FUZZY COLOR IMAGE ENHANCEMENT USING EVOLUTIONARY ALGORITHM

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CERTIFICATE

This is to certify that **Payal Gupta (2K13/ISY/15)** has carried out the major project titled "**Fuzzy Color Image Enhancement using Evolutionary Algorithm**" in partial fulfilment of the requirements for the award of Master of Technology degree in Information Systems by **Delhi Technological University**.

The major project is bonafide piece of work carried out and completed under my supervision and guidance during the academic session 2013-2015. To the best of my knowledge, the matter embodied in the thesis has not been submitted to any other University/Institute for the award of any degree or diploma.

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ABSTRACT

In this study, we represent a new optimal simplified approach for image enhancement of color images using fuzzy logic and particle swarm optimization (PSO). The image exposure defined in [13] is simplified and is used to categorize the image into underexposed and overexposed regions. Objective measures like visual factors, contrast factors and fuzzy contrast defined in [13] are further removed to make the color image enhancement algorithm less complex. The hue, saturation and value (HSV) color space is utilized for the enhancement process. The hue component is kept same to preserve the original color of the image. The luminance component associated with each pixel intensity is fuzzified using gaussian membership function for underexposed as well as overexposed regions. These membership values are then modified using sigmoidal membership function to obtain the enhanced membership values and then defuzzified in order to obtain the enhanced image. The power-law transformation is used for the enhancement of the saturation component. A new objective function comprising entropy, edge information and the image exposure is introduced and optimized using PSO to learn the parameters used for the enhancement of a given image. Entropy, histogram flatness, histogram spread and tenengrad value are used for the quantitative analysis of the enhanced image. The proposed approach is evaluated using different test images that include underexposed, overexposed, mixed-exposed and low contrast images. The proposed approach is compared with other enhancement techniques available in the literature. On comparison, it is found that the proposed algorithm out performs most of the existing algorithms available in literature.

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Chapter 1

INTRODUCTION

Image enhancement includes processing the observable information of the image. It highlights certain characteristic to improve the image quality for better perception, understanding and interpretability of the information in the images. It is application specific i.e. for a particular application the results must be better than the original image. Narrow capabilities of hardware that is used for capturing the image, uneven lightning conditions and external disturbances are some of the reasons that requires the need of image enhancement.

The image enhancement methods are broadly classified into two domains: spatial domain and transform domain methods [1]. Spatial domain enhancement is based on direct modification of the pixels in the image. It includes point processing and neighbourhood processing methods. The logarithmic transformation, power law transformation, linear contrast stretching are the some of the commonly used method for image enhancement in spatial domain. The transform domain methods operate upon the transformed images in the frequency domain. This method cannot be used for real time processing and is also time consuming.

The Red, Green and Blue (RGB) color space cannot be used for the image enhancement purpose because the chrominance and the luminance data are mixed. Change in luminance will also change the chrominance values and will result in a completely different color. Also, RGB color space does not correspond to the human perception and there is a high correlation between the three components-red, green and blue. So we need a color space that separates the chromatic and achromatic information and also take into account the human visual system. One such color space is HSV having three components: hue (H) representing the actual color, the purity of the color is given by saturation (S) and value (V) is the perceived brightness of the color. This model can be used for enhancement purpose where the hue is kept intact and the other two components are processed separately.

Many optimization algorithms which have been developed proved a great source of research. We have seen a growing tendency or interest towards the optimization algorithms. These algorithms solved many complex computational problems related to various fields like image processing, pattern recognition, control objectives etc. In the field of economics also optimization algorithms proved very useful in predicting the economic behavior of the market.

Particle swarm optimization (PSO) [2-4] is an optimization algorithm based on the movement of the flock of birds. In this algorithm particles are guided not only through their local best but also through their global best. It is an iterative type of optimization algorithm which iteratively finds new positions and velocities and updates them accordingly. The particles in the algorithm share the information with each other to find the local best and also to find the global best in the group.

The main purpose of the enhancement process is to improve the image exposure to obtain a better image for a specific application. So, exposure must be a part of the enhancement procedure and also should be included in the objective function. But in the technique presented in [13], exposure has no role except categorizing the image into underexposed and overexposed regions. Also, the objective function used in [13] incorporates the quality factors, fuzzy contrast measures, entropy and visual factors which increases the complexity. Calculating the values of these factors is a tedious task and is time consuming. So, in this study, exposure is also included as a part of the objective function. The fitness of the enhanced image is calculated considering its exposure along with the other information. Also the mathematical values obtained for the fitness more clearly reflect the characteristics of the enhanced image.

In this study the image contrast is enhanced using the fuzzy logic technique that uses Gaussian MF for fuzzification and sigmoidal membership function (MF) for intensification of underexposed and overexposed regions of the image. Image exposure is used to categorize the image into underexposed and overexposed regions. HSV color space has been used for the enhancement process because it separates the chromatic information from the intensity information. A new objective function which considers entropy, image exposure and the edge information, is used for measuring the enhancement. The best enhanced image according to the objective criterion is obtained by optimizing the parameters used in the transformation function with the help of PSO. Different performance metrics [22-25]-entropy, histogram flatness (HFM), histogram spread (HS) and tenengrad value, are used to measure the performance of the proposed technique.

Chapter 2

LITERATURE REVIEW

2.1. Different Image Enhancement Techniques

Numerous image enhancement methods have been developed in the past. Some of them are described below:

2.1.1. Histogram Equalization (HE) [1]

The histogram of an $M \times N$ image with intensity levels in the range $[0, L-1]$ is given by:

$$h(\mathrm{r}_k) = n_k \tag{1}$$

Where, r_k is the k^{th} intensity level and n_k is the number of image pixels with r_k intensity level. The normalize histogram is represented as:

$$\mathrm{p}(\mathrm{r}_k) = \frac{n_k}{MN},\ k = 0,1,\ldots L-1 \tag{2}$$

$\mathrm{p}(\mathrm{r}_k)$ represents the probability of occurrence of the r_k intensity level in the image. Sum of all the levels of a normalized histogram is 1. Image enhancement can be done by manipulating the image histogram.

HE due to its ease of implementation and simplicity, is the most broadly used contrast enhancement technique. It is a *global enhancement method*. In order to improve the overall image contrast, HE stretches the range of gray levels of the image and flattens the intensity distribution. Cumulative density function (CDF) of original image is used for transformation of the gray levels to obtain the enhanced image. The transformation function is given by:

$$\mathrm{s}_k = T(\mathrm{r}_k) = \sum_{j=0}^{k} p(\mathrm{r}_j) \tag{3}$$

Thus, enhanced image is obtained by mapping r_k in the input image into a corresponding s_k in the output image.

Being a global enhancement method, it results in noise over-enhancement because it is extensive and may increase the background noise, while distorting the actual details of the image. The HE adjusts the image's histogram in order to improve the image contrast. But, it often results in noise over-enhancement which alters the image details. It does not define any criteria to limit the amount of enhancement required for a particular application. Even if the image already has good quality, still the enhancement is done which then results in an unpleasing image. Though it results in a higher histogram spread and flatness, it also results in the transformation of those pixels for which the enhancement is not required.

2.1.2. Exposure based Sub-Image Histogram Equalization [5]

Poor contrast images do not occupy the complete dynamic range of the gray levels. The histogram of dark images is concentrated towards the lower side of the gray scale and has a lower exposure [13] value and that of a brighter image is concentrated towards the higher side of the gray scale and hence has a higher exposure value. Thus, based on the exposure value the images can be classified as underexposed or overexposed.

The enhancement of the image is done in three steps:

1. Image exposure is used to calculate a threshold value that is used to divide the image into underexposed and overexposed sub-images.

2. Histogram clipping is done to avoid overenhancement of the image. Average number of gray level occurrences is calculated to obtain the clipping threshold. The histogram bins having the value greater than the clipping threshold are clipped to the threshold.

3. The histogram is now divided into sub-images. Each sub-image is then individually enhanced using histogram equalization method. The enhanced sub-images are then integrated into one complete image.

2.1.3. Adaptive Contrast Enhancement (ACE) [6-7]

ACE is a local enhancement method for gray scale images. Local enhancement methods modifies a pixel considering its neighbouring pixels as well. It uses the concept of un-sharp masking. The image is divided into two components: low frequency component (unsharp mask) and the high frequency component. Unsharp mask is obtained by low pass filtering of the image and high frequency component is obtained by subtracting the unsharp mask from the original image. The high frequency component is then amplified and then added back to the unsharp mask to obtain the enhanced image. The contrast gain required for the amplification of the high frequency component is obtained using the local standard deviation of the image. Thus, the amount of the enhancement for a pixel depends upon the standard deviation of the neighbourhood. Large intensity deviation represents good contrast, so less enhancement is required and if the deviation of the neighbourhood is small, more enhancement is required. The transformation function is given by:

$$g(i,j)=\frac{k.D}{\sigma(i,j)+b}\left[f(i,j)-c\times m(i,j)\right]+m(i,j)^{a} \tag{4}$$

Where, $f(i,j)$ is the original value of $(i,j)^{th}$ pixel, $g(i,j)$ is the enhanced value of $(i,j)^{th}$ pixel, D is the global mean, $\sigma(i,j)$ is the local standard deviation of $(i,j)^{th}$ pixel, $m(i,j)$ is the local mean of $(i,j)^{th}$ pixel and k,a,b,c are the constants.

This method do not consider the human visual system i.e. different people have different perspective ,so only by seeing the image, one cannot decide whether a pixel should be made darker or brighter from its original intensity level. Color image enhancement based on hue preservation is presented in [8], and it uses the concept of ACE for enhancement of the intensity component of the HSV color space. Also it describes a method, to avoid the gamut problem in such transformations. But, this method can only be used for a certain kind of degraded images and also is not robust.

