A NEW OPTIMAL FUZZY APPROACH TO HUE AND EDGE PRESERVING COLOR IMAGE ENHANCEMENT

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By

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CERTIFICATE

This is to certify that this thesis dissertation titled ***“A New Optimal Fuzzy Approach To Hue And Edge Preserving Color Image Enhancement”*** submitted by Krishna Kumar Yadav Nukala, roll no. 08/E&C/05, University Roll No. 2805, towards the fulfillment of the partial requirement for the award of Degree of Master Of Engineering, in Electronics & Communications Department, Delhi College of Engineering , Delhi University, Delhi, is a record of bona fide work carried out and completed under my supervision and guidance during the academic session 2005-2007.

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Abstract

IMAGE enhancement can be treated as transforming one image to another so that the look and feel of an image can be improved for machine analysis or visual perception of human beings. It is a task in which the set of pixel values of one image is transformed to a new set of pixel values so that the new image formed is visually pleasing and is also more suitable for analysis. The generalization of the techniques of grey scale image enhancement, such as contrast stretching, slicing, histogram equalization, to color images is not straight forward. Unlike grey scale images, there are some factors in color images like hue which need to be properly taken care of it for enhancement.

Color image enhancement using RGB color space is found to be inappropriate as it destroys the color composition in the original image. It is also used for low level vision applications. However, generalizing grayscale image enhancement to color image enhancement is not a trivial task. Several factors, such as selection of a color model, characteristics of the human visual system, and color contrast sensitivity, must be considered for color image enhancement.

The fuzzy approach to image enhancement yields better results as it can manage the vagueness in the image efficiently. In many image processing applications, we have to use expert knowledge to overcome the difficulties (e.g. object recognition, scene analysis). Fuzzy set theory and fuzzy logic offer us powerful tools to represent and process human knowledge in the form of fuzzy if-then rules.

In this thesis work, a new approach for the enhancement of color images using fuzzy logic theory is presented. An objective measure called exposure is proposed which gives the amount of under and over exposed regions in the image. This quantity acts as the dividing line

between under exposed and over exposed regions of the image. HSV (Hue, Saturation, and intensity Value) color space is used in the process of enhancement, where the hue component is preserved to keep original colors not to be disturbed. This approach is robust in the sense it can be applied to any type of degraded image, as it deals with the over exposed images, under plus over exposed images in addition to the under exposed images. A parametric sigmoid function and power law transformation operators are used for the enhancement of luminance component of the image. Saturation component has also been used to enhance the color of the image using another power law transformation operator.

Objective measures like fuzzy contrast, quality and visual factors have been defined to make the operators adaptive to the image characteristics. Entropy and the visual factors are used to form the objective function which is optimized using bacterial foraging optimization algorithm, gives image specific values to the parameters. Gaussian and Triangular membership functions are defined separately for under and over exposed regions of the image. Separate operators and membership functions for the two regions makes the approach universal to all types of contrast degradations. It is observed that the new technique outperforms the conventional techniques in terms of the quality of the enhanced images.

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1. Introduction

1.1. Introduction

IMAGE enhancement is used to improve the quality of an image for visual perception of human beings. It is also used for low level vision applications. These techniques are needed to improve the appearance of the image or to extract the finer details in the degraded images. It is a task in which the set of pixel values of one image are transformed to a new set of pixel values so that the new image formed is visually pleasing and is also more suitable for analysis. One of the most common defects found in the recorded image is its poor contrast. This degradation may be caused by inadequate lighting, aperture size, shutter speed and nonlinear mapping of the image intensity. The effect of such defects is reflected on the range and shape of the gray level histogram of the recorded image. Image enhancement technique achieves improvement in the quality of the original image or provides additional information which was not apparent in the original image. It means improvement of the appearance of an image by increasing the dominance of some features, or by decreasing the ambiguity between different regions of the image.

The enhancement techniques can be divided into three categories, 1. Contrast intensification, 2. Noise removal, and 3. Edge sharpening. The contrast of an image can be improved by scaling the gray level of each pixel so that the gray levels of an image occupy the entire dynamic range available. The contrast intensification algorithms are developed using one of the two basic approaches: spatial domain techniques that operate directly on the pixel values of the image and frequency domain techniques that operate on the Fourier transformed image. However, computing a two-dimensional (2-D) Fourier transform for a large array (image) is a very time consuming task even with fast transformation techniques and is not suitable for real time processing. Contrast enhancement is one of the important image enhancement techniques in spatial domain. The spatial domain operator may be local, i.e. convolution is applied between the image local area and the mask called a filter; or global, in which case an operator is defined for all intensities of an image. The main techniques for image enhancement such as contrast stretching, slicing, histogram equalization, etc., works for grey scale images. The generalization of these techniques to color images is not straight forward. Unlike grey scale images, there are some factors in color images like hue which needs to be properly taken care for enhancement.

Color image enhancement using RGB color space is found to be inappropriate as it destroys the color composition in the original image. Image enhancement can be treated as transforming one image to another so that the look and feel of an image can be improved for machine analysis or visual perception of human beings. For grayscale image enhancement, the most popular method is histogram equalization, which is based on the assumption that a uniformly distributed grayscale histogram will have the best visual contrast. Some other methods are the variants of histogram equalization. However, generalizing grayscale image enhancement to color image enhancement is not a trivial task. Several factors, such as selection of a color model, characteristics of the human visual system, and color contrast sensitivity, must be considered for color image enhancement.

Image enhancement is a task of paramount importance for image-based instrumentation because it aims at improving the image quality and can increase the accuracy of the subsequent measurement procedures. As an example, in image-based diagnosis systems contrast enhancement can highlight important features embedded in the data and thus can reduce the uncertainties related to parameter estimation and object recognition. The main objective of image enhancement is to process the image so that the result is more suitable than the original image.

1.2. Related work

Several image enhancement algorithms exist in the spatial domain. One of these kinds is reported in [1] where the image enhancement based on the human perception (retinex) provides color constancy and dynamic range compression. Velde et al. [2] enhance the color image in Luv color space where each component is used to find the gradients and these gradients (differences) are enhanced using conventional gray level enhancement techniques like contrast stretching etc.

Hue, saturation, and intensity are the attributes of color. Hue decides what kind of color it is, i.e., a red or an orange. In the spectrum, each color is at the maximum purity (or strength or richness) that the eye can appreciate, and the spectrum of colors is diluted by mixing with other colors or with white light; its richness or saturation is decreased. Tao et al. [3] extend the approach in [1], where the color saturation adjustment for producing more natural colors is implemented.

Eschbach et al [4] propose a method for altering the exposure in an image, by iteratively comparing the intensity signal with a pair of preset thresholds T_{light}, T_{dark} respectively indicating satisfactory brightness, darkness and further processing the image if these not satisfy the threshold conditions. Eschbach et al [5] also suggest a method for correcting the color saturation in natural scene images, by iteratively processing and comparing the average saturation with the preset threshold T_{sat}.

Image enhancement approaches if applied directly to the three components (R, G, B) of a degraded color image may produce color artifacts. Therefore, direct enhancement of the RGB color space is inappropriate for the human visual system. A proper color space should decouple the chromatic and achromatic information. The characteristics generally used to distinguish one color from another are Hue, saturation, and intensity Value (HSV). In the process of color image enhancement, the original color (hue) of the image should not be disturbed and the values of other components should not exceed the maximum value of the image. Hue preserved color image enhancement is presented in [6] and this generalizes the existing grey scale contrast intensification techniques to color images. Here a principle is suggested to make the transformations' 'gamut problem' free. But these methods are not robust as each approach is geared to a particular degraded image.

Shyu et al. [7] present a better approach based on genetic algorithms for the color image enhancement, where linearly weighted combination of four types of nonlinear (s- curves) transforms is used as a transformation function, and the weighting coefficients are calculated by optimizing an objective function, and this objective function is formed by the objective measures of the image like Brenner's measure and some noise information. But this approach doesn't consider the ambiguities in the image.

Image processing has to deal with many ambiguous situations. Fuzzy set theory is a useful mathematical tool for handling the ambiguity or uncertainty. Many researchers have used fuzzy logic in dealing with image processing; Pal [8] and Russo [9] are the few to note. The gray level maximum has not been changed in the classical fuzzy enhancement method proposed by Pal, so this method is not fit for the enhancement problem of degraded images with less gray levels and low contrasts. To deal with the problems mentioned above, a generalized iterative fuzzy enhancement algorithm is proposed by Dong-liang et al. [10].

In the field of image enhancement and smoothing using the fuzzy framework, two contributions merit an elaboration. The first one deals with "IF…THEN…ELSE" fuzzy rules [9] for image enhancement. Here, a set of neighborhood pixels forms the antecedent and the consequent clauses that serve as the fuzzy rule for the pixel to be enhanced. These fuzzy rules give directives much similar to human-like reasoning. The second one relates to a rule-based smoothing [11] in which different filter classes are devised on the basis of compatibility with the neighborhood. Russo et al. [12] discuss all recent advances in the fuzzy image processing. S-curve is used in [13] as the transformation function where the parameters of the S-curve (a,b,c) 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. The approaches some times over enhance or under enhance the image as these do not consider the shape and range of the original histogram.

Hanmandlu *et al.* [14] propose a new intensification operator, NINT, which is a parametric sigmoid function for the modification of the Gaussian type of membership on the basis of optimization of entropy by a parameter involved in the intensification operator. The approach in Li et al. [15] describes an efficient enhancement based on the fuzzy relaxation technique. Different orders of fuzzy membership functions and different statistics are attempted to improve the enhancement speed and quality, respectively. These works have been confined to the enhancement of gray images only.

In [16] the 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.

1.3. Approach

In this work, we extend the approach in [16] for the enhancement of all types of degraded color images, i.e. to make it work for all sorts of images. Saturation component is also made variable along with the luminance (intensity), while keeping the hue of the image fixed to enhance the color image. An objective measure called exposure gives the amount of light exposure of the image by considering the shape of the histogram of the intensity component for the image. Based on this measure, image can be divided into under and over exposed regions and these can be enhanced separately by GINT and power law transformation operators. The parameters of these operators adjust the operators to make them applicable to a particular type of degradation in the image. For the calculation of these parameters, an objective function is formed by considering the entropy, the quality and visual factors of the image. The minimization of objective function leads to enhancement of the image by stretching V component of the pixels about the crossover point.

1.4. Thesis Organization

For better understanding we have given various chapters on the proposed approach, organized in a systematic way as explained below.

Chater-1 Introduction: presents a brief overview of the proposed approach, such as how the membership functions have been taken and what kind of operators used and how the image can be enhanced without distorting the basic color etc. Also it explains the research survey, i.e. the present state of art for the research in image enhancement.

Chapter-2 Image Enhancement: gives the basic concepts related to image enhancement and the basic techniques till now used to enhance image such as spatial domain and frequency domain methods.

Chapter-3 Fuzzy Image Processing: explains the basic concepts of fuzzy logic theory by giving certain examples. It also explains the basics and advantages of the fuzzy image processing by examples and explains how this theory can be applied to image processing.

Chapter-4 Bacterial Swarm Foraging for optimization: gives an introduction to bacterial foraging for optimization. An Algorithm and flowchart is also given with some example problems.

Chapter- 5 A New Approach to Image Enhancement: presents the formulation of the proposed approach and gives an idea to calculate the basic parameters involved in those formulations. It also gives a detailed procedure (Algorithm) that explains how to use the proposed approach for the enhancement of Color images.

Chapter-6 Results and Discussions: explains the proposed approach by summarizing it and presents the test images in comparison with the enhanced images with the proposed approach. And a comparison of results obtained with the proposed approach and that of Histogram equalization technique is given. Also it presents various problems encountered during the preparation of this work and explains how those were overcome.

Chapter-7 Conclusion: concludes the approach by a brief summary.

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.

Image enhancement is also used to generate a visually desirable image. For instance, we may perform image restoration to eliminate image distortion and find that the output image has lost most of its contrast. Here, we can apply some basic image enhancement methods to restore the image contrast. Alternatively, after a compressed image has been restored to its original state (decompressed), some post processing enhancement may significantly improve the look of the image. For example the standard JPEG compression algorithm may generate an image with undesirable blocky artifacts, and processing it with a smoothing filter (low pass or mean) will improve the appearance.

2.2. The Image Enhancement process

Figure below 2.1 illustrates the importance of application by the feedback loop from the output image back to the start of enhancement process and models the experimental nature of the development. In this figure we define the enhanced image as E(r, c). The range of applications includes using enhancement techniques as preprocessing step to ease the next processing step or as post processing step to improve the visual perception of a processed image, or image enhancement may be an end itself. Enhancement methods operate in the spatial domain by manipulating the pixel data or in the frequency domain by modifying the spectral components. Some enhancement algorithms use both the spatial and frequency domains.

The type of techniques includes point operations, where each pixel is modified according to a particular equation that is not dependent on other pixel values; mask operations, where each pixel is modified according to the values of the pixel's neighbors (using convolution masks); or global operations, where all pixel values in the image (or sub image) are taken into consideration.

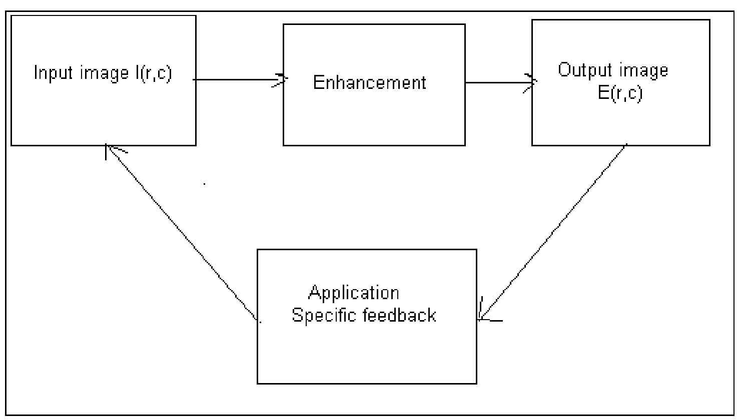


Fig. 2.3 Image enhancement process

Spatial domain processing methods includes all three types, but frequency domain operations can become "mask operations," based only on a local neighborhood, by performing the transform on small image blocks instead of the entire image.

Image enhancement techniques can be divided into two broad categories:

1. Spatial domain methods, which operate directly on pixels, and

2. Frequency domain methods, which operate on the Fourier transform of an image.

Unfortunately, there is no general theory for determining what is good' image enhancement is when it comes to human perception. If it looks good, it is good! However, when image enhancement techniques are used as pre-processing tools for other image processing techniques, then quantitative measures can determine which techniques are most appropriate.

2.3. Spatial domain methods

The value of a pixel with coordinates (x, y) in the enhanced image $\hat{F}$ is the result of performing some operation on the pixels in the neighborhood of (x, y) in the input image, F.

Neighborhoods can be any shape, but usually they are rectangular.

2.3.1. Gray scale manipulation

The simplest form of operation is when the operator T only acts on a 1x1 pixel neighborhood in the input image F(x,y), that is only depends on the value of F at (x,y). This is a *grey scale transformation* or mapping.

The simplest case is thresholding where the intensity profile is replaced by a step function, active at a chosen threshold value. In this case any pixel with a grey level below the threshold in the input image gets mapped to 0 in the output image. Other pixels are mapped to 255.

Other grey scale transformations are outlined in figure 2.2 below.

2.3.2. Histogram Equalization

Histogram equalization is a common technique for enhancing the appearance of images. Suppose we have an image which is predominantly dark. Then its histogram would be skewed towards the lower end of the grey scale and all the image detail is compressed into the dark end of the histogram. If we could `stretch out' the grey levels at the dark end to produce a more uniformly distributed histogram then the image would become much clearer.

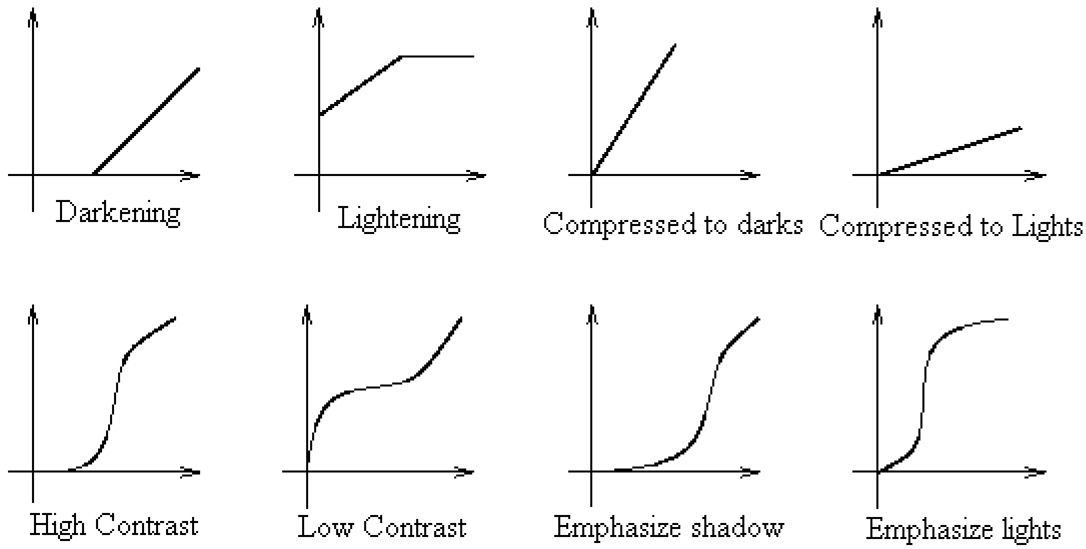


Fig.2.2 Tone adjustment

Histogram equalization involves finding a grey scale transformation function that creates an output image with a *uniform histogram* (or nearly so). How do we determine this grey scale transformation function? Assume our grey levels are continuous and have been normalized to lie between 0 and 1.

We must find a transformation *T* that maps grey values *r* in the input image *F* to grey values

$s = T(r)$ in the transformed image $\hat{F}$.

It is assumed that

- T is single valued and monotonically increasing, and
- $0 \le T(r) \le 1$ for $0 \le r \le 1$.

The inverse transformation from *s* to *r* is given by

$$r = T^{-1}(s). \tag{2.1}$$

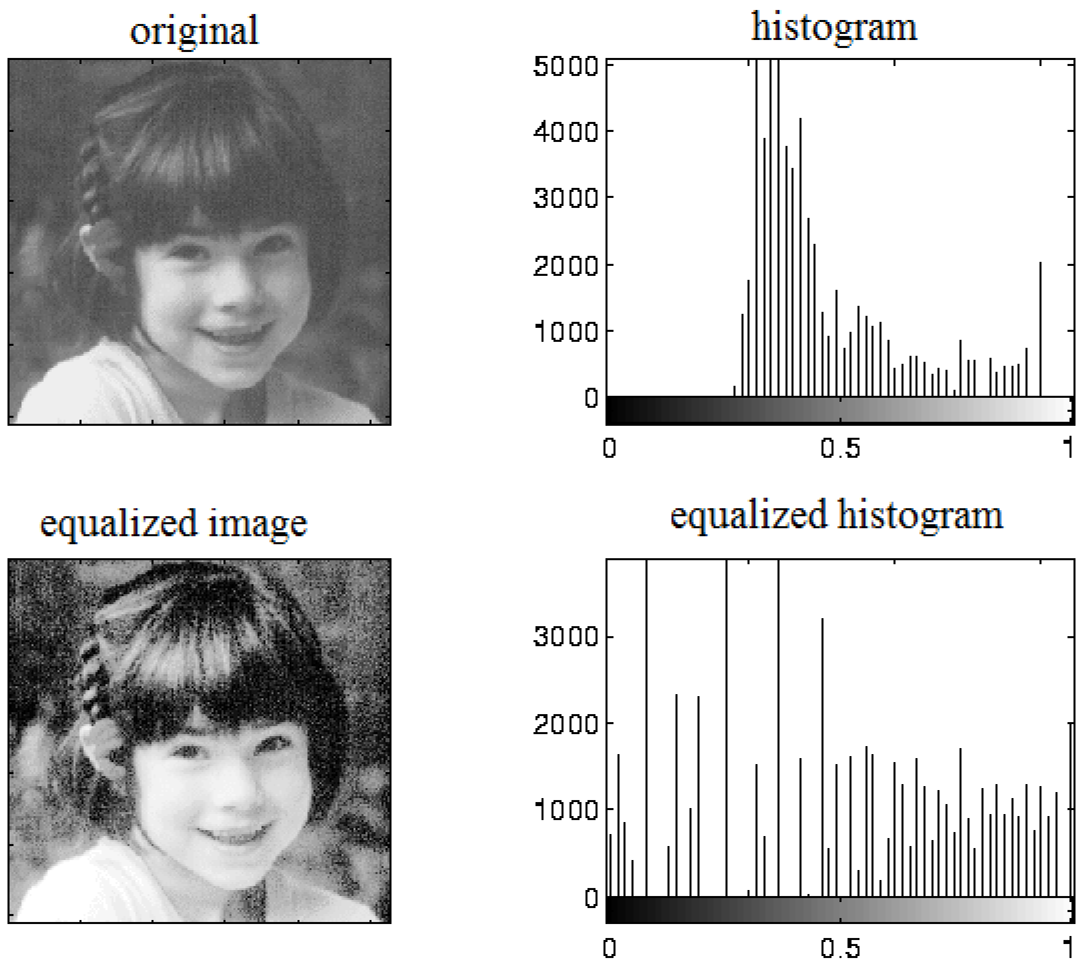


Fig. 4.3 the original image and its histogram, and the equalized versions. Both images are quantized to 64 grey levels.

If one takes the histogram for the input image and normalizes it so that the area under the histogram is 1, we have a probability distribution for grey levels in the input image $P_r(r)$. If we transform the input image to get $s = T(r)$ what is the probability distribution $P_s(s)$?

From probability theory it turns out that

$$P_s(s) = P_r(r)\frac{dr}{ds}, \tag{2.2}$$

where $r = T^{-1}(s)$.

Consider the transformation

$$s = T(r) = \int_0^r P_r(w)dw. \tag{2.3}$$

This is the cumulative distribution function of *r*. Using this definition of *T* we see that the derivative of *s* with respect to *r* is

$$\frac{ds}{dr} = P_r(r) \tag{2.4}$$

Substituting this back into the expression for P_s, we get

$$P_s(s) = P_r(r)\frac{1}{P_r(r)} = 1 \tag{2.5}$$

for all s, where $0 \le s_k \le 1$).Thus, $P_s(s)$ is now a uniform distribution function, which is what we want.

2.3.3. Discrete Formulation

We first need to determine the probability distribution of grey levels in the input image. Now

$$P_r(r) = \frac{n_k}{N} \tag{2.6}$$

Where n_k is the number of pixels having grey level k, and *N* is the total number of pixels in the image.

The transformation now becomes

$$s_k = T(r_k) = \sum_{i=0}^{k} \frac{n_i}{N} = \sum_{i=0}^{k} P_r(r_i). \tag{2.7}$$

Note that $0 \le r_k \le 1$, the index $k = 0,1,2,....,255$, and $0 \le s_k \le 1$.

The values of s_k will have to be scaled up by 255 and rounded to the nearest integer so that the output values of this transformation will range from 0 to 255. Thus the discretization and rounding of s_k to the nearest integer will mean that the transformed image will not have a perfectly uniform histogram.

2.3.4. Image Smoothing

The aim of image smoothing is to diminish the effects of camera noise, spurious pixel values, missing pixel values etc. There are many different techniques for image smoothing; we will consider neighborhood averaging and edge-preserving smoothing.

2.3.4.1. Neighborhood Averaging

Each point in the smoothed image, $\hat{F}(x, y)$ is obtained from the average pixel value in a neighborhood of (x,y) in the input image.

For example, if we use a 3X3 neighborhood around each pixel we would use the mask

$$\begin{matrix} 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \\ 1/9 & 1/9 & 1/9 \end{matrix}$$

Each pixel value is multiplied by $\frac{1}{9}$, summed, and then the result placed in the output image. This mask is successively moved across the image until every pixel has been covered. That is, the image is *convolved* with this smoothing mask (also known as a spatial filter or kernel).

However, one usually expects the value of a pixel to be more closely related to the values of pixels close to it than to those further away. This is because most points in an image are spatially coherent with their neighbors; indeed it is generally only at edge or feature points where this hypothesis is not valid. Accordingly it is usual to weight the pixels near the centre of the mask more strongly than those at the edge.

Some common weighting functions include the rectangular weighting function above (which just takes the average over the window), a triangular weighting function, or a Gaussian.

In practice one doesn't notice much difference between different weighting functions, although Gaussian smoothing is the most commonly used. Gaussian smoothing has the attribute that the frequency components of the image are modified in a smooth manner.

Smoothing reduces or attenuates the higher frequencies in the image. Mask shapes other than the Gaussian can do odd things to the frequency spectrum, but as far as the appearance of the image is concerned we usually don't notice much.

2.3.4.2 Edge preserving smoothing

Neighborhood averaging or Gaussian smoothing will tend to blur edges because the high frequencies in the image are attenuated. An alternative approach is to use *median filtering*. Here we set the grey level to be the median of the pixel values in the neighborhood of that pixel.

The median *m* of a set of values is such that half the values in the set are less than *m* and half are greater. For example, suppose the pixel values in a 3X3 neighborhood are (10, 20, 20, 15, 20, 20, 20, 25, 100). If we sort the values we get (10, 15, 20, 20, |20|, 20, 20, 25, 100) and the median here is 20.

The outcome of median filtering is that pixels with outlying values are forced to become more like their neighbors, but at the same time edges are preserved. Of course, median filters are non-linear.

Median filtering is in fact a morphological operation. When we erode an image, pixel values are replaced with the smallest value in the neighborhood. Dilating an image corresponds to replacing pixel values with the largest value in the neighborhood. Median filtering replaces pixels with the median value in the neighborhood. It is the rank of the value of the pixel used in the neighborhood that determines the type of morphological operation.

2.3.5. Image sharpening

The main aim in image sharpening is to highlight fine detail in the image, or to enhance detail that has been blurred (perhaps due to noise or other effects, such as motion). With image sharpening, we want to enhance the high-frequency components; this implies a spatial filter shape that has a high positive component at the centre (see figure 4 below).

A simple spatial filter that achieves image sharpening is given by

-1/9	-1/9	-1/9
-1/9	8/9	-1/9
-1/9	-1/9	-1/9

Since the sum of all the weights is zero, the resulting signal will have a zero DC value (that is, the average signal value, or the coefficient of the zero frequency term in the Fourier expansion). For display purposes, we might want to add an offset to keep the result in the 0,…255 range.

2.3.5.1. High boost filtering

We can think of high pass filtering in terms of subtracting a low pass image from the original image, that is,

$$\text{High pass} = \text{Original} - \text{Low pass}. \tag{2.8}$$

However, in many cases where a high pass image is required, we also want to retain some of the low frequency components to aid in the interpretation of the image. Thus, if we multiply the original image by an amplification factor *A* before subtracting the low pass image, we will get a *high boost* or *high frequency emphasis* filter. Thus,

$$\begin{aligned} High\ boost &= A.Original - Lowpass \\ &= (A-1).(Original) + \ Original - Lowpass \\ &= (A-1).(Original + High\ pass \end{aligned} \tag{2.9}$$

Now, if A = 1 we have a simple high pass filter. When A > 1 part of the original image is retained in the output.

A simple filter for high boost filtering is given by

Where $\omega = 9A - 1$

-1/9	-1/9	-1/9
-1/9	ω/9	-1/9
-1/9	-1/9	-1/9

2.4. Frequency domain methods

Image enhancement in the frequency domain is straightforward. We simply compute the Fourier transform of the image to be enhanced, multiply the result by a filter (rather than convolve in the spatial domain), and take the inverse transform to produce the enhanced image.

The idea of blurring an image by reducing its high frequency components or sharpening an image by increasing the magnitude of its high frequency components is intuitively easy to understand. However, computationally, it is often more efficient to implement these operations as convolutions by small spatial filters in the spatial domain. Understanding frequency domain concepts is important, and leads to enhancement techniques that might not have been thought of by restricting attention to the spatial domain.

2.4.1. Filtering

Low pass filtering involves the elimination of the high frequency components in the image. It results in blurring of the image (and thus a reduction in sharp transitions associated with noise). An ideal low pass filter would retain all the low frequency components, and eliminate all the high frequency components. However, ideal filters suffer from two problems: *blurring* and *ringing*. These problems are caused by the shape of the associated spatial domain filter, which has a large number of undulations. Smoother transitions in the frequency domain filter, such as the Butterworth filter, achieve much better results.

2.4.2. Homomorphic filtering

Images normally consist of light reflected from objects. The basic nature of the image $F(x, y)$ may be characterized by two components: (1) the amount of source light incident on the scene being viewed and (2) the amount of light reflected by the objects in the scene. These portions of light are called the *illumination* and *reflectance* components, and are denoted $i(x,y)$ and $r(x,y)$ respectively. The functions i and r combine multiplicatively to give the image function F:

$$F(x, y) = i(x, y)\, r(x, y), \tag{2.10}$$

where $0 < i(x, y) < \infty$ and $0 < r(x, y) < 1$. We cannot easily use the above product to operate separately on the frequency components of illumination and reflection because the Fourier transform of the product of two functions is not separable; that is

$$\mathcal{F}(\mathrm{F}(\mathrm{x}, \mathrm{y})) \neq \mathcal{F}(i(x, y))\, \mathcal{F}(r(x, y)). \tag{2.11}$$

Suppose, however, that we define

$$z(x, y) = \ln F(x, y)$$

$$z(x, y) = \ln i(x, y) + \ln r(x, y) \tag{2.12}$$

Then

$$\mathcal{F}\big(z(x, y)\big) = \mathcal{F}(\ln F(x, y)$$

$$\mathcal{F}(z(x, y) = \mathcal{F}(\ln i(x, y)) + \mathcal{F}(\ln r(x, y)) \tag{2.13}$$

or

$$Z(\omega, v) = I(\omega, v) + R(\omega, v) \tag{2.14}$$

where Z, I and R are the Fourier transforms of $z, \ln i$ and $\ln r$ respectively. The function Z represents the Fourier transform of the *sum* of two images: a low frequency illumination image and a high frequency reflectance image.

If we now apply a filter with a transfer function that suppresses low frequency components and enhances high frequency components, then we can suppress the illumination component and enhance the reflectance component. Thus

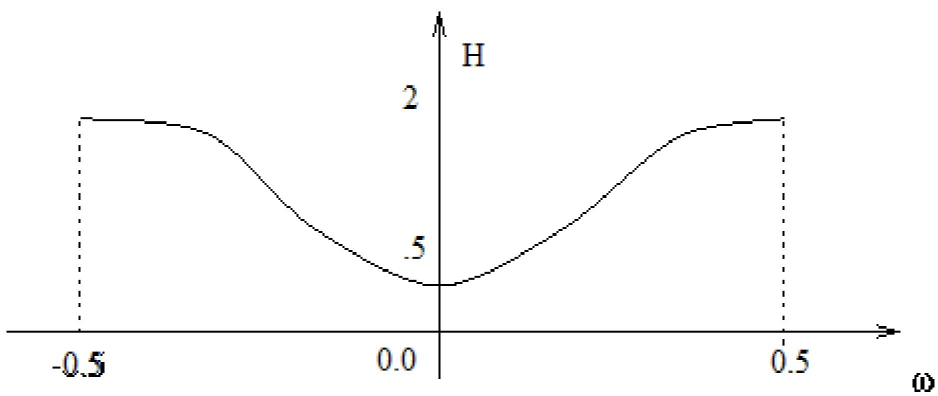


Fig. 2.4. Transfer function for homomorphic filtering

$$S(\omega, \upsilon) = H(\omega, \upsilon)Z(\omega, \upsilon)$$

$$S(\omega, \upsilon) = H(\omega, \upsilon)\, I(\omega, \upsilon) + H(\omega, \upsilon)\, R(\omega, \upsilon) \tag{2.15}$$

where S is the Fourier transform of the result. In the spatial domain

$$s(x, y) = \mathcal{F}^{-1}\big(S(\omega, \upsilon)\big)$$

$$s(x, y) = \mathcal{F}^{-1}\big(H(\omega, \upsilon)I(\omega, \upsilon)\big) + \mathcal{F}^{-1}(H(\omega, \upsilon)R(\omega, \upsilon)) \tag{2.16}$$

By letting

$$i'(x,y) = \mathcal{F}^{-1}(H(\omega,v)I(\omega,v)) \tag{2.17}$$

and

$$r'(x,y) = \mathcal{F}^{-1}(H(\omega,v)R(\omega,v)) \tag{2.18}$$

we get

$$s(x,y) = i'(x,y) + r'(x,y). \tag{2.19}$$

Finally, as z was obtained by taking the logarithm of the original image F, the inverse yields the desired enhanced image $\hat{F}$: that is

$$\hat{F}(x,y) = \exp\,[s(x,y)]$$

$$\hat{F}(x,y) = \exp[i'(x,y)]\exp[r'(x,y)]$$

$$\hat{F}(x,y) = i_0(x,y)r_0(x,y) \tag{2.20}$$

Thus, the process of homomorphic filtering can be summarized by the following diagram:

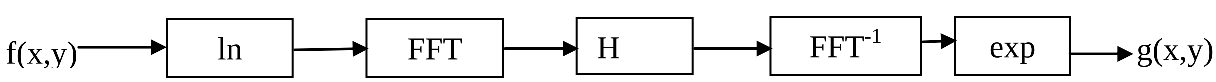


Fig.2.5. The process of homomorphic filtering.

3. Fuzzy logic Theory and Image processing

3.1. Fuzzy Logic

Fuzzy logic is a mathematical technique for dealing with imprecise data and problems that have many solutions rather than one. Although it is implemented in digital computers which ultimately make only yes-no decisions, fuzzy logic works with ranges of values, solving problems in a way that more resembles human logic.

Fuzzy logic, a multi valued (as opposed to binary) logic developed to deal with imprecise or vague data. Classical logic holds that everything can be expressed in binary terms: 0 or 1, black or white, yes or no; in terms of Boolean algebra, everything is in one set or another but not in both. Fuzzy logic allows for partial membership in a set, values between 0 and 1, shades of gray, and maybe—it introduces the concept of the "fuzzy set." When the approximate reasoning of fuzzy logic is used with an expert system, logical inferences can be drawn from imprecise relationships.

Fuzzy logic is used for solving problems with expert systems and real-time systems that must react to an imperfect environment of highly variable, volatile or unpredictable conditions. It "smoothes the edges" so to speak, circumventing abrupt changes in operation that could result from relying on traditional either-or and all-or-nothing logic.

Fuzzy logic was conceived by Lotfi Zadeh, former chairman of the electrical engineering and computer science department at the University of California at Berkeley. In 1964, while contemplating how computers could be programmed for handwriting recognition, Zadeh expanded on traditional set theory by making membership in a set a matter of degree rather than a yes-no situation

3.2. Fuzzy IF-THEN Rules

A fuzzy if-then rule associates a *condition* described using linguistic variables and fuzzy sets to a *conclusion*. From a knowledge representation viewpoint, a fuzzy if-then rule is a scheme for capturing knowledge that involves imprecision. The main feature of reasoning using these rules (i.e. fuzzy rule-based reasoning) is its *partial matching* capability, which enables an inference to be made from a fuzzy rule even when the rule's condition is only partially satisfied.

Rules are usually expressed in the form.

```
IF variable IS set THEN action
```

For example, an extremely simple temperature regulator that uses a fan might look like this.

```
IF temperature IS very cold THEN stop fan
IF temperature IS cold THEN turn down fan
IF temperature IS normal THEN maintain level
IF temperature IS hot THEN speed up fan
```

Notice there is no "ELSE". All of the rules are evaluated, because the temperature might be "cold" and "normal" at the same time to differing degrees.

3.3. Fuzzy Operators

The AND, OR, and NOT operators of Boolean logic exist in fuzzy logic, usually defined as the Minimum, Maximum, And Complement; when they are defined this way, they are called the *Zadeh operators*, because they were first defined as such in Zadeh's original papers. So for the fuzzy variables x and y:

NOT x = (1 - truth(x))

x AND y = minimum (truth(x), truth(y))

x OR y = maximum (truth(x), truth(y))

There are also other operators, more linguistic in nature, called *hedges* that can be applied. These are generally adverbs such as "very", or "somewhat", which modify the meaning of a set using a mathematical formula.

3.4. Example of Fuzzy Applications

Fuzzy logic can be used to control household appliances such as washing machines (which sense load size and detergent concentration and adjust their wash cycles accordingly) and refrigerators.

A basic application might characterize sub ranges of a continuous variable. For instance, a temperature measurement for anti-lock brakes might have several separate membership functions defining particular temperature ranges needed to control the brakes properly. Each function maps the same temperature value to a truth value in the 0 to 1 range. These truth values can then be used to determine how the brakes should be controlled.

In this image, *cold*, *warm*, and *hot* are functions mapping a temperature scale. A point on that scale has three "truth values" — one for each of the three functions. For the particular temperature shown, the three truth values could be interpreted as describing the temperature as, say, "fairly cold", "slightly warm", and "not hot".

3.5. Fuzzy Image Processing

Fuzzy image processing is the collection of all approaches that understand, represent and process the images, their segments and features as fuzzy sets. The representation and processing depends on the selected fuzzy technique and on the problem to be solved.

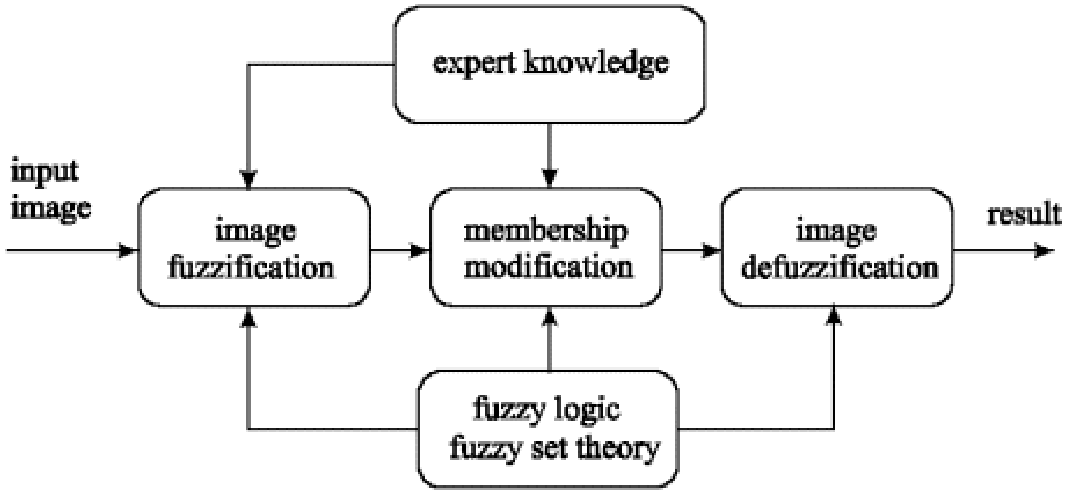


Fig. 3.1 Block diagram for general structure of fuzzy image processing

Fuzzy image processing has three main stages:

1. Image Fuzzification,

2. Modification of membership values,

3. If necessary, Image Defuzzification (see Fig.3.1.).

The Fuzzification and Defuzzification steps are due to the fact that we do not possess fuzzy hardware. Therefore, the coding of image data (Fuzzification) and decoding of the results (Defuzzification) are steps that make possible to process images with fuzzy techniques. The main power of fuzzy image processing is in the middle step (modification of membership values, see Fig.3.2). After the image data are transformed from gray-level plane to the membership plane (Fuzzification), appropriate fuzzy techniques modify the membership values. This can be a fuzzy clustering, a fuzzy rule-based approach, and a fuzzy integration approach and so on.

3.6. Advantages of Fuzzy Image Processing.

Many colleagues (not only the opponents of fuzzy logic) ask why we should use fuzzy techniques in image processing. There are many reasons to do this. The most important of them are as follows:

1. Fuzzy techniques are powerful tools for knowledge representation and processing.

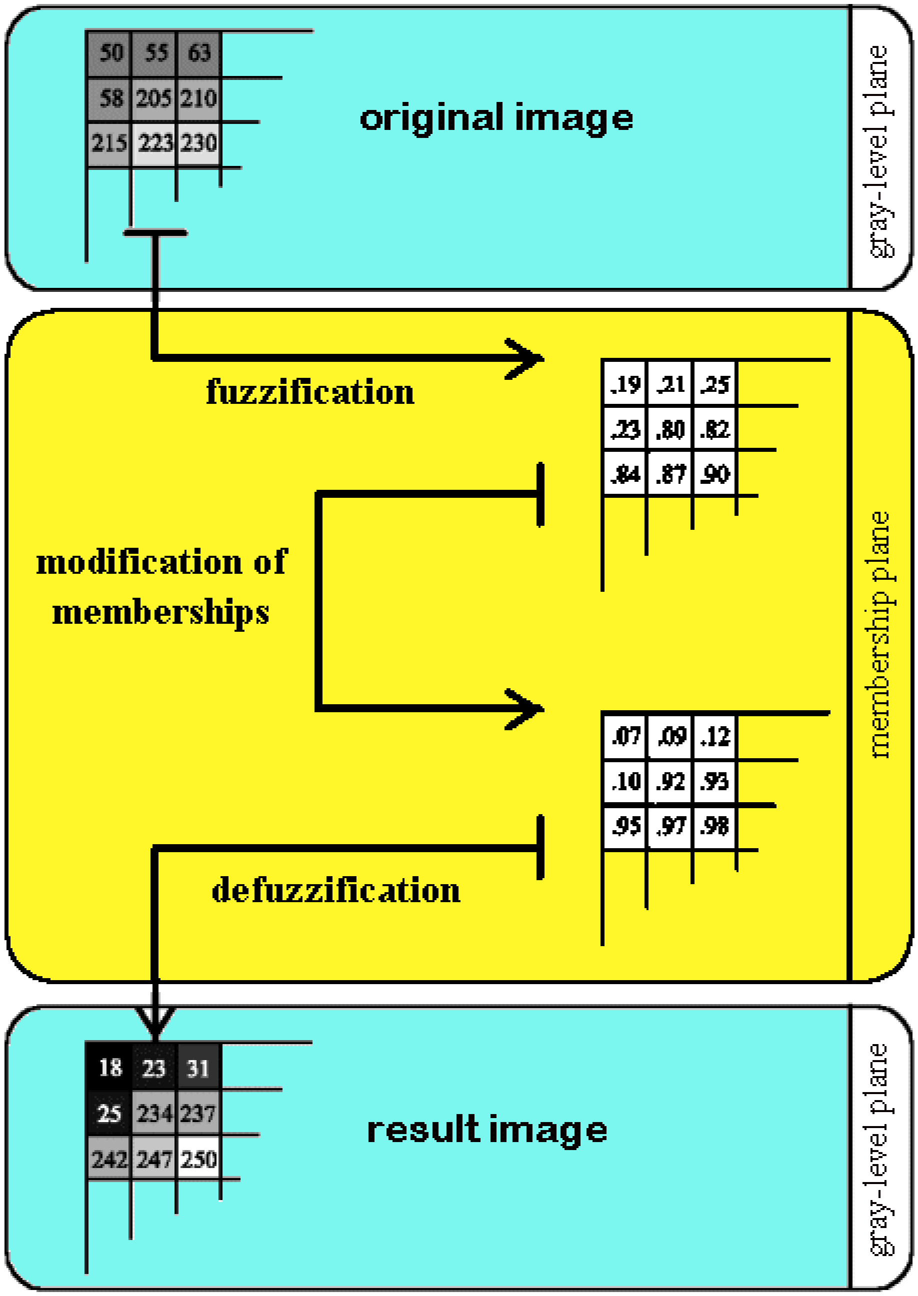


Fig. 3.2 General Structure of Fuzzy Image Processing

2. Fuzzy techniques can manage the vagueness and ambiguity efficiently.

In many image processing applications, we have to use expert knowledge to overcome the difficulties (e.g. object recognition, scene analysis). Fuzzy set theory and fuzzy logic offer us powerful tools to represent and process human knowledge in form of fuzzy if-then rules. On the other side, many difficulties in image processing arise because the data/tasks/results are uncertain. This uncertainty, however, is not always due to the randomness but to the ambiguity and vagueness. Besides randomness which can be managed by probability theory we can distinguish between three other kinds of imperfection in the image processing (see Fig.3.3):

- Grayness ambiguity
- Geometrical fuzziness
- Vague (complex/ill-defined) knowledge

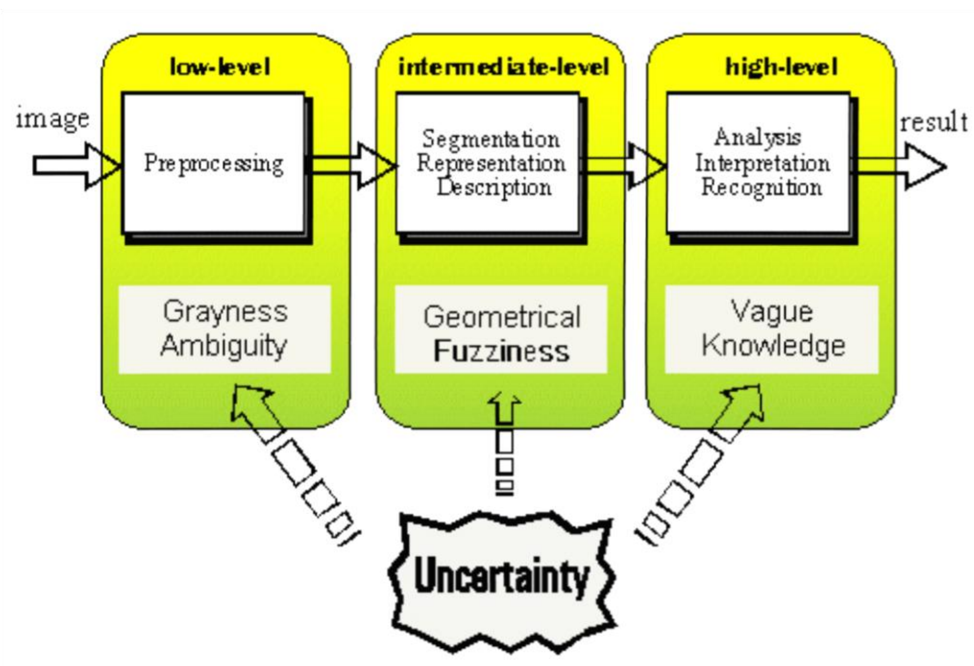


Fig.3.3 Uncertainty/imperfect knowledge in image processing

These problems are fuzzy in the nature. The question whether a pixel should become darker or brighter than it already is, the question where is the boundary between two image segments, and the question what is a tree in a scene analysis problem, all of these and other similar questions are examples for situations that a fuzzy approach can be the more suitable way to manage the imperfection.

As an example, we can regard the variable color as a fuzzy set. It can be described with the subsets yellow, orange, red, violet and blue:

Color = {yellow, orange, red, violet, blue}

The non-crisp boundaries between the colors can be represented much well. A soft computing becomes possible (see Fig.3.4).

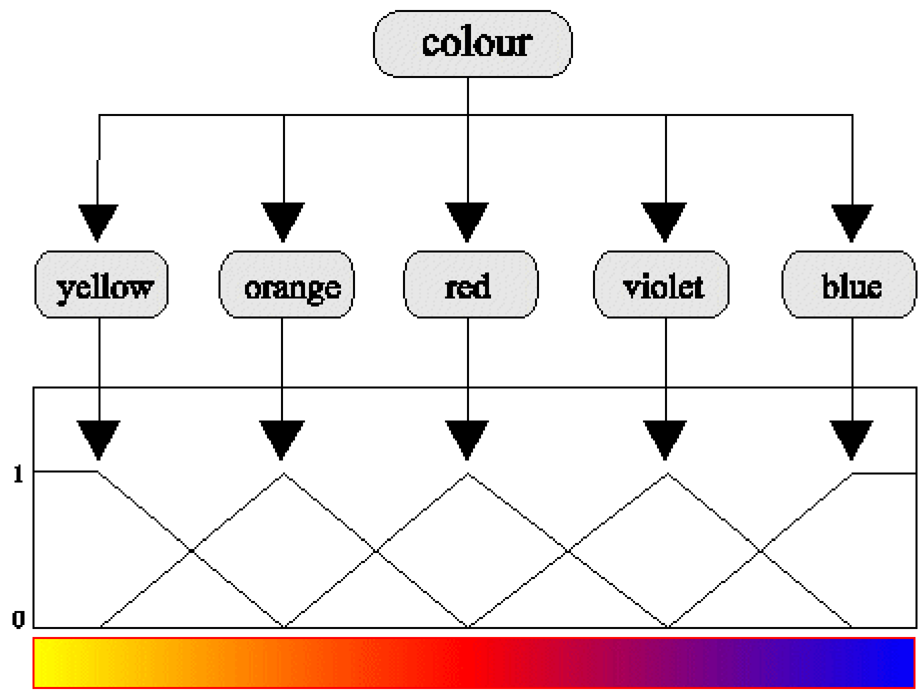


Fig.3.4. Representation of colors as fuzzy subsets

3.7. Examples for Fuzzy Techniques in Image Processing

Fuzzy techniques can be used to solve a lot of problems in image processing, few of them given below with a brief description.

1. Fuzzy Contrast Adjustment

2. Subjective Image Enhancement
3. Fuzzy Image Segmentation
4. Fuzzy Edge Detection

3.7.1. Fuzzy Contrast Adjustment

In recent years, many researchers have applied the fuzzy set theory to develop new techniques for contrast improvement. Following, some of these approaches are briefly described.

(a) Contrast Improvement with INT- Operator

1. Step 1: Define the membership functions

$$\mu_{mn} = G(g_{mn}) = \left[1 + \frac{g_{max} - g_{mn}}{F_d}\right]^{-Fe} \tag{3.1}$$

2. Step 2: Modify the membership values

$$\mu'_{mn} = \begin{cases} 2.[\mu_{mn}]^2 & 0 \le \mu_{mn} \le 0.5 \\ 1 - 2.[1 - \mu_{mn}]^2 & 0.5 \le \mu_{mn} \le 1 \end{cases} \tag{3.2}$$

3. Step 3: Generate new gray-levels

$$g'_{mn} = G^{-1}(\mu'_{mn}) = g_{max} - F_d\left((\mu'_{mn})^{\frac{-1}{Fe}} - 1\right) \tag{3.3}$$

(b) Contrast Improvement using Fuzzy Expected Value

1. Step 1: Calculate the image histogram

2. Step 2: Determine the fuzzy expected value (FEV)

3. Step 3: Calculate the distance of gray-levels from FEV

$$D_{mn} = \sqrt{|(FEV)^2 - (g_{mn})^2|} \quad (3.4)$$

4. Step 4: Generate new gray-levels

$$g'_{mn} = \max(0, FEV - D_{mn}) \qquad if\ g_{mn} < FEV$$

$$g'_{mn} = \min(L-1, FEV + D_{mn}) \qquad if\ g_{mn} > FEV$$

$$g'_{mn} = FEV \qquad otherwise \quad (3.5)$$

(c) Contrast Improvement with Fuzzy Histogram Hyperbolization

1. Step 1: Setting the shape of membership function (regarding to the actual image)

2. Step 2: Setting the value of fuzzifier Beta (a linguistic hedge)

3. Step 3: Calculation of membership values

4. Step 4: Modification of the membership values by linguistic hedge

5. Step 5: Generation of new gray-levels

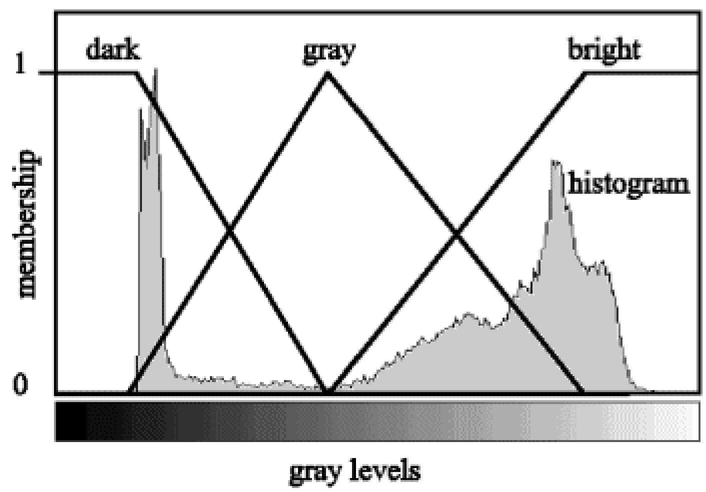


Fig.3.5 Histogram Fuzzification with three membership functions

$$g'_{mn} = \left(\frac{L-1}{e^{-1}-1}\right).\left[e^{-\mu_{mn}(g_{mn})^{\beta}} - 1\right] \quad (3.6)$$

(d) Contrast Improvement based on Fuzzy If-Then Rules

1. Step: Setting the parameter of inference system (input features, membership functions...)

2. Step: Fuzzification of the actual pixel (memberships to the dark, gray and bright sets of pixels)

3. Step: Inference (e.g. if dark then darker, if gray then gray, if bright then brighter)

4. Step: Defuzzification of the inference result by the use of three singletons

(e) Locally Adaptive Contrast Enhancement

In many cases, the global fuzzy techniques fail to deliver satisfactory results. Therefore, a locally adaptive implementation is necessary to achieve better results.

3.7.2. Subjective Image Enhancement

In image processing, some objective quality criteria are usually used to ascertain the goodness of the results (e.g. the image is good if it possesses a low amount of fuzziness indicating high contrast). The human observer, however, does not perceive these results as good because his judgment is subjective. This distinction between objectivity and subjectivity is the first major problem in the human-machine-interaction. Another difficulty is the fact that different people judge the image quality differently. This inter-individual difference is also primarily due to the aforesaid human subjectivity.

