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Color Image Enhancement Using Steady State Genetic Algorithm

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Abstract— The purpose of this paper is to enhance the colored images using the enhancement developed steady state genetic algorithm, SSGA, with modified fitness function to get more accurate result and less noise. In this paper the Hue Saturation Intensity (HSV) color model will be used, after enhance the S, H and V components the transformation will be made to RGB color model. We have developed three models for enhancing the colorful and chromaity of the image with different types of input - output and different type of parameter. The models are compared based on their ability to train with lowest error values. To use these models the input RGB color image is converted to an intensity image using Space Variant Luminance Map SVLM.

Keywords- Image processing; color enhancement; steady state genetic algorithm; the hue saturation intensity; space variant luminance map.

I. INTRODUCTION

Noise in digital images has always been one of the most troubling dilemmas photographers to deal with. The main objective of image enhancement is to process the image so that the result is more suitable than the original image. Image enhancement very often deals with such improvement of image contrast as it is related to the sharpness of the details. In order to improve the visual quality of the input image captured in dynamic illumination environments, luminance and color information is characterized in terms of the spatial frequency.

Images enhancements mean adjusting the brightness, changing the tone of the color, sharpening the image and reducing noise. The process of editing or modifying the images is, in general, called Image Processing. Image Enhancement (IE) transforms images to provide better representation of the subtle details. It is an indispensable tool for researchers in a wide variety of fields including medical imaging, art studies, forensics and atmospheric sciences.

The Images enhancement method suitable for one problem might be inadequate for another. For example forensic images and videos employ techniques that resolve the problem of low resolution and motion blur while medical imaging benefits more from increased contrast and sharpness. Image enhancement methods may be categorized into two broad classes: transform domain methods and spatial domain methods [1].

The display of a color image depends upon three fundamental factors, namely its brightness, contrast, and colors. Interestingly, all the previous work have considered either the brightness (such as adjustment of dynamic ranges) or the contrast (such as image sharpening operations), and even in some cases a combination of both attributes. But none of these algorithms have considered the preservation of colors in the enhanced image.

II. RELATED WORKS

There were many researches on the image enhancement, histogram equalization like Han and Yang [2] proposed a novel 3-D color histogram equalization method.

Lee and Kang [3] presented a color image enhancement method that makes use of a space-variant luminance map (SVLM) for the local brightness characterization. Xu and Yu [4] introduced a new hybrid image enhancement approach driven by both global and local processes on luminance and chrominance components of the image. This approach, based on the parameter-controlled virtual histogram distribution method, can enhance simultaneously the overall contrast and the sharpness of an image where increased the visibility of specified portions and maintaining image color. But this method ignored the chromatic with the luminance components.

Wang and Tingzhi [5] have developed an Improved Adaptive Genetic Algorithm (IAGA) based on Simple Genetic Algorithm (SGA) and Adaptive Genetic Algorithm (AGA). Praveena and Vennila [6] designed new segmentation method that combined both K-means and genetic algorithm, they used the SGA simple genetic algorithm without any modification, they focused on colors model more than the modification of GA.

Mahia and Izabatene [7] merged the Radial Basis Function Neural Network (RBFNN) with Genetic Algorithm, their work developed and tested successfully. Payel and Melanie [8] designed a new method depended on the genetic algorithm, GA, they used thermography images of hands. They performed segmentation using several methods, Gabor wavelet method, Chan-Vese method and level set genetic algorithm, LSGA. The drawback of this research is the small population size N.

There are different color models used in the enhancement, some of them used the RGB. Naik and Murthy [9] applied their image enhancement method to each R, G, B component image of RGB color images, but they then transform to into HSV color images and enhancing only the V component image. Chang and Chiu [10] presented a colored enhancement scheme to virtually restore ancient Chinese paintings color conversion in the CIE XY color space, retrieved the original color of the paint paper by modifying colors based on their similarity to the background color.

III. THE PROPOSED MODEL

The proposed model consists of three phases which are: the preprocessing phase, the SSGA enhancement algorithm, and the testing phase.

A. *phase one: the prepocessing phase*

This phase will represent three conversions for the image, first the continues image will be converted to digital image, then it will be converted from RGB to HSI model, after SVLM will be calculated, then each component R, G and B will be enhanced through its algorithm as shown in Fig. 1. After that R', G' and B' will be restored.

