Image Enhancement using Accelerated Particle Swarm Optimization

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***Abstract*— This paper proposes a new variant of Particle Swarm Optimization (PSO) called Accelerated Particle Swarm Optimization (APSO) in gray level image enhancement application. Image enhancement is mainly done by maximizing the information content of the enhanced image with intensity transformation function. In this paper image enhancement is considered as an optimization problem and APSO is used to solve it. APSO is simpler to implement and it has faster convergence when compared to the PSO algorithm. Hence as an alternative to PSO based image enhancement algorithm, APSO is introduced in this present paper. In this present work a parameterized transformation function is used, which uses local and global information of the image. Here an objective criterion for measuring image enhancement is used which considers entropy and edge information of the image. We have achieved the best enhanced image according to the objective criterion by optimizing the parameters used in the transformation function with the help of APSO. The enhancement is done using three techniques: Histogram equalization (HE), Contrast stretching (LCS) and APSO. Different gray level images are taken and processed through these techniques, simulated in MATLAB. Results obtained using all these techniques are in good agreement and are compared using performance graphs and image based enhancement results. Simulation result proves that APSO based image enhancement algorithm is superior to the traditional techniques.**

Keywords*— Accelerated Particle Swarm Optimization; Contrast stretching; Histogram equalization; Image enhancement; Particle Swarm Optimization Introduction (HEADING 1)

I. INTRODUCTION

Digital Image Processing involves the modification of digital data for improving the image qualities with the aid of computer. The processing helps in maximizing clarity, sharpness and details of features of interest towards information extraction and further analysis. Image enhancement is a technique in which an image is processed to bring out specific features of an image.

It can be categories into following: enhancement by point processing, enhancement in the spatial domain, enhancement in the frequency domain and pseudo-color image processing [4]. We have concentrated on spatial domain and carried out our work. Spatial domain techniques are performed to the image plane itself and they are based on direct manipulation of pixels in an image.

The enhancement process can be denoted by

$$g(i, j) = T\,[\,f(i, j)] \qquad (1)$$

where f(i, j) is the gray value of the (i, j)th pixel of the input image and g(i, j) is the gray value of the (i, j)th pixel of the enhanced image. ***T*** is the transformation function defined over some neighborhood of (i, j) [12]-[5]. Histogram transformation is considered as one of the fundamental processes for contrast enhancement of gray level images [3] which facilitates subsequent higher level operations such as detection and identification. Linear contrast stretching employs a linear transformation that maps the gray-levels in a given image to fill the full range of values [1].

In this paper we have performed gray-level image contrast enhancement by APSO. In comparison to PSO, APSO has a first convergence and give good result. At the same time PSO takes more time to converge to better optima [8]. The resulted gray-level enhanced images by APSO are found to be better as compared to the traditional methods of image enhancement.

II. LIST OF FUNCTIONS USED

In order to implement enhancement operation, we have taken a transformation function and a fitness function. The transformation function is used to generate a new intensity value of original image and produce an enhanced image. To evaluate the quality of the enhanced image simultaneously, a fitness function is used.

A. Transformation Function

Here we have applied Local enhancement method on a pixel considering intensity distribution among its neighboring pixels. Local information is extracted from a user defined window of size. The transformation is defined as:

$$g(i,j) = Z(i,j)[\,f(i,j) - c \times m(i,j)] + m(i,j)^a \qquad (2)$$

In eq. (2) a, and c are two parameters, $m(i,j)$ is the local mean of the $(i,j)^{th}$ pixel of the input image over a $n{\times}n$ window and $Z(i,j)$ is enhancement function which takes both local and global information into account [5]. Expression for local mean and enhancement function are defined as:

$$m(i,j) = \frac{1}{n \times n} \sum_{x=1}^{n} \sum_{y=1}^{n} f(x,y) \qquad (3)$$

$$Z = \frac{k.G}{\sigma(i,j) + b} \qquad (4)$$

where k, and b are two parameters, G is the global mean and $\sigma(i,j)$ is the local standard deviation of $(i,j)^{th}$ pixel of the input image over a $n \times n$ window, which are defined as:

$$G = \frac{1}{M \times N} \sum_{i=1}^{M} \sum_{j=1}^{N} f(i,j) \tag{5}$$

$$\sigma(i,j) = \sqrt{\frac{1}{n \times n} \sum_{x=1}^{n} \sum_{y=1}^{n} (f(x,y) - m(i,j))^2} \tag{6}$$

Thus, the transformation function is

$$g(i,j) = \frac{k.G}{\sigma(i,j) + b} \left[f(i,j) - c \times m(i,j) \right] + m(i,j)^a \tag{7}$$

Using eq. (7), contrast of the image is stretched considering local mean as the center of stretch. Four parameters, *a, b, c, k* are introduced in the transformation function to produce large variations in the processed image.

B. Fitness Criterion

One of the requirements of the APSO based image enhancement is to choose a criterion that is related to a fitness function. The proposed technique needs the enhanced image to have a relatively high intensity of the edges. Consequently, the fitness criterion is proportional to the number and intensities of the pixels in the edges that might give an over-sized credit to an image that doesn't have a natural contrast.

In fact, we need a fitness criterion to evaluate the quality of the processed image with uniform intensity distribution. The fitness function shown in eq.(8), [5]-[6] is used for an enhancement criterion:

$$F(I_E) = log(log(E(I_S))) \times \frac{n\_edge\_I_S}{M \times N} \times H(I_E) \tag{8}$$

In the above mentioned equation I_E is the enhanced image of the original image produced by the transformation function defined in eq. (7). $E(I_S)$ is the sum of $M \times N$ pixel intensities of Sobel edge image I_S. $n\_edge\_I_S$ is the number of edge pixels as detected with the Sobel edge detector. The Sobel detector used here is an automatic threshold detector [13]-[14]. Lastly, $H(I_E)$ measures the entropy of the image.

III. ACCELAERTED PARTICLE SWARM OPTIMIZATION (APSO)

PSO is an optimization algorithm developed by J. Kennedy and R. C. Eberhart in 1995 [10]-[11]. This optimization algorithm is a multi-agent based search strategy [8], modeled on the social behavior of organisms such as flocking bird. PSO has generated much wider interests, and forms an exciting, ever-expanding research subject, called swarm intelligence. It is an optimization tool provides a population based search procedure in which individuals called particles change their position with time. PSO has been applied to almost every area in optimization, computational intelligence, and design/ scheduling applications. There are at least two dozens of PSO variants, and hybrid algorithms by combining PSO with other existing algorithms are also increasingly popular. In a PSO system, particles fly around in a multidimensional search space. During flight, each particle adjusts its position according to its own experience, and the experience of its neighboring particles, making use of the best position encountered by itself and its neighbors. Thus, a PSO system combines local search with global search, attempting to balance exploration and exploitation.

A. PSO Algorithm

PSO algorithm is a population-based search algorithm. It is based on the simulation of the social behavior of birds within a flock. In PSO, each single solution (individual bird) is a "particle". All of the particles have fitness values which are evaluated by the objective function to be optimized the randomness and to get a better solution, and have velocities which direct the flying of these particles. The particles fly through the problem space by following the personal and global best particles.

The swarm is initialized with a group of random particles or population and it then searches for optima by updating through iterations. In all iteration, each particle is updated by following two "best" values. The first one is the best solution of each particle achieved so far. This value is known as *pbest* solution. Another one is that, best solution experienced by any particle among all generations of the swarm. This best value is known as *gbest* solution. These two best values are responsible to drive the particles to move to new better position.

