IMAGE ENHANCEMENT USING IMPROVIESED PARTICLE SWARM OPTIMIZATION

MAJOR PROJECT SUBMITTED IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR THE AWARD OF DEGREE OF

Master of Technology

In

Information Systems

Submitted By

KRATIKA SHARMA

(2K14/ISY/22)

Under the Guidance

Of

Dr. O. P. Verma

(Prof. and Head, Department of CSE)

DEPARTMENT OF COMPUTER SCIENCE AND ENGINEERING

DELHI TECHNOLOGICAL UNIVERSITY

(2014-2016)

CERTIFICATE

This is to certify that **Kratika Sharma (2K14/ISY/22)** has carried out the major project titled "**Image Enhancement using improvised Particle Swarm Optimisation**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2014-2016. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

Dr. O. P. Verma

Professor and Head

Department of Computer Science and Engineering

Delhi Technological University

Delhi-110042

ACKNOWLEDGEMENT

I take the opportunity to express my sincere gratitude to my project mentor Dr. O. P. Verma, Prof. and Head of Department, Department of Computer Science and Engineering, Delhi Technological University, Delhi, for providing valuable guidance and constant encouragement throughout the project. It is my pleasure to record my sincere thanks to him for his constructive criticism and insight without which the project would not have shaped as it has.

It humbly extend my words of gratitude to other faculty members of this department for providing their valuable help and time whenever it was required.

Kratika Sharma
Roll No. 2K14/ISY/22
M.Tech(Infromation Systems)
Email: kratika22sharma@gmail.com

ABSTRACT

Due to non-ideal image acquisition process, for example poor illumination, coarse quantization etc the visual quality of image is compromised. This needs to be addressed by the process of image enhancement which includes processing the image to bring out specific details of the image. The image is processed so that the resultant image is more suitable than the original for a particular application. Image enhancement on spatial domain will be carried out.

An optimal simplified approach for image enhancement of color images using adaptive contrast enhancement and improvised Particle Swarm Optimisation (PSO) is introduced. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling. PSO shares many similarities with evolutionary computation techniques such as Genetic Algorithms (GA). PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. The equation for the updates of velocity and position of particles in PSO is modified. For that, the values of two variables, iteration IT and α are evaluated through a newly developed Fuzzy Inference System. In PSO, each iteration updated the velocity of the particle, the velocity is dependent on the acceleration of the particle, which in turn is dependent on force applied, this force is optimized using Newton's law of gravity and motion. This makes the convergence of the PSO to yield better result as compared to the classical PSO, when applied for the enhancement of the images When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest. The particles in the algorithm share the information with each other to find the local best and also to find the global best in the group. . A new objective function will be introduced and optimized using PSO to learn the parameters used for the enhancement of a given image. The proposed approach is evaluated using different test images. Different performance measures are used for the quantitative analysis of the proposed approach.

Table of Contents

Figures and Tables

Chapter 1

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

Histogram transformation is considered as one of the fundamental processes for contrast enhancement of gray level images, 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. 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.

The image enhancement methods are broadly classified into two domains: spatial domain and transform domain methods. Spatial domain enhancement is based on direct modification of the pixels in the image. It includes point processing and neighborhood processing methods. The logarithmic transformation, power law transformation, linear contrast stretching are the some of the commonly used method for image enhancement in spatial domain. The transform domain methods operate upon the transformed images in the frequency domain. This method cannot be used for real time processing and is also time consuming.

Combination of different transformation functions with different parameters are used to produce the enhanced image by GA. Particle swarm optimization (PSO) is a population based stochastic optimization technique developed by Dr. Eberhart and Dr. Kennedy in 1995, inspired by social behavior of bird flocking or fish schooling.

Particle swarm optimization (PSO) is an optimization algorithm based on the movement of the flock of birds. In this algorithm particles are guided not only through their local best but also through their global best. It is an iterative type of optimization algorithm which iteratively finds new positions and velocities and updates them accordingly. The particles in the algorithm share the information with each other to find the local best and also to find the global best in the group.

Compared to GA, the advantages of PSO are that PSO is easy to implement and there are few parameters to adjust. PSO has been successfully applied in many areas: function optimization, artificial neural network training, fuzzy system control, and other areas where GA can be applied.

1.1 BACKGROUND

Different image enhancement techniques have been proposed and been applied to numerous applications in real world [12]. For a particular application, the image is processed so that the resultant image is more suitable than the original. It increases the content of information of the image. It sharpens the image features such as boundaries, edges or contrast for better visual perception and understanding. Some main reasons for poor contrast of images is that as, most of the satellite captured images, medical images or real life photographs may have inadequate lightning background conditions, external disturbances due to various reasons and incorrect settings of camera exposure and therefore there arises the need of enhancing the image

The various methods for enhancement may be classified into two categories: spatial domain and transform domain methods [1]. When direct modification of the pixels of the image is carried out, it is called spatial domain. For example, point processing and neighborhood processing methods, logarithmic transformation, power law transformation, linear contrast. When changes in the frequency domain of the image is carried out, it is called transform method. This method cannot be used for real time processing as it is time consuming

The Gravitational Search Algorithm (GSA) uses a constant value of parameter α for the calculation of gravitational constant. In the beginning, smaller value of α allows for a greater exploration of the search space. Furthermore, higher value of α during the last few iterations enhances the search space exploitation. Therefore, the approach based on GSA can be improved by adapting and controlling the value of parameter α as the algorithm proceeds.

1.2 MOTIVATION

Image enhancement Image enhancement techniques are used to emphasize and sharpen image features to obtain a visually more pleasant, more detailed, or less noisy output image. Distorted images are needed to be retrieved for various purposes. Be it satellite imagery, images for medical diagnostic purposes, application for security purposes, or for general day to day usage of images, enhanced versions are desirable. Though various algorithms are already in use, but most of them treats and enhances local pixels as individual unit, thus there is a need to enhance image as a whole. Use of Particle Swarm Optimization serves that purpose.

1.3 GOAL OF MASTER THESIS

Our focus is to enhance images using biologically inspired algorithm, Particle Swarm optimization. In this work, the velocity and position are updated of the particles, using PSO. The velocity is dependent on the acceleration which in turn is dependent on force, this force is modified using the Newton's concept of gravity and motion. Then, the image is enhanced, using this improvised PSO. The entropy, histogram spread and histogram flatness measure of the original and enhanced images are used to compare and analyze the result.

1.4 THESIS ORGANIZATION

Chapter two gives the detail of the previously done work in this field and also the description of the enhancement techniques.
Chapter three covers the working of Particle Swarm Optimization Algorithm and its advantage are discussed.

Chapter four presents the proposed work. The approach used for enhancement of images is covered here. Also the applicability of PSO in enhancement of an image to get global optimal results is shown.

Chapter four presents the results of our current approach and validate the results against ground truth. Comparison with basic PSO and discussion is also shown.

Chapter five concludes the thesis and further ideas for future work has been presented.

Chapter 2

Particle Swarm Optimization

Particle swarm optimization (**PSO**) optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position but, is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.

PSO is originally attributed to Kennedy, Eberhart and Shi and was first intended for simulating social behaviour,[as a stylized representation of the movement of organisms in a bird flock or fish school. The algorithm was simplified and it was observed to be performing optimization. The book by Kennedy and Eberhart describes many philosophical aspects of PSO and swarm intelligence. An extensive survey of PSO applications is made by Poli.

2.1. THE ALGORITHM

A basic variant of the PSO algorithm works by having a population of particles. These particles are moved around in the search-space according to a few simple formulae. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered.

As stated before, PSO simulates the behaviors of bird flocking. Suppose the following scenario: a group of birds are randomly searching food in an area. There is only one piece of food in the area being searched. All the birds do not know where the food is. But they know how far the food is in each iteration. So what's the best strategy to find the food? The effective one is to follow the bird which is nearest to the food.

PSO learned from the scenario and used it to solve the optimization problems. In PSO, each single solution is a "bird" in the search space. We call it "particle". All of particles have fitness values which are evaluated by the fitness function to be optimized, and have velocities which direct the flying of the particles. The particles fly through the problem space by following the current optimum particles.

