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Gray level image enhancement using nature inspired optimization algorithm: An objective based approach

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Abstract. Image enhancement plays a crucial role in almost every image processing system. The main aim of the image enhancement is to improve image quality by maximizing the information content in the given input image. Histogram Equalization (HE) and Adaptive Histogram Equalization (AHE) are most popular non-heuristic or classical techniques for image enhancement by preserving main features of the input image. These techniques are failed in offering good enhancement. Histogram equalization is an algorithmically complex task and also exhaustive approach. So, artificial intelligence techniques have been proposed for image enhancement problem. The quality of the input image is improved by selecting the optimal parameters based on objective function during optimization process. So the objective function plays an important role in optimization problem. In this context, this paper presents an efficient objective approach for gray level image enhancement using novel optimization algorithm State of Matter Search (SMS). The proposed approach has been tested on standard test gray level images and the results obtained are compared with existing objective approach/algorithms such as CS (Cuckoo Search), ABC (Artificial Bee Colony), APSO (Adaptive Particle Swam Optimization) and DE (Differential Evolution). The proposed approach/algorithm has proven its superiority. All simulations are self-developed MATLAB scripts using MATLAB R2010a on an Intel Core 2 Duo 2.93 GHz processor with 4 GB RAM.

Keywords: image enhancement, state of matter search algorithm, novel objective approach, image quality evaluation.

1 Introduction

Image processing is a wide and active area of research in computing. It has many applications in everyday life tasks, i.e. medicine, transportation and industrial etc. Image enhancement is one of the most important image processing techniques, which can be treated as transforming one image to another image to improve the perception or interpretability of information for human viewers, or to provide better input for other automated image processing techniques. A Genetic Algorithm (GA) for image enhancement was proposed in [14] for image enhancement through contrast enhancement using a multi-objective function consisting four non-linear mapping functions. It uses the genetic algorithm to look for the optimal mapping of the grey levels of the input image into new grey levels offering better contrast for the image. Recently, some image quality measures have been proposed and used for grey-level and colour image enhancement. Contrast enhancement of digital gray level images by preserving the mean image intensity using PSO has been proposed in [11]. In this paper, enhancement is achieved by maximizing the information content in the image with a continuous intensity transform function using multi objective optimization approach. Authors[16] presents, Differential Evolution (DE) as a searching tool for global optimal solutions to enhance the contrast and details in a gray scale image. Contrast enhancement of an image is performed by gray level modification using parameterized intensity transformation function that is considered as an objective function. Hybrid intelligent algorithm

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was proposed[12] to optimize parameters of image enhancement operator to take the advantage of local gray distribution and the global statistical information of source image. Bacterial foraging algorithm and particle swarm optimization were combined into the hybrid intelligent algorithm for the optimization of fitness function which is based on entropy and edge information of image. Improved PSO (Particle Swarm Optimization) was proposed[5] for image enhancement. A parameterized transformation function is used, which uses global and local information of the image. A novel image enhancement method is proposed[2] based on Particle Swarm Optimization (PSO) and DWT to improve the image quality. Experimental results demonstrate that this method outperforms the existing well known methods. A new approach is proposed for the enhancement of colour images using the fuzzy logic technique[9]. A parametric sigmoid function was used for the enhancement of the luminance component of the underexposed image. Entropy and the visual factors are involved in the objective function, which is optimized using the bacterial foraging algorithm. Authors[8] presented a new approach for contrast enhancement of colour images. The intensity component of Hue, Saturation and Intensity (HSI) colour model is fuzzified using Global intensification operator. A new objective measure called contrast information factor is introduced which is optimized using particle swarm optimization technique. One powerful category of measures is that combining the number of edge pixels, the intensities of these pixels and the entropy of the whole image. This category of measures has been successfully exploited in the context of image enhancement using Differential Evolution (DE)[3], Particle Swarm Optimization (PSO)[7], Cuckoo Search (CS)[1] and Artificial Bee Colony (ABC)[4], Evolutionary[13] proposed algorithms as optimization approaches.

From the literature study it is observed that HE and AHE are most popular classical methods for gray level image enhancement. These techniques produce poor quality images and found to be exhaustive. Many authors applied global contrast enhancement technique via heuristic algorithms on an objective function which is a combination of image performance measures such as image intensity, number of edge pixels and entropy. During the optimization process the algorithm search for optimal parameters based on objective function. But the objective function contains two or three performance measures which return a value during evaluation of objective function. The main aim of the optimization is to maximize the objective function that should produce an enhanced image. Hence, all three performance measures are improved during the optimization process. But the question is this improvement does really enhance the image up to the required level or not. After image enhancement quantitative evaluation has conducted with the help of image quality metrics such as PSNR, RMSE and MSSIM. High PSNR value, RMSE value close to zero and MSSIM value close to one indicates the quality of the enhanced image. Whatever may be enhancement technique the quality of the enhanced image will be quantified by image quality metrics. This idea drives the authors to consider PSNR as one of the objectives in the objective function.

In the present paper an attempt has been presented for gray level image enhancement based on global intensity transformation function using state of matter search algorithm in which objective functions will search for the optimal alternative set of gray levels. SMS algorithm is novel optimization technique which is easy to understand and simple to implement for various engineering optimization problems. Image enhancement is done using parameterized global intensity transformation function in which the parameters are to be optimized using SMS algorithm considering blend of objectives such as edge intensity, number of edge pixels, entropy and PSNR of the image in a multi objective function. Three different cases have been conducted using SMS algorithm in order to assess the effect of objective function on image enhancement. The proposed approach has been evaluated by applying it on set of test images and offered very promising results.

In order to validate the outcomes, detailed qualitative, quantitative and statistical analysis has been presented. The rest of the paper is organized as follows: In section 2, mathematical treatment of image enhancement (transformation function) is described for gray image enhancement. In section 3, evaluation criterion and parameter setting is discussed. In section 4, proposed approach (SMS algorithm and problem specific implementation) is discussed. Implementation results and discussions are furnished in section 5. In section 6, conclusion of the work is reported.

2 Background of image enhancement

The main aim of the image enhancement is to convert the input image into the better quality output image. There are various techniques which can improve the quality of the input image without losing its original properties for visual judgement and/or machine understanding. There are four basic classifications in image enhancement approaches: point operations, spatial operations, transformations, pseudo coloring methods. Contrast stretching, window slicing, modelling of histogram are zero memory operations that remap a given input gray scale image into output gray scale image. Of which linear contrast stretch and histogram equalization are most popular. In spatial operations, the original value of each and every pixel is replaced by its neighborhood pixel value. This process might suffer from excessive enhancement of the noise in the input image or conversely over smoothing the image where that needs sharp details. Linear filtering, homomorphic filtering and root filtering falls under transform operations based on inverse transformation of the transformed image. In pseudo coloring methods, gray scale image is artificially colored using a suitable color map. Due to non-uniqueness of the color maps, lot of trails has been required to select an appropriate mapping. Manipulating gray level distribution in the neighborhood of each pixel of the given input image by applying transformation function is called local enhancement technique[1, 4, 6, 7, 13]. Traditional local enhancement transformation function is given in Eq. (1).

$$g(x, y) = \frac{G}{\sigma(x, y)}(f(x, y) - m(x, y)), \tag{1}$$

where, $m(x, y)$ and $\sigma(x, y)$ are the gray level mean and standard deviation computed in a neighbourhood centered at (x, y) having MXN pixels. G is the global mean of the input image, $f(x, y)$ and $g(x, y)$ is the gray level intensity of the input and output image pixel at location (x, y) . Adaptive histogram equalization is also a local enhancement technique which gains most popularity due to its good results shown in medical image processing[7, 15, 17].