3.7.3. Fuzzy Image Segmentation

The different theoretical components of fuzzy image processing provide us with diverse possibilities for development of new segmentation techniques. The following theory gives a brief overview of different fuzzy approaches to image segmentation:

(a) Fuzzy Clustering Algorithms

Fuzzy clustering is the oldest fuzzy approach to image segmentation. Algorithms such as fuzzy c-means (FCM, Bezdek) and possibilistic C-means (PCM, Krishnapuram & Keller) can be used to build clusters (segments). The class membership of pixels can be interpreted as similarity or compatibility with an ideal object or a certain property.

(b) Fuzzy Rule-Based Approach

If we interpret the image features as linguistic variables, then we can use fuzzy if-then rules to segment the image into different regions. A simple fuzzy segmentation rule may seem as follows:

IF the pixel is *dark* **AND** its neighborhood is also *dark* **AND** *homogeneous* **THEN** it *belongs* to the background.

(c) Measures of Fuzziness and image information

Measures of fuzziness (e.g. fuzzy entropy) and image information (e.g. fuzzy divergence) can be also used in segmentation and thresholding tasks.

3.7.4. Fuzzy Edge Detection

There are different possibilities for development of fuzzy edge detectors:

(a) Definition of appropriate membership functions

This is the easiest way. One can define a membership function indicating the *degree of edginess* in each neighborhood:

This approach can only be regarded as a true fuzzy approach if fuzzy concepts are additionally used to modify the membership values. The membership function is determined heuristically. It is fast but the performance is limited.

(b) Rule-based fuzzy edge detection

Using appropriate fuzzy if-then rules, one can develop general or specific edge detectors in pre-defined neighborhoods.

4. Bacterial Swarm Foraging for Optimization

4.1. Introduction

Natural selection tends to eliminate animals with poor foraging strategies (methods for locating, handling, and ingesting food) and favor the propagation of genes of those animals that have successful foraging strategies, since they are more likely to enjoy reproductive success (they obtain enough food to enable them to reproduce). After many generations, poor foraging strategies are either eliminated or shaped into good ones (redesigned). Logically, such evolutionary principles have led scientists in the field of foraging theory to hypothesize that it is appropriate to model the activity of foraging as an optimization process: a foraging animal takes actions to maximize the energy obtained per unit time spent foraging, in the face of constraints presented by its own physiology (e.g., sensing and cognitive capabilities) and environment (e.g., density of prey, risks from predators, physical characteristics of the search area). Evolution has balanced these constraints and essentially engineered what is sometimes referred to as an optimal foraging policy.

4.2. Foraging Theory

Animals search for and obtain nutrients in a way that maximizes the ratio E/T (where E is the energy obtained and T is the time spent foraging) or maximizes the long-term average rate of energy intake. Evolution optimizes the foraging strategies, since animals that have poor foraging performance do not survive. Generally, a foraging strategy involves finding a patch of food (e.g., group of bushes with berries), deciding whether to enter it and search for food, and when to leave the patch. There are predators and risks, energy required for travel, and physiological constraints (sensing, memory, cognitive capabilities). Foraging scenarios can be modeled and optimal policies can be found using, for instance, dynamic programming. Search and optimal foraging decision-making of animals can be broken into three basic types: cruise (e.g., tuna fish, hawks), saltatory (e.g., birds, fish, lizards, and insects), and ambush (e.g., snakes, lions). In a cruise search, the animal searches the perimeter of a region; in an ambush, it sits and waits; in saltatory search, an animal typically moves in some directions, stops or slows down, looks around, and then changes direction (it searches throughout a whole region).

Some animals forage as individuals and others forage as groups. While to perform social foraging an animal needs communication capabilities, it can gain advantages in that it can exploit essentially the sensing capabilities of the group, the group can gang-up on large prey, individuals can obtain protection from predators while in a group, and in a certain sense the group can forage with a type of collective intelligence. Social foragers include birds, bees, fish, ants, wild beasts, and primates. Note that there is a type of cognitive spectrum where some foragers have little cognitive capability and other higher life forms have significant capabilities (e.g., compare the capabilities of a single ant with those of a human). Generally, endowing each forager with more capabilities can help them succeed in foraging, both as an individual and as a group. From an engineering perspective, both ends of such a spectrum are interesting.

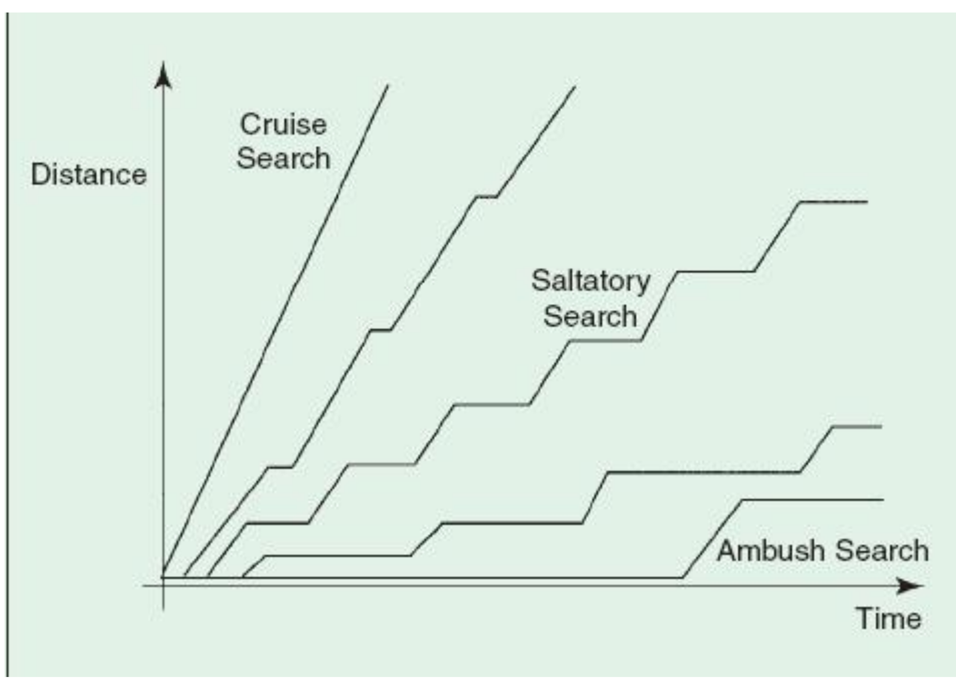


Fig. 4.1 Search strategies for foraging animals

4.3. Chemotactic Behavior of E. coli. type Bacteria

Here, we consider the foraging behavior of E. coli, which is a common type of bacteria (it lives in your gut) with a diameter of 1 μm and a length of about 2 μm, and which under appropriate conditions can reproduce (split) in 20 min. Its ability to move comes from a set of up to six rigid 100–200 rps spinning flagella, each driven by a biological motor. An E. coli bacterium alternates between running (at 10–20 μm_sec, but they cannot swim straight) and tumbling (changing direction). When the flagella rotate clockwise (counterclockwise), they operate as propellers and hence an E. Coli may run or tumble.

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 sensors it uses are receptor proteins which are very sensitive, and overall there is a high gain i.e., a small change in the concentration of nutrients can cause a significant change in behavior. The sensor averages sensed concentrations and computes a time derivative.

Bacteria are often killed and dispersed and this can be viewed as part of their motility. Mutations in E. coli affect, e.g., the reproductive efficiency at different temperatures, and occur at a rate of about 10−7 per gene and per generation. E. coli occasionally engages in a type of sex called conjugation that affects the characteristics of a population of bacteria. There are many types of taxes that are used by bacteria. For instance, some bacteria are attracted to oxygen (aero taxis), light (photo taxis), temperature (thermo taxis), or magnetic lines of flux (magneto taxis). Some bacteria can change their shape and number of flagella based on the medium to reconfigure so as to ensure efficient foraging in a variety of media. E. coli and S. typhimurium can form intricate stable spatio-temporal patterns in certain semisolid nutrient media.

They can eat radially their way through a medium if placed together initially at its center. Moreover, under certain conditions, they will secrete cell-to-cell attractant signals so that they will group and protect each other. These bacteria can swarm.

Optimization models are also valid for social foraging where groups of animals communicate to cooperatively forage. Foraging can be modeled as an optimization process where an animal seeks to maximize the energy obtained per unit time spent foraging. First, suppose that θ is the position of a bacterium and $J(\theta)$ represents the combined effects of attractants and repellants from the environment, with, for example, $J(\theta)<0$, $J(\theta)=0$, and $J(\theta)>0$ representing that the bacterium at location θ is in nutrient-rich, neutral, and noxious environments, respectively. Basically, Chemo taxis is a foraging behavior that implements a type of optimization where bacteria try to climb up the nutrient concentration (find lower and lower values of $J(\theta)$), avoid noxious substances, and search for ways out of neutral media (avoid being at positions θ where $J(\theta)\geq 0$). It implements a type of biased random walk.

4.4. Chemo taxis, Swarming, Reproduction, Elimination, and Dispersal

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. Let

$$P(j,k,l) = \{\theta^i(j,k,l) \mid \mathrm{i} = 1,2,..., S\} \tag{4.1}$$

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 $\theta^i(j,k,l) \in \Re^p$.

Let N_c be the length of the lifetime of the bacteria as measured by the number of chemotactic steps they take during their life. Let $C(i) > 0, i = 1,2,...,S,$ denote a basic chemotactic step size that we will use to define the lengths of steps during runs. To represent a tumble, a unit length random direction, say $\varphi(j),$ is generated; this will be used to define the direction of movement after a tumble. In particular, we let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\varphi(j) \tag{4.2}$$

so that $C(i)$ is the size of the step taken in the random direction specified by the tumble. If at $\theta^i(j+1,k,l)$, the cost $J(i,j+1,k,l)$ is better (lower) than at $\theta^i(j,k,l)$, then another step of size $C(i)$ in this same direction will be taken, and again. This swim is continued as long as it continues to reduce the cost, but only up to a maximum number of steps, N_s.

It is always desired that the bacterium that has searched the optimum path of food should try to attract other bacteria so that they reach the desired place more rapidly. Swarming makes the bacteria congregate into groups and hence move as concentric patterns of groups with high bacterial density. Mathematically, swarming can be represented by $J_{cc}(\theta, P(j,k,l)$, and it is the cost function value to be added to the actual cost function to be minimized to present a time varying cost function.

Let $d_{attract}$ be the depth of the attractant released by the cell, and let $w_{attract}$ be a measure of the width of the attractant signal. A cell repels another one via local consumption, and cells are not food for each other. Let $h_{repellant} = d_{attract}$ be the height of the repellant effect (magnitude), and let $w_{repellant}$ be a measure of the width of the repellant. Then, we may use functions $J^i_{cc}(\theta)$, i=1, 2. . . S, to model the cell-to-cell signaling via an attractant and a repellant. Let

$$J_{cc}(\theta) = \sum_{i=1}^{s} J_{cc}^{i} = \sum_{i=1}^{s}\left[-d_{attract}\, exp\left(-w_{attract}\, \sum_{j=1}^{p}\left(\theta_j - \theta_j^i\right)^2\right)\right]$$

$$+ \sum_{i=1}^{s}\left[-h_{repellant}\, exp\left(-w_{repellant}\, \sum_{j=1}^{p}(\theta_j - \theta_j^i)^2\right)\right] \tag{4.3}$$

where $\theta=[\theta_1, \ldots, \theta_p]^T$ is a point on the optimization domain. The expression of $J_{cc}(\theta)$ implies that its value does not depend on the nutrient concentration at position θ. Actually, it is reasonable to assume that the depth of the chemical secreted by a bacterium is affected by environment; i.e., bacteria with high nutrient concentration will secret stronger attractant than one with low nutrient concentration. In our model, we use the function $J_{ar}(\theta)$ to represent the environment-dependent cell-to-cell signaling.

Let

$$J_{ar}(\theta) = \exp\left(M - J(\theta)\right) J_{cc}(\theta), \tag{4.4}$$

where M is a tunable parameter. Then, for swarming, we will consider minimization of $J(i,j,k,l) + \mathrm{J_{ar}}\left(\theta^{\mathrm{i}}(j,k,l)\right)$, so that the cells will try to find nutrients, avoid noxious substances, and at the same time try to move toward other cells, but not too close to them. Note the function $J_{ar}(\theta^i(j, k, l))$ implies that, with M being constant, the smaller $J(\theta)$, the larger $J_{ar}(\theta)$ and thus the stronger attraction, which is intuitively reasonable. In tuning the parameter M, it is normally found that, when M is very large, $J_{ar}(\theta)$ is much larger than $J(\theta)$ and thus the profile of the search space is dominated by the chemical attractant secreted by E. coli. On the other hand, if M is very small, then $J_{ar}(\theta)$ is much smaller than $J(\theta)$ and it is the effect of the nutrients that dominates. In $Jar(\theta)$, we choose the scaling factor of $J_{cc}(\theta)$ as in exponential form, but this is not the only choice. Other functions which decrease monotonically and approach zero asymptotically are feasible candidates, though some additional constraints may be required.

Let N_{re} be the number of reproduction steps to be taken also let

$$S_r = \frac{S}{2} \tag{4.5}$$

be the number of population members who have had sufficient nutrients so that they will reproduce (split in two) with no mutations. For reproduction, the population is sorted in order of ascending accumulated; then the S_r least healthy bacteria die and the other healthiest S_r bacteria each split into two bacteria, which are placed at the same location. Where S indicates the total number of bacteria which should be an even integer.

Let N_{ed} be the number of elimination-dispersal events, and for each elimination-dispersal event each bacterium in the population is subjected to elimination-dispersal with probability p_{ed} . It is possible that in the local environment, the life of a population of bacteria changes either gradually by consumption of nutrients or suddenly due to some other influence. Events can kill or disperse all the bacteria in a region. They have the effect of possibly destroying the chemotactic progress, but in contrast, they also assist it, since dispersal may place bacteria near good food sources. Elimination and dispersal helps in reducing the behavior of *stagnation* (i.e., being trapped in a premature solution point or local optima).

4.5. Modified bacterial foraging: the algorithm

The BF algorithm suggested in [17] is modified so as to expedite the convergence. The modifications are discussed below. In [17], 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 [17], 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.
The algorithm is discussed here in brief.

Step 1—Initialization

The following variables are initialized.
1) Set number of bacteria (S) to 50 to be used in the search.
2) 'p' number of parameters to be optimized. Here we have four parameters t, μ_c, f_h, and γ.
Hence p=4.
3) Swimming length N_s to be 4.
4) N_c, the number of iterations in a chemo tactic loop is set to 100 $(N_c > N_s)$.

5) N_{re}, the number of reproduction steps and is set to 4.

6) N_{ed} , the number of elimination and dispersal events and set it to 2.

7) p_{ed} , the probability of elimination and dispersal is set to 0.25. The probability that each bacteria will be eliminated/dispersed (assume that elimination/dispersal events occur at a frequency such that there can be several generations of bacteria before an elimination/dispersal event but for convenience make the elimination/dispersal events occur immediately after reproduction).

8) Location of each bacterium P(p,S,Nc,Nre,Ned) i.e., random numbers on [0–1].

Step 2—Iterative algorithm for optimization

1) Elimination-dispersal loop: $\mathrm{l} = \mathrm{l} + 1$

2) Reproduction loop: $\mathrm{k} = \mathrm{k} + 1$

3) Chemo taxis loop: $\mathrm{j} = \mathrm{j} + 1$

a) For $\mathrm{i} = 1,2,\ldots,\mathrm{S}.$ take a chemotactic step for bacterium i as follows.

b) Compute $\mathrm{J(i,j,k,l)}$ Let $\mathrm{J(i,j,k,l)} = \mathrm{J(i,j,k,l)} + \mathrm{J_{cc}}(\theta^i(j,k,l), P(j,k,l))$ (4.6)

(i.e., add on the cell attractant effect to the nutrient concentration).

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 $\Delta_m(i)$, $m = 1,2,..., p.$ a random number on$[-1,1]$.

e) Move: Let

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}. \tag{4.7}$$

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

f) Compute $\mathrm{J(i,j,k,l)}$, and then let.

$$\begin{aligned} &\mathrm{J(i, j+1, k, l)} = J(i, j+1, k, l) + \\ &J_{cc}(\theta^i(j+1, k, l), P(j+1, k, l)). \end{aligned} \tag{4.8}$$

g) Swim (note that we use an approximation since we decide swimming behavior of each cell as if the bacteria numbered $\{1,2,\ldots,i\}$ have moved and $\{i+1, i+2,\ldots,S\}$ have not; this is much simpler to simulate than simultaneous decisions about swimming and tumbling by all bacteria at the same time):

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

ii) While $m < N_s$ if have not climbed down too long) • Let $m = m+1$.

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

$J_{last} = J(i, j, k, l)$ and let $\theta^i(j+1, k, l) = \theta^i(j+1, k, l) + C(i)\dfrac{\Delta^i}{\sqrt{\Delta^T(i)\Delta(i)}}$ 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).

4) If $J < N_c$, go to step 3. In this case, continue chemo taxis, since the life of the bacteria is not over.

5) Reproduction:

a) For the given *k* and *l*, and for each $i = 1,2,\ldots,S$, let

$$J^i{}_{health} = \sum_{j=1}^{N_c+1} J(i, j, k, l) \tag{4.9}$$

be the health of 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 other S_r bacteria with the best values split (and the copies that are made are placed at the same location as their parent).

6) If $k < N_{re}$ go to step 2. In this case, we have not reached the number of specified reproduction steps, so we start the next generation in the chemotactic loop.

7) Elimination-dispersal: For $i = 1,2,\ldots,S$, with probability P_{ed}, eliminate and disperse each bacterium (this keeps the number of bacteria in the population constant). To do this, if you eliminate a bacterium, simply disperse one to a random location on the optimization domain.

8) If $l < N_{ed}$, then go to step 1; otherwise end.

The flow chart of modified bacterial foraging optimization algorithm is shown in figure.4.2.