PSO is initialized with a group of random particles (solutions) and then searches for optima by updating generations. In every iteration, each particle is updated by following two "best" values. The first one is the best solution (fitness) it has achieved so far. (The fitness value is also stored.) This value is called pbest. Another "best" value that is tracked by the particle swarm optimizer is the best value, obtained so far by any particle in the population. This best value is a global best and called gbest. When a particle takes part of the population as its topological neighbors, the best value is a local best and is called lbest.

Thus, Each Particle has:

1. Position : one of the possible solutions to the given problem
2. Velocity : updates a particle’s current position
3. Fitness Value : calculated using objective function that is to be optimized corresponding to the current position
4. Best Position : best solution achieved so far by each particle
5. Best Fitness Value : best fitness value achieved so far corresponding to the particle’s best position

   And Swarm is represented using:

   1. Global Best Position : best solution tracked by any particle in the complete swarm
   2. Global Fitness Value : fitness value corresponding to the global best position

After finding the two best values, the particle updates its velocity and positions with following equation:

$$v_{id}^{(t+1)} = w^{(t)} v_{id}^{(t)} + c_1 R_1 \left(pbest_{id}^{(t)} - \zeta_{id}^{(t)} \right) + c_2 R_2 \left(gbest_{d}^{(t)} - \zeta_{id}^{(t)} \right) \tag{1}$$

$$\zeta_{id}^{(t+1)} = \zeta_{id}^{(t)} + v_{id}^{(t+1)} \qquad (2)$$

Where v_{id} is the ith particle's velocity in dth dimension, t represents the iteration counter, ζ_{id} is the ith particle's position in dth dimension, $pbest_{id}$ is ith particle's historically best position in dth dimension, $gbest_d$ is the global best position of the swarm in dth dimension, R_1 and R_2 are two random numbers selected in the range of [0, 1], c_1 is the cognitive parameter and c_2 is the social parameter. These parameters control the relative importance of particle's personal experience and swarm's social experience.

The **pseudo code** of the procedure is as follows

```
For each particle
   Initialize particle
END

Do
   For each particle
      Calculate fitness value
      If the fitness value is better than the best fitness value (pBest) in history
         set current value as the new pBest
   End

   Choose the particle with the best fitness value of all the particles as the gBest
   For each particle
      Calculate particle velocity according equation (a)
      Update particle position according equation (b)
   End
While maximum iterations or minimum error criteria is not attained
```

Particles' velocities on each dimension are clamped to a maximum velocity Vmax. If the sum of accelerations would cause the velocity on that dimension to exceed Vmax, which is a parameter specified by the user. Then the velocity on that dimension is limited to Vmax.

Formally,

Create N_p number of N_d dimensional particles

for each particle i = 1 : N_p **do**

Initialize all the dimensions (randomly within their range) and corresponding random velocities

Calculate the fitness value

end for

for iterations j = 1 : N_i **do**

for each particle i = 1 : N_p **do**

Calculate new fitness value

//Set $pbest$ as the personal best solution of i^{th} particle achieved so far

if $(J((\mathrm{I}_e)_i) > J(\mathrm{pbest}_i))$ **then**

$pbest_i = (N_p)_i$

//$(N_p)_i$ is the i^{th} particle

end if

//Set $gbest$ as the global best solution achieved so far among all generations

if $\left(J((\mathrm{I}_e)_i) > J(\mathrm{gbest})\right)$ **then**

$gbest = (N_p)_i$

end if

end for

for each particle i = 1 : N_p **do**

Update the velocity using (1)

Update the position using (2)

end for

end for

2.2. PARAMETER SELECTION

The choice of PSO parameters can have a large impact on optimization performance. Selecting PSO parameters that yield good performance has therefore been the subject of much research,

2.3 COMPARISON BETWEEN GENETIC ALGORITHM AND PSO

Most of evolutionary techniques have the following procedure:

1. Random generation of an initial population
2. Reckoning of a fitness value for each subject. It will directly depend on the distance to the optimum.
3. Reproduction of the population based on fitness values.
4. If requirements are met, then stop. Otherwise go back to 2.

From the procedure, we can learn that PSO shares many common points with GA. Both algorithms start with a group of a randomly generated population, both have fitness values to evaluate the population. Both update the population and search for the optimium with random techniques. Both systems do not guarantee success.

However, PSO does not have genetic operators like crossover and mutation. Particles update themselves with the internal velocity. They also have memory, which is important to the algorithm.

Compared with genetic algorithms (GAs), the information sharing mechanism in PSO is significantly different. In GAs, chromosomes share information with each other. So the whole population moves like a one group towards an optimal area. In PSO, only gBest (or lBest) gives out the information to others. It is a one -way information sharing mechanism. The evolution only looks for the best solution. Compared with GA, all the particles tend to converge to the best solution quickly even in the local version in most cases.

Chapter 3

Image Enhancement

Image enhancement is basically improving the interpretability or perception of information in images for human viewers and providing `better' input for other automated image processing techniques. The principal objective of image enhancement is to modify attributes of an image to make it more suitable for a given task and a specific observer. During this process, one or more attributes of the image are modified. The choice of attributes and the way they are modified are specific to a given task. Moreover, observer-specific factors, such as the human visual system and the observer's experience, will introduce a great deal of subjectivity into the choice of image enhancement methods. There exist many techniques that can enhance a digital image without spoiling it. The enhancement methods can broadly be divided in to the following two categories:

1. Spatial Domain Methods
2. Frequency Domain Methods

In spatial domain techniques [1], we directly deal with the image pixels. The pixel values are manipulated to achieve desired enhancement. In frequency domain methods, the image is first transferred in to frequency domain. It means that, the Fourier Transform of the image is computed first. All the enhancement operations are performed on the Fourier transform of the image and then the Inverse Fourier transform is performed to get the resultant image. These enhancement operations are performed in order to modify the image brightness, contrast or the distribution of the grey levels. As a consequence the pixel value (intensities) of the output image will be modified according to the transformation function applied on the input values.

Image enhancement is applied in every field where images are ought to be understood and analyzed. For example, medical image analysis, analysis of images from satellites etc.
Image enhancement simply means, transforming an image f into image g using T. *(Where* T is the transformation. The values of pixels in images f and g are denoted by r and s, respectively. As said, the pixel values r and s are related by the expression,

$s = T(r)$

Where T is a transformation that maps a pixel value r into a pixel value s. The results of this transformation are mapped into the grey scale range as we are dealing here only with grey scale digital images. So, the results are mapped back into the range [0,L-1], where L=2k, k being the number of bits in the image being considered. So, for instance, for an 8-bit image the range of pixelvalues will be [0, 255].

The enhancement of the luminance component is done using unsharp masking technique. Local enhancement method is used that transforms a pixel based in the information of the neighboring pixels.

For an image of size $M \times N$, the transformation function used for enhancement is given by:

$$\mathrm{T}(i,j) = K(i,\mathrm{j})\left[f(i,j) - c \times m(i,j)\right] + m(i,j)^{a}$$

$i = 1,2,....,\mathrm{M}$ and $j = 1,2,....,\mathrm{N}$

Where, $f(i,j)$ is the original value of $(i,j)^{th}$ pixel, $\mathrm{T}(i,j)$ is the enhanced value of $(i,j)^{th}$ pixel, $m(i,j)$ is the local arithmetic mean of $(i,j)^{th}$ pixel , a,c are the constants and $K(i,j)$ is the *contrast gain* given by:

$$K(i,j) = \frac{g(i,\mathrm{j})}{m(i,j)}$$

Where $\mathrm{g}(i,j)$ is the local geometric mean of $(i,j)^{th}$ pixel.

The local geometric mean and local arithmetic mean of $(i,j)^{th}$ pixel of the input image over an $n \times n$ window are represented as:

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

$$\mathrm{g}(i,j) = \left(\prod_{x=0}^{n-1} \prod_{y=0}^{n-1} f(x,y) \right)^{\frac{1}{n \times n}} \tag{4}$$

Thus, the transformation function is represented as:

$$\mathrm{T}(i,j) = \frac{g(i,\mathrm{j})}{m(i,j)}\left[f(i,j) - c \times m(i,j)\right] + m(i,j)^{a} \tag{5}$$

The parameters i.e. a and c produce large variations in the processed image.

