A

Major Project

On

Image Enhancement Using Evolutionary Algorithm

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By

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CERTIFICATE

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This is certified that the major project report entitled "**Image Enhancement Using Evolutionary Algorithm"** is a work of '**Vivek Kumar Singh'** (College Roll No 17/E&C/09 & University Roll No- 8523) is a student of Delhi College of Engineering. This work is completed under my direct supervision and guidance and forms a part of master of engineering (Electronics & Communication Engineering) course and curriculum. He has completed his work with sincerity and diligence.

The work embodied in this major project has not been submitted for the award of any other degree to the best of my knowledge.

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Abstract

A new approach is presented for the enhancement of color images using the fuzzy logic technique. Here we propose 'Fork point' a measure of exposure by which we can divide the gray levels of the image in over and under exposed region. Image of different kind can have both underexposed and overexposed region. The enhancement of underexposed and overexposed regions is the more attentive part of this paper. The new transformation operator is proposed to modify the fuzzy membership values of underexposed region of an image. For overexposed region, a rectangular hyperbolic function is used while for underexposed region a non linear function is applied in which order of non linearity is depended upon membership function. The shape and range of these functions are controlled by the parameters involved and these parameters are optimized using the bacterial foraging optimization algorithm.

In terms of image enhancement we are considering only saturation and intensity parts. We are excluding to hue parts because hue contains the original colour composition, and we should preserve it for proper colour information about image. This approach is applicable to a degraded image of mixed type. On comparison, the proposed transforms yield better results than existing transforms, used in [12] for overexposed region.

CONTENTS

Chapter. 1

Introduction

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques. Image processing modifies pictures to improve them (enhancement, restoration), extract information (analysis, recognition), and change their structure (composition, image editing). Images can be processed by optical, photographic, and electronic means, but image processing using digital computers is the most common method because digital methods are fast, flexible, and precise.

Image enhancement improves the quality (clarity) of images for human viewing. Removing blurring and noise, increasing contrast, and revealing details are examples of enhancement operations. For example, an image might be taken of an endothelial cell,

which might be of low contrast and somewhat blurred. Reducing the noise and blurring and increasing the contrast range could enhance the image. The original image might have areas of very high and very low intensity, which mask details. An adaptive enhancement algorithm reveals these details. Adaptive algorithms adjust their operation based on the image information (pixels) being processed. In this case the mean intensity, contrast, and sharpness (amount of blur removal) could be adjusted based on the pixel intensity statistics in various areas of the image. For image enhancement in spatial domain, several algorithms have been developed.

Dong-Shu Wang [1] proposed image enhancement algorithm. In this algorithm, weighted mean value of the image about structuring elements of different directions is calculated and used to identify edge of image**.** Another technique developed by Dileep Md et.al [2] studied different color image contrast enhancement algorithms to bring about the comparison between their performance which shows the improvement in the visual quality of the color images captured under poor illumination or other color illumination conditions. Karen A. Panetta [3] introduced two novel image enhancement algorithms: Edge-preserving contrast enhancement, which is able to preserve edge details while enhancing contrast in images with varying illumination, and A novel multi histogram equalization method which utilizes the human visual system to segment the image, allowing a fast and efficient correction of non uniform illumination ,then extend this HVS-based multi histogram equalization approach to create a general enhancement method that can utilize any combination of enhancement algorithms for an improved performance**.** Melkamu H. Asmare et.al [4] analyzed and evaluated the various color spaces in color image enhancement applications. Conversion accuracy and structural similarity measure are the two objective parameters to measure the performance of each color space. Fuzzy image enhancement explained M. Russo et.al [5] deals with "IF… THEN…ELSE" fuzzy rules; and Y. S. Choi et.al [6] used rule-based smoothing in which different filter classes are devised on the basis of compatibility with the neighborhood. Beilei Xu et.al. [7] proposed an object-based multilevel contrast stretching method to enhance image structure. First segments the image into its constitute objects, which are treated as image structural components, using morphological watersheds and region merging Then separately stretches the image contrast at inter object level and intra-object

level in different ways. An approach of stretching between adjacent local extremes is used to adequately enlarge the local dynamic range of gray levels between objects. A generalized iterative fuzzy enhancement algorithm for degraded images has been developed by Peng Dong-Liang et.al.[8] which used image quality assessment criterion based.

Hanmandlu et. al [9] proposed a new intensification operator in which sigmoid function used for the modification of the Gaussian type of membership operator. Image adaptive contrast stretching enhancement is also a popular and practical approach in automated image recognition systems. This scheme adapts to intensity distributions to improve the image quality. In general, quality improvement via adaptive image enhancement can be observed directly from enhanced images. In this case, concepts from the information theory are proposed by Zhengmao Ye, et.al [10] ,evaluated the effects of adaptive image enhancement and applied discrete entropy, relative entropy and mutual information to indicate the impact of adaptive image contrast enhancement techniques for both gray level images and true color images. Hanmandlu et.al [11] presented the method in which luminance part of the image is enhanced in the fuzzy domain using GINT operator (parametric sigmoid function). The parameters of this operator can be found by optimizing the image entropy and propose the image quality factors. This approach works well for under exposed images but fails when it is applied to over exposed images as well as under plus over exposed images.Hanmandlu et.al [12] presented the enhancement of color images using the fuzzy logic technique. An objective measure called exposure has been defined to provide an estimate of the underexposed and overexposed regions in the image. This measure serves as the dividing line between the underexposed and overexposed regions of the image. The hue, saturation, and intensity (HSV) color space employed for the process of enhancement. A parametric sigmoid function used for the enhancement of the luminance component of the underexposed image. A power-law operator used to improve the overexposed region of the image, and the saturation component of HSV changed through another power-law operator to recover the lost information in the overexposed region. Objective measures like fuzzy contrast and contrast and visual factors defined to make the operators adaptive to the image characteristics. Entropy and the visual factors involved in the objective function, which optimized using the bacterial foraging

algorithm to learn the parameters. Zhengmao et.al.[13] introduced concepts from the information theory to evaluate the effects of adaptive image enhancement by using discrete entropy, relative entropy and then mutual information have been applied to indicate the impact of adaptive image contrast enhancement techniques for both gray level images and true color images. Li et.al.[14] introduced global histogram equalization to produce color distortion when color images are enhanced, first each component of original RGB image is implemented global histogram equalization separately, then original RGB image and equalized RGB image are executed for wavelet transform, and then wavelet coefficients are used ,that time wavelet approximate coefficients of original image are hold the line. Finally wavelet reconstructed image and original image are fused. Xiuqiong et.al.[15] introduced the method in which original color visible image is transformed into a perceptually decorrelated color space in order to treat the achromatic and chromatic components separately. Then the achromatic component and infrared image are combined by a statistical fusion method based on dual tree complex wavelet transform (DT-CWT) using the generalized Gaussian distribution (GGD). The means and variances between the fused component and the original achromatic component are matched by a linear remapping for image enhancement .Shu Yang et.al[16] applied method of image enhancement, which only depends on the difference of grey values of adjacency flat zones of an image, according to the theory of morphological reconstruction. First of all, a non idempotent connected operator which can be the criterion for multi-scale enhancement is defined and the criterion is a key to enhancement of an image. Subsequently, the grey values in same the simple connected zones of an image are enhanced overall so the way can keep the immovability of the image contour. At last the connected zones of an image and their relations are described and the way of the multi-scale morphological reconstruction enhancement for an image is implemented by using maximum tree or minimum tree structure. Zhang Ming-Hui et.al[17] applied CR medicine image adaptive enhancement algorithm in which combined the human visual property ,which is more sensitive to smooth area noise compared with detail area noise. In another domain Karen Panetta et.al [18] applied logarithmic image processing (LIP) model for several applications of image processing such as image enhancement and segmentation and introduced a parameterized LIP (PLIP) model that spans both the linear

arithmetic and LIP operations and all scenarios in between within a single unified model. Also introduced both frequency and spatial-domain PLIP-based image enhancement methods, including the PLIP Lee's algorithm, PLIP bi histogram equalization, and the PLIP alpha rooting. Russo et al. [19] discuss all recent advances in the fuzzy image processing s-curve is used [20] as the transformation function where the parameters of the s curve are calculated by optimizing the entropy to maximize the image information. These parameters select the shape and range of the transformation operator. All these methods apply the operators to the Luminance part of the color image. They sometimes over enhance or under enhance the image as they do not consider the shape and range of the original histogram.

Chapter. 2

Image Enhancement

2.1 Introduction

The aim of image enhancement is to improve the interpretability or perception of information in images for human viewers, or to provide `better' input for other automated image processing techniques.

Enhancement is used as a preprocessing step used to ease the vision task, for example, to enhance the edges of an object to facilitate the guidance of a robotic gripper.

Enhancement is also used as a preprocessing step in applications where human viewing of an image is required before further processing. For example, in one application, high speed film images had to be correlated with a computer simulated model of an aircraft. This process was labor intensive because of the fact that the images all dark. This task

was made considerably easier by enhancing the images before correlating them to the model, enabling the technician to process many more images in one session.

2.2 Proposed New Function For Image Classification:

Many images appear degraded because of their poor contrast as the usable data of the image is represented by compact contrast values of the histogram. When the gray levels contains only the lower part of the histogram area, the image appears dark and it appears very bright image when its gray levels occupy only the upper area of the histogram. In both the case image information is distorted. We consider the images based on the exposition as under exposed images and over exposed images. There are some images which use the entire region of the histogram area but do not appear fine and it is called mixed exposed images.

In reality we observe that most of the images are mixed exposed only which contains the both under exposed regions as well as over exposed regions of certain percentage. In this way, we consider every image as a mixed exposed image with some percentage of exposition.

We therefore introduce a parameter called "Fork" for denoting what percentage the image gray levels are exposed to brightness. Hence every image is now considered as a mixed exposed image containing certain percentage of both the regions.

So terms of fork point defined here below:

Fork arithmetic mean value $F_m = \frac{1}{L} \times \frac{\sum(P(x)\times(x)^2)}{\sum(P(x)\times(x))}$ (2.2.1)

The normalized value of F_m is F_e and it is presented by

$$(F_e) = (1+\frac{e}{2}) - F_m \quad (2.2.2)$$

Where 'e' is the exponential value.

Fork ratio $(F_c) = \frac{F_m}{F_e}$ (2.2.3)

Fork point (F) $= (F_e) \times L \times (1 - F_c)$ (2.2.4)

Where x indicates the intensity level in the range 0 to L-1, P(x) denotes the histogram of the image and L denotes the total number of gray levels. Separate operators have been defined for enhancing the under and overexposed region of the image. This is achieved by dividing the intensity range [0, L-1] into two parts: [0, F] and [F, L-1]. Here if the value of Fork ratio of a tested image is greater than 0.5,we consider that this image has more underexposed region than overexposed and if less than 0.5 it means image has less underexposed region.

2.3. Fuzzification And Enhancement :

An image of size M×N with intensity levels in the range (0 to L-1) can be considered as collection of fuzzy singletons in the fuzzy set notation

$$I = \bigcup\{\mu(x_{mn})\} = \sum \frac{\mu_{mn}}{x_{mn}}$$

M=1,2,3…….M ; n=1,2,3……N (2.3.1)

Where $\mu(x_{mn})$ or $\frac{\mu_{mn}}{x_{mn}}$ represents the membership or grade of some property $\mu(x_{mn})$ of x_{mn} . x_{mn} is the colour intensity at (m.n)th pixels.for a colour image the membership function is taken for the luminance component of the colour image x ,($x \in \{V\}$) where V is the value of intensity. For computational efficiency ,histogram of color x [0,L-1] is considered for fuzzification instead of taking the intensity levels at each pixel value.

2.4. Fuzzification Of Underexposed Region

The gray level of an image can be divided into two regions underexposed and overexposed by the fork point "F". In the case of highly overexposed image in which underexposed parts is less than 33% of the total gray level value (L), the intensity level of the region of underexposed get quite degraded. So for enhancing underexposed region of image, we categories two types of image, one in which underexposed part is lesser than 33% of total gray level and second one underexposed part is greater than 33% of the total gray level[L] . Here introducing a factor β to separate both types of images. So the modified membership function is

$$\mu_{xu}(x) = \left[exp\left\{\frac{x_{max}-(x_{avg}-x)}{\sqrt{2}\times F_h}\right\}\right]^{2\beta} \qquad (2.4.1)$$

$$\beta = \begin{cases} 0.8 & if \quad F \geq 85 \\ 4 & if \quad F < 85 \end{cases}$$

β is a deciding factor to operate the membership function of underexposed region. Above values has been chosen of β experimentally and it yields the best results.
The order of the membership function is different for image which has less underexposed region (F< 85) and which has normal underexposed region (F>85). The image which has less underexposed region need a sharp enhancement than the image which has normal underexposed region .So in proposed method we have taken that if the fork point is less than 33% of total gray level (L), we can put the image in the lesser underexposed side, and it need more sharply enhancement so the value of factor β is greater .On opposite side if the image fork point is greater than 33% of gray level we keep this image on having on normal underexposed side ,so the deciding factor β value is lesser. Both value of β will enhance the underexposed region but the former one do it sharply and later one do it normally. We can see the effect of the value of factor β in the Fig.(1.4.1)and(1.4.2) respectively .

Here x indicates the gray level of the underexposed region in the range [0,L-1].x_{max} is the maximum intensity level in the image and x_{avg} is the average gray level value in the image . f_h is called fuzzifier and its initial value is found from:

$$f_h = \frac{1}{2} \frac{\sum_{x-0}^{x=L-1}(x_{max}-x)^4 P(x)}{\sum_{x=0}^{x=L-1}(x_{max}-x)^2 P(x)} \qquad (2.4.2)$$

The value of f_h is higher for a brighter image .the membership function gives larger values to the underexposed region and smaller values to overexposed region. The characteristics of underexposed functions are shown in fig.

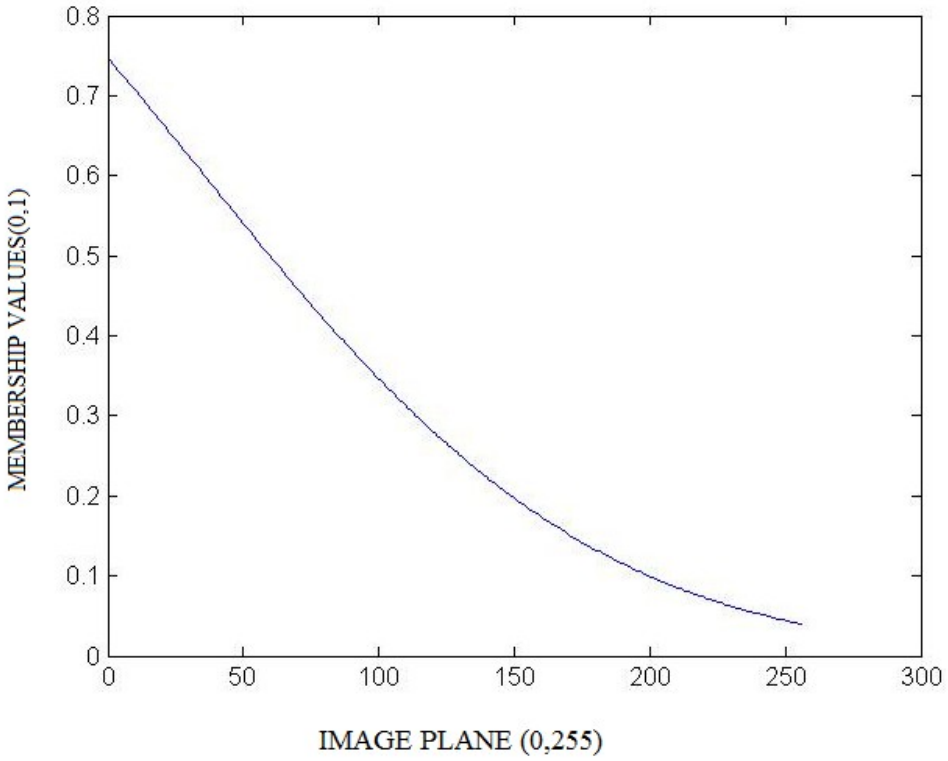


Fig. 2.4.1 . Gaussian membership function characteristics for β =0.8

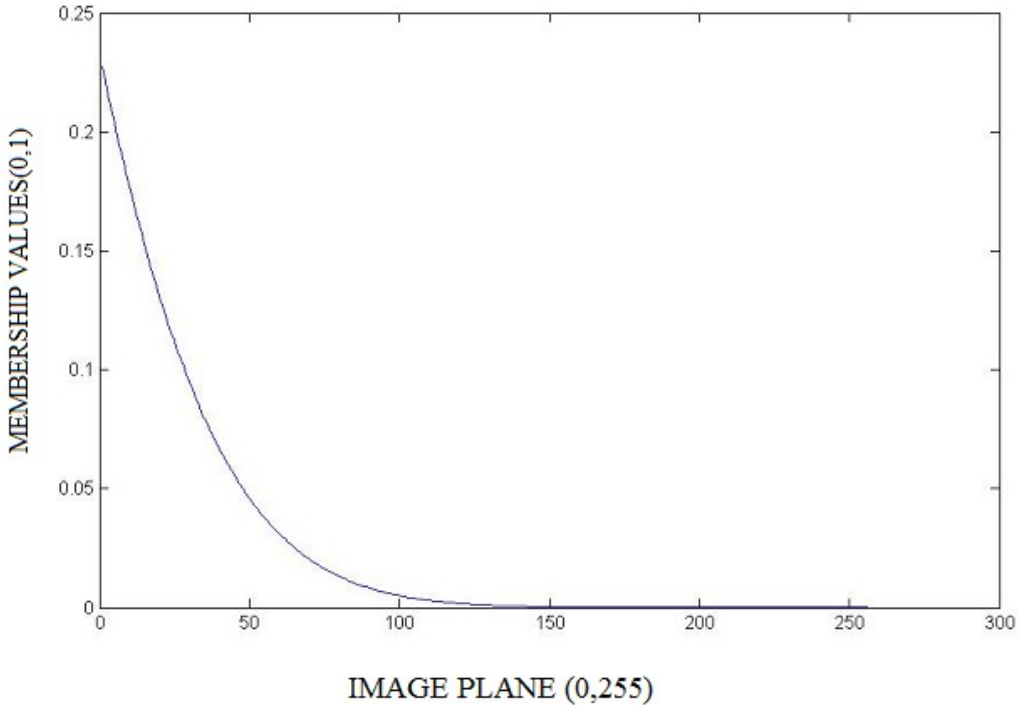


Fig.2.4.2. Gaussian membership function characteristics for β =4

By an example of histogram of image "ROSE" we can see below the comparison of [12] and proposed membership function

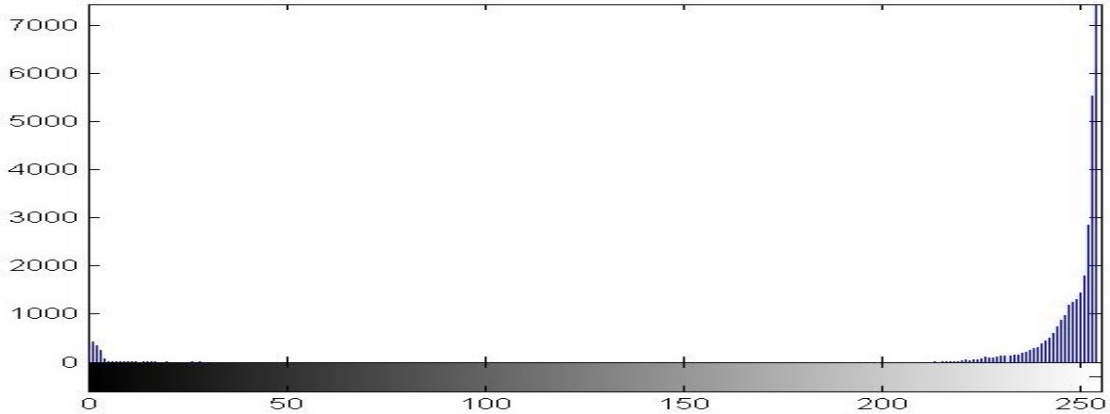


Fig2.4.3. Histogram of original image(Rose, fig.7.1.a)