One of the easiest and most popular ways to accomplish the task of contrast enhancement is global intensity transformation. In this approach, factors like locality and adaptability of the method to the given image are taken into account unlike classical global enhancement techniques. Global intensity transformation function is derived from Eq. (1) and is applied to each pixel at location (x, y) of the given image is given in Eq. (2).

$$g(x, y) = \frac{k \cdot G}{\sigma(i, j) + b}[f(x, y) - c \times m(x, y)] + m(x, y)^a, \tag{2}$$

where, $b \neq 0$ allows for zero standard deviation in the neighborhood, $c \neq 0$ allows for only fraction of the mean $m(x, y)$ to be subtracted from original pixel gray level. The last term might have brighten and smooth the effects on the image. G is the global mean, $m(x, y)$ is the local mean and $\sigma(x, y)$ is the local standard deviation of (x, y) th pixel of the input image over a $n \times n$ window, which are expressed as [7]:

$$m(x, y) = \frac{1}{n \times n}\sum_{x=0}^{n-1}\sum_{y=0}^{n-1} f(x, y), \tag{3}$$

$$G = \frac{1}{M \times N}\sum_{x=0}^{M-1}\sum_{y=0}^{N-1} f(x, y), \tag{4}$$

$$\sigma(x, y) = \sqrt{\frac{1}{n \times n}\sum_{x=0}^{n-1}\sum_{y=0}^{n-1}(f(x, y) - m(x, y))^2}. \tag{5}$$

Proper tuning of a, b, c and k parameters in the Eq. (2), will produce large variations in the processed output image by preserving its originality and natural look.

In this paper, SMS task is to produce better enhanced image for the given input image using global intensity transformation function based on combination of different objectives. SMS will find optimal set of four parameters according to an objective criterion that describes the contrast of the image.

3 Formation of objective function

In order to evaluate the quality of output image without human intervention, we require an objective function that combines important image performance measures such as the number of edge pixels, entropy of the whole image and the intensity of the edge pixels [1, 3, 4, 7, 13]. Some authors [10] excluded the entropy of the whole image in their objective function. In fact, entropy is one of the important quality measures in the image enhancement. As mentioned in the introduction, the final quality of the enhanced image has been quantified by using image quality metrics[7]. Hence, PSNR is considered as one of the objectives in the objective function. So, we modelled aggregated weight based objective function as follows:

$$OF = W_1 \times OF_1 + W_2 \times OF_2. \tag{6}$$

OF is called objective function W_1 and W_2 are weight factors such that $W_1 = 0.5$ and $W_2 = 0.5$ (equal weight age)

$$OF_1 = F(I_e) = \log(\log(E(I_s))) \times \frac{n_{edgels(I_s)}}{M \times N} \times H(I_e), \tag{7}$$

$$OF_2 = PSNRI(I_e). \tag{8}$$

- $F(I_e)$ is the objective function that denotes the quality of the obtained output image with transformation function Eq. (2).
- $E(I_s)$ is the sum of edge pixel intensities of the resulting image which can be calculated by Sobel edge detector.
- n_{edgels} is the number of edge pixels of the resulting image.
- $H(I_e)$ is the entropy value.
- M and N are the number of pixels in the horizontal and vertical direction of the image.
- $PSNR$ is peak signal to noise ratio of the enhanced image

The main aim of SMS algorithm is to select better solution (a, b, c and k) that maximizes OF based on objectives in the objective function. The purpose of weight factors is to convert individual objectives into a single objective. In this work, three scenarios have been tested for image enhancement problem using SMS algorithm in order to assess the importance of objective function. The three cases are as follows:

Case 1 Considering single objective i.e., OF_1
Case 2 Considering single objective i.e., OF_2
Case 3 Considering single objective i.e., OF

3.1 Parameter setting

Parameters a, b, c, and k are defined over the real positive numbers and they are same for the whole image. Comparing Eq. (1) to Eq. (2) the values of the parameters are taken as constants (i.e. $b = 0$, $c = 1$ and $k = 1$) and the term $m(x, y)^a$ is taken as 0. In Eq. (2), $b = 0$ prohibits the Not A Number (NAN) values, $c = 1$ allows for only a fraction of the mean to be subtracted from the pixel's input gray-level intensity value, while the last term may have brighten and smooth the effects on the image. Accordingly, the Eq. (2) broadened the spectrum of the transformation output range by modifying the original equation. The task of optimization algorithm is to solve the image enhancement problem by tuning the four parameters (a, b, c and k) in order to find the best combination according to an objective criterion that describes the contrast in the image[7].

In this paper the limits of variables are chosen as in [10, 12]; $a \in [0, 1.5]$, $b \in [0, 0.5]$, $c \in [0, 1]$ and $k \in [0.5, 1.5]$. However, they failed to produce good output with the supplied range of b. It is noticed that, small variation in the value of b will have a large effect on intensity stretch. The originality of the image is lost due to normalized intensity values crossed the limit [0, 255]. To avoid this problem, the limit of b has been modified to $[1, G/2]$. where, G is the global mean of the input image [7].

4 Overview of algorithm

4.1 State of matter search algorithm

State of matter search is novel and efficient nature inspired evolutory algorithm for solving global optimization problems. The SMS algorithm is based on the simulation of states of matter phenomenon. In SMS, individuals emulate molecules which interact to each other by using evolutionary operations based on the physical principles of the thermal-energy motion mechanism. Such operations allow the increase of the population diversity and avoid the concentration of particles within a local minimum. The proposed approach combines the use of the defined operators with a control strategy that modifies the parameter setting of each operation during the evolution process. In contrast to other approaches that enhance traditional EA (evolutory algorithms) by incorporating some procedures for balancing the exploration-exploitation rate, the proposed algorithm naturally delivers such property as a result of mimicking the states of matter phenomenon. The algorithm is devised by considering each state of matter at one different exploration-exploitation ratio. Thus, the evolutionary process is divided into three stages which emulate the three states of matter: gas, liquid and solid. At each state, molecules (individuals) exhibit different behavior. Beginning from the gas state (pure exploration), the algorithm modifies the intensities of exploration and exploitation until the solid state (pure exploitation) is reached. As a result, the approach can substantially improve the balance between exploration-exploitation, yet preserving the good search capabilities of an evolutionary approach [7].