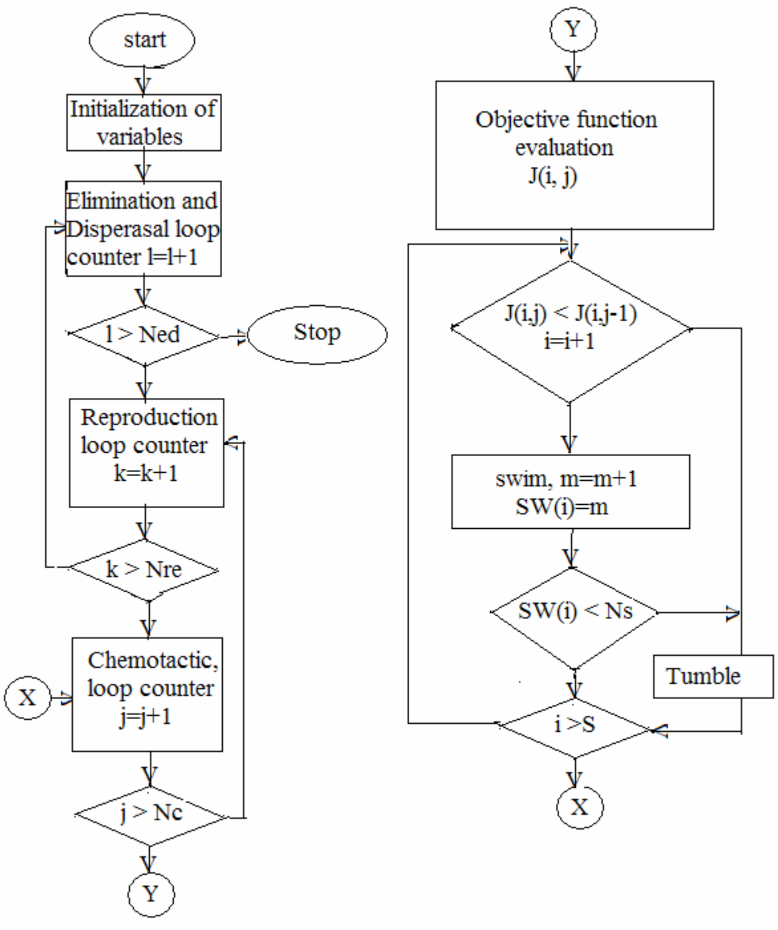


Fig.4.2. Flow chart of Bacterial Foraging Optimization Algorithm

4.6. Example:

As an illustrative example, we use bacterial foraging algorithm to try to find the location with highest nutrient concentration on a certain map and show the results on Fig. 4.3. The nutrient map is constructed by summing up several Gaussian functions with different magnitude and variance. The contour plots of the map are shown in the figure, with the best nutrient concentration located at $[15, 5]^T$.

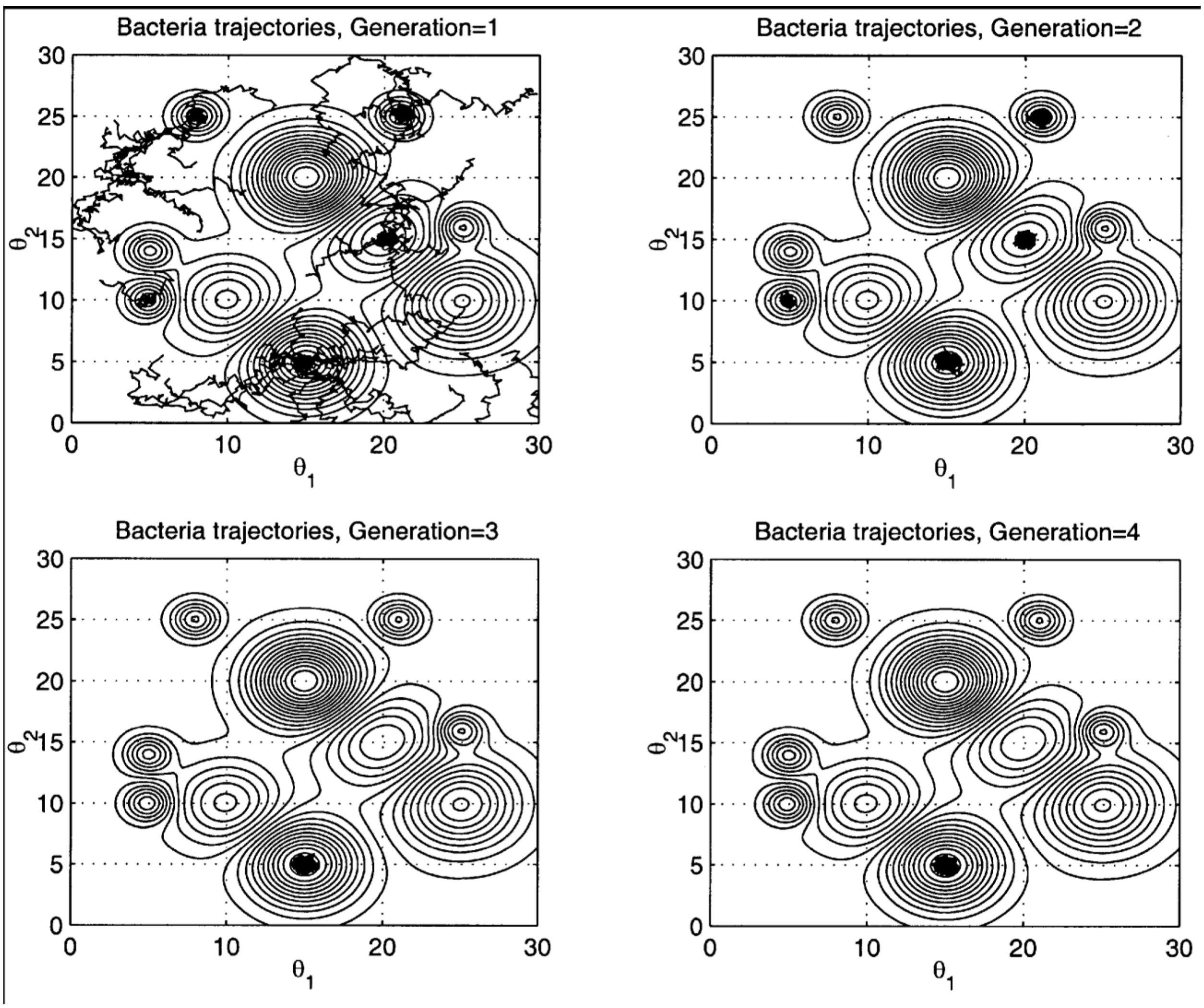


Fig. 4.3. Foraging of E. coli with reproduction, elimination and dispersion: Contour plot before elimination and dispersion.

In this example, we include reproduction, elimination, and dispersion of E. coli and demonstrate the roles which these processes play in the E. coli evolution. In the simulation, we choose N_{re}=4 and N_{ed}=2, which means that, during the simulation, E. coli evolve four generations and experience elimination and dispersal event once, respectively.

Initially, the bacteria are distributed randomly over the nutrient map. In Fig. 4.3, we see that the first generation of E. coli are moving around to search for places with a better nutrient concentration, as shown by those curvy trajectories on the contour plot. In the second generation, almost all the bacteria have found such places, though all of them are not global optimal points. With evolution, all in the third generation find the position on the map with the best nutrient concentration, and the fourth generation stays there firmly. Simulation results in Fig. 4.4. are a continuation of Fig. 4.3, but an elimination and dispersal process happens in between. In Fig. 4.4., some bacteria of the first generation appear in some bad positions. But after reproduction, almost all of the E. coli locate the global optimal position quickly and stay there from the second generation.

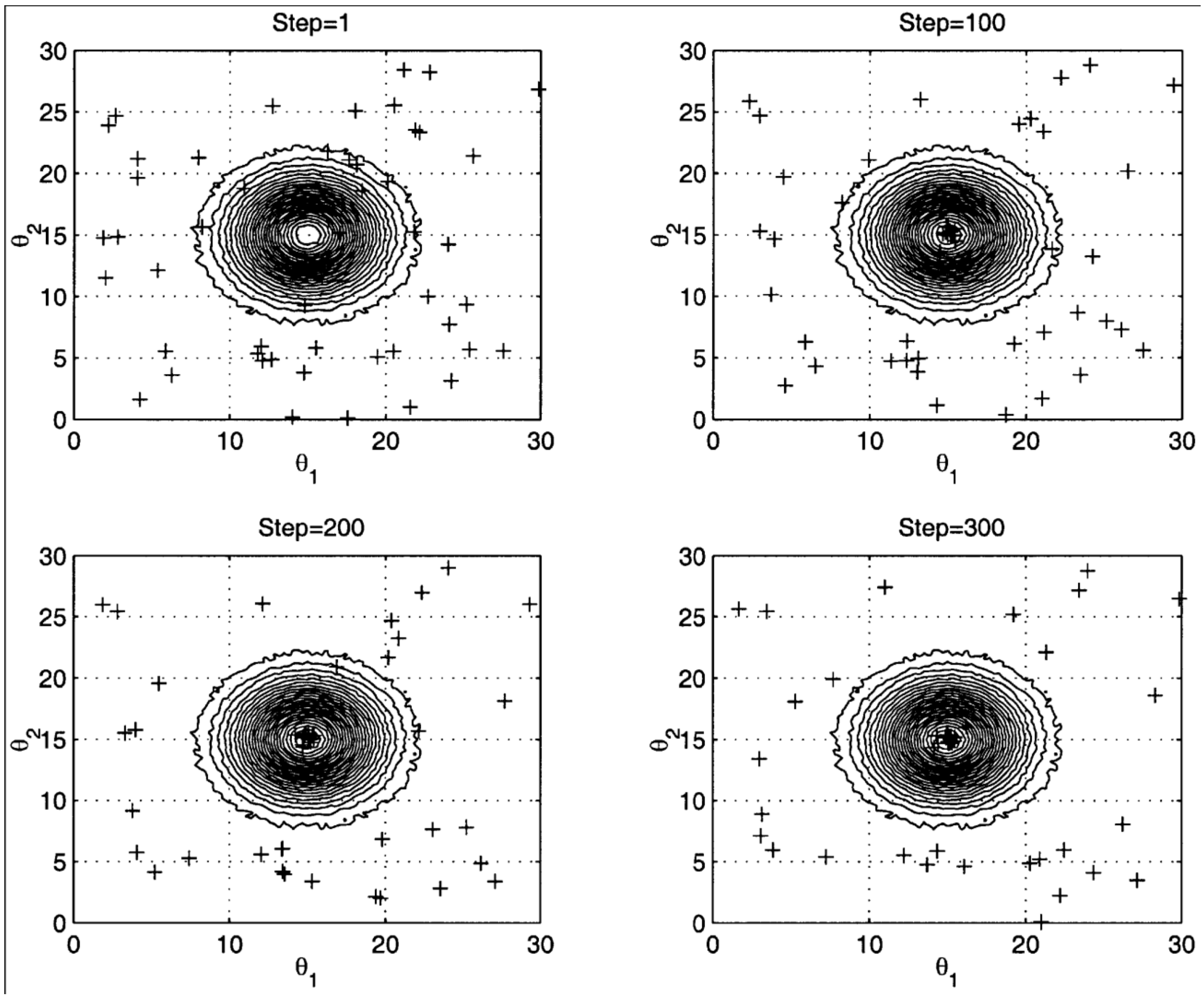


Fig. 4.4. Foraging of E. coli with reproduction, elimination and dispersion: Contour plot after elimination and dispersion.

5. A New Approach to Image Enhancement

5.1. Image Classification Based on Intensity Exposition

Many images appear bad because of their poor contrast as the image doesn't occupy the whole area of the histogram. The image gray levels may use only the lower part or the upper part or the entire region of the histogram area. When the gray levels use 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 cases we cannot readily perceive the details in the image. 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 as different local areas of the image use different histogram regions, which come under another category called mixed exposed images containing both the under exposed and over exposed regions.

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. Either under exposed or over exposed images are very rare in the nature. In this way, we consider every image as a mixed exposed image with some percentage of exposition.

We therefore introduce a parameter called "exposure" 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. The parameter "exposure" is given by

$$\exp osure = \frac{1}{L}\frac{\sum_{x=1}^{L} p(x).x}{\sum_{x=1}^{L} p(x)} \tag{5.1}$$

where x, indicates the gray level values of the image, $p(x)$ the histogram of the whole image and L , the total number of gray levels. This parameter is normalized in the range$[0,1]$. If the value of exposition for a certain image is found to be more than 0.5, it implies that there is more over exposed region than the under exposed region. Similarly if the exposition value is found to be less than 0.5, it implies that there is more under exposed region than the over exposed region. An exposition value in the range $[0.45,0.55]$ is found to yield a pleasing image. This parameter gives a good measure for the images ranging from the under exposed to the over exposed regions, but not at all times. Initially we presume a mixed image and then attempt to segment the image into under and over exposed regions so that the exposition value is in the range near to 0.5 as fixed for a pleasing image. This exposure value does not give the correct picture in those cases. But this parameter still has an importance as most of the images do not come under this category.

We define separate operators for enhancing the under and over exposed images. Note that no image is solely under exposed or over exposed. For a mixed exposed image, both of these operators should be applied simultaneously to achieve the pleasing nature. This can be done by first dividing the image gray levels into two parts so that both the operators can be applied separately. The following factor denoted by 'a' is the gray level value in the range $[0, L-1]$, divides the gray levels into two parts as $[0, a-1]$ and$[a, L-1]$.

$$a = L.(1 - \exp osure) \tag{5.2}$$

The range of intensity levels $[0, a-1]$ indicates the under exposed region of the image and the rest of the region $[a, L-1]$ indicate the over exposed regions.

5.2. Fuzzification and Intensification of Intensity (V)

An image of size MXN with intensity levels x_{mn} in the range $[0, L-1]$ can be considered as a collection of fuzzy singletons in the fuzzy set notation.

$$I = \bigcup \{\mu(xmn)\} = \left\{\frac{\mu mn}{xmn}\right\}$$
$$m = 1,2,\ldots,M; n = 1,2,\ldots,N \tag{5.3}$$

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

5.2.1. Fuzzification of under exposed region

An image can be divided into two parts as under exposed region and over exposed regions by using the value 'a'. A modified Gaussian membership function is used to fuzzify the under exposed region of the image as follows

$$\mu_{Xu}(x) = \exp\left[\frac{x_{\max} - (x_{avg} - x)}{\sqrt{2} f_h}\right]^2 \tag{5.4}$$

where x indicates the gray level of the under exposed region in the range $[0, L-1]$, x_{mn} 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 :

$$f_h^2 = \frac{1}{2}\frac{\sum_{x=0}^{L-1}(x_{\max}-x)^4\,p(x)}{\sum_{x=0}^{L-1}(x_{\max}-x)^2\,p(x)} \tag{5.5}$$

As outlined in the introduction, we will consider to modify its membership function without disturbing the membership functions of other component (Hue). It is observed that values of f_h are higher for a brighter image. This membership function gives larger values to the under exposed region and smaller values (almost zero) to the over exposed region. The characteristics of Gaussian member ship function are shown in the fig. 5.1.

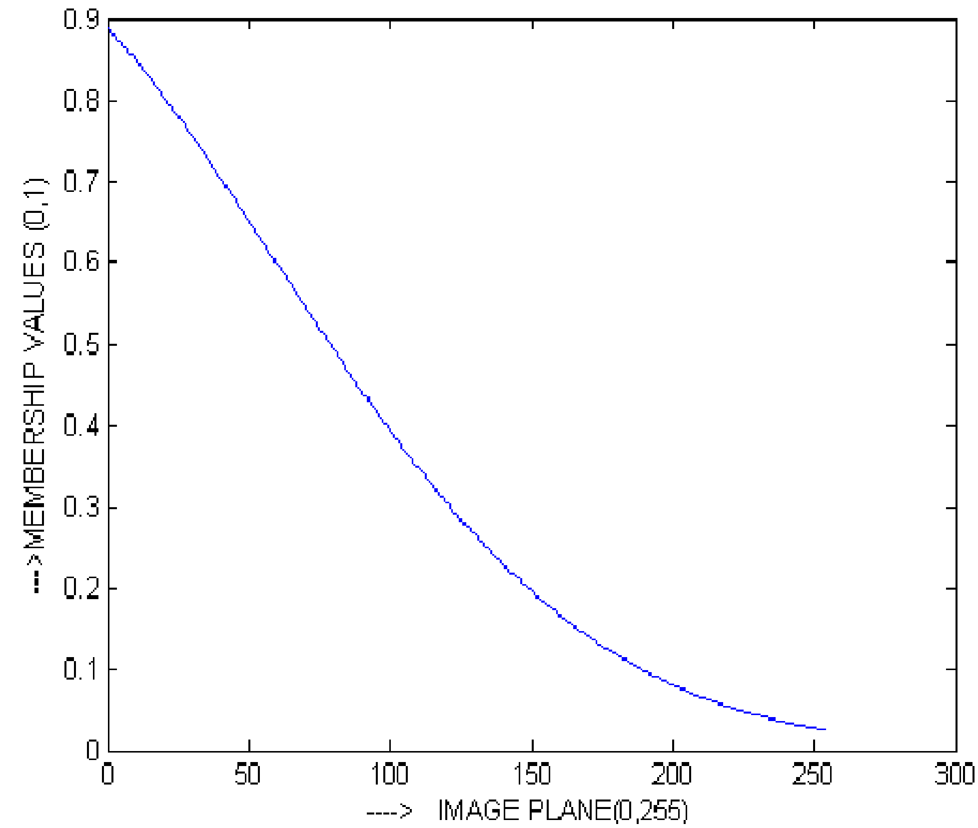


Fig. 5.1 Gaussian membership function characteristics

5.2.2. Fuzzification of over exposed region

A triangular membership function is used for the fuzzification of over exposed region of the image, given by

$$\mu_{Xo}(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{L-a} & x \geq a \end{cases} \tag{5.6}$$

where x is in the interval $(a \text{ to } \mathrm{L} - 1)$, which covers only the over exposed region of the intensity image while giving zeros to the under exposed values (below value a).This has only one parameter a and is calculated by the equation (5.2). 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].