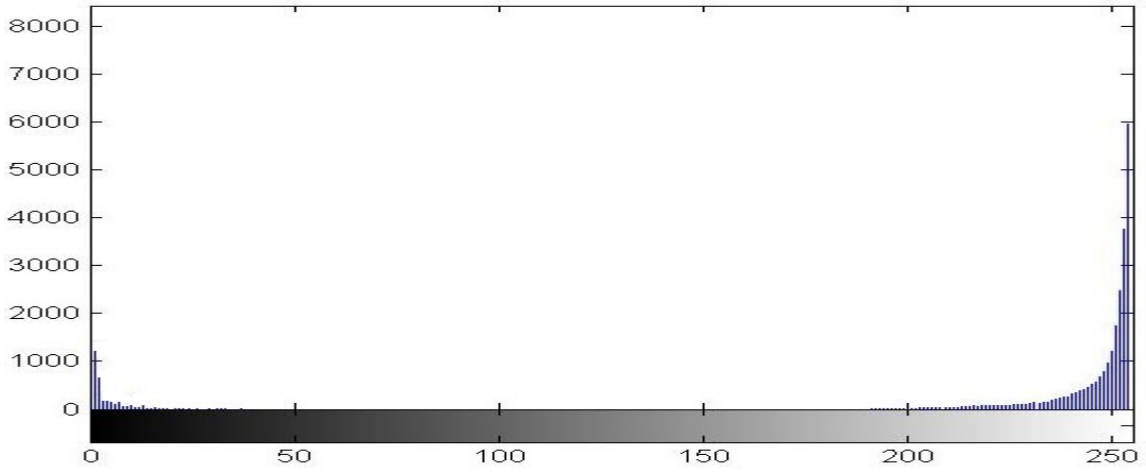


Fig2.4.4 Histogram of modified image(Rose, fig7.1.b) by 12

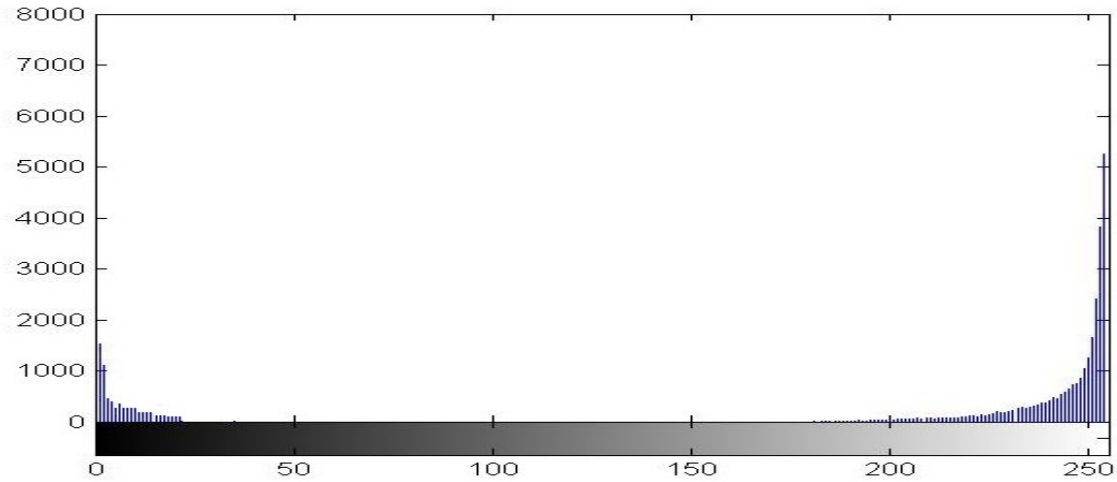


Fig2.4.5. Histogram of image (Rose,fig7.1.c) by proposed method

So we can here analyze that proposed operator is enhancing underexposed parts better than i.e.[12].Because by proposed method the pixels intensities near of dark side of gray levels are enhancing better.

2.5. Fuzzification Of Overexposed Region:

In an image overexposed region intensity values should be reduced to make image more pleasant, so here we introducing a normalized triangular membership function for the fuzzification of the overexposed region of the image

$$\mu_{xo}(x) = \begin{cases} 0, & x < F \\ \frac{x-F}{L-F}, & x \geq F \end{cases} \quad (2.5.1)$$

Where x is in the interval (F to L-1), which covers only the over exposed region of the intensity image while giving zeros to the under exposed values (below value F).This has only one parameters F .These membership functions transform the image intensity levels from the spatial domain into the fuzzy domain where the membership values are in the range [0,1].

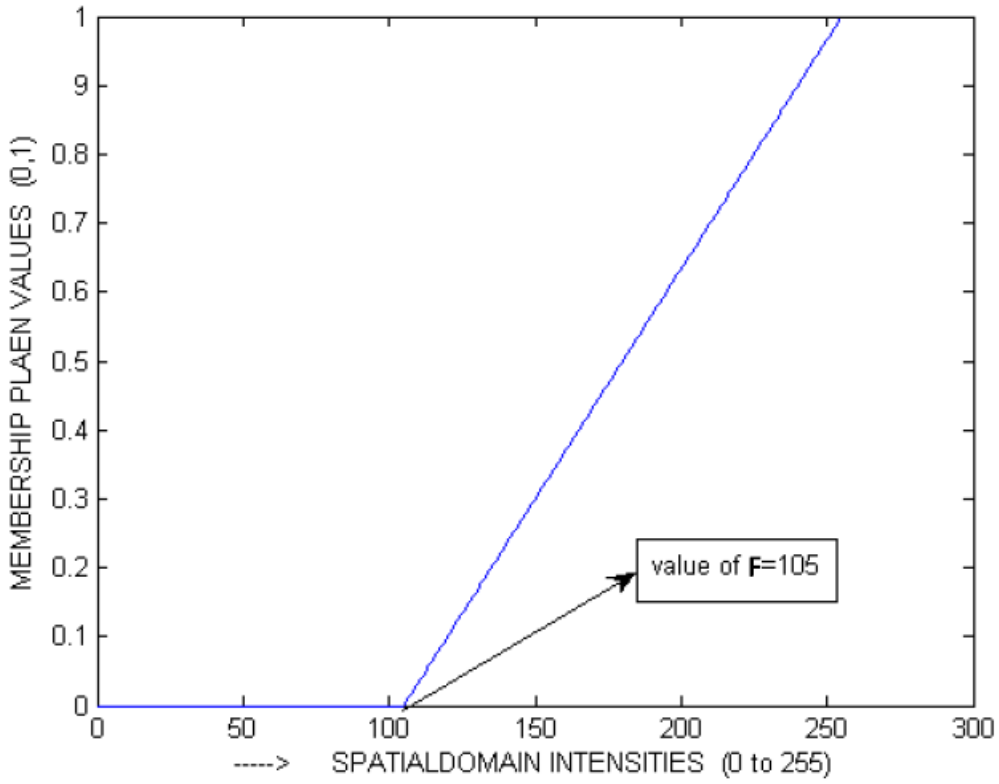


Fig.2.5.1. Membership function for over exposed region for F=105

2.6. Enhancement Operators

To make operator more reliable on pixels intensity values of image here we are introducing new enhancement operator for underexposed region:

$$\mu'_{xu}(x) = \begin{cases} \mu_c\left(\frac{\mu_{xu}(x) - t_1}{\mu_c - t_1}\right)^{\alpha(\mu_{xu}(x) - t_1)}, & 0 < \mu_{xu}(x) < \mu_c \\ (1-\mu_c)\left(\frac{t_2 - \mu_{xu}(x)}{t_2 - \mu_c}\right)^{\beta(t_2 - \mu_{xu}(x))}, & \mu_c < \mu_{xu}(x) < 1 \end{cases} \quad (2.6.1)$$

Where μ_c is the cross over point, $t_1$and t_2 are the stand for lower and upper limit respectively and α, β are constants. Here the power of the operator is itself membership function value ($\mu_{xu}(x)$) instead of only any constants (α,β) .So it increase the order of the equation with respect to membership function value and this one make the operator more depended on membership function.

We use rectangular hyperbolic functions the transformation operator for modifying the membership values of overexposed pixels given as:

$$\mu'_{xo}(x) = \frac{k\mu_{xo}(x)}{1+k-\mu_{xo}(x)} \quad (2.6.2)$$

Where k is a parameter which controls the shape of the hyperbola. $\mu_{xo}(x)$ Is the membership function of the overexposed region. In overexposed region the grey scale values are stacked near the higher intensity values and it is complicated to discriminate levels of neighbouring pixels. Approaching through this operator the information content in these regions is improved.

2.7 Deffuzification :

The membership function defined for the under exposed region deals with only the under exposed region and similarly the membership function of the over exposed region. This ensures that the operator applied on one region does not affect the other region. With this we can apply the respective operators separately and simultaneously to enhance both the regions. The modified membership values of these two regions are converted back to image plane i.e. defuzzification using the respective inverse membership functions given below.

$$x'_u = x_{avg} - x_{max} + \left(-2\left[\{\ln(\mu'_{xu}(x))\}\frac{1}{\beta}\right] f_h^{\,2}\right)^{1/2} \quad (2.7.1)$$

Where $\mu'_{xu}(x)$ is the modified value of the under exposed region and x'_u is the corresponding values of the under exposed region after applying equation (2.4.1).

For over exposed region:

$$x'_o = \begin{cases} 0 \text{ to } a-1 & \mu'_{xo}(x) = 0 \\ a + (L-a)\mu'_{xo}(x) & else \end{cases} \quad (2.7.2)$$

Where x'_o is the modified intensity value for the over exposed region in the range [a,L-1] and $\mu'_{xo}(x)$ indicates the corresponding membership values for the over exposed region after applying the triangular operators i.e. equation (2.5.1)

Chapter 3

Entropy

Entropy is a measure of the uncertainty associated with a random variable. In image the values of intensity of pixels are also random in nature. The image enhancement is based on information content of an image. The low intensities represent the pixels with low information contribution. The high intensities represent the pixels with high information contribution so we introduce the entropy phenomenon for image enhancement.

We use here Shannon entropy concept .

$$E = \sum_{x=0}^{x=r} -(\mu'_{xu}(x) \times \log(\mu'_{xu}(x)) - (1-\mu'_{xu}(x)) \times (\log(1-\mu'_{xu}(x)) + \sum_{x=r}^{x=L-1} (-(\mu'_{xo}(x) \times (\log(\mu'_{xo}(x))) - (1-\mu'_{xo}(x)) \times (\log(-\mu'_{xo}(x))) \quad \textbf{(3.1)}$$

Where $\mu'_{xu}(x)$is the membership operator value at any intensity in underexposed region and $\mu'_{xo}(x)$ is the membership operator value at any intensity in overexposed region and it lies between 0 to 1.

3.1.Maximum Entropy Theorem :

If *X* is a discrete random variable with distribution given by

$$\Pr(X= x_k) = p_k \quad \text{for} \quad k= 1,2\ldots\ldots\ldots\ldots L.$$

The entropy of X is defined as

$$E(k) = \sum_{k\geq 1} [-p_k(log\, p_k) \text{-}(1\text{-}p_k)(\log(1 - p_{k)})] \qquad (3.1.1)$$

When the information provided is uniform then the Maximum entropy comes. In terms of image the image looks pleasant when the histogram is uniform in nature.

So

$$E(k) = [-(p_k)\log p_k\text{-}(1\text{-}p_k)(\log (1 - p_{k)})]$$

$$= -p_k\log p_k\text{-}(1\text{-}p_k)(\log (1 - p_{k)})$$

For the maximum value of E(k) , $\frac{dE(k)}{d\, p_k}$ should be equal to zero.

