Gray-level Image Enhancement By Particle Swarm Optimization

Conference Paper · January 2010

DOI: 10.1109/NABIC.2009.5393603 · Source: IEEE Xplore

2 authors:

Apurba Gorai
Institute for Development & Research in Banking Technology

Ashish Ghosh
Indian Statistical Institute

Gray-level Image Enhancement By Particle Swarm Optimization

Apurba Gorai
Machine Intelligence Unit.
Indian Statistical Institute,
Kolkata-700108, India
apurbagorai@gmail.com

Ashish Ghosh
Center for Soft Computing Research.
Indian Statistical Institute,
Kolkata-700108, India
ash@isical.ac.in

***Abstract*—Particle Swarm Optimization (PSO) algorithms represent a new approach for optimization. In this paper image enhancement is considered as an optimization problem and PSO is used to solve it. Image enhancement is mainly done by maximizing the information content of the enhanced image with intensity transformation function. In the 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 tried to achieve the best enhanced image according to the objective criterion by optimizing the parameters used in the transformation function with the help of PSO. Results are compared with other enhancement techniques, viz. histogram equalization, contrast stretching and genetic algorithm based image enhancement.**

Keywords: Particle swarm optimization, image enhancement, genetic algorithms, histogram equalization.

I. Introduction

Image enhancement, one of the important image processing techniques, can be treated as transforming one image to another to improve the interpretability or perception of information for human viewers, or to provide better input for other automated image processing techniques. According to [16], image enhancement techniques can be divided into four main categories: point operation, spatial operation, transformation, and pseudocoloring. The work done in this paper is based on spatial operation.

Histogram transformation is considered as one of the fundamental processes for contrast enhancement of gray level images [15], 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. Pseudocoloring is an enhancement technique that artificially ”color” the grayscale image based on a color mapping, with the extensive interactive trials required to determine an acceptable mapping [16]. Color images can be enhanced by separating the image into the chromaticity and intensity components [17]. Majority of the image enhancement work usually manipulates the image histogram by some transformation function to obtain the required contrast enhancement. Consequently, this operation also delivers the maximum information contained in the image. Evolutionary algorithms have been previously used to perform image enhancement [1] - [5]. In [1], the authors applied a global contrast enhancement technique using genetic programming (GP) [11] to adapt the color map in the image so as to fit the demands of the human interpreter. In [2] a real coded GA is used with a subjective evaluation criterion to globally adapt the gray-level intensity transformation in the image. Combination of different transformation functions with different parameters are used to produce the enhanced image by GA in [5].

In this paper we have performed gray-level image contrast enhancement by PSO. In comparison to GA, PSO does not require selection, crossover and mutation operations (for details of PSO refer to [8]). At the same time PSO takes less time to converge to a better optima. The resulted gray-level enhanced images by PSO are found to be better compared with other automatic image contrast enhancement techniques. Both objective and subjective evaluations are performed on the resulted image which says about the goodness of PSO.

The rest of the paper is organized as follows: In Section II, functions used for the proposed work (transformation and evaluation function) are described. In Section III, theory of PSO (basic PSO, proposed methodology, parameter setting) is discussed. In Section IV, results and discussion are put, and finally in Section V, conclusion of the work are made.

II. Functions used

For image enhancement task, a transformation function is required which will take the intensity value of each pixel from the input image and generate a new intensity value for the corresponding pixel to produce the enhanced image. To evaluate the quality of the enhanced image automatically, an evaluation function is needed which will tell us about the quality of the enhanced image. In this section we describe the function used for the proposed work.