After finding the two best values, a particle updates its velocity and position with the help of the following equations [11]:

$$v_i^{t+1} = w^t . v_i^t + c_1 \times rand \times (pbest_i^t - X_i^t) + c_1 \times rand \times (gbest^t - X_i^t) \tag{9}$$

$$X_i^{t+1} = X_i^t + v_i^{t+1} \tag{10}$$

where X_i^t and v_i^t denotes the position and velocity of i^{th} particle at time instance t, w^t is inertia weight at t^{th} instant of time, c_1 and c_2 are positive acceleration constants, and *rand* is the random values generated in the range [0,1], sampled from a uniform distribution. $pbest_i$ is the best solution of i^{th} individual particle over its flight path, *gbest* is the best particle obtained over all generations so far[10]-[16]-[17]-[18].

B. APSO Algorithm

The particle swarm optimization uses both the current global best, $gbest^t$ and the individual best, $pbest_i^t$. The reason of using the individual best is to increase the diversity in the quality solutions. A simplified version which could increase the convergence of the algorithm is to use the global best only. Thus, in the accelerated particle swarm optimization (APSO) [7], the updated velocity vector is generated by a simpler formula

$$v_i^{t+1} = v_i^t + \alpha * \epsilon_n + \beta(gbest^t - X_i^t) \tag{11}$$

Where ϵ_n is from [0, 1] of d dimension, where d is the dimension of the parameter set. The update position is given by

$$X_i^{t+1} = X_i^t + v_i^{t+1} \quad (12)$$

In order to increase the convergence criteria further, we update the position as

$$X_i^{t+1} = (1-\beta)X_i^t + \beta(gbest^t) + \alpha * \epsilon_n \quad (13)$$

Typically, α = 0.1~0 .5 and β= 0.2 ~0 .7. A further improvement is done by reducing randomness in every iteration. $\alpha = 0.7^t$, where t ∈ [0, max_iteration].