4.2 SMS implementation procedure

The overall SMS algorithm is comprised of three phases corresponding to the three states of matter: the gas, the liquid and the solid state. Each phase has its own behavior. In the gas phase exploration is intensified whereas in liquid phase a mild transition between exploration and exploitation is executed. Finally, in the solid phase, solutions are refined by emphasizing the exploitation process.

At each phase, the same operations are implemented. However, depending on which phase is referred, they are employed considering a different parameter configuration. The procedure in each phase is shown in algorithm steps for SMS. Such procedure is composed of nine steps and maps the current population P_k to a new population P_{k+1}. The algorithm receives the current population Pk as input and the configuration parameters α, β, ρ, and H will help to yield the new population P_{k+1}.

4.3 Steps for implementation of sms algorithm

Step 1. Initialization of optimization problem and algorithm parameters Initialize population size (Pop), N, α, β, ρ, H for all phases, D, maxit, Phase and limits for a, b, c and k parameters.

Step 2. Initialization of Population of molecules (Generation of random solution) The (P) is generated randomly; where, elements of P represent the sets of decision variables (a, b, c and k). P matrix is represented by:

$$P = \begin{bmatrix} x_1^1 & x_2^1 & \cdots & x_{N-1}^1 & x_N^1 \\ x_1^2 & x_2^2 & \cdots & x_{N-1}^2 & x_N^2 \\ \vdots & \vdots & \vdots & \vdots & \vdots \\ x_1^{Pop-1} & x_2^{Pop-1} & \cdots & x_{N-1}^{Pop-1} & x_N^{Pop-1} \\ x_1^{Pop} & x_2^{Pop} & \cdots & x_{N-1}^{Pop} & x_N^{Pop} \end{bmatrix}, \tag{9}$$

$$x_j^i = x_j^{\min} + (x_j^{\max} - x_j^{\min}) \times rand,$$
$$[x_1^1 \, x_2^1 \, x_{N-1}^1 \, x_N^1] = [a^1 b^1 c^1 k^1] = P_1,$$

where, N is the number of decision variables (dimension of the problem), represents parameter output, i.e., i^{th} population of j^{th} parameter, which is generated randomly between the limits, as and are the j^{th} parameter maximum and minimum limits and rand() is a random number between 0 and 1.

Step 3. Evaluate the objective function and record the best solution of the population P Construct new images based on P using Eq. (2) and evaluate the constructed images according to objective function in Eq. (8) and record the best solution (gbest)

$$P \in \{P\} \text{ and } f(P^{best}) = \max\{f(P_1), f(P_2), \cdots, f(P_{Pop})\} \tag{10}$$

Step 4. Calculate V_{init} (initial velocity of each molecule) and r (collision radius)

$$V_{\text{init}} = \frac{\sum_{j=1}^{N}(x_j^{\max} - x_j^{\min})}{N} \times \beta, \quad r = \frac{\sum_{j=1}^{N}(x_j^{\max} - x_j^{\min})}{N} \times \alpha, \tag{11}$$

where, $\beta \in [0, 1]$ and $\alpha \in [0, 1]$

Step 5. Compute new molecules (solutions) by using the direction vector operator (Eq. (13)).

For $(i = 1; i < Pop + 1; i + +)$

$$a_i = \frac{P^{\text{best}} - P_i}{\|P^{\text{best}} - P_i\|} \tag{12}$$

For $(j = 1; j < N + 1; j + +)$

$$dik_{i,j}^{k+1} = dir_{i,j}^{k} \times (1 - \frac{itr}{\text{maxit}}) \times 0.5 + a_{i,j}, \tag{13}$$

$$v_{i,j} = dir_{i,j}^{k+1} \times v_{\text{init}}, \tag{14}$$

$$P_{i,j}^{k+1} = P_{i,j}^{k} + v_{i,j} \times \text{rand} \times \rho \times (x_j^{\max} - x_j^{\min}) \tag{15}$$

End for j

End for i

Step 6. Solve collisions by using Collision operator (Eq. (16))

For $(i = 1; i < Pop + 1; i + +)$

For $(j = 1; j < N + 1; j + +)$

$$\begin{aligned} &\text{if } ((\|P_i - P_j\| < r) \; and \; (i \neq j)) \\ &\quad t = dir_i, \\ &\quad dir_i = dir_j, \\ &\quad dir_j = t. \end{aligned} \tag{16}$$

End for if

End for j

End for i

Step 7. Generate new random positions by using the random position operator (Eq. (17))

For $(i = 1; i < Pop + 1; i + +)$

if $(r_m < H)$ then; where $r_m \in$ rand

For $(j = 1; j < N + 1; j + +)$

$$P_{i,j}^{k+1} = \begin{cases} x_j^{\min} + (x_j^{\max} - x_j^{\min}) \times \text{rand} & \text{with probability } H \\ P_{i,j}^{k+1} & \text{with probability } (1 - H) \end{cases} \tag{17}$$

End for j

End for if

End for i

Step 8. Initiate change of phase, evaluate the new solution P and update gbest Construct new images based on new P using Eq. (2) and evaluate the constructed images according to objective function in Eq. (8) and select the best solution in new P. If the new solution is better than the previous solution then record the best solution (gbest) so far otherwise discard new solution and preserve the previous solution.

Step 9. Stopping criterion If the maximum number of iterations is reached, computation is terminated. Otherwise, Step 4 to Step 8 is repeated.

The detailed implementation flow chart for SMS algorithm in the context of image enhancement is given in Fig. 1.