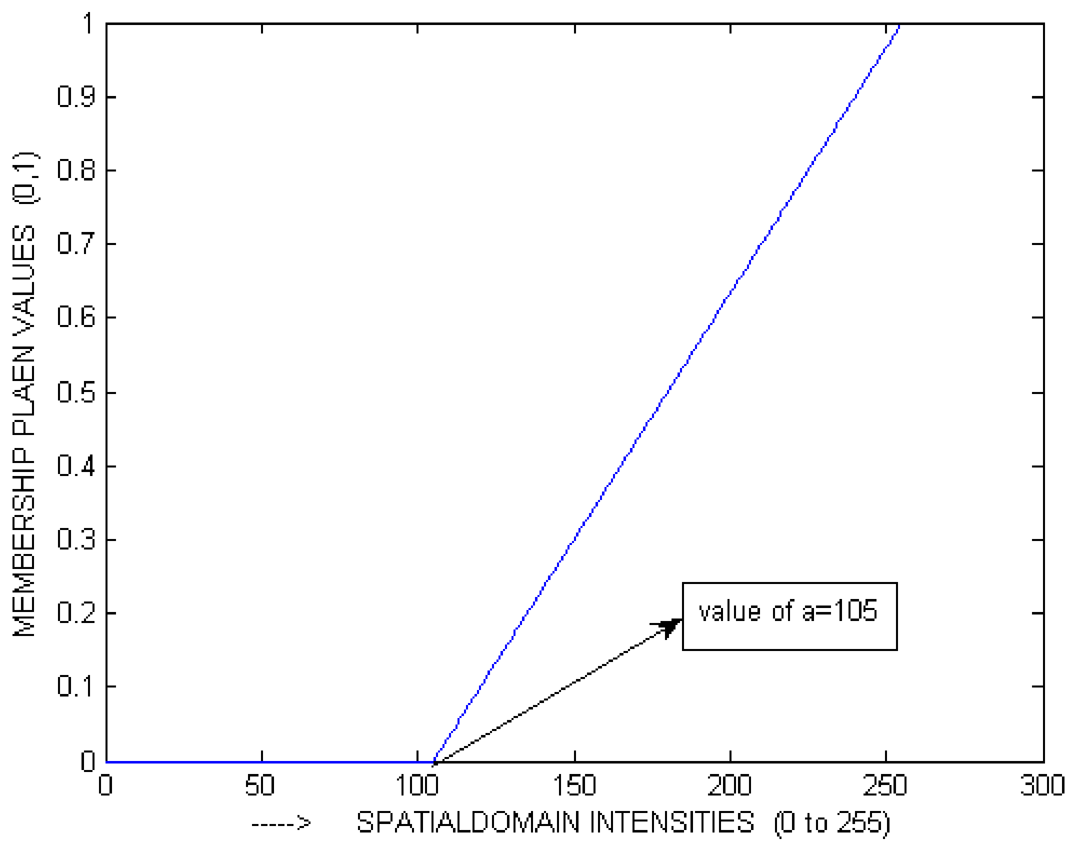


Fig. 5.2. Membership function for over exposed region for a=105

5.2.3. Defuzzification

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. defuzzified using the respective inverse membership functions given below.

$$x'_u = x_{avg} - x_{\max} + (-2\ln[\mu'_{Xu}(x)] f_h^2)^{1/2} \tag{5.7}$$

$\mu'_{Xu}(x)$ is the modified intensity value of the under exposed region and x'_u is the corresponding values of the under exposed region after applying the GINT operator defined in equation (5.9).

Similarly the defuzzication of the over exposed region can be carried out by

$$x'_o = \begin{cases} 0 \quad to.a-1 & \mu'_{Xo}(x)=0 \\ a+(L-a)\mu'_{Xo}(x) & else \end{cases} \tag{5.8}$$

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 respective operator i.e. power law transformation operator (5.10).

5.3. Enhancement Operators

5.3.1. GINT Operator for Under Exposed Region

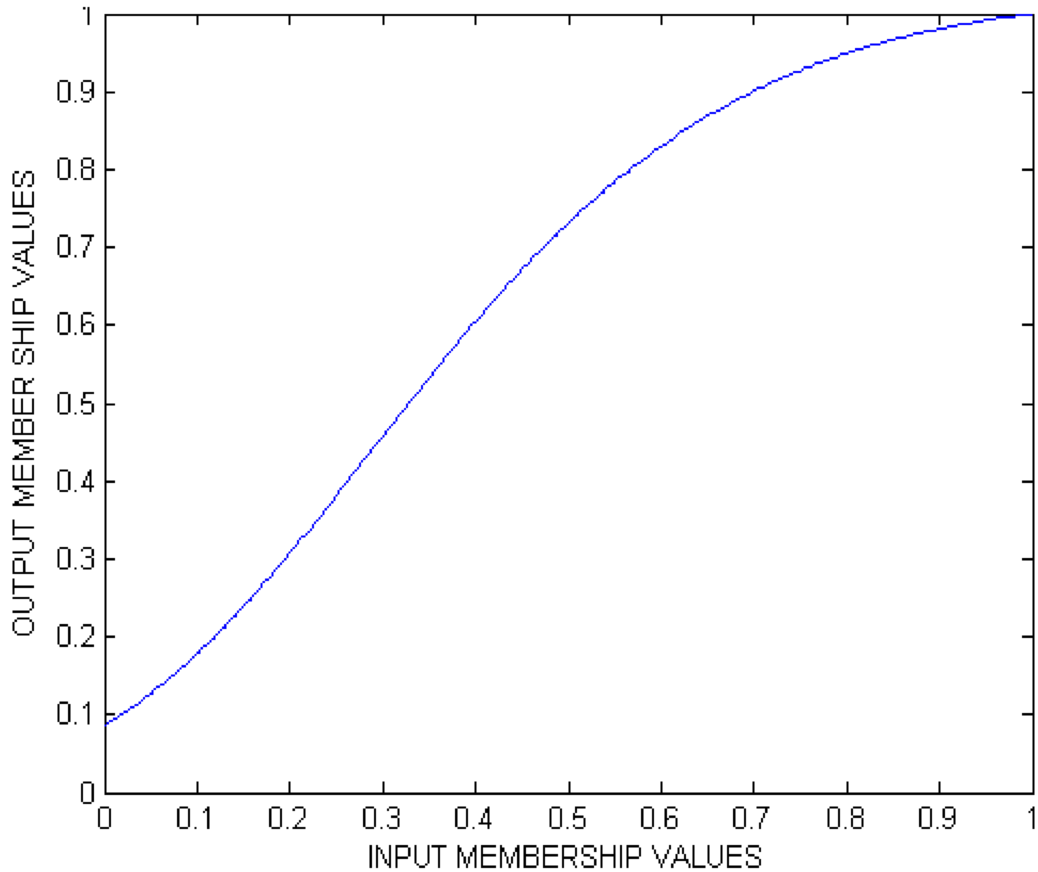


Fig. 5.3 GINT operator for under exposed region

A parametric sigmoid function in [16] is used as an operator for the under exposed region for enhancing the original gray level values, given by

$$\mu'_{Xu}(x) = \frac{1}{\left(1 + e^{-t(\mu_{Xu}(x) - \mu_c)}\right)} \tag{5.9}$$

Where μ'_{Xu} indicates the modified membership values and μ_{Xu} indicates the original membership values of the under exposed region. μ_c is the cross over point and its value is taken as 0.5. It stretches the intensity values in the interval (0, 1) from the arbitrary value 0.5. The characteristics of this operator are shown in fig. 5.3.

5.3.2. Power Law Transformation Operator for Over Exposed Region

A power law transformation operator is defined for the enhancement of the over exposed region of the image.

$$\mu'_{Xo}(x) = C.(\mu_{Xo}(x) + \varepsilon)^{\gamma} \tag{5.10}$$

Here C is a constant for boosting the amount of enhancement ε is offset, and γ the gamma factor is used for controlling enhancement. Default values of C and ε are taken as 1 and 0 respectively.

This operator reduces the original gray level values of the over exposed region. We consider the information in the image as the difference among the gray levels of neighboring pixels. For an over exposed image, the gray levels of the image are stacked near the maximum gray level. The difference between any neighboring gray levels is very low, i.e. information content. The defined operator in the equation (5.10) displaces the gray levels in the histogram of the image so that information content increases. The maximum gray level value is 1.0 and the pixel containing the maximum gray level, appears as white. With this operator we cannot increases the information if all the gray levels of the over exposed region or some part of the image are at maximum intensity value. We call the part of the image area where the pixels are all at the maximum intensity levels as 'permanent damaged area' of the image. In this case, as there is no information i.e. difference is zero among them, enhancement cannot be achieved by simply operating on the intensity values.

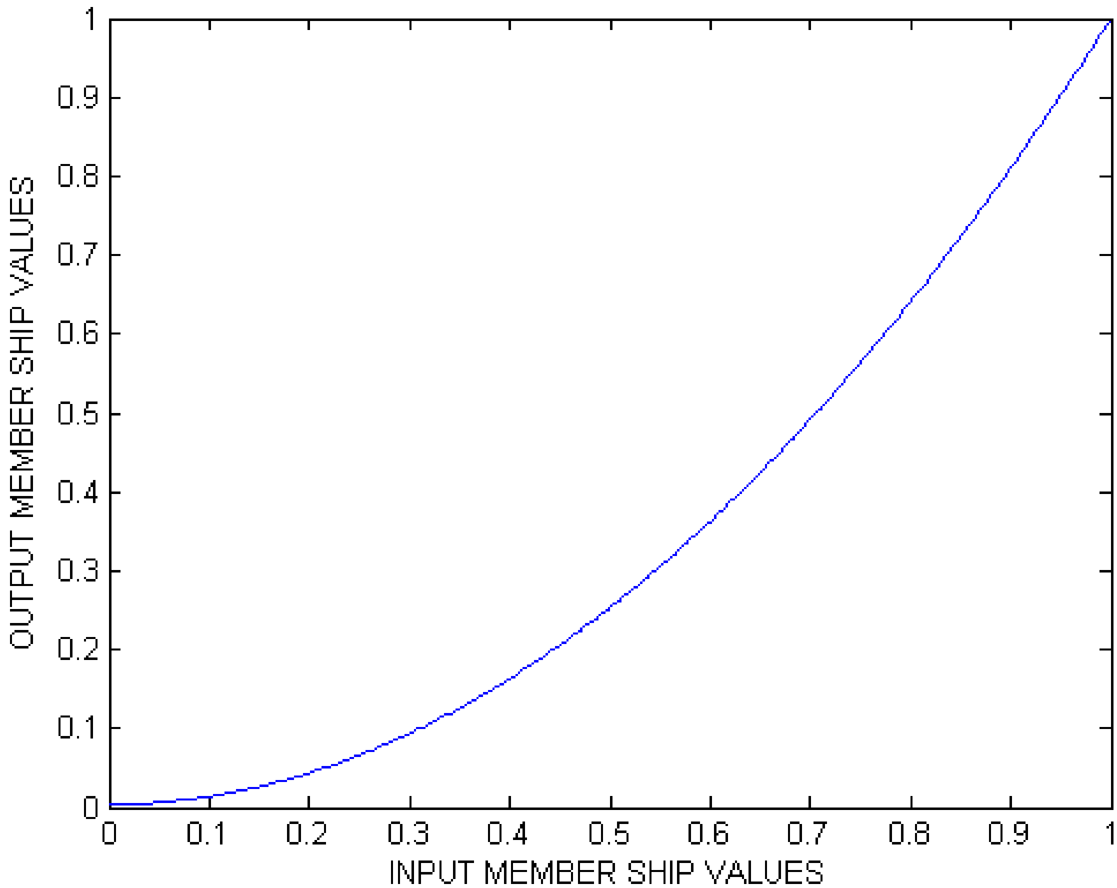


Fig. 5.4 Power Law Transformation Operator for Over Exposed Region

Fig. 5.4. shows the characteristics of the proposed power law transformation operator.

5.4. Enhancement of Saturation

A true color image contains the image information as a combination of three basic color components RGB (Red, Green, and Blue). The color image can also be expressed as a combination of Hue, saturation and Intensity values. Hue is the basic (original) color contained in the image; Intensity indicates the brightness information, while the saturation indicates how much percentage the original color (Hue) is diluted, i.e. the amount of white light mixed with the Hue. But generally the saturation is disregarded while enhancing a color image. The important property of the HSV color model is that it separates the chromatic information from the achromatic information.

Direct application of enhancement technique on a color image as for gray images generates color artifacts, as it disturbs the original color composition of the image. To enhance the color image, the original color (Hue) should be preserved. We have observed that saturation plays an important role while enhancing the over exposed color images especially in the case of permanent damaged images. As we reduce the value of saturation, images regain their details thus attaining the pleasing nature.

We can observe here that enhancement of saturation for all types of images is not trivial as it sometimes over enhances the colors. We should not blindly vary the saturation; instead judge how much the saturation of a particular image has to be varied so that image cannot be over enhanced. The under exposed images which have exposure values less than 0.5 do not need enhancement of saturation and it needs to be varied only for the over exposed images and the amount of variation should depend on portion of the over exposed region in the image.

A power law operator for the enhancement of image through saturation is defined by

$$S'(x) = [S(x)]^{(1-(0.5-exposure))} \tag{5.11}$$

$S'(x)$ is the modified saturation value and $S(x)$ is the original saturation of the image. Fig. 5.5 shows the characteristics of the enhancement operator for saturation. The information in the saturation may not be zero even though the information in the intensity is zero in the case of permanent damaged images. Enhancement of saturation brings back the pleasing nature for such images.

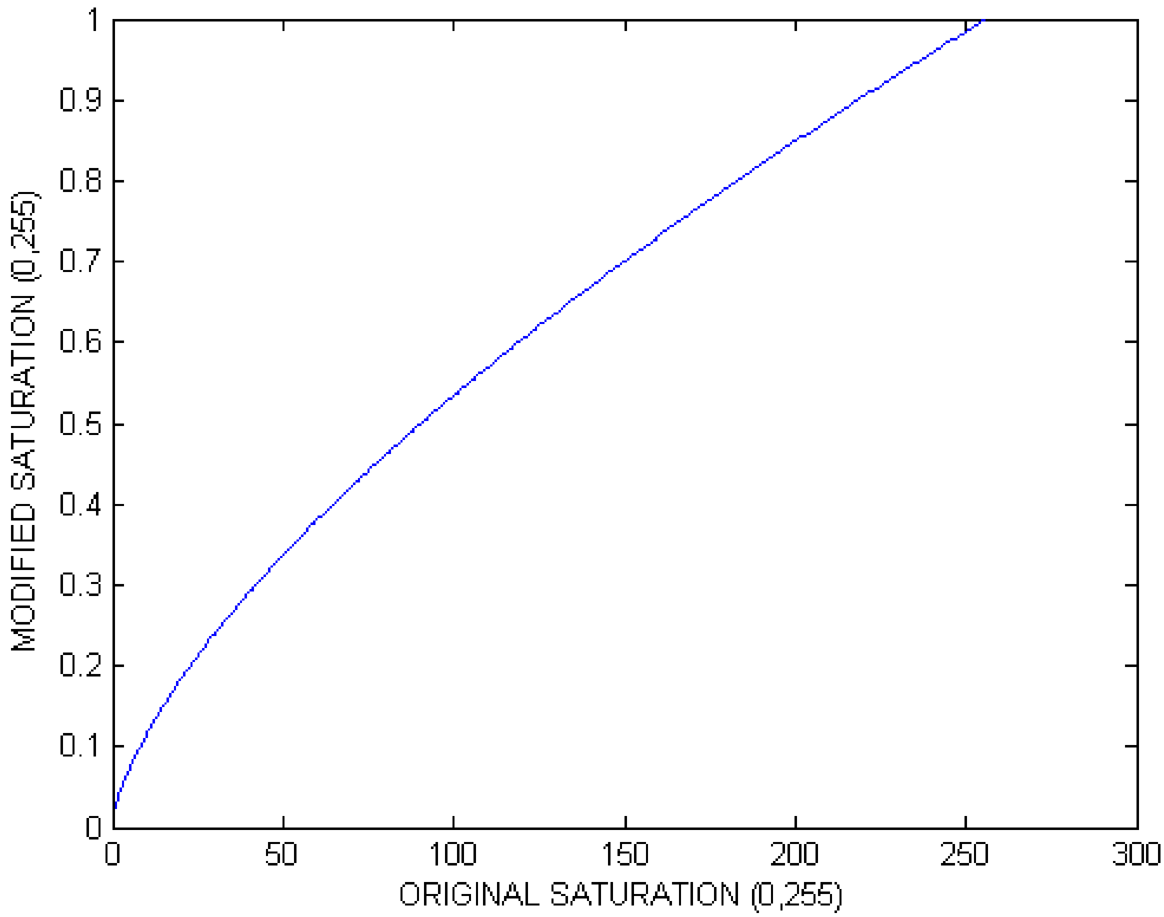


Fig. 5.5. Enhancement of saturation by Power law transformation

5.5. Measures of fuzzy image

5.5.1. Fuzzy contrast factors

We now compute the fuzzy contrast for the image by calculating the deviation of the membership values from the cross over point. The fuzzy contrast for an image proposed in [16] is given by

$$C_f = \frac{1}{L} \cdot \sum_{x=0}^{L-1} (\mu'_x(x) - \mu_c)^2 \tag{5.12}$$

The average fuzzy contrast is

$$C_{af} = \frac{1}{L} \cdot \sum_{x=0}^{L-1} (\mu'_X(x) - \mu_C) \tag{5.13}$$

Where $\mu'_x(x)$ is the modified membership value and μ_c is the crossover point.

In this paper, we define two fuzzy contrast factors separately for both the under exposed and the over exposed regions. The value of cross over point for the under exposed region is zero while that for the over exposed region is 1.0.

