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A Survey on Image Contrast Enhancement Using Genetic Algorithm

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Abstract- This paper reviews an introduction to various approaches to image contrast enhancement in the spatial domain using genetic algorithm and its extension based on population based incremental learning (PBIL). GA performs efficient search in global spaces to get an optimal solution. The algorithm does not require any prior knowledge about image in Order to select the appropriate enhancement function. GA is more effective in the contrast enhancement and produce image with natural contrast. Histogram equalization and similar methods for image contrast enhancement produce unnatural brightness. This paper introduces various approaches based on genetic algorithm to get image with good and natural contrast.

Index Terms- GA, PBIL, Contrast Enhancement.

I. Introduction

A genetic algorithm is a type of search algorithm that takes input and computes an output where multiple solutions might be taken. It is a mechanism based on natural selection and natural genetic. It works well in global search space. Genetic algorithm uses the principle of selection and evolution to produce solutions at each generation. In simple genetic algorithm the size of whole population is same [2]. It uses strings to represent a chromosome. Genetic algorithm works as – The initial population of solutions is created by a group of individuals randomly. These candidate solutions are called chromosomes. The individuals in the population are evaluated using a fitness function to measure the work of chromosome towards solving the problem. Two individuals are selected based on their fitness, the higher fitness, and the higher chance of being selected. Only fittest individuals are allowed to survive for next generation [1]. These individuals perform crossover to reproduce one or more offspring using crossover function. Some individuals are mutated randomly.

Basically genetic algorithm used in any study are characterised by parameters- population size, selection, crossover, type, crossover rate and mutation rate. The population size shows the number of chromosomes that are present in every generation. Selection is used to select the individuals for next generation. The crossover type is used to get a way to recombine information. Crossover is used to recombine two strings to get better string. The two strings that are involved in the crossover operation are known as parent string and resulting strings are known as child strings. Crossover operation is done by randomly selecting two strings for crossover operation. Many crossover operators exist in genetic algorithm. Single point crossover, a point of exchange is selected randomly in the two individual's genomes and swaps the content of chromosomes to produce an offspring's. Two point crossover, two crossover points are selected randomly and swaps the contents of chromosomes to produce an offspring's. Uniform crossover, the value at any given location in the offspring's is either the value of genome of one parent at that position or the value of genomes of the other parent at that position. Following exemplify the crossover process.

One point	Parent A	00100100**1**0000
Crossover	Parent B	11011011**0**1111
	Child A	0010010011111
	Child B	1101101100000
Two point	Parent A	00**1**00100**1**0000
Crossover	Parent B	11**0**11011**0**1111
	Child A	0000010000000
	Child B	1111101111111
Uniform	Parent A	0**010010010000**
Crossover	Parent B	1**101101101111**
	Child A	0101101101111
	Child B	1010010010000

The percentage of the time that crossover occurs when two chromosomes are selected to combine is known as crossover rate. Mutation rate is the probability of adding new information randomly. Mutation may be the chromosomes of individuals to be different from their parent individuals.

This paper is introducing various approaches for image contrast enhancement based on genetic algorithm. Contrast enhancement improves the quality of images for human viewer by increasing the dynamic range of input gray level. It has an important role in image processing. Various contrast enhancements techniques exist in literature like linear transformation in which the end points of the data distribution are pulled to the end points of the palette and all values in between are re-scaled accordingly. Histogram equalization attempts to assign the same number of pixels to each gray level in the output image. It produces unnatural image with extreme contrast. Local histogram equalization (LHE) method is the extension of HE that uses the transformation function of HE for the block and processes the image on block-by-block basis to modify its centre pixel. But it produces unacceptable and Unnatural image modification due to noise amplification.

Adaptive histogram equalization (AHE) works on small regions in the image known as sub images. The contrast of each sub image is enhanced by performing histogram equalization. Then they are combined by bilinear interpolation. Gray level grouping (GLG) [5], in the given input image the histogram components are categorized into some groups according to a certain parameter, then these groups are redistributed uniformly over the gray scales. Adaptive GLG (AGLG) is an extension of GLG, in that the input image is divided into sub images and then applied GLG method to each of these sub images.

The histogram matching (HM) [7] is another method for contrast enhancement. In this method, the contrast of the original image is enhanced by specifying the histogram of the desired image. This method requires user involvement to define desired histogram.

II. CONCEPT1- CHROMOSOME STRUCTURE BASED ON LUT TECHNIQUE

This approach was introduced for gray images with low contrast that are captured by a camera and image capturing system. In this approach a relation between input and output gray level is determined to convert an original gray image into an enhanced images with good contrast [3]. This relation is represented by a look up table (LUT). Here the number of gray levels is 256. Therefore the range of minimum input gray level is 0 and the maximum input gray level is 255 and the range of output gray level is the same.