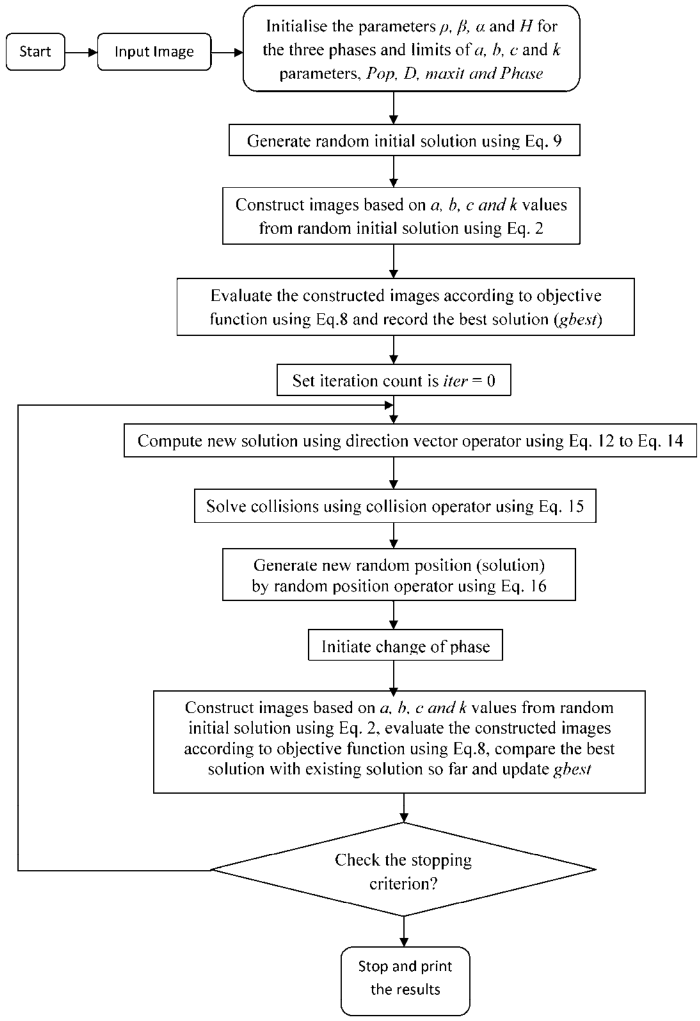

Fig. 1: Implementation flow chart for SMS algorithm

5 Implementation results and discussions

In this section, the SMS algorithm is validated through applying it on a set of test images. Algorithm parameter selection plays major role for any optimization algorithms in terms of performance. Hence, parameter tuning is required for optimization techniques before implementation. The values assigned for these parameters are selected by the number of trails on the performance of the proposed method. The parameter description and assigned values for SMS are furnished in Tab. 1. The performance of the optimization algorithms is dependent on algorithm parameters like size of the population number of iterations, etc. The proposed objective approach with SMS algorithm is compared with well existing approach/algorithms in the literature. The process is comprised of two sections. In the first section, comparisons are done based on three scenarios for gray scale image enhancement using SMS algorithm. Later implementation of proposed approach on set of test images using SMS, CS, ABC, DE and PSO algorithms followed by performance analysis of SMS algorithm based on proposed objective approach has been presented. All simulations are self-developed MATLAB codes using MATLAB R2010a on an Intel Core 2 Duo 2.93 GHz processor with 4 GB RAM.

5.1 Gray scale image enhancement with various objective approaches using sms

Gray level image enhancement is evaluated based on three scenarios using SMS algorithm and the obtained results have been compared qualitatively, Fig. 2, and numerically, Table 2. Fig. 2 shows from left to right, the instances of input images and the results obtained after the optimization process in each case. It is

Table 1: Tuned algorithm parameters for SMS algorithm

Algorithm	Parameter	Description	Assigned value
SMS	Pop	Size of population	50
	N	Dimension of the problem	4
	maxit	Maximum number of iterations	1000
	β	Movement operator	[0.9, 0.5, 0.1]
	α	Collision operator	[0.3, 0.05, 0.0]
	H	Threshold operator	[0.9, 0.2, 0.0]
	ρ	Direction operator	[0.85, 0.35, 0.1]

clear from the Fig. 2 that these three scenarios have successfully enhanced the input images. But a human eye cannot judge the quality of enhanced images. For this reason there are so many metrics developed to analyze the quality of the enhanced images. So, a numerical comparison seems to be necessary here. Six metrics basically used for the statistical comparison of results are: the objective function value, number of edge pixels, entropy, PSNR (Peak-Signal to Noise Ratio), RMSE (Root Mean Square Error) and MSSIM (Modified Structural Similarity Index Measure). Table 2 provides information about the all input images and shows the comparisons of the three cases for all six metrics for the case of gray level images and the results furnished are best values obtained in 20 runs for all the algorithms.

Case 1: Form Tab. 2 by observing the values of number of edge pixels and entropy, they are increased more than required. So the image is over enhanced (over brighten and over darken). The same can be observed in Case 1 of Fig. 2. And this is similar for all figures. The convergence characteristics of SMS algorithm for all images are shown in Fig. 3. The PSNR values for enhanced images range from 59 to 69.

Case 2: Form Tab. 2 it is noticed that this case has been successful in the enhancement of given images. The PSNR values for enhanced images range from 82 to 89. That means the given images are enhanced up to required level. It is observed that RMSE value is nearer to zero and mSSIM value is one for all enhanced images. The enhanced images obtained with this approach produce neither noise artefacts nor over enhancement to achieve the highest PSNR values. The convergence characteristics of this approach have shown in Fig. 4. The convergence time is short as compared to Case1.

Table 2: Comparison of fitness, n_{edgels}, entropy, PSNR, RMSE, MSSIM and time for SMS algorithms for standard gray scale images

Image	Image information	Method	Fitness value		No of edge pixels		Entropy		PSNR	RMSE	m SSIM	Time (S)
Name			Initial	Final	Initial	Final	Initial	Final				
Airplane	Format: GIFF	Case-I	0.8393	1.2205	3694	4440	6.7186	7.1778	69.9039	0.0819	0.9995	803.24
	Dimension: 512X512	Case-II	0	87.8986		3934		6.761	87.8986	0.0103	1	43.6
	Bit depth: 8	Case-III	0.8393	18.2582		3945		6.7634	87.86	0.0103	1	797.25
Man	Format: TIFF	Case-I	1.2239	1.4786	4218	4948	7.5346	7.7177	69.0298	0.0905	0.9991	763.57
	Dimension: 512X512	Case-II	0	86.7541		4502		7.5358	86.7541	0.0118	1	52.22
	Bit depth: 8	Case-III	1.2239	18.3675		4511		7.5333	86.7195	0.0118	1	758.57
Boat	Format: TIFF	Case-I	1.0642	1.3605	4535	5584	7.1452	7.5186	64.3273	0.1556	0.9971	871.93
	Dimension: 512X512	Case-II	0	88.2203		4935		7.1836	88.2203	0.0099	1	49.91
	Bit depth: 8	Case-III	1.0642	18.5262		4935		7.1842	88.185	0.0099	1	843.45
Living room	Format: GIFF	Case-I	1.7515	2.1851	5068	6200	7.3841	7.6807	65.3056	0.139	0.9978	764.74
	Dimension: 512X512	Case-II	0	87.0877		5048		7.3941	87.0877	0.0113	1	46.82
	Bit depth: 8	Case-III	1.7515	18.8042		5090		7.3955	87.0504	0.0113	1	739.81
Breast	Format: TIFF	Case-I	0.7917	1.1656	3678	5317	5.4212	5.6793	82.4601	0.0193	1	914.91
	Dimension: 482X571	Case-II	0	86.2321		4149		5.5392	86.2321	0.0125	1	44.02
	Bit depth: 8	Case-III	0.7917	17.96		4230		5.5556	86.1664	0.0125	1	901.24
X-Ray	Format: TIFF	Case-I	0.792	1.1404	2428	5377	6.8201	4.8582	59.7702	0.2629	0.9904	845.36
	Dimension: 596X416	Case-II	0	89.3554		2866		6.8625	89.3554	0.0087	1	46.37
	Bit deptxzh: 8	Case-III	0.792	18.62		2897		6.8717	89.3075	0.0087	1	831.75

Case 3: By observing the values of PSNR, RMSE and mSSIM in Table 2, it is noticed that these results are much more similar to Case 2 results. Quite interesting point is even though giving high priority to parameterized objective function and less priority to PSNR, the results of this approach are almost similar to Case 2 results. But the convergence time is more compared to Case 2 and approximately equal to Case 1. The convergence characteristics of this approach have shown in Fig. 5.

