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Image Brightness Enhancement of Visible and Infrared Images Using Genetic Algorithm

Rimpi Mahajan[1], Ajay Kumar[2], Sonakshi Sharma[3], Parveen Lehana[3]
[1, 2]Department of ECE, BCET, Gurdaspur, India
[3]Department of Physics and Electronics, University of Jammu, J & K , India
Email address: [3]pklehana@gmail.com

***Abstract*—**This paper discusses the image brightness enhancement of the visible and infrared image using Genetic Algorithm. In this paper, Genetic Algorithm has been investigated for the enhancement of the brightness of the images. The algorithm was effective as the brightness of the images got enhanced with the successive iterations.

***Keywords*—** Digital image processing; DNA; genetic algorithm; mutation; enhancement.

I. Introduction

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

Image enhancement techniques are used to improve image quality or extract the fine details in the degraded images. Most existing image enhancement techniques usually have three weaknesses: (1) image enhancement applied in the RGB (red, green, blue) colour space is inappropriate for the human visual system; (2) the uniform distribution constraint employed is not suitable for human visual perception; (3) they are not robust, i.e., one technique is usually suitable for one type of degradations only. [1] GA has the ability to determine optimal number of regions of a segmentation result or to choose some features such as the size of the analysis window or some heuristic thresholds. Basically in Genetic Algorithm the new child or chromosome obtained is made up of combination of features of their parents. So, Genetic algorithm is applied on any image to get the new enhanced image which is much better than the original one that contains features of parents.

This paper is organised as follows: Infrared Imaging has been discussed in next Section .The details of genetic algorithm have been presented in the Section III. The mathematical formulations used in the algorithm are presented in Section IV. The proposed work and the methodology adopted for the investigations are discussed in Section V. The experimentation and results are presented in Section VI. The paper is concluded in section VII.

II. IR Imaging

Infrared (IR) light is electromagnetic radiation with a wavelength longer than that of visible light, measured from the nominal edge of visible red light at 0.74 micrometers, and extending conventionally to 300 micrometers [2]. Images received through various infrared (IR) devices in many applications are distorted due to the atmospheric aberration mainly because of atmospheric variations and aerosol turbulence [2], [3].

Infrared imaging, which provides visual information not detectable by the human eye, is widely used in both military and, increasingly, commercial applications, such as surveillance and personal hand-held cameras, and night-vision systems in vehicles [4]. The enhancement of infrared images is slightly different from traditional image enhancement in dealing with the large black areas and the small details.

III. Genetic Algorithm

Genetic algorithm is a powerful tool to solve optimization problem. It can search for good solutions adaptively by using a collection of search points known as a population in order to maximize some desirable Criterion [5]. GA is a heuristic search technique for obtaining the best possible solution in a vast solution space. It employs mechanisms analogous to those involved in natural selection to conduct a search through a given parameter space for the maximum/minimum of some objective function. To apply a GA, an initial population is generated and the fitness of each member of the population is evaluated. The algorithm then iterates the following: members from the population are selected for reproduction in accordance to their fitness evaluations. The reproduction operator is then applied, which generally include a crossover operator that models the exchange of genetic material between the parent chromosomes and a mutation operator to maintain diversity and introduce new alleles into the generation, or next generation. The fitness of the offspring is then evaluated, and the algorithm starts a new iteration. The algorithm stops when either a sufficiently good solution is found, or after a predetermined number of iterations. GA has been successfully applied in numerous commercial and industrial fields. For

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image processing problems, some recent attempts in image segmentation, primitive extraction, scene recognition and image interpretation are reported in the literature [6-9]. In this paper genetic algorithm is used for enhancing the quality of infrared images and to determine their mean brightness, sharpness and contrast.

IV. Mathematical Formulation

The mathematical framework for enhancing the images and the selection parameters are defined in [10], [25].

A. Transformation Parameters Selection

The intensity I of the color image I_c can be determined by:

$$I(m,n) = 0.2989r(m,n) + 0.587(m,n) + 0.114b(m,n) \quad (1)$$

Where r, g, b are the red, green, and blue components of I_c, respectively and m and n are the row and column pixel locations respectively [26]. Assuming I to be 8-bits per pixel, I_n is the normalized version of I, such that:

$$I_n(m.n) = \frac{I(m,n)}{255} \quad (2)$$

It has been studied that linear input-output intensity relationships doesn't produce a good visual in comparison to direct viewing of scene. The non-linear transformation for DRC is used which is based on the extraction of some information from the range histogram. I_n is mapped to I_n^{drc} using the following:

$$I_n^{drc} = \begin{cases} (I_n)^x + \alpha & 0 < x < 1 \\ \left(0.5 + (0.5 I_n)^x\right) + \alpha & x \geq 1 \end{cases} \quad (3)$$

For $0 < x < 1$, the details in the dark regions are enhanced and for $x \geq 1$, the overshoots in the image are suppressed so as to make the content viewable for the observer.

The value of x is given by:

$$x = \begin{cases} 0.2,\ if\,(f(r_1+r_2) \geq f(r_3+r_4)) \Lambda (f(r_1) \geq f(r_2)) \\ 0.5,\ if\,(f(r_1+r_2) \geq f(r_3+r_4)) \Lambda (f(r_1) \geq f(r_2)) \\ 3.0,\ if\,(f(r_1+r_2) \geq f(r_3+r_4)) \Lambda (f(r_3) \geq f(r_4)) \\ 5.0,\ if\,(f(r_1+r_2) \geq f(r_3+r_4)) \Lambda (f(r_3) \geq f(r_4)) \end{cases} \quad (4)$$

where $f(r)$ refers to number of pixels between the range (r), $f(a_1+a_2) = f(a_1+a_2)$ and Λ is the logical AND operator. α is the offset parameter, helping to adjust the brightness of image.

B. Surround and Color Restoration Parameter Selection

Many local enhancement methods rely on center /surround ratios .Gaussian has been investigated as the optimal surround function. It has been investigated that Gaussian form produced good dynamic range compression over a range of space constants .The Luminance information of surrounding pixels is obtained by using 2D discrete spatial convolution with a Gaussian Kernel, $G(m,n)$ defined as:

$$G(m,n) = K \exp\left[\frac{-(m^2+n^2)}{\sigma^2_s}\right] \quad (5)$$

Where σ_s is the surround space constant equal to the standard deviation of $G(m,n)$ and K is determined under the constant that $\sum_{m,n} G(m,n) = 1$

The center-surround contrast enhancement is defined as:

$$I_{enh}(m,n) = 255(I_n^{drc}(m,n))^{E(m,n)} \quad (6)$$

where, $E(m,n)$ is given by:

$$E(m,n) = \left[\frac{I_{filt}(m,n)}{I(m,n)}\right]^S \quad (7)$$

$$I_{filt}(m,n) = I(m,n) * G(m,n) \quad (8)$$

δ Is an adaptive enhancement parameter related to the global standard deviation of the input intensity image, $I(m,n)$ and $*$ is the convolution operator, $I(m,n)$ is defined by:

$$S = \begin{cases} 3 & for\ \sigma \leq 7 \\ 1.5 & for\ 7 < \sigma \leq 20 \\ 1 & for\ \sigma \geq 20 \end{cases} \quad (9)$$

σ is the contrast-standard deviation of the original intensity image, if $\sigma < 7$, the image has poor contrast and the contrast of the image will be increased. If $\sigma \geq 20$, the image has sufficient contrast and the contrast will not be changed. Finally, the enhanced image can be obtained by linear color restoration based on chromatic information contained in the original image as:

$$S_j(x,y) = I_{enh}(x,y)\frac{I_j(x,y)}{I(x,y)}\lambda_j \quad (10)$$

C. Normalized Intensity Parameter

If μ_n be the normalized intensity parameter, then, for grey scale images, normalized intensity parameter can be evaluated as:

$$\mu_n = \begin{cases} \frac{\mu}{225} & for\ \mu < 154 \\ 1 - \frac{\mu}{225} & otherwise \end{cases} \quad (11)$$

Where μ is the mean brightness of the image. A region is considered to have adequate brightness for $0.4 \leq \mu \leq 0.6$ [13].

D. Normalized Contrast Parameter

The normalized contrast parameter (σ_n) can be given as:

$$\sigma_n = \begin{cases} \frac{\sigma}{225} & for\ \sigma < 154 \\ 1 - \frac{\sigma}{225} & otherwise \end{cases} \quad (12)$$

where σ is the standard deviation. A region is considered to have enough contrast when $0.25 \leq \sigma_n \leq 0.5$, for $\sigma_n < 0.25$ the region has poor contrast and for $\sigma_n > 0.5$, the region has too much contrast [10].

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E. Normalized Sharpness Parameter

Let S_n be normalized sharpness parameter given as:

$$S_n = \min(2.0, \frac{S}{100}) \tag{13}$$

When $S_n > 0.8$, the region has sufficient sharpness. Sharpness (S) is directly proportional to the high frequency content of an image and is given as,

$$S = \sqrt{\|h \otimes I\|^2} = \sqrt{\sum_{v_1=0}^{M_1-1} \sum_{v_2=0}^{M_2-1} \left|\hat{h}[v_1, v_2] \hat{I}[v_1, v_2]\right|} \tag{14}$$

where h is a high pass filter obtained from the inverse discrete Fourier transform (IDFT) and $\hat{h}$ is its direct Discrete Fourier Transform (DFT). $\hat{I}$ is the DFT of Image *I*. The role of $\hat{h}$ (or *h*) is to weight the energy at the high frequencies relative to the low frequencies, thereby, emphasizing the contribution of the high frequencies to *S*. The larger the value of *S*, greater is the sharpness of *I*.

Conversely,

$$h = IDFT\left(1 - \exp\left(-\frac{v_1^2 + v_2^2}{\alpha^2}\right)\right) \tag{15}$$

where v_1 and v_2 are the spatial parameters. Here, α is the attenuation parameter representing decaying of the impulse response of the Gaussian filter. A smaller value of α implies that fewer frequencies are attenuated and vice versa. The parameter I represents the given image.

F. Image Quality Factor

The parameters σ_n, μ_n and S_n are used for evaluating the image quality or quality factor (Q) defined as:

$$Q = 0.5\mu_n + \sigma_n + 0.1S_n \tag{16}$$

where the value of Q lies between 0 and 1. The quality of an image expresses the hidden details in the image.

V. Proposed Work and Methodology

In this paper, an attempt has been made to enhance the quality of the infrared images using the improved genetic algorithm so that they are better in visualization by the observer than the original images. The modified Continuous Genetic Algorithm is shown in figure 2 in the form of a flow chart. Following steps have been performed to achieve this objective.

A. Capture infrared Images

B. Initializing the population

In this paper, an initial population of 10 random DNAs was generated. We have used continuous genetic algorithm in which real coding is used to represent a solution. The advantage of GA with real values is that they are more consistent, precise and faster in execution as compared to binary representations. In our research, each random DNA consists of 10 genes defined by $r_{1a}, r_{1b}, r_{2a}, r_{2b}, r_{3a}, r_{3b}, r_{4a}, r_{4b}, \alpha, y$.

Here, l_1, l_2, l_3 and l_4 are the differences between the sub ranges. $r_{1a} - r_{1b}, r_{2a} - r_{2b}, r_{3a} - r_{3b}, r_{4a} - r_{4b}, \alpha, y$ respectively.l_1, l_2, l_3 and l_4 are random lengths generated between ranges 20 to 150.The sum of l_1, l_2, l_3 and l_4 should not exceed 255. Therefore, reduction factor is introduced with which the respective differences l_1, l_2, l_3 and l_4 are their multiplied. It is described as:

$$reduction\ \ factor = \frac{255}{\sum_{i=1}^{4} l_i} \tag{17}$$

The DNA is defined by parameters:

$r_{1a} = 0, r_{1b} = r_{1a} + l_1, r_{2a} = r_{1b} + 1, r_{2b} = r_{2a} + l_2, r_{3a} = r_{2b} + 1, r_{3b} = r_{3a} + l_3,$

$r_{4a} = r_{3b} + 1, r_{4b} = 255$

,one value of α is taken from -1 to 1 with an auto increment of 0.1 and y is taken from -10 to 10 with an auto increment of 0.1.

