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High Dynamic Range Color Image Enhancement Using Fuzzy Logic and Bacterial Foraging

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ABSTRACT

High dynamic range images contain both the underexposed and the overexposed regions. The enhancement of the underexposed and the overexposed regions is the main concern of this paper. Two new transformation functions are proposed to modify the fuzzy membership values of under and the overexposed regions of an image respectively. For the overexposed regions, a rectangular hyperbolic function is used while for the underexposed regions, an S-function is applied. The shape and range of these functions can be controlled by the parameters involved, which are optimized using the bacterial foraging optimization algorithm so as to obtain the enhanced image. The hue, saturation, and intensity (HSV) color space is employed for the purpose of enhancement, where the hue component is preserved to keep the original color composition intact. This approach is applicable to a degraded image of mixed type. On comparison, the proposed transforms yield better results than the existing transformation functions[17] for both the underexposed and the overexposed regions.

Keywords: Entropy, exposure, rectangular hyperbolic, s-function, contrast, visual factor, quality factor, under and overexposed regions, optimization.

1. INTRODUCTION

Image enhancement is one of the most interesting and visually appealing areas of image processing. The aim of image enhancement is to improve the interpretability or perception of information in images for viewers, or to provide `better' input for other automated image processing tasks. Image enhancement can be treated as transforming one image to another so that the look and feel of an image can be improved for the machine analysis and the visual perception. Visual evaluation of image quality is highly subjective in the absence of a definition of a 'good image' or 'pleasing image'.

The main objective of image enhancement is to modify the image such that it is more pleasing than the original image. By improving the image quality to this level of appearance it permits feature extraction or interpretation. For grayscale images, the popular methods of enhancement are histogram equalisation and contrast stretching. Some other variants of these methods also exist. But generalization of these methods for color images is not simple.

Image enhancement methods may be categorized into two broad classes: transform domain methods and spatial domain methods. The techniques in the first category operate on the transformed images in the frequency domain. However, computing a two dimensional (2-D) transform of a large array (image) is a very time consuming task even with fast transformation techniques and is not suitable for real time processing. We are concerned with the techniques in the second category that directly operate on the pixels.

For the image enhancement in the spatial domain, attention is paid on a few important papers. Goshtasby[1], *et al*. has developed a method using fusion of multi-exposure images to obtain an enhanced image of a scene. Another technique by Kokkeong and Oakley[2] deals with enhancing color and contrast in images degraded by atmospheric effects like haze, fog, mist and cloud that scatter different light wavelengths. This method is based on the underlying physics of the degradation and the parameters required for enhancement are estimated from the image itself.

Bockstein[3] has proposed a color image equalisation method for the color image enhancement using the LHS color model. Then equalisation is applied on the luminance (L) and the saturation (S) histograms for the smaller regions whereas the hue (H) is preserved. A method for altering the exposure in an image is given by Eschbach[4], *et al*. It operates by iteratively comparing the intensity signal with a pair of preset thresholds τ_{light}, τ_{dark} that indicate satisfactory brightness and darkness respectively till they satisfy the threshold conditions.

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The color saturation in the natural scenes is corrected[5], by iteratively processing and comparing the average saturation with the preset threshold τ_{sat}.

Direct enhancement of the RGB color space is inappropriate for the human visual system since it may produce color artifacts and distort the original color composition of the image. Hence, the chromatic and achromatic information should be decoupled, which is possible with HSV color model. An algorithm to separate the color data into chromaticity and brightness components, and then to process each one of these components with partial differential equations or diffusion flows is given[6]. A novel histogram method[7] takes into account the original image's pixel distribution in the equalisation process. This method uses a single parameter to control the degree of contrast enhancement to ensure that the output has an enhanced appearance being freed from the undesirable and visually disturbing artifacts. Hue preserved color image enhancement is presented[8] and this generalizes the existing grey scale contrast intensification techniques for color images. Here a principle is suggested to make the transformations 'gamut problem' free. All these methods are not robust as each one is geared to a particular degraded image.

As our interest is in the use of fuzzy based approaches for image enhancement, we will look into the problems of uncertainty or vagueness associated with images. Vagueness is introduced in the acquired images due to poor and non uniform lighting conditions and the nonlinearity of the imaging system. This leads to imprecision in the color values of a pixel. Fuzzy sets[9] offer a problem-solving tool between the precision of classical mathematics and the inherent imprecision of the real world using linguistic variables like 'good contrast' or 'sharp boundaries. 'light red. 'dark green, etc., called hedges, which can be perceived qualitatively by the human reasoning. Two important contributions to the field of fuzzy image enhancement merit an elaboration. The first one[10] deals with 'IF…THEN…ELSE' fuzzy rules; and the second one[11] employs the rule-based smoothing performed with different filter classes devised on the basis of compatibility with respect to the neighborhood.

Russo[12], *et al*. discuss the recent advances in the fuzzy image processing. S-curve is used[13] as the transformation function where the parameters of the S-curve (a, b, c) are calculated by optimizing the entropy. These parameters determine the shape and range of the transformation operator. Here the operator is applied 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. A generalized iterative fuzzy enhancement algorithm is developed[14] for the degraded images with less gray levels and low contrast and it makes use of the image quality assessment criterion based on the statistical features of the gray-level histogram of images to control the iterative procedure.

Wang[15], *et al*. introduce a high dynamic range (HDR) image hallucination for accruing HDR details to the underexposed regions of a low dynamic range (LDR) image. Their method requires user's discretion to identify which patch needs to be applied on the degraded region. It only tackles the issue of permanent degraded regions and ignores the gray level or saturation enhancement of other regions.