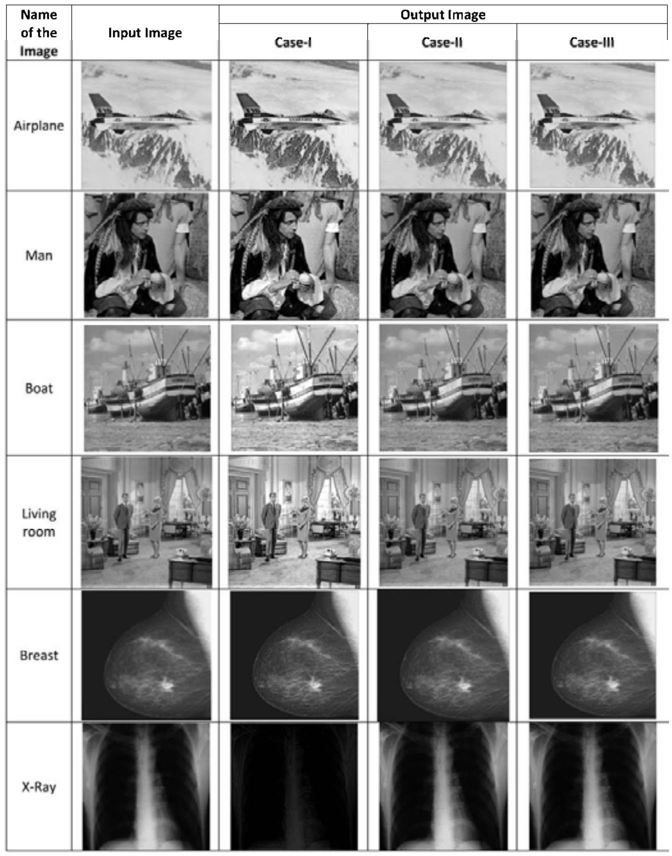

Fig. 2: Enhancement of standard gray scale images with different objective approaches using SMS algorithm

From above three cases, it is noticed that Case 2 is a better approach for gray level image enhancement. Because, Case 1 and Case 3 approaches are computationally burden. Case 1 approach is over enhancing the images and hence image quality is poor. Case 3 produces better results but convergence time is more; Case 2 is producing the best results with less convergence time. The success behind Case 2 is strong objective function. As we all know that any optimization algorithm will search for optimal parameters based on designed objective function (minimization or maximization) for a particular problem and it was proved form results of Case 1 and Case 2. In Case 1, selection (tuning) of parameters has been done based on parameterized objective function, which contains entropy, intensity of the edge pixels and number of edgels. So, improper parameters may give over enhanced or under enhanced images which will have poor quality (low PSNR value). But in Case 2, one of the popular image quality metric i.e. PSNR has been considered as an objective function to be maximized for the image enhancement and it was successful in achieving the desired target. Coming to execution time, Case 1 objective function has to calculate the values of entropy, intensity and n_{edgels} of the output image at each evaluation, which is very tedious and time consuming. But in Case 2 PSNR is just a quality metric which is simple to evaluate. Hence, it has been converged very quickly. Whereas in Case 3 two objectives i.e. OF_1 and OF_2 are converted into single objective function by using aggregated weighted method. In which equal weightage has been given for the two objectives by treating weights as $W_1 = 0.5$ and $W_2 = 0.5$. But the results obtained are surprisingly close agreement with Case 2 results. From the analysis of objective function in Case 3, it is noticed that the first objective function value is smaller than second objective function value. So, the second objective function has more domination than first objective function even though equal priority has been given to both objectives. Hence, dominated objective will have more impact on combined objective function. This will enable the objective function to search for optimal parameters in the direction of dominated objective function during the optimization process. However, this particular approach yields good results but consumed lot of time to converge. In fact computation time is one of the major concerns in engineering optimization. Form this section it is clear that Case 2 scenario has been successful in achieving the desired target with good quality solution than Case 1 and Case 2 scenarios.

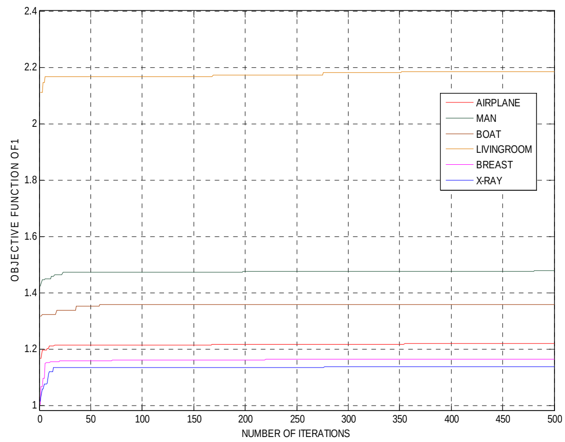

Fig. 3: Convergence characteristics of SMS algorithm with parameterized objective approach

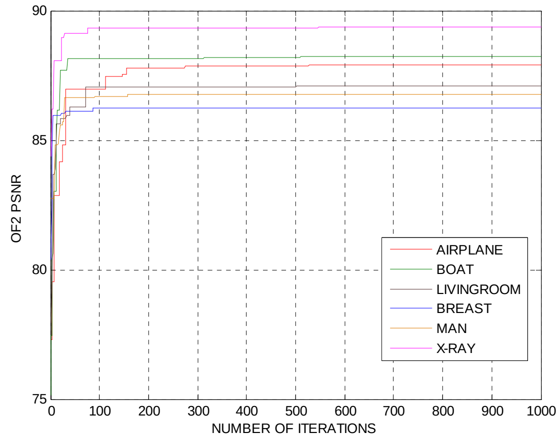

Fig. 4: Convergence characteristics of SMS algorithm with PSNR as objective approach