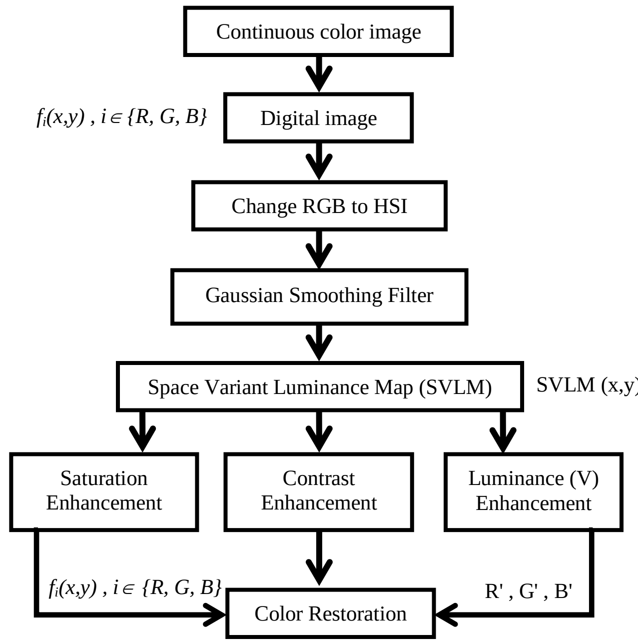


Figure 1. The phase 1 representation.

1) *Color transformation*

The transformation from RGB to HSV is described as shown in (1-3) [14].

$$S = \begin{cases} 0 & , if\ max = 0 \\ \frac{max - min}{max} \times 255 & , \quad otherwise \end{cases} \qquad (1)$$

$$V = max \times 255 \qquad (2)$$

$$H = \begin{cases} undefined & if\ max = min \\ 60 \times \frac{g-b}{max-min} + 0, & if\ max = r, g \geq b \\ 60 \times \frac{g-b}{max-min} + 360, & if\ max = r, g < b \\ 60 \times \frac{b-r}{max-min} + 120, & if\ max = g \\ 60 \times \frac{r-g}{max-min} + 240, & if\ max = b \end{cases} \qquad (3)$$

2) *Gaussian Smoothing Filter*

The Gaussian convolution of a luminance histogram HL(x) depends upon both x and σg, namely, the Gaussian standard deviation. The convolution function SHL(x, σg) is provided as follows [14]:

$$\begin{aligned} S_{HL}(x, \sigma_g) &= H_L(x) * g(x, \sigma_g) \\ &= \int_{-\infty}^{\infty} H_L(u)\ g(x - u, \sigma_g)\ du \qquad (4) \\ &= \int_{-\infty}^{\infty} H_L(u)\ \frac{1}{\sqrt{2\pi}\,\sigma_g}\ e^{\frac{-(x-u)^2}{2\sigma_g^2}}\ du \end{aligned}$$

3) Selection of Luminance Distributions

The Luminance Distributions level will be chosen in this level.

4) Space Variant Luminance Map (SVLM)

The input RGB color image is converted to an intensity image as shown in (5) [3].

$$I(x, y) = 0.299 \times R(x, y) + 0.587 \times G(x, y) + 0.114 \times B(x, y) \qquad (5)$$

Where R(x,y), G(x,y) and B(x,y) represent the Red, the Green and the Blue, respectively, for the pixel at location (x,y). I(x,y) represents the intensity (luminance) value of the each pixel of the intensity image.

The intensity image is low-pass filtered using a 2-D discrete Gaussian filter to estimate its luminance as expressed in (6) [3].

$$\mathrm{L}(x, y) = \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} \mathrm{I(x, y)Gaussian(x + m, y + n)} \quad (6)$$

Where L(x,y)represents the estimated illuminance value and the Gaussian(x,y) represents the 2-D Gaussian function with size m by n. The Gaussian(x,y) is defined as shown in (7) [3].

$$\mathrm{Gaussian}(x,y) = q.e^{\left(-\frac{(x^2+y^2)}{c^2}\right)} \quad (7)$$

5) *Luminance Enhancement*

The luminance enhancement has been proposed using the combination of the 2D exponential gamma correction fed by the SVLM. The enhancement of gamma correction on the image shown in Fig. 2.

(a) (b)

Figure 2. The performance comparison of Gamma correction. (a) The input image, (b) Conventional gamma correction ($\gamma = 0.5$) [11].