A. *Transformation function*

Image enhancement done on spatial domain uses a transform function which generates a new intensity value for each pixel of the M × N original image to generate the enhanced image, where M denotes the number of columns and N denotes the number of rows. The enhancement process can be denoted by

$$g(i,j) = T[f(i,j)]. \tag{1}$$

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. Local enhancement method apply transformation on a pixel considering intensity distribution among its neighboring pixels [14]. Adaptive histogram equalization (AHE) is one such local enhancement method which gives good result on medical images [16]. However AHE is quite expensive. The method used in this paper is less time consuming and is similar to statistical scaling presented in [16]. The function used here is designed in such a way that takes both global as well as local information to produce the enhanced image. Local information is extracted from a user defined window of size $n \times n$. The transformation T is defined as:

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

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 $K(i,j)$ is enhancement function which takes both local and global information into account, Expression for local mean and enhancement function are defined as:

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

One form of the enhancement function $K(i,j)$, used in this work is

$$K(i,j) = \frac{k.D}{\sigma(i,j) + b}. \quad (4)$$

where k, and b are two parameters, D 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:

$$D = \frac{1}{M \times N} \sum_{i=0}^{M-1} \sum_{j=0}^{N-1} f(i,j). \quad (5)$$

$$\sigma(i,j) = \sqrt{\frac{1}{n \times n} \sum_{x=0}^{n} \sum_{y=0}^{n} (f(x,y) - m(i,j))^2}. \quad (6)$$

Thus the transformation function looks like:

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

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

B. Evaluation Criterion

To evaluate the quality of an enhanced image without human intervention, we need an objective function which will say all about the image quality. Many objective functions are presented in literature [6] [7] [9]. In this study the objective function is formed by combining three performance measures, namely entropy value, sum of edge intensities and number of edgels (edge pixels). It is observed that compared to the original image good contrast enhanced image has more number of edgels [16] and enhanced version should have a higher intensity of the edges [4]. But these two are not sufficient to test an enhanced image and that is why one more measure has been taken i.e. entropy value of the image. Entropy value reveals the information content in the image. If the distribution of the intensities are uniform, then we can say that histogram is equalized and the entropy of the image will be more. The objective function considered here is:

$$F(I_e) = log(log(E(I_s))) \times \frac{n\_edgels(I_s)}{M \times N} \times H(I_e). \quad (8)$$

In the above mentioned equation I_e is the enhanced image of I_o (the original image) produced by the transformation function defined in eq. (7). In the above equation the edges or edgels can be detected by many efficient edge detector algorithms such as Sobel [16], Laplacian [16], Canny [21] etc. In this study Sobel [16] is used as an automatic threshold detector [12]. After using Sobel edge operator we produce an edge image I_s on the produced enhanced image I_e as:

$$I_s(i,j) = \sqrt{\delta m_{I_e}(i,j)^2 + \delta n_{I_e}(i,j)^2}. \quad (9)$$

$\delta m_{I_e}(i,j) = g_{I_e}(i+1,j-1) + 2g_{I_e}(i+1,j) + g_{I_e}(i+1,j+1) - g_{I_e}(i-1,j-1) - 2g_{I_e}(i-1,j) - g_{I_e}(i-1,j+1)$
and
$\delta n_{I_e}(i,j) = g_{I_e}(i-1,j+1) + 2g_{I_e}(i,j+1) + g_{I_e}(i+1,j+1) - g_{I_e}(i-1,j-1) - 2g_{I_e}(i,j-1) - g_{I_e}(i+1,j-1)$.

$E(I_s)$ is the sum of $M \times N$ pixel intensities of Sobel edge image I_s. n_edgels is the number of pixels, whose intensity value is above a threshold in the Sobel edge image. Based on the histogram, entropy value is calculated on the enhanced image I_e as:

$$H(I_e) = -\sum_{i=0}^{255} e_i \quad (10)$$

where $e_i = h_i log_2(h_i)$ if $h_i \neq 0$ otherwise $e_i = 0$. And h_i is the probability of occurrence of i^{th}intensity value of I_e image.

III. Theory of PSO

PSO is an optimization algorithm proposed by J. Kennedy and R. C. Eberhart in 1995 [13]. This optimization algorithm is a multiagent based search strategy [18] [19] modeled on the social behavior of organisms such as bird flocking and fish schooling. PSO as an optimization tool, provides a population-based search procedure in which individuals called particles change their position with time. 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, as in modern GAs and memetic algorithms, 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 based on the simulation of the social behavior of birds within a flock. In PSO, each single solution is a "particle". All of the particles have fitness values which are evaluated by the objective function to be optimized, and have velocities which direct the flying of the 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 and it then searches for optima by updating through iterations. In every 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 tracked 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:

$$v_i^{t+1} = W^t.v_i^t + c_1.r_1.(pbest_i^t - X_i^t) + c_2.r_2.(gbest^t - X_i^t). \quad (11)$$

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

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 r_1 and r_2 are 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.

