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Gray level image enhancement using chaotic inertia weighted Particle Swarm Optimization Algorithm

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Abstract

In an image processing system, Image enhancement plays a crucial role. Improvement of image quality by maximizing the information content in the given input image is the main aim of the image enhancement. Adaptive Histogram Equalization and Histogram Equalization are most popular non-heuristic or classical techniques for image enhancement by preserving main features of the input image. These techniques failed in achieving good quality enhancement. Optimization 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 formulated during optimization process. The formulation of objective function plays an important role in optimization problem. This paper presents an efficient objective approach for gray level image enhancement using chaotic inertia weighted Particle swarm optimization algorithm. The proposed algorithm have been tested on standard test gray level images. The proposed algorithm is successful in searching optimal parameters.

Keywords: Image enhancement, Chaotic Inertia weighted PSO algorithm, Image quality evaluation, Peak signal-to-Noise ratio, Root Mean Square Error

I INTRODUCTION

Image processing has many applications in every- day life tasks, i.e. medicine, transportation and industrial etc. and is a wide and active area of research in computing. Image processing techniques are one which can be treated as transforming one image to another image to improve the perception or interpretability of information for human viewers. For image enhancement a Genetic Algorithm was proposed in [1] through contrast enhancement using a multi-objective function consisting 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. Some image quality measures have been proposed recently and used for grey-level enhancement. Contrast enhancement of digital gray level images by preserving the mean image intensity using PSO has been proposed in [2]. 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 in [3] presents, Differential Evolution as a searching tool for global optimal parameters to enhance the contrast and details in a gray scale image. Parameterized intensity transformation function is used to perform Contrast enhancement of an image by gray level modification which is considered as an objective function. Hybrid intelligent algorithm was proposed [4] 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. A parameterized transformation function is used, which uses global and local information of the image. 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. Author [5] presented a new approach for contrast enhancement of color images. A new objective approaches was introduced by the authors [6] using SMS algorithm by combining the number of edge pixels, the intensities of these pixels and the entropy of the whole image. Authors in [7] introduced differential evolution for gray level image enhancement.

It is observed from the literature study that 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. The objective function contains two or three performance measures which return a value during evaluationof objective function. The aim of the optimization is to maximize the objective function that should produce an enhanced image. Hence, all performance measures are improved during the optimization process. After image enhancement quantitative evaluation has conducted with the help of image quality metrics such as Peak signal-to-Noise ratio, RMSE and MSSIM. High Peak signal-to-Noise ratio 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 Peak signal-to-Noise ratio as one of the objectives in the objective function.

In this paper, an attempt has been presented for gray level image enhancement based on global intensity transformation function using Chaotic Inertia weighted PSO algorithm (CIPSO), in which objective functions will search for the optimal set of gray levels. CIPSO algorithm is the novel optimization technique which can be simply understood and easy 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 CIPSO algorithm considering number 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 CIPSO algorithms 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 like butterfly, rock, Zelda and camera man which offered excellent results. In order to validate the outcomes, quantitative, detailed qualitative and statistical analyses have also been presented.

II IMAGE ENHANCEMENT

The conversion of the input image into the better quality output image is the main aim of the image enhancement . Without losing original properties of the input image, the quality can be improved by various techniques for better visual judgement and machine understanding. Image enhancement approaches are basically classified into: 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. Linear contrast stretch and histogram equalization are most popular among above. The original value of each and every pixel is replaced by its neighborhood pixel value in spatial operations. 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. Root filtering, Linear filtering technique and homomorphic filtering technique falls under transform operations based on inverse transformation of the transformed image. Gray scale image is artificially colored using a suitable color map in pseudo coloring methods. Due to non-unique features of the color maps, numbers of trails are 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 techniques [8]. Traditional local enhancement transformation function is given below in Eq. (1).

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

Where, $m(x, y)$ and $\sigma(x, y)$ are the gray level mean and standard deviation computed in a neighbourhood centred 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 [9][10].

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).

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

Where, $b \neq 0$ allows for zero standard deviation in the neighbourhood, $c \neq 0$ 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 [6]:

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

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

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

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

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

III Formulation of objective function

In order to evaluate the quality of output image without human intervention, we require an objective function that compares important image performance measures such as the number of edge pixels, entropy of the whole image and the intensity of the edge pixels [8]. Some authors [11] 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[12]. Hence, PSNR is considered as one of the objectives in the objective function.

$$OF_1 = F(I_e) = \log(\log(E(I_S))) \times \frac{n_{edgels(I_S)}}{M\times N} \times H(I_e) \qquad (6)$$

$$OF_2 = PSNRI(I_e). \qquad (7)$$

- The objective function that denotes the quality of the output image with transformation function Equation (2) *is F*

(Ie).