The pertinent local dependency obtained from the SVLM effectively enhance the luminance of the input image, combining the input intensity I(x,y) with the power factor of the SVLM. The 2D gamma correction can be expressed as shown in (8) [3].

$$O(x,y) = 255\left(\frac{I(x,y)}{255}\right)^{\gamma}, \gamma = \alpha^{\frac{128-SVLM(x,y)}{128}} \quad (8)$$

Using the enhanced luminance information above, we enhance the contrast .The visual quality improvement is accomplished using the SVLM(x,y) in the adaptive contrast enhancing process as show in (9)-(11) [3].

$$S(x,y) = 255\left[\frac{O(x,y)}{255}\right]^{E(x,y)} \quad (9)$$

Where:

$$E(x,y) = r(x,y)^{p} = \left[\frac{SVLM(x,y)}{O(x,y)}\right]^{P} \quad (10)$$

and the adaptive factor P is

$$P = \begin{cases} 2 & for\ \sigma \le 40 \\ -0.025\sigma + 3 & for\ 40 < \sigma \le 80 \\ 1 & for\ \sigma > 80 \end{cases} \quad (11)$$

In (10), r(x,y) is the ratio, and the P is an image-dependent parameter containing the standard deviation of an image to tune the contrast enhancing. The standard deviation is calculated from the I(x,y) indicating the contrast level of the input intensity image. The contrast enhancing process in (8)-(11) produces the output image pixels depending on their neighboring pixels.

The luminance of the dark regions becomes boosted and the luminance of the bright regions becomes attenuated. Therefore, the image contrast and fine details are effectively enhanced without degrading the image quality as shown in Fig. 3.

Figure 3. The image contrast enhancement effect.

6) *The saturation enhancement*

The best way to enhance the saturation contrast of a given image is to histogram equalize the saturation distribution of the image. However, the image resulting from applying saturation histogram equalization could be rather unnatural.

The color enhancement methods proposed by Rabin, Delon, and Gousseauare [12] implemented by saturating all the chromatic colors and then de-saturating them using the center of gravity law for color mixture. In Mukherjee method [13] mixing a fully saturated color with a neutral color (white) does not always yield a producible color and an extra gamut clipping process. The two steps mentioned below achieve the proposed color enhancement. Firstly, the enhancement procedure finds the most saturated color, which is producible while preserving the hue and the luminance. Secondly, the saturation ratio of color is defined and adjusted according to a specified saturation ratio transfer function.

a) *Step 1 : Finding the Most Saturated Color*

Saturating a color C = (x, y, Y) to S = (xs, ys, Ys) while preserving its hue can be expressed as shown in (12) [10].

$$\begin{pmatrix} xs \\ ys \end{pmatrix} = \begin{pmatrix} x \\ y \end{pmatrix} + k\begin{pmatrix} x-xw \\ y-yw \end{pmatrix} \quad (12)$$

The scalar k is termed the saturation gain here. It is generally accepted that as *k* increases, the saturation of the resultant color also increases. Since no luminance components are modified, Ys equals Y. The saturated color s is converted back to the RGB space through (13) [10].

$$\begin{pmatrix} R_S \\ G_S \\ B_S \end{pmatrix} = T^{-1}\begin{pmatrix} X_S \\ Y_S \\ Z_S \end{pmatrix} = T^{-1}\begin{pmatrix} X_S \\ Y \\ Z_S \end{pmatrix} = T^{-1}\frac{Y}{y_S}\begin{pmatrix} x_S \\ y_S \\ z_S \end{pmatrix} \quad (13)$$

Where T represents the conversion matrix from RGB to X Y Z and zs = 1 – xs - ys.