The contrast factor for the under exposed region of the image is given by

$$C_{fu} = \frac{1}{a} \cdot \sum_{x=0}^{a-1} (\mu'_{Xu}(x))^2 \tag{5.14}$$

The average fuzzy contrast for the under exposed image is :

$$C_{fu} = \frac{1}{a} \cdot \sum_{x=0}^{a-1} (\mu'_{Xu}(x)) \tag{5.15}$$

The fuzzy contrast factor for the over exposed region is :

$$C_{fo} = \frac{1}{L-a} \cdot \sum_{x=a}^{L-1} (1 - \mu'_{Xo}(x))^2 \tag{5.16}$$

The average fuzzy contrast for the over exposed region of the image is given by

$$C_{afo} = \frac{1}{L-a} \cdot \sum_{x=a}^{L-1} (1 - \mu'_{Xo}(x)) \tag{5.17}$$

The respective fuzzy contrast and average fuzzy contrast factors for both the under exposed and over exposed regions of the 'original' image are as follows:

$$C_{fuO} = \frac{1}{a} \cdot \sum_{x=0}^{a-1} (\mu_{Xu}(x))^2 \tag{5.18}$$

$$C_{afuO} = \frac{1}{a} \cdot \sum_{x=0}^{a-1} (\mu_{Xu}(x)) \tag{5.19}$$

$$C_{foO} = \frac{1}{L-a} \cdot \sum_{x=a}^{L-1} (1-\mu_{Xo}(x))^2 \tag{5.20}$$

$$C_{afoO} = \frac{1}{L-a} \cdot \sum_{x=a}^{L-1} (1-\mu_{Xo}(x)) \tag{5.21}$$

In the above definition, the fuzzy average contrast gives the overall intensity of the image whereas the fuzzy contrast gives the spread of the gradient with respect to the reference (the cross over point). Their ratio is found to give the quality of the image. The amount of enhancement will be indicated by the visual factor defined later.

5.5.2. Fuzzy quality factors

Definition: The quality factor of an image is defined as the ratio of absolute average fuzzy contrast to the fuzzy contrast.

The quality factor for the under exposed region of the modified image is given by

$$Q_{fu} = \frac{|C_{afu}|}{C_{fu}} \tag{5.22}$$

The respective quality factor for the over exposed region of the modified image is given by

$$Q_{fo} = \frac{|C_{afo}|}{C_{fo}} \tag{5.23}$$

In view of the above definition, the image quality of the original image for the under exposed region is given by

$$Q_{fuO} = \frac{|C_{afuO}|}{C_{fuO}} \tag{5.24}$$

The respective quality factor for the over exposed region of original image is given by

$$Q_{foO} = \frac{|C_{afoO}|}{C_{foO}} \tag{5.25}$$

5.6. Fuzzy optimization using entropy

Entropy that makes use of Shannon's function is regarded as a measure of quality of information in an image in the fuzzy domain. It gives the value of indefiniteness of an image defined by:

$$E = \frac{-1}{L\ln 2}\left[\sum_{x=0}^{a-1}[\mu'_{Xu}(x)\ln(\mu'_{Xu}(x)) + (1-\mu'_{Xu}(x))\ln(1-\mu'_{Xu}(x))] + \right.$$
$$\left. + \sum_{x=a}^{L-1}[\mu'_{Xo}(x)\ln(\mu'_{Xo}(x)) + (1-\mu'_{Xo}(x))\ln(1-\mu'_{Xo}(x))]\right] \tag{5.26}$$

Since it provides the useful information about the extent to which the information can be retrieved from the image, optimization of this should pave the way for the determination of the parameters: t, μ_c, f_h, and γ.

5.7. Visual factors

For the purpose of judging the quality factor, we define the normalized quality factor called the visual factor. It specifies the amount of enhancement caused. We use separate visual factors for both the under and over exposed regions, and then combine them with weighting factors depending on the value of exposure.

The visual factor for the under exposed region of the image is defined as

$$V_{fu} = \frac{Q_{fu}}{Q_{fuo}} \tag{5.27}$$

Where Q_{fu}, and Q_{fuo} indicate the quality factors of the under exposed region of the modified image and original image respectively. The visual factor defined for the over exposed region of the image is

$$V_{fo} = \frac{Q_{foO}}{Q_{fO}} \tag{5.28}$$

Where Q_{fO}, and Q_{foO} indicate the quality factors of the over exposed region of the modified image and original image respectively. These factors have values greater than 1 for all the images. These two factors have to be combined based on the amount of the under and the over exposed regions contained in the original image to yield an over-all visual factor defined as:

$$V_f = V_{fu}.(\exp osure) + V_{fo}(1 - \exp osure) \tag{5.29}$$

The definition of the visual factor allows us to specify a range for the desired normalized quality factor. Increasing beyond this range, the image would start losing the pleasing nature. By experimentation, we have found a value for the visual factor in the range of 1.0 to 1.5 to yield a pleasing image.

5.8. Constrained fuzzy optimization

If we know the desired visual factorV_{df} corresponding to V_f, then it is possible to satisfy this desired visual factors treated as constraints by the constrained fuzzy optimization. However, we need to set up the objective function as under

$$J_v = E + \left| V_{df} - V_f \right| \tag{5.30}$$

The optimization of the objective function gives values of the parameters t,μ_c, f_h, and γ by subjecting to the constraints such as$t \geq 1$, $0 \leq \mu_c \leq 1$, and $\gamma \geq 1$. We have used Bacterial Foraging optimization algorithm for the optimization of the objective function, which gives the global minimum as the optimum value.

5.9. Algorithm for Image Enhancement

1) Input the given image file and convert RGB to HSV.

2) Calculate histogram $p(x)$ where $x \epsilon V$.

3) Calculate the initial value of f_h using (5).

4) Compute the values of a, and $exposure$ using (1) and (2).

5) Fuzzify V to get $\mu_{Xu}(x)$ and $\mu_{Xo}(x)$ using (4) and (6).

5) Initialize $\mu_c \leftarrow 0.5$, and calculateC_{fuO} , C_{foO}, C_{afuO},C_{afoO}, Q_{fuO} and Q_{foO}.

6) Set initially $t \leftarrow 5$ and $\gamma \leftarrow 2$, calculate the modified membership values $\mu'_{Xu}(x)$ and$\mu'_{Xo}(x)$ for under exposed region and over exposed region using equations (9) and (10).

7) Now calculateC_{fu}, C_{fo} , C_{afu} , C_{afo} , Q_{fu}, and $Q_{fo}$for the initial assumed parameters (t, μ_c, f_h, γ).

8) Calculate the visual factor V_f and set desired visual factor $V_{df} \leftarrow 1.5$ to learn the parameters (t, μ_c, f_h, γ) iteratively.

9) Optimize the objective function using Modified Bacterial Foraging Algorithm.

10) Modify the membership function with the optimized parameters(t, μ_c, f_h, γ).

11) Defuzzify the modified membership values of both the under and over exposed regions and combine them based on the value of $exposure$, to form intensity (V) for the enhanced value using (7) and (8).

12) Enhance the saturation for the over exposed images using equation (11). Display the enhanced HSV image.

5.10. Conclusion of the chapter

The approach introduced in Hanmandlu [16] works well for the under exposed images. In this project work the procedure [16] is modified to yield better results for the enhancement of the under exposed images. For the over exposed images, a new power law operator is proposed which reduces the intensity values which are stacked at maximum intensity value i.e. 1. For the enhancement of under plus over exposed images we propose a approach that classifies the image into under exposed and over exposed regions, and applies separate operators simultaneously on these separate regions.

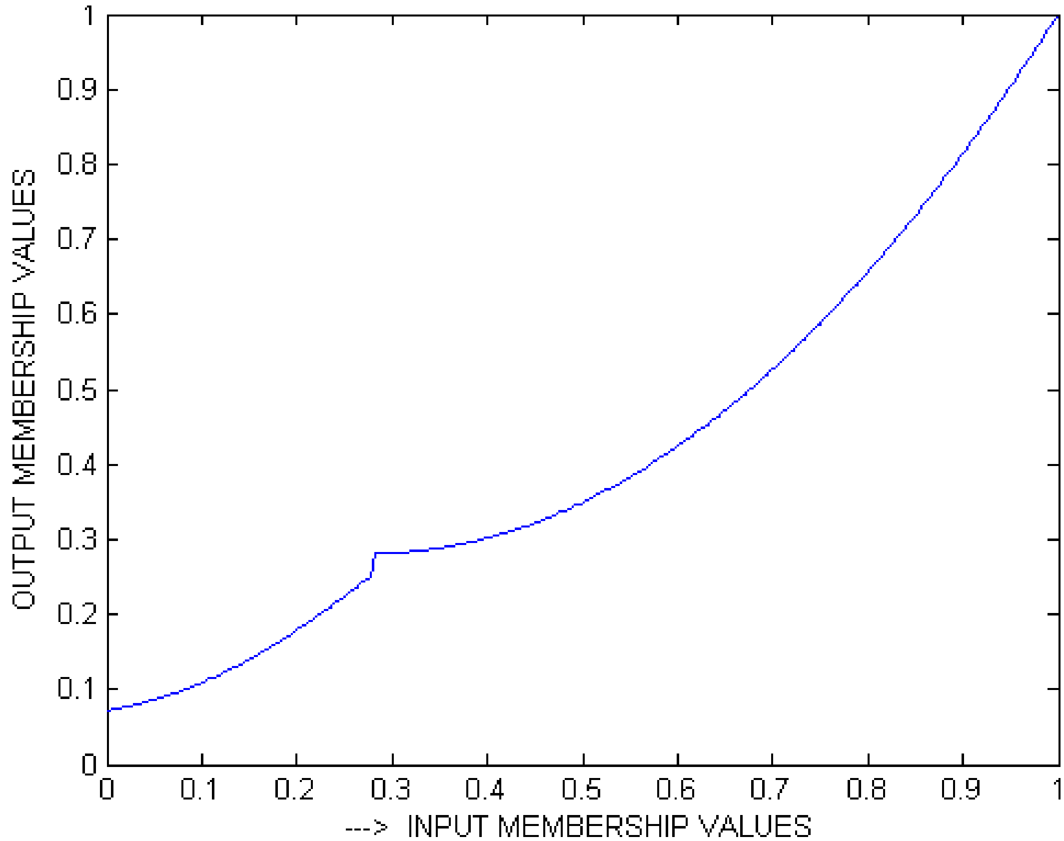


Fig. 5.6 Over-all Enhancement Curve for a Image of Value a =70

GINT [16] operator is used on the under exposed region of the image and the power law transformation operator is used on the over exposed region of the image. These two regions are combined back to form the overall modified intensity (V').

The proposed approach removes all types of contrast degradations in image. It determines the type of the image by the equation (5.1), and classifies total image intensity levels into two regions called under exposed region and over exposed region and applies separate operators with appropriate parameters determined by the optimization. The image with more brightness area needs to be adjusted i.e. the intensity values have to be reduced accordingly to maintain the desired contrast. To do this we have proposed two operators. The GINT operator improves the intensity values. Therefore, this operator is applicable for the case of under exposed regions.

The power law transformation operator reduces the intensity values and it is adaptable through its parameter called gamma. It reduces the values if $\gamma > 1.0$, hence it can be used for over exposed regions. The combination of these two operators makes the image enhancement technique more efficient. Our approach considers every image as a mixed exposed image i.e. combination of under and over exposed regions and applies the appropriate operators according to the type of the image. The overall enhancement operator will be the combination of the both operators, and the participation of each operator in the overall operator depends on the value of exposure and a.

Fig. 5.6 shows the over-all enhancement curve for a image of value a =70 (i.e. over exposed image), and the Fig. 4.7 shows the over-all enhancement curve for a image of value a =240 (i.e. under exposed image).

With this technique, as the GINT operator increases those pixel values which are below 0.5, while the other operator reduces the pixel values which are above 0.5, there is a discontinuity exist at the intensity point a. As a result the overall intensity operator becomes non-monotonic and the results became unexpected. To overcome this problem, we used an approach that iteratively reduces one of the operators (i.e. the higher one at a) values by certain percentage until the values of the two operators at the point a become equal.

The parameters of these operators adjust the operators to make the overall operator fit to any particular type of contrast degradation in the image. For the calculation of these parameters, an objective function is formed by considering the entropy, the quality and visual factors of the image. The minimization of objective function leads to enhancement of the image by stretching V-component of the pixels about the crossover point. Also modified Bacterial Foraging algorithm has been used for the fuzzy optimization of entropy, an efficient optimization algorithm.

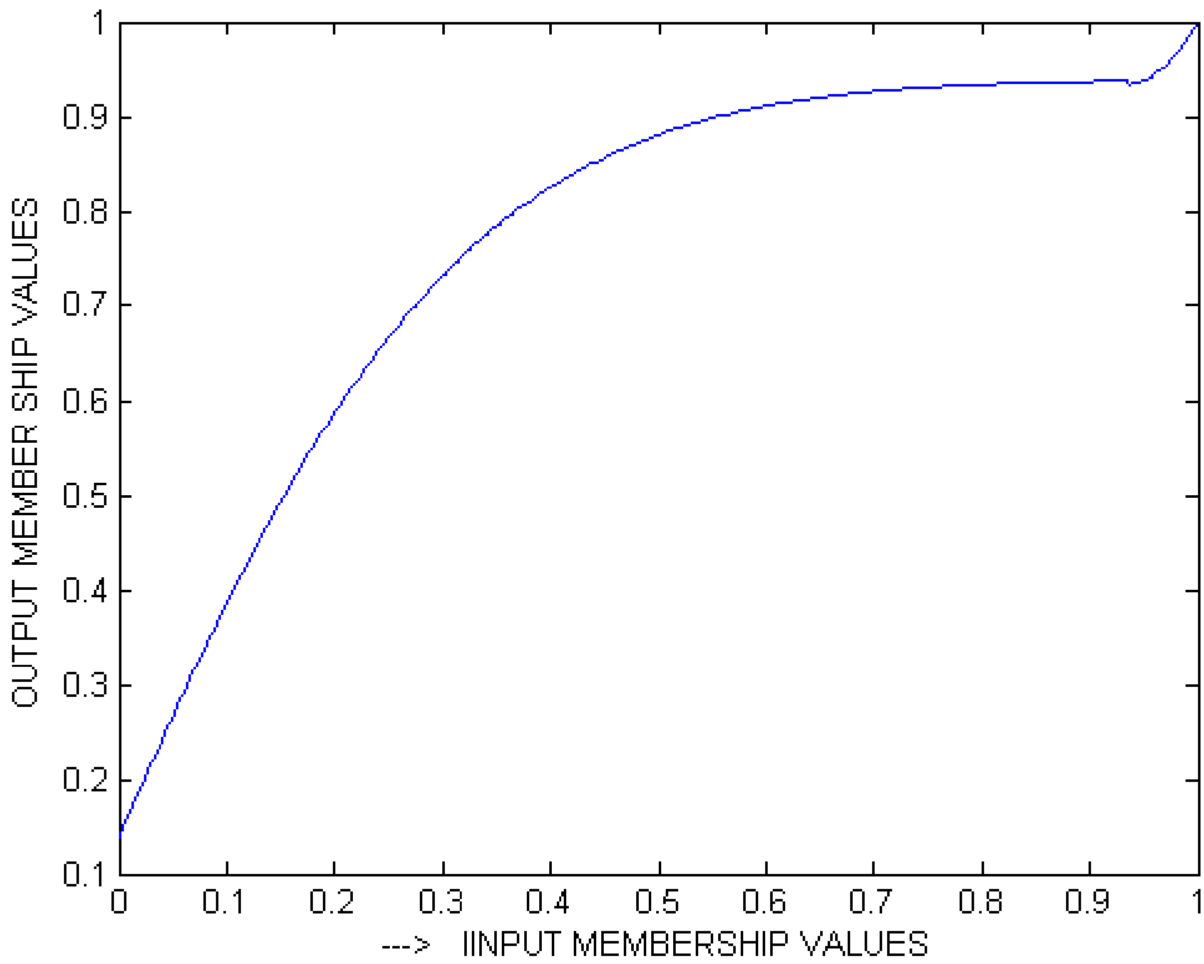


Fig. 5.7. Over-all Enhancement Curve for a Image of Value a =240

Saturation component is also made variable along with the luminance (intensity), while keeping the hue of the image fixed in the process of enhancement. There are some images which have no information in the intensity component. So, the sole enhancement of intensity component does not make the enhancement. The enhancement of saturation for the case of over exposed images improves the quality of color makes the image pleasing.

6. Results and Discussions

6.1. Summary

First the original RGB image is converted to HSV (Hue, saturation and intensity value) color space to preserve the hue of the image. 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 (exposure). These two regions of the image have been separately enhanced with separate operators defined. The fuzzifier, f_h, the crossover point μ_c, the intensification parameter t, and the gamma factor γ for the V component are calculated separately. The operators defined in this work enhance the image indefinitely i.e. they may under or over enhances the image. To control the amount of enhancement needed for the image the four parameters (fuzzifier f_h, fuzzy domain crossover point μ_c, intensification parameter t, and gamma factor γ) are used. The initial value of the intensification parameter is taken as 5, the crossover point as 0.5 and that of gamma factor as 2.0 and these parameters are trained by optimizing the entropy of the image and visual factor with respect to desired visual factor with constraints. The visual factor indicates the amount of enhancement over the original image and this factor should have the value that satisfies all the constraints to produce pleasing nature in image. Throughout the intensification process, the value of hue is kept constant to preserve the basic color of the image.

As one operator enhances, while the other reduces the intensity values in the process of enhancement of intensity (V) of the HSV image, a discontinuity at the intensity level $'a'$ is formed. This discontinuity causes unexpected blurring in the image. The over-all operator (combination of both the operators) should be increasing monotonic to avoid this effect. To overcome this problem we have iteratively reduced the enhancement of one operator while increased the other operator values until the values of both matched at the intensity value a to achieve positive monotonicity.