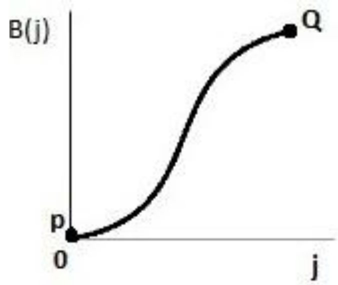

Figure 1: mapping Curve for enhanced image

In this method, a relation between input gray level and output gray level is determined using a genetic algorithm. The minimum gray level is converted to 0 and maximum gray level is converted to 255 to enhance the contrast of an image. In this case, each chromosome *k* is represented by a byte string that represents a relation between input gray level and output gray level. Where each byte represented the difference b(j-1) between values of transformed carve B(j) and B(j-1). Here j is a bit position form left edge of a chromosome [3].

B(j)=0 (j=0)

B(j)=B(j-1)+b(j-1) $(1 <= j <= I_{max} - I_{min})$ (1)

Evaluate the fitness of an individual by the sum of intensities of edges E(k) in an enhance image.

The intensity of an edge is calculated by Prewitt operator [4].

$$E(I) = \sum_x \sum_y \sqrt{\delta h_1(x,y)^2 + \delta V_1(x,y)^2}$$

$$\delta h_k(x,y) = g_k(x+1,y-1) + g_k(x+1,y) + g_k(x+1,y+1) - g_k(x-1,y-1) - g_k(x-1,y) - g_k(x-1,y+1)$$

$$\delta v_k(x,y) = g_k(x-1,y+1) + g_k(x,y+1) + g_k(x+1,y+1) - g_k(x-1,y-1) - g_k(x,y-1) - g_k(x+1,y-1)$$

C(k) is calculated using the sum of intensities of edge E(k).

$C(k)=E(k)+\eta L(k)$ (2)

Here η is a positive efficient. L(k) means difference between $I_2(k) - I_1(k)$ [3]. The fitness of the individual *k* is calculated by the following expression.

$F(k) = C(k)/C_0$ (3)

G is the number of individuals in the population. Only those individuals are selected that have higher fitness in the population and survived to the next generation. The individuals that have low fitness are discarded in the population because they do not have abilities to survive to next generation. Number of child individuals that are survived in next generation is same as the number of discarded individuals to keep the number of individuals constant in all generation. At the survived rate *S%* only G.S/100 individuals in all individuals are selected to survive to next generation. The number of discarded individuals are G(100-S)/100 [3]. Two parent individuals are selected randomly to generate the child individuals. The number of generated child individuals is G(100-S).

III. CONCEPT2- CHROMOSOME STRUCTURE BASED ON RANDOM SELECTION OF INTEGER'S

This concept [5] was introduced for those images that are suitable to use in application like consumer electronic products. In this concept a simple chromosome is a sorted array of random integer number. The size of chromosome is equal to the number of gray levels in the image.

To enhance the contrast of image, the first gray level is replaced with the value of first gray level of the enhanced chromosome and so on.

$T(G(k)) = C_i(k)$ K=1,2,3.......n (4)

Where T is the function. G is the sorted array of input gray level, k is the number of gray levels in the input image and C_i is the ith chromosome in the population. In this method the number of input gray level is calculated to generate initial population. After constructing initial population the fitness for all individuals is evaluated. If the number Of individuals is Ps then only Ps-Ps*Pc number of individuals are passed to next generation at crossover rate Pc. So the number of new generated individuals in each generation is Ps*Pc [5]. The number of edges and their overall intensities are used as fitness value as fitness value for each chromosome[3],

fitness(x)= log(log(E(I(X)))*n_edge(I(X)) (5)

where X is the chromosome and fitness(x) is the fitness value of X and I(X) is the enhanced image n_edge(I(X)) is the number of detected edges in the enhanced image [5]. The intensity of an edge is calculated by Sobel edge detector[6]s. E(I(X)) is calculated by the following expression [5],

$$E(I) = \sum_x \sum_y \sqrt{\delta h_1(x,y)^2 + \delta V_1(x,y)^2}$$

$$\delta h_I(x,y) = g_I(x+1,y-1) + 2g_I(x+1,y) + g_I(x+1,y+1) - g_I(x-1,y-1) - 2g_I(x+1,y) - g_I(x-1,y+1)$$

$$\delta V_I(x,y) = g_I(x-1,y+1) + 2g_I(x,y+1) + g_I(x+1,y+1) - g_I(x-1,y-1) - 2g_I(x,y-1) - g_I(x+1,y-1)$$

Here, log-log is used to prevent producing un-natural images [7].Roulette wheel selection is used for the selection of the individuals. Only *Ps*Pc* individuals are selected for generating the same number of individuals. Two point crossovers is used for generating the child individuals for the next generation. To perform crossover operation parent individuals are selected randomly if it is lower than some mutation constant then mutation operation will be performed.