So,

$$\frac{dE(k)}{d\, p_k} = \frac{d[-p_k\log p_k-(1-p_k)(\log (1- p_k))]}{d\, p_k} =0$$

Or, $(-p_k)\frac{\mathrm{d}\log p_k}{\mathrm{d}\, p_k} +(\log p_k)\frac{d(-p_k)}{dp_k} \text{-}(1 - p_k)\frac{\mathrm{d}(\log (1- p_k))}{\mathrm{d}\, p_k} \text{-}(\log (1 - p_k))\frac{d(1-p_k)}{dp_k} = 0$

Or , $(-p_k)\times\frac{1}{(p_k)} + \log((p_k))\times(-1) \text{-}\frac{1-p_k}{1-p_k}(-1) + \log (1 - p_k) = 0$

Or, $-1 - \log (p_k) + 1 + \log (1 - p_k) = 0$

Or, $-\log p_k + \log (1 - p_k) = 0$

Or, $\log (p_k) = \log (1 - p_k)$

$$(1 - p_k)= p_k$$

$$p_{k=} \frac{1}{2}$$

Now at $p_{k=}$ $\frac{1}{2}$

The maximum value of entropy (E) will be.

$$E_m = [-(\frac{1}{2})\log(\frac{1}{2}) - (1-\frac{1}{2})(\log(1-\frac{1}{2}))] = 1 \qquad (3.1.2)$$

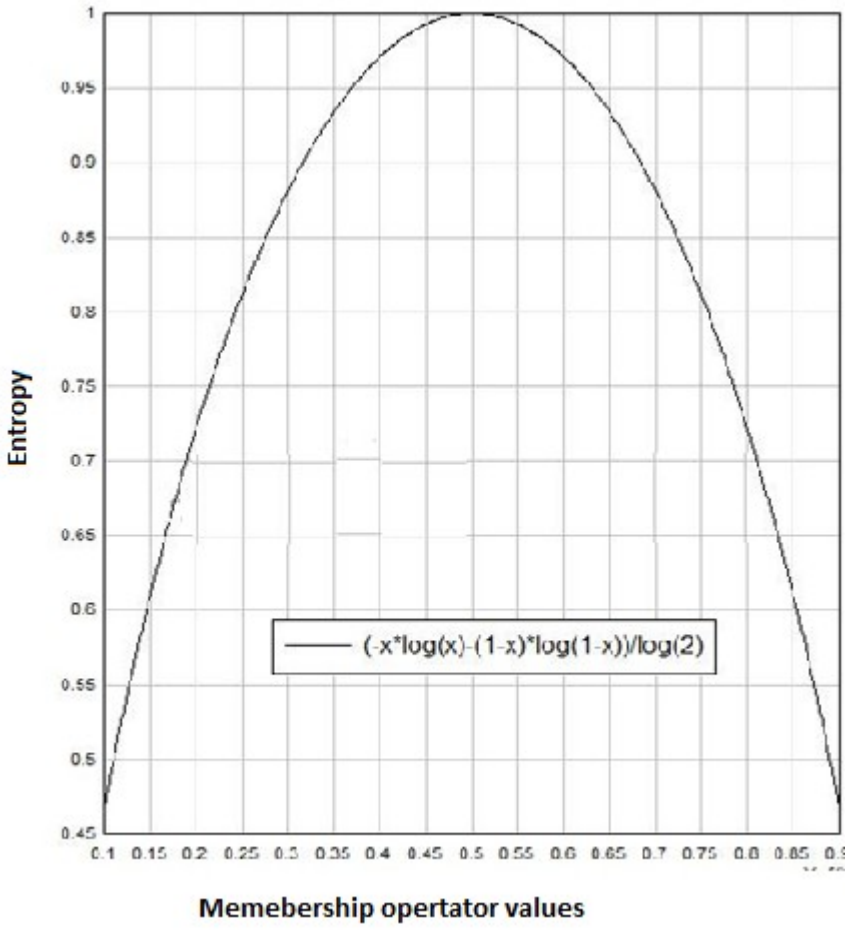


Fig. 3.1 Function of Entropy (E)

3.2 Optimization

We know that if image has uniform intensity in nature it looks pleasant and also approach to desirable entropy value. So here we optimize the entropy value of the degraded image with respect to the maximum entropy value .The optimization equation is:

$$J = E_m - E \qquad (3.2.1)$$

Where E is the entropy of the degraded image and E_m is the maximum entropy. According to our used equation of entropy the maximum value of entropy is 1. So by optimization, entropy (E) will approach towards desired value of entropy and try to achieve the desired value of intensity.

3.3 Enhancement Of Saturation:

Saturation plays an important role in enhancing the overexposed color images especially those containing the degraded regions, where all pixels are at the maximum intensity level. Reduction of saturation in these cases helps regain details, bringing back the pleasing nature of the image. For this the following power law operator is used :

$$S'(x) = [S(x)]^{(Fork\ ratio)} \qquad (3.3.1)$$

Here S(x) is saturation values of the original image and S'(x) is of modified image. The saturation value should be enhance for over exposed type of image and the amount of variation should depend on portion of the over exposed region in the image. Enhancement of saturation brings back the pleasing nature for such images.

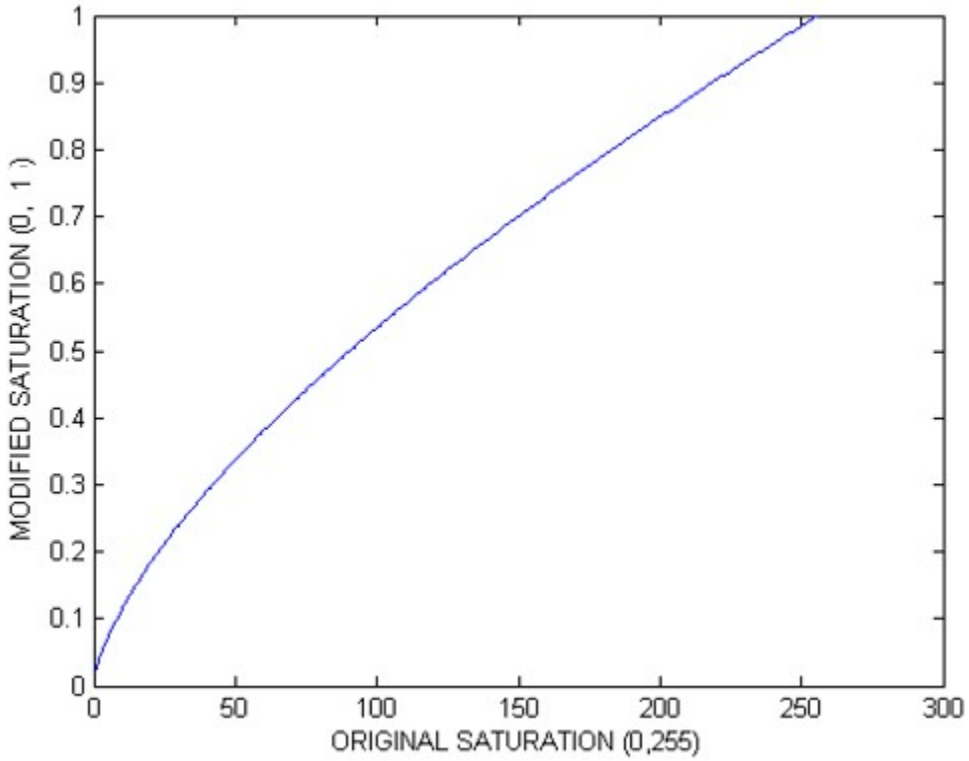


Fig.3.3.1 Enhancement of saturation by fork ratio

Chapter 4

Bacterial Foraging For Optimization

4.1 Introduction

Optimal foraging theory is an idea in ecology based on the study of foraging behavior and states that organisms forage in such a way as to maximize their net energy intake per unit time. In other words, they behave in such a way as to find, capture and consume food containing the most calories while expending the least amount of time possible in doing so .when a population of bacteria dries out without a protectant.Many of the cells break open and release their internal contents. Among these contents are proteins, gums and sugars, all of which are protective. If the population is sufficiently dense, so that significant amounts of protectant are released, material released from the majority which died first can protect a few of their surviving fellows.

4.2 Foraging :

Foraging is the act of searching for food. As a field of study, foraging theory is a branch of behavioral ecology that studies the foraging behavior of animals in response to the environment in which the animal lives. Foraging theory considers the foraging behavior of animals in reference to the payoff that an animal obtains from different foraging options. Foraging theory predicts that the foraging options that deliver the highest payoff should be favored by foraging animals because it will have the highest fitness payoff. More specifically, the highest ratio of energetic gain to cost while foraging.Human societies that subsist mainly by foraging wild plants and animals are known as hunter-gatherers. *E. coli* is a common type of bacteria that can get into food, like beef and vegetables. *coli* normally lives inside your intestines, where it helps your body break down and digest the food you eat. We explain here the behavior of their life :

4.3 Chemotactic Behavior Of E. Coli. Type Bacteria:

Chemotactic is the phenomenon in which , E. coli. type bacteria, and other single-cell or multi cellular organisms direct their movements according to certain chemicals in their environment. This is important for bacteria to find food by swimming towards the highest concentration of food molecules,

Chemotactic Actions:

(1) If in neutral medium, alternate tumbles and runs ⇒search.

(2) If swimming up a nutrient gradient (or out of noxious substances), swim longer

(climb up nutrient gradient or down noxious gradient) ⇒seek increasingly favorable

environments.

(3) If swimming down a nutrient gradient (or up noxious substance gradient), then search avoid unfavorable environments.

In this way, it can climb up nutrient hills and at the same time avoid noxious substances. The overall movement of a bacterium is the result of alternating tumble and swim phases. If one watches a bacterium swimming in a uniform environment, its movement will look like a random walk with relatively straight swims interrupted by random tumbles that reorient the bacterium. Bacteria such as E. coli are unable to choose the direction in which they swim, and are unable to swim in a straight line for more than a few seconds due to rotational diffusion. In other words, bacteria "forget" the direction in which they are going. By repeatedly evaluating their course, and adjusting if they are moving in the wrong direction, bacteria can direct their motion to find favorable locations with high concentrations of attractants (usually food) and avoid repellents (usually poisons).In the presence of a chemical gradient bacteria will chemotax, or direct their overall motion

based on the gradient. If the bacterium senses that it is moving in the correct direction (toward attractant/away from repellent), it will keep swimming in a straight line for a longer time before tumbling. If it is moving in the wrong direction, it will tumble sooner and try a new direction at random. In other words, bacteria like E. coli use temporal sensing to decide whether life is getting better or worse. In this way, it finds the location with the highest concentration of attractant (usually the source) quite well. Even under very high concentrations, it can still distinguish very small differences in concentration. Fleeing from a repellent works with the same efficiency. This purposeful random walk is a result of simply choosing between two methods of random movement; namely tumbling and straight swimming. In fact, chemotactic responses such as *f*orgettin*g* direction and *choosing* movements resemble the decision-making abilities of higher life-forms with brains that process sensory data.. Each bacterium tries to maximize the amount of nutrient while minimizing time and energy cost by following four stages: 1) Chemo taxis, 2) Swarming, 3) Reproduction, and 4) Elimination & Dispersal. In the beginning, there will be as many solutions as the number of bacteria. So, each bacterium produces a solution for set of optimal values of parameters iteratively, and gradually all the bacteria converge on the global optimum.