The saturation represents the colorfulness of an area with respect to its brightness. It describes the dullness of the color. The saturation of the image must be enhanced such that it does not result in over-enhancement. It plays an important role in the enhancement of the overexposed images. The underexposed images need only a small amount of the saturation modification. The saturation is enhanced using the power-law operator given by:

$$S^{'}(x) = [S(x)]^{(1-0.5*exposure)} \tag{6}$$

Where, $S(x)$ is the original saturation component of the HSV color space and $S^{'}(x)$ is the enhanced saturation component. Exposure is the measure of intensity exposition of the image and is represented as:

$$exposure = \frac{1}{L-1}\sum_{x=0}^{L-1} p(x)x \tag{7}$$

Where, L represents the number of intensity levels (for 8-bit image $L = 256$), x is intensity level $[0, L-1]$ and $p(x)$ is the probability of the occurrence of x^{th} intensity level in the image. The value of the Exposure is in the range [0, 1].

Enhancement of the saturation re-establish the pleasing nature of the degraded images.

Chapter 4

Proposed Approach

In this work, a Fuzzy Inferencing System is developed to calculate and update the position and velocity of the particle in PSO, once that PSO starts updating the velocity and position of the particles, image is enhanced. For enhancement of image an objective function is used to measure the quality of the image. The objective function uses: entropy, image exposure, histogram flatness and histogram spread.

1) *Entropy*

Entropy gives the amount of information contained in the image. Lower entropy value represents less information content and higher value represents more information content. For a perfect histogram equalized image, i.e. when the dynamic range of gray levels is occupied equally, the entropy is high. If only one gray level is occupied by all the image pixels, then entropy for such image is zero. Maximum entropy of an image is the number of bits required to represent all the gray levels (8 bits for 256 gray levels) when all the levels are occupied equally and minimum entropy of an image is zero when all the image pixels have same gray level. Thus, a good contrast image will have a higher entropy than a low contrast image. The entropy of the image I is calculated as:

$$H(I) = -\sum_{x=0}^{L-1} p(x) log_2 p(x) \tag{8}$$

where, $p(x)$ is the probability of occurrence of x^{th} intensity level of image I .

2) *Image Exposure*

The image exposure is the measure of intensity exposition of an image i.e. how dark or bright the image appears when it is captured by a camera. Exposure setting is responsible for making the photos too dark or too bright.

Image exposure can be calculated using. The value of the exposure lies in the range [0, 1]. If the exposure value of the original image is less than 0.5, then for enhanced image it must increase and is the original image exposure is more than 0.5, then enhanced image must have a lesser exposure than the original.

3) *Histogram Flatness Measure*

HFM is given by:

$$HFM = \frac{Geometric\ Mean\ of\ Histogram\ Count}{Arithmetic\ Mean\ of\ Histogram\ Count}$$
$$HFM = \frac{\left(\prod_{i=1}^{L} count_i\right)^{\frac{1}{L}}}{\frac{1}{L}\sum_{i=1}^{L} count_i} \qquad (9)$$

Where, $count_i$ is the histogram count for the i^{th} histogram bin and L is the total number of histogram bins.

Geometric mean of data is always less than or equal to the arithmetic mean. The value of AM and GM is equal when all the bins of histogram are equally occupied. The value of HFM is in the range $[0,1]$.

If all the intensity levels are equally occupied i.e. uniformly distributed, it results in a completely flat histogram. More the histogram of an image is flat, higher is the contrast of the image. For low contrast image, there is a large difference between the intensity levels distribution of the image. When the image histogram is almost flat, the arithmetic mean (AM) is nearly equal to the geometric mean (GM) of the histogram and thus the ratio of AM to GM is approximately equal to 1. For the non-uniform distribution of image intensity levels, the AM is much larger than the GM of the image histogram and thus the ratio approaches to 0. Hence, low contrast images have low value of HFM and high contrast images have high value of HFM.

4) Histogram Spread

HS is given by:

$$HS = \frac{Quartile\ distance\ of\ histogram}{Possible\ range\ of\ pixel\ values}$$
$$HS = \frac{\left(3^{rd}\ quartile - 1^{st}\ quartile\right) of\ histogram}{\left(\mathrm{maximum} - \mathrm{minimum}\right) of\ the\ pixel\ value\ range}$$

Where, $\mathrm{maximum}$ is 255, $\mathrm{minimum}$ is 0, $3^{rd}\ quartile$ represents the histogram bin at which cumulative histogram have 75% of the maximum value and $1^{st}\ quartile$ represents the histogram bin at which cumulative histogram have 25% of the maximum value. The value of HS is in the range $[0,1]$.

For a good contrast image, the image intensity values occupy more number of the possible intensity levels. For low contrast images, i.e. underexposed and overexposed images, the gray levels are skewed to either ends of the histogram. Though histogram equalization results in a higher histogram spread, it also results in the transformation of those pixels for which the enhancement is not required. More the distance between the 1st and 3rd quartile of the image cumulative histogram, more is the spread and thus better is the image contrast.

The objective function is represented as:

$$J = H(I_e) \times (\text{exposure})^r \times HFM \times HS \tag{10}$$

where, I_e is the enhanced Image, r is equal to 1 if exposure of original image is less than 0.5 and -1 if exposure of original image is greater than 0.5. Enhanced image will have a higher fitness value than the original image.

Gravitational Search Algorithm (GSA) is an optimization algorithm proposed by Rashedi [8] in 2009. It is based on the Newton's laws of gravity and motion. The law of gravity states that "Every particle in the universe attracts every other particle with a force that is directly proportional to the product of the masses of the particles and inversely proportional to the square of the distance between them". By this definition, the gravitational force is determined using the following equation [8]:

$$F = G\,\frac{M_1 M_2}{R^2} \tag{11}$$

where, F is the gravitational force acting between two masses $M_1$and M_2, G is the gravitational constant with a value of 6.67259 × 10-11 N m2/kg2, and R is the distance between the two masses.

Newton's second law of motion states that when a force acts on a mass, acceleration is produced. The magnitude of acceleration produced is obtained using the equation below [8]:

$$a = \frac{F}{M} \tag{12}$$

where, F and M denote the net force acting on a given particle and its mass, respectively.

The Gravitational Search Algorithm (GSA) employs this physical phenomenon for solving optimization problems. Consider a system with N masses or agents. The position of ith mass is defined as:

$$X_i = (x_i^1, \ldots, x_i^d, \ldots, x_i^n) \text{ , for i = 1, 2, . . . , N,} \tag{13}$$

where, x_i^d is the position of ith agent in dth dimension and n is the total number of dimensions in the search space. The positions of agents correspond to the solutions of the problem. The mass of each agent is computed, after evaluating the present population's fitness, using the following equations:

$$m_i(t) = \frac{fit_i(t) - worst(t)}{best(t) - worst\ (t)} \tag{14}$$

$$M_i(t) = \frac{m_i(t)}{\sum_{j=1}^{N} m_j(t)} \tag{15}$$

where, $fit_i(t)$, denotes the fitness value of ith agent at time t, and best(t) and worst(t) are computed as follows (for minimization problems):

$$best(t) = \min\ fit_j(t) \text{ , j = 1, 2, . . . , N} \tag{16}$$

$$worst(t) = \max\ fit_j(t)\ ,\ \text{j = 1, 2, . . . , N} \tag{17}$$

Similarly, for maximization problems best(t) and worst(t) are computed by taking the maximum and minimum fitness values respectively.

The acceleration of an agent is computed next, by considering the total forces from a set of heavier masses using the laws of gravity and motion using Equations 8 and 9. The new velocity of an agent is computed next by adding a fraction of its current velocity to its acceleration (Equation 10), followed by the calculation of its new position (Equation 11).

$$F_i^d(t) = \sum_{j \in kbest, j \neq i} rand_j\, G(t) \frac{M_j(t) M_i(t)}{R_{ij}(t) +\ \varepsilon} \left(x_j^d(t) -\ x_i^d(t)\right) \tag{18}$$

$$a_i^d(t) =\ \frac{F_i^d(t)}{M_i(t)} = \sum_{j \in kbest, j \neq i} rand_j\, G(t) \frac{M_j(t)}{R_{ij}(t) +\ \varepsilon} \left(x_j^d(t) -\ x_i^d(t)\right) \tag{19}$$

$$v_i^d(t+1) =\ rand_i \times v_i^d(t) +\ a_i^d(t) \tag{20}$$

$$x_i^d(t+1) =\ \ x_i^d(t) +\ v_i^d(t+1) \tag{21}$$

where, $rand_i$ and $rand_j$ are two random numbers uniformly distributed in the range of [0, 1], ε is a small value to prevent division by zero, $R_{ij}(t)$ is the Euclidean distance between agent i and agent j. Kbest is the set of first K agents with best fitness values and thus, largest mass. Kbest is dependent on time, initialized to Ko at the start and decreases as time progresses. The gravitational constant, $G(t)$, decreases with time to control the search accuracy. The value of $G(t)$ is calculated using the following equation:

$$G(t) = G_o e^{\frac{-\alpha t}{T}} \tag{22}$$

where, Go is the initial value of gravitational constant, α is a parameter which governs the degree of exploration versus exploitation of the search and T is the maximum number of iterations.

The FIS is developed with two input variables and one output variable. The input variables are as follows:

- *IT*: The current iteration number.
- *Fbest*: The best value of fitness achieved till the current iteration.

IT enables us to consider how far we have reached in the search process. During the initial iterations, i.e. when *IT* is low, a lower value of *α* is desired since lower the value of *α,* higher the value of gravitational constant, *G(t)*, will be (Equation 12) and thus, higher the force, *F*, (Equation 8) resulting in a higher acceleration, *a*, (Equation 9) and velocity, *v(t)* (Equation 10). This allows for higher exploration at the beginning of search. Similarly, towards the final few iterations, i.e. when *IT* is high, a higher value of *α* is desired to promote higher exploitation. Figure 2 depicts the membership function for *IT*. The iterations are represented as a fraction of the maximum number of iterations allowed, such that 0.5 means half of the total iterations and 1 represents the maximum iterations.

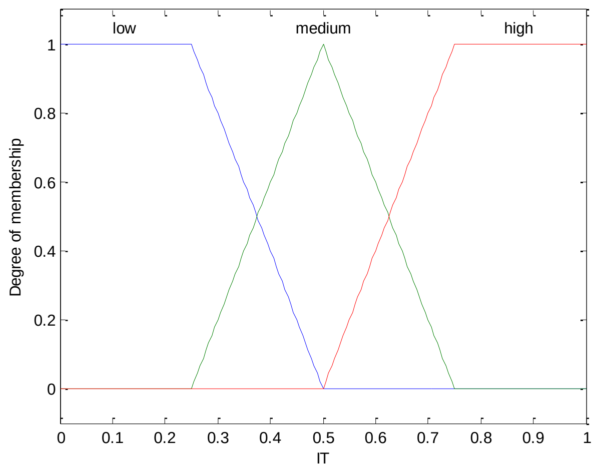


Fig 4.1: Membership Function for *IT*

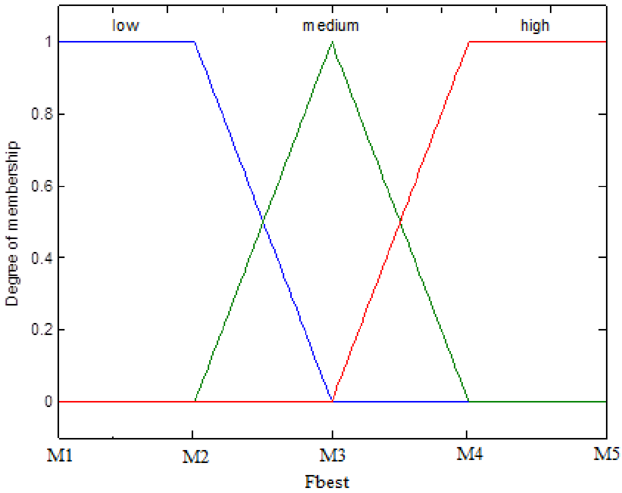


Fig 4.2: Membership Function for *Fbest*

Fbest represents the lowest value of fitness, since clustering is a minimization problem with the fitness function as mean square error, achieved till the current iteration. If the value of *Fbest* is high, then we need to reduce α to promote a greater exploration, since higher values for *Fbest* mean we are still far from the solution. However, if *Fbest* is low, we should increase α to allow for a higher exploitation as we are near the solution. Figure 3 shows the membership function for *Fbest*. Note that the membership function for *Fbest* needs to be tuned as per the input dataset being considered, since the acceptable values of fitness function will vary for different datasets.

The following eight fuzzy rules were formulated to control the parameter α in the calculation of the gravitational constant:

i. If (*IT* is low) and (*Fbest* is low) then (*alpha(t)* is high)
ii. If (*IT* is low) and (*Fbest* is medium) then (*alpha(t)* is medium)
iii. If (*IT* is low) and (*Fbest* is high) then (*alpha(t)* is low)
iv. If (*IT* is medium) and (*Fbest* is high) then (*alpha(t)* is low)
v. If (*IT* is medium) and (*Fbest* is medium) then (*alpha(t)* is medium)
vi. If (*IT* is high) and (*Fbest* is high) then (*alpha(t)* is medium)
vii. If (*IT* is high) and (*Fbest* is medium) then (*alpha(t)* is medium)
viii. If (*IT* is high) and (*Fbest* is low) then (*alpha(t)* is high)

The method used in the developed fuzzy inference system for “And” was min and for “Or” was max. The implication method was min, aggregation method was max and defuzzification method was centroid.

4.2Algorithm for Image Enhancement using improvised PSO

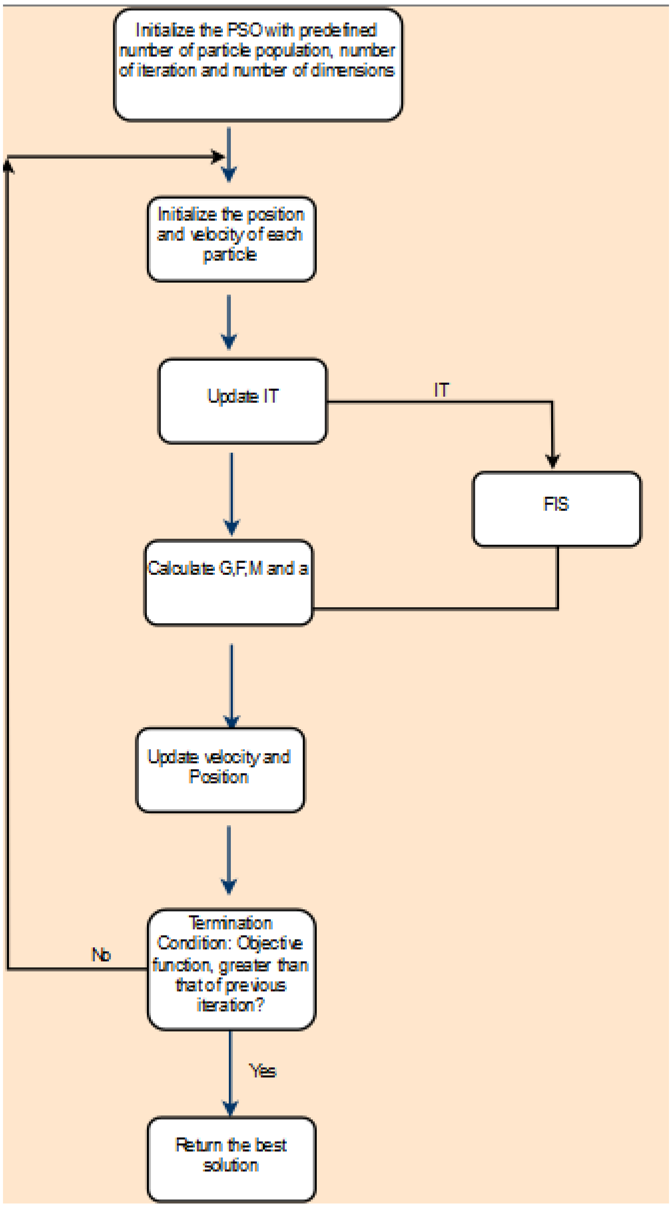


Fig 4.3: Flowchart of the proposed algorithm

4.3 PARAMETER SELECTION

It includes two sets of parameters: the parameters needed are N_p, N_i, N_d, g, ρ and $v_{\max}$ and the parameters to be optimized, i.e. a and c.