In the case of over exposed images, the purity of the color decides the amount of enhancement for the image. The operator defined for the saturation enhancement, readily enhanced the original color to produce the pleasing nature, especially for permanent damaged images which do not have any information in the intensity part, are also enhanced sufficiently. We can observe permanent damaged areas in the images -*viz*. man.jpg, rose.jpg shown in fig. 6.4 and fig.6.8 respectively. The sole enhancement of intensity in this case is not sufficient to produce pleasing nature as the intensity contains no information about the image. These types of images are called as permanent damaged images and the parts of the image where all the pixels are at maximum intensity level (appear white) called the permanent damaged areas of the image. We can recover the information in these areas up to some extent through the enhancement of saturation. By experimentation, we have observed that most of the under exposed images do not need enhancement in saturation.

TABLE 6.1.
INITIAL VALUES OF THE PARAMETERS

Test Images	t	μ_C	f_h	γ	E	V_f
Hills.jpg	5.00	0.5	113.41	2.00	0.7161	1.3920
Man.jpg	5.00	0.5	84.29	2.00	0.6778	1.3835
Cricketer.jpg	5.00	0.5	128.73	2.00	0.4496	1.8812
Cougar.jpg	5.00	0.5	155.76	2.00	0.3989	2.0018
Doctor.jpg	5.00	0.5	91.76	2.00	0.3567	1.7023
Face.jpg	5.00	0.5	137.51	2.00	0.3449	2.4337
Scene.jpg	5.00	0.5	100.38	2.00	0.7052	1.2525
Rose.jpg	5.00	0.5	179.82	2.00	0.6574	1.6495

We have considered many images, *viz.*, Lena.jpg, face.jpg, doctor.jpg, cricketer.jpg, of type under exposed and the images *viz.*, man.jpg, scene.jpg, cougar.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. 6.1 to fig. 6.9. In the case of over exposed images, the results obtained with the proposed technique have compared with that of histogram equalization method. As shown in the figs.6.6- 6.9 (c), the histogram equalization technique instead of reducing the degradation in the image, itself damages the original image.

TABLE 6.2

OPTIMIZATION OF $J_v = E + \left|V_{df} - V_f\right|$ WITH V_{df}=1.5

Test Images	t	μ_C	f_h	γ	E	V_f
Hills	7.0700	0.7500	116.680	2.4700	0.5797	1.8900
Man	4.7065	0.4633	76.200	2.1990	0.6506	1.2129
Cricketer	5.6693	0.5837	126.8339	2.3037	0.6312	1.3174
cougar	5.5317	0.5665	154.0238	2.2880	0.7194	1.2958
Doctor	5.9579	0.6197	89.481	2.3373	0.4177	1.8889
Face	4.1153	0.3894	142.5473	2.1441	0.8248	0.7613
Scene	8.9975	0.9997	98.827	2.7078	0.5899	1.4640
Rose	2.6487	0.2061	181.3745	2.0419	0.5741	1.4396

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-6.1 represents the initial values of the parameters, the entropy and visual factors of the test images with the application of the initial values. The initial value of f_h is higher for the over exposed images. The table-6.2 represents the resultant values of the parameters (the fuzzifier f_h, the cross over point μ_c, the intensifier t and the gamma γ, after optimizing the entropy and the deviation of visual factor from the desired visual factor value. Also indicates the optimized values of the entropy E and the visual factor V_f for the test image. The resultant values of the parameters have been used to produce the required amount of enhancement for the images.

6.2. Results of the proposed approach in comparison with Histogram Equalization technique

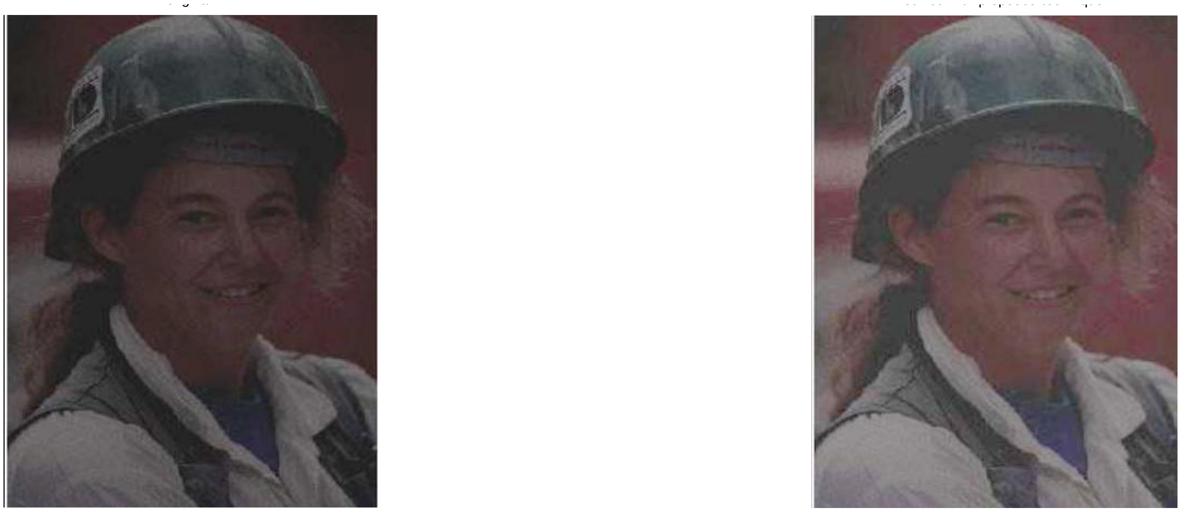
The original images and the enhanced images are shown in Figs.6.1- 6.9. A clear improvement is seen as far as the details are concerned after the application of the proposed enhancement method. This can be seen from different case studies, from which we can say it is nonlinear. Note that the pleasing nature arises from proper stretching of the membership values.

For the under exposed images the parametric sigmoid function i.e. GINT operator works well as it stretches the pixel values from the point 0.5. That means it gives higher values for the pixels which have the values lower than 0.5, and gives lower values for the pixels which have more than 0.5.The Figs.6.1 to 6.3 shows the under exposed images, Lena.jpg, Face.jpg, and Doctor.jpg. As we observe, these images have been enhanced perfectly.

The original over exposed images have much higher brightness, the exact details cannot be viewable as the most of pixels have much higher values, and the information i.e. the change among the pixel values is much lower or even zeros. These over exposed images will be generated when the object area is exposed with more brightness.

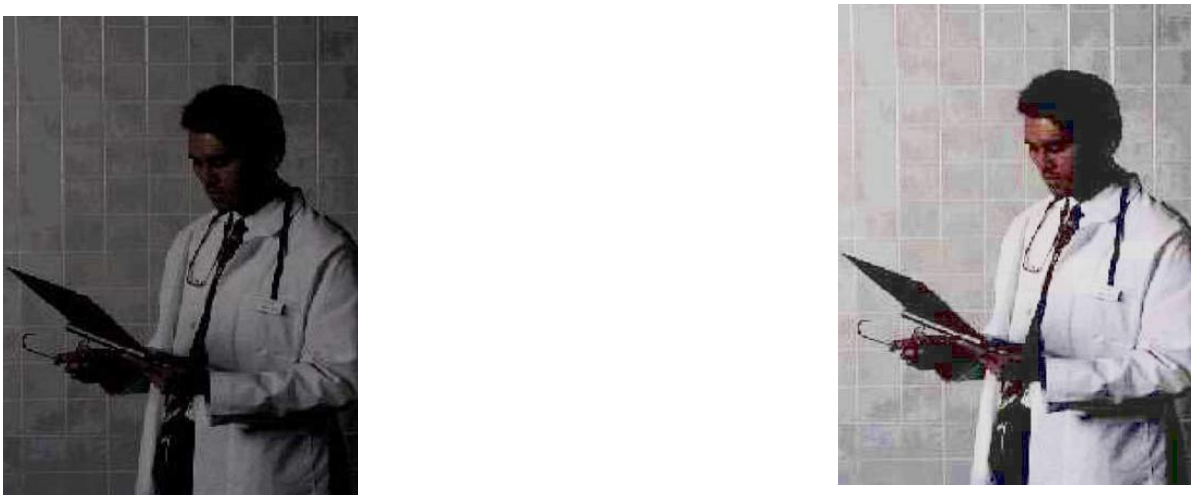
(a) (b)

Fig. 6.1 Left to Right (a) Original image and (b) Enhanced image of 'Lena.jpg'



(a) (b)

Fig. 6.2 Left to Right (a) Original image and (b) Enhanced image of 'Face.jpg'



(a) (b)

Fig. 6.3 Left to Right (a) Original image and (b) Enhanced image of ‘Doctor.jpg’

Fig. 6.4 (a) Original over exposed image ‘Rose.jpg’

Fig.6.4 (b) Enhanced image of ‘Rose.jpg’ with proposed technique

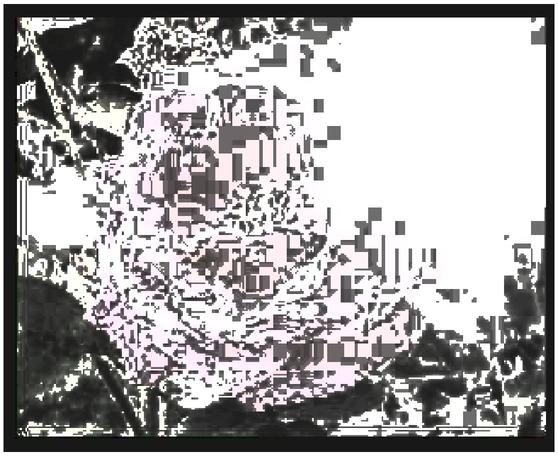


Fig.6.4 (c) Histogram equalized image of 'Rose.jpg'

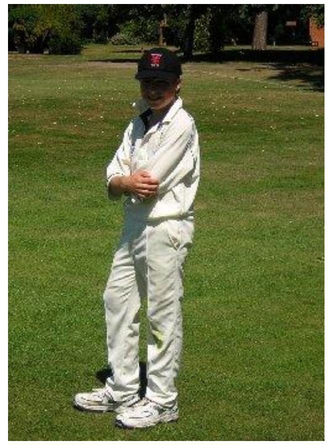


Fig.6.5 (a) Original under plus image 'Cricketer.jpg'

Fig.6.5 (b) Enhanced image of 'cricketer.jpg' with the proposed technique

Fig.6.5 (c) Histogram equalized image of 'Cricketer.jpg'

Fig. 6.6 (a) Original under plus over exposed image of 'Hills.jpg'

Fig.6.6 (b) Enhanced image of 'Hills.jpg' with proposed technique

Fig.6.6 (c) Histogram equalized image of 'Hills.jpg'

Fig.6.7 (a) Original under plus over exposed image 'Cougar.jpg'

Fig.6.7 (b) Enhanced image of ‘Cougar.jpg’ with the proposed technique

Fig.6.7 (c) Histogram equalized image of ‘Cougar.jpg’

Fig.6.8 (a) Original over exposed image ‘man.jpg’

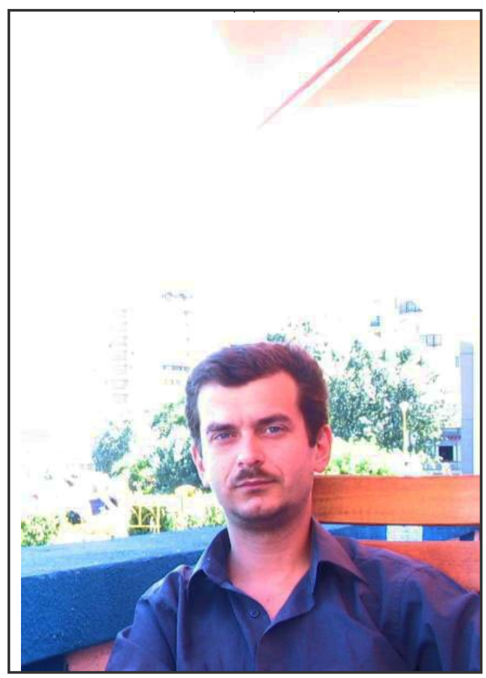


Fig.6.8. (b) Enhanced image of ‘man.jpg’ with proposed approach

Fig.6.8. (c) Histogram equalized image of ‘man.jpg’

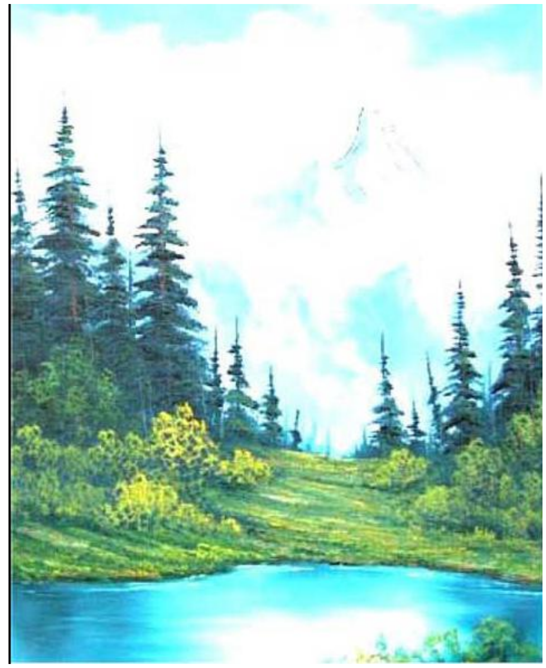


Fig.6.9 (a) Original over exposed ‘natural scene.jpg’

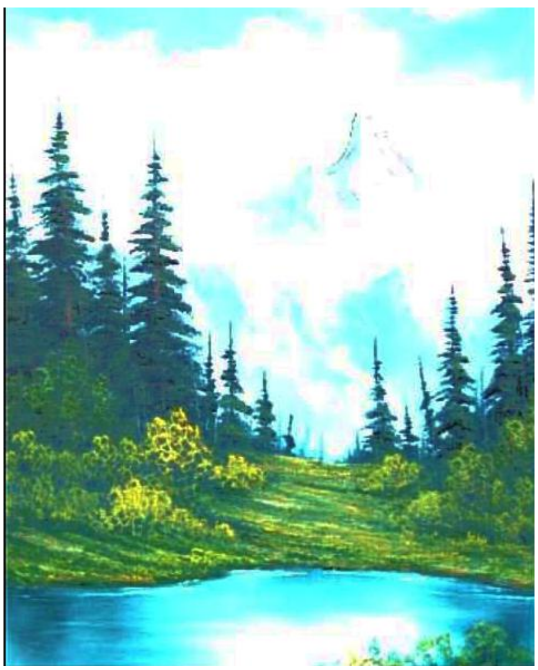


Fig.6.9. (b) Enhanced image of ‘natural scene.jpg’ with the proposed approach

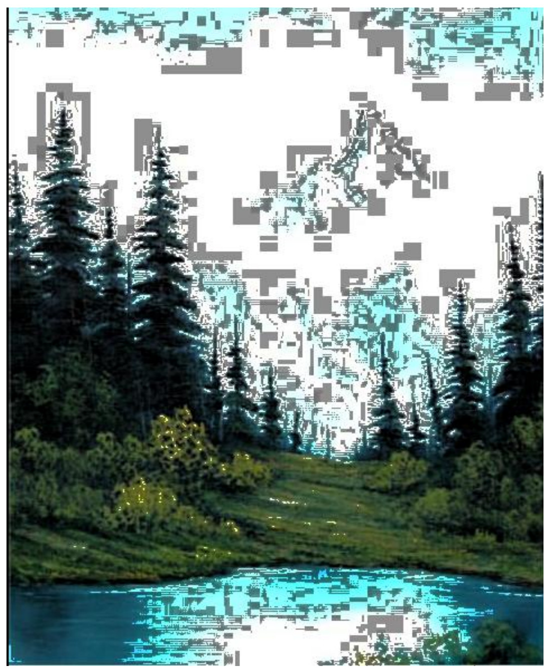


Fig.6.9. (c) Histogram equalized image of ‘natural scene.jpg’

Table-6.3 Percentage reduction of GINT

Images	**Exposure**	f_h	**Percentage reduction GINT**
Lena.jpg	62.88	142.3627	4%
Doctor.jpg	67.24	91.7695	4%
Face.jpg	67.70	137.5162	4%
Rose.jpg	223.54	179.8247	0%
Cricketer.jpg	104.87	128.7328	8%
Hills.jpg	200.02	113.4121	10%
Man.jpg	234.22	84.2980	10%
Cougar.jpg	64.16	155.7640	4%
Scene.jpg	212.06	100.3832	0%

For the over exposed images, the operator power law transformation increases the change among the pixels, by pulling down the intensity values from the highest intensity point. The figs.6.8 and 6.9 show the overexposed images. The quality of these images has been enhanced with the proposed technique.

The results of the proposed technique have been compared with those of Histogram Equalization method for the images shown in Fig. 6.4 to 6.9. The proposed technique preserves the histogram modes of the original image at the same time intensifies the color composition whereas the histogram equalization makes the image more brighter. The table-6.3 shows the values of the exposure and fuzzifier for the test images.

With this technique, as the GINT operator increases those pixel values which are below 0.5, while the other operator reduces the pixel values which are above 0.5, there is a discontinuity exist at the intensity point a. As a result the overall intensity operator becomes non-monotonic and the results became unexpected. To overcome this problem, we used an approach that iteratively reduces one of the operators (i.e. the higher one at a) values by certain percentage until the values of the two operators at the point a become equal. The third column of the table.6.3 shows the percentage the GINT operator has been reduced to match the two operators at the point, $'a'$ of the image.

7. Conclusions

7.1. Conclusions

Fuzzy logic-based image enhancement method is presented by the modified bacterial foraging algorithm in this project work. Image can be classified into two parts as under and over exposed regions with the parameter exposure. A Gaussian membership function is used, which is suitable for under exposed region of the image. Enhancement of the fuzzified image is carried out using a general intensification operator GINT of sigmoid type, which depends on the crossover point and the intensification parameter. A Triangular membership function is used for the fuzzification and a power law transformation 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 visual factors to form the objective function with certain constraints in the optimization process. A visually pleasing image is obtained with the appropriate choice of quality factors. It may be noted that GINT and power law operators are controlled by these factors since ultimate enhancement leads to the binarization of the image. The results of proposed enhancement technique using fuzzy entropy optimization are compared with those of histogram equalization. The parameter exposure gives knowledge of knowing type of image.

8. References

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