The dynamic range of the red, green, and blue channels of a given display is assumed to be constrained in [0, 1]. Consequently, given a color C, the most saturated color of the same hue and with the same luminance must satisfy (14) [10].

$$0 \le \begin{pmatrix} \mathrm{Rs} \\ \mathrm{Gs} \\ \mathrm{Bs} \end{pmatrix} = \mathrm{T}^{-1}\frac{\mathrm{Y}}{\mathrm{ys}}\left(\begin{pmatrix} \mathrm{x} \\ \mathrm{y} \\ \mathrm{z} \end{pmatrix} + \mathrm{k}\begin{pmatrix} \mathrm{x-xw} \\ \mathrm{y-yw} \\ \mathrm{z-zw} \end{pmatrix}\right) \quad (14)$$

Otherwise, this saturated color cannot be correctly produced on the display.

b) *Step 2 : Adjusting the Saturation Ratio*

Step 1 obtains the most saturated color S, which can be displayed without hue shift. Adapted from the definition of colorimetric purity, in Fig. 4, we define an argument called the saturation ratio of a color C as shown in (15).

$$r = \frac{\overline{CW}}{\overline{SW}} \tag{15}$$

Where W denotes the reference white of the display in the CIE xy diagram.

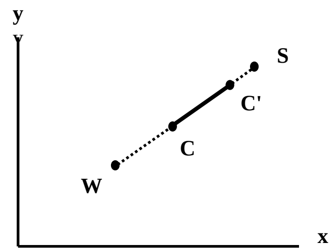


Figure 4. C and C' have the same hue and luminance. C is enhanced to C' with larger saturation ratio than C by using the color gamut constraint.

While the colorimetric purity of a color indicates the amount of white mixed with the spectral color, the saturation ratio represents the quantity of white mixed with the color which could be displayed on a given display device with the maximum saturation of its hue.

The saturation ratio of an achromatic color is close to zero. Mean while colors which are almost saturated have saturation ratios very close to one. Hence, the saturation of a color is altered by tuning its saturation ratio. By increasing the saturation ratio, the color becomes more saturated [16]. The adjustment over the saturation ratio r is somewhat arbitrary. However, reversing or changing the saturation relationship among pixels of a painting is undesirable.

For instance, after the saturation enhancement is applied, a pixel that is originally pale blue should not be more saturated than a pixel that is originally blue. A monotonically increasing saturation ratio transfer function is used to maintain the saturation relationship among image pixels. Besides, it is not advisable to saturate colors close to the reference white, since such achromatic colors belong to a region of hue ambiguity. Fig. 5 shows the suggested saturation transfer function.

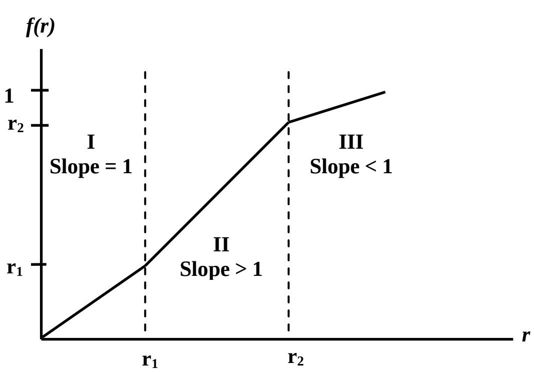


Figure 5. Possible choice of the saturation ratio transfer function for saturation enhancement.

For colors with small saturation ratio, below the threshold r1, the saturation remains unchanged owing to hue ambiguity at low saturation, the colors in the middle saturation region, with saturation ratio below r2, but larger than r1, are enhanced more than the colors with low or high saturation. Resorting to a certain saturation transfer function f(r), saturating a pixel C = (x, y, Y) with original saturation ratio r to C' = (x', y', Y) can be represented as shown in (16) [10].

$$\begin{pmatrix} x' \\ y' \end{pmatrix} = (1 - f(r))\begin{pmatrix} x_s \\ y_w \end{pmatrix} + f(r)\begin{pmatrix} x_s \\ y_s \end{pmatrix} \tag{16}$$

where (xs , ys) is the most saturated color from step 1. The proposed saturation enhancement can be easily controlled by f(r).

7) *Color transformation HSV to RGB*

This process covert the HSV TO RGB as shown in (17-21) [14].

$$hi = \left[\frac{H}{60}\right] mod\ 6 \tag{17}$$

$$p = v \times (1 - s) \tag{18}$$

$$\mathrm{f} = \frac{\mathrm{H}}{60} - \mathrm{q} = \mathrm{v} \times (1 - \mathrm{f} \times \mathrm{s}) \tag{19}$$

$$t = v \times (1 - (1 - f) \times s) \tag{20}$$

$$(r, g, b) = \begin{cases} (v, t, p), & if\ (h = 0) \\ (q, v, p), & if\ (h = 1) \\ (p, v, t), & if\ (h = 2) \\ (p, q, v), & if\ (h = 3) \\ (t, p, v), & if\ (h = 4) \\ (v, p, q), & if\ (h = 5) \end{cases} \tag{21}$$