1) PSO Parameters:

TABLE I

Parameters values used in PSO initialization

Parameters	Values
The number of particles N_p.	10
The number of iterations N_i	10
The number of dimensions N_d	4
c_1 and c_2	[0,4]
R_1 and R_2	[0, 1]

a) The number of particles N_p =10.
b) The number of iterations N_i =10.
c) The number of dimensions N_d =4.
d) Parameters, c_1 and c_2 are initialized to a random number in [0, 4]. Each particle has same values of c_1 and c_2 throughout its life.
e) R_1 and R_2 are random numbers in [0, 1]. Each dimension has its own random number.
f) Maximum velocity can be calculated using:

$$v_{\max} = \frac{\zeta_d^{\max} - \zeta_d^{\min}}{K}$$

Where, $\zeta^{\min}$ and $\zeta^{\max}$ are the minimum and maximum position values of the particle in the d^th^ dimension and K is a parameter that controls the shift intervals. Here, we have taken $K = 1$. So the velocity range can now be given by $(-v_{\max,} v_{\max})$.

2) Parameters to be optimized:

a) $a \in [0, 1.5]$.

b) $c \in [0, 1]$.

TABLE II

Parameters to be optimized

Parameters	Values
a	[0, 1.5]
c	[0, 1]

Chapter 5

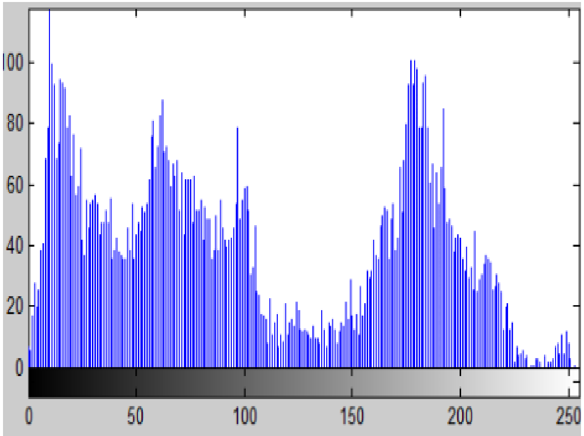
EXPERIMENTAL RESULTS

The following system configuration has been used while conducting the experiments:

- Processor: Intel Core i3
- Clock Speed: 2.40 GHz
- Main Memory: 4 GB
- Hard Disk Capacity: 512 GB
- Software Used: MATLAB R2010a

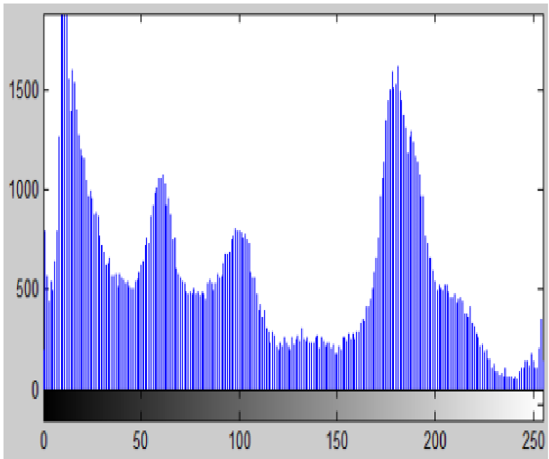
The images has been taken from Berkley database of images. . The database is an Open Access on-line publication that covers domain of image processing and visualization. The basic PSO algorithm is applied to it. And also the improvised PSO is applied to the same dataset. Then the enhanced image is checked against the original image. For evaluation, Quantitative measures are taken. Here entropy, histogram flatness measure, histogram spread are used to quantitatively evaluate.

(a)



(b)

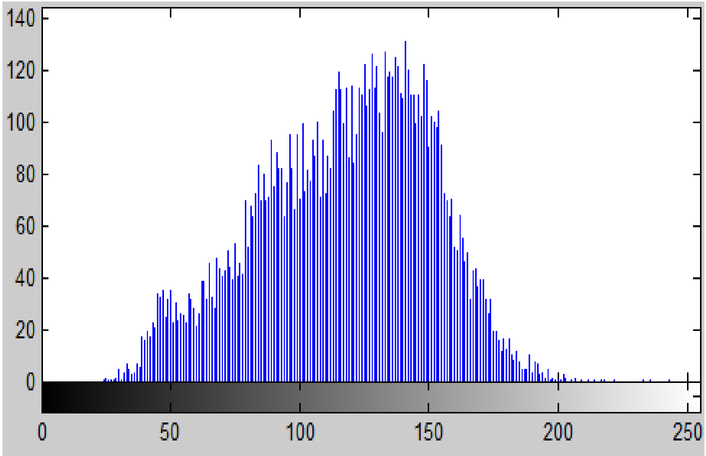
(c)



(d)

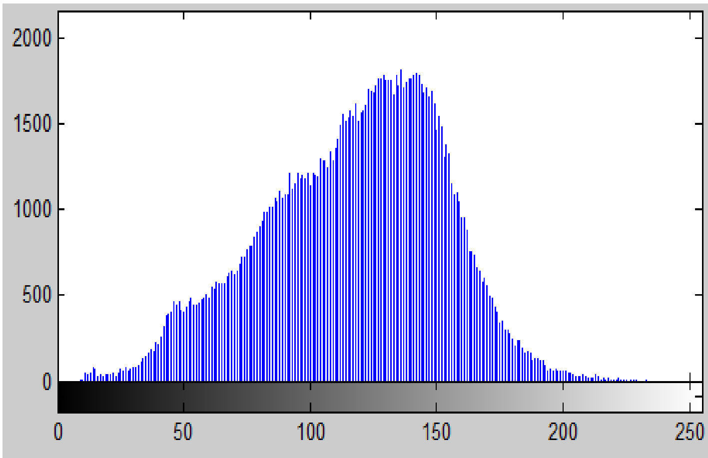
Fig 1: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

(a)



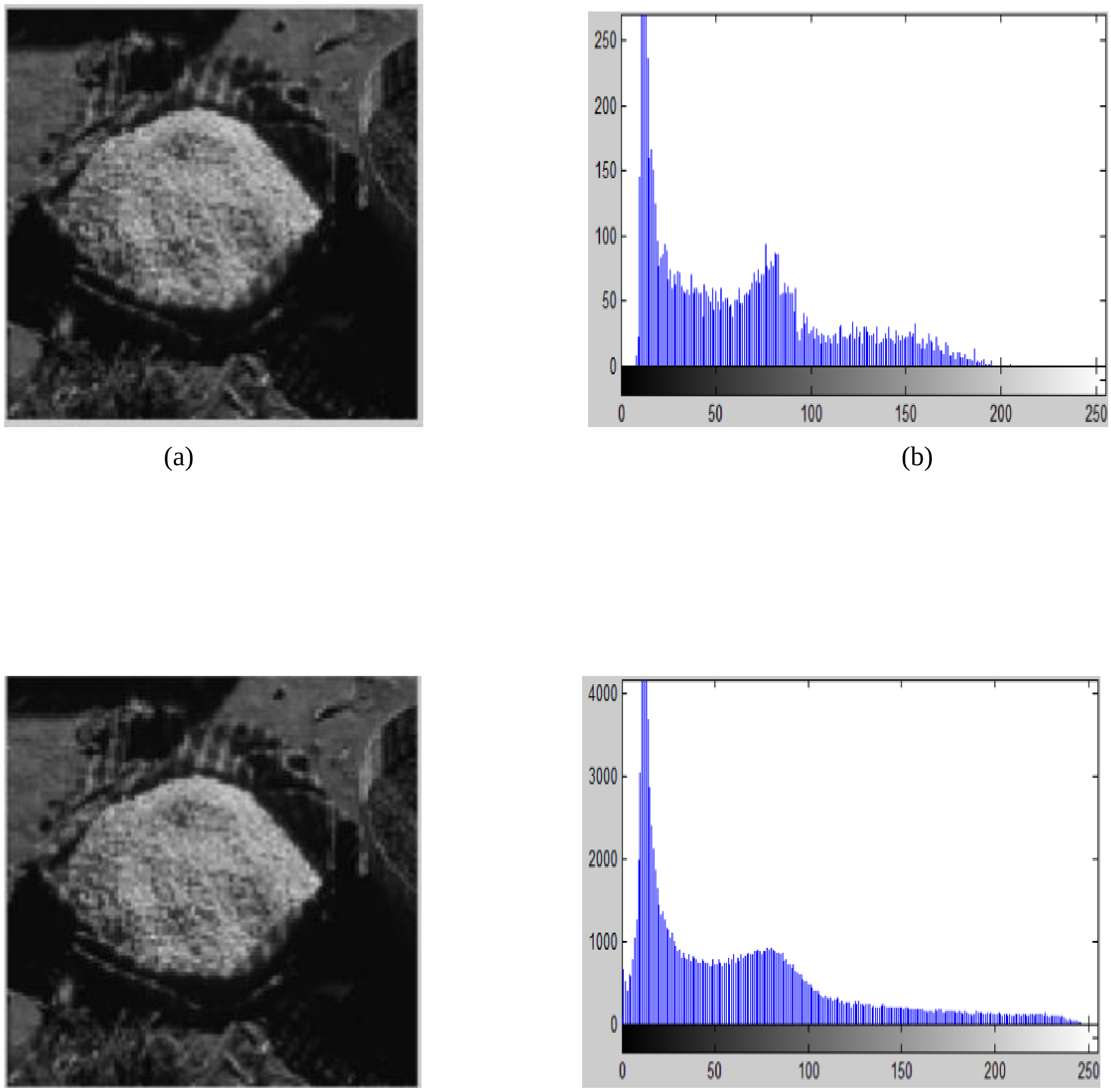
(b)