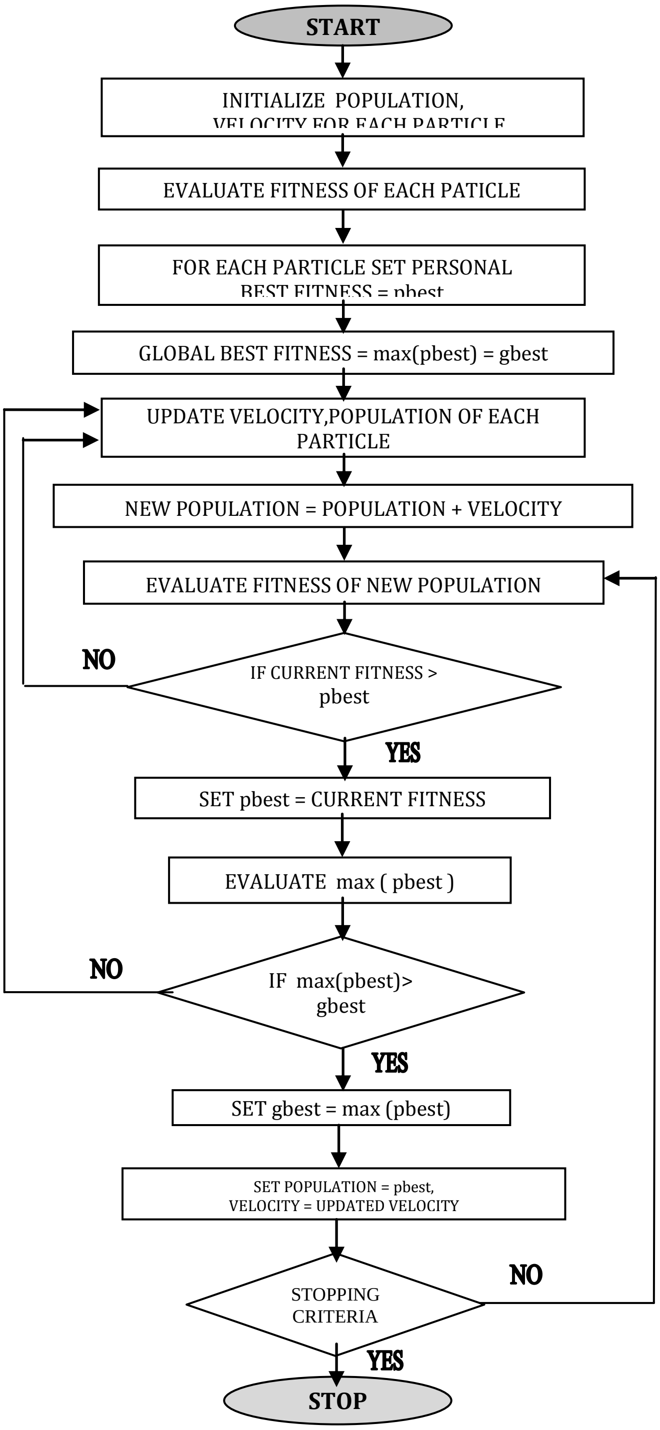


Fig. 1 Flow Chart for Optimization

IV. PROPOSED METHODOLOGY

The original image is read by executing the algorithm. The local mean, global mean and standard deviation are calculated by the eq.(3), eq.(5) and eq.(5) in order to produce an enhanced image, that is described in eq.(7), which holds both global and local information of the input image. The function containing four parameters *a, b, c,* and *k* are used to produce different result. These four parameters have their defined range which is mentioned in the parameter setting section.

Now our aim is to find the best set of values for these four parameters which can produce the optimal result and to perform this work APSO has been used. *P* number of particles are initialized, each with four parameters *a, b, c,* and *k* by the random values within their range and corresponding random velocities. It means position vector of each particle has four components *a, b, c,* and *k*, using these parameter values, each particle generates an enhanced image. Quality of the enhanced image is then calculated by the fitness function defined in eq. (8). Fitness values of all the enhanced images generated by all the particles are calculated. From these fitness values *pbest* and *gbest* are found. In APSO, *pbest* and *gbest* are highly responsible to drive each particle (solution) to the direction of best location using the eq. (11), eq. (12) and eq.(13).

In each step (iteration) groups of P number of new particles are generated. From every generation *pbest* and *gbest* are found according to their fitness values. With the help of these best values, component wise new velocity of each particle is calculated to get the new solution. In this way new positions of particles are created for generations. When the process is completed the enhanced image is created by the particle, as it provides the maximum fitness value and the image is displayed as the final result. The detail flow chart is given in figure 1.

A. *Proposed Algorithm*

***Algorithm for** APSO based image enhancement*

*Initialize population size (**P**), max iteration, dimension (**d**), window size (**n**).*
Read the image. Convert it into gray image.
Calculate Mean eq.(3), Global Mean eq.(5),
Standard Deviation. eq.(6)
for** each particle i=1 to P **do
  Initialize parameters a,b,c and k (randomly within their range) and corresponding random velocities.
end for
Generate enhanced image using eq. (7)
Calculate fitness functional value using eq. (8)
//Set pbest=pop and pbest_value=fitness as the personal best
//solution of i^{th} particle achieved so far among.
//gbest_value=max(fitness) and gbest=pop_i i.e the solution of
// i^{th} particle having maximum fitness.

While** (t < maximum iteration) **do
for** each particle i=1 to P **do
  $\alpha=0.7^t$

β = [0.2, 0.7]
$\epsilon = randn(1, d)$
Update velocity using eq. (11)
Update population using eq. (12) and eq.(13)
Calculate fitness using eq. (8)
If $F((I_e)_i) > F(pbest_i)$ ***then***
$pbest_i=pop_i$
$pbest\_value_i= F((Ie)_i)$
// pop_i is the i^{th} particle
end if
//set gbest as the global best solution achieved
//so far among all generation.
If $F((I_e)_i) > F(gbest)$ ***then***
$gbest=pop_i$
$gbeat\_value = new\_max\_fitness$
end if
end for
end while