During foraging of the real bacteria, locomotion is achieved by a set of tensile flagella. Flagella help an *E.coli* bacterium to tumble or swim, which are two basic operations performed by a bacterium at the time of foraging. When they rotate the flagella in the clockwise direction, each flagellum pulls on the cell. That results in the moving of flagella independently and finally the bacterium tumbles with lesser number of tumbling whereas in a harmful place it tumbles frequently to find a nutrient gradient. Moving the flagella in the counterclockwise direction helps the bacterium to swim at a very fast rate. In the above-mentioned algorithm the bacteria undergoes chemotactic, where they like to move towards a nutrient gradient and avoid noxious environment. Generally the bacteria move for a longer distance in a friendly environment..

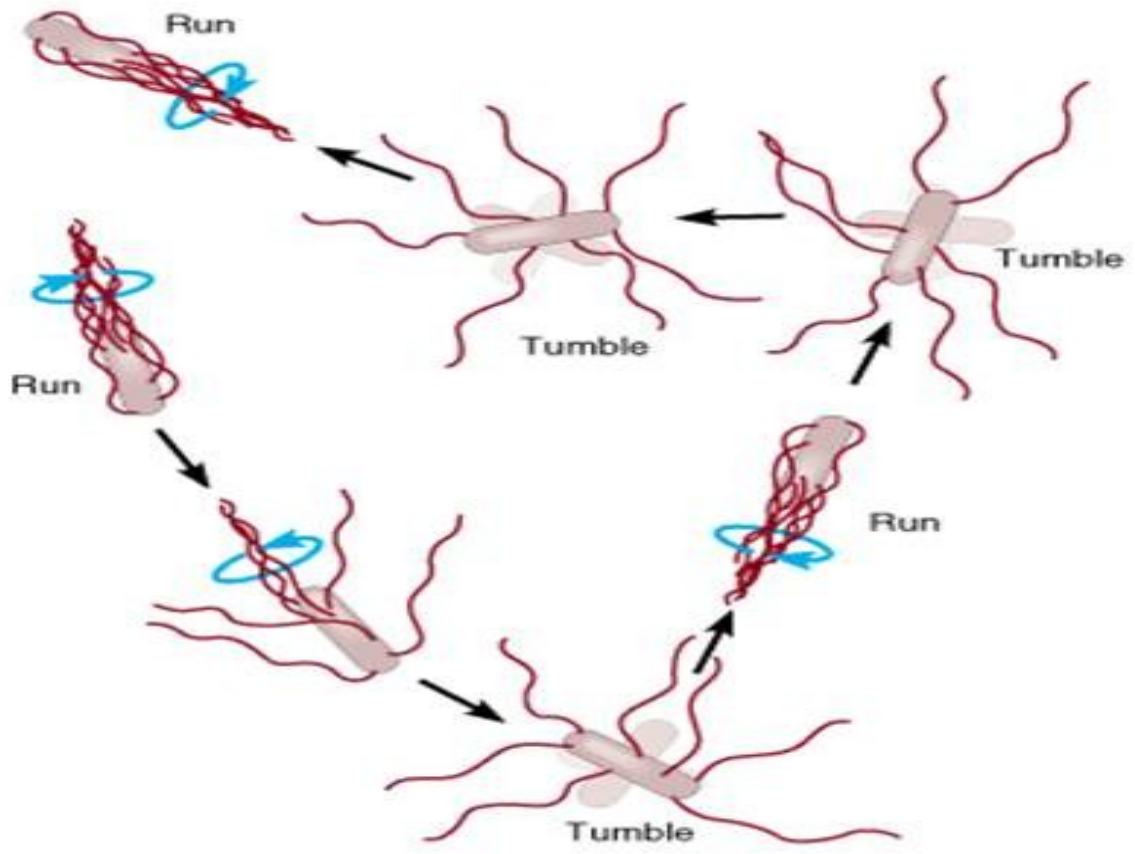


Fig.4.3.1. Run and tumble of a bacterium

When they get food in sufficient, they are increased in length and in presence of suitable temperature they break in the middle to from an exact replica of itself. Due to the occurrence of sudden environmental changes or attack, the chemotactic progress may be destroyed and a group of bacteria may move to some other places or some other may be introduced in the swarm of concern. This constitutes the event of elimination-dispersal in the real bacterial population, where all the bacteria in a region are killed or a group is dispersed into a new part of the environment.

Now suppose that we want to find the minimum of $J(\theta)$where $\theta\ p \in \Re$ (i.e. θ is a p-dimensional vector of real numbers), and we do not have measurements or an analytical description of the gradient $\nabla J(\theta)$. BFOA mimics the four principal mechanisms

observed in a real bacterial system: chemotexis, swarming, reproduction, and elimination-dispersal to solve this non-gradient optimization problem. Let us define a chemotactic step to be a tumble followed by a tumble or a tumble followed by a run. Let j be the index for the chemotactic step. Let k be the index for the reproduction step. Let l be the index of the elimination-dispersal event. Also let

p: Dimension of the search space,

S: Total number of bacteria in the population,

N_c : The number of chemotactic steps,

N_s: The swimming length.

N_{re} : The number of reproduction steps,

N_{ed} : The number of elimination-dispersal events,

P_{ed} : Elimination-dispersal probability,

$C(i)$: The size of the step taken in the random direction specified by the tumble.

Let $P(j, k, l)$ $\{ (j, k, l) \mid i$ 1,2,..., $S\}$ $i = \theta =$ represent the position of each member in the population of the S bacteria at the j-th chemotactic step, k-th reproduction step, and l-th elimination-dispersal event. Here, let $J(i, j, k, l)$ denote the cost at the location of the i-th bacterium $\theta_p^i(j, k, l) \in \Re$ (sometimes we drop the indices and refer to the i-th bacterium position as θ_t). Note that we will interchangeably refer to J as being a "cost" (using terminology from optimization theory) and as being a nutrient surface (in reference to the biological connections). For actual bacterial populations, S can be very large (e.g., S =109), but $p = 3$. In our computer simulations, we will use much smaller population sizes and will keep the population size fixed. BFOA, however, allows $p > 3$ so that we can

apply the method to higher dimensional optimization problems. Below we briefly describe the four prime steps in BFOA.

i) Chemotaxis: This process simulates the movement of an *E.coli* cell through swimming and tumbling via flagella. Biologically an *E.coli* bacterium can move in two different ways. It can swim for a period of time in the same direction or it may tumble, and alternate between these two modes of operation for the entire lifetime. Suppose θ(*i, j, k, l*) represents *i*-th bacterium at *j*th chemotactic, *k*-th reproductive and *l*-th elimination-dispersal step. *C*(*i*) is the size of the step taken in the random direction specified by the tumble (run length unit). Then in computational chemotaxis the movement of the bacterium may be represented by

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \qquad (\mathbf{4.3.1})$$

Where Δ indicates a vector in the random direction whose elements lie in [-1, 1].

ii) Swarming: An interesting group behavior has been observed for several motile species of bacteria including *E.coli* and *S. typhimurium*, where intricate and stable spatio-temporal patterns (swarms) are formed in semisolid nutrient medium. A group of *E.coli* cells arrange themselves in a traveling ring by moving up the nutrient gradient when placed amidst a semisolid matrix with a single nutrient chemo-effecter. The cells when stimulated by a high level of *succinate*, release an attractant *aspertate*, which helps them to aggregate into groups and thus move as concentric patterns of swarms with high bacterial density. The cell-to-cell signaling in *E. coli* swarm may be represented by the following function.

$$J_{cc}(\theta, P(j,k,l)) = \sum_{i=1}^{S} J_{cc}\left(\theta, \theta^i(j,k,l)\right)$$
$$= \sum_{i=1}^{S}\left[-d_{attractant}\exp\left(-w_{attractant}\sum_{m=1}^{p}\left(\theta_m - \theta_m^i\right)^2\right)\right]$$
$$+ \sum_{i=1}^{S}\left[-h_{repellant}\exp\left(-w_{repellant}\sum_{m=1}^{p}\left(\theta_m - \theta_m^i\right)^2\right)\right]$$

(4.3.2)

where $J\ cc\ (\theta,\ P\ (j,\ k,\ l))$ is the objective function value to be added to the actual objective function (to be minimized) to present a time varying objective function, S is the total number of bacteria, p is the number of variables to be optimized, which are present in each bacterium and $\theta = [\theta_1, \theta_2, \ldots, \theta_p]^T$ is a point in the p-dimensional search domain. $d_{attractant}, w_{attractant}, h_{repellant}, w_{repellant}$ are different coefficients that should be chosen properly.

iii) Reproduction: The least healthy bacteria eventually die while each of the healthier bacteria (those yielding lower value of the objective function) asexually split into two bacteria, which are then placed in the same location. This keeps the swarm size constant.

iv) Elimination and Dispersal: Gradual or sudden changes in the local environment where a bacterium population lives may occur due to various reasons e.g. a significant local rise of temperature may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. Events can take place in such a fashion that all the bacteria in a region are killed or a group is dispersed into a new location. To simulate this phenomenon in BFOA some bacteria are liquidated at random with a very small probability while the new replacements are randomly initialized over the search space.

The pseudo-code of the complete algorithm is presented below:

4.4. The BFOA Algorithm

Parameters:

[Step 1] Initialize parameters *p, S, N_c, N_s, N_{re}, N_{ed}, P_{ed}, C(i)(i=1,2…S)*, θ^i.

Algorithm:

[Step 2] Elimination-dispersal loop: *l*=*l*+1

[Step 3] Reproduction loop: *k*=*k*+1

[Step 4] Chemotaxis loop: *j*=*j*+1

[a] For *i* =1,2…S take a chemotactic step for bacterium *i* as follows.

[b] Compute fitness function, *J (i, j, k, l)*.

Let, $J(i,j,k,l) = J(i,j,k,l) + J_{cc}(\theta^i(j,k,l), P(j,k,l))$ (i.e. add on the cell-to cell Attractant–repellant profile to simulate the swarming behavior)

Where, J_{cc} is defined in (2).

[c] Let J_{last}=*J (i, j, k, l)* to save this value since we may find a better cost via a run.

[d] Tumble: generate a random vector $\Delta(i) \in \Re p$ with each element (i),m 1,2,..., p,

m Δ = a random number on [-1, 1].

[e] Move: Let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \qquad (4.4.1)$$

This results in a step of size $C(i)$ in the direction of the tumble for bacterium *i*.