IV. CONCEPT3- IMAGE ENHANCEMENT USING REAL CODED GENETIC ALGORITHM

This concept [7] was introduced for a new automatic image enhancement technique based on real coded genetic algorithm. Automatic enhancement is a method that enhanced image without human interaction. This method is based on local enhancement technique. Local enhancement methods apply transformation function that is based on the gray level distribution [7]. This method was applied on each pixel at location (x,y).

$$g(x,y) = \left(k.\frac{M}{\sigma(x,y)+b}\right).[F(x,y) - c.m(x,y)] + m(x,y)^{a}$$

0.5<k<1.5;

$$a\epsilon\Psi_1, b\epsilon\Psi_2, c\epsilon\Psi_3 \ with \Psi_1, \Psi_2, \Psi_3 \subset R_+ \quad (6)$$

Where M is the global mean of image and f(x,y) is the gray level intensity of input image pixel at location (x,y). g(x,y) is the pixel's output gray level intensity value at the same location. σ(x,y) and m(x,y) are standard deviation computed in a neighbourhood centred at (x,y) having n*n pixels [7]. In this method b≠0 that allows for zero standard deviation in the neighbourhood and c≠0 allows for original pixel gray level [7]. a,b,c and k are four parameters that is a string of four real genes are same for the entire image [8].

g(x,y)=T(f(x,y);a,b,c,k) (7)

Where T is the operation given in equation (6). A enhanced image with good contrast has a high number of edges and also has a high intensity of the edges. The number of edges and their intensity are not enough to define a valid fitness criteria. So they have found following fitness.

$$F(x) = \log\left(\log\left(E\left(I(x)\right)\right)\right).\frac{n_{edgels\,(I(x))}}{H_{size} * V_{size}}.H(I(x)) \quad (8)$$

In the above equation F(x) is the fitness function and x is the chromosome. I(x) is the original image I with the transformation T applied according to equation (1). H_size and V_size are the number of pixels presented in both direction of the image. H(I(x)) is a measure of the entropy in the image [7]. E(I(x)) is the intensity of edges detected by Sobel edge detector.

$$E(I) = \sum_x \sum_y \sqrt{\delta h_1(x,y)^2 + \delta V_1(x,y)^2}$$

$$\delta h_i(x,y) = g_i(x+1,y-1) + 2g_i(x+1,y) + g_i(x+1,y+1) - g_i(x-1,y-1) - 2g_i(x+1,y) - g_i(x-1,y+1)$$

$$\delta V_i(x,y) = g_i(x-1,y+1) + 2g_i(x,y+1) + g_i(x+1,y+1) - g_i(x-1,y-1) - 2g_i(x,y-1) - g_i(x+1,y-1)$$

A combination between binary tournament that has a constant and high selection pressure with a K elitist scheme is used for selection. Arithmetic crossover is used to produce the children. Arithmetic crossover is defined as

$$x_1^0 = ax_1^p + (1-a)x_2^p \quad (9)$$

$$x_2^0 = (1-a)x_1^p + ax_2^p \quad (10)$$

Where $x^p_{[1,2]}$ are parents and $x^0_{[1,2]}$ are offspring. **a** is a random number that is generated from a uniform distribution. PCA mutation is used as the mutation operator that has very good capabilities in maintaining higher levels of diversity in the population [7].

V. CONCEPT4- IMAGE-CONTRAST ENHANCEMENT BASED ON A COMPREHENSIVE APPROACH

This Concept [9] was introduced for a novel comprehensive approach to image contrast enhancement. This method has a general functional form that is able to map different transformation function and uses a learning technique to select the parameter values that are used in image processing- a) each pixel of the image has assigned local measures of spatial activity. b) Human visual response based function is used to determine local contrast value for each pixel. c) On the basis of spatial activity of the image obtained from the transformation, parameters of a comprehensive contrast enhancement function are selected using a GA.