B. Parameter setting

The result of APSO algorithm is parameter dependent. Fine tuning of the parameters can provide better result than other optimization algorithms. Parameters α, and β are positive acceleration constants or learning parameters, given α = 0.1~0.5 and β= 0.2 ~0.7. Here, we have taken α = 0.7^t.. In this study there are four problem specific parameters, *a*, *b*, *c*, and *k*. The ranges of these parameters are the same as $a \in [0.8,1.5]$, $b \in [1, 22]$, $c \in [0.01, 0.6]$, and $k \in [0.5, 2]$. The ranges of velocities for each parameter are velocity maximum = [0.1 2 0.1 0.1] and velocity minimum = [-0.1 -2 -0.1 -0.1].

V. RESULTS AND DISCUSSIONS

The proposed method is tested on many gray-level images. Here we put results of only five images due to space limitation. Results of the proposed method is compared with three other methods, namely (i) linear contrast stretching (LCS), (ii) histogram equalization (HE). All the algorithms are evaluated using the same evaluation function, and the results are put in Table-2. The description of the input images and details about size of the image, Edge information (E), Entropy (H) and Fitness (F) are given in the Table 1.

TABLE 1

DETAILS ABOUT THE ORIGINAL IMAGES

Image	Size	E	H	F
Keyboard	378×384	2165	6.0266	0.0547
Bean	280×280	1151	5.2823	0.0451
Bus	182×290	2206	6.5466	0.1434
Toy	220×317	2165	7.6170	0.1237
Outdoor	224×300	3201	6.4513	0.1674

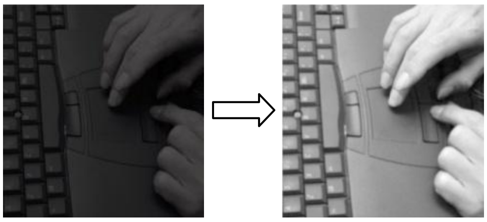
In experimental result we tested the algorithm for varieties of test image which include some indoor to outdoor scene image for better performance.

A. Objective Evaluation:

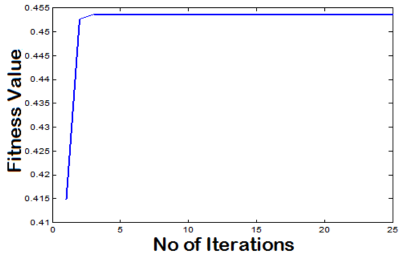
The objective criterion taken into consideration is the quality of the image, entropy, edge information of the enhanced image. In APSO we can get a higher number of edge information, optimum fitness and a good entropy value

TABLE 2
ENTROPY, EDGE INFORMATION AND FITNESS OF THE ENHANCED IMAGES

Image	Criteria	HE	LCS	APSO
Keyboard	Entropy	5.6147	5.3453	0.8649
	Edge Info.	24933	5947	103480
	Fitness	0.6459	0.1364	0.4624
Bean	Entropy	5.2044	3.6742	0.7739
	Edge Info.	22589	1173	60552
	Fitness	0.9826	0.0306	0.4544
Bus	Entropy	5.9451	5.7653	0.2998
	Edge Info.	2382	3040	49972
	Fitness	0.1418	0.1800	0.2169
Toy	Entropy	5.9720	4.5753	0.6919
	Edge Info.	2615	2786	56804
	Fitness	0.1195	0.0982	0.4413
Outdoor	Entropy	5.6222	5.0861	0.7787
	Edge Info.	3783	3355	51717
	Fitness	0.1752	0.1390	0.4551



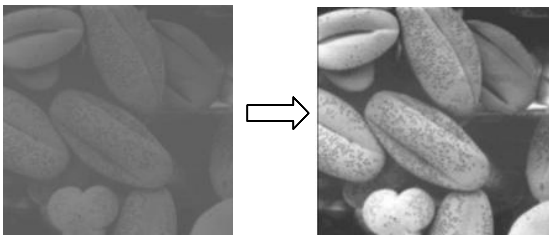
(a) (b)