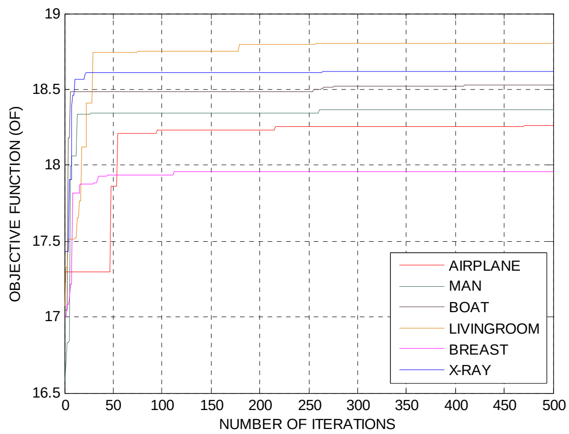

Fig. 5: Convergence characteristics of SMS algorithm with multi-objective approach

5.2 Performance analysis of sms algorithm

In order to test the efficiency of considered algorithm and also for the case of comparison along with SMS algorithm existing algorithms like CS, ABC, DE and PSO were also implemented on standard test images by considering PSNR maximization as an objective function. For this the size of population, maximum number of iterations and dimension of the problem has been taken constant for all algorithms i.e. population size is 50, maximum number of iterations is 1000 and dimension of the problem is 4 and remaining parameters of CS, ABC, DE and PSO are as follows. For CS algorithm, fraction of worst nests is 0.25, for ABC, number of food sources is 25, abandonment limit is 100 and modification rate is 0.5, for DE, crossover rate is 0.45 and for PSO, cognitive parameters C_1 is 1and C_2 is 2.

A comparison has been presented quantitatively in Table 3 and qualitatively in Fig. 6. From Tab. 3, it is clear that the proposed SMS algorithm outperforms the CS, ABC, DE and PSO algorithms in terms of all metrics. Number of edge pixels, entropy, PSNR, RMSE and mSSIM are maximized for all five test images in case of all algorithms. Coming to the image quality measurements SMS algorithm has given the best results than other algorithms for all test images which are presented in bold. And it is also observed that results obtained with CS algorithm are close agreement with SMS algorithm. The convergence characteristics of

Table 3: Comparison of n_{edgels}, entropy, PSNR, RMSE, MSSIM and time for SMS, CS, ABC, DE and PSO algorithms for standard gray scale images

Image Name	Algorithm	No of n_{edgels} Initial	Final	Entropy Initial	Final	PSNR	RMSE	mSSIM	Time (S)
Man	SMS	4218	4502	7.5346	7.5358	86.7541	0.0118	1	39.22
	CS		4509		7.5428	86.4937	0.0121	1	86.63
	ABC		4590		7.5899	81.5902	0.0213	1	69.99
	DE		4509		7.533	86.7507	0.0118	1	43.93
	PSO		4502		7.5334	86.754	0.0118	1	44.01
Boat	SMS	4535	4935	7.1452	7.1836	88.2223	0.0099	1	35.91
	CS		4935		7.1812	88.1654	0.01	1	88.33
	ABC		4818		7.224	79.674	0.0266	1	69.3
	DE		4935		7.1837	88.22	0.0099	1	43.74
	PSO		4907		7.1833	88.2202	0.0099	1	43.39
Living room	SMS	5068	5048	7.3841	7.3941	87.0877	0.0113	1	36.82
	CS		5048		7.3962	87.0714	0.0113	1	83.25
	ABC		5104		7.3731	85.8968	0.013	1	67.81
	DE		5054		7.3945	87.0854	0.0133	1	43.85
	PSO		5019		7.3935	87.0866	0.0133	1	43.71
Breast	SMS	3678	4149	5.4212	5.5392	86.2321	0.0125	1	34.02
	CS		4143		5.5381	86.2292	0.0125	1	84.14
	ABC		4162		5.589	85.7008	0.0133	1	67.73
	DE		4145		5.5378	86.2296	0.0125	1	43.23
	PSO		4148		5.5389	86.23	0.0125	1	44.06
X-Ray	SMS	2428	2866	6.8201	6.8625	89.3554	0.0087	1	36.37
	CS		2879		6.8655	89.3513	0.0087	1	83.98
	ABC		2560		6.8832	83.7885	0.0166	1	67.59
	DE		2862		6.8619	89.3549	0.0087	1	43.64
	PSO		2863		6.8625	89.3535	0.0087	1	43.48

three algorithms for man, boat, living room, breast and x-ray are shown in Fig. 7, Fig. 8, Fig. 9, Fig. 10 and Fig. 11 respectively. From Fig. 7 to Fig. 11, it is observed that SMS algorithm has attained the better solution after 500th iteration for most of the test images. But the time consumed by SMS algorithm is comparatively less than other algorithms. The last column of the Tab. 3 shows the execution time of all algorithms for the respective images. This column has significance in the present problem. Because choosing optimization for solving any engineering problem is meant for getting good quality outcome (near optimal solution) within less execution time. From Tab. 3 it is understood that SMS has consumed relatively less execution time than CS, ABC, DE and PSO for all test images. Tab. 4 shows the comparative analysis between non-heuristic and heuristic methods. From Table 4 it is observed that all heuristic methods gave better results than non-heuristic methods. The PSNR values of non-heuristic methods for all the test images are comparatively less than that of heuristic methods. In heuristic methods SMS algorithm has been performed well in obtaining good solution with quality.

6 Statistical analysis of sms algorithm

This section presents statistical analysis to analyze the efficiency of SMS algorithm. For this the algorithm has been executed for 20 times by considering population size of 50 and maximum number of iterations as 1000 for three objective approaches. From the obtained results the best, worst, mean and the standard deviation of all six metrics has been presented in Tab. 5 and 6 for all gray scale test images. From Table 5 and 6, it is observed that all metrics seems to be better in Case 2 than Case 1 and Case 3. It is observed that the difference between best and mean values of all metrics for Case 2 is almost zero. Hence, it is clear that SMS algorithm has been succeeded in the enhancement of gray scale images with PSNR as an objective function (Case 2).

7 Conclusions

This paper presents an objective based approach for gray level image enhancement using novel optimization algorithm state of matter search. Three types of objective approaches are discussed for gray level image

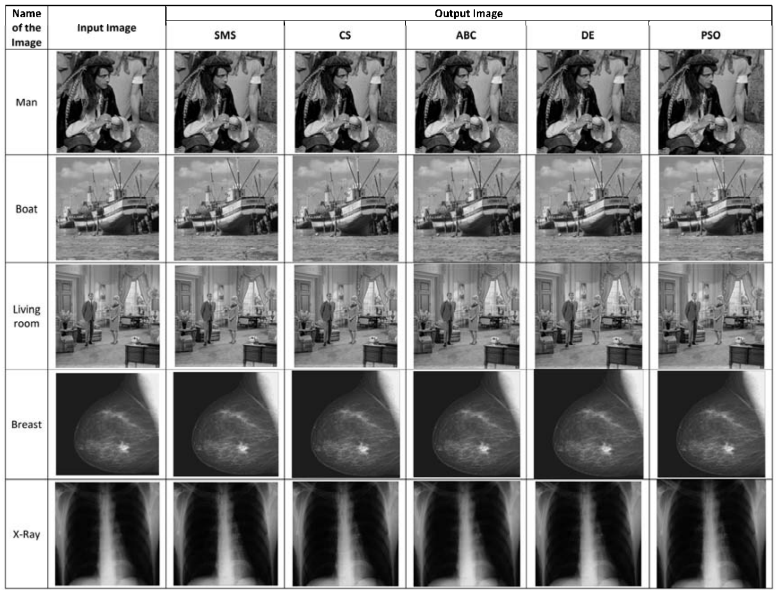

Fig. 6: Qualitative comparisons for enhanced images of SMS, CS, ABC, DE and PSO algorithms

