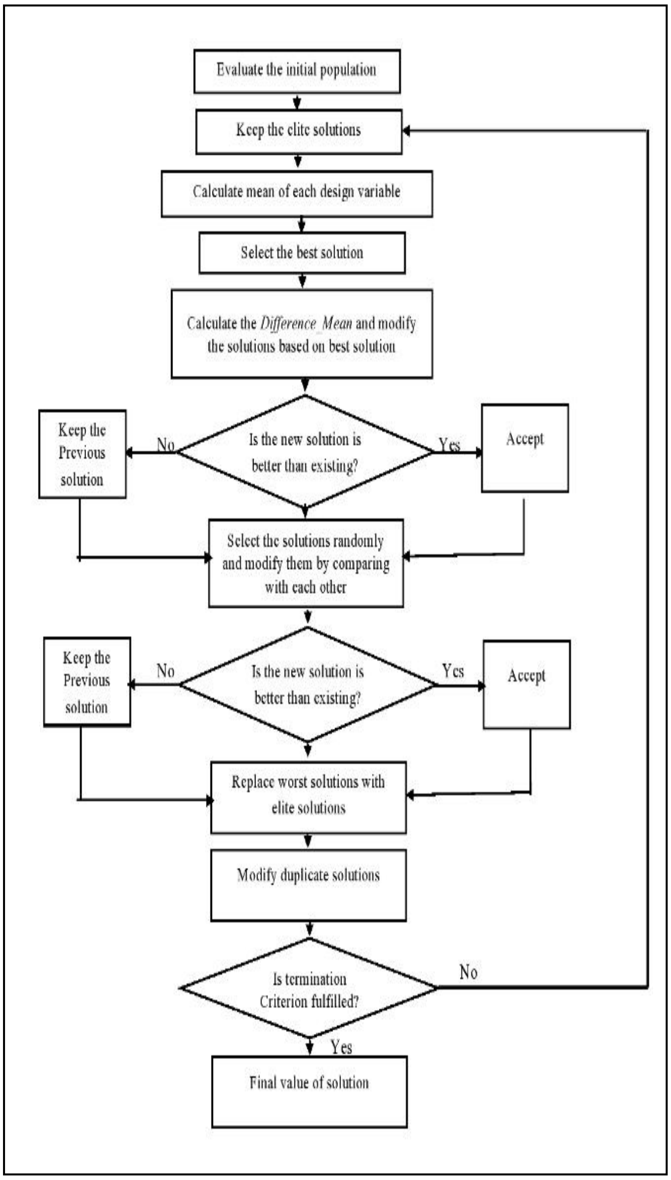


Fig.1.Flow Chart of Elitist TLBO Algorithm

*B. Learner Phase*

It is the second part of the TLBO algorithm where Learners increase their knowledge by interaction among themselves. A learner learns new things if the other learner has more knowledge than him or her. Mathematically, the learning phenomenon of this learning phase is expressed below [14]. At any iteration $i$, consider two different learners $X_i$ and $X_j$ where

$$X_{new,i} = X_{old,i} + r_i(X_i - X_j), \text{ if } F(X_i) > F(X_j) \text{, where } i \neq j \tag{4}$$

$$X_{new,i} = X_{old,i} + r_i(X_j - X_i), \text{ if } F(X_j) > F(X_i) \tag{5}$$

The elitist TLBO algorithm shown in Fig. 1 is same as conventional TLBO [12] algorithm except the two additional steps which are mentioned below.

i. Replacing the worst solutions with elite solutions at the end of learner phase.
ii. Modifying the duplicate solutions to avoid trapping in the local optima.

## Proposed Method: TLBO with Modified Fitness Function

Non linear transforms described by a set of parameters is used to enhance various type of image degradations. Regularized incomplete beta functions are used to simulate all four types of transforms like stretching dark regions, stretching lighter regions, stretching middle and compressing two ends and compressing middle and stretching two ends[5]. The standard density function and the regularized incomplete beta function are respectively given below.

$$f(x) = \frac{x^{\alpha-1}(1-x)^{\beta-1}}{B(\alpha,\beta)} \tag{6}$$

$$f(x,\alpha,\beta) = B^{-1}(\alpha,\beta).\int_0^x t^{\alpha-1}(1-t)^{\beta-1}\,dt \tag{7}$$

where ‘ $x$ ’ value lies between 0 and 1, α , β are positive constants and $B(\alpha,\beta)$ is the beta function defined by

$$B(\alpha,\beta) = \int_0^1 t^{\alpha-1}(1-t)^{\beta-1}\,dt \tag{8}$$

Therefore, the generalized transform can be given by

$$T(i_{x,y}) = f(i_{x,y},\alpha,\beta) = \int_0^{i_{x,y}} \frac{t^{\alpha-1}(1-t)^{\beta-1}}{B(\alpha,\beta)}\,dt \tag{9}$$

where $x, y$ are spatial co-ordinates, $i_{x,y}$, $T(i_{x,y})$ denotes the normalized input gray level value and corresponding transformed gray value and both the value lies between 0 and 1.

