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Image Content Enhancement of Natural Images Using Genetic Algorithm

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Authors' contributions

This work was carried out in collaboration between all authors. All authors read and approved the final manuscript.

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ABSTRACT

Image contents play a vital role in various images. In this paper, genetic algorithm has been investigated for the content enhancement of the natural images. The algorithm was effective as the contents of the images became clear with the successive iterations. The algorithm was applied on the image for 1000 random DNAs with successive iterations. The analysis of the results showed that the contents of processed images were enhanced with the successive iterations with respect to the unprocessed input images. For comparison, the preliminary investigations were also carried out by comparing the results of enhancement of the images using GA and other techniques such as used in Photoshop. The analysis showed that for obtaining a comparable quality using other techniques such as Photoshop, a lot of manual adjustments of brightness, colour, and contrast are needed to get an enhanced image.

Keywords: Digital image processing; genetic algorithm; DNA; image quality; content enhancement.

1. INTRODUCTION

Digital image processing refers to the process of processing digital images by means of digital signal processing algorithms using a digital computer [1]. The image can be defined as an array, a matrix, or a square pixel arrangement in form of rows and columns. Image

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processing includes several techniques for the purpose of segmentation, recognition, restoration, differencing, morphing, color corrections, etc. [2]. The field of digital image processing has experienced significant and continuous expansion is the recent years and the application of it is visible in almost every discipline such as in medical, transmission and coding, remote sensing, robotic vision, pattern recognition, multidimensional image processing, video processing, high resolution displays, etc. [3-8]. Mostly among these applications, enhancement of the image as a whole or enhancement of its specific content is of utmost significance.

Enhancement is the technique to improve the interpretability or perception of information in images for human viewers. Enhancement technique for uniformly and non-uniformly illuminated dark images and wavelet based enhancement technique for uniformly and non-uniformly illuminated dark images which provides high color accuracy and good balance between the luminance and contrast in images to improve the visual representations of digital images have been developed and investigated for fusion of visual and thermal images [9,10]. Most of the enhancement techniques [11,12] require manual adjustments of the parameters to obtain satisfactory results. In some applications, automatic adjustment of the parameters is desired and Genetic Algorithms [13] are best suited for these types of applications.

The Content Based Image Retrieval (CBIR) technique uses image content to search and retrieve digital images and they were introduced to address the problems associated with the text based image retrieval. Content based image retrieval is a set of techniques for retrieving semantically relevant images from an image database based on automatically derived image features [14]. Content based image retrieval has several applications ranging from defense, satellites, fingerprinting, mug-shot-capturing, scientific experiments, biomedical imaging to home entertainment systems [15]. The main purpose of the image processing in content retrieval is to enhance the required details in the image.

Genetic algorithms, introduced by John Holland in 1960s [16,17], 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 [18,19].Genetic algorithms (GAs) 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 [20] and other fields [21,22].

In this paper, we have investigated the effect of genetic algorithm on the content enhancement of natural images. The details of genetic algorithm have been presented in the next section. The mathematical formulations used in the algorithm are presented in Section 3. The methodology adopted for the investigations is discussed in Section 4. The results are presented in Section 5.

2. GENETIC ALGORITHM

Genetic algorithms are the heuristic search optimization techniques that mimic the process of natural evolution. Genetic Algorithm (GA) performs efficient search in global spaces to get an optimal solution GAs are basically the natural selection process invented by Charles Darwin. Optimization is performed through natural exchange of genetic material between parents. Children are formed from parent genes. 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. GAs manipulates 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. The various GA uses operators such as selection, crossover and mutation to get the next generation which may contain chromosomes providing better fitness [23]. 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 [24]. The crossover operator is used to create new solutions from the existing solutions available in the mating pool after applying selection operator. The most popular crossover selects any two solution strings randomly from the mating pool and some portions of the strings are 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 [25].

A Genetic algorithm provides the systematic random search. Genetic Algorithms provide a generic and simple method to solve complex optimization problems. A genetic algorithm is a derivative-free and stochastic optimization method. A Genetic Algorithm needs less prior information about the problems to be solved than the conventional optimization schemes, such as the steepest descent method, which often requires the derivative of the objective functions [19,26]. Genetic Algorithms can be used as a very promising unbiased optimization method. It is constantly gaining popularity in image processing.

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

2.1 Continuous Genetic Algorithm

The various components of Continuous Genetic Algorithm are discussed as follows:

The various components of the CGA [27,28] are shown in the Fig. 1 in the form of a flow chart.

2.1.1 Cost function

The goal of GA is to find solutions to optimization and various search problems with various parameters involved. In CGA, the parameters are organized as a vector known as a chromosome. If the chromosome has N_{var} variables (N dimensional optimization problem) given by $p_1, p_2, p_3, ..., p_{N_{\mathrm{var}}}$, then the chromosome is written as an array with $1 \times N_{\mathrm{var}}$ elements as [28].

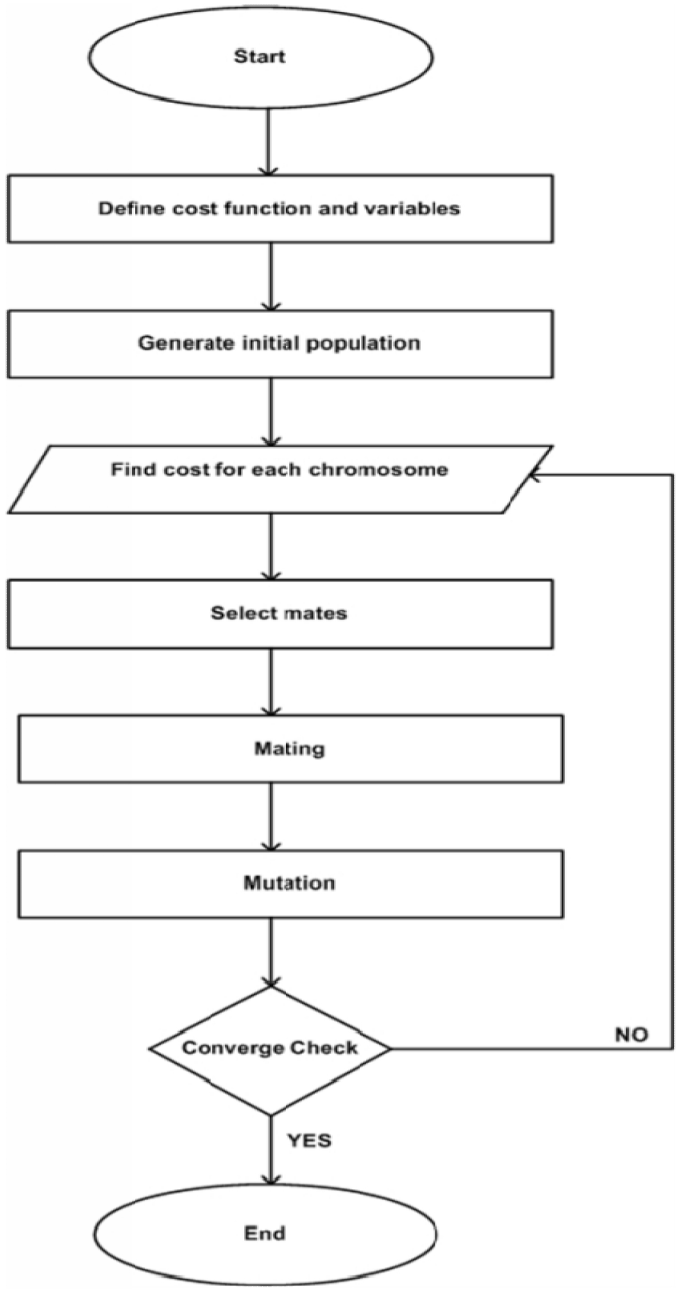


Fig. 1. Flowchart of CGA

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

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

$$Cost = f(chromosome) = f(p_1, p_2, p_3, ..., p_{N_{var}})$$

2.1.2 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 $1 \times N_{\mathrm{var}}$ chromosome of continuous values [28]. Given an initial population of N_{pop} chromosome the full matrix of $N_{pop} \times N_{\mathrm{var}}$ random values are generated. All variable are normalized to have values between 0 and 1.

2.1.3 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 offsprings to carry the traits of the parents.