- The sum of edge pixel intensities of the output image which can be calculated by Sobel edge detector is $E(Is)$
- The number of edge pixels of the resulting output image is *nedgels*.
- The entropy value is given by $H(Ie)$.
- 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 CIPSO 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, two scenarios have been tested for image enhancement problem using CIPSO algorithm in order to assess the importance of objective function. The two cases are as follows:

Case 1 Single objective i.e., $OF1$

Case 2 Single objective i.e., $OF2$

IV Particle swarm optimization algorithm

The Particle swarm optimization is based on the simulation of social and behavioral patterns of organized groups. The .method is based on the same principles on which the birds in a flock and fishes in a shoal behave remarkably in sync moving in one direction or another as a one unit. The authors of this method are J. Kennedy and R. Eberhart, who proposed the initial idea of particle swarm optimization in 1995[13]. In the particle swarm optimization particles play the role of agents and are distributed in the parameter space of optimization problem. The particles move in parameter space and change their direction and speed of motion based on certain rules. At each iteration the value of target function is calculated according to the current particle position. Also each particle knows the position of best particle among its neighbouring and the information about its own best value on previous iterations. According to this information the rule for changing particle position and speed in the parameter space is determined. This algorithm is easy to implement with basic mathematical and logical operations. It has less parameter adjustment unlike other algorithms. The insertion of several inertia weight strategies without disturbing basic update equation is possible[14].

Let a swarm have *'n'* number of particles in a d-dimensional search space, the position of i^{th} particle at the t^{th} iteration can be expressed as:

$$x_i^t = (x_{i1}^t, x_{i2}^t, \ldots, x_{id}^t)$$

and the best previous position(pbest) of the i^{th} particle can be expressed as:

$$pbest_i^t = (pbest_{i1}^t, pbest_{i2}^t, \ldots, pbest_{id}^t)$$

Calculating the objective function of each particle and after comparison the pbest of the current iteration is to be recorded:

$$pbest_i^{t+1} = \begin{cases} pbest_i^t & if f_i^{t+1} \geq f_i^t \\ x_i^{t+1} & if f_i^{t+1} \leq f_i^t \end{cases}$$

The best position among all the particles (gbest) can be expressed as:

$$gbest_i^t = (gbest_{i1}^t, gbest_{i2}^t, \ldots, gbest_{id}^t)$$

Calculation of global best i.e the objective function associated with pbest among n number of particles is compared with previous iteration and the minimum among all is recorded as the current overall gbest

$$gbest_i^{t+1} = \begin{cases} gbest_i^t \; if f_i^{t+1} \geq f_i^t \\ pbest_i^{t+1} if f_i^{t+1} \leq f_i^t \end{cases}$$

The velocity of the i^{th} particle in search space can be expressed as:

$$v_i^t = (v_{i1}^t, v_{i2}^t, \ldots, v_{id}^t) \tag{13}$$

Each particle changes its position in search space according to its current velocity as:

$$x_{id}^{t+1} = (x_{id}^t + v_{id}^{t+1}) \tag{14}$$

where x_{id}^t is current position of particle i at iteration t.

The velocity of the i^{th} particle in the original PSO algorithm can be expressed as:

$$v_{id}^{t+1} = v_{id}^t + c_1 rand_1(pbest_{id} - x_{id}^t) + c_2 rand_2(gbest_d - x_{id}^t) \tag{15}$$

Where *'t'* represents index of the iteration C1, C2 are the acceleration constants usually in the range [1, 2], while rand1 and rand2 are the random numbers in the range [0,1] and v_{id}^t is velocity of particle i at the iteration t.

The equation (16) is the basic velocity update equation with no inertia weight in it. Some improvements are to be made to the original PSO to improve capability of PSO. Several inertia weight strategies are proposed in this thesis for the PSO.

Chaotic Inertia Weighted PSO

Chaos is a phenomenon of non-linear dynamics. The chaotic moment has regularity, randomness and ergordic nature. Owing to these characteristics chaos becomes impellent optimization means. The fundamental idea of chaotic inertia weight is chaotic mapping to fix inertia weight using logistic mapping[15].

The expression for logistic mapping is given by

$$z = \mu * z(1 - z)$$

When 3.57<μ<4 chaotic phenomenon, by taking μ=4, the chaotic result will be in interval [0, 1]. 'z' is an unknown number in the range [0,1] The chaotic inertia weight in terms of 'z' can be given as:

(8)

$$w_c = \frac{0.5(maxit - iter)}{maxit + 0.4z}$$

The steps of chaotic inertia weight in PSO is as follows:

(9)

Step 1: Selection of a random number 'z'in interval [0, 1]

Step 2: Make logistic mapping using equation (5.20)

Step 3: Determination of the chaotic inertia weight by equation (5.21) Step 4: Include equation (5.21) in basic velocity equation (5.14) Therefore the chaotic inertia weighted velocity update equation is:

$$v_{id}^{t+1} = [w_c * v_{id}^t + c_1 rand_1(pbest_{id} - x_{id}^t) + c_2 rand_2(gbest_{id} - x_{id}^t)] \quad (18)$$

Where 'w_C' is the chaotic inertia weight,'t' represents index of the iteration C_1, C_2 are the acceleration constants usually in the range [1, 2], while $rand_1$ and $rand_2$ are the random numbers in the range [0,1] and v_{id}^t is velocity of particle i at the iteration t.