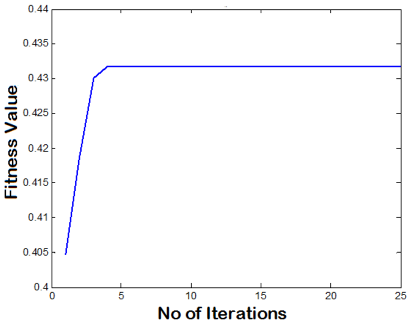
(c)

Fig. 2 (a) Original Image (b) APSO output image (c) Performance Plot

In average we have tested by taking 50 populations with around 50 iterations. Some of the results have shown below which shows that in average around it takes 15 to 20 iterations to converge in to the optimal parameters. The performance plot shows the relationship between numbers of iteration to the corresponding fitness values.

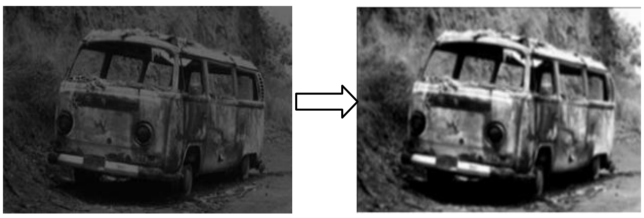


(a) (b)

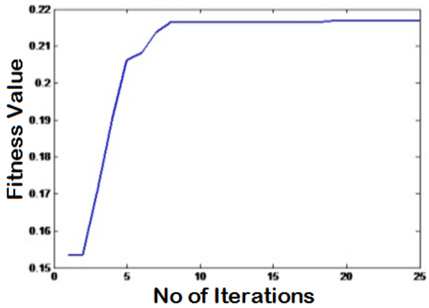


(c)

Fig. 3 (a) Original Image (b) APSO output image (c) Performance Plot

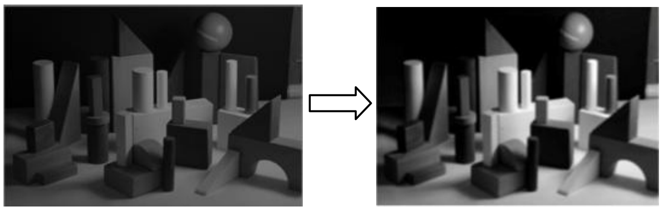


(a) (b)

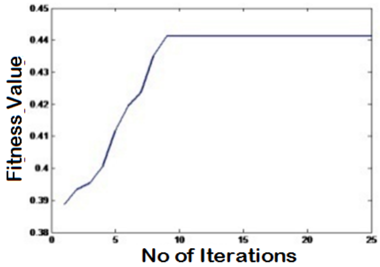


(c)

Fig. 4 (a) Original Image (b) APSO output image (c) Performance Plot



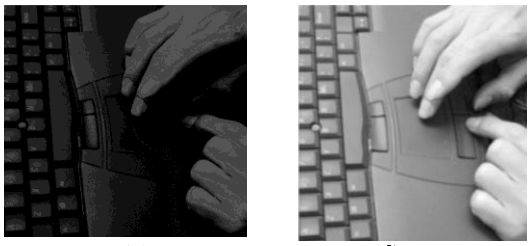
(a) (b)



(c)

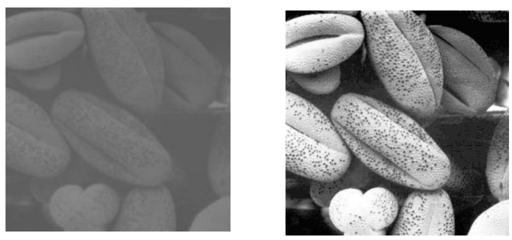
Fig. 5 (a) Original Image (b) APSO output image (c) Performance Plot