There are N numbers of individuals in GA population $f_i(x,y)$ is a contrast transformation function with k_i parameter that is represented by a string of length **p** processing then k_n*p is sufficient to represent the parameter set of contrast transformation function. So $c + (k_n * p) * 3$ string length is used for the processing alternatives where **C** is the length of the function's code number [9]. The spatial activity classification is a primary task that is defined as the value of the sum of the differences of gray level intensities between adjacent pixels over a neighborhood. The measure of spatial activity SA_{xy} can be described by a masking function defined as [10].

$$SA_{XY} = \sum_{i=x-m}^{x+m} \sum_{j=y-n}^{y+n} w_{ij} \Delta B_{ij} \quad (11)$$

Where m and n are the dimensions of neighborhoods and ΔB_{ij} is the result of the edge operator on the location (i,j) and w_{ij} is the weight [9]. The constant value that is based on the Weber function [11] associated to the pixel(x,y) is defined as

$$C_{xy} = \frac{f(x,y) - I(x,y)}{I(x,y)} = \Delta I(x,y)/I(x,y)$$

$$I(x,y) = \sum_{i=x-p}^{x+p} \sum_{j=y-q}^{y+q} w_{ij}\, f(x-i, y-i) \quad (12)$$

Where p and q are the dimensions of the neighborhoods. I(x,y) is the average intensity of the neighborhoods and w_{ij} is the weight, four different function of the perceived constant curve for each region are observed- Constant, De Varies- Rose, Weber and Saturation [9].

To measure the fitness of each solution GA uses objective function that determined an optimal solution having the fitness values higher than a given threshold and representations condition for the iteration of the GA.

To analyze the local variations of the spatial activity in the image the original image is divided into small blocks [9]. The change of the average **SA** values are relative to same blocks can be calculated as

$$\Delta SA(i) = \left|\overline{SA(i)^a} - \overline{SA(i)^b}\right| \quad (13)$$

that represents the absolute variation of the average spatial activity in the **ith** range before $(SA(i)^b)$ and after $(SA(i)^a)$the processing [9].

The ideal spatial activity $I\Delta SA$ is defined as

$$F = w_1 F_1 + w_2 F_2 + W_3 F_3 \quad (14)$$

Where w_1, w_2 and w_3 are the number of pixels belonging to each spatial activity domain and

$$F_j = \sum_i (\Delta(SA(i) - I\Delta SA(i)) \quad (15)$$

for $i\epsilon SA$ class j, where j=1,2,3.

If F is less than 0, then the contribution of the second term of the sum, $w_2 F_2$ is low. So that the transformation function will heavily change the low and/or the high SA regions, that provides a large enhancement of the background. Higher value for F represents a greater enhancement of the image.

The GA fitness function is based on F so that the GA fitness function is represented by the weight product of the above term.

VI. Concept 5 - Population based incremental learning

As a GA works randomly. So it can be possible to lose the best solution due to random search. It also can be possible that the solutions are selected from the current population for recombination is best and if it is selected then the crossover and mutation operation will not lose some information of it. Its speed is very slow as compare to other search algorithm because it works globally. To avoid such problem of GA PBIL algorithm was introduced. It is the extension of GA. It is a combination of evolutionary optimization, the probabilistic incremental evolution algorithm and Bayesian optimization algorithm [12].

In PBIL algorithm population is generated from a single prototype vector of attributes to generate candidate solutions. Mutation and updates operation are performed using prototype vector. PBIL works in three phase- First is the number of samples that are generated using each probability vector before an update. Second is the number of steps for good solution. Third is the number of vectors to update.

A structure of prototype vector [12] is based on competitive learning in that activation of output unit is calculated by

$$output_i = \sum_j w_{ij} * input_j \quad (16)$$

Where w is the weight of connection between node i and j. Weight of the winning output is calculated by

$$\Delta w_{ij} = LR * (input_j - w_{ij}) \quad (17)$$

Replacement of the population of generation G from generation G-1 is computed by following formula

$$P(i,j) = P(x_i = j) = \frac{\sum_{V\epsilon\, Population_{G-1} V_i = j} Evaluate\ Vector(V)}{\sum_{V\epsilon\, Population_{G-1}} Evaluate\ Vector(V)} \quad (18)$$

Probability update operation can be performed using the update rule of competitive learning.

$$probability_i = (probability_i * (1.0 - LR)) + (LR * vector_i) \quad (19)$$

VII. Conclusion

In this paper we discussed about genetic algorithm based methods that measures the fitness of an individual by evaluating the intensity of spatial edges included in the image for image contrast enhancement. Chromosome structure based on LUT technique was introduced for those images contrast that are captured by a camera and image capturing system. Chromosome structure based on random selection of integer's technique is well suitable for those images that are used in area like consumer electronic products and other optical system. Automatic image enhancement using genetic algorithm method enhanced image automatically without human interaction. Comprehensive approach to image contrast enhancement does not require any prior knowledge of image to select the enhancement function. PBIL algorithm is the extension of GA. It was used to avoid the drawbacks of GA. It gives the result better than the above methods of contrast enhancement. If time is not constraint then PBIL gives better response as compare to GA.

In comparison to linear transformation and histogram equalization, genetic algorithm treats the image globally and produces image with natural contrast.

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