Image Brightness Enhancement of Natural and Unnatural Images Using Continuous Genetic Algorithm

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Abstract: This paper discusses the image brightness enhancement of the natural and unnatural images using Continuous Genetic Algorithm. Image contents play a vital role in various images. 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 image got enhanced with the successive iterations as compared to the unprocessed input image.

Keywords: Digital Image Processing, DNA, Genetic Algorithm, Mutation, Enhancement.

I. INTRODUCTION

An image is a 2-D function f(x, y), where x and y are called spatial co-ordinates. Amplitude of f at any pair of coordinates is called intensity or gray level of image. When x, y and intensity value of f are finite and discrete, image is called digital image. Digital image processing refers to the process of processing digital image by means of a digital computer [1]. Image processing takes image as input, processes it and produces the output. The image can be defined as an array, or a matrix, square pixel arranged in rows and columns. Most image processing techniques involves treating the image as a two-dimensional signal and applying standard signal processing techniques to it. Image processing includes many techniques which are image segmentation, image recognition, image restoration image differencing and morphing, color corrections etc [2].

The field of digital image processing has experienced significant and continuous expansion in recent years. The application of this technology can be seen in many different disciplines. The various applications of image processing can be seen in medical applications, restorations and enhancements, image transmission and coding, color processing, remote sensing, robot vision, pattern recognition, multidimensional image processing, video processing, high resolution displays, high quality color representation etc [3][8]. Genetic algorithms are very powerful unbiased optimization techniques for sampling a large solution space. Because of unbiased sampling, they were quickly adapted in image processing. Genetic algorithms are applied for the feature extraction, image enhancement, segmentation, and classification as well as for the image generation [9][11]. Genetic algorithms (GAs) [12] are a relatively new paradigm for a search, based on principles of natural selection. This explains the increasing popularity of GAs applications in image processing [12] and other fields [13][14]. GAs were proven to be the most powerful optimization technique in a large solution space [15]. For the first time they have been introduced by John Holland in 1960s [16][17]. In this paper, the effect of continuous genetic algorithm on the enhancement of brightness of natural and unnatural images has been investigated. The details of genetic algorithm have been presented in the next Section. The continuous genetic algorithm is discussed in 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.

II. GENETIC ALGORITHM

Genetic algorithms are the heuristic search optimization techniques that mimic the process of natural evolution. GA performs efficient search in global spaces to get an optimal solution [10]. Genetic Algorithms (GAs) are basically the natural selection process invented by Charles Darwin [11]. The term Genetic Algorithm was used by John Holland for the first time [18]. Optimization is performed through natural exchange of genetic material between parents. Children are formed from parent genes. Fitness of children is evaluated. The fittest individuals are only allowed to survive. In computer world, genetic material is replaced by strings of bits and natural selection replaced by fitness function [9]. Genetic algorithms manipulate a population of potential solutions for the problem to be solved. Usually, each solution is
coded as a binary string that is equivalent to the genetic material of individuals in nature. Each solution is associated with a fitness value which is used to rank a particular solution against all other solutions [10]. The various Genetic algorithm uses operators such as selection, crossover and mutation to get the next generation which may contain chromosomes providing better fitness [19].Selection determines which solutions are to be preserved and allowed to reproduce and which are deserve to die out. There are different techniques to implement selection in genetic algorithms. They are Tournament selection, Roulette wheel selection, Rank selection, Steady-State Selection, etc [20]. The crossover operator is used to create new solutions from the existing solutions available in the mating pool after applying selection operator [10]. The most popular crossover selects any two solutions strings randomly from the mating pool and some portion of the strings is exchanged between the strings. A probability of crossover is also introduced in order to give freedom to an individual solution string to determine whether the solution would go for crossover or not. Another operation, called mutation, leads to the introduction of new features in to the solution strings of the population pool to maintain diversity in the population [21].

III. CONTINUOUS GENETIC ALGORITHM

For many applications, it is convenient to denote solutions as real numbers known as Continuous Genetic Algorithms (CCGA). CGAs have the advantage of requiring less storage and are faster than the binary counterparts. Continuous Genetic Algorithm is discussed as follows:

A. Components of Continuous Genetic Algorithm

The various components of the CGA [23]-[24] are shown in the Fig.1 in the form of a flow chart.