2.1.4. Fuzzy Color Image Enhancement

Image enhancement involves a number of ambiguities due to the vagueness present in the image information. The fuzzy approach can be utilized to decide whether a pixel should be made darker or lighter from its original intensity. Different people perceive the image quality differently i.e. their judgement is subjective. So fuzzy set theory [9] is used to represent the pixel intensity values. Generally, fuzzy logic based image processing involves three stages: fuzzification, intensification, and defuzzification. Different fuzzification, intensification and defuzzification functions can be used depending upon a particular application.

Various fuzzy logic based image enhancement techniques have been proposed in the past. Hanmandlu *et al.* [10] used Gaussian type MF to fuzzify the image pixels and proposed the concept of NINT- a parametric sigmoid function for the modification of the membership values based on the optimization of entropy with respect to the parameters involved in the intensification operator. But this work was limited only to the enhancement of gray-scale images. Hanmandlu *et al.* [11] then proposed an extended NINT operator i.e. GINT, a global contrast intensification operator for the enhancement of membership values obtained during fuzzification process, and also proposed the quality factors. The image entropy optimization was used to obtain the parameters of the GINT operator. But this approach was confined only to underexposed images and failed for overexposed images and mixed exposed images. A fuzzy logic and histogram based color image enhancement method proposed in [12] uses HSV color space where only the luminance component is stretched and the chromatic information i.e. hue and saturation are preserved. But this method can also be applied only to underexposed images.

Hanmandlu *et al.* [13] proposed the concept of exposure based on which the sub-images are formed and enhanced separately using fuzzy logic. The Gaussian MF was used to fuzzify the pixels in underexposed region and triangular MF was used for the overexposed pixels. The Sigmoidal MF and power-law transformation function [1] was used for the transformation of underexposed and overexposed region. Khairunnisa *et al.* [14] used s-function for fuzzification and power-law function for intensity transformation. O.P. Verma et al. [15] used a new power-law transformation operator along with exposure to enhance underexposed images. Hanmandlu *et al.* [16] used particle swarm optimization technique to optimize the fuzzy image enhancement process. O.P.Verma et al. [17] used ant colony optimization technique to enhance the image using fuzzy logic. But these fuzzy logic enhancement methods do not take into consideration the image exposure for optimization purpose and therefore some time results in under-enhancement or over-enhancement.

2.1.5. Recent Developments

Recently, Karan Panetta *et al.* [18] presented a parametrized logarithmic approach (PLIP) for enhancing the gray level images and introduced both spatial and transform domain PLIP methods, thus making the enhancement procedure much more complex. Also the method was not tested for color images making in unsuitable for real world scenarios. Suprijanto *et al.* [19] presented a number of objective criterion for image contrast analysis: peak signal to noise ratio, standard deviation, mean square error etc. The method presented used contrast stretching and HE for image contrast enhancement which does not always give good results for mixed type images. Shih-Chia Huang *et al.* [20] used local HE technique for image enhancement. It uses multiple thresholding and peak signal to noise ratio to divide the histogram. Shanmugavadivu *et al.* [21] also used a similar technique i.e. histogram division based on Otsu's threshold and then enhancing the sub-images independently. But these techniques are also limited to gray-scale images.

2.2. Particle Swarm Optimization [2-4]

PSO is a multi-agent based search strategy introduced by J.Kennedy and R.Eberhart in 1995. It is a swarm intelligence technique i.e. collective behaviour of decentralized, self-organized system that is used to find optimal solutions to minimization and maximization problems. Swarm is a collection of agents or particles that interact among themselves and their environment, without any centralized control and result in the emergence of a global behaviour. PSO uses a set of particles each with its own position and velocity. The velocities are updated based on the particles' historical performance as well as the whole swarm performance. In PSO, each particle is a possible solution to the given problem. The fitness values are calculated for each particle of the swarm using the objective function to be optimized. These fitness values are then used to compare each particle of swam and find the best particle i.e. the best optimal solution to the given problem.

Each Particle has:

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

Swarm is represented using:

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

The PSO algorithm is represented by the following velocity and position update equations, shown below:

$$v_{id}^{(t+1)} = w^{(t)} v_{id}^{(t)} + c_1 R_1 \left(pbest_{id}^{(t)} - \zeta_{id}^{(t)} \right) + c_2 R_2 \left(gbest_d^{(t)} - \zeta_{id}^{(t)} \right) \quad (5)$$

$$\zeta_{id}^{(t+1)} = \zeta_{id}^{(t)} + v_{id}^{(t+1)} \quad (6)$$

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

2.2.1. PSO Algorithm

Create N_p number of N_d dimensional particles

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

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

end for

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

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

    Calculate new fitness value
    //Set $pbest$ as the personal best solution of i^{th} particle achieved so far
    if $\left(J((\mathrm{I}_e)_i) > J(\mathrm{pbest}_i) \right)$ **then**

      $pbest_i = (N_p)_i$

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

    end if
    //Set $gbest$ as the global best solution achieved so far among all generations
    if $\left(J((\mathrm{I}_e)_i) > J(\mathrm{gbest}) \right)$ **then**

      $gbest = (N_p)_i$

    end if

  end for

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

    Update the velocity using (5)
    Update the position using (6)

  end for

end for

2.3. Performance Metrics

2.3.1. Entropy [22]

Entropy represents the information content in the image. If all the intensity levels are occupied equally i.e. perfect histogram is obtained for the image, then the entropy for that image is high. If all the image pixels have same intensity values then, entropy is zero. For a high contrast image, i.e. an image whose pixels occupy the entire range of possible gray levels and are distributed uniformly, the entropy will be higher than that of the image whose pixels occupy a narrow range of gray levels and are non-uniformly distributed. So, enhanced image will have a higher entropy value than the original image. Entropy is calculated as:

$$H(I_e) = -\sum_{x=0}^{L-1} p(x) log_2 p(x) \tag{7}$$

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

2.3.2. Histogram Flatness [23-24]

HFM is given by:

$$HFM = \frac{Geometric\ Mean\ of\ Histogram\ Count}{Arithmetic\ Mean\ of\ Histogram\ Count} = \frac{\left(\prod_{i=1}^{L} count_i\right)^{\frac{1}{L}}}{\frac{1}{L}\sum_{i=1}^{L} count_i} \tag{8}$$

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

- Geometric mean of data is always less than or equal to the arithmetic mean.
- The value of AM and GM is equal when all the bins of histogram are equally occupied.
- $HFM \in [0, 1]$
- Low contrast images results in low value of HFM and High Contrast Images results in high value of HFM .

2.3.3. Histogram Spread [23]

HS is given by:

$$HS = \frac{Quartile\ distance\ of\ histogram}{Possible\ range\ of\ pixel\ values} = \frac{\left(3^{rd}\ quartile - 1^{st}\ quartile\right) of\ histogram}{\left(\text{maximum} - \text{minimum}\right) of\ the\ pixel\ value\ range} \tag{9}$$

Where, maximum is 255, minimum is 0, 3^{rd} *quartile* represents the histogram bin at which cumulative histogram have 75% of the maximum value and 1^{st} *quartile* represents the histogram bin at which cumulative histogram have 25% of the maximum value.

- $HS \in [0,1]$
- Low contrast images have low value of HS and high contrast images have high value of HS .

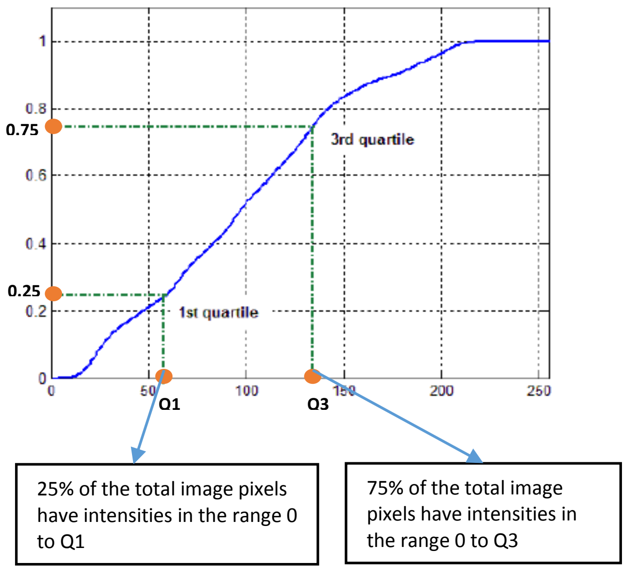


Fig. 2.1. Quartile

2.3.4. Tenengrad Criterion [25]

It is image Sharpness Measure. Based on Gradient at each image pixel. Gradient is calculated using Sobel Operator [1]. For the enhanced image the tenengrad value is larger than that of the original image.

$$G(\mathrm{m,n}) = \sqrt{\left(\left(i_m * I(\mathrm{m,n})\right)^2 + \left(i_n * I(\mathrm{m,n})\right)^2\right)} \tag{10}$$

where, $G(\mathrm{m,n})$ is the gradient magnitude of the $(\mathrm{m,n})^{th}$ pixel.

$$TEN = \sum_m \sum_n G(\mathrm{m,n})^2 \text{, for } G(\mathrm{m,n}) > T \tag{11}$$

where, T is the threshold and i_m and i_n are the convolution kernels of Sobel Operator.

Chapter 3

PROPOSED METHODOLOGY

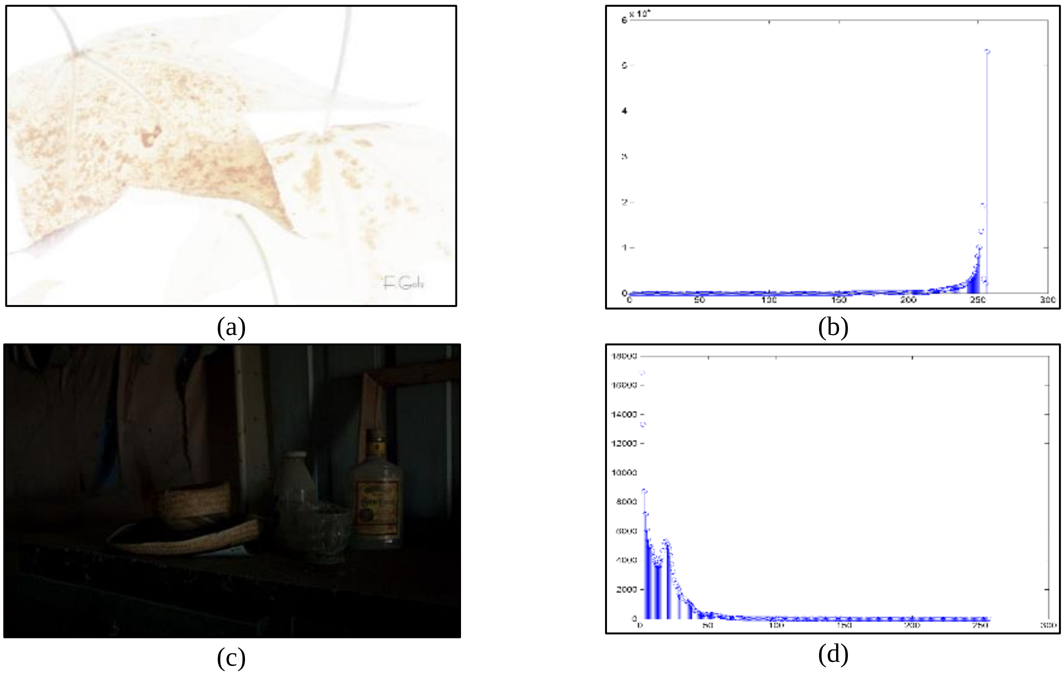
3.1. Modified Image Exposure

The image exposure is the measure of intensity exposition of an image i.e. how dark or bright the image appears when it is captured by a camera. Exposure setting is responsible for making the photos too dark or too bright. It represents what percentage of the image intensity levels are underexposed or overexposed.

1) *Underexposed Image*: When the gray levels are skewed towards lower range of the histogram, the image appears dark and said to be underexposed image.

2) *Overexposed Image*: When the gray levels are skewed towards higher range of the histogram, the image appears too bright and said to be overexposed image.

The underexposed and overexposed images along with their respective histogram are shown in Fig. 3.1.



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

Fig. 3.1. (a) Overexposed Image (b) Histogram of Overexposed Image (c) Underexposed Image (d) Histogram of Underexposed Image.

No image is entirely underexposed or overexposed, i.e. the images may contain both the underexposed and overexposed regions and are referred to as the *mixed exposed images*. So, image exposure represents what percentage of the image intensity levels are underexposed or overexposed.

In [13] the exposure was defined as:

$$exposure = \frac{1}{L-1}\frac{\sum_{x=0}^{L-1} p(x)x}{\sum_{x=0}^{L-1} p(x)} \tag{12}$$

In the above equation, the denominator $\sum_{x=0}^{L-1} p(x)$ represents the sum of the normalized histogram whose value will always be equal to 1. So, there is no requirement of this term for calculating the exposure. Hence, the simplified exposure can be represented as:

$$exposure = \frac{1}{L-1}\sum_{x=0}^{L-1} p(x)x \tag{13}$$

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

The value of the Exposure is in the range [0, 1]. If the exposure value is less than 0.5, it means that the image contains more of the underexposed region and if the value is greater than 0.5 the image has more overexposed region.

Since no image is entirely underexposed or overexposed, so for a mixed-exposed image both the Gaussian and Sigmoidal operators for underexposed and overexposed regions defined further in this section must be applied together to obtain the enhanced image. Thus, the image exposure value is used to obtain a threshold which is used to divide the image into underexposed and overexposed regions.

Threshold can be given by,

$$\mathrm{A} = L(1 - exposure) \tag{14}$$

The pixels having intensity value in the range $[0, \mathrm{A}-1]$ are categorized as underexposed pixels and those with intensity value in the range $[\mathrm{A}, L-1]$ are the overexposed pixels.

3.2. Fuzzification, Intensification and Defuzzification

The hue represents the original color of the image pixel. During the enhancement process the original color must be preserved, so the hue component is kept untouched. Saturation represents the color purity. Luminance is the perceived brightness of the color. The saturation and intensity components are processed separately. The intensity component is enhanced using the following process:

3.2.1. Fuzzification

Each image pixel intensity value is represented as a membership value in the range [0, 1]. These membership values represent the degree of brightness of a pixel. If the grade of membership is low, it means that the pixel is dark otherwise the pixel is bright.

Fuzzy representation of an image of size $M \times N$ having intensity levels in the range $[0, L-1]$ is given by:

$$I = \cup \{ \mu(x_{mn}) \} = \{ \mu_{mn} / x_{mn} \}$$

$$m = 1, 2, ..., \mathrm{M} \text{ and } n = 1, 2, ..., \mathrm{N} \tag{15}$$

Where, $\mu(x_{mn})$ or μ_{mn} / x_{mn} is the membership value at $(m,n)^{th}$ pixel. The image is divided into the underexposed and overexposed regions using the threshold value A. Both the regions are enhanced separately to obtain a complete enhanced mixed image.

To fuzzify the pixels in underexposed region, *Gaussian MF* is used as:

$$\mu_{xu}(x) = exp\left[-\left\{ \frac{x_{\max} - x}{\sqrt{2} f_h} \right\}^2 \right] \tag{16}$$

Where, x is in the range $[0, \mathrm{A}-1]$, $x_{\max}$ represents the maximum intensity value of the image and f_h is the fuzzifier [26] and is calculated using:

$$f_h^2 = \frac{1}{2} \frac{\sum_{x=0}^{L-1} (x_{\max} - x)^4 p(x)}{\sum_{x=0}^{L-1} (x_{\max} - x)^2 p(x)} \tag{17}$$

The overexposed region is fuzzified as:

$$\mu_{xo}(x) = exp\left[-\left\{ \frac{x_{\max} - (L - x)}{\sqrt{2} f_h} \right\}^2 \right] \tag{18}$$

Where, x is in the range $[\mathrm{A}, L-1]$. The image intensity levels are transformed to fuzzy domain from the spatial domain using the MFs, i.e. the intensity values in the range [0, 255] are now transformed into the range [0, 1] for 8 bit image. The MFs used for underexposed and overexposed regions are mutually exclusive and do not alter other region's values.

3.2.2. Intensification

It involves modifying the MF values for enhancing the underexposed and overexposed regions.

To modify the membership values in the underexposed region, *Sigmoid MF* is used as:

$$\mu'_{xu}(x) = \frac{1}{1 + \exp\left(-\delta\left(\mu_{xu}(\mathrm{x}) - \mu_{cu}\right)\right)} \tag{19}$$

Where, δ represents the intensification parameter, μ_{cu} is the cross-over point at which the value of MF is 0.5 and $\mu_{xu}(x)$ is the original MF value. For the modification of the membership values in the overexposed region, *Sigmoid MF* is used as:

$$\mu_{xo}^{'}(x) = \frac{1}{1+\exp\left(-\beta\left(\mu_{xo}(\mathrm{x})-\mu_{co}\right)\right)} \tag{20}$$

Where, β represents the intensification parameter, μ_{co} is the cross-over point and $\mu_{xo}(x)$ is the original MF value.

The Sigmoid operator used for the intensification purpose enhances the intensity of the underexposed pixels and reduces the intensity of the overexposed pixels depending upon the parameters δ, μ_{cu}, β and μ_{co}. For the underexposed pixels, the crossover point (μ_{cu}) must be low so that the lower intensity values are mapped into the higher intensity levels. For overexposed pixels, the crossover point (μ_{co}) must have a higher value to reduce the intensity of the higher intensity levels.

3.2.3. Defuzzification

The modified MF values are defuzzified in order to obtain the desired image in spatial domain. Defuzzification is done using the inverse of the MF that was used for fuzzification in step 1.

Underexposed region is defuzzified using:

$$x' = x_{\max} - \sqrt{\left(-2log\left(\mu_{xu}^{'}(\mathrm{x})\, f_h^2\right)\right)} \tag{21}$$

Where, $x_{\max}$ is the maximum intensity value of the image, $\mu_{xu}^{'}(x)$ is the modified MF value and f_h is the fuzzifier. Defuzzification of Overexposed Region is performed using:

$$x' = L - \left(x_{\max} - \sqrt{\left(-2log\left(\mu_{xo}^{'}(\mathrm{x})\, f_h^2\right)\right)}\right) \tag{22}$$

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

$$S^{'}(x) = \left[S(x)\right]^{(1-0.5*exposure)} \tag{23}$$

Where, $S(x)$ is the original saturation component of the HSV color space and $S^{'}(x)$ is the enhanced saturation component. Enhancement of the saturation re-establish the pleasing nature of the degraded images.

3.3. Proposed Optimization

3.3.1. Objective Function for Optimization

An objective function is used to measure the quality of the image. The objective function used in [13] does not consider the concept of exposure and also is very complex as it includes different fuzzy contrast measures for calculating the fitness value which involves complex mathematical calculations. The main aim of image enhancement process is to improve the exposure of the image and so it must be included as a part of the objective function. Moreover, calculating the values of fuzzy contrast measures, quality factors, entropy and visual factors is a tedious task and is time consuming. So, in this work, exposure is also included as a part of the objective function. The objective function uses: entropy, image exposure, number of edge pixels and sum of edge intensities.

The proposed objective function is represented as:

$$J = log\left(log\left(E\left(I_s\right)\right)\right)\times\frac{n\_edgels\left(I_s\right)}{M\times N}\times H\left(I_e\right)\times\left(exposure\right)^r \tag{24}$$

where, I_e is the enhanced Image, I_s is the edge image of the enhanced image and r is equal to 1 for underexposed region and -1 for overexposed region, $E\left(I_s\right)$ is the sum of all the pixel intensities of I_s, n_edgels is the number of edge pixels whose intensity value is above a threshold and H represents the entropy of the enhanced image.

As compared to the original image, the enhanced image will have more number of edges and the higher intensity of the edges. Different edge detection techniques such as Sobel, Laplacian, and Canny etc. can be used to detect the edges in the image. Here we have used Sobel edge detector [1] for edge detection in the given image.

Entropy represents the information content in the image. The entropy value of the enhanced image I_e is calculated using (7).

3.3.2. Algorithm for Image Enhancement using PSO

Step 1: Initialize the number of particles N_p, number of iterations N_i and number of dimensions N_d.

Step 2: Initialize the position and velocity of each particle in each dimension (t, μ_{cu}, g and μ_{co}) of the solution space.

Step 3: For each particle generate the enhanced image as follows:

- Step 3.1: Convert image from RGB to HSI color space.
- Step 3.2: Extract the I component from HSI image.
- Step 3.3: Calculate the histogram $p(x)$ of the image from the I component of HSI
- Step 3.4: Calculate the image exposure using Eq. (13) and compute the threshold value using Eq. (14).
- Step 3.5: Calculate the value of the fuzzifier f_h using Eq. (17).
- Step 3.6: Classify the image into 2 sub-images: underexposed and overexposed.
- Step 3.7: Fuzzify the image intensity values using Gaussian membership function using Eqs. (16) and (18) to obtain $\mu_{xu}(x)$ and $\mu_{xo}(x)$.

Step 3.8: Obtain the values of t, μ_{cu}, g and μ_{co} using PSO.

Step 3.9: Intensify the fuzzy membership values using Sigmoidal membership function using Eqs. (19) and (20).

Step 3.10: Defuzzify the membership value corresponding to each membership value using inverse Gaussian function using Eqs. (21) and (22) to obtain the enhanced HSI image in spatial domain.

Step 3.11: Enhance the saturation component for overexposed images using (23).

Step 3.12: Convert the HSI image to RGB color space to get the enhanced RGB image.

Step 4: For each particle, compute the entropy using Eq. (7), edge information and exposure using Eq. (13) of the enhanced image and hence calculate the fitness value using the objective function defined in Eq. (24).

Step 5: For each particle, update its historically best position $pbest_i$, if its current fitness is better than its historically best one.

Step 6: Update the swarm's global best position $gbest$ to the position of the particle having the best fitness value among all the particles in the swarm.

Step 7: Update the velocity and position of each particle in the swarm using Eq. (5) and Eq. (6).

Step 8: Repeat steps 3–7 for N_i iterations.

The flowchart of the algorithm is given in Fig. 3.2.

3.3.3. Parameter Selection

It includes two sets of parameters: the parameters needed in particle swarm optimization, i.e. N_p, N_i, N_d, w, c_1, c_2, R_1 and R_2 and the parameters to be optimized, i.e. δ, μ_{cu}, β and μ_{co}.

1) <u>*PSO Parameters:*</u>

a) The number of particles N_p =10.

b) The number of iterations N_i =10.

c) The number of dimensions N_d =4.

d) Maximum velocity can be calculated using:

$$v_{\max} = \frac{\zeta_d^{\max} - \zeta_d^{\min}}{K} \tag{26}$$

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

e) The linearly decreasing inertia(w) weight value for each iteration can be given by:

$$w(t) = w_{hi} - \left(w_{hi} - w_{low}\right)\frac{t}{T_{\max}} \tag{27}$$

where, t is the iteration counter; w_{hi} (1.2) and w_{low} (0.4) are the desired maximum and minimum values of the inertia weight and $T_{\max}$ is the maximum value of iteration. Inertia weight is a linearly decreasing time dependent parameter with initial value, w_{hi}, at the first iteration, t = 0, and final value, w_{low}, at the last iteration, $T_{\max}$.

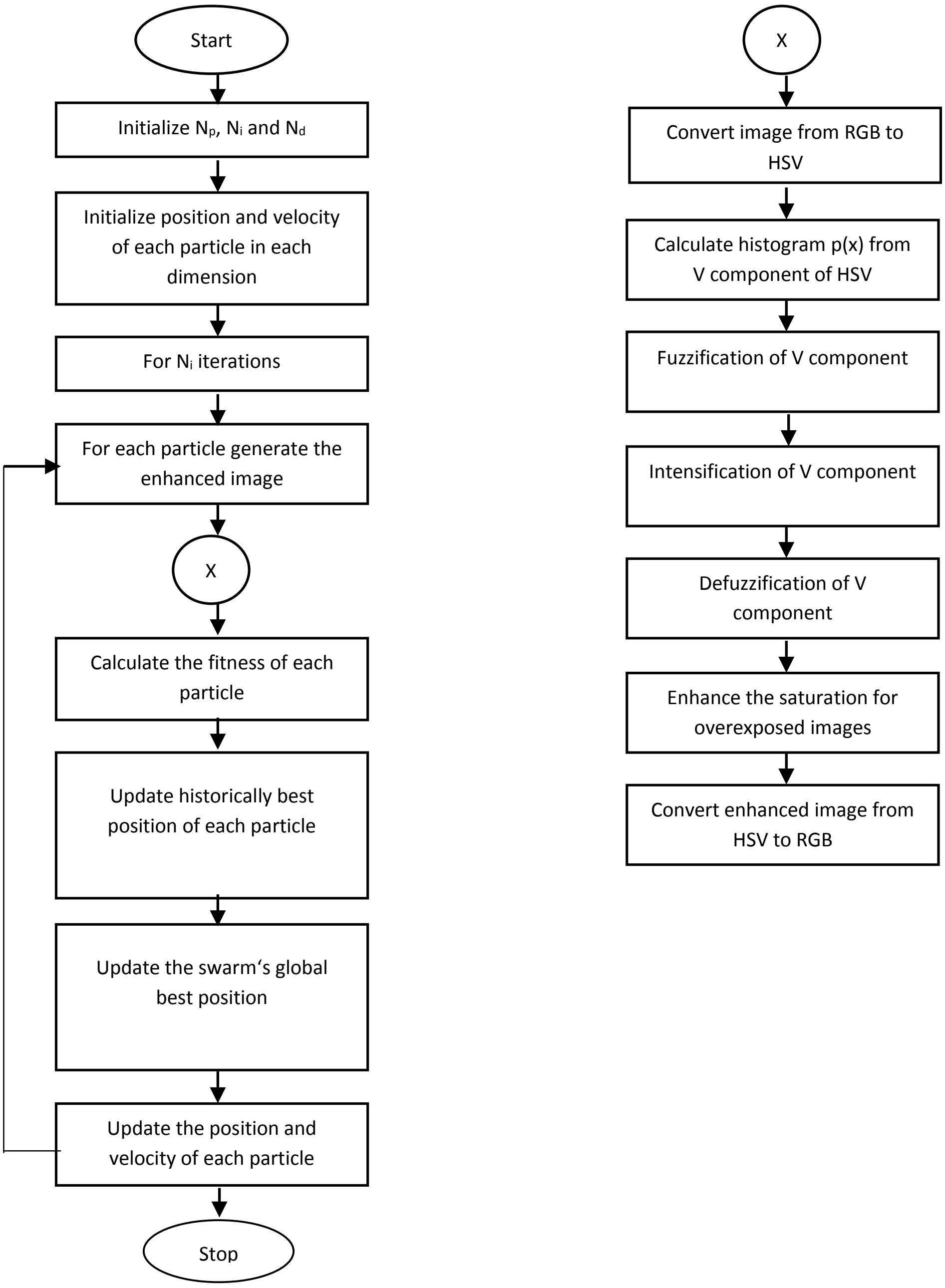


Fig. 3.2. Flowchart of the Proposed Algorithm

f) Parameters, c_1 and c_2 are initialized to a random number in [0, 4]. Each particle has same values of c_1 and c_2 throughout its life.

g) R_1 and R_2 are random numbers in [0, 1]. Each dimension has its own random number.

2) <u>Parameters to be optimized:</u>

a) Intensification parameter for underexposed region $\delta \in [0, 1]$.

b) Crossover point for underexposed region $\mu_{cu} \in [1, 30]$.

c) Intensification parameter for overexposed region $\beta \in [0, 1]$.

d) Crossover point for overexposed region $\mu_{co} \in [1, 30]$.

Chapter 4

EXPERIMENTAL RESULTS

The Intel Core i5 CPU at 2.50 GHz and MATLAB is used to implement the proposed approach. More than 100 images of underexposed, overexposed, mixed-exposed and low-contrast types have been used as test images to evaluate the performance of the proposed approach and some of these images are presented here.

The performance of the proposed approach is evaluated using the objective measures such as the image tenengrad value, histogram flatness, histogram spread and entropy. A direct application of the operators on the image results in unlimited enhancement of the image and cause noise over-enhancement. So, to control the amount of enhancement, the parameters (δ, μ_{cu}, β, μ_{co} and f_h) are learned using the optimization of the objective function.

The proposed approach is evaluated using different test images that include underexposed, overexposed, mixed-exposed and low contrast images shown in Fig. 4.2-4.19. In the underexposed image, the gray levels are skewed towards the lower range of the histogram, i.e. contains more underexposed region and so the image appears dark. In the overexposed image, the gray levels are skewed towards the higher range of the histogram, i.e. contains more overexposed region and so the image appears brighter. The mixed-exposed image contains both the overexposed and underexposed region. An image with low contrast has a histogram that will be narrow and will be centred toward the middle of the gray scale. In all the cases, the details are not recognizable, and the colors are not observable to the eyes. Fig. 4.1 represents all four types of test images and their respective histograms.

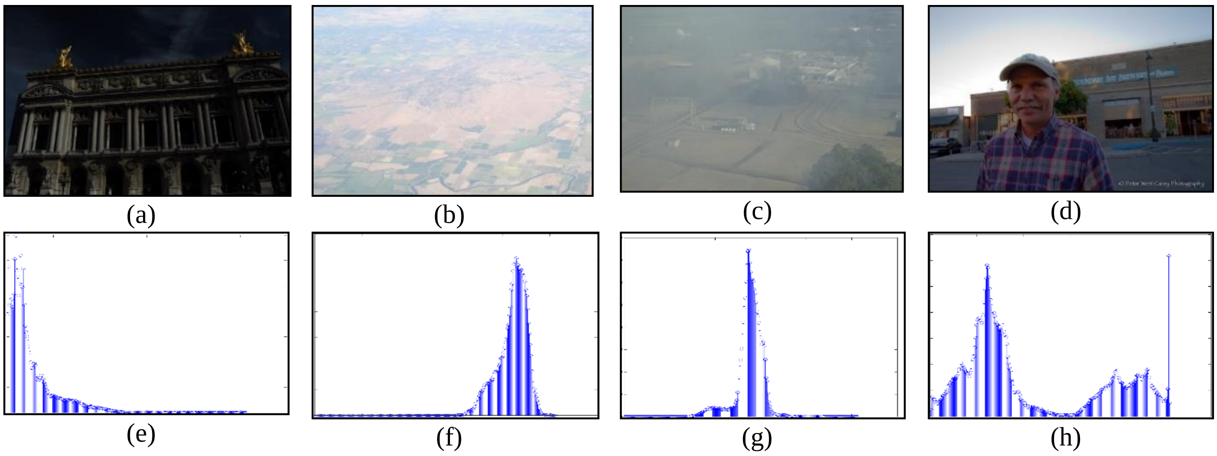
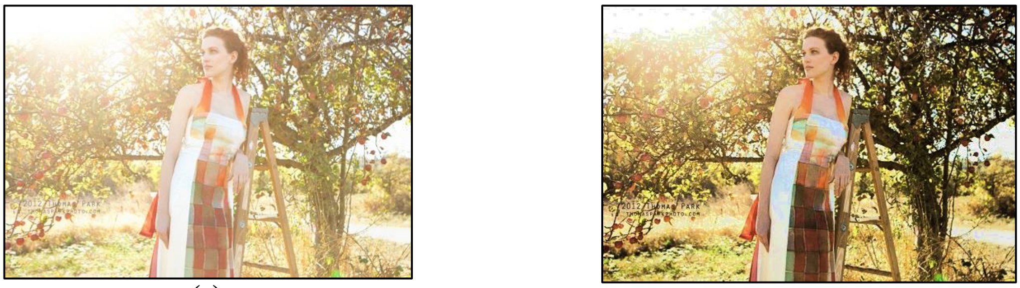


Fig. 4.1. (a) Underexposed image (b) Overexposed image (c) Low contrast image (d) Mixed-exposed image (e-h) Histograms of (a-d)

(a) (b)

Fig. 4.2. (a) Original Image of “Face” (b) Enhanced Image.

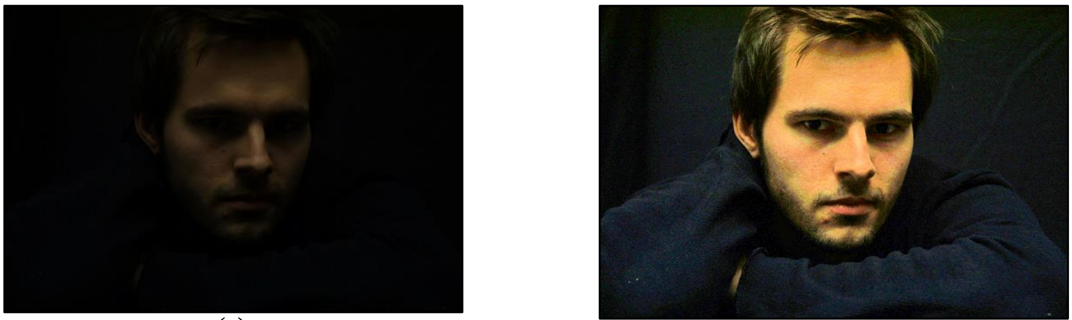


(a) (b)

Fig. 4.3 (a) Original Image of “Lady” (b) Enhanced Image.

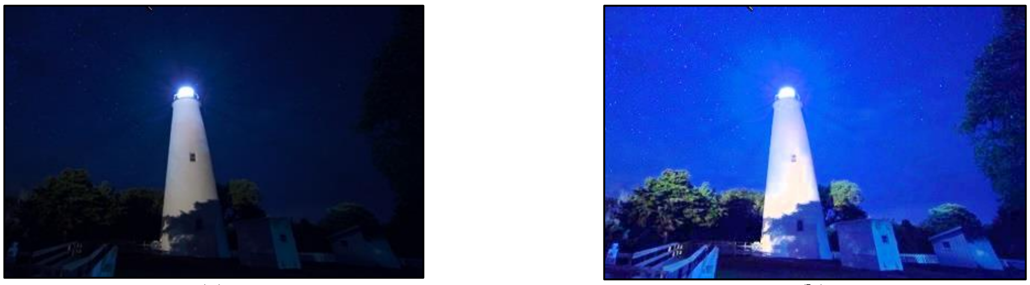
(a) (b)

Fig. 4.4. (a) Original Image of “Flowers” (b) Enhanced Image.



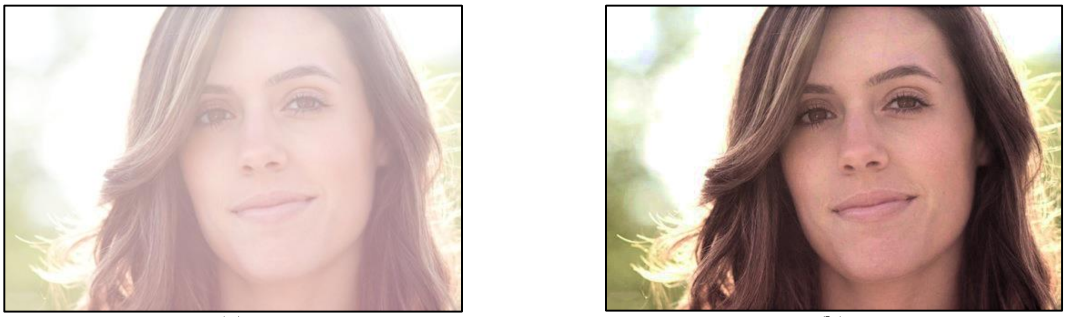
(a) (b)

Fig. 4.5. (a) Original Image of “Boy” (b) Enhanced Image.



(a) (b)

Fig. 4.6. (a) Original Image of “Tower” (b) Enhanced Image.

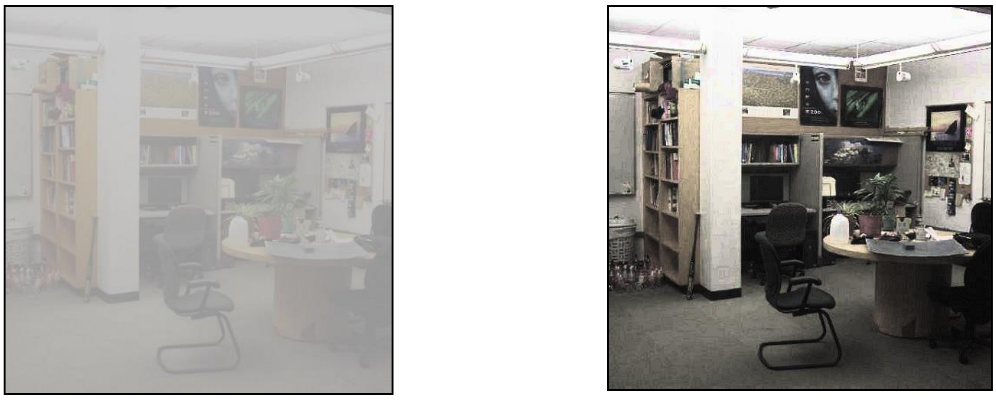


(a) (b)

Fig. 4.7. (a) Original Image of “Woman” (b) Enhanced Image.

(a) (b)

Fig. 4.8. (a) Original Image of “Window” (b) Enhanced Image



(a) (b)

Fig. 4.9. (a) Original Image of “Room” (b) Enhanced Image

Table 4.1 represents the fitness and exposure values and Table 4.2 represents tenengrad, entropy, HFM and HS values of original and enhanced images shown in Fig. 4.2-4.10. It can be seen from the Table 4.1 and 4.2 that in enhanced image we have achieved higher fitness, tenengrad, HFM, HS and entropy values than the original image. For the underexposed images we have achieved higher exposure value and for overexposed images we have achieved lower exposure value of the enhanced image.

TABLE 4.1.
FITNESS AND EXPOSURE VALUES OF FIG. 4.2-4.10

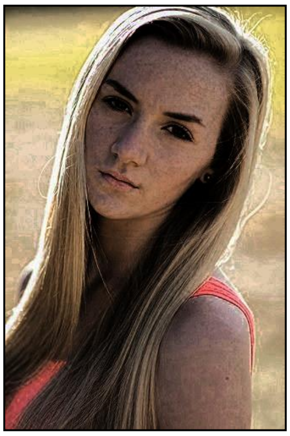
Test Images	Fitness		Exposure	
	Original	Enhanced	Original	Enhanced
Face	0.002	0.025	0.012	0.164
Flowers	0.176	0.227	0.898	0.773
Woman	0.392	0.625	0.828	0.578
Boy	0.005	0.075	0.027	0.320
Lady	0.667	1.127	0.773	0.543
Tower	0.007	0.087	0.082	0.273
Girl	0.402	0.617	0.844	0.656
Window	0.200	0.206	0.496	0.498
Room	0.531	0.718	0.695	0.473

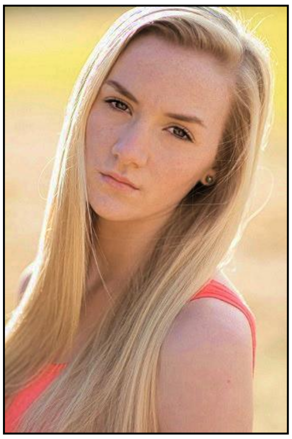
TABLE 4.2.
TENENGRAD, ENTROPY, HFM AND HS VALUES OF FIG. 4.2-4.10

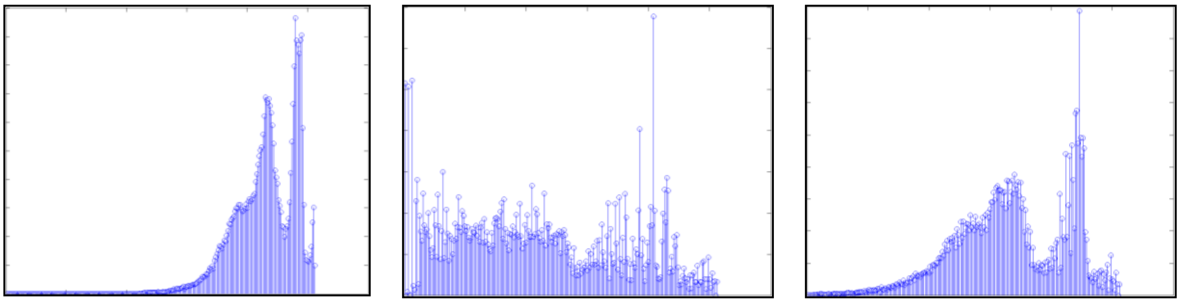
Test Images	Tenengrad		Entropy		Histogram Flatness		Histogram Spread	
	Original	Enhanced	Original	Enhanced	Original	Enhanced	Original	Enhanced
Face	3319	4743	2.164	2.700	0.020	0.048	0.020	0.314
Flowers	3428	3516	3.709	4.422	0.274	0.381	0.137	0.271
Woman	5832	5870	4.353	5.118	0.580	0.664	0.204	0.486
Boy	6173	6188	2.641	4.079	0.094	0.183	0.012	0.184
Lady	8092	8685	4.897	5.420	0.494	0.852	0.278	0.475
Tower	1021	3052	3.661	4.569	0.088	0.291	0.047	0.110
Girl	5938	6234	4.427	5.033	0.362	0.427	0.362	0.427
Window	3428	3559	4.761	5.317	0.329	0.657	0.157	0.396
Room	10771	10879	3.902	4.991	0.406	0.546	0.094	0.569

The proposed approach is compared with the existing HE approach [1], exposure based sub-image HE approach [5], ACE approach [6] and fuzzy contrast measures based approach [13]. For the evaluation, Fig 4.11-4.19 represents the comparison between the above mentioned approaches.


(a)


(b)


(c)



(d) (e) (f)

Fig. 4.10. (a) Original Image "Girl" (b) Histogram Equalized Image (c) Enhanced Image using Proposed Approach (d) Original Image Histogram (e) Histogram Equalized Image (f) Histogram of Enhanced Image using Proposed Approach.

Table 4.3 represents the fitness values of the enhanced images obtained by applying different enhancement techniques. The fitness values are calculated using the objective function defined in (24). The fitness of the image depends on the edge information, exposure and entropy value. The enhanced image must have higher fitness value than the original image. But in some approaches such as HE, the enhanced image may have a very high fitness value which indicates a noisy and distorted image. "Leaves" image gives a very high fitness value for HE approach, but the enhanced image does not satisfy the result as shown in Fig. 4.11.

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

(e) (f)

Fig. 4.11. (a) Original Image "Leaves" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

Table 4.4 represents the image exposure values obtained by applying different enhancement techniques to obtain the enhanced image. For the underexposed images, initially the exposure is less than 0.5 and must be increased in order to enhance the image. For the overexposed images, initially the exposure is more than 0.5 and must be decreased in order to enhance the image. If there is very large increase or decrease in the image exposure, it may result in over-enhancement and distort the image details as reflected in case of "Baby" image for HE based approach as shown in Fig. 4.12. Being an overexposed image, its initial exposure value is 0.87 and using HE approach it is reduced to 0.45 which is more than required and hence results in over-enhancement.

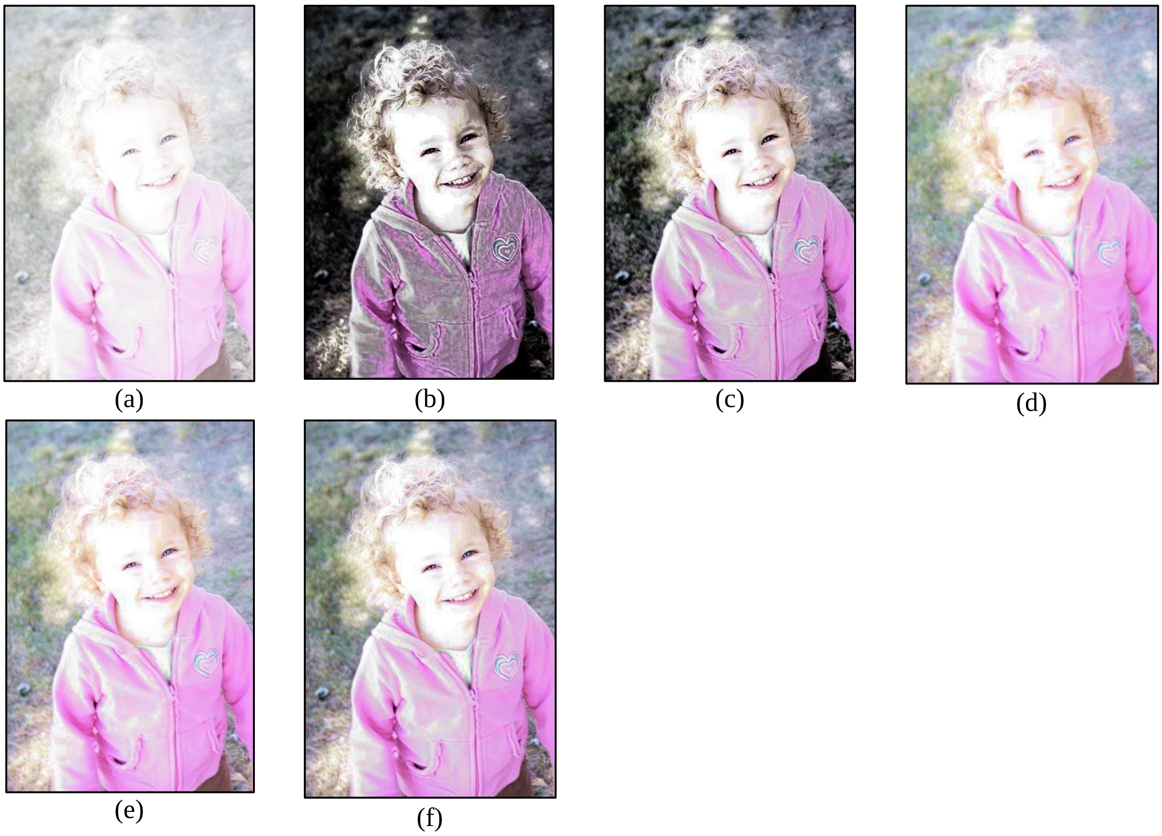


Fig. 4.12. (a) Original Image "Baby" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

Table 4.5 represents histogram flatness values of the enhanced images obtained from different approaches. HFM is a contrast measure that is used to analyse the image quantitatively. If all the intensity levels are equally occupied i.e. uniformly distributed, it results in a completely flat histogram. More the histogram of an image is flat, higher is the contrast of the image. For low contrast image, there is a large difference between the intensity levels distribution of the image. When the image histogram is almost flat, the arithmetic mean (AM) is nearly equal to the geometric mean (GM) of the histogram and thus the ratio of AM to GM is approximately equal to 1. For the non-uniform distribution of image intensity levels, the AM is much larger than the GM of the image histogram and thus the ratio approaches to 0. Hence, low contrast images have low value of HFM and high contrast images have high value of HFM .

Another contrast measure, i.e. histogram spread for the enhanced images obtained from different approaches is given in Table 4.6. For a good contrast image, the image intensity values occupy more number of the possible intensity levels. For low contrast images, i.e. underexposed and overexposed images, the gray levels are skewed to either ends of the histogram. Though histogram equalization results in a higher histogram spread, it also results in the transformation of those pixels for which the enhancement is not required. In "Monument" image, the histogram equalization results in more enhancement and less improvement as shown in Fig. 4.13. More the distance between the 1st and 3rd quartile of the image cumulative histogram, more is the spread and thus better is the image contrast. Fig. 4.10 justifies the concept of both histogram flatness and histogram spread. Histogram of the enhanced image is more flat and occupies more intensity levels than the histogram of the original image.

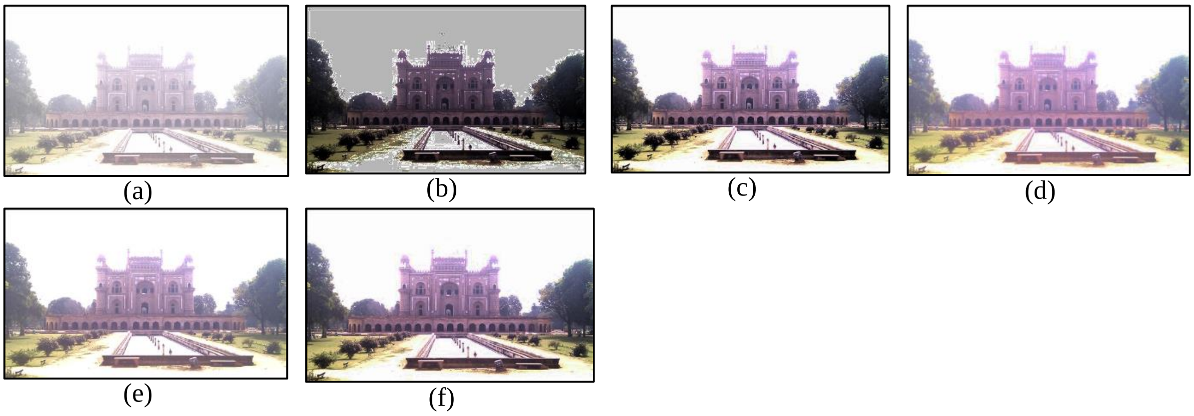


Fig. 4.13. (a) Original Image "Monument" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

Table 4.7 gives the sharpness measure, i.e. the tenengrad values of the enhanced images obtained using different techniques. The tenengrad measure considers the edge information of the images for quantitative analysis. The enhanced image will be sharper than the original image and hence will have a higher tenengrad value. The gradient is calculated at each pixel using the Sobel operator and a threshold is used to calculate the tenengrad value. The enhanced "Robot" image, shown in Fig. 4.14, is much sharper than the original image and thus have a higher tenengrad value.

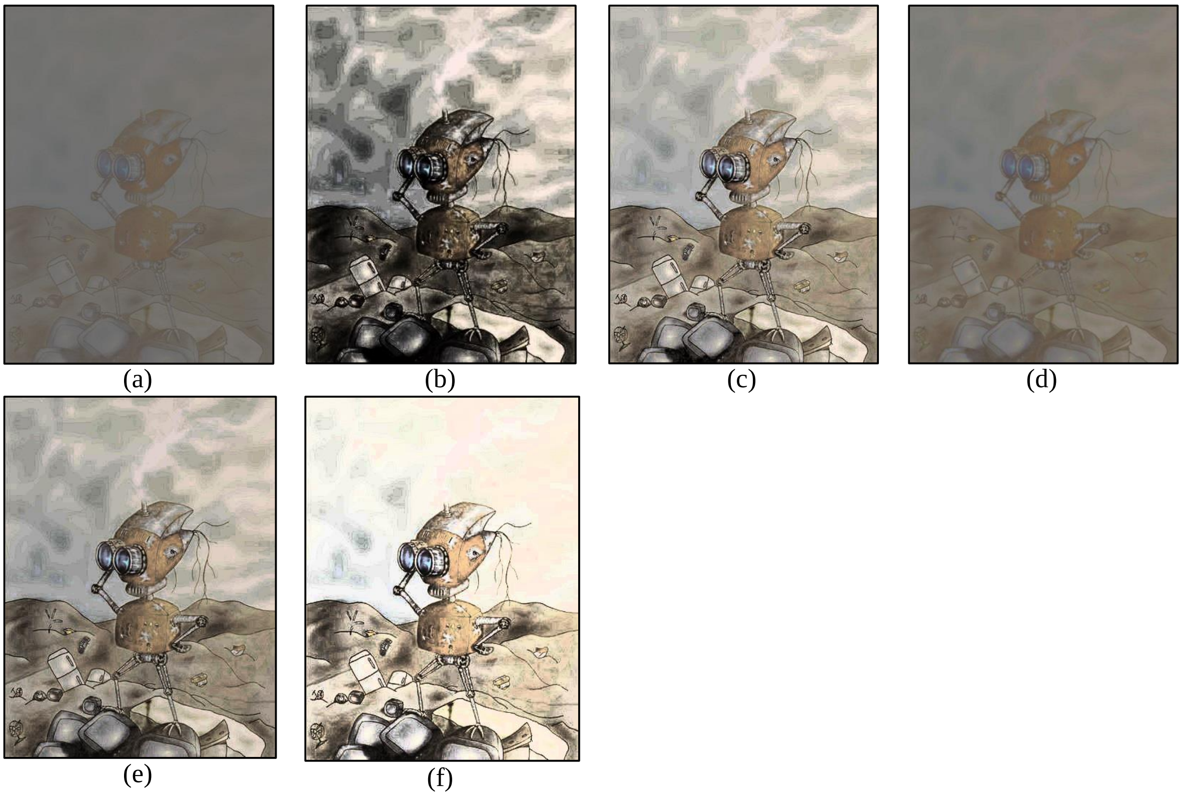


Fig. 4.14. (a) Original Image "Robot" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

Table 4.8 represents the entropy values of the enhanced images obtained using different enhancement techniques. Entropy represents the information content in the image. If all the intensity levels are occupied equally i.e. perfect histogram is obtained for the image, then the entropy for that image is high. If all the image pixels have same intensity values then, entropy is zero. For a high contrast image, i.e. an image whose pixels occupy the entire range of possible gray levels and are distributed uniformly, the entropy will be higher than that of the image whose pixels occupy a narrow range of gray levels and are non-uniformly distributed. So, enhanced image will have a higher entropy value than the original image.

Table 4.9 represents the values of the parameters (δ, μ_{cu}, β, μ_{co} and f_h) obtained after optimizing the objective function using BA.

In all the above measures, we can observe from Tables 4.3-4.8 that HE based approaches give unexpected results. The HE adjusts the image's histogram in order to improve the image contrast. But, it often results in noise over-enhancement which alters the image details. It does not define any criteria to limit the amount of enhancement required for a particular application. Even if the image already has good quality, still the enhancement is done which then results in an unpleasing image. Though it results in a higher histogram spread and flatness, it also results in the transformation of those pixels for which the enhancement is not required. That is why most of the images are having very high values for image entropy, HFM, HS and tenengrad in case of HE based approaches. Fig. 4.10 represents the results of HE approach. As it can be seen from Fig. 4.10(e), the histogram is more flat than other two histograms in Fig. 4.10(d) and Fig. 4.10(f). But, more histogram flatness does not always result in a good contrast image as shown in Fig. 4.10(b).

As the proposed approach operates on the frequency of occurrence of gray levels rather than individual intensities of pixels, therefore the proposed image enhancement approach is computationally efficient. Note that the proposed approach reserves the histogram shape of the image.

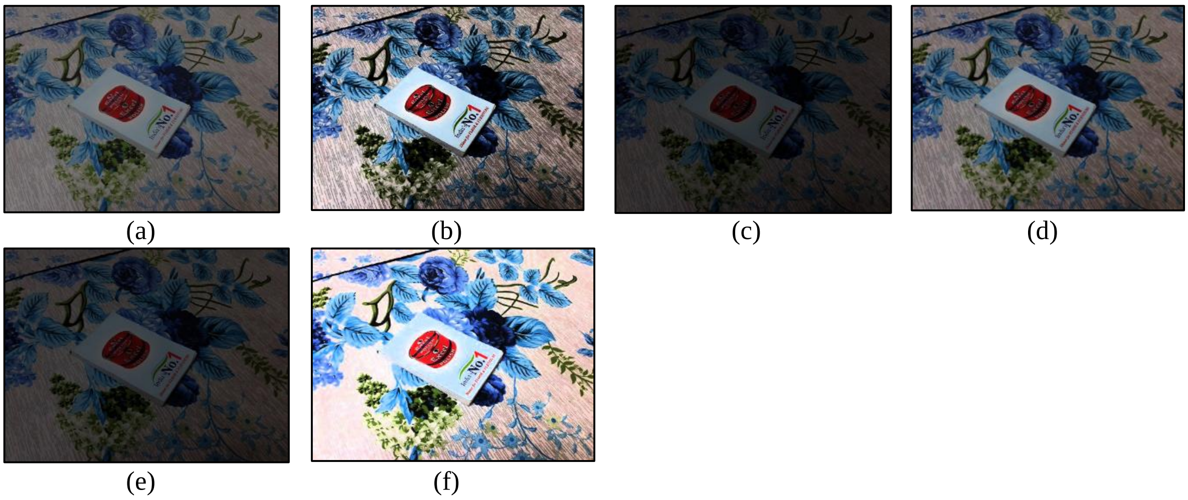


Fig. 4.15. (a) Original Image "Diary" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

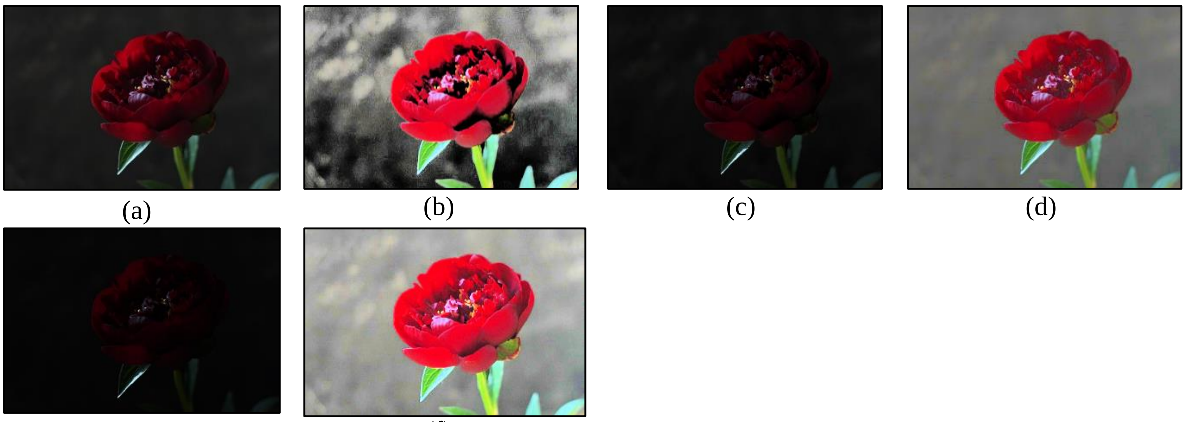


Fig. 4.16. (a) Original Image "Rose" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

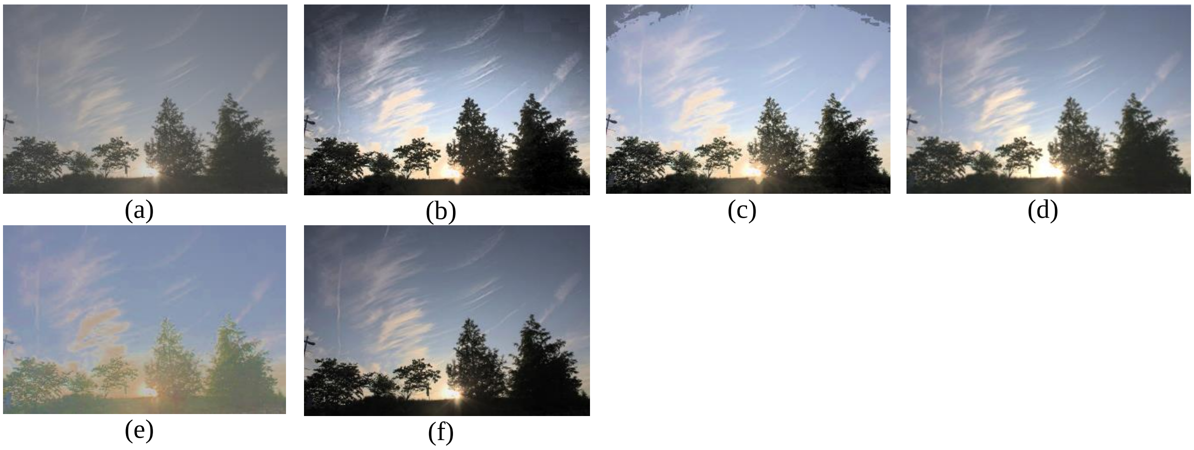


Fig. 4.17. (a) Original Image "Landscape" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

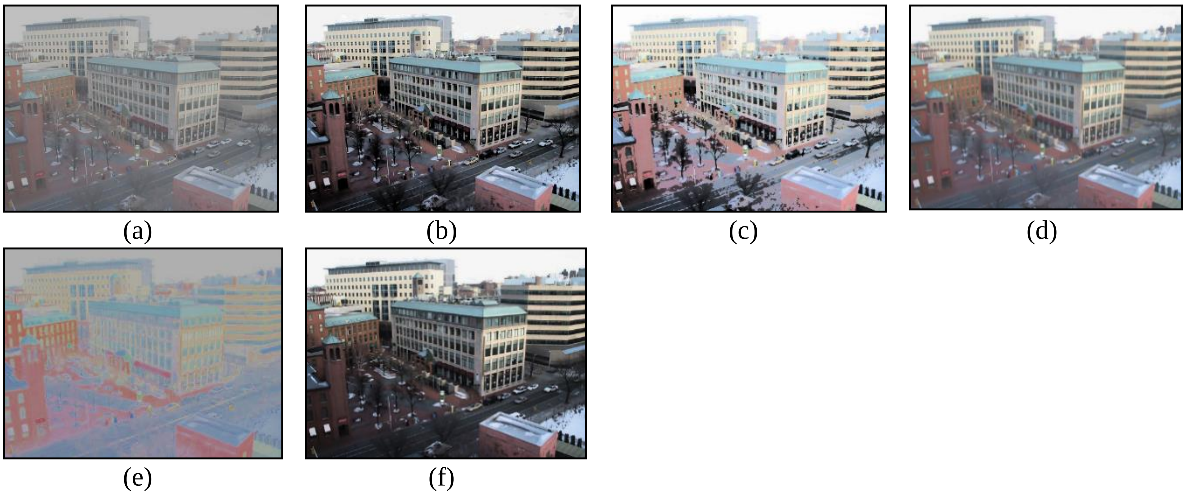


Fig. 4.18. (a) Original Image "Building" (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

Fig. 4.19. (a) Original Image “Text” (b) Histogram Equalized Image (c) Approach 2 [5] (d) Approach 3 [6] (e) Approach 4 [13] (f) Proposed Approach.

TABLE 4.3.
COMPARISON OF FITNESS VALUES OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	Original	HE	[5]	[6]	[13]	Proposed
Baby	0.251	0.219	0.542	0.298	0.352	0.397
Monument	0.368	0.173	0.550	0.416	0.419	0.520
Diary	0.132	0.205	0.045	0.126	0.674	0.785
Rose	0.010	0.079	0.003	0.056	0.035	0.335
Leaves	0.244	0.593	0.481	0.304	0.218	0.347
Landscape	0.194	0.166	0.691	0.735	0.652	0.266
Robot	0.131	0.197	0.707	0.156	0.359	0.574
Building	0.974	0.283	0.986	0.953	0.576	0.975
Text	0.169	0.051	0.055	0.234	0.042	0.219

TABLE 4.4.
COMPARISON OF EXPOSURE OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	Original	HE	[5]	[6]	[13]	Proposed
Baby	0.875	0.453	0.621	0.781	0.789	0.723
Monument	0.867	0.480	0.703	0.793	0.789	0.723
Diary	0.320	0.426	0.121	0.316	0.586	0.680
Rose	0.113	0.391	0.055	0.379	0.246	0.574
Leaves	0.965	0.539	0.805	0.934	0.961	0.887
Landscape	0.477	0.453	0.602	0.527	0.570	0.582
Robot	0.426	0.480	0.633	0.461	0.684	0.797
Building	0.531	0.465	0.645	0.559	0.582	0.634
Text	0.520	0.289	0.246	0.559	0.379	0.598

TABLE 4.5.
COMPARISON OF HFM OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	**Original**	**HE**	**[5]**	**[6]**	**[13]**	**Proposed**
Baby	0.091	0.698	0.762	0.229	0.237	0.263
Monument	0.321	0.257	0.546	0.381	0.408	0.393
Diary	0.467	0.794	0.607	0.406	0.372	0.696
Rose	0.049	0.295	0.028	0.121	0.140	0.242
Leaves	0.076	0.158	0.330	0.207	0.079	0.102
Landscape	0.433	0.674	0.528	0.733	0.312	0.527
Robot	0.173	0.251	0.300	0.277	0.173	0.252
Building	0.420	0.684	0.542	0.570	0.217	0.646
Text	0.043	0.084	0.069	0.106	0.073	0.073

TABLE 4.6.
COMPARISON OF HS OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	**Original**	**HE**	**[5]**	**[6]**	**[13]**	**Proposed**
Baby	0.118	0.427	0.333	0.169	0.212	0.224
Monument	0.251	0.506	0.569	0.404	0.443	0.549
Diary	0.157	0.471	0.082	0.204	0.196	0.369
Rose	0.027	0.392	0.024	0.067	0.067	0.169
Leaves	0.039	0.765	0.275	0.098	0.043	0.161
Landscape	0.145	0.471	0.361	0.251	0.078	0.247
Robot	0.035	0.475	0.204	0.067	0.043	0.216
Building	0.212	0.482	0.247	0.329	0.078	0.529
Text	0.000	0.000	0.000	0.000	0.000	0.000

TABLE 4.7.
COMPARISON OF TENENGRAD VALUE OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	**Original**	**HE**	**[5]**	**[6]**	**[13]**	**Proposed**
Baby	4063	6805	5028	3927	4675	4596
Monument	7425	7162	7388	6778	7398	7453
Diary	7403	7440	7350	6751	7239	8818
Rose	1923	3482	1344	2811	2644	3482
Leaves	6569	7031	7878	6640	6957	6768
Landscape	6497	5313	6450	5881	6916	6595
Robot	8422	7596	8434	7861	7488	9254
Building	9974	9677	11015	9350	7655	10213
Text	5495	5113	5247	3862	5491	5527

TABLE 4.8.
COMPARISON OF ENTROPY VALUE OF PROPOSED APPROACH WITH OTHER APPROACHES.

Test Image	**Original**	**HE**	**[5]**	**[6]**	**[13]**	**Proposed**
Baby	4.290	5.288	5.275	4.711	4.683	4.931
Monument	3.211	3.653	3.929	3.659	3.350	3.832
Diary	4.638	5.422	3.971	4.934	4.766	5.216
Rose	3.533	4.502	3.063	4.084	4.145	4.462
Leaves	2.779	3.537	3.777	3.307	2.329	3.520
Landscape	4.704	5.240	5.026	5.176	4.183	5.086
Robot	3.030	4.528	4.592	3.594	2.853	4.244

Building	4.465	5.201	4.925	4.909	3.811	5.112
Text	0.577	1.188	1.456	1.246	0.695	1.132

TABLE 4.9.
OPTIMIZATION PARAMETERS

Test Image	δ	μ_{cu}	β	μ_{co}	f_h
Baby	1.000	12.104	0.088	29.081	77.966
Monument	0.123	16.538	0.417	28.005	114.137
Diary	0.336	17.294	0.442	9.623	129.518
Rose	0.000	30.000	0.942	1.000	72.448
Leaves	0.000	1.000	0.000	29.682	58.829
Landscape	1.000	2.324	0.341	24.063	137.110
Building	1.000	20.334	0.550	1.000	138.835
Robot	0.221	13.487	0.228	10.645	108.055
Text	1.000	30.000	0.990	1.000	156.919
Face	0.274	30.000	0.689	3.554	167.327
Flowers	0.864	1.000	0.000	26.329	121.871
Woman	1.000	1.000	0.000	16.491	124.335
Boy	0.432	22.191	1.000	1.000	159.902
Lady	1.000	4.468	0.000	1.000	131.745
Room	0.423	16.395	0.779	16.024	129.619
Light House	0.099	19.239	0.138	19.748	112.279
Window	0.973	29.269	0.122	20.900	127.698
Girl	0.945	11.156	0.265	21.910	84.814

Chapter 5

CONCLUSION

In the work presented, the image enhancement is done using the "Fuzzy Logic" technique. Fuzzy Enhancement associates with each pixel intensity a membership value that represents the degree of brightness of the pixel. These membership values are then modified to obtain the enhanced membership values and hence defuzzified in order to obtain the enhanced image. The transformation function used for enhancement involves some of the parameters i.e. δ, μ_{cu}, β and μ_{co} that produce diverse results and helps in finding an optimal solution according to the objective function. So, for this purpose PSO is used to find the best set of values for the parameters in order to produce the optimal result. Results of Fuzzy technique are better than the Histogram Equalization as this technique does not result in noise over-enhancement. A number of enhanced images are produced based on the values of the parameters, and the one with the best fitness value is selected as the result. Instead, histogram equalization produces only a single enhanced image. The proposed algorithm is not only used for enhancing the underexposed and overexposed images but also enhances the low contrast images as well.

Chapter 6

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