(a) (b)

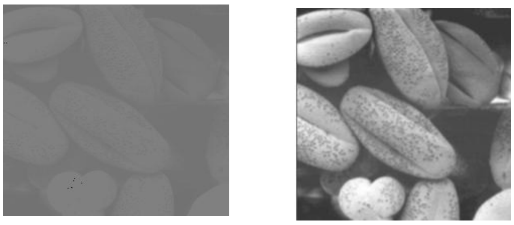


(c) (d)

Fig. 6 Resulted Outputs (keyboard)

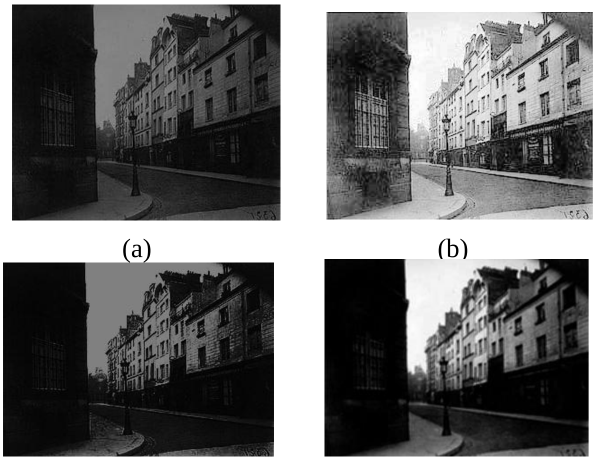


(a) (b)



(c) (d)

Fig. 7 Resulted Outputs (bean)



(a) (b)

(c) (d)

Fig. 8 Resulted Outputs (outdoor)

The output results showed in figure 6, 7 and 8. Here we have compared the output result with histogram equalization and linear contrast stretching with APSO based proposed method. Here the figures (a) are the original image, (b) are histogram equalized image, (c) are contrast stretching image and (d) are APSO output.

VI. CONCLUSION

In this paper we have propose an APSO based automatic image enhancement technique for gray level images. Results of the proposed technique are compared with some other image enhancement techniques, like linear contrast stretching and histogram equalization based image enhancement. We found better result compared to other techniques mentioned above. In APSO, the most important property is that, it can produce better result with proper tuning of parameters. But in case of contrast stretching and histogram equalization, they always produce only one enhanced image for a particular input image.

In future we have planned to compared this APSO with other optimization methods like ACO, Water cycle algorithm etc.

REFERENCES

[1]. Raja Rajeswari. V, N.Ramesh, "Contrast Stretching enhancement Techniques For Acute Leukemia Images," International Journal Pulications of Problems and Application in Engineering Research Paper, vol. 4, Special Issue01, 2013.

[2]. Mr. Salem Saleh Al-amri, Dr.N.V.Kalyankar, Dr.S.D.Khamitkar, "Linear and Non-linear Contrast Enhancement Image," International Journal of Computer Science and Network Security, Vol.10 No.2, February 2010.

[3]. Raju. A, Dwarakish. G. S and D. Venkat Reddy, "A Comparative Analysis of Histogram Equalization based Techniques for Contrast Enhancement and Brightness Preserving ," International Journal of Signal Processing, Image Processing and Pattern Recognition Vol.6, No.5 (2013), pp.353-366.

[4]. Vijay A. Kotkar, Sanjay S. Gharde, "Review of Various Image Contrast Enhancement Techniques," International Journal of Innovative Research in Science, Engineering and Technology Vol. 2, Issue 7, July 2013.

[5]. Apurba Gorai, Ashish Ghosh, "Gray-level Image Enhancement By Particle Swarm Optimization," 2009 World Congress on Nature & Biologically Inspired Computing (NaBIC 2009).