B. Proposed Methodology

To produce an enhanced image a transformation function defined in eq. (7) is used, which incorporates both global and local information of the input image. The function also contains four parameters namely, a, b, c, and k which are used to produce diverse result and help to find the optimal one according to the objective function. 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 PSO is 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 X has four components a, b, c, and k. Now using these parameter value, each particle generates an enhanced image. Quality of the enhanced image is calculated by an objective function defined in eq. (8) which is termed as fitness of the particle. Fitness value of all the enhanced images generated by all the particles are calculated. From these fitness values $pbest$ and $gbest$ are found. In PSO the most attractive property is that $pbest$ and $gbest$ are highly responsible to drive each particle (solution) to the direction of best location as it is reflected in the eq. (11) and eq. (12). In each step (iteration) a swarm 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 $gbest$ particle, as it provides the maximum fitness value and the image is displayed as the final result.

Algorithm 1 PSO based image enhancement

```
Create P number of d dimensional particles.
for Each Particle i = 1 to P do
    Initialize parameters a, b, c, k (randomly within their
    range) and corresponding random velocities.
end for
while (Termination condition ≠ true) do
    for each Particle i = 1 to P do
        Generate enhanced image using eq. (7).
        Calculate objective functional value using eq. (8).
        //Set pbest as the personal best solution of i^th
        // particle achieved so far.
        if F((I_e)_i) > F(pbest_i) then
            pbest_i = P_i
            // P_i is the i^th particle
        end if
        //Set g_best as the global best solution achieved
        // so far among all generation.
        if F((I_e)_i) > F(gbest)  then
            gbest = P_i
        end if
    end for
    for Each Particle i = 1 to P do
        Update the velocity using eq.(11).
        Update the position using eq.(12).
    end for
end while
```

C. Parameter setting

The result of PSO algorithm is very much parameter dependent. Fine tuning of the parameters can provide better result than other optimization algorithms. Parameter W used in eq. (11) is called the inertia weight. Maximum and minimum value for W is set to two and zero respectively, which is same for all particles. The process starts with maximum inertia value and gradually reduces it to minimum. Therefore initially inertia component is big and explore larger area in the solution space, but gradually inertia component becomes small and exploit better solutions in the solution space. Inertia value W is calculated as:

$$W^t = W_{max} - \frac{W_{max} - W_{min}}{t_{max}} \times t. \quad (13)$$

Parameters c_1, and c_2 are positive acceleration constants, given a random number in [0,2]. These parameters are fixed for each particle throughout its life. r_1 and r_2 are random numbers in [0,1] and varies for each component of the particles in every generation.

In this study there are four problem specific parameters, a, b, c, and k. The range of these parameters are the same as [14]. $a \in [0, 1.5]$, $b \in [0, 0.5]$, $c \in [0, 1]$ and $k \in [0.5, 1.5]$. We have changed the range for parameter b as that range does not produces good result. It has been observed that small value for b stretch the intensity in a large amount. So, after normalizing those intensity values between [0,255] to display the image, it becomes very discritized and the originality of the image is lost. So, we increase the range to overcome this specific problem, and the range is fixed to $[1, (D/2)]$, where D is the global mean of the original image.

IV. Results and Discussion

The proposed method is tested on many gray-level images. Here we put results of only four 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) and (iii) GA based image enhancement (GAIE). 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 $Detail\ Variance (DV)$, $Background\ Variance\ (BV)$, $fitness$ are given in the Table 1.

TABLE I
Details about the original images

Image	Size(M×N)	P/t/w	Fitness	DV	BV
Lady	256 × 256	30/20/5	0.43474	5.78243	0.02089
Hut	250 × 150	30/20/3	1.25004	14.30051	0.00796
Couple	256 × 256	30/20/5	0.40667	5.84054	0.07256
Duck	576 × 768	40/20/7	0.85790	9.26883	0.00824

P, t, and w in third column of Table-1 signify the number of particles, maximum number of generations and window size taken to extract the local information, correspondingly.

$Objective\ Evaluation$: The objective evaluation criterion considered here is the Detail Variance (DV) and Background Variance (BV) [20]. DV and BV values are calculated by computing the local variance considering the neighbors of each pixel over an $n \times n$ window ($n = 3$ is taken) of the enhanced image. The pixel is classified as a foreground when the variance is more than a threshold, otherwise it is classified as a background pixel. The averaged variance of all pixels included in the foreground class is DV, and the averaged variance of all pixels included in the background class is BV. An image is said to be efficiently enhanced if the DV value of the resulted image increases, while BV value is not changed much compared to the input image. From Table 2 it is very much clear that our proposed technique is giving better results than other techniques in most of the cases according to the $fitness$, DV, and BV values.

TABLE II
Fitness,DV and BV values of the enhanced images

Image	Meas.	LCS	HE	GAIE	PSO
Lady	Fitness	0.51088	1.12475	0.85754	1.9363
	DV	6.34578	11.1305	9.22854	11.7985
	BV	0.01725	0.00432	0.00325	0.00264
Hut	Fitness	1.25004	1.90515	1.39686	2.03482
	DV	14.3005	14.6951	7.1818	18.0417
	BV	0.00796	0.00531	0.03080	0.00645
Couple	Fitness	0.42902	1.61869	1.72281	2.38565
	DV	6.03474	14.507	17.7442	23.7313
	BV	0.07181	0.0079	0.00522	0.00532
Duck	Fitness	0.8579	1.70078	1.37262	1.89644
	DV	9.26883	13.41989	12.24874	14.74616
	BV	0.00824	0.01848	0.00186	0.00769

$Visual\ analysis\ of\ the\ enhanced\ images$: Results of four enhanced images have been displayed. If we visually analyze the images then we will see that, in the $Lady$ image the PSO based enhanced result is comparable with the result of HE only as other methods did not provide good visibility. But in HE the folds on the throat are not clearly visible in the darker region, whereas all these are visible in PSO. The statement is justified if we see the shadow portion on the throat. Similarly in Hut image the front portion of the hut is clearly visible in PSO based enhanced image only. GA also provided a clear view but the image became little blur. In most of the images LCS did not produce any enhancement as lower and upper bound of the intensity values of the input images are the same as that of the full intensity range i.e (0-255). HE provided smooth result than GA and PSO; but in PSO, design on the sofa and lower darker area of chair behind the lady were more prominent than any other results. In the $Duck$ image HE produced a good contrast result, GA also produced equivalent result with PSO, but the image was quite faded. In PSO, the detail information on the wing, ground and stone are more clearly visible than other methods. So overall we can conclude that PSO provided better results.

V. Conclusion

In this paper we have propose a PSO 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, histogram equalization and genetic algorithm based image enhancement. Most of the times it is observed that our technique is giving better result compared to other techniques mentioned above. In PSO, the most important property is that, it can produce better result with proper tuning of parameters. It is also true for GA based image enhancement. But in case of contrast stretching and histogram equalization, they always produce only one enhanced image for a particular input image.

ACKNOWLEDGMENT

Authors would like to thank the Department of Science and Technology, Government of India and University of Trento, Italy, the sponsors of the ITPAR program and the Center for Soft Computing Research, Indian Statistical Institute, Kolkata for providing computational facilities.

REFERENCES

[1] R. Poli, S. Cagnoni, "Evolution of pseudo-coloring algorithms for image enhancement," *Univ. Birmingham*, Birmingham, U.K., Tech. Rep. CSRP-97-5, 1997.

[2] C. Munteanu, V. Lazarescu, "Evolutionary contrast stretching and detail enhancement of satellite images," *In Proc. Mendel*, Berno, Czech Rep., pp. 94-99, 1999.

[3] C. Munteanu , A. Rosa, "Evolutionary image enhancement with user behavior modeling," *ACM SIGAPP Applied Computing Review*, vol. 9, no. 1, pp. 8-14, 2001.