Hanmandlu[16], *et al*. propose a new intensification operator, NINT, which is a parametric sigmoid function for the modification of the Gaussian type of membership. The parameter involved in NINT is found by optimizing the entropy function. GINT operator the modified form of NINT is devised by Hanmandlu[17], *et al*. for enhancing the luminance component of a color pixel and its parameters are found by optimizing an objective function consisting of the entropy involving the quality factors. This approach works well for the underexposed images but fails for the overexposed regions. This approach is extended to include the overexposed images[18] by correcting both luminance and saturation components of color pixels. An image is separated into the under and the overexposed regions by defining the term exposure and they are enhanced separately by GINT and power law transformation operators whose parameters are found by minimizing an objective function involving the entropy, the quality and visual factors using an evolutionary algorithm like bacterial foraging[19]. We introduce here two new transformation operators, viz., modified S-function operator for the underexposed regions and rectangular hyperbolic operator for the overexposed regions.

2. CLASSIFICATION OF IMAGE PIXELS-BASED ON EXPOSURE

Images are degraded due to defocussing during their acquisition with a camera, corrupted by noise during their transmission, and suffer from non-uniform exposure to the illumination which is borne out of the histogram of an image. When the gray-levels are skewed to towards lower part of the histogram, the region appears dark, whereas it appears very bright when the gray levels occupy the upper part of the histogram. In both the cases, the human eye cannot easily distinguish fine details in the image. The images we commonly come across are mixed images which contain the under and overexposed regions in the same image. Since our aim is to enhance color images, without affecting the hue information we will first convert the image in the RGB color space to the image in HSV color space then use the intensity, i.e. V component of HSV to demarcate the pixel intensity range into the under and overexposed regions.

The parameter Exposure, introduced[17], is given by

$$Exposure = \frac{1}{L} \cdot \frac{\sum_{x=1}^{L} p(x).x}{\sum_{x=1}^{L} p(x).x} \tag{1}$$

where x indicates the intensity level in the range 0 to L-1, $p(x)$ - the histogram of the image and L denotes the total number of gray levels. The partitioning of an image is achieved by dividing the intensity range [0, L-1] into two parts: the under exposed in the interval [0, a-1] and the overexposed in the interval [a, L-1] where

$$a = L.(1-Exposure) \quad (2)$$

Separate operators need to be defined for enhancing the under and overexposed regions of the image and applied simultaneously on a mixed image.

Image information contains ambiguity. Human judgment is subjective and different people judge the image appearance differently. The decision as to whether a pixel's intensity should be increased or reduced in order to improve the appearance of an image has to be made. For this, some objective quality criteria are needed to ascertain the appearance or image quality. Here we will develop the fuzzy based image enhancement that involves mainly 3 steps: (a) Fuzzification, (b) Transformation, and (c) Defuzzification. Fuzzification is concerned with the conversion of a spatial domain image into the fuzzy domain in which each pixel of the image is given a degree of association also called membership function value with respect to its intensity value. Next the membership function values are modified by using the transformation operators that accomplish the desired image quality which will be defined later. The modified membership values are defuzzified to yield the desired image in the spatial domain. We will now detail out the three steps.

An image of size M X N with intensity levels in the range (0, L-1) can be represented in the fuzzy domain in the range (0, 1) as

$$I = \cup\{\mu(x_{mn})\} = \left\{\frac{\mu_{mn}}{x_{mn}}\right\}$$

m = 1,2,...M; n=1,2,...N

where $\mu(x_{mn})$ or μ_{mn}/x_{mn} represents the membership value of x_{mn}, which is the color intensity (i.e., colour property) at (m, n)th pixel. The membership functions are computed for the intensity components of the color image, i.e., X {V}. Intensity levels less than a belong to the underexposed regions of the image. They are fuzzified by a modified Gaussian membership function as defined[16].

$$\mu_{Xu}(x) = exp\left[-\left\{\frac{x_{max} - (x_{avg} - x)}{\sqrt{2}fh}\right\}^2\right] \quad (3)$$

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

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

A triangular membership function is used for the fuzzification of the overexposed region of the image for x as introduced[17]

$$\mu_{Xo}(x) = \begin{cases} 0 & x<a \\ \frac{x-a}{L-a} & x\geq a \end{cases} \quad (5)$$

These membership functions map the intensity levels from spatial domain into fuzzy domain. Once we have the fuzzy membership values of all the intensity levels, we can apply the transformation operators on these values to modify them. The modified membership values of both the regions are then converted back to the spatial domain i.e. defuzzified using the inverse of the respective membership functions.

3. THE PROPOSED NEW OPERATORS

3.1. The Modified S-function for the Underexposed Region

The modified S-function used for enhancing the original gray levels of the underexposed pixels is given by

$$\mu'_{Xu}(x) = \begin{cases} \mu_c\left(\frac{\mu_{Xu}(x)-t_1}{\mu_c-t_1}\right)^{\alpha} & 0<\mu_{Xu}(x)<\mu_c \\ (1-\mu_c)\left(\frac{t_2-\mu_{Xu}(x)}{t_2-\mu_c}\right)^{\beta} & \mu_c<\mu_{Xu}(x)<1 \end{cases} \quad (6)$$

where, μ_c is the crossover point, t_1 and t_2 are the lower and upper limits respectively and α, β are constants. These parameters can be varied to control the shape and range of the transformation function, thus, giving more flexibility to the user.

We propose a rectangular hyperbolic function which is used as transformation operator for modifying the membership values of the overexposed pixels given as

$$\mu'_{Xo}(x) = \frac{g\mu_{Xo}(x)}{(1+g-\mu_{Xo}(x))} \quad (7)$$

where, g is a parameter which controls the shape of the hyperbola. In the overexposed regions the grayscale values are stacked near the higher intensity values and difference in levels of the neighboring pixels is also low. By applying this operator the information content in these regions is improved and the results are better than those obtained with the power law transformation operator.

4. RECTANGULAR HYPERBOLIC OPERATOR FOR THE OVEREXPOSED REGION

A rectangular hyperbola with x and y axes as its asymptotes is expressed as

$$(x-\alpha)(y-\beta) = -c^2 \quad (8)$$

The graph for this function for α = β = 0 is shown in Fig. 1. By translating the vertical asymptote to x = 1 and solving for the boundary conditions x = y = 0 and x = y = 1, we get (See Appendix 'A')

$$y = \frac{\alpha x}{1+\alpha-x} \quad (9)$$

When α is decreased then the curvature of the hyperbola for x in the range [0, 1] increases, whereas if α is increased then curvature decreases. In the above function α is a parameter used to control the curvature of the hyperbola for x in the range [0, 1]. The curve for α=1 appears as in Fig. 2. So, when we use this operator to modify the fuzzy values μ'_{xo} of the overexposed pixels of the image 'rose', then we get the transformed fuzzy values as shown in Fig. 3(a). A comparison of this curve with that obtained using the power law operator $y = x^{\gamma}$ on the same image 'rose' is shown in Fig. 3(b).

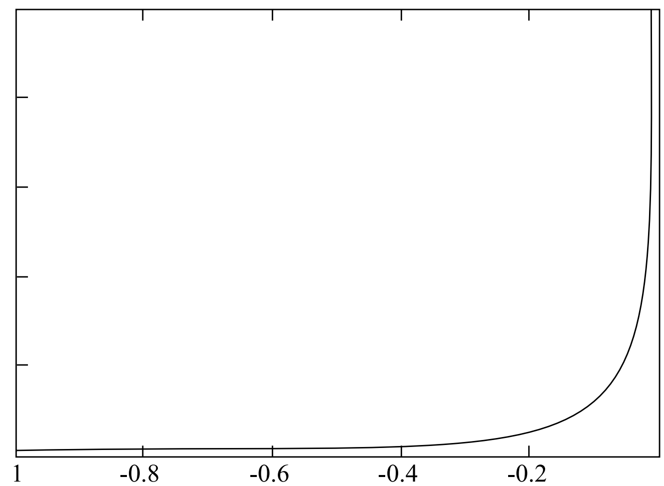


Figure 1. Graphical plot of Eqn (8).

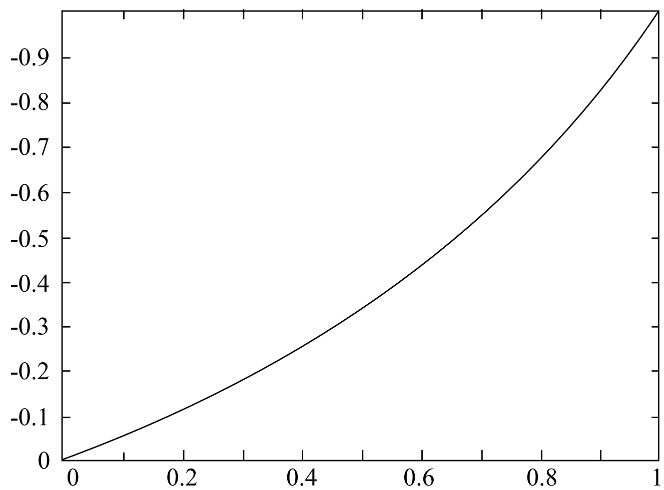
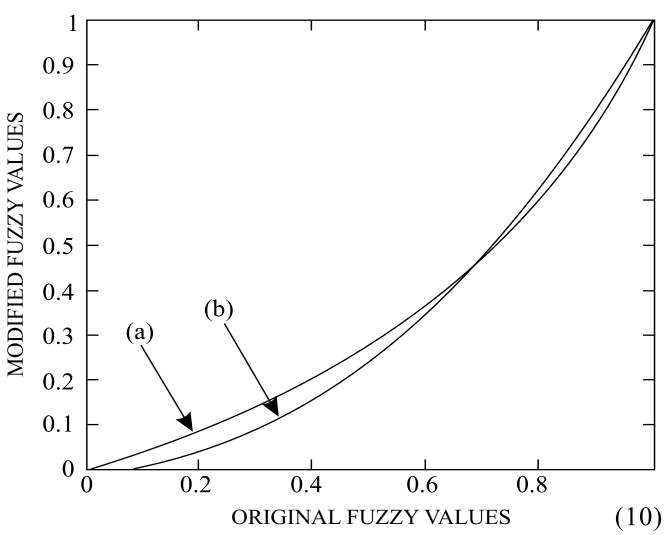


Figure 2. Graphical plot of Eqn (9) for=1.



(10)

Figure 3. The plot of modified fuzzy value versus original fuzzy for the rose image (a) Proposed rectangular hyperbola with =0.5957 and (b) The power law operator[17] with γ=2.0419.

A plot of the new pixel gray levels (on the y-axis) and original pixel gray levels (on-the-axis) using rectangular hyperbola and the power law operator is shown in Fig. 4. From these figures, we find that the power law operator reduces the gray levels of the pixels in the overexposed region for a = 82 more than the rectangular hyperbola. Hence, we use the hyperbolic function which does not suffer from this problem and has a relatively symmetric curve.

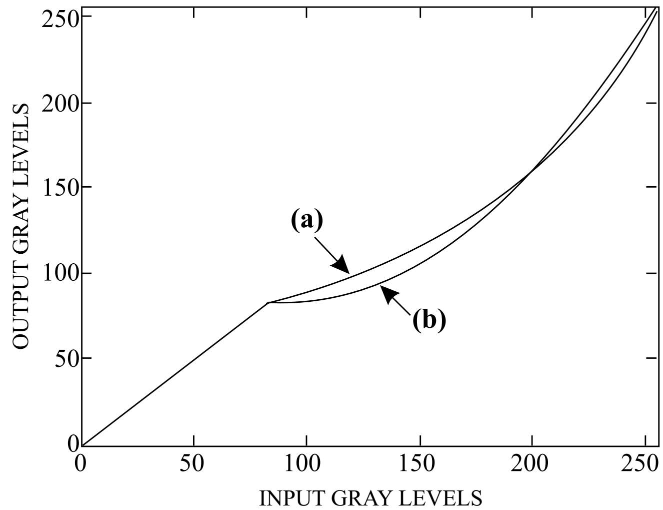


Figure 4. Transformed pixels for the overexposed region for the Rose image with a=82 using (a) Proposed hyperbolic operator and (b) Power law operator[17].