C. Enhancement Process Using the Respective DNA

Enhancement of the image for the individual DNA is carried out using the mathematical formulation given in equations (1-16).The equation (4) is applied as the DNA parameters .The output of the enhancement process is an enhanced content of the image.

D. Calculate Fitness Function

The images are resized to 510 * 510 pixels and sub-images of 50 * 50 pixels were constructed .The quality for each sub-image in calculation. In our research, it has been investigated that the following fitness function (image quality) is a good choice for an objective criterion.

$$Q_n = \frac{\sum p_i}{(M-1)} \tag{18}$$

where, M is the total sub-images in the image, $\sum p_i$ is the total number of sub-images in the image with $Q > 0.55$ and Q is defined by equation (16).

E. Sort the Fitness Function in Descending Order

The fitness function obtained for the population of DNAs is sorted in descending order.

F. Obtain DNAs Corresponding to Sorted Fitness Function

The DNAs corresponding to the sorted fitness functions are obtained and are now these represent the DNA population to be used in further steps. Here, the first DNA represents the best DNA corresponding to best parameter set as obtained by using the fitness function.

G. Enhancement Process to Display the Best Image Corresponding to DNA1

All the mathematical formulations used in step 3 are repeated and the output is displayed.

H. Mating

Mate the first DNA with one random DNA "m" selected from positions 2 to 10.

The $string_1$ obtained from DNA_1 is represented as:

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$$string_1 = [l_{1_1}, l_{2_1}, l_{3_1}, l_{4_1}, \alpha_1, y_1] \quad (19)$$

where $l_{1_1}, l_{2_1}, l_{3_1}$ and l_{4_1} are the differences between the sub-ranges and $string_2$ obtained from DNA$_2$ is represented as:

$$string_1 = [l_{1_m}, l_{2_m}, l_{3_m}, l_{4_m}, \alpha_m, y_m] \quad (20)$$

A random position for crossover between 1 and 5 is chosen. The DNAs are spliced and are represented as:

$$string_3 = [string_1(1:i), string_2(i+1:6)] \quad (21)$$

$$string_4 = [string_2(1:i), string_1(i+1:6)] \quad (22)$$

From $string_3$;

$l_1 = string_{3(1)}$, $l_2 = string_{3(2)}$), $l_3 = string_{3(3)}$), $l_4 = string_{3(4)}$,

$\alpha = string_{3(5)}$, $y = string_{3(6)}$

Equation (15) is used and after that the respective differences l_1, l_2, l_3 and l_4 are multiplied with it. The DNA is defined by parameters:

$r_{1a} = 0,$

$r_{1b} = r_{1a} + l_1, r_{2a} = r_{1b} + 1, r_{2b} = r_{2a} + l_2, r_{3a} = r_{2b} + 1, r_{3b} = r_{3a} + l_3, r_{4a}$
$= r_{3b} + 1, r_{4b} = 255$

, one value of α is taken from -1 to 1 with an auto increment of 0.1 and *y* is taken from -10 to 10 with an auto increment of 0.1. Thus offspring 1st is reconstructed from *string$_3$*. Similarly, offspring 2nd is reconstructed from *string$_4$*. Place the DNAs of the new off springs in place of DNA$_N$ and DNA$_{N-1}$

I. *Mutation*

Mutate a random DNA through position $N-1$ and N which contains the new offspring's DNA. The difference between the sub-ranges of the random DNA chosen is calculated to give the respective differences as:

$$l_1 = r_{1b} - r_{1a} \quad (23)$$

$$l_2 = r_{2b} - r_{2a} \quad (24)$$

$$l_3 = r_{3b} - r_{3a} \quad (25)$$

$$l_4 = r_{4b} - r_{4a} \quad (26)$$

The string is represented as:

$$string_5 = [l_1, l_2, l_3, l_4, \alpha, y] \quad (27)$$

Then a random gene from string$_5$ is selected and the change is introduced accordingly. The DNA is reconstructed using equation (17) by multiplying the respective differences l_1, l_2, l_3 and l_4 with it. The DNA is defined by parameters $r_{1a} = 0, r_{1b} = r_{1a} + l_1, r_{2a} = r_{1b} + 1,$