[4] F. Saitoh, "Image contrast enhancement using genetic algorithm," *in Proc. IEEE SMC*, Tokyo, Japan, pp. 899-904, 1993.

[5] S. K. Pal, D. Bhandari, M. K. Kundu, "Genetic algorithms for optimal image enhancement," *Pattern Recognition Letter*, vol. 15, pp. 261-271, 1994.

[6] S. Jingquan, F. Mengyin, Z. Chanjian, "An image enhancement algorithm based on chaotic optimization," *Computer Engineering and Applications*, vol. 27, pp. 4-6, 2003.

[7] G. Runqiu, L. Junfeng, L. Xiaochun, "The infrared image enhancement and the correlative technique based on the parallel genetic algorithm," *XIDIAN Univ.J.*, vol. 31, pp. 6-8, 2004.

[8] A. P. Engelbrecht, *Computational Intelligence-An Introduction.*, Chichester, England: John Wiley and Sons, 2007

[9] T. Xiaodong, L. Zhong, "Compare and analysis of enhancement methods of sonar image," *Ship Electronics Eng.J.*, vol. 26, pp. 154-157, 2006.

[10] Z. Xiang, Z. Yan, "Algorithm based on local variance to enhance contrast of fog-degraded image," *Computer applications*, vol. 27, pp. 510-512, 2007.

[11] T. Bäck, D. Fogel, Z. Michalewicz "Handbook of Evolutionary Computation," *Oxford Univ. Press*, London, U.K., 1997.

[12] P. L. Rosin, "Edges:saliency measures and automatic thresholding," *in Machine Vision and Applications*,Berlin, Germany:Springer-Verlag, vol. 9, pp. 139-159, 1997.

[13] R. C. Eberhart, J. Kennedy, "A new optimizer using particle swarm theory," *Proceedings of the sixth International Symposium on Micromachine and Human Science*, Nagoya, Japan, pp. 39-43, 1995.

[14] C. Munteanu, A. Rosa, "Gray-scale enhancement as an automatic process driven by evolution," *IEEE Transaction on Systems,Man and Cybernatics-Part B:Cybernetics*, vol. 34, no. 2, pp. 1292-1298, 2004.

[15] R. C. Gonzalez, B. A. Fittes, "Gray-level transformations for interactive image enhancement," *Mechanism and Machine Theory*, vol. 12, pp. 111-122, 1977.

[16] R. C. Gonzales, R. E. Woods, *Digital Image Processing*. New York: Addison-Wesley, 1987

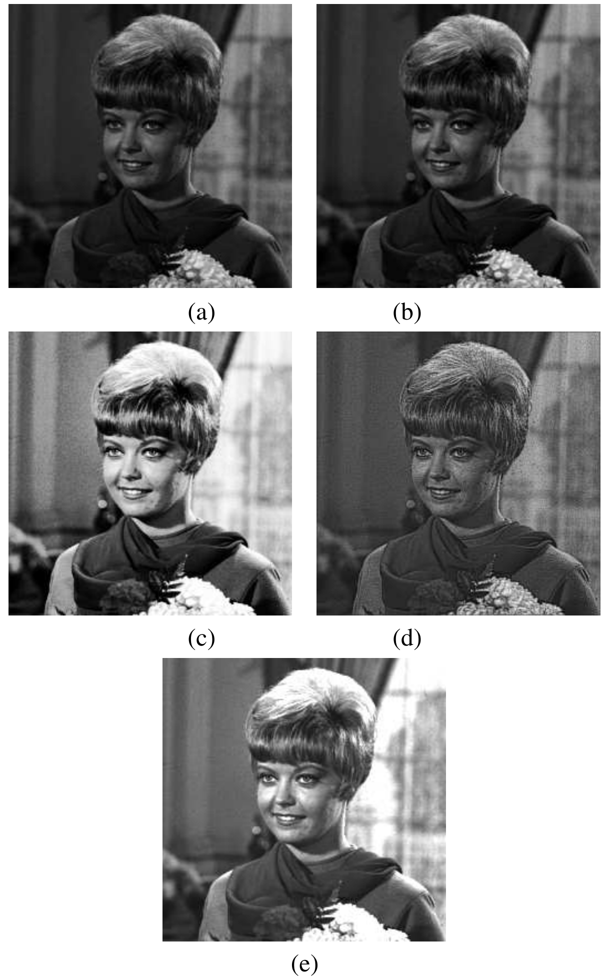
[17] B. Tang, G. Sapiro, V. Caselles, "Color image enhancement via chromaticity diffusion," *IEEE Trans. Image Processing*, vol. 10, no. 5, pp. 701-707, 2001.