(c)



(d)

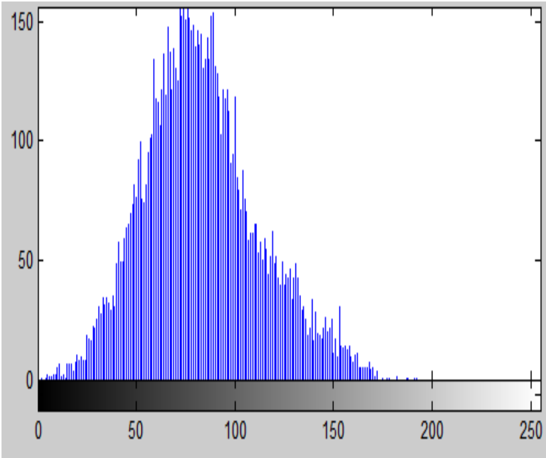
Fig 2: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image



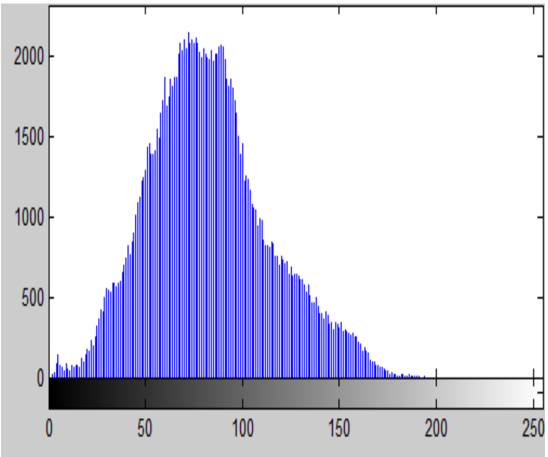
(a) (b)

(c) (d)

Fig 3: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image



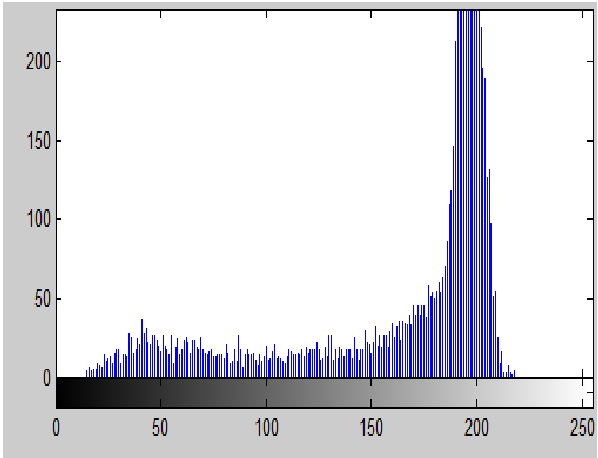
(a) (b)



(c) (d)

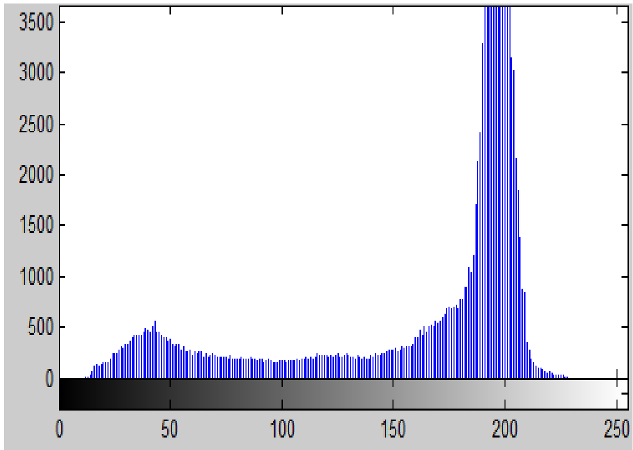
Fig 4: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

(a)



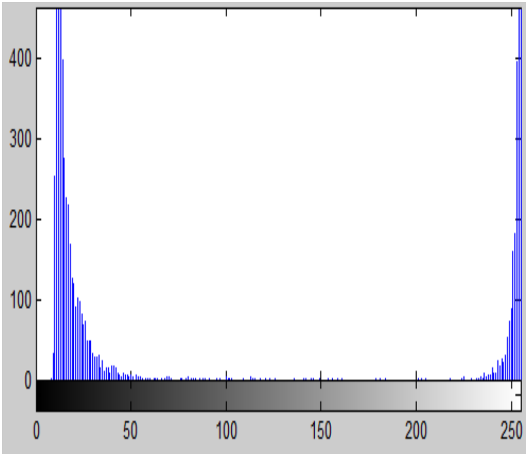
(b)

(c)

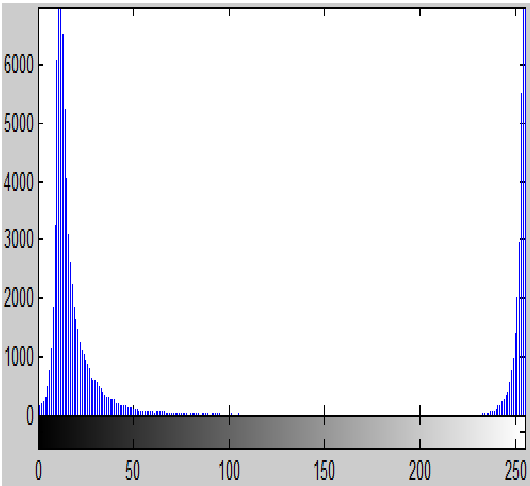


(d)

Fig 5: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image



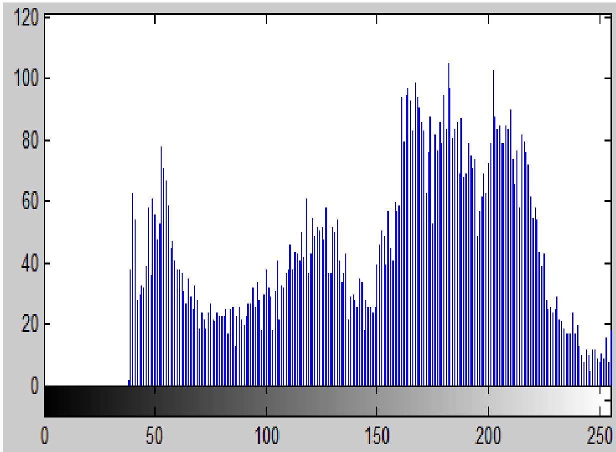
(a) (b)



(c) (d)