5. ENHANCEMENT OF SATURATION

Saturation plays an important role in enhancing the overexposed color images especially those containing permanent degraded regions, where all pixels have the maximum intensity level. Reduction of saturation in these regions helps to regain details, bringing back the pleasing nature of the image. For this a power law operator is chosen as

$$S_{new}(x) = [S_{old}(x)]^{(1-0.5*Exposure)} \tag{10}$$

where S_{new} and S_{old} are the new and the old saturation values respectively of the of HSV color space.

6. FORMULATION OF AN OBJECTIVE FUNCTION

A set of fuzzy contrast measures, quality factors and visual factors are defined so as to construct an objective function that serves as the quantitative measure of color image quality.

6.1. Fuzzy Contrast

The fuzzy contrast is defined as the sum of the squared differences between the membership values and the crossover point, which is taken to be 0 for the under exposed region and 1 for the over exposed region.

(a) Fuzzy contrast for the underexposed regions are computed from:

Modified image $$C_{fu} = \frac{1}{L}\sum_{x=0}^{a-1}\left[\mu'_{Xu}(x) - \mu_c\right]^2 p(x) \tag{11}$$

Original image $C_{fus} = \frac{1}{L}\sum_{x=0}^{a-1}\left[\mu'_{Xu}(x) - \mu_c\right]^2 p(x)$ (12)

(b) Fuzzy contrast for the over exposed regions is computed from:

Modified image $C_{fo} = \frac{1}{L}\sum_{x=a}^{L-1}\left[\mu'_{Xo}(x) - \mu_c\right]^2 p(x)$ (13)

Original image $C_{fos} = \frac{1}{L}\sum_{x=a}^{a-1}\left[\mu_{Xo}(x) - \mu_c\right]^2 p(x)$ (14)

(c) The average fuzzy contrast for the under exposed regions is computed from:

Modified image $C_{afu} = \frac{1}{L}\sum_{x=0}^{a-1}\left[\mu'_{Xu}(x) - \mu_C\right] p(x)$ (15)

Original image $C_{afus} = \frac{1}{L}\sum_{x=0}^{a-1}\left[\mu_{Xu}(x) - \mu_c\right] p(x)$ (16)

(d) The average fuzzy contrast for the over exposed regions is computed from:

Modified image $C_{afo} = \frac{1}{L}\sum_{x=0}^{a-1}\left[\mu'_{Xo}(x) - \mu_c\right] p(x)$ (17)

Original image $C_{afos} = \frac{1}{L}\sum_{x=a}^{L-1}\left[\mu_{Xo}(x) - \mu_c\right] p(x)$ (18)

6.2. Quality Factors

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 underexposed region of the modified image is

$$Q_{fu} = \left|C_{afu} / C_{fu}\right| \quad (19)$$

The respective quality factor for the overexposed region of the modified image is

$$Q_{fo} = \left|C_{afo} / C_{fo}\right| \quad (20)$$

In view of the above definition, the image quality of the original image for the underexposed region is

$$Q_{fus} = \left|C_{afus} / C_{fus}\right| \quad (21)$$

The respective quality factor for the overexposed region of original image is

$$Q_{fos} = \left|C_{afos} / C_{fos}\right| \quad (22)$$

Entropy

A measure of information quality in the fuzzy domain is the entropy based on Shannon's function

$$E = \frac{-1}{L\ln 2}\left[\sum_{x=0}^{a-1}\left[\mu'_{xu}(x)\ln(\mu'_{xu}(x)) + (1-\mu'_{xu}(x))\ln(1-\mu'_{xu}(x))\right] + \sum_{x=a}^{L-1}\left[\mu'_{xo}(x)\ln(\mu'_{xo}(x)) + (1-\mu'_{xo}(x))\ln(1-\mu'_{xo}(x))\right]\right] \quad (23)$$

Since the entropy is a measure of information, therefore its optimisation will help us determine the parameters: f_h, μ_c, t_1, t_2, α, β and g.

6.3. Visual Factors

A normalised quality factor called the visual factor is used to specify the amount of enhancement caused. Separate visual factors for both underexposed and over exposed regions are needed.

The visual factor for the underexposed region is

$$V_{fu} = \frac{Q_{fu}}{Q_{fus}} \quad (24)$$

The visual factor for the over exposed region is

$$V_{fu} = \frac{Q_{fos}}{Q_{fo}} \quad (25)$$

The above visual factors are combined based on the extent of under and the overexposed regions contained in the original image to obtain an overall visual factor as

$$V_f = (V_{fu}(a) + V_{fo}(L-a)/L \quad (26)$$

A visual factor of 1.2 is found to give the most pleasing images from a set images considered for the experimentation.

6.4. An Objective Function

To satisfy the desired visual factor V_{df} of 1.2, constrained fuzzy optimisation is performed. For this an objective function is framed as

$$J = E + \lambda e^{|Vdf - Vf|} \quad (27)$$

where λ is the Lagrange multiplier. λ is chosen to be 0.1 for which it is found to yield the best results.

The optimisation of this objective function is undertaken subject to the constraints:

$$-1 < t_1 \le 0, -1 < t_2 \le 0, 0 \le \mu_c \le 1, \alpha \ge 1, \beta \ge 1$$

and g>0 to estimate the parameters f_h, μ_c, t_1, t_2, α, β and g using the modified bacterial optimisation algorithm[17].