[18] M. Clerc, J. Kennedy, "The particle swarm-explosion, stability, and convergence in a multidimensional complex space," *IEEE Trans. Evol. Comput.*, vol. 6, no. 1, pp. 58-73, Feb. 2002.

[19] K. E. Parsopoulos, M. N. Vrahatis, "Recent approaches to global optimization problems through particle swarm optimization," *Neural Comput.*, vol. 1, pp. 235-306, 2002.

[20] G. Ramponi, N. Strobel, S. K. Mitra, T. H. Yu, "Nonlinear Unsharp Masking Methods for Image Contrast Enhancement," *Journal of Electronic Imaging.*, vol. 5, no. 3, pp. 353-366, 1996.

[21] J. Canny, "A Computational Approach To Edge Detection," *IEEE Trans. Pattern Analysis and Machine Intelligence.*, vol. 8, pp. 679-714, 1986.



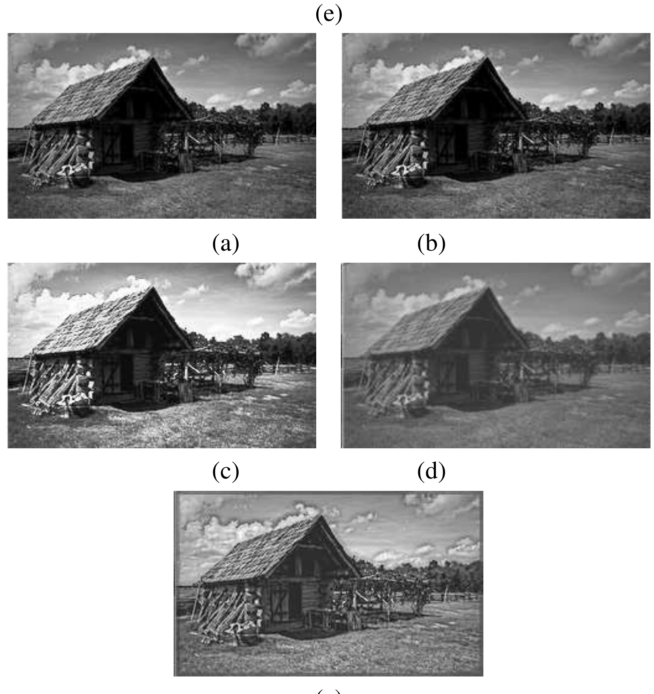


Fig. 1. Lady Image

(a) Original Image (b) Linear Contrast Stretching (c) Histogram Equalization (d) GA based Enhancement, and (e) Proposed PSO based Method