B. *Phase two : The SSGA algorithm*

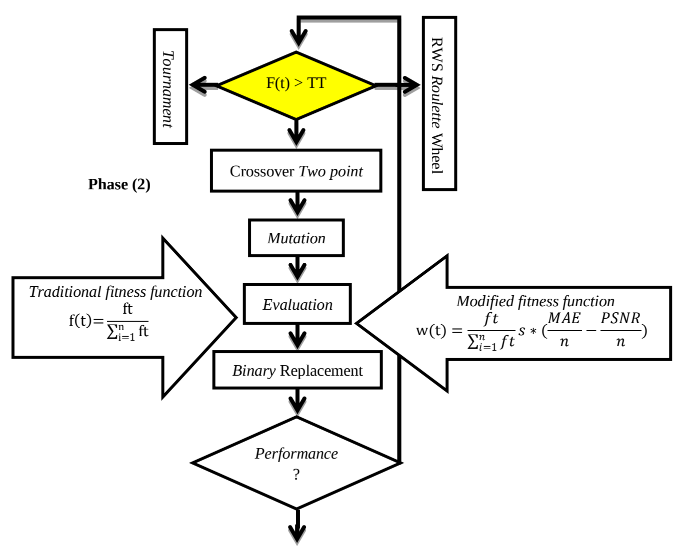


Figure 6. Phase (2) SSGA enhancement.

1) *The selection*

The selection strategy addresses on which of the chromosomes in the current generation will be used to reproduce offspring in hopes that next generation will have even higher fitness. The selection operator is carefully formulated to ensure that better members of the population (with higher fitness) have a greater probability of being selected for mating or mutate, but that worse members of the population still have a small probability of being selected, and this is important to ensure that the search process is global and does not simply converge to the nearest local optimum.

Different selection strategies have different methods of calculating selection probability. The differing selection techniques all develop solutions based on the principle of survival of the fittest. Fitter solutions are more likely to reproduce and pass on their genetic material to the next generation in the form of their offspring. Depended on the threshold value the model decided which selection we will used.

a) Tournament Selection

Tournament selection is probably the most popular selection method in genetic algorithm due to its efficiency and simple implementation In tournament selection, n individuals are selected randomly from the larger population, and the selected individuals compete against each other. The individual with the highest fitness wins and will be included as one of the next generation population. The number of individuals competing in each tournament is referred to as tournament size, commonly set to 2 (also called binary tournament).Tournament selection also gives a chance to all individuals to be selected and thus it preserves diversity, although keeping diversity may degrade the convergence speed. The tournament selection has several advantages which include efficient time complexity, especially if implemented in parallel, low susceptibility to takeover by dominant individuals, and no requirement for fitness scaling or sorting.

b) Proportional Roulette Wheel Selection

In proportional roulette wheel, individuals are selected with a probability that is directly proportional to their fitness values an individual's selection corresponds to a portion of a roulette wheel. The probabilities of selecting a parent can be seen as spinning a roulette wheel with the size of the segment for each parent being proportional to its fitness. Obviously, those with the largest fitness (i.e. largest segment sizes) have more probability of being chosen. The fittest individual occupies the largest segment, whereas the least fit have correspondingly smaller segment within the roulette wheel. The circumference of the roulette wheel is the sum of all fitness values of the individuals. The basic advantage of proportional roulette wheel selection is that it discards none of the individuals in the population and gives a chance to all of them to be selected. Therefore, diversity in the population is preserved. However, proportional roulette wheel selection has few major deficiencies. Outstanding individuals will introduce a bias in the beginning of the search that may cause a premature convergence and a loss of diversity.

For example, if an initial population contains one or two very fit but not the best individuals and the rest of the population are not good, then these fit individuals will quickly dominate the whole population and prevent the population from exploring other potentially better individuals. Such a strong domination causes a very high loss of genetic diversity which is definitely not advantageous for the optimization process.

2) The *crossover*

In this unit we apply the two point crossover, 2x.

3) *The mutation unit*

This makes random mutation. Mutation is a random changing of genes in chromosome. The process of changing genes is concerned in introducing certain diversity in the population. One of the strong points of mutation is producing new individuals different from the existing ones and to get more exploration in order to discover unknown situations in the search space.