6.5. Modified Bacterial Foraging

We now give a brief description of the modified bacterial foraging algorithm[17]. Foraging can be modeled as an optimisation process where bacteria seek to minimize the effort spent per unit time in foraging. In this scheme, the objective function is posed as the effort or a cost incurred by the bacteria in search of food. A set of bacteria tries to reach an optimum cost by following four stages such as chemo taxis, swarming, reproduction, and elimination and dispersal.

Let θ be the position of a bacterium and $J(\theta)$ in Eqn. (27) represents the value of the objective function, i.e. a measure of nutrients available at θ. Chemotaxis is a foraging behavior where bacteria try to climb up the nutrient concentration.

Let j be the index for the chemo tactic step, k be the index for the reproduction step and l be the index of the elimination-dispersal event and let 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 be given by

$$P(j.k.l) = \left\{\theta^i(j+1,k,l) \middle| i = 1,2,\ldots,S\right\} \quad (28)$$

Instead of $J(\theta)$, we consider $J(I, j, k, l)$ to be the cost at the location of the i^{th} bacterium.

(a) *Chemo taxis*: A chemo tactic step consists of tumble or swim. To represent a tumble, a unit length of random direction, say $\varphi(j)$ is generated as

$$\theta^{i}(j+1,k,l)=\theta^{i}(j+1,k,l)+C(i)\varphi(j) \quad (29)$$

so that $C(i)$ is the size of the step taken in the random direction specified by the tumble by the ith bacterium. If the cost $J(i, j+1, k, l)$ at $\theta_i(j+1, k, l)$ is lower) than at $\theta i(j, k, l)$, then another step of size $C(i)$ in the same direction will be taken, and again. The swim is continued as long as it continues to reduce the cost, but only up to a maximum number of steps Ns. The total lifetime of a bacterium is represented by the number of chemo tactic steps taken N_c during its life.

(b) *Swarming*: It is always desired that the bacterium searching for the optimum path of food should try to attract other bacteria so that it reaches the desired source of food more rapidly. This is represented by a time-varying cell-cell attractant function that is added to the cost function. But this step is neglected in the case of modified bacterial foraging for the sake of simplicity.

(c) *Reproduction*: Let N_{re} be the number of reproduction steps to be taken and S be the population of bacteria. The population is sorted in the ascending order of accumulated nutrients; such that half of the population

$$S_r=S/2 \quad (30)$$

containing the least healthy bacteria dies and the other half containing the healthiest bacteria reproduces each of which splitting into two bacteria that are placed at the same location. Here the minimum value of all the cost functions in the chemo tactic step is retained for deciding the bacterium's health to speed up convergence.

(d) *Elimination and Dispersal*: 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}. This helps in reducing stagnation (i.e., being trapped in a premature solution point or local optima).

The selection of the initial parameters of the algorithm such as the number of iterations, the final error value etc. plays a key role in arriving at the optimum value in less time. These parameters depend on the application. The flow chart of modified BF optimisation algorithm is shown in Fig. 5.

6.5.1 Initialisation of Parameters

Two sets of parameters have to be initialised: the parameters (Np) to be optimised, i.e. f_h,μ_c,t_1,t_2,α,β, and g in the original objective function J, and the parameters of the BF to make J a time-varying cost function during the optimisation.

We first initialise the parameters of the modified

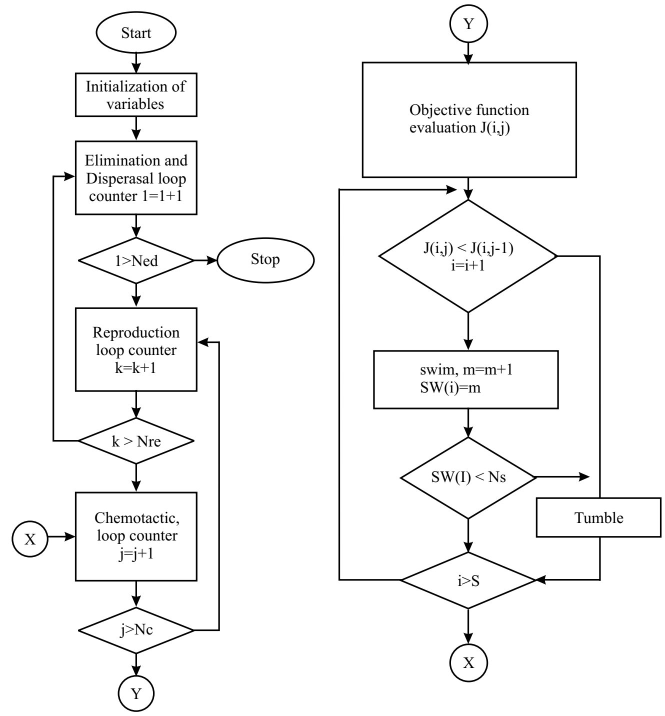


Figure 5. Modified bacterial foraging[17].

BF as follows:

1. The number of bacteria S is 8.
2. The swimming length N_s is 10.
3. The number of iterations in a chemo tactic loop N_c is set to 10 ($N_c > N_s$).
4. The number of reproduction steps N_{re} is set to 2.
5. The number of elimination and dispersal events N_{ed} is set to 6.
6. The probability of elimination/dispersal ped is set to 0.25.
7. The location of each bacterium, which is a function of several parameters, i.e., $f(p_{ed},N_b,N_c,N_{re},N_{ed})$, is specified by a random number in the range [0, 1].