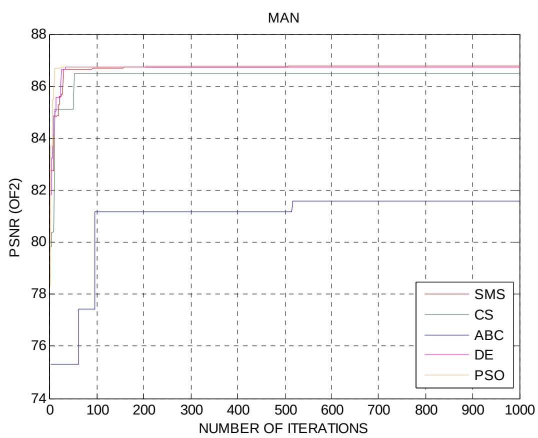

Fig. 7: Convergence characteristics of SMS, CS, ABC, DE and PSO algorithms for man image

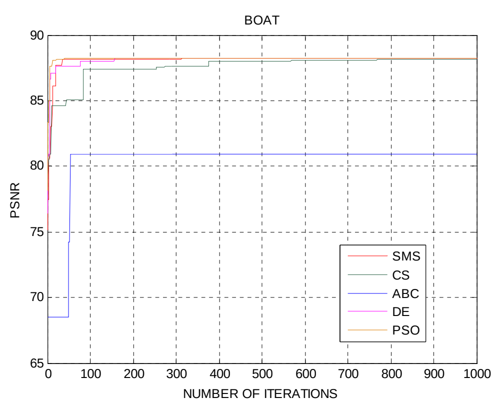

Fig. 8: Convergence characteristics of SMS, CS, ABC, DE and PSO algorithms for boat image

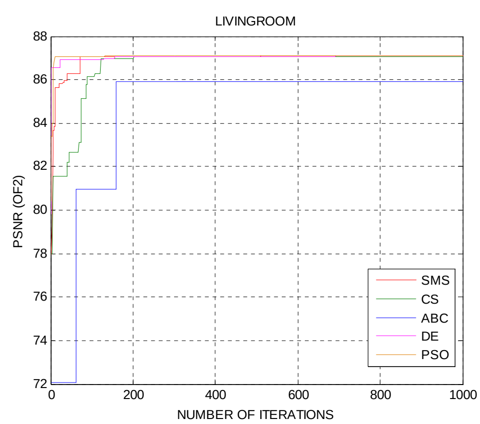

Fig. 9: Convergence characteristics of SMS, CS, ABC, DE and PSO algorithms for living room image

Table 4: Numerical comparison of image quality metrics for heuristic and non-heuristic methods

Image Name	Type	Method	PSNR	RMSE	mSSIM	Time (s)
Man	Non-Heuristic	HE	63.5906	0.1693	0.9962	N/A
		AHE	63.7765	0.1653	0.9968	N/A
	Heuristic	SMS	86.7541	0.0118	1	39.22
		CS	86.4937	0.0121	1	86.63
		ABC	81.5902	0.0213	1	69.99
		DE	86.7507	0.0118	1	43.93
		PSO	86.754	0.0118	1	44.01
Boat	Non-Heuristic	HE	64.7832	0.1476	0.998	N/A
		AHE	66.706	0.1183	0.9987	N/A
	Heuristic	SMS	88.2223	0.0099	1	35.91
		CS	88.1654	0.01	1	88.33
		ABC	79.674	0.0266	1	69.3
		DE	88.22	0.0099	1	43.74
		PSO	88.2202	0.0099	1	43.39
Livingroom	Non- Heuristic	HE	65.2166	0.1404	0.998	N/A
		AHE	65.3548	0.1382	0.9981	N/A
	Heuristic	SMS	87.0877	0.0113	1	36.82
		CS	87.0714	0.0113	1	83.25
		ABC	85.8968	0.013	1	67.81
		DE	87.0854	0.0133	1	43.85
		PSO	87.0866	0.0133	1	43.71
Breast	Non- Heuristic	HE	58.9293	0.2896	0.9876	N/A
		AHE	67.9581	0.1024	0.9986	N/A
	Heuristic	SMS	86.2321	0.0125	1	34.02
		CS	86.2292	0.0125	1	84.14
		ABC	85.7008	0.0133	1	67.73
		DE	86.2296	0.0125	1	43.23
		PSO	86.23	0.0125	1	44.06
X-Ray	Non- Heuristic	HE	58.8751	0.2914	0.9882	N/A
		AHE	64.7675	0.1479	0.997	N/A
	Heuristic	SMS	89.3554	0.0087	1	36.37
		CS	89.3513	0.0087	1	83.98
		ABC	83.7885	0.0166	1	67.59
		DE	89.3549	0.0087	1	43.64
		PSO	89.3535	0.0087	1	43.48

Table 5: Statistical analysis (20 runs) of SMS algorithm with different objective approaches