4) *The evaluation unit*

The function of this unit is computed as follow: Apply the traditional fitness function that is used in simple genetic algorithm (SGA) as shown in (31).

$$\mathrm{f(t)} = \frac{ft}{\sum_{n=1}^{n} ft} \qquad (22)$$

1. Calculate **Mean absolute error (MAE**) as shown in (32).

$$\mathrm{MAE} = \frac{1}{MN}\sum \quad \sum F(i,j) - F(i,j) \qquad (23)$$

Where the F(i,j) is an image pixel repersentation with M,N diminsion.

2. Calculate **Peak Signal noise rate PSNR** as shown in (24).

$$\mathrm{PSNR}\ \log_{10}\left(\frac{255^2}{M}\right) \qquad (24)$$

3. Apply the suggested fitness function as shown in (25).

$$\mathrm{w(t)} = \frac{ft}{\sum_{i=1}^{n} ft} s * \left(\frac{MAE}{n} - \frac{PSNR}{n}\right) \qquad (25)$$

5) *Replacement unit*

Replacement is described as a deletion process performed on the worst individuals in order to be replaced by better new individuals. This unit applies Binary Tournament Replacement (BTR), BTR is intended for binary sets of chromosomes to replace them by the worst chromosome from previous generations which have been selected randomly. The following can be used to explain BTR [14]:

$$replace_n = \begin{cases} ind_i & if(f(ind_i) < f(ind_j)) \\ ind_j & otherwise \end{cases} \quad (26)$$
$$For\ n = \{1,2\}, random\ numbers\ i,j \in \{1,2,\dots\dots\dots, N_{pop}\}, i \neq j$$

Where:

$replace_n$: $individual\ n\ that\ will\ be\ replace$,

$f(ind_i)$: fitness of individual i,

$f(ind_j)$:fitness of individual j.

BTR sustains better individuals by performing replacement always with better individuals. Furthermore, the best individual will be never replaced. To enhance the probability and to sustain the best individuals, we can use other methods of replacements.

6) *The stopping condition*

We repeat the steps of SSGA until satisfy the performance condition.

On-line performance:

This method is a measurement of GA performance depending on individual fitness, the mathematical equation (27) [14] for online performance is as follows:

$$On - line\ (T) = \frac{1}{T}\sum_{t=1}^{T} F(T) \quad (27)$$

Where

T: number of times to find fitness,

F (t): binary evaluation for fitness values.

C. *Phase three : The testing phase*

After performing SSGA using modified or traditional fitness function, on the data from phase we ensure that image should satisfy the conditions of segmentation, then we compare the SSGA result with objective image. We need to ensure that the image has good segmentation rate and less noise. If the result identify the objective image then we will store the result in knowledge base, if it doesn't identify we may repeat the SSGA with different type of parameter, to perform better performance.

There are three basic approach for evaluating the effectiveness of a segmentation method: subjective evaluation, supervise devaluation, unsupervised evaluation, we used the supervised evaluation in our proposed model because the segmented image is compared against a manually-segmented or pre-processed reference image. We will use the Dice Similarity Coefficient (DSC) and the partial Hausdorff distance (H) for evaluating the performance of our algorithm. The Dice Similarity Coefficients DSC [17] provides a measure of the degree of overlap between two segmentations of the result image A and the objective image B.

$$\mathrm{DSC(A, B)} = \frac{2|A \cap B|}{(|A|+|B|)} \quad (28)$$

DSC of 1 indicates a perfect match and 0 indicates no match.

The partial Hausdorff [18] distance is derived between the boundary points of two contours. If A = {a1 , … , ap} and B = {b1 , … , bq} be finite sets of points on two images then the partial Hausdorff distance between them

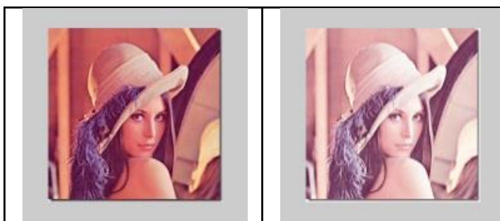
$$H(A,B) = \max\big(h(A,B), h(B,A)\big) \quad (29)$$

Where : $h(A,B) = \max_{a \in A} \min_{b \in B} \|a - b\|$

The function h(A,B) takes each point in A and finds the closest point in B from that point. It then ranks the points in A based on the distance values and finds the point with the greatest "mismatch". Thus, the partial Hausdorff distance is a measure of the distance of the two images.