2.1.4 Mating

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

$$parent_1 = [p_{m1}, \ldots\ldots, p_{mN_{\mathrm{var}}}]$$

$$parent_2 = [p_{d1}, \ldots\ldots, p_{mN_{\mathrm{var}}}]$$

Two offsprings might be method be produced as:

$$offspring_1 = [p_{m1}, p_{m2}, p_{d3}, p_{d4}, p_{m5}, p_{m6}, \ldots, p_{mN_{\mathrm{var}}}]$$

$$offspring_2 = [p_{d1}, p_{d2}, p_{m3}, p_{md4}, p_{d5}, p_{d6}, \ldots, p_{dN_{\mathrm{var}}}]$$

2.1.5 Natural selection

The extreme case is selection of 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 [28].

2.1.6 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 then 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.

3. MATHEMATICAL FORMULATION

Image enhancement technique is use to convert the original image into the better image. In this paper, GA has been used for content enhancement of the image. The aim is to enhance the content properties of original image for the better output. Content is the basic features of an image, which carry valuable information useful in image analysis. The mathematical framework for enhancing the content of the images and the selection parameters are defined in [13,29].

3.1 Transformation Parameters Selection

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

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

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 [30]. Assuming I to be 8-bits per pixel, I_n is the normalized version of I, such that:

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

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:

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

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:

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

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.

3.2 Surround and Color Restoration Parameter Selection

Many local enhancement methods rely on center/surround ratios [31].Gaussian has been investigated as the optimal surround function [32]. It has been investigated that Gaussian form produced good dynamic range compression over a range of space constants [33] [34].The Luminance information of surrounding pixels is obtained by using 2D discrete spatial convolution with a Gaussian Kernel, $G(m,n)$ defined as:

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

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:

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

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

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

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

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:

$$S = \begin{cases} 3 & for\ \sigma \le 7 \\ 1.5 & for\ 7 < \sigma \le 20 \\ 1 & for\ \sigma \ge 20 \end{cases} \tag{9}$$

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 $\sigma \ge 20$, 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:

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

3.3 Normalized Intensity Parameter

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

$$\mu_n = \begin{cases} \dfrac{\mu}{255} & \text{for } \mu < 154 \\ 1 - \dfrac{\mu}{255} & \text{otherwise} \end{cases} \tag{11}$$

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

3.4 Normalized Contrast Parameter

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

$$\sigma_n = \begin{cases} \dfrac{\sigma}{255} & \text{for } \sigma \le 64 \\ 1 - \dfrac{\sigma}{255} & \text{otherwise} \end{cases} \tag{12}$$

Where σ is the standard deviation. A region is considered to have enough contrast when $0.25 \le \sigma_n \le 0.5$, for $\sigma_n < 0.25$ the region has poor contrast and for $\sigma_n > 0.5$, the region has too much contrast [13].

3.5 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,

$$\mathrm{h} = \mathrm{IDFT}\left(1 - \exp\left(-\frac{\mathrm{v}_1^2 + \mathrm{v}_2^2}{\alpha^2}\right)\right) \tag{15}$$

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.

3.6 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.

4. METHODOLOGY

In this paper, investigations are carried out to enhance the contents of the natural digital images using a modified objective criterion in CGA. The modified CGA is shown in Fig. 2 in the form of a flow chart. The natural images were captured using 16.1 megapixel digital camera. In our research work, an initial population of 10 random DNAs was generated. We have used CGA 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 then 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. 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.

The natural digital images are resized to 510×510 pixels and sub-images of 50×50 pixels were constructed .The quality for each sub-image is calculated. 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). The fitness function obtained for the population of DNAs is sorted in descending order. The DNAs corresponding to the sorted fitness functions are obtained and a now these represent the DNA population to be used in further steps. DNA first represents the best DNA corresponding to best fitness function Q_1.

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

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:

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

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:

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

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

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

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

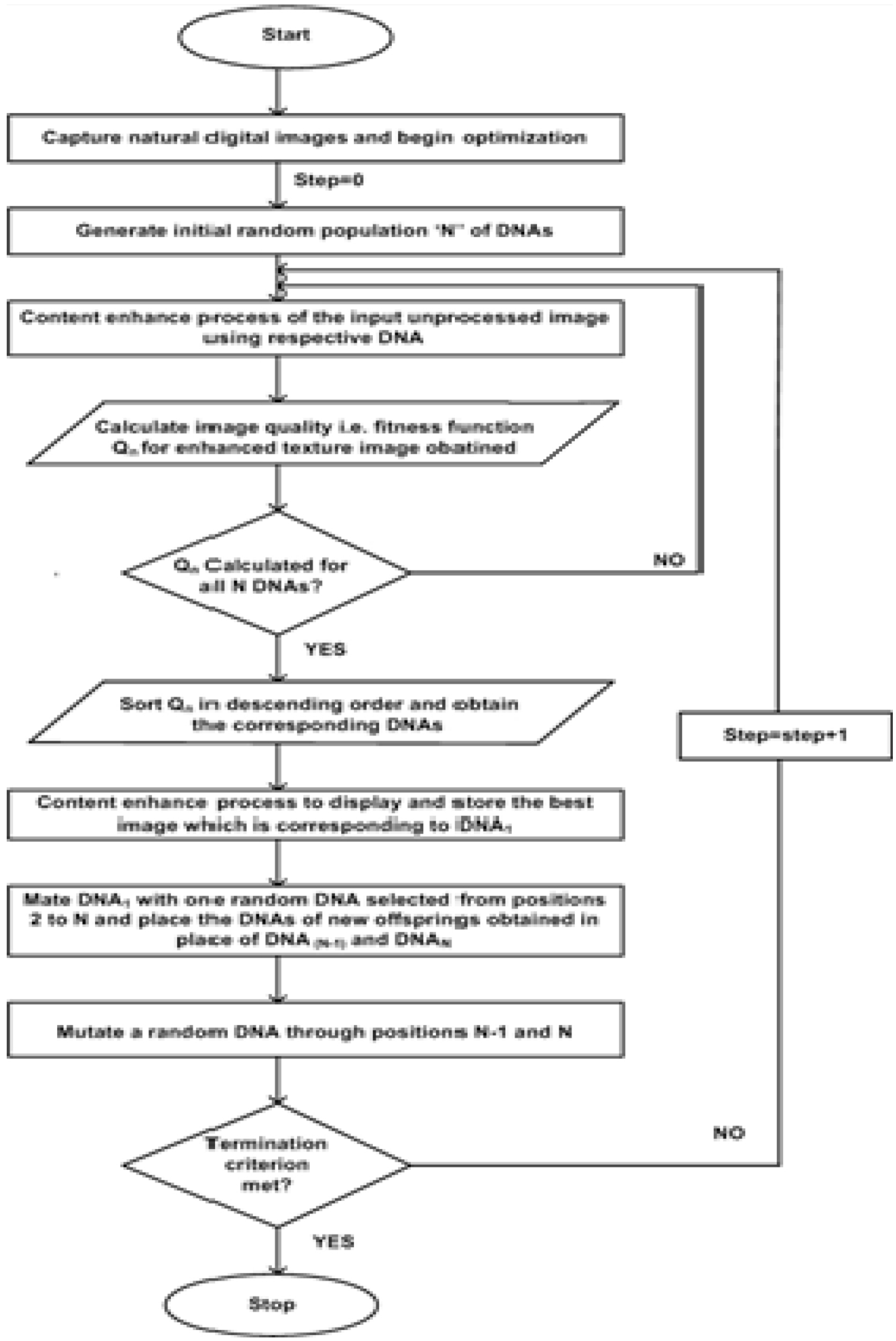


Fig. 2. Flowchart of content enhancement of natural images using modified CGA

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 offsprings in place of DNA_N and DNA_{N-1}. 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:

$$l_1 = r_{1b} - r_{1a} \tag{23}$$

$$l_2 = r_{2b} - r_{2a} \tag{24}$$

$$l_3 = r_{3b} - r_{3a} \tag{25}$$

$$l_4 = r_{4b} - r_{4a} \tag{26}$$

The string is represented as:

$$string_5 = [l_1, l_2, l_3, l_4, \alpha, y] \tag{27}$$

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. 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.

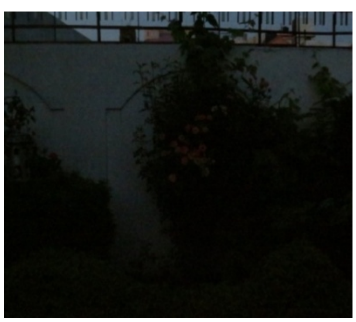
Both input images included various hidden content details which were not visible otherwise to the observer. The images in the two sets were processed as per modified CGA described in previous section.

Some of the processed images are shown in Fig. 3. The unprocessed input images are shown in row I. The corresponding processed images for different iterations of CGA are shown in rows II-IV, respectively.

For both set of input images, it was observed that that the results began to stabilize after 300 iterations. Therefore, 1000 iterations were chosen as the stopping criterion for the algorithm to rule out any further de-stabilization in the enhancement process.

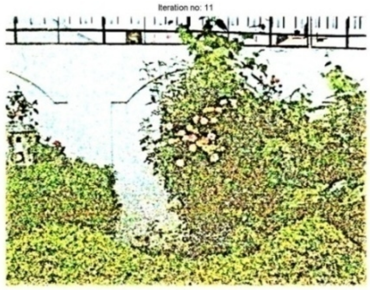
The visual analysis of the processed images with respect to the unprocessed input image 1(a) shows that the contents of the input image were enhanced at iteration numbers 11, 48 and 1000 of CGA. The left lower half and right half of the image show the details of the leaves which were not visible before. The values of the parameters of the DNA at iteration 11 are [0 89 90 116 117 171 172 255 0.2 1.8].The mean and standard deviation of the brightness parameter of the image at iteration 11 are 0.14 and 0.34 respectively. The mean and standard deviation of the contrast parameter of the image at iteration 11 are 0 and 0.09 respectively. The mean and standard deviation of the sharpness parameter of the image at iteration 11 are 0 and 2 respectively. The quality of enhanced image at iteration 11 is 0.14.The values of the respective parameters of the enhanced image at iteration 48 are [0 91 92 118 119 177 178 255 0.2 1.6 1.7 0.38 0 0.08 0 2 0.17].The values of the respective parameters of the enhanced image at iteration 1000 are [0 92 93 119 120 179 180 255 0.2 1.4 0.2 0.42 0 0.08 0 2 0.2].

Similarly, it was observed for the input image 2(a) that the contents of the input image were enhanced and the details of the image became visible at iteration numbers 28, 31 and 1000 for the modified CGA. The bricks which were behind the trees were also enhanced. Also the contents of the trunk of trees became visible. The lower right part of the image shows some grass in the image which was not visible in original input image. The values of the respective parameters of the enhanced image at iteration 28 are [0 58 59 114 115 188 189 255 -0.3 4.9 0.46 0.38 0 0.16 0 2 0.46].It is seen by the experimentation that the values of the respective parameters of the enhanced image at iteration 31 are [0 65 66 117 118 194 255 -0.3 5.1 0.48 0.38 0 0.16 0 2 0.48].The values of the respective parameters of the enhanced image at iteration 1000 are [0 85 86 135 136 201 202 255 -0.3 5.6 0.5 0.38 0 0.16 0 2 0.5].



1(a). Unprocessed input image 1

2(a). Unprocessed input image 2

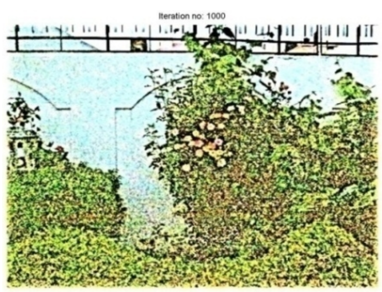


1(b). Enhanced content at iteration 11

2(b). Enhanced content at iteration 13

1(c). Enhanced content at iteration 148

2(c). Enhanced content at iteration 142



1(d). Enhanced content at iteration1000

2(d). Enhanced content at iteration 1000

Fig. 3. Unprocessed input images and the corresponding processed enhanced contents of the images at different iterations

For comparison, the preliminary investigations were also carried out by comparing the results of enhancement of the images using GA and other techniques such as used in Photoshop. The analysis showed that for obtaining a comparable quality using other techniques such as Photoshop, a lot of manual adjustments of brightness, colour, and contrast are needed to get an enhanced image.

5. CONCLUSION

In this study, investigations were carried out to enhance the content of the natural digital images using a modified objective criterion in CGA. 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 images were enhanced in content 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. The present investigations were carried out only with dark images. Although, our previous investigations confirmed its suitability for other images as well.Comparison of objective and subjective quality is on the plan of our future work.

COMPETING INTEREST

Authors have declared that no competing interests exist.

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