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Grey Wolf Optimization Algorithm for Colour Image Enhancement Considering Brightness Preservation Constraint

Authors

J.Vinothini[1], R. Ashok Bakkiyaraj[2]

[1]P.G, Scholar, Annamalai University, Tamilnadu

Email: *vinoece33@gmail.com*

[2]Assistant Professor, Annamalai University, Tamilnadu

Email: *auashok@gmail.com*

Abstract

Colour image enhancement plays an important role in Digital Image Processing. Color images provide more and better off information for visual perception than that of the gray images. The purpose of image enhancement is to get finer details of an image and highlight the useful information. During poor illumination conditions, the images appear darker or with low contrast. Such low contrast images needs to be enhanced. Image enhancement can be achieved by applying Histogram Equalization (HE) and it is widely used due to its simplicity and effectiveness. However, together with some advantages HE hampers the mean brightness, due to these grounds it is not enviable to implement HE in colour image enhancement. In order to overcome this problem this paper proposes a new-fangled contrast enhancement and brightness preservation technique based on Grey Wolf Optimizer (GWO) algorithm for quality improvement of the low dynamic range images. The proposed method is expected to provide better enhanced output image and preserve brightness of the enhanced image very close to the input image and the resulted images were suitable for consumer electronic products.

Keywords-*Image Enhancement, Optimization Algorithm, Contrast, Brightness Preservation*

Introduction

Digital images is enticing an vital source of information in a wide range of existing applications. Images enhancement are valuable in numerous applications such as in the field of agriculture, geology, forestry, biodiversity conservation, weather forecast, etc. The objective of image enhancement is to advance the interpretability of the information at hand in the image for individual spectators. An enhancement algorithm is one that achieves a improved image for the intention of some particular application. It is normally accomplished in the course of suppressing noise or by escalating contrast. Genetic Algorithm was used for optimal mapping of grey levels of the input image into new grey levels which offer better contrast for the image reference number, as in [1].

Yeong-Taeg-kim reference number, as in [2] “Contrast Enhancement using Brightness Preservation Bi-Histogram Equalization” discussed Brightness preserving as an emerging new technology. In this paper a novel extension of the histogram equalization referred to as the mean preserving bi-histogram equalization (BBHE) is proposed to overcome the problems of typical histogram equalization.

WANG Zhiming, TAO Jianhua reference number, as in [3] “A Fast Implementation of Adaptive Histogram Equalization” discussed Adaptive Histogram Equalization(AHE) is a popular and effective algorithm for image contrast enhancement.

Hojat Yeganeh, Ali Ziaeu, Rezaie reference number, as in [4] “Novel Approach for Contrast Enhancement Based on Histogram Equalization” discussed

Histogram based techniques is one of the important digital image processing techniques which can be used for image enhancement. Soong-Der C hen, Abd. Rahman Ramli reference number, as in [5] "Preserving brightness in histogram equalization equalization (HE) has been a simple yet effective image enhancement technique.

However it tends to change the brightness of an image significantly, causing annoying artifacts and unnatural contrast enhancement. Brightness preserving bi-histogram equalization (BBHE) and dualistic sub-image histogram equalization (DSIHE) have been proposed to overcome these problems but they may still fail under certain conditions. This paper proposed a extension of BBHE referred to as minimum mean brightness error bi-histogram equalization (MMBEBHE). MMBEBHE has the feature of minimizing the difference between input and output image's mean.Ibrahim, H.Kong, N.S.P reference number, as in [6] "Brightness Preserving Dynamic Histogram Equalization for Image Contrast Enhancement" discussed Histogram equalization as one of the common method used for improving contrast in digital images. However, this technique is not very well suited to be implemented in consumer electronics, such as television, because the method tends to introduce unnecessary visual deterioration such as saturation effect. In this proposed methodology Grey Wolf Optimization (GWO) algorithm reference number, as in [2] has been applied for searching the best alternative set of grey levels for image contrast enhancement. The dominant category of measures combines the number of edge pixels, the intensities of these pixels and the entropy of the whole image while achieving the objective of maximizing the image quality.

This paper is organized as follows: Section I introduces the existing approaches, Section II explains the methodology in the proposed work, Section III discusses the parameters formulation and their evaluation, Section IV focuses with steps involved in the search process of GWO algorithm, Section V discusses about implementation of GWO for image enhancement, Section VI shows the prototype of the software simulation and its results, Section VII concludes the work.

Basic Methodology

The set of grey levels of the input image is substituted by a new set that gives more homogeneity to the image histogram, and so offers better quality of the image. The new set of grey levels are obtained by using the GWO algorithm as an optimizer. Considering contrast enhancement as an optimization problem gives rise to the necessity of defining two aspects: the representation of solutions and the objective function.

A vectorial representation of each possible solutions has been used in [1]. The same representation is adopted in the present work. Accordingly, a solution to the problem is an ordered vector of N integers in the interval 0 to 255, representing a possible mapping of the grey levels of the input image, where N is the number of grey levels in the input image. Hence, the population of solutions is a set of ascendantly sorted integer vectors of dimension N having values in the interval (0; 255). Of course the descendant ordering of solutions can also be used, in this case the mapping will correspond to the descendent order of the input vector.

Image Parametrs Relation

In order to evaluate the quality of solutions by the GWO algorithm this work adopted a formula that combines the number of edge pixels, the intensity of edge pixels and the entropy of the whole image

Transformation:

Image enhancement done on spatial domain uses a transform function which generates a new intensity value for each pixel. The enhancement process can be denoted

$$T(G(K))=C_i\,(K) \qquad (1)$$

T is the function used for changing original image gray levels, G gray level in input image,

C_i represents the chromosome value.

where k=1,2,….n

Fitness function:

To evaluate the quality of an enhanced image without human intervention, objective function which will say all about the image quality. In this method the objective function is formed by combining three performance measures, namely entropy value, sum of edge intensities and number of edges.

Quality of the image is given by

$$F(Z) = \log(\log(E(I(Z)))) * ne(I(Z)) * H(I(Z)) \qquad (2)$$

H((I(Z)) is the entropy of the output image

Where intensity of enhanced image is

$$E(I(x)) = \sum_x \sum_y \sqrt{\partial h_1 (x,y)^2 + \partial v_1 (x,y)^2} \qquad (3)$$

E(I(Z) is the sum of edge intensities of the image. ne(I(Z)) is the number of edges in the resulting image.

Entropy:

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image which is given by,

E = -sum(p.*log2(p)) (4)

where p contains the histogram counts returned from imhist.

Peak-Signal to Noise Ratio:

Peak signal-to-noise ratio, often abbreviated PSNR, is an engineering term for the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation. The PSNR (in dB) is defined as:

PSNR=10log10(peakval2/MSE) *(5)*

where peakval is either specified by the user or taken from the range of the image data type (e.g. for unit 8 image it is 255). MSE is the mean square error.

Edge Detection:

Edge detection is an image processing technique for finding the boundaries of objects within images. It works by detecting discontinuities in brightness. The Canny edge detector used in the proposed method is an edge detection operator that uses a multistage algorithm to detect a wide range of edges in images.

Grey Wolf Optimization

Grey wolf optimizer (GWO) is a population based meta-heuristics algorithm simulates the leadership hierarchy and hunting mechanism of gray wolves in nature proposed by Mirjalili et al. in 2014 [2]. Grey wolf (Canis lupus) belongs to Canidae family. Grey wolves are considered as apex predators, meaning that they are at the top of the food chain. Grey wolves mostly prefer to live in a pack. Of scrupulous interest is that they have a very strict social dominant hierarchy

Alpha

The leaders either a male and a female, called alphas. The alpha is mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alpha's decisions are dictated to the pack.

Beta

The second level in the hierarchy of grey wolves is beta. The betas are subordinate wolves that help the alpha in decision-making or other pack activities.

Omega

The lowest ranking grey wolf is omega. The omega plays the role of scapegoat. Omega wolves always have to submit to all the other dominant wolves.

Delta

If a wolf is not an alpha, beta, or omega, he/she is called subordinate (or delta in some references). Delta wolves have to submit to alphas and betas, but they dominate the omega. Scouts, sentinels, elders, hunters, and caretakers belong to this category.

Algorithm

In order to mathematically model the social hierarchy of wolves when designing GWO, we consider the fittest solution as the alpha(α). Consequently, the second and third best solutions are named beta (β) and delta (δ) respectively. The rest of the candidate solutions are assumed to be omega (ω). In the GWO algorithm the hunting (optimization) is guided by α, β, δ and. The ω wolves follow these three wolves.

Encircling the Prey

Grey wolves encircle prey during the hunt. In order to mathematically model encircling behaviour the following equations are proposed:

$$D = |C \,.\, X_p(t) - A \,.\, X(t)| \qquad (6)$$

$$X(t+1) = X_p(t) - A \,.\, D \qquad (7)$$

Where *t* is the current iteration, A and C are coefficient vectors, Xp is the position vector of the prey, and X indicates the position vector of a grey wolf. The vectors A and C are calculated as follows:

$$A = 2a \cdot r_1 \cdot a \qquad (8)$$

$$C = 2 \cdot r_2 \qquad (9)$$

where components of *a* are linearly decreased from 2 to 0 over the course of iterations and r_1, r_2 are random vectors in [0, 1]. So a grey wolf can update its position inside the space around the prey in any random location by using equations above.

Hunting

Grey wolves have the ability to recognize the location of prey and encircle them. The hunt is usually guided by the alpha. The beta and delta might also participate in hunting occasionally. However, in an abstract search space we have no idea about the location of the optimum (prey). In order to mathematically simulate the hunting behaviour of grey wolves, we suppose that the alpha (best candidate solution) beta, and delta have better knowledge about the potential location of prey. Therefore, we save the first three best solutions obtained so far and oblige the other search agents (including the omegas) to update their positions according to the position of the best search agents. The following formulas are proposed in this regard.
It can be observed that the final position would be in a random place within a circle which is defined by the positions of alpha, beta, and delta in the search space. In other words alpha, beta, and delta estimate the position of the prey, and other wolves updates their positions randomly around the prey.

$$D_\alpha = |C_1 \cdot X_\alpha - X|$$
$$D_\beta = |C_2 \cdot X_\beta - X| \qquad (10)$$
$$D_\delta = |C_3 \cdot X_\delta - X|$$

$$\left.\begin{aligned} X_1 &= X_\alpha - A_1 \cdot (D_\alpha) \\ X_2 &= X_\beta - A_1 \cdot (D_\beta) \\ X_3 &= X_\delta - A_1 \cdot (D_\delta) \end{aligned}\right\} \qquad (11)$$

$$X(t+1) = (X_1 + X_2 + X_3) / 3 \qquad (12)$$

Attacking the prey (Exploitation)

The grey wolf finish the hunt by attacking the prey when it stop moving. The vector A is a random value in interval [-2a, 2a], where *a* is decreased from 2 to 0 over the course of iterations, when $|A| < 1$, the wolves attack towards the prey, which represents an exploitation process. With the operators proposed so far, the GWO algorithm allows its search agents to update their position based on the location of the alpha, beta, and delta; and attack towards the prey.

Search for prey (Exploration)

Grey wolves mostly search according to the position of the alpha, beta, and delta. They diverge from each other to search for prey and converge to attack prey. The exploration process modeled mathematically by utilizing A with random values greater than 1 or less than -1 to oblige the search agent to diverge from the prey, when $|A| > 1$, the wolves are forced to diverge from the prey to find a fitter prey.

GWO Implementation For Image Contrast Enhancement

In this approach, a Teaching Learning based algorithm is used as an optimizer to search for the best mapping that maximizes the objective function. The following steps need to be applied to enhance the image,

1. **Initialisation:**

A random initial population of solutions Pop_0 is generated. It consists of s ascendantly ordered integer vectors having values in the interval [0,255], 'S' represents the number of solutions; The number of elements of these vectors is N which represents the number of grey levels of the input image.
After this initialization, the algorithm repeats the following steps cyclically till a stopping condition is met. In this work, the stop condition has been chosen to be a predefined number of iterations.

2. **Assigning Best Solution:**

(i) Generate an initial population $X_i(t)$ randomly.
(ii) Evaluate fitness function for each search agent $f(x_i)$

(iii) Assign the first, second and third best values as X_α , X_β , X_δ respectively.

3. **Solution Updating:**

(i) Update each search agent in the population by using Eqn.(10)

(ii) Decrease the parameter a from 2 to 0.

(iii) Update the co-efficient A and C using Eqn.(8) and (9) respectively.

(iv) Evaluate the fitness function of each search agent $f(x_i)$.

(v) Update the vectors X_α , X_β , X_δ using Eqn.(11).

(vi) Compute for next iteration using Eqn.(12).

4. **Termination Criteria**:

Stop if the maximum number of generations is reached.

The implementation flowchart of GWO for image contrast enhancement is given in Figure1.

Simulation and Result

The proposed approach is applied to two standard images for the validation of the GWO approach in image enhancement. The GWO parameters are initialized by setting the Population size as 50, teaching factor as 1, Number of generations as 100,Number of grey levels of the image chosen is 10 which is the unknown design variable in GWO.

Case1-Lena

Figure 2 (a) Input image (b)Edge (Enhanced) (c) Enhanced image

Table 1 Comparison of image parameters(1-Lena.jpg)

Parameters	Input Image	GA[1]	Proposed GWO
Entropy	7.75	7.15	6.78
Edges	5420	3256	2135
PSNR(db)	17.43	15.72	14.23
Quality	36.72	48.31	67.80(3.7105e+4)
STD	13.89	12.58	12.78

In case 1 the number of edges in input image is found to be 5420 which is reduced to 3256 in GA by proposed GWO it reduces to 2135. Peak Signal to Noise Ratio is found to be higher in case of input image 17.43 and it is reduced to 15.72 and 14.23 in GA and proposed GWO method respectively. Entropