Dynamic Contrast Enhancement Algorithm

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ABSTRACT

This article describes a dynamic contrast enhancement technique to improve the visual quality of low contrast images. Also, this proposed algorithm is recovered the images from a blurred and darkness specimen of the given area of the images, and get better quality of the images. In this article, Image enhancement is performed using evolutionary algorithm (i.e. Genetic Algorithm). Here, a special type of sigmoid function is used for contrast enhancement. For the best match of this transformation function, genetic algorithm (GA) finds the optimum parameter value of the functions for image enhancement. Experimental result shows that the proposed method gives the better result in comparison to other conventional techniques.

General Terms:

1st General Term, 2nd General Term

Keywords:

Image Enhancement, Genetic algorithm, Contrast Stretching, Sigmoid Function.

1. INTRODUCTION

Image enhancement is used to improve the quality of an image for visual perception of human beings. The main technique for image enhancement is contrast stretching, slicing, histogram equalization etc [2]. For image enhancement, one needs to improve the visual quality of an image without distorting it. Several algorithms are available for contrast enhancement in gray scale images, which change the gray values of pixels depending on the criteria for enhancement.

Contrast enhancement is one of the most important problems in image processing both digital and analog. In several cases the image acquired in severe conditions are too dark and blur and therefore difficult to recognize the different objects or scenery contained in the image. Therefore image enhancement algorithms are applied to improve the appearance of an image for human visual analysis or occasionally for subsequent machine analysis. The image enhancement methodology depends on the application context; criteria for enhancement are often subjective or too complex to be easily converted to useful tools. However, it is well known that a global image enhancement method for all classes of imagery is missing.

Classical techniques [2][4][5][6][7] for digital image contrast enhancement are usually based on the analysis of the histogram, and known as point-operation global methods. In the global histogram equalization based methods, various constraints are added to the equalization procedure to achieve better performance. Moreover the mean brightness of the image is not preserved. The global techniques completely fail when the original image is already occupying the full dynamic range, or when the contrast is varying in different parts of the image. Linear stretching of the brightness in monochrome images are the standard methods to cover the available dynamic-range. Nonlinear functions like the exponential and logarithmic can also be used to preferentially stretch the contrast in bright and dark regions respectively. Adaptive histogram equalization techniques [10][11]use statistical information in the neighborhood of each pixel to perform equalization. The major problem with adaptive histogram equalization methods is the over-enhancement effect, creating objects that were not visible in the original image. The enhanced image often does not look natural and is disturbing [9][10][12].

In this article, we propose a contrast enhancement algorithm in spatial domain. The basic idea of this approach is to enhance automatically the optical quality of low contrast images. This is achieved by using transformation mapping function and genetic algorithm. Actually, Genetic Algorithm finds the optimum parameter value of the functions for image enhancement. When the global contrast of an image is degraded, the contrast enhancement is achieved using a suitable transformation function. The proposed algorithm performs global transformation of the original image, increasing the contrast only in the low-quality regions.

The structure of the paper is as follows: in section 2 the proposed method is described. Section 3 describes the concept of Genetic Algorithms. The experimental results applying on real images are presented and discussed in section 4. Finally, the paper is concluded in section 5.

2. PROPOSED METHOD FOR CONTRAST ENHANCEMENT

Contrast stretching, slicing, histogram equalization and some other enhancement are necessary for a specific application, more specifically, to improve the visual judgment of the picture. But all the above techniques for image enhancement are problem dependent. Basically, each linear and nonlinear functions work in different ways and their effectiveness are very much problem dependent or image dependent. Contrast enhancement is usually applied to input images to obtain a superior visual representation of the image by transforming original pixel values using a transform function of the form

$$g(x, y) = T[f(x, y)], \tag{1}$$

where g(x,y) and f(x,y) are the output and input pixel values at pixel position (x,y) respectively. Usually for correct enhancement, it is desirable to impose certain restrictions on the transformation function T in the form of:

(a) the nature of the function which should be monotonically increasing and

(b) the output range of T which should be congruent with the input to the function [4]. It is usual to find the function T producing an output in the range [0,1].

The first condition negates gray value reversal in the output image so that pixels having smaller values in the original image continue to be smaller in respect of higher valued pixels. The second condition ensures that the output image is scaled to the same domain as the input image. Numerous functions have been proposed to perform contrast enhancement including the exceedingly common techniques of histogram equalization, piecewise contrast stretching, specific range contrast stretching etc. In the proposed algorithm, a variation of the sigmoid function is used as the transformation function. Choice is influenced by the mathematical consistency of the sigmoid function [3] and also the simplicity of implementing the sigmoid function in practice. Sigmoid function is a continuous nonlinear activation function. The name, sigmoid, obtained from the fact that the function is "S" shaped. Statisticians call this function the logistic function, Using f (x) for input, and with a as a gain term, the sigmoid function is:

$$f(x) = \frac{1}{1+e^{-ax}} \tag{2}$$

The sigmoid function has the characteristics that it is a smooth continuous function, the function outputs within the range 0 to 1, mathematically the function is easy to deal with; it goes up smoothly. Our algorithm uses a modified form of the sigmoid function given by

$$\Phi(x,y) = \Theta(x,y) + \frac{\zeta}{\lambda + \beta^{-\Theta(x,y)}} \tag{3}$$

Where $\Phi(x, y)$ is the output image, $\Theta(x, y)$ is the input image and ζ is the degree of contrast enhancement and λ is parameter. It is easy to observe that in the limiting case the transformation tends to the binarization of gray scale images. For effective contrast enhancement the output image should ideally span the entire available gray scale and also have equal distribution of pixels over all the gray scale. These conditions are often satisfied mathematically but cannot be essentially satisfied for discrete images. Suitable choice of ζ and λ in the previous equation so as to produce an output image as close as possible to the optimal distribution without distorting the image in any appreciable manner or introducing artifacts. The mentioned algorithm has used genetic algorithm for determining the optimal value of the parameters ζ and λ. $\Psi(x, y)$ is the range of the gray values present in the output image after application of the transformation equation:

$$\Psi(x,y) = |max(f(x,y) - min(f(x,y)|_{x=0,1,..,M-1,y=0,1,..N-1} \tag{4}$$

3. GENETIC ALGORITHM

Genetic algorithms are adaptive and robust computational procedure modeled on the mechanics of natural genetic systems. GAs act as a biological metaphor and try to emulate some of the process observed in natural evaluation. They are viewed as randomized search and optimization techniques. They express their ability by efficiently exploiting the historical information to speculate on new offspring with expected improved performance. GAs is executed iteratively on a set of coded solutions, called population, with three basic operators: selection/reproduction, crossover and mutation. Genetic algorithms generate a sequence of population by using a selection mechanism, and use crossover and mutation as search mechanism [1][8].

3.1 Simple GA

Essential to the SGA's working is a population of binary strings. Each string of 0s and 1s is the encoded version of a solution to the optimization problem. Using genetic operators, crossover and mutation, the algorithm creates the subsequent generation from the strings of the current population. This generational cycle is repeated until a desired termination criterion is reached (e.g., a predefined number of generations are processed or a predefined optimized value is being reached) summarizes the working of SGA. The main components of SGA are given bellow.

1. population of binary strings
2. fitness function
3. selection mechanism
4. genetic operators
5. mechanism to encode the solutions as binary strings.

Population-To solve an optimization problem, GA starts with the chromosome (structural) representation of the parameter con. This parameter is to be coded as a finite length string over an alphabet of finite length. Usually, the chromosomes are strings of 0's and 1's. Each chromosome actually refers to a coded solution. A set of such chromosomes in a generation is called a population. The size of the population may vary from one generation to another or it can be kept constant. The initial population is chosen randomly.
Fitness function- The objective function, the function to be optimized, provides the mechanism for evaluating the fitness value of each string. It is chosen in a way such that highly fitted strings have high fitness values. It is the only index for selecting the chromosomes to reproduce for the next generation. In this proposed algorithm, the fitness function is used :

$$\Psi(x,y) = |max(f(x,y)) - min(f(x,y))|_{x=0,1,..,M-1,y=0,1,..N-1} \tag{5}$$

where max(f(x,y)) and min(f(x,y) is the maximum and minimum intensity values. It actually signifies the upper and lower intensities of the histogram thereby representing by how much the histogram stretches. Higher the value of Ψ fitter is the chromosome.
Selection Mechanism-Selection mechanism models nature's survival-of the fittest mechanism. Fittest solutions survive while weaker ones perish. Selection procedure copies individual strings (called, parent chromosome) into a tentative new population (known as mating pool) for genetic operations. Roulette wheel parent selection and linear normalization selection are the most frequently used selection procedures. We have used the Roulette wheel selection scheme, each string is allocated a sector of a roulette wheel with the angle subtended by the sector at the center of the wheel equal to $2\pi fi/f$, where *fi* is the fitness value of the ith string and f is the average fitness value of the population. Genetic Operators- Genetic operators are applied on parent chromosome and new chromosomes are generated. Frequently used genetic operators are discussed below.
Crossover- The main purpose of crossover is to exchange information between randomly selected parent chromosomes with the aim of not losing any important information. Here in the first step, pairs of strings (known as mating pair) are picked at random by selection procedure from the population. The second step determines, on the basis of the crossover probability, whether this pair of chromosome should go for crossover or not. Interchange of chromosome segments between mating pairs is done in the last step. Some commonly used crossover techniques are one point crossover, two point crossovers and multi point crossover. We illustrate here one point crossover. In this crossover technique position k is selected at random between 1 and *l*-1, where *l* is the string length. Two new strings are created by swapping all characters from position (k+1) to *l*.

For an example, two chromosomes a and b are considered as:

a=1100010101010000111110001
b=1000101110111010011010100
be two parent strings selected for the crossover operation and the random number generated be 11(eleven). Then new produced offspring will be

a_1=1100010101011010011010100
b_1=1000101110110000111110001

Mutation- After crossover, strings are subjected to do mutation. Mutation of a bit involves flipping it: changing from 0 to1 or vice versa. Just as crossover probability controls the crossover, here in mutation another control parameter, mutation probability controls mutation. A random number position of a random string is being selected and mutation flips that bit. Let, 1100010101010000111110001 be a string to perform mutation and 3rd bit of the string is selected for mutation. Then the transformed string after mutation will be 1110010101010000111110001. The main aim of mutation is to introduce genetic diversity into the population. Sometimes it helps to regain the information lost in earlier generations.

4. EXPERIMENTAL RESULTS

The efficiency of the proposed algorithm is evaluated by conducting experiments on seven standard images, namely, Balloon, Barbara, Cameraman, Donald, House, Lena, and Couple. Figure 1 shows output results for some low contrast images. Table1 and Table 2 clearly shows that the proposed algorithm gives better RMSE and PSNR value than the histogram equalization. The assumptions used for the implementation of the proposed algorithm are given as follows. The value of the parameter con, that is size of the population, P, is taken as 30, crossover rate, μ_c, as 0.9 and mutation rate, μ_m, as 0.01. The algorithm uses number of iterations as the terminating condition and it is set to 30. The maximum intensity level for each picture element in the image is taken as 255. The Quality of the image measured in terms of RMSE and PSNR. The RMSE and PSNR may be defined, respectively, as

$$RMSE = \sqrt{\frac{1}{MN}\sum_{x=1}^{M}\sum_{y=1}^{N}[f(x,y) - f'(x,y)]^2} \qquad (6)$$

$$PSNR = 20\log\frac{255}{MN} \qquad (7)$$

Where M: number of row, N: number of column,$f(x,y)$: original image matrix and $f'(x,y)$: output image.

5. CONCLUSIONS

Dark and blurred images are very common outputs vast range of imaging application e.g. medical imaging , GIS, low light photography etc . This paper presents a new algorithm for enhancing the visual quality of such images without distorting the contrast balance and introducing artifacts which is simple to implement on a wide variety of images.

6. REFERENCES

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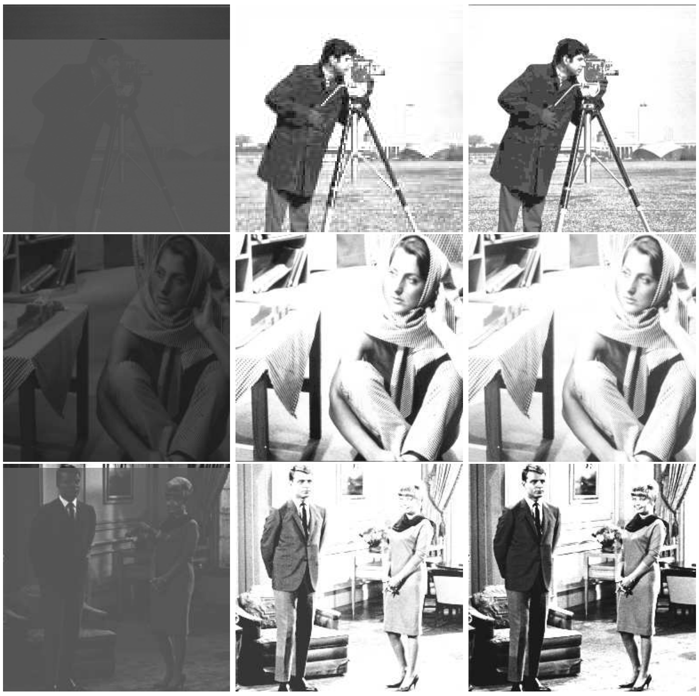

(a) (b) (c)

Fig. 1. (a) Original image (b) Output image using Histogram equalization (c)Output image using Proposed algorithm .

Table 1. RMSE VALUES COMPARISON FOR NATURAL IMAGES

Image	Balloon	Barbara	Cameraman	Donald	House	Lena	Couple
Original image	0.3690	0.4064	0.4245	0.2560	0.4627	0.3228	0.3765
Histogram equalization	0.3392	0.3446	0.3846	0.2660	0.4191	0.3520	0.3447
Proposed method	0.2607	0.2937	0.3528	0.2145	0.3266	0.2450	0.3600

Table 2. PSNR VALUES COMPARISON FOR NATURAL IMAGES

Image	Balloon	Barbara	Cameraman	Donald	House	Lena	Couple
Original image	56.80	55.95	55.57	59.97	54.82	57.95	56.62
Histogram equalization	57.52	57.38	56.43	59.63	55.68	57.20	57.38
Proposed method	59.80	58.77	57.18	61.50	57.85	60.32	57.63