$r_{2b} = r_{2a} + l_2, r_{3a} = r_{2b} + 1,\ r_{3b} = r_{3a} + l_3,\ r_{4a} = r_{3b} + 1, r_{4b} = 255$

one value of α is taken from -1 to 1 with an auto increment of 0.1 and y is taken from -10 to 10 with an auto increment of 0.1.

J. *Go Step 3 and Repeat*

The algorithm stops after a predetermined number if iterations. The algorithm repeats itself by going to step 3 unless and until the predetermined number of iterations to enhance the content of image are not over. The investigations were carried out using two sets of natural images.

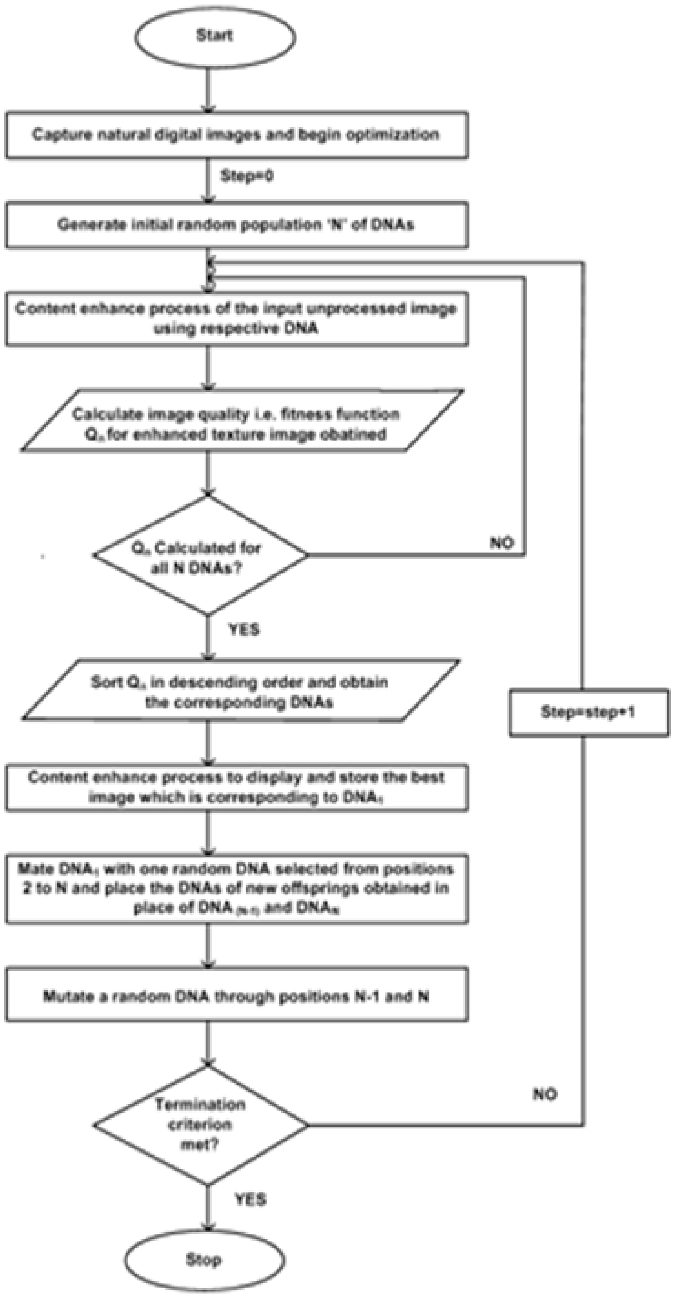

Fig. 1. Flowchart of genetic algorithm.

VI. EXPERIMENTS AND RESULT

The brightness of the image is very important. The original image is divided into various sub images and the brightness for each sub-image is calculated separately. The objective of this experiment is to calculate the mean brightness of the overall image as the iterations vary. The experiment is conducted on two sets, visible and infrared images of a single person.

The values of the mean brightness of the visible and infrared image are shown in table I and table II. The investigations are carried out for iteration numbers for the input images. Figure 3 and figure 5 shows the graphs of the mean brightness of visible and infrared images for different values of iteration numbers.

The mean brightness of the image becomes to stabilize after 200 iterations and there is hardly any change in the mean brightness of the image. Therefore, 200 iterations are chosen as the stopping criterion for the proposed algorithm to rule out any further destabilization in the brightness enhancement process.

1) Visible Image

a) Original visible image

b) Iteration no. 1

c) Iteration no. 2

d) Iteration no. 134

e) Iteration no. 142

f) Iteration no. 200

Fig. 2. Original visible image and images at successive iterations.

Table I. Effect of successive iterations on image brightness of visible image.

Iteration Number	Mean Brightness
1	0.000
2	0.118
134	0.435
142	0.436
200	0.469

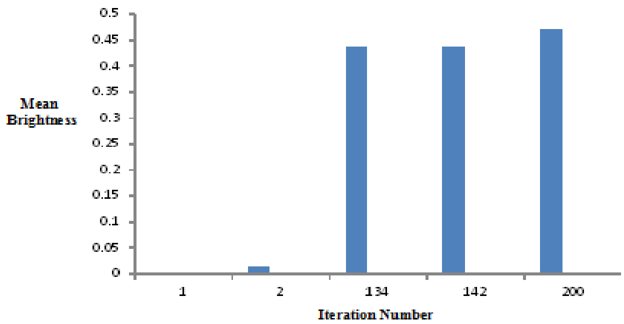

Fig. 3. Effect of successive iterations on brightness of visible image.

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From table I, figure 2 and figure 3 it can be observed that

- The mean brightness of the image increases with the successive iterations.
- The mean brightness of the image becomes to stabilize after 200 iterations and there is hardly any change in the mean brightness of the image after that.
- Therefore, 200 iterations are chosen as the stopping criterion for the proposed algorithm to rule out any further destabilization in the brightness enhancement process.

Infrared Image

a) Original infrared image

b) Iteration no. 1

c) Iteration no. 2

d) Iteration no. 100

e) Iteration no. 180

f) Iteration no. 200

Fig. 4. Original infrared image and images at successive iterations.

Table II. Effect of successive iterations on image brightness of infrared image.

Iteration Number	Mean Brightness
1	0.289
2	0.308
100	0.330
180	0.330
200	0.330

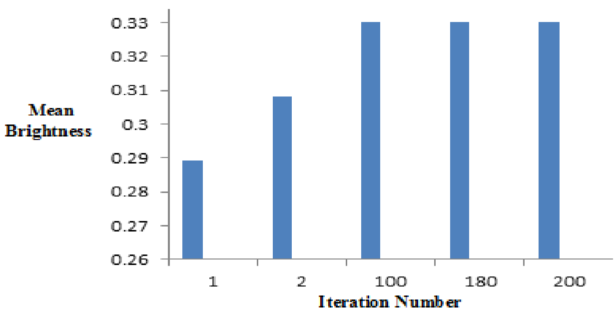

Fig. 5. Effect of successive iterations on brightness of infrared image.

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From table II, figure 4 and figure 5 it can be observed that

- The mean brightness of the image increases with the successive iterations.
- The mean brightness of the image becomes to stabilize after 200 iterations and there is hardly any change in the mean brightness of the image after that.
- Therefore, 1000 iterations are chosen as the stopping criterion for the proposed algorithm to rule out any further destabilization in the brightness enhancement process

VII. Conclusion

In this study, investigations were carried out to enhance the brightness of the visible and infrared images using Genetic Algorithm. It was observed that GA can be used as a very prominent unbiased optimization method. The method is automatic and robust. The investigation further showed that visible and infrared images were enhanced in brightness during the successive iterations.

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