IV. RESULTS

The image shown in Fig. 7(a), is used for testing our algorithm, this image had a poor contrast. The resulted image after executing the given algorithm (SSGA) is shown in Fig. 7(b). We can observe from the resultant image, that it has more contrast than the input image. This shows that our algorithm enhancing the image in contrast. The following figure show comparison between the input image and after the contrast enhancement using the histogram equalization.



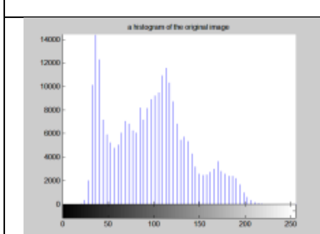
(a) (b)

Figure 7. The colored image enhancement.

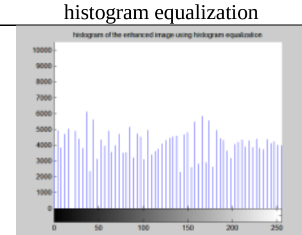
A. *Result related to histogram equalization*

(a)
Original image

(B)
contrast enhancement using histogram equalization



(C)
Original image histogram



(D)
Histogram after the contrast enhancement

Figure 8. Comparison between the input image and after the contrast enhancement.

One example of the histogram equalization is illustrated in Fig. 8(a) and 8(b), where the first image (a) is an original image and the second one (b) is the result of the histogram equalization. This result shows the high performance of the histogram equalization in enhancing the contrast of an image as a consequence of the dynamic range expansion, which can be easily understood by comparing the respective histograms of those images shown in Fig. 8(c) and 8(d). The original image has the high contrast, while the enhancement result of histogram equalization has the highest brightness.

Figure 9. Results on Lenna image. (a) Original Image (b) proposed method (SSGA) (c) S-type enhancement with n = 2 and m = 1.5, (d) histogram equalization (e) Yang et al.'s method in LHS system, and (f) Weeks et al.'s method.

Figs. 9 provide results of applying the proposed methods, Yang et al. [15] and Weeks et al.'s [16] methods on Luna. The results from Yang et al.'s method and our methods are comparable for Lenna. Note that the effect of clipping is not distinctly visible in these images. Our proposed method preserves the order of occurrence of intensity. It may also be stated that, visually, edges are not deleted in the enhanced versions of the artificial image, using the proposed histogram equalization method and the S-type function based scheme. Weeks et al. have applied normalization to bring back the out of bounds values to within the bounds. Effect of it can be seen that the image (d) in Fig. 9 is not as bright as the other images in the respective figures. Equalization of saturation sometimes degrades the quality of the image since it leads to very large saturation values that are not present in the natural scenes [19].

- Based on following, results calculate :-

A lower value for MSE means lesser error, and as seen from the inverse relation between the MSE and PSNR, this translates to a high value of PSNR. Logically, a higher value of PSNR is good because it means that the ratio of Signal to Noise is higher. Here, the 'signal' is the original image, and the 'noise' is the error in reconstruction. So, having a lower MSE (and a high PSNR), it is a better one. High PSNR means less noise in image and Low value of RMSE indicates good contrast. If RMSE approaches zero, it should be in very good contrast.

TABLE I. For Luna image.

No.	Enhancement Method	PSNR	MSE	RMSE
1.	proposed method	18.38	952.34	30.85
2.	S-type enhancement	17.94	1054.24	32.47
3.	histogram equalization	18.36	955.71	30.92
4.	Yang et al.'s method	18.63	898.65	29.98
5.	Weeks et al.'s method	17.33	1211.21	34.80

Where : Peak signal to signal noise ratio (PSNR), Mean squared error (MSE), Root Mean squared error (RMSE).

From Table I. Yang et al.'s method in LHS system has high PSNR value and Less value of MSE, i.e., low noise in image. Value of RMSE is also very less from all others, i.e., image is good in contrast. Our proposed method has high PSNR value and less value of MSE, value of RMSE is also very less from all the others, i.e., Luna image is good in contrast.