6.5.2. Algorithm for the Image Enhancement

1. Input the given image and convert RGB to HSV.
2. Calculate the histogram $p(x)$, where $x \in V$.
3. Calculate the initial value of f_h using (4).
4. Compute the values of exposure and a using (1) and (2), respectively.
5. Fuzzify V to get $\mu_{Xu}(x)$ and $\mu_{Xo}(x)$ using (3) and (5), respectively.
6. Initialise $\mu_c \leftarrow 0.4$, calculate C_{fus}, C_{fos}, C_{afus}, C_{afos}, Q_{fus}, and Q_{fos}, and initially set $t_1 \leftarrow -1$, $t_2 \leftarrow 2$, $\alpha \leftarrow 2.4$, $\beta \leftarrow 2.7$, $g \leftarrow 0.5$. Calculate the modified membership values $\mu'_{Xu}(x)$and $\mu'_{Xo}(x)$ for the the underexposed region and the the overexposed region using (6) and (7), respectively.
7. Now, calculate C_{fu}, C_{fo}, C_{afu}, C_{afo}, Q_{fu}, and Q_{fo}, from the initial assumed values for parameters, f_h, μ_c, t_1, t_2, α, β and g.
8. Calculate the visual factor V_f and set the desired visual factor $V_{df} \leftarrow 1.5$ to iteratively learn the

parameters.

9. Optimize the cost (i.e., objective) function using the modified BF algorithm and repeat Step 7 to calculate the modified membership values for the parameter set (f_h, μ_c, t_1, t_2, α, β and g).
10. Defuzzify the modified membership values $\mu_{Xu}(x)$ and $\mu_{Xo}(x)$ using the inverse MF.

7. RESULTS OF IMPLEMENTATION

The proposed approach has been implemented on around 20 images using MATLAB. The original and enhanced images of beach, bridge, city, village, man and hills which belong to the underexposed type are shown in Figs. 6-11 and the original, enhanced images by the approach[17] and the proposed approach of rose and camera belonging to the overexposed type are shown in Figs. 12 and 13 respectively. In both types, the details are not discernable and colors are not perceivable to the eye. The value of the objective function is used for evaluating the performance of the proposed approach. The image quality is inversely proportional to the value of the objective function; lower the value higher the quality. The original and enhanced images (by the proposed approach) of Café, rose which belong to the mixed type are shown in Figs. 14 and 15 respectively.

The modified S-function enhances the intensities of the image pixels whereas the rectangular hyperbolic function reduces the intensities resulting in a discontinuity at the intensity level after the enhancement. This discontinuity is eliminated by increasing the values of the S-function while reducing the values of the hyperbolic function iteratively until both become equal at the intensity level.

Table 1 represents the initial values of the parameters (f_h,μ_c,t_1,t_2, α, β, g), entropy, visual factor and the objective function of the test images. Table 2 represents the optimized parameters, visual factor, entropy, objective function of the modified images.

Most of the underexposed images do not need enhancement of saturation. But some highly overexposed images have permanently degraded regions, as in face, rose etc. and the information in these areas can be recovered to some extent by reducing the saturation using the saturation operator.

This method compares favorably in terms of time taken to optimize the parameters as the number of bacteria required is less due to which the algorithm becomes computationally fast. The new transformation operators perform better than those[17] since the modified S-function allows more flexibility through the control of a number of parameters while the rectangular hyperbolic operator provides a better dynamic range for the overexposed regions.

Figure 16 shows the histogram of the image, 'village' before and after applying the proposed approach. Figure 17 shows the same for the image 'camera'. As can be seen from the histogram of the overexposed image 'Village' that the peak near the maximum intensity level is reduced in the enhanced image, and also the dynamic range of intensity values increases. In the histogram of the underexposed image 'camera', most of the pixels concentrated near the minimum intensity get spread out after the enhancement. Moreover, the intensity peak is shifted towards the brighter pixel values.

8. CONCLUSIONS

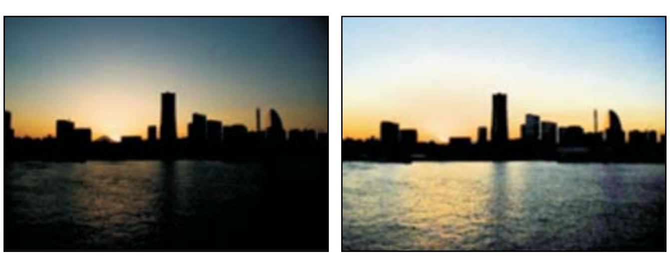
A fuzzy based enhancement approach is developed for enhancing both under and over exposed regions which are demarcated from an image by the using a

(a) (b)

Figure 6. (a) Original image of a beach and (b) Enhanced image of the beach.

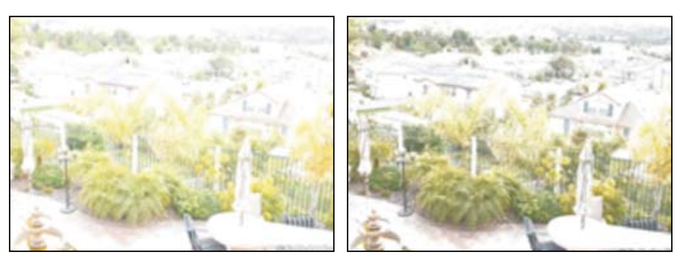
(a) (b)

Figure 7. (a) Original image of a bridge and (b) Enhanced image of the bridge.



(a) (b)

Figure 8. (a) Original image of a city and (b) Enhanced image of the city.



(a) (b)

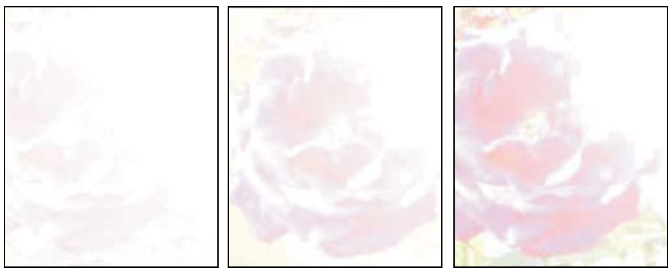
Figure 9. (a) Original image of village and (b) Enhanced image of village.

(a) (b)

Figure 10. (a) Original image of a man and (b) Enhanced image of the man.