[f] Compute $J(i, j+1, k, l)$ and let

$$J(i,j+1,k,l) = J(i,j,k,l) + J_{cc}(\theta^i(j+1,k,l), P(j+1,k,l))$$

[g] Swim

i) Let *m*=0 (counter for swim length).

ii) While $m < N_s$ (if have not climbed down too long).

• Let $m=m+1$.

• If $J(i, j+1, k, l) < J_{last}$ (if doing better), let $J_{last} = J(i, j+1, k, l)$ and let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}} \qquad (4.4.2)$$

And use this $\theta^i(j+1,k,l)$ to compute the new $J(i, j+1, k, l)$ as we did in

[f] Else, let $m= N_s$. This is the end of the while statement.

[h] Go to next bacterium $(i+1)$ if $i \neq S$ (i.e., go to [b] to process the next bacterium).

[Step 5] If $j < N_c$, go to step 4. In this case continue chemotaxis since the life of the bacteria is not over.

[**Step 6**] Reproduction:

[a] For the given k and l, and for each $i = 1,2,..., S$

$$J^i_{health} = \sum_{j=1}^{N_c+1} J(i,j,k,l) \qquad (4.4.3)$$

Let be the health of the bacterium i (a measure of how many nutrients it got over its lifetime and how successful it was at avoiding noxious substances). Sort bacteria and chemotactic parameters $C(i)$ in order of ascending cost J_{health} (higher cost means lower health).

[b] The S_r bacteria with the highest J_{health} values die and the remaining S_r bacteria with the best values split (this process is performed by the copies that are made are placed at the same location as their parent).

[**Step 7**] If $k < N_{re}$, go to step 3. In this case, we have not reached the number of specified reproduction steps, so we start the next generation of the chemotactic loop.

[**Step 8**] Elimination-dispersal: For $i = 1,2...,\ S$ with probability P_{ed} , eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, if a bacterium is eliminated, simply disperse another one to a random location on the optimization domain. If $l < N_{ed}$, then go to step 2; otherwise end.

In the chemo taxis stage, the bacteria either resort to a tumble followed by a tumble or make a tumble followed by a run or swim. This is the movement stage of bacteria through swimming and tumbling. On the other hand, in swarming, each *E. coli* bacterium signals another via attractants to swarm together. This is basically the cell to cell signaling stage. Furthermore, in reproduction bacterium with the least energy dies and the other bacteria with high energy survive. While in the elimination and dispersal stage, any bacterium from the total set can be either eliminated or dispersed to a random location during the optimization process. This stage helps the bacteria avoid the local optimum.

4.5 Modified Bacterial Foraging Algorithm

The BF algorithm suggested in [12] is modified so as to expedite the convergence. The modifications are discussed below. In [12], the author has taken the average value of all the chemotactic cost functions, to decide the health of particular bacteria in that generation, before sorting is carried out for reproduction. In this paper, instead of the average value, the minimum value of all the chemotactic cost functions is retained for deciding the bacterium‘s health. This speeds up the convergence, because in the average scheme [12], it may not retain the fittest bacterium for the subsequent generation. On the contrary, in this paper, the global minimum bacteria among all chemotactic stages pass on to the subsequent stage. For simplicity, we have ignored the cell to cell attractant function for swarming.

4.6 Initialization Of Parameters

Here we divided our image in two parts so we have to initialized two parameters to be optimized i.e. F_h,μ_c,α,β,t_1,t_2 and k. the original objective function J, and the parameters of the Bacterial Foraging Algorithm to make J a time-varying cost function during the optimization. We first initialize the parameters of modified Bacterial Foraging. Bacterial foraging has four parts we first decide what value of them to take so that we can get the better optimization. So here we are presenting the behaviour of the bacterial parts with respect to objective function J. We are taking here the image"hill"(fig.7.5) for observing the bacterial parameters.

4.6.1 Swimming Length

When we change the length of the swimming the value of objective function (J) is also changed .The following fig.5.6.1 show relation between swimming length (N_s) and optimize objective function value(J).We have taken the samples between these two and then decide the value of N_s at which we can get better optimum value.

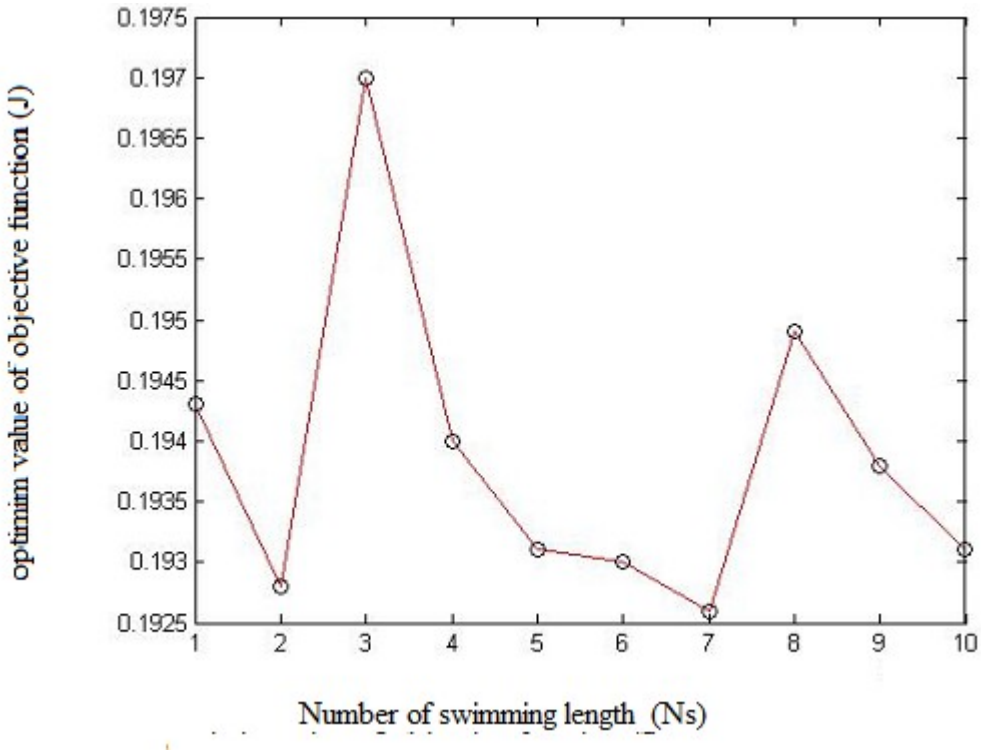


Fig. 4.6.1 Function of swimming length

4.6.2 Chemotactic Steps:

When we change the length of the swimming the value of objective function (J) is also changed .the following fig. 5.6.2 show relation between swimming length (N_c) and optimize objective function value(J).we have taken the samples between these two and then decide the value of N_c at which we can get better optimum value.

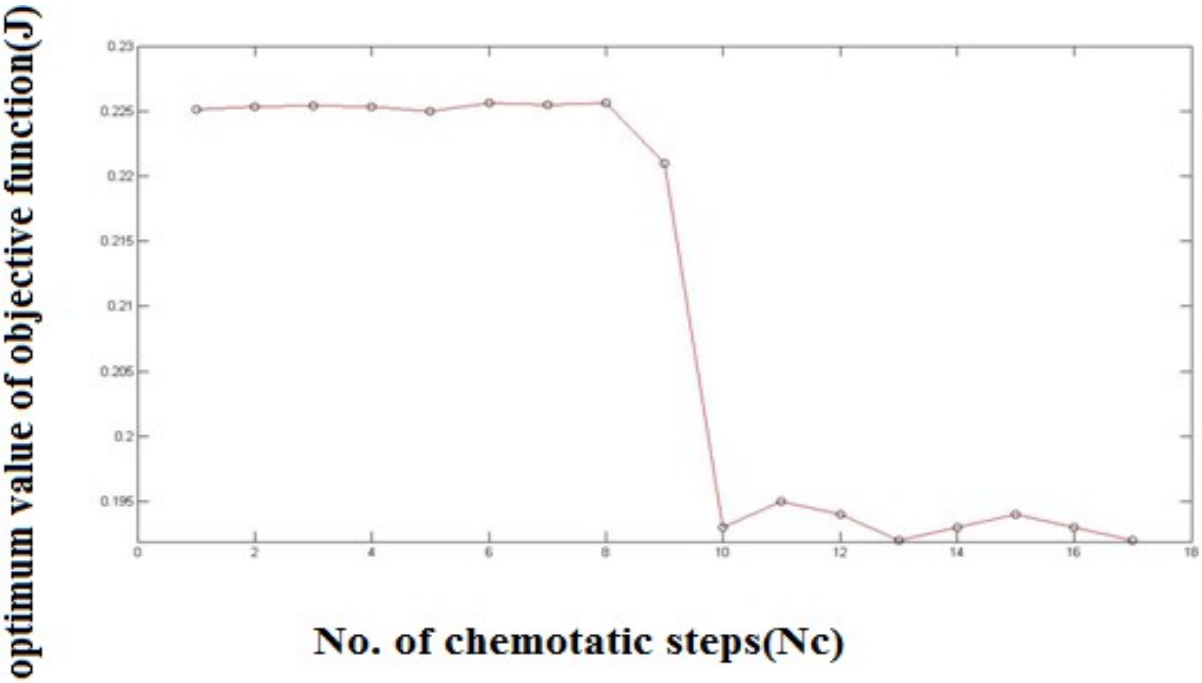


Fig 4.6.2 Function of chemotactic steps(N_c)

4.6.3 Reproduction Steps

When we change the length of the swimming the value of objective function (J) is also changed .the following fig. 5.6.3 show relation between swimming length (N_r) and optimize objective function value(J).we have taken the samples between these two and then decide the value of N_r at which we can get better optimum value.