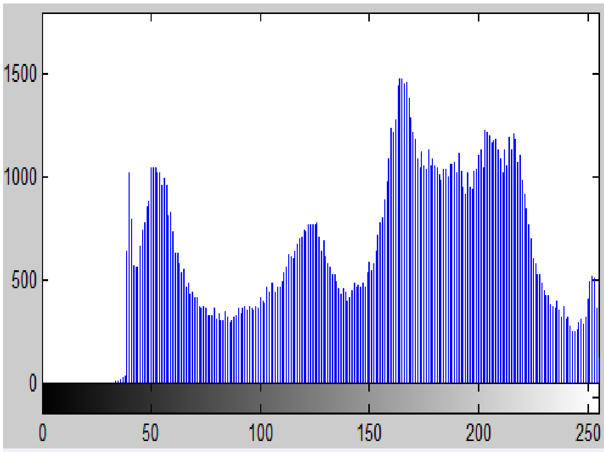
Fig 6: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

(a)



(b)

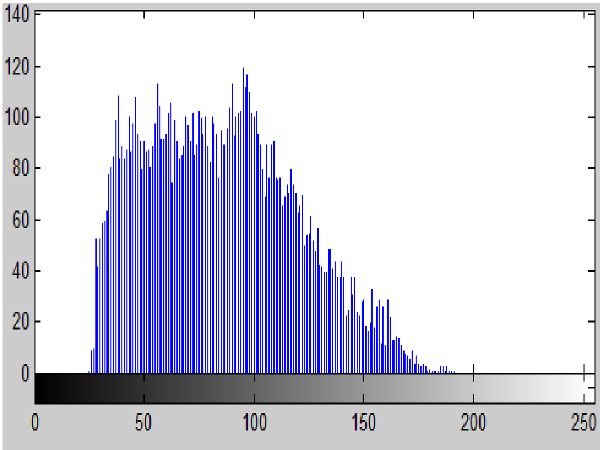
(c)



(d)

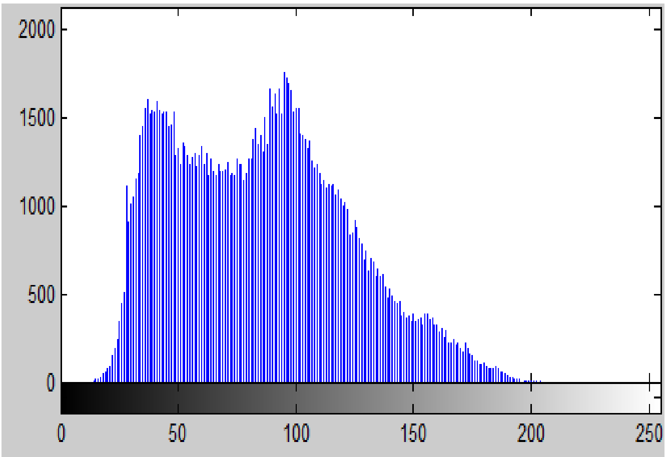
Fig 7: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

(a)



(b)

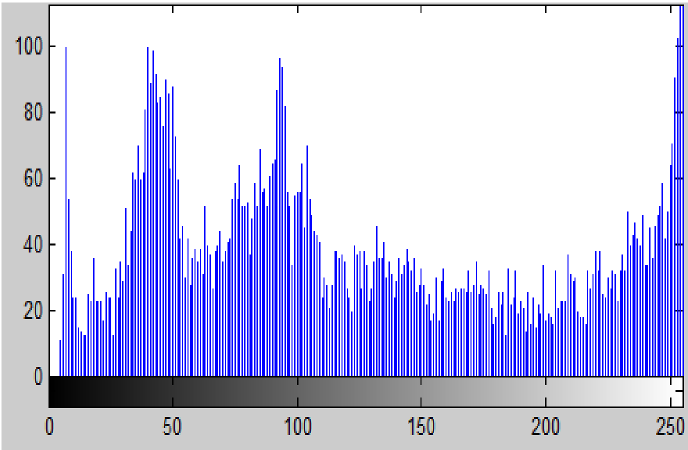
(c)



(d)

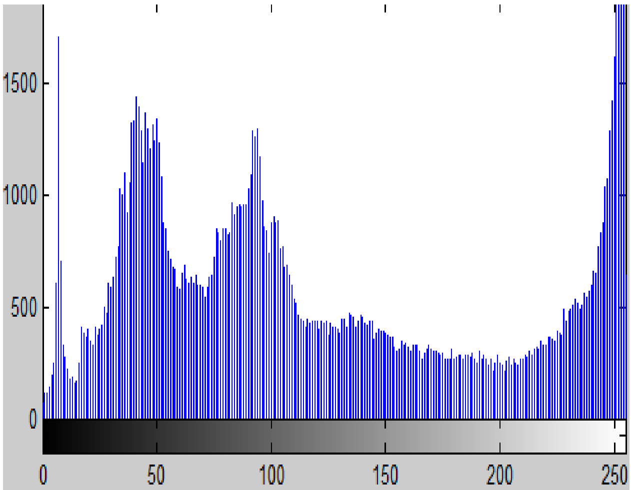
Fig 8: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

(a)



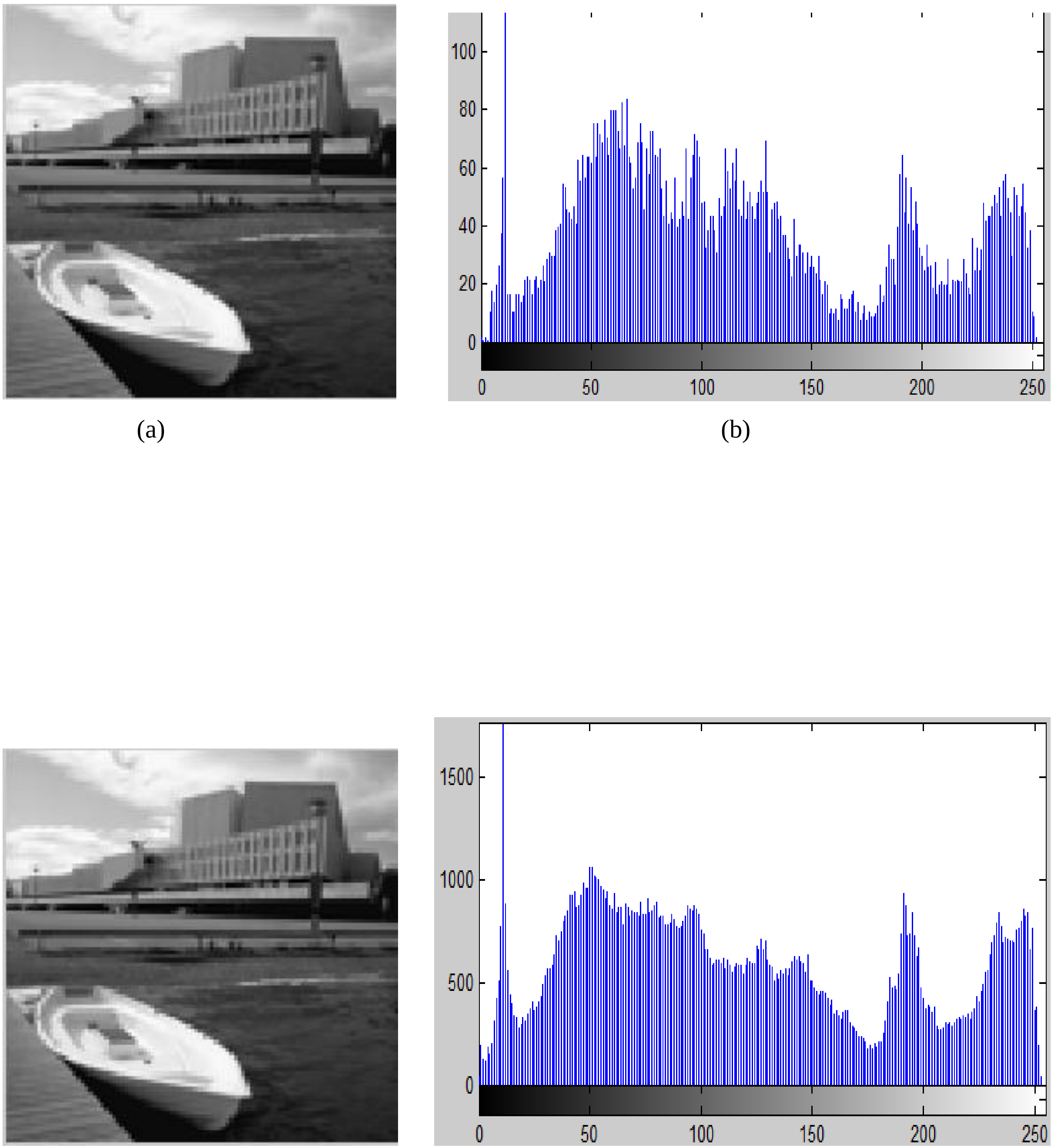
(b)