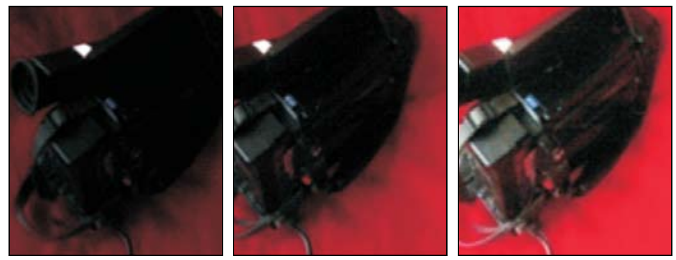
(a) (b)

Figure 11. (a) Original image of hills and (b) Enhanced image of hills.



(a) (b) (c)

Figure 12. (a) Original image of rose, (b) Enhanced image[17], and (c) Enhanced image by the new operators.



(a) (b) (c)

Figure 13. (a) Original image of a camera, (b) Enhanced image[17], and (c) Enhanced image by the new operators.

(a) (b)

Figure 14. (a) Original image of a face and (b) Enhanced image of the face.

(a) (b)

Figure 15. (a) Original image of a café and (b) Enhanced image of the café.

Table 1. Initial value of parameters.

Images	t_1	t_2	f_h	g	α	μ_c	β	J	V_f	E
Beach	-0.5	1.5	142.979	0.5	2.4	0.4	2.7	0.774	1.015	0.756
Bridge	-0.5	1.5	162.095	0.5	2.4	0.4	2.7	0.762	0.982	0.741
City	-0.5	1.5	159.017	0.5	2.4	0.4	2.7	0.733	0.980	0.711
Camera	-0.5	1.5	153.168	0.5	2.4	0.4	2.7	0.688	0.987	0.666
Hills	-0.5	1.5	160.940	0.5	2.4	0.4	2.7	0.721	0.967	0.698
Village	-0.5	1.5	71.900	0.5	2.4	0.4	2.7	0.704	1.300	0.694
Man	-0.5	1.5	84.298	0.5	2.4	0.4	2.7	0.675	1.343	0.661
Face	-0.5	1.5	88.949	0.5	2.4	0.4	2.7	0.673	1.290	0.664
Café	-0.5	1.5	150.314	0.5	2.4	0.4	2.7	0.678	1.075	0.665
Rose	-0.5	1.5	179.824	0.5	2.4	0.4	2.7	0.675	1.933	0.602

Table 2. Optimisation of $J = E + \lambda e^{|V_{df} - V_f|}$ with V_{df}=1.2 & λ=0.1

Images	t_1	t_2	f_h	g	α	μ_c	β	J	V_f	E
Beach	-0.500	2.456	75.274	0.573	3.607	0.598	2.73	0.383	1.632	0.339
Bridge	-0.503	1.736	79.313	0.590	3.877	0.559	4.03	0.251	1.247	0.246
City	-0.501	2.440	78.411	0.571	3.895	0.599	3.90	0.217	1.190	0.216
Camera	-0.500	1.557	83.269	0.562	3.893	0.6	3.47	0.200	1.191	0.199
Hills	-0.502	1.577	80.446	0.455	3.897	0.6	3.43	0.199	1.193	0.199
Village	-1.497	1.501	95.507	0.400	3.586	0.201	4.19	0.557	1.268	0.550
Man	-1.365	1.502	93.315	0.411	2.400	0.200	4.20	0.550	1.239	0.546
Face	-1.453	1.503	91.283	0.439	3.436	0.216	4.19	0.563	1.198	0.563
Café	-0.691	1.504	78.819	0.4	3.621	0.202	4.19	0.683	1.170	0.680
Rose	-0.802	1.500	93.632	0.595	2.571	0.200	4.18	0.672	1.967	0.596

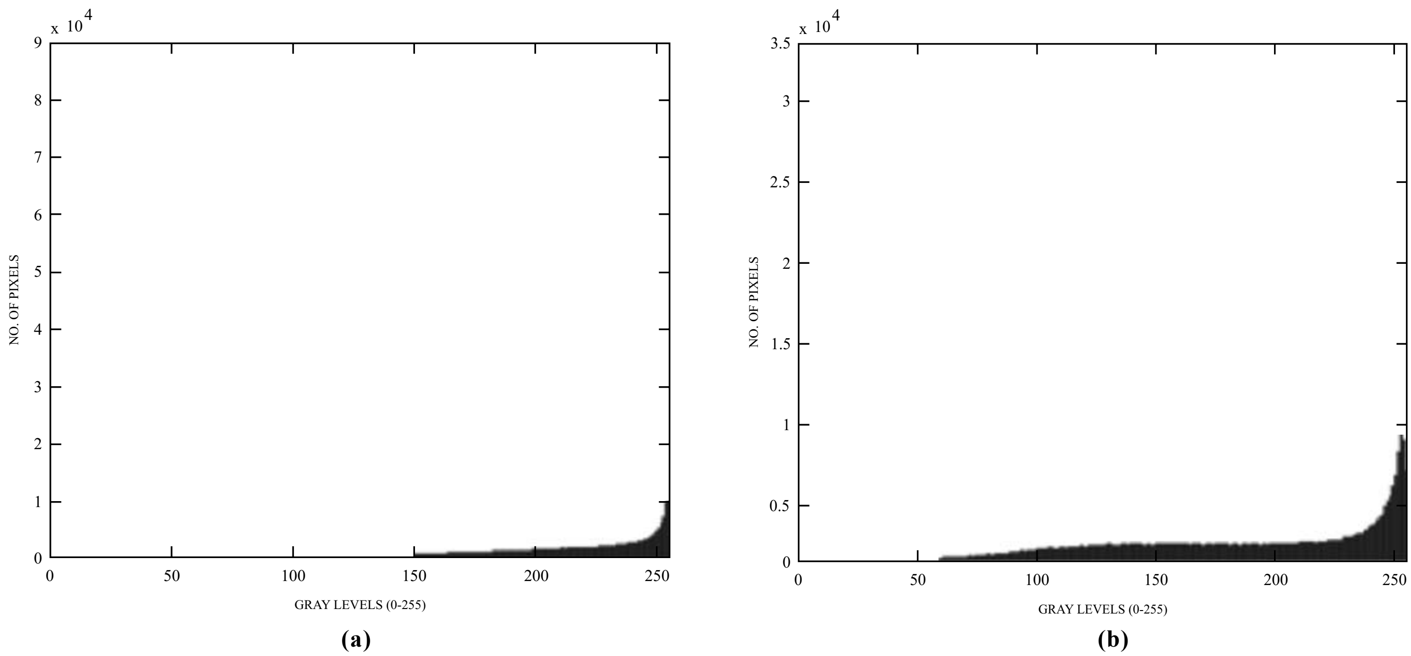


Figure 16. (a) Histogram of original image village and (b) Histogram of image village after modification.