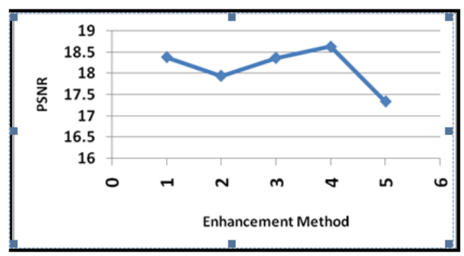


Figure 10. Graph showing PSNR for Luna image using different methods of enhancement.

Fig. 10 shows PSNR for five different methods of image enhancement. Five different points shows different techniques. In this PSNR is high for our proposed method (SSGA) for Luna image in comparison with the other methods.

Fig. 11 shows MSE for five different methods of image enhancement. Five different points shows different techniques. In this MSE is low for our proposed method (SSGA) for Luna image in comparison with the other methods.

Fig. 12 shows RMSE for five different methods of image enhancement. Five different points shows different techniques. In this RMSE is low for our proposed method (SSGA) for Luna image in comparison with the other methods.

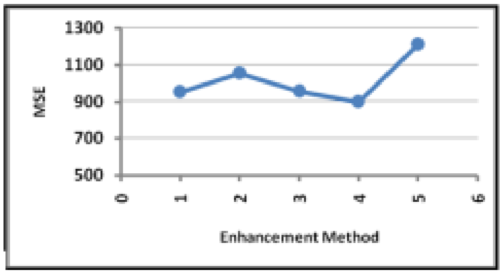


Figure 11. Graph showing MSE for Luna image using different methods of enhancement

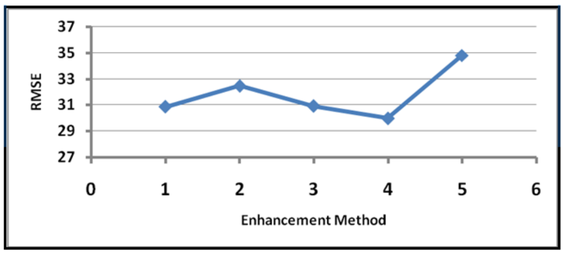


Figure 12. Graph showing RMSE for Luna image using different methods of enhancement

B. Comparison Of Performance Of SGA and SSGA for "Luna" Image.

In our model, the SSGA, the population size is 30, (default crossover probability) is 0.8, (default mutation probability) is 0.01, predetermined number of generations is 40. Natural evolution of the population continues until the predetermined number of generations is reached or the optimal threshold of each generation remains same for 10 generations. We introduce 4 measures: average computational time (Time), average optimal threshold (Threshold), average number of generations to obtain global optimal threshold (Generations), and the number of runs for which the GA gets stuck at a local optimum (Stuck), i.e., fail to locate the global optimal threshold. The images in the experiments are 256 color-level with the size of 256×256.

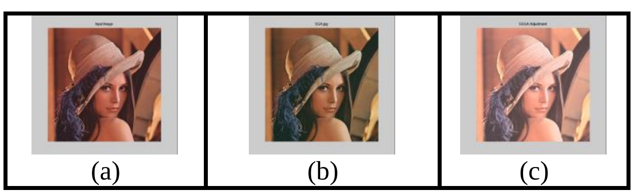


Figure 13. Color-level image of "Luna" : (a) original image; (b) SGA (average threshold = 122.06); (c) SSGA (average threshold = 124.2)

TABLE II. Comparison Of Performance Of SGA and SSGA for "Luna" Image

	Time	Threshold	Generations	Stuck
SGA	0.06549	122.06	10.15	15
SSGA	0.0655	124.2	10.42	1

We measured the performance of the SSGA segmentation relative to that of SGA. SGA produced the optimal threshold in 10~16% of the experimental runs while SSGA determined the optimal threshold in only 0~2% of the experimental runs using the same data.

V. Conclusion

We have developed a Steady State Genetic Algorithm (SSGA) based on Simple Genetic Algorithm (SGA) and Adaptive Genetic Algorithm (AGA). Though based on AGA, SSGA is not concerned with the evolution of a single individual, but instead is concerned with the evolution of the whole group. In SSGA, the settings of Pc and Pm are adjusted automatically depending on the evaluation.

The SSGA is applied to enhance a color-level image where Otsu method's [11] criterion is adapted to determine the optimal threshold. Experiments are conducted to evaluate the performance of SSGA and their results show that the SSGA yield better enhancement than the SGA.

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