The equation (19) describe the velocity update equation with chaotic inertia weight, this equation calculates new velocity for each particle based on the previous velocity and equation updates position according to current velocity of the particle.

Parameter setting

The 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]. The problem specific implementation flow chart for CIPSO algorithm is shown in figure.1

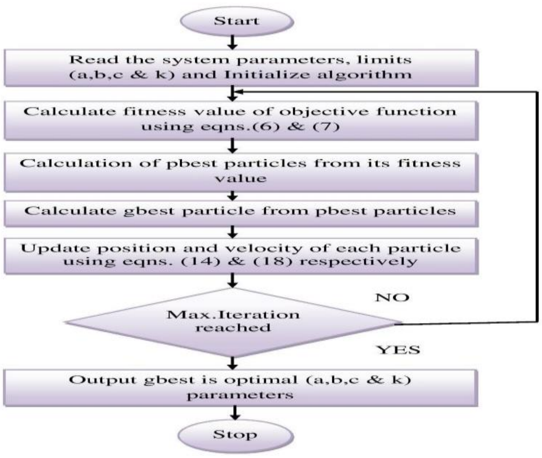


Fig. 1: Implementation flow chart for CIPSO algorithm

Implementation results and discussions

The performance of the image is analyzed with CIPSO. After rigorous testing of performance with range of algorithm parameters, the best values are choosen, which are provided in Table1shown below. The range of tuning parameters are given above.The CIPSO algorithm progressively maximizes the objective functions given in equations over the iterations while searching the optimal set of a,b,c & sk parameters. The program stops if the maximum number of iterations reached. The maximum number of iterations given for CIPSO algorithm is 500 and the population size given is 50. The entire optimization procedure is carried out in Matlab-R2021a, script under Windows 7, on core i3 processor system. Totally, 20 trials have been performed on each objective function to confirm the convergence.

Table 1: Tuned algorithm parameters for CIPSO algorithm

Algorithm		**Description**	**Value**
PSO	Pop	Size of population	50
	N	Dimension of the problem	4
	Maxit	Maximum number of iterations	500
	C1	Cognitive parameter	1
	C2	Cognitive parameter	2

Gray scale image enhancement with Case 1 and Case 2 using CIPSO

Gray level image enhancement is evaluated based on two scenarios using CIPSO algorithm and the obtained results have been compared qualitatively in Fig. 2, and numerically in Table 2. It can be seen in Fig. 2 shows from left to right, the input image and the results obtained after the optimization process in each case 1 and case 2.

It is clear from the Fig. 2 that these two scenarios have successfully enhanced the input images. There are so many metrics developed to analyse the quality of the enhanced images. Six metrics basically used for the statistical comparison of results are: the fitness value, number of edge pixels, entropy, PSNR, RMSE and Modified Structural Similarity Index Measure. Table 2 provides comparison of the two cases for all six metrics for the case of gray level Butterfly, Rock, Zelda and Cameraman images and the results obtained are best values obtained in 20 runs for all the algorithms.

Case 1: It is observed from Tab. 2 number of edge pixels and entropy are increased. The MSSIM value is approximately unity but not exact. The convergence characteristics of CIPSO algorithm for Butterfly, Rock, Zelda and Cameraman images foe case1 are shown in Fig. 3. The PSNR values for enhanced images range from 60 to 67. RMSE value is more and convergence time is very small in this case.

Case 2: It is observed from Tab. 2 number of edge pixels and entropy are decreased. The MSSIM value is exactly unity. The convergence characteristics of CIPSO algorithm for Butterfly, Rock, Zelda and Cameraman images for case 2 are shown in Fig. 4. The PSNR values for enhanced images range from 86 to 93. RMSE value is less and convergence time is more in this case.