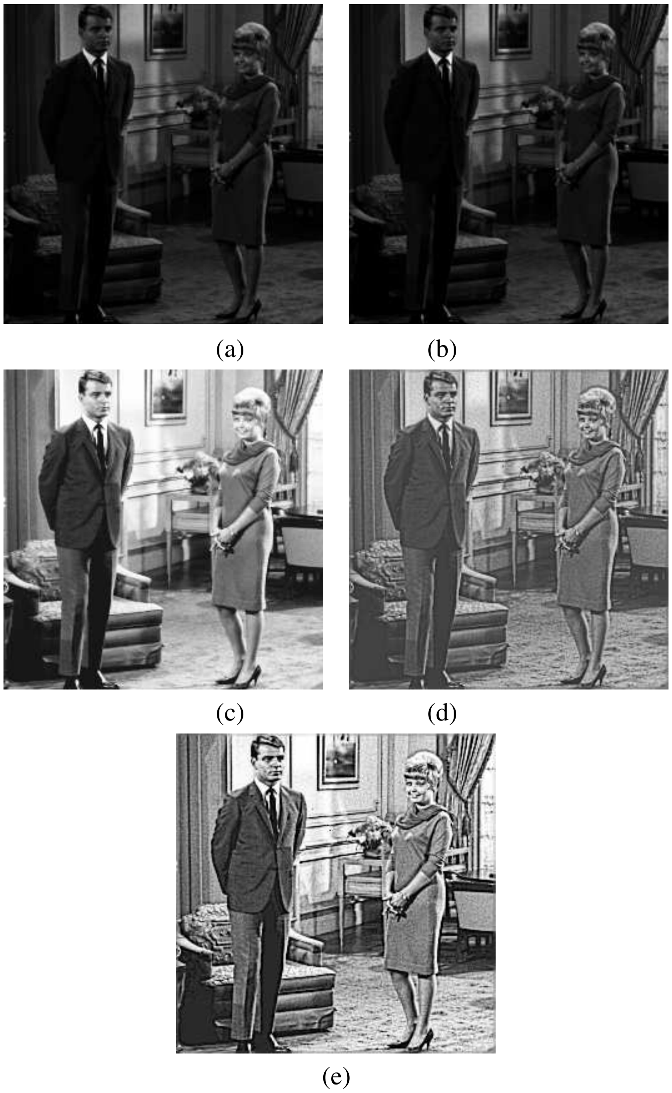


Fig. 2. Lady Image
(a) Original Image (b) Linear Contrast Stretching (c) Histogram Equalization (d) GA based Enhancement, and (e) Proposed PSO based Method

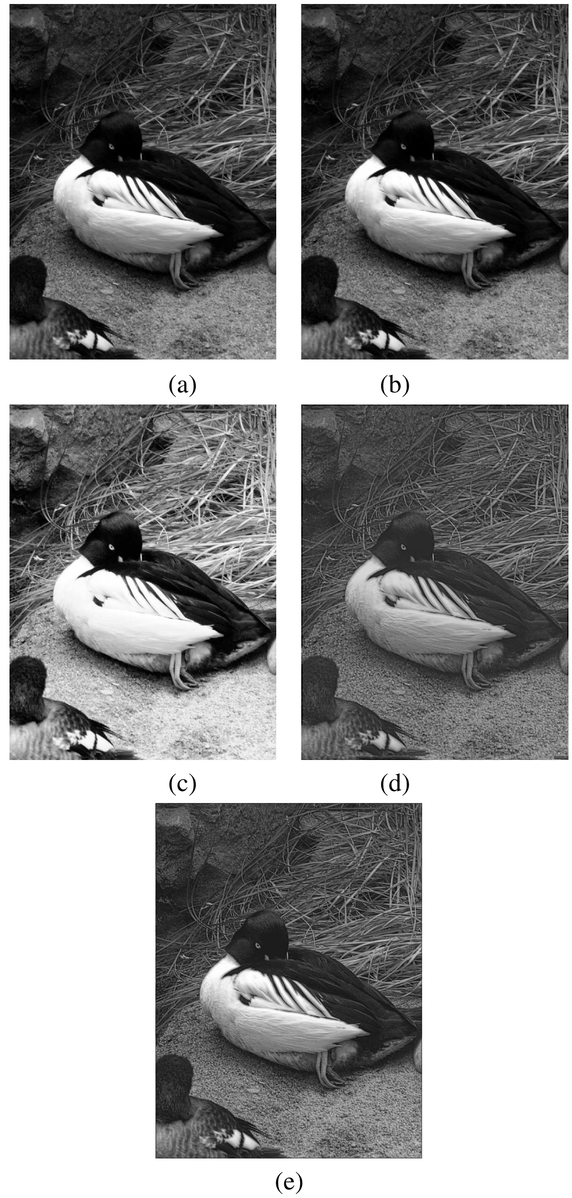


Fig. 3. Duck Image
For all images: (a) Original Image (b) Linear Contrast Stretching (c) Histogram Equalization (d) GA based Enhancement, and (e) Proposed PSO based Method