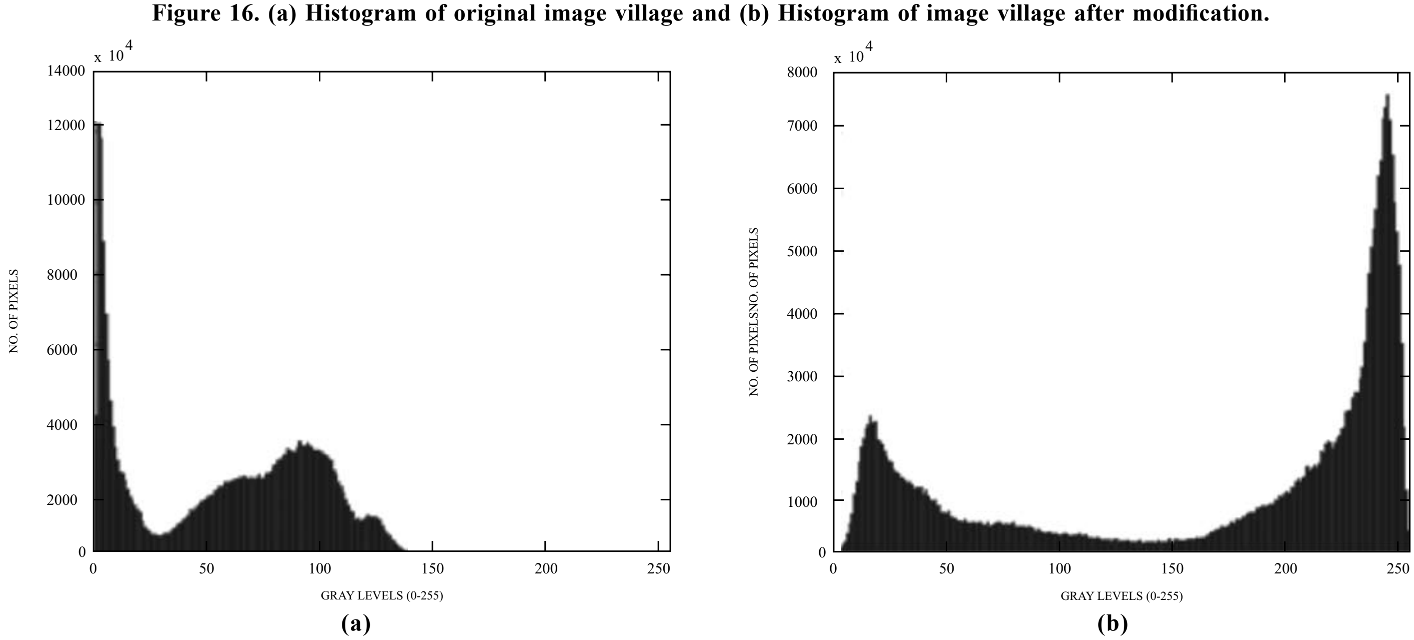


Figure 17. (a) Histogram of original image camera and (b) Histogram of image camera after modification.

parameter called exposure. The membership function chosen for the fuzzification of spatial domain intensities is of Gaussian type. Two new transform operators, the Modified S-function for the underexposed region and the hyperbolic function for the overexposed region are presented. These transformation operators perform better than those[17] since the modified s-function allows more flexible control through more number of parameters while the rectangular hyperbolic operator provides better dynamic range in the overexposed regions. The proposed approach is computationally efficient in terms of the time taken to optimize the parameters as the number of bacteria required is less. Further work must be directed towards evolving new membership function and new operators for the recovery of the permanently degraded image.

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Appendix 'A'

Derivation of rectangular hyperbolic operator

Equation for rectangular hyperbola with x and y axis as its asymptotes is given by

$$(\mathrm{x}-\alpha)(\mathrm{y}-\beta)=-\mathrm{c}^2 \quad \text{(A.1)}$$

The above equation has asymptotes $x = 0$, $y = 0$. Translating the x asymptote to $x = 1$ by replacing x by x-1, we have

$$(\mathrm{x}-1-\alpha)(\mathrm{y}-\beta)=-\mathrm{c}^2 \quad \text{(A.2)}$$

By applying the boundary conditions, these conditions ($x = 0$, $y = 0$) and ($x = 1$, $y = 1$) in (Eqn. A.2) we get

(A.3)

$$(\alpha)(\beta-1)=-c^2 \quad \text{(A.4)}$$

Solving Eqn. (A.3) and (A.4) we get β

$$\beta=-\alpha \quad \text{(A.5)}$$

We can rearrange Eq. (A.2) as

$$y=\frac{c^2+\beta(1+\alpha)-\beta x}{1+\alpha-x} \quad \text{(A.6)}$$

Using Eqn. (A.3)

$$(1+\alpha)\beta=-c^2$$

$$y=\frac{-\beta x}{1+\alpha-x} \quad \text{(A.7)}$$

and using Eqn. (A.5)

$$y=\frac{\alpha x}{1+\alpha-x} \quad \text{(A.8)}$$