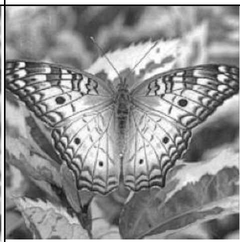
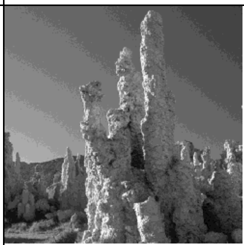
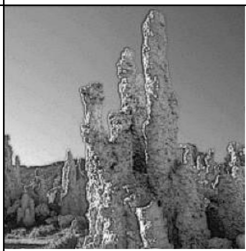
Name of the image	Input image	Output image	
		Case I	Case II
Butterfly			
Rock			
Zelda			
Cameraman			

Fig. 2: Enhancement of standard gray scale images with CIPSO algorithm using case1 & Case2

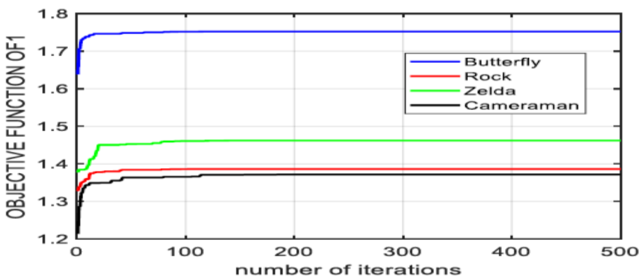


Fig. 3: Convergence characteristics of CIPSO algorithm with Case 1

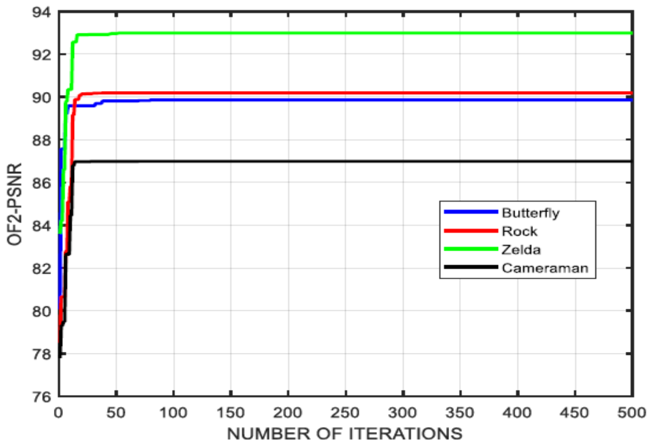


Fig. 4: Convergence characteristics of CIPSO algorithm with Case 2

Table 2: Comparison of fitness, $n$edgels, entropy, PSNR, RMSE, MSSIM and time for CIPSO algorithms for Butterfly, Rock, Zelda and Cameraman gray scale images

Image Name	**Image Information**	**Method**	**Fitness value**		**No of edge pixels**		**Entropy**		**PSNR**	**RMSE**	**MSSIM**	**Time (s)**
			Initial	Final	Initia l	Final	Initial	Final				
Butterfly	Format: Gif	Case I	1.5076	1.7528	6058	6761	7.300	7.6889	66.386	0.1227	0.995	217.38
	Dimension: 512x512	Case II	0	89.861	6058	6106	7.3003	7.3180	89.861	0.0082	1	9.90
Rock	Format: Gif	Case I	0.9507	1.3865	4250	5793	7.055	7.4760	66.835	0.1165	0.996	218.23
	Dimension: 512x512	Case II	0	90.189	4250	4187	7.0556	7.0661	90.189	0.0079	1	9.66
Zelda	Format: Gif	Case I	1.167	1.4619	4586	5027	7.2478	7.8662	60.819	0.2321	0.998	212.47
	Dimension: 512x512	Case II	0	92.989	4586	4716	7.2478	7.2586	92.989	0.0057	1	9.89
Cameraman	Format: Gif	Case I	1.0576	1.3717	3620	4454	7.0415	7.4502	65.227	0.1402	0.9904	235.96
	Dimension: 512x512	Case II	0	86.990	3620	3965	7.0415	7.1112	86.990	0.0114	1	9.49

Conclusion

This paper presents two types of objective approaches for gray level image enhancement using Chaotic Inertia Weighted particle swarm optimization algorithm. It is evident from the two cases that Case 2 is a better approach for gray level image enhancement. Because, Case 1 with CIPSO algorithm is little over enhancing the images and hence image quality is little poor. Case 2 with CIPSO algorithm is producing the best results with less convergence time. The reason behind this Case 2 is its 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 quality images. The execution time is more in Case 1 because it has to calculate the values of entropy, intensity and *nedgels of* the output image at each iteration. But in Case 2 with CIPSO algorithm, PSNR is just a quality metric which is very simple to evaluate. Hence, its convergence is quick. But the results obtained are surprisingly close agreement with Case 2 results. From the two cases, it is noticed that the case1 objective value is smaller than case2 objective value. So, case2 has more domination than case1 though equal priority has been given to both cases. The computation time is one of the major concerns in engineering optimization problems. Hence it is concluded that case 2 with CIPSO algorithm has been successful in achieving good quality images with less convergence time than case 1.

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