The algorithm of our proposed work is mentioned below.

Step 1: Normalization of the gray value of each pixel of an input degraded image. $u(x,y) = \frac{[f(x,y) - i_{\min}]}{(i_{\max} - i_{\min})}$ where $i_{\min}$ and $i_{\max}$ are the minimum and maximum values of the degraded image respectively and the values of $u(x,y)$ after normalization lies in the range 0 and 1.

Step 2: The normalized image $u(x,y)$ is then transformed using incomplete beta function based on α, β values and the transformed image is represented as $T(x,y)$.

Step 3: Conversion of the transformed image $T(x,y)$ as follows $f'(x,y) = (i_{\max} - i_{\min}).T(x,y) + i_{\min}$

Step 4: The obtained image $f'(x,y)$ is divided into 4 blocks and SDME fitness function value is calculated for each block and the average of all 4 blocks are taken as a maximization problem.

Step 5: The above steps are implemented by initializing the populations as 50 learners and two subjects (α, β) are considered as design variables and 100 iterations are considered to train with TLBO algorithm.

Step 6: In Elitist TLBO, the worst solutions are replaced with elite solutions and the number is varied from 2 to 5 in the experiment in order to obtain optimized solution.

*A. Evaluation Parameters for Image Enhancement*

There are several metrics proposed to evaluate the quality of the optimization algorithms. Five metrics are considered for image quality assessment process, like i) Second derivative like measurement which is also considered as the fitness function in this paper. ii) Edge content in the image iii) Over all pixel intensity (Average value) of the image iv) Standard deviation v) AC power measure. We are comparing our enhancement scheme using ABC, TLBO and elitist TLBO algorithms using a group of metrics given above and the performance of these algorithms are tabulated.

*i. Second Derivative like Measurement of Enhancement (SDME)*

For better image quality assessment, a SDME [16] was introduced and this measure is shown to have better performance than other measures in evaluating the image visual quality after enhancement.

$$SDME = -\frac{1}{K_1 K_2}\sum\sum 20\ln\left|\frac{I^{l,m}_{\max} - 2I^{l,m}_{cen} + I^{l,m}_{\min}}{I^{l,m}_{\max} + 2I^{l,m}_{cen} + I^{l,m}_{\min}}\right| \tag{10}$$

where $I^{l,m}_{\min}, I^{l,m}_{cen}$ and $I^{l,m}_{\max}$ refers to the minimum value, center pixel value and maximum gray level values of an image block and $K_1, K_2$ are the number of rows and columns of each block respectively. In this paper we proposed SDME as the fitness function and its value to be maximized.

*ii. Edge Content*

A service Edge content of an image is also known as average gradient of an image which measures sharpness of an image.

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$$EC = \frac{1}{MN}\sum_{x}\sum_{y}\left|\nabla f(x,y)\right| \tag{11}$$

where $\nabla f(x,y)$ is the gradient of an enhanced image $f(x,y)$, $x, y$ are known as the spatial co-ordinates and $M, N$ are number of pixels in a row and column respectively.

*iii.* *Overall Pixel Intensity*

Overall pixel intensity is also known as average value of an image under consideration. The value should be higher when the image is enhanced comparatively with the degraded image.

$$\overline{F} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y) \tag{12}$$

*iv.* *Standard Deviation*

Standard deviation is also known as spread of gray levels of an image from its mean. Higher the value of standard deviation indicates improvement in the enhancement of an image.

$$SD = \frac{\sum_{x=1}^{M}\sum_{y=1}^{N}(f(x,y)-\overline{F})^2}{MN-1} \tag{13}$$

.