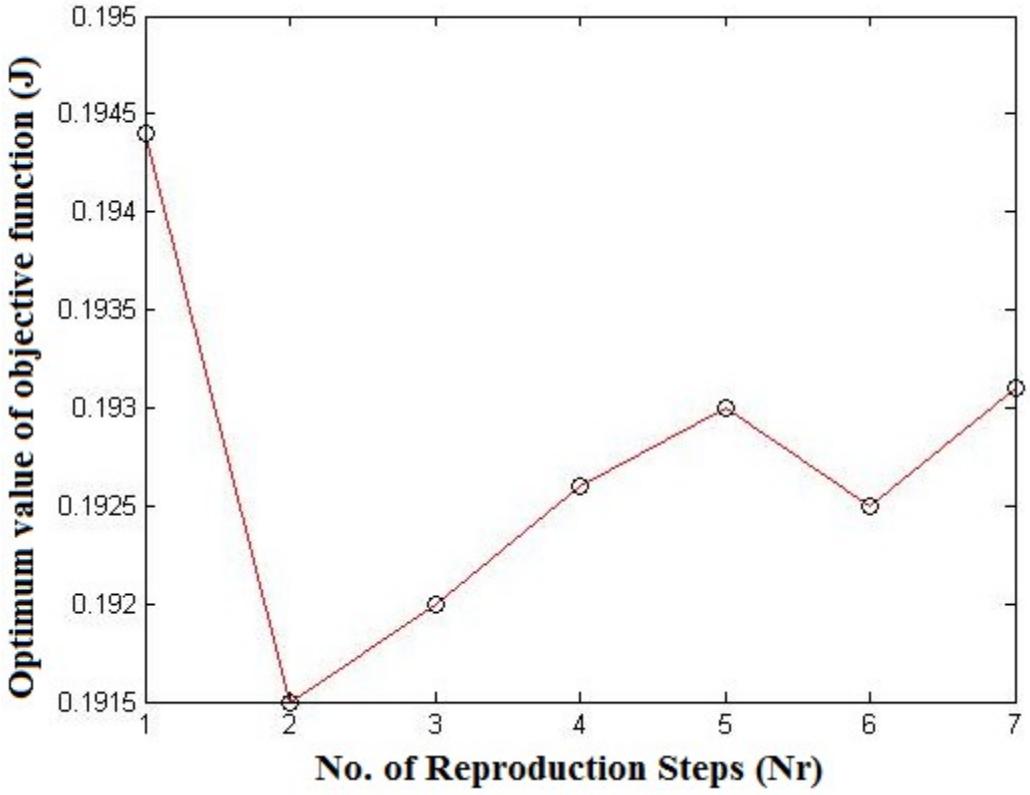


Fig 4.6.3 Function of Reproduction steps (N_r)

4.6.4 Elimination And Dispersal Events

When we change the length of the swimming the value of objective function (J) is also changed .the following fig. 5.6.4 show relation between swimming length (N_s) and optimize objective function value(J).we have taken the samples between these two and then decide the value of N_s at which we can get better optimum value.

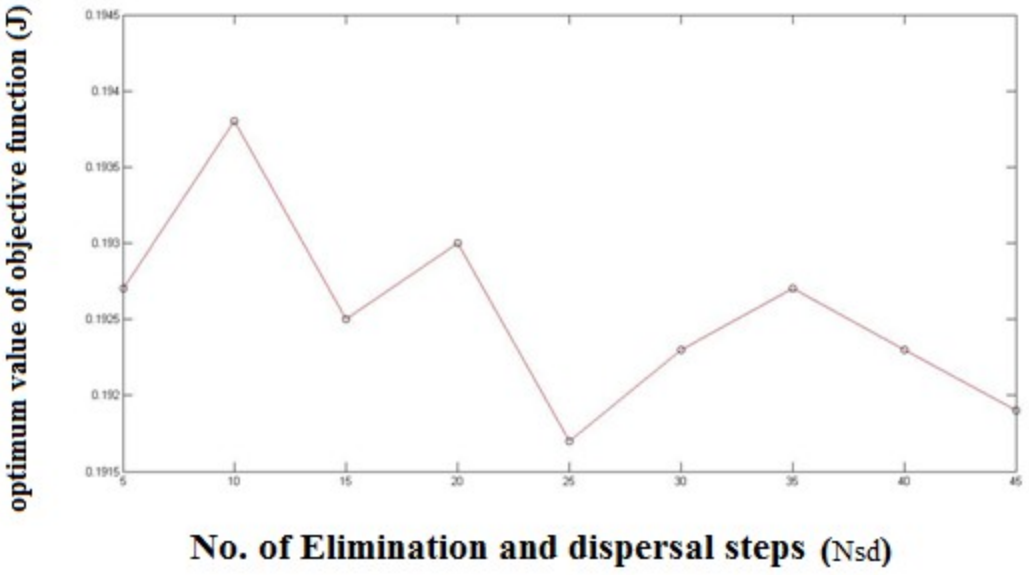


Fig.4.6.4 Function of Elimination and Dispersal steps

4.6.5 Number Of Bacteria In The Population (s)

When we change the no. of bacteria in the population the value of objective function (J) is also changed .The following fig. 5.6.4 show relation between no. of bacteria in the population (S) and optimize objective function value (J). We have taken the samples between these two and then decide the value of 'S' at which we can get better optimum value

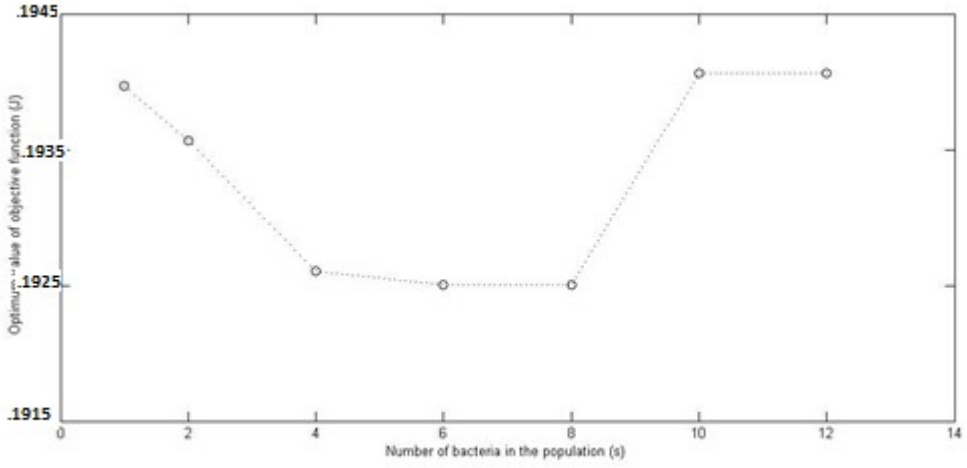


Fig 4.6.5 Function of No. of bacteria in the population (s)

So considering all the functions we have taken the value of the parameters of the modified bacterial foraging algorithm [12]:

1) The number of bacteria S =7.
2) The swimming length N_s=7.
3) The number of iterations in a chemotactic loop $N_c$is set to 10.
4) The number of reproduction steps $N_r$is set to 2.
5) The number of elimination and dispersal events N_{ed} is set to 25.
6) The probability of elimination/dispersal $p_{ed}$is set to 0.25.
7) The location of each bacterium, which is a function of several parameters, i.e., $f(p_{ed},N_{ed},N_r,N_c)$ is specified by a random number in the range [0–1].

4.6.6 Algorithm For Image Enhancement:

The algorithm is given below orderly

1) Input the given image and convert into HSV from RGB.
2) Calculate histogram of image p(v) .
3) Calculate the initial value of F_h. Using Eqn.(2.4.2).
4) Compute the value of fork point using Eqn. (2.2.4).
5) Fuzzify V to get μ_{xu} and μ_{xo} using Eqns. (2.4.1) and(2.5.1) respectively.
6) Calculate the modified membership values μ'_{xu} and $\mu'_{xo}(x)$ for under exposed region and over exposed region using Equations(2.6.1),(2.6.2) respectively .
7) Calculate the Entropy value using Eqn.(3.1)
8) Optimize the objective function using bacterial foraging algorithm by Equation(3.2).
9) Modified the membership functions with optimized parameters.
10) Defuzzify the modified membership values of both the underexposed and overexposed region and combined based on the value of fork (F) to form

intensity(V) for the enhanced value using Eqn.(.2.7.1)and(2.7.2) respectively.

11) Enhance the saturation for the overexposed images using equation (3.3.1).and display it.

Chapter 5
Results And Discussions

We have implemented the proposed approach using MATLAB. Around 40 images (both under and overexposed) have been processed and some of them (camera, rose, hill,face,etc) are presented here .

First the original RGB image is converted to HSV (Hue, saturation and intensity value) color space to preserve the hue of the image. Our contribution is to define a new exposure parameter by which the original intensity V has been divided into two regions as under

exposed region and over exposed region based on the amount of brightness exposition . These two regions of the image have been separately enhanced with separate operators defined. . The modified non linear function enhances the intensity of the image pixels where as the rectangular hyperbolic function reduces the intensity. We proposed β a deciding factor to operate the membership function of underexposed region. The order of the membership function is different for image which has very less underexposed region and which has normal underexposed region.The nonlinear transformation curves are presented for the images. Table I represents the initial values of the parameters ($F_h, \alpha, \beta, t_1, t_2, k, \mu_c$) and the objective function of the test images. Table (II) gives the optimized parameters and objective function of the modified images obtained. The fuzzifier F_h the crossover point μ_c and the intensification parameter t for the component are calculated separately. For optimization we use here the desired entropy concept, we compare the calculated entropy value of image with maximum entropy and optimize the difference. By this the entropy value will approach to desired value and through this we can get the optimized values of parameters. Throughout the intensification process, the value of hue is kept constant to preserve the basic color of the image.

Most of the underexposed images do not need enhancement of saturation. But some highly overexposed images have permanent degraded regions, and the information in these areas can be recovered up to some extent by reducing the saturation using the saturation operator. In highly overexposed image the underexposed region are better enhance by the proposed operator Eqn.(1.4.1). We have observed the parts of the bacterial foraging for effect upon objective function (J) and chosen the value at which we get better optimized value. The proposed approach is computationally efficient in terms of the time taken to optimize the parameters as the number of bacteria required is less. Further work must be directed towards evolving new membership function and new operators for the recovery of the permanently degraded images.

The original images and the enhanced images are shown in Figs.5.1a- 5.10.c A clear improvement is seen as far as the details are concerned after the application of the proposed enhancement method. This can be seen from different case studies, from which we can say it is nonlinear. Note that the pleasing nature arises from proper stretching of the membership values.

TABLE I : Initial Value Of Parameters

Images	t_1	t_2	f_h	K	α	B	μ_c
Rose	-0.5	1.5	179.8247	0.5	2.4	2.7	0.4
Hill	-0.5	1.5	161.5643	0.5	2.4	2.7	0.4
camera	-0.5	1.5	153.1682	0.5	2.4	2.7	0.4
cricketer	-0.5	1.5	157.134	0.5	2.4	2.7	0.4
face	-0.5	1.5	168.178	0.5	2.4	2.7	0.4
bridge	-0.5	1.5	149.234	0.5	2.4	2.7	0.4
Village	-0.5	1.5	154.143	0.5	2.4	2.7	0.4
doctor	-0.5	1.5	139.123	0.5	2.4	2.7	0.4

We have considered many images, *viz.* face.jpg, doctor.jpg, cricketer.jpg, of type under exposed and the images *viz.*, man.jpg, hills.jpg, and rose.jpg of type over and mixed exposed images. The original under exposed images have poor brightness and the original over exposed images have much higher brightness. In both the cases, the details are not discernable. Also colors are not perceivable to the eye. The original and the enhanced images of some test images are shown the fig. 5.1.a to fig. 5.9.c.