[6]. Malik Braik, Alaa Sheta and Aladdin Ayesh, "Image Enhancement Using Particle Swarm Optimization," Proceedings of the World Congress on Engineering 2007 Vol I, WCE 2007, July 2 - 4, 2007, London, U.K.

[7]. Xin-She Yang, Suash Deb and Simon Fong, "Accelerated Particle Swarm Optimization and Support Vector Machine for Business Optimization and Applications", Communications in Computer and Information Science, Vol. 136, Springer, pp. 53-66 (2011).

[8]. Yamille del Valle, Ganesh Kumar Venayagamoorthy, Salman Mohagheghi, Jean-Carlos Hernandez, Ronald G. Harley, "Particle Swarm Optimization: Basic Concepts, Variants and Applications in Power Systems," IEEE Transactions on Evolutionary Computation, Vol. 12, No.2, April 2008.

[9]. Fahd Mohsen, Mohiy Hadhoud, Kamel Mostafa and Khalid Amin, "A New Image Segmentation Method Based on Particle Swarm Optimization," The International Arab Journal of Information Technology, Vol. 9, No.5, September 2012.

[10]. Xin-She Yang, "Nature-Inspired Metaheuristic Algorithms Second Edition," Luniver Press, University of Cambridge, U.K., 2010.

[11]. Manas Yetirajam, Pradeep Kumar Jena, "Enhanced Color Image Segmentation of Foreground Region using Particle Swarm Optimization," International Journal of Computer Applications (0975 – 8887) Volume 57– No.8, November 2012.

[12]. Rafael C. Gonzalez, and Richard E. Woods, "Digital Image Processing", 2nd edition, Prentice Hall, 2002.

[13]. Pooja Sharma, Gurpreet Singh, Amandeep Kaur, " Different Techniques Of Edge Detection In Digital Image Processing," International Journal of Engineering Research and Applications (IJERA), Vol. 3, Issue 3, May-Jun 2013, pp.458-461.

[14]. M. Kalpana, G. Kishorebabu, K.Sujatha, "Extraction of Edge Detection Using Digital Image Processing Techniques," International Journal Of Computational Engineering Research (ijceronline.com) Vol. 2 Issue.5, September 2012.

[15]. Serene Bhaskaran, Ruchi Varma, Dr.Jayanta Ghosh, " A Comparative study of GA, PSO and APSO : Feed point optimization of a patch antenna" International Journal of Scientific and Research Publications, Volume 3, Issue 5, May 2013

[16]. Wei Zhang, Di Ma, Jin-jun Wei, Hai-feng Liang, "A parameter selection strategy for particle swarm optimization based on particle positions," Expert Systems with Applications 41, 2014.

[17]. Chaoli Sun , Jianchao Zeng, Jengshyang Pan, Songdong Xue, Yaochu Jin, "A new fitness estimation strategy for particle swarm optimization," Information Sciences 221 (2013).

[18]. Qinghai Bai, "Analysis of Particle Swarm Optimization Algorithm," Computer and Information Science, Vol.3, No.1, February 2010.

[19]. S. Talatahari, E. Khalili and S.M. Alavizadeh, "Accelerated Particle Swarm for Optimum Design of Frame Structures," Hindawi Publishing Corporation Mathematical Problems in Engineering Volume 2013.

[20]. Amanpreet Kaur, M.D. Singh, "An Overview of PSO- Based Approaches in Image Segmentation," International Journal of Engineering and Technology Volume 2 No. 8, August, 2012.

[21]. Michala Jakubcová, Petr Máca and Pavel Pech, "A Comparison of Selected Modifications of the Particle Swarm Optimization Algorithm," Hindawi Publishing Corporation Journal of Applied Mathematics Volume 2014.

[22]. D. P. Rini, S.M.Shamsuddin, S.S.Yuhaniz, "Paricle Swarm Opimization : Technique, System and Challenges," International Journal of Computer Applications (0975-8887), Volume 14 – No.1, January 2011