*v.* *AC Power Measure*

AC power measure can be obtained as the difference between average squared magnitude of an image and square of the average value of the image.

$$F_{ac} = \frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N} f(x,y)^2 - \overline{F}^2 \tag{14}$$

## Simulation Results and Discussions

Here, we adapted the modified fitness function in TLBO method and have been utilized in different degraded images which are mapped from normalized gray scale range [0, 1] to [0.2, 0.5] are shown in Fig. 1. The proposed method we have optimized the fitness SDME value to maximum, the corresponding parameters α and β and other values like edge content, overall pixel intensity, standard deviation and AC power measure are calculated which shows the good enhanced values of degraded image.

TABLE.1. Evaluation Parameters for 'lena.jpg' Image

| Parameters | ABC | TLBO | Elitist TLBO |
|---|---|---|---|
| α | 5.3796 | 5.3684 | 5.4002 |
| β | 9.7206 | 9.6907 | 9.7732 |
| SDME | 63.4119 | 63.4119 | 63.4119 |
| Edge Content | 0.1521 | 0.1520 | 0.1525 |
| Overall Pixel Intensity | 98.1553 | 98.0101 | 98.3399 |
| Standard Deviation | 38.7896 | 38.7753 | 38.8806 |
| AC Power Measure | 1504.5477 | 1503.4386 | 1511.6107 |


Fig.2. Degraded Input Images and Corresponding Enhanced Images outputs of Elitist TLBO

TABLE.2. Evaluation Parameters for ‘house.jpg’ Image

| **Parameters** | ABC | TLBO | Elitist TLBO |
|---|---|---|---|
| α | 4.8168 | 4.8973 | 4.9071 |
| β | 7.8834 | 8.0904 | 8.1109 |
| SDME | 53.1004 | 53.1421 | 53.1833 |
| Edge Content | 0.1410 | 0.1425 | 0.1426 |
| Overall Pixel Intensity | 119.7730 | 121.1602 | 121.3314 |
| Standard Deviation | 37.6863 | 38.1754 | 38.2633 |
| AC Power Measure | 1420.1727 | 1457.2785 | 1463.9935 |

TABLE.3. Evaluation Parameters for ‘camera.jpg’ Image

| **Parameters** | ABC | TLBO | Elitist TLBO |
|---|---|---|---|
| α | 2.6055 | 2.6056 | 2.7155 |
| β | 5.7340 | 5.7364 | 6.0721 |
| SDME | 47.6190 | 47.6190 | 47.6269 |
| Edge Content | 0.1598 | 0.1599 | 0.1633 |
| Overall Pixel Intensity | 150.7360 | 150.8135 | 152.7637 |
| Standard Deviation | 42.0845 | 42.1286 | 43.0129 |
| AC Power Measure | 1771.0026 | 1774.7130 | 1850.0028 |

TABLE.4. Evaluation Parameters for ‘baboon.jpg’ Image

| **Parameters** | ABC | TLBO | Elitist TLBO |
|---|---|---|---|
| α | 6.3523 | 6.2033 | 6.3297 |
| β | 9.9633 | 9.6094 | 10 |
| SDME | 76.4203 | 76.2984 | 76.6283 |
| Edge Content | 0.1824 | 0.1784 | 0.18305 |
| Overall Pixel Intensity | 101.9133 | 100.1494 | 103.2317 |
| Standard Deviation | 32.5338 | 31.8265 | 32.5938 |
| AC Power Measure | 1058.3848 | 1012.8659 | 1062.2914 |

TABLE.5. Evaluation Parameters for ‘barbara.jpg’ Image

| **Parameters** | ABC | TLBO | Elitist TLBO |
|---|---|---|---|
| α | 1.8565 | 2.1552 | 2.1666 |
| β | 2.6812 | 3.8015 | 3.8288 |
| SDME | 67.9370 | 72.5705 | 72.6502 |
| Edge Content | 0.1214 | 0.1448 | 0.1453 |
| Overall Pixel Intensity | 98.7087 | 117.3587 | 117.6335 |
| Standard Deviation | 26.1997 | 31.1017 | 31.2031 |
| AC Power Measure | 686.3846 | 967.2607 | 973.5777 |

## Conclusion

We have been using the SDME, normalized beta functions for enhancement of degraded images. The degraded images and their corresponding enhanced image outputs are shown in Fig. 2. From the Tables 1-5, it concludes that the Elitist TLBO provides better results when compared to other optimization algorithms like ABC and TLBO algorithms. The strength of our work is based upon the change of contrast value so that image quality is enhanced as the fitness function is modified according to SDME which is not proposed earlier with adaptive algorithms.

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