1) Cost Function: The goal of GAs is to solve an optimization problem defined of parameter involved. In CCA, the parameters are organized as a vector known as a chromosome. If the chromosome has $N_{var}$ variables ($N$ dimensional optimization problem) given by $p_1, p_2, p_3,..., p_{N_{var}}$, then the chromosome is written as an array with $1 \times N_{var}$ elements as [23].

\[
\text{chromosome} = [p_1, p_2, p_3, ..., p_{N_{var}}]
\]

In the case, the variable values are represented as floating numbers. Each chromosome has a cost found by evaluating the cost function at the variables $p_1, p_2, p_3, ..., p_{N_{var}}$.

\[
\text{Cost} = f(\text{chromosome}) = f(p_1, p_2, p_3, ..., p_{N_{var}})
\]

2) Initial Population: To begin the CGA process, an initial population of $N_{pop}$ must be defined, a matrix represents the population with each row begin a $1 \times N_{var}$ chromosome of continuous values [24]. Given an initial population of $N_{pop}$ chromosome the full matrix of $N_{pop} \times N_{var}$ random values are generated. All variable are normalized to have values between 0 and 1.

3) Pairing: A set of eligible chromosomes is randomly selected as parents to generate next generation. Each pair produces two offsprings that contain traits from each parent. The more similar the two parents, the more likely are the offspring to carry the traits of the parents.

4) Mating: As for the binary algorithm, two parents are chosen to produce offsprings, many different approaches have been tried for crossing over in continuous Gas. The simplest method is to mark a crossover points first, then parents exchange their elements between the marked crossover points in the chromosomes. Consider two parents as

\[
\text{parent}_1 = [p_{m1}, ..., p_{mN_{var}}]
\]
\[
\text{parent}_2 = [p_{d1}, ..., p_{dN_{var}}]
\]

Two offspring’s might be method be produced as:

\[
\text{offspring}_1 = [p_{m1}, p_{m2}, p_{d3}, p_{d4}, p_{m5}, ..., p_{mN_{var}}]
\]
\[
\text{offspring}_2 = [p_{d1}, p_{d2}, p_{m3}, p_{m4}, p_{d5}, p_{d6}, ..., p_{dN_{var}}]
\]
5) **Natural Selection:** The extreme case is selection $N_{var}$ points and randomly choosing which of the two parents will contribute its variable at each position. Thus one goes down the line of the chromosomes and, at each variable, randomly chooses whether or not to swap information between the two parents. This method is called uniform crossover [24].

6) **Mutation:** If care is not taken, the GA can converge too quickly into one region on the cost surface. If this area is in the region of the global minimum, there is no problem. However, some functions have many local minima. To avoid overly fast convergence, other areas on the cost surface must be explored by randomly introducing changes, or mutations, in some of the variables. Random numbers are used to select the row and columns of the variables that are to be mutated.
IV. MATHEMATICAL FORMULATION

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

A. Transformation Parameters Selection

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

$$I(m,n) = 0.2989r(m,n) + 0.587g(m,n) + 0.114b(m,n)$$  \hspace{1cm} (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:

$$I_n(m,n) = \frac{I(m,n)}{255}$$  \hspace{1cm} (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 sued which is based on the extraction of some information from the range histogram. $I_n$ is mapped to $I_n^{drc}$ using the following:

$$I_n^{drc} = \begin{cases} (I_n)^x + \alpha & 0 < x < 1 \\ (0.5 + 0.5I_n)^y + \alpha & x \geq 1 \end{cases}$$  \hspace{1cm} (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 as to make the content viewable for the observer.