Case	Name of	Fitness function value				n_{edgels}				Entropy			
	the image	Best	Worst	Mean	Std	Best	Worst	Mean	Std	Best	Worst	Mean	Std
Case-I	Airplane	1.2205	1.2209	1.2207	2.00E-06	4440	3587	3765	377	7.1776	6.9582	6.6517	0.5758
	Man	1.4786	1.4716	1.4771	0.003	5145	4946	4987	88.328	7.7666	7.7176	7.7277	0.0217
	Boat	1.3624	1.3608	1.3619	6.00E-04	5650	5591	5634	24.228	7.5393	7.5203	7.5351	0.0083
	Living room	2.1858	2.1829	2.1847	0.0012	6200	6196	6197	2.1902	7.6809	7.6809	7.6805	2.9239
	Breast	1.1656	1.1656	1.1656	1.00E-05	5317	5317	5317	0	5.6793	5.6792	5.6793	3.00E-05
	X-ray	1.148	1.1404	1.143	0.0032	5638	5155	5357	183.52	5.0191	4.6164	4.8604	0.1523
Case-II	Airplane	87.8986	87.898	87.8983	3.00E-04	3934	3934	3934	1.00E-05	6.761	6.761	6.761	1.00E-06
	Man	86.7541	86.7541	86.7541	1.00E-08	4502	4502	4502	1.00E-04	7.5358	7.5328	7.5338	1.00E-05
	Boat	88.2203	88.2203	88.2203	1.00E-05	4935	4907	4929	11.805	7.1837	7.1835	7.1836	1.00E-05
	Living room	87.0877	87.0877	87.0877	1.00E-06	5048	5048	5048	1.00E-05	7.3941	7.3941	7.3941	1.00E-06
	Breast	86.2321	86.2321	86.2321	1.00E-06	4149	4149	4149	1.00E-06	5.5392	5.539	5.539	1.00E-04
	X-ray	89.3554	89.3554	89.3554	1.00E-05	2866	2865	2865	1.00E-04	6.8624	6.8624	6.8624	1.00E-06
Case-III	Airplane	18.2582	17.9289	18.2621	0.2386	3945	3606	3851	147.06	6.7958	6.7181	6.7607	0.0277
	Man	18.3675	18.3641	18.3667	0.0014	4511	4501	4508	4.3359	7.5336	7.5322	7.533	5.00E-04
	Boat	18.5262	18.5208	18.5237	0.0025	4942	4933	4937	3.8079	3.8079	7.1855	7.181	0.0018
	Living room	18.8041	18.8024	18.8032	6.00E-04	5101	5090	5094	5.8566	7.3978	7.3952	7.3965	0.0011
	Breast	17.96	17.9586	17.959	3.00E-04	4249	4229	4236	10.256	5.5596	5.5554	5.5572	0.0022
	X-ray	18.62	18.6171	18.6188	0.0012	2898	2890	2893	3.7683	6.8718	6.8696	6.871	8.00E-04

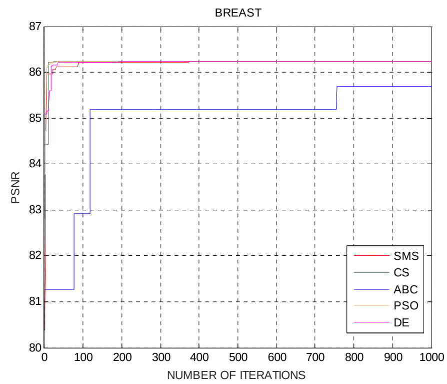

Fig. 10: Convergence characteristics of SMS, CS, ABC, DE and PSO algorithms for breast image

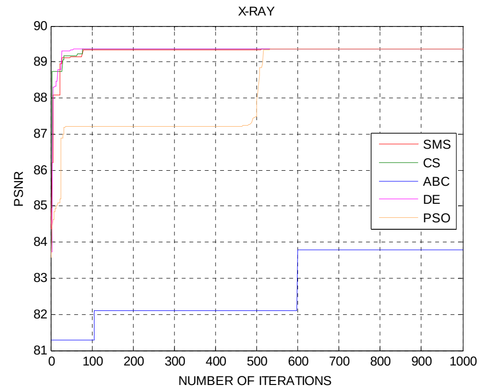

Fig. 11: Convergence characteristics of SMS, CS, ABC, DE and PSO algorithms for x-ray image

Table 6: Statistical analyses (20 runs) of SMS algorithm with different objective approaches and image quality metrics

Case	Name of	PSNR				RMSE				mSSIM			
	the image	Best	Worst	Mean	Std	Best	Worst	Mean	Std	Best	Worst	Mean	Std
Case-I	Airplane	76.5489	75.2324	75.8954	5.177	0.1693	0.0381	0.0822	0.0526	1.0000	0.9964	0.999	0.0015
	Man	69.0437	65.7478	68.3704	1.4662	0.1321	0.0904	0.0989	0.0186	0.999	0.9989	0.9989	4E-004
	Boat	66.4813	64.4813	65.8378	0.9256	0.1578	0.1214	0.1313	0.0149	0.9984	0.997	0.998	5E-004
	Living room	65.8575	64.9788	65.3667	0.382	0.1443	0.1304	0.1381	0.0061	0.9981	0.9976	0.9978	2E-004
	Breast	82.4625	82.601	82.4625	0.0011	0.0193	0.0193	0.0193	2E-006	1.0000	1.0000	1.0000	1E-08
	X-ray	60.0411	59.4521	59.7821	0.2211	0.2727	0.2548	0.2623	0.0067	0.9909	0.9896	0.9904	5E-004
Case-II	Airplane	87.8986	87.898	87.8983	3E-004	0.0103	0.0103	0.0103	1E-007	1.0000	1.0000	1.0000	1E-008
	Man	86.7541	86.7541	86.7541	1E-008	0.0118	0.0118	0.0118	1E-006	1.0000	1.0000	1.0000	1E-008
	Boat	88.2203	88.2203	88.2203	1E-005	0.0099	0.0099	0.0099	1E-007	1.0000	1.0000	1.0000	1E-008
	Living room	87.0877	87.0877	87.0877	1E-006	0.0125	0.0125	0.0125	1E-007	1.0000	1.0000	1.0000	1E-008
	Breast	86.2321	86.2321	86.2321	1E-006	0.0087	0.0087	0.0087	1E-007	1.0000	1.0000	1.0000	1E-008
	X-ray	89.3554	89.3554	89.3554	1E-005	0.0113	0.0113	0.0113	1E-007	1.0000	1.0000	1.0000	1E-008
Case-III	Airplane	89.7477	75.359	85.7328	5.8569	0.0435	0.0083	0.0166	0.0151	1.0000	0.9999	1.0000	4E-005
	Man	86.7154	86.7197	86.7183	0.0017	0.0018	0.0018	0.0018	2E-006	1.0000	1.0000	1.0000	1E-008
	Boat	88.186	88.1599	88.1731	0.0119	0.099	0.01	0.01	1E-005	1.0000	1.0000	1.0000	4E-008
	Living room	87.0502	87.0262	87.0379	0.0096	0.0114	0.0113	0.0113	1E-005	1.0000	1.0000	1.0000	5E-008
	Breast	86.164	86.1394	86.1539	1.00E-05	0.0126	0.0125	0.0125	4.00E-05	1.0000	1.0000	1.0000	4E-008
	X-ray	89.3097	89.2968	89.3058	0.0052	0.0087	0.0087	0.0087	5E-006	1.0000	1.0000	1.0000	1E-008

enhancement using SMS algorithm, in which PSNR based objective approach is successful in achieving the target. Form the obtained results it may be concluded that PSNR based objective approach is better than parameterized objective approach and multi objective approach. The latter part is looked for SMS algorithm performance and efficiency in the view of gray level image enhancement. The proposed SMS algorithm has been tested on a set of input standard images and proved to be better than other existing algorithms. And the execution time for SMS algorithm is relatively less than CS, ABC, DE and PSO algorithms. All quantitative and qualitative results have proved efficiency of the proposed algorithm for gray level image enhancement. Hence, it can be concluded that for gray level image enhancement SMS algorithm based on PSNR as an objective approach outperforms the others.

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