(c)



(d)

Fig 9: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image



(a) (b) (c) (d)

Fig 10: (a): Original Image (b): Histogram of Original Image (c):Enhanced Image (d): Histogram of Enhanced Image

TABLE III

Entropy, HFM and HS of original and enhanced images

Image	Measure	Input Image	Basic PSO	Improvised PSO
I1	Entropy	4.392	5.327	6.043
	HFM	0.285	0.324	0.367
	HS	0.157	0.176	0.194
I2	Entropy	4.135	5.196	5.934
	HFM	0.506	0.587	0.605
	HS	0.169	0.193	0.210
I3	Entropy	4.237	5.383	5.863
	HFM	0.396	0.410	0457
	HS	0.235	0.254	0.274
I4	Entropy	4.413	5.192	5.843
	HFM	0.420	0.486	0.528
	HS	0.129	0.153	0.179
I5	Entropy	4.712	5.469	6.145
	HFM	0.329	0.389	0.428
	HS	0.212	0.256	0.267
I6	Entropy	4.055	5.483	6.374
	HFM	0.126	0.176	0.236
	HS	0.145	0.197	0.215
I7	Entropy	4.736	5.210	5.692
	HFM	0.235	0.268	0.318
	HS	0.075	0.106	0.149
I8	Entropy	3.904	4.294	4.746
	HFM	0.157	0.194	0.237
	HS	0.063	0.084	0.102
I9	Entropy	4.468	4.973	5.359
	HFM	0.348	0.354	0.382
	HS	0.245	0.256	0.271
	Entropy	4.527	5.369	5.837

I10	**HFM**	0.746	0.767	0.785
	HS	0.023	0.057	0.83

Table III represents the entropy, HFM and HS values of original and enhanced images shown in Fig. 3-11. It can be seen from the Table I that in enhanced image we have achieved higher, HFM, and HS values than the original image.

The performance of the proposed approach has been measured by evaluating the values of entropy, HFM and HS values of original and enhanced image. The performance of basic PSO, where no FIS was applied to converge the particle swarm optimization algorithm.

Chapter 6

CONCLUSION

In the work presented, image enhancement is done using improvised PSO. The iteration of PSO algorithm is governed by the fuzzy parameter IT and α. A, which is fuzzy gives degree of exploration. Higher the number of iterations, higher the α, higher the exploration. A number of enhanced images are produced using Barkley database, based on the values of the parameters, and the one with best fitness value is selected as a result. Newton's concept of gravity and motion applied to the moving particles of Particle Swarm Optimization algorithm. Fuzzy Inference rules are developed for controlling the parameter α as search progress. Gravitation is a universal force, this force provides acceleration to the moving particle, this acceleration is used to update the velocity of particles in each iteration of the PSO algorithm. The transformation function used for enhancement involves some of the parameters i.e. a and c that produce diverse results and helps in finding an optimal solution according to the newly proposed objective function. So, for this purpose PSO is used to find the best set of values for the parameters in order to produce the optimal result. A number of enhanced images are produced based on the values of the parameters, and the one with the best fitness value is selected as the result.

REFERENCES

[1] R.C.Gonzalez and R.E.Woods,"Digital Image Processing",Third Edition, 2008.

[2] E. Rashedi, H. Nezamabadi-pour, S. Saryazdi, "GSA: a gravitational search algorithm", Information Sciences, vol. 179, issue 13, pp. 2232–2248, 2009.

[3] A. Hatamlou, S. Abdullah, H. Nezamabadi-pour, "Application of gravitational search algorithm on data clustering", Rough Sets and Knowledge Technology, Springer, pp. 337–346, 2011.

[4] John Yen and Reza Langari, Fuzzy Logic – Intelligence, Control and Information, Prentice Hall, 1st edition.

[5] A. Hatamlou, S. Abdullah, H. Nezamabadi-pour, "A combined approach for clustering based on K-means and gravitational search algorithms", Swarm and Evolutionary Computation, vol. 6, pp. 47–52, 2012.

[6] Apurba Gorai and Ashish Ghosh,"Gray-level Image Enhancement by Particle Swarm Optimization", World Congress on Nature & Biologically Inspired Computing, Coimbatore , pp. 72-77, 2009.

[7] Dah-Chung Chang and Wen-RongWu,"Image Contrast Enhancement Based on a Histogram Transformation of Local Standard Deviation," IEEE Transactions on Medical Imaging, vol. 17, no. 4, pp. 518 - 531, 1998.

[8] Apurba Gorai and Ashish Ghosh," Hue-Preserving Color Image Enhancement Using Particle Swarm Optimization," Recent Advances in Intelligent Computational Systems, Trivandrum, pp. 563 – 568, 2011.

[9] Nitin Sharma and Om Prakash Verma," Gamma Correction Based Satellite Image Enhancement using Singular Value Decomposition and Discrete Wavelet Transform", International Conference on Advanced Communication Control and Computing Technologies (ICACCCT), Ramanathapuram, pp. 1286-1289, 2014.

[10] Raju Aedla, Dwarakish G. S and D. Venkat Reddy," Satellite Image Contrast Enhancement Algorithm based on Plateau Histogram Equalization", IEEE Region 10 Symposium, Kuala Lumpur, pp. 213-218, 2014.

[11] Randa Atta and Mohammad Ghanbari, "Low-contrast satellite images enhancement using discrete cosine transform pyramid and singular value decomposition", Published in IET Image Processing, pp. 472-483, 2013.

[12] Ismail A. Humied, Fatma E.Z. Abou-Chadi and Magdy Z. Rashad, “A new combined technique for automatic contrast enhancement of digital images”, Egyptian Informatics Journal, vol. 13, issue 1, pp. 27-37, 2012.

[13] ZhiYu Chen, Besma R. Abidi, David L. Page and Mongi A. Abidi, “Gray-level grouping (GLG): an automatic method for optimized image contrast Enhancement-part I: the basic method”, IEEE Transactions on Image Processing, vol. 15, no. 8, pp. 2290-2302, 2006.

[14] James Kennedy and Russell Eberhart, “Particle Swarm Optimization”, Proceedings of IEEE International Conference on Neural Networks, Piscataway, pp. 1942-1948, 1995.

[15] James McCaffrey, “http://msdn.microsoft.com/en-us/magazine/hh335067.aspx”, Artificial Intelligence, Particle Swarm Optimization.

[16] “Swarm Intelligence: Concepts, Models and Applications”, Technical Report 2012-585, Queen’s University.

[17] Madasu Hanmandlu, *Senior Member*, *IEEE*, Om Prakash Verma, Nukala Krishna Kumar, and Muralidhar Kulkarni, “A Novel Optimal Fuzzy System for Color Image Enhancement Using Bacterial Foraging”, IEEE Transactions On Instrumentation And Measurement, vol. 58, no. 8, pp. 2867 - 2879 , 2009.

[18] Shannon, CE, Weaver, W (1949),” The Mathematical Theory of Communication”, University of Illinois Press, Urbana.

[19] A. K. Tripathi, S. Mukhopadhyay, and A. K. Dhara, "Performance metrics for image contrast" Proceedings of IEEE Conference on Image Information Processing, Shimla, India, pp. 1-4, 2011.

[20] Mark Eramian and David Mould, “Histogram Equalization using Neighborhood Metrics”, The 2nd Canadian Conference onComputer and Robot Vision, pp. 397 – 404, 2005.

[21] Rekha Lakshmanan, Madhu S. Nair, M. Wilscy and Rao Tatavarti,” Automatic Contrast Enhancement for Low Contrast Images: A DITComparison of Recent Histogram Based Techniques”, International Conference on Computer Science and Information Technology, Singapore, pp. 269 – 276, 2008.