TABLE ii : Optimization Of $J_v = E_{max}$- E

Images	t_1	t_2	f_h	k	A	B	μ_c	J
Rose	- 0.5010	1.5010	60.5565	0.5997	2.4004	2.7032	0.5222	0.2556
Hill	- 0.5109	1.5018	47.7473	0.6000	2.4030	2.7015	0.5048	0.1921
Camera	-0.5003	1.5775	87.014	0.5314	2.4020	3.9233	0.5934	0.2278
Cricketer	-0.5021	2.0523	107.4517	0.5996	2.4001	4.1627	0.5994	0.1831
Face	-0.5111	1.5005	70.6312	0.5995	2.4156	2.7119	0.4700	0.2369

Bridge	**-0.5001**	**1.7327**	**102.1039**	**0.5928**	**2.4001**	**2.9505**	**0.6000**	**0.2111**
Village	**-0.5035**	**1.5007**	**73.546**	**0.5993**	**2.4032**	**2.7008**	**0.4760**	**0.2318**
Doctor	**-0.5001**	**1.6412**	**102.9024**	**0.5909**	**2.4023**	**2.9705**	**0.5933**	**0.1503**

As we have seen, the most important feature of the proposed technique is application of this to already good images retains the pleasing nature in addition to reducing the degradation. The table-5.1 represents the initial values of the parameters and Table 5.2 represents the modified values .

Fig.5.1.a original image

Fig 5.1.b Enhanced image by [12]

Fig 5.1.c Enhanced image by proposed method

Fig.5.2.a original image

Fig 5.2.b Enhanced image by [12]

Fig5.2.c Enhanced image by proposed method

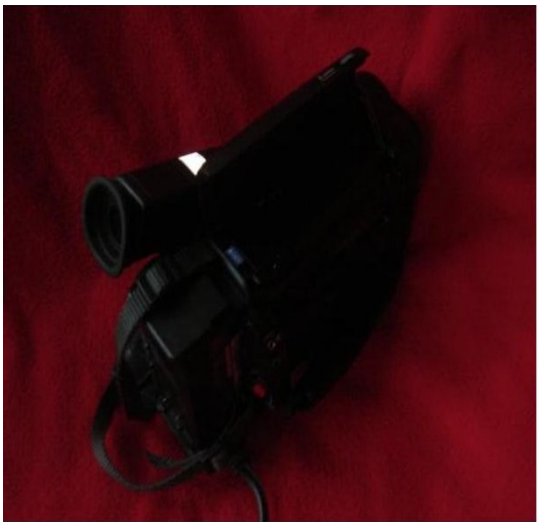


Fig.5.3.a original image

Fig 5.3.b Enhanced image by [12]

Fig5.3.cEnhanced image by proposed method

Fig.5.4.a original image

Fig 5.4.b Enhanced image by [12]

Fig5.4.c Enhanced image by proposed method

Fig.5.5.a Original image

Fig 5.5.b Enhanced image by [12]

Fig5.5.c Enhanced image by proposed method

Fig.5.6.a Original image

Fig 5.6.b Enhanced image by [12]

Fig5.6.c Enhanced image by proposed method

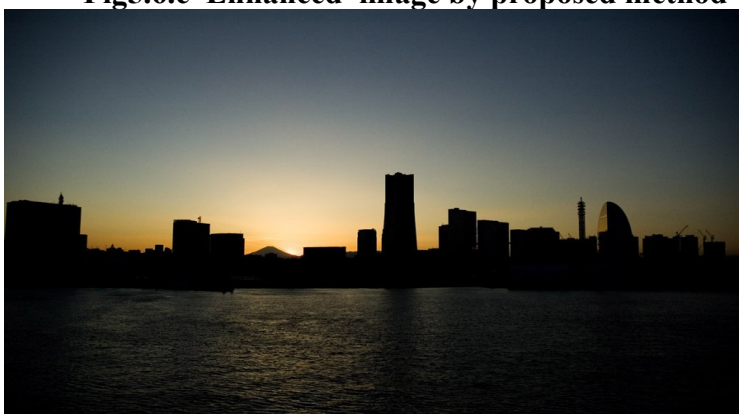


Fig.5.7.a Original image

Fig 5.7.b Enhanced image by [12]

Fig5.7.c Enhanced image by proposed method

Fig.5.8.a Original image

Fig 5.8.b Enhanced image by [12]

Fig5.8.c Enhanced image by proposed method

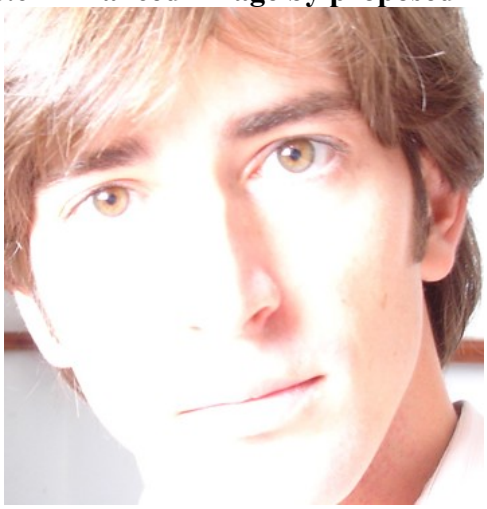


Fig.5.9.a Original image

Fig 5.9.b Enhanced image by [12]

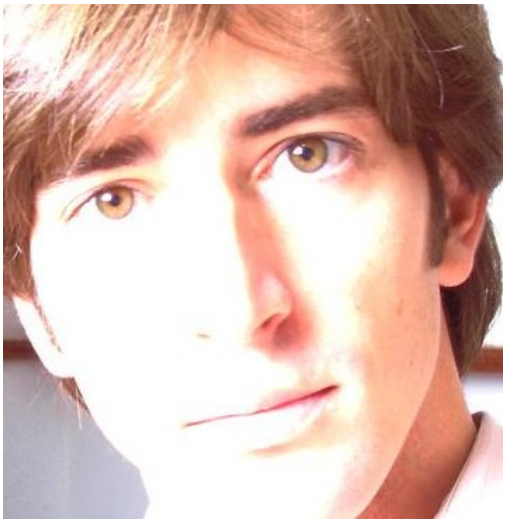


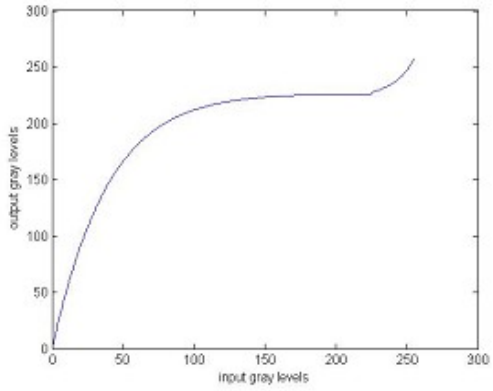
Fig5.9.c Enhanced image by proposed method

Fig.5.10.a Original image

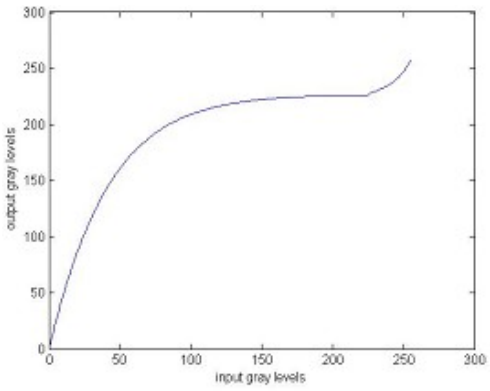
Fig 5.10.b Enhanced image by [12]

Fig 5.10.c Enhanced image by proposed method

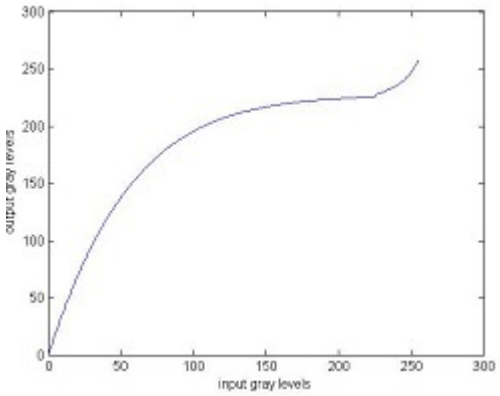
5.1 Transformation Curves of Some Test Images:

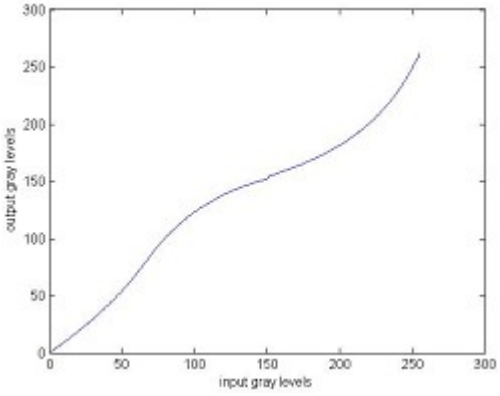


(a)

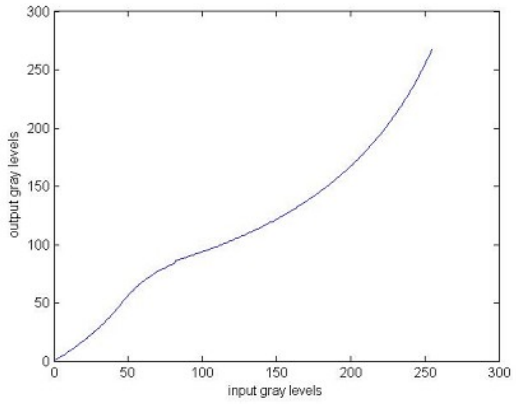


(b)





(c) **(d)**



(e)

Transformation curve employed for (a) the "Bridge" image (b) the "camera" image (c) the "cricketer" image (d) the "hill" image (e) the "Rose " image.

5.2 Conclusions

We used Fuzzy logic-based image enhancement method for enhancing the image and for optimization point of view we used bacterial foraging algorithm here. Image grey level can be divide into two regions as under and over exposed with the parameter fork. A nonlinear membership function is used for under exposed region of the image. We divide the under exposed region in two parts one which has lesser underexposed parts and another one in which not lesser. We operate both by different manner in underexposed region .A Triangular membership function is used for the fuzzification and a hyperbolic operator is used for the enhancement of over exposed region of the image. To control the amount of enhancement of the image, these parameters have been trained by the constrained fuzzy optimization.

A modified Bacterial Foraging Optimization method involving iterative learning is used for the optimization. We have also introduced entropy and maximum entropy to form the objective function so that it achieve to the desirable entropy. The low intensities represent the pixels with low information contribution. The high intensities represent the pixels with high information contribution. So we take the image histogram and try to make it uniform so that the image will be pleasant in nature. The results of proposed

enhancement technique using fuzzy entropy optimization are compared with those of histogram equalization.

Chapter 6
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