The value of $X$ is given by:

$$x = \begin{cases} 0.2, \text{if } (f(r_1 + r_2) \geq f(r_1 + r_2)) \land (f(r_1) \geq f(r_2)) \\ 0.5, \text{if } (f(r_1 + r_2) \geq f(r_1 + r_2)) \land (f(r_1) \geq f(r_2)) \\ 3.0, \text{if } (f(r_1 + r_2) \geq f(r_1 + r_2)) \land (f(r_1) \geq f(r_2)) \\ 5.0, \text{if } (f(r_1 + r_2) \geq f(r_1 + r_2)) \land (f(r_1) \geq f(r_2)) \end{cases}$$  \hspace{1cm} (4)

where $f(r)$ refers to number of pixels between the range $(r)$, $f(a_1 + a_2) = f(a_1 + a_2)$ and $\land$ is the logical AND operator. $\alpha$ 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:

$$G(m,n) = K \exp \left[ \frac{-(m^2 + n^2)}{\sigma^2} \right]$$  \hspace{1cm} (5)

where $\sigma$ 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:

$$I_{emb}(m,n) = 255(I_n^{drc}(m,n))^{E(m,n)}$$  \hspace{1cm} (6)

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

$$E(m,n) = \left[ \frac{I_{filt}(m,n)}{I(m,n)} \right]^\delta$$  \hspace{1cm} (7)

$$I_{filt}(m,n) = I(m,n) \ast G(m,n)$$  \hspace{1cm} (8)

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

$$S = \begin{cases} 3 & \text{for } \sigma \leq 7 \\ 1.5 & \text{for } 7 < \sigma \leq 20 \\ 1 & \text{for } \sigma > 20 \end{cases}$$  \hspace{1cm} (9)

$\sigma$ 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
The modified 1 ≤ σ, the region has too much contrast [10].

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

$$\mu_n = \begin{cases} \frac{\mu}{225} & \text{for } \mu < 154 \\ 1 - \frac{\mu}{225} & \text{otherwise} \end{cases}$$

(11)

where μ is the mean brightness of the image. A region is considered to have adequate brightness for 0.4 ≤ μ ≤ 0.6 [10].

D. Normalized Contrast Parameter

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

$$\sigma_n = \begin{cases} \frac{\sigma}{225} & \text{for } \sigma < 154 \\ 1 - \frac{\sigma}{225} & \text{otherwise} \end{cases}$$

(12)

where σ is the standard deviation. A region is considered to have enough contrast when 0.25 ≤ σ_n ≤ 0.5 for σ_n < 0.25, the region has poor contrast and (σ_n > 0.5), the region has too much contrast [10].

E. Normalized Sharpness Parameter

Let S_n be normalized sharpness parameter given as:

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

(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,

$$S = \sqrt{\sum_{v_1=0}^{N_1-1} \sum_{v_2=0}^{N_2-1} |\hat{h}[v_1, v_2]|^2}$$

(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,

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

(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 Guassian 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:

$$Q = 0.5\mu_n + \sigma_n + 0.1S_n$$

(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 brightness of the natural and un-natural di 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 Fig.2 in the form of a flow chart. Following steps have been performed to achieve this objective.

A. Capture Natural Digital Images
   The natural were captured using 16.1 megapixel digital camera.

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:

$$\text{reduction factor} = \frac{255}{\sum_{i=1}^{4} l_i}$$  \hspace{1cm} (17)

The DNA is defined by parameters:

$$r_{1a} = 0, r_{1b} = r_{1a} + l_1, r_{2a} = r_{1b} + l_1, r_{2b} = r_{2a} + l_2, r_{3a} = r_{2b} + l_2, r_{3b} = r_{3a} + l_3, r_{4a} = r_{3b} + l_3, r_{4b} = 255$$

one value of $\alpha$ 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. Content Enhance process using the respective DNA
   Content 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 $r_{1a}, r_{1b}, r_{2a}, r_{2b}, r_{3a}, r_{3b}, r_{4a}, r_{4b}$. The output of the content enhancement process is an enhanced content of the image.

D. Calculate fitness function $Q_r$
   The natural digital images are resized to $510 \times 510$ pixels and sub-images of $50 \times 50$ 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.

$$Q_r = \frac{\sum_{i=1}^{M} p_i}{(M - 1)}$$ \hspace{1cm} (18)

where, $M$ is the total sub-images in the image, $\sum_{i=1}^{M} p_i$ 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 $Q_n$ 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. Content enhance process to display the best image corresponding to DNA $i$
   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 $s_1$ obtained from DNA $i$ is represented as:

$$\text{string}_1 = [l_1, l_2, l_3, l_4, \alpha, y]$$ \hspace{1cm} (19)

where $l_1, l_2, l_3$ and $l_4$ are the differences between the sub-ranges and string $s_2$ obtained from DNA $m$ is represented as:

$$\text{string}_2 = [l_{1m}, l_{2m}, l_{3m}, l_{4m}, \alpha, y]$$ \hspace{1cm} (20)

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

$$\text{string}_3 = [\text{string}_1(1:i), \text{string}_2(i+1:6)]$$ \hspace{1cm} (21)

$$\text{string}_4 = [\text{string}_2(1:i), \text{string}_1(i+1:6)]$$ \hspace{1cm} (22)
From $\text{string}_3$:

$$l_1 = \text{string}_3(1), \ l_2 = \text{string}_3(2), \ l_3 = \text{string}_3(3), \ l_4 = \text{string}_3(4), \ \alpha = \text{string}_3(5), \ y = \text{string}_3(6)$$

Equation (15) is used and after that the respective differences

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

one value of $\alpha$ 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 $\text{string}_3$. Similarly, offspring 2nd is reconstructed from $\text{string}_4$. Place the DNAs of the new offsprings in place of DNA$_N$ and DNA$_{N-1}$.

---

**Fig. 2 Flowchart of Content Enhancement of Natural Images using modified CGA**

1. **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:

   $$l_1 = r_{lb} - r_{ia}$$

   $$l_2 = r_{2b} - r_{2a}$$

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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. Therefore, the mean brightness for the overall image is calculated. The objective of this experiment is to calculate the mean brightness of the overall image and as the iterations vary.

The experiment is conducted on two sets, natural and unnatural (buildings) images. The values of the mean brightness of the overall image are shown in Table 1. The investigations are carried out for iteration numbers 1, 40, 100, 500, 700 and 1000 for the input images. Fig.3 and Fig.4 shows the various unprocessed input images and the corresponding processed enhanced brightness of the images at different values of iteration numbers 1, 40, 100, 500, 700 and 1000, respectively. Fig.5 shows the graphs of the mean brightness of input images for different values of iteration numbers 1, 40, 100, 500, 700 and 1000. The mean brightness of the image becomes to stabilize after 500 iterations and there is hardly any change in the mean brightness of the image. Therefore, 1000 iterations are chosen as the stopping criterion for the proposed algorithm to rule out any further destabilization in the brightness enhancement process.

The unprocessed input images are shown in row I in Fig.3 and Fig.4. The corresponding processed images for different iterations of CGA are shown in rows II-VI, respectively.
Fig. 3 Unprocessed input images and the corresponding processed enhanced brightness of the images at different iterations.
Fig. 4 Unprocessed input images and the corresponding processed enhanced brightenss of the images at different iterations

Table 1: Effect of Successive Iterations on the brightness of images.

<table>
<thead>
<tr>
<th>Iteration Number</th>
<th>Mean Brightness</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Image 1</td>
</tr>
<tr>
<td>1</td>
<td>0.010</td>
</tr>
<tr>
<td>40</td>
<td>0.020</td>
</tr>
<tr>
<td>100</td>
<td>0.030</td>
</tr>
<tr>
<td>500</td>
<td>0.050</td>
</tr>
<tr>
<td>700</td>
<td>0.050</td>
</tr>
<tr>
<td>1000</td>
<td>0.050</td>
</tr>
</tbody>
</table>

(a)
From Table 1, Fig.3, Fig.4 and Fig.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 500 iterations and there is hardly any change in the mean brightness of the image except for 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 natural and unnatural images using a modified objective criterion in Continuous 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 the processed natural and unnatural images were enhanced in brightness during the successive iterations. The details of the unprocessed images which were not visible before could be seen in the processed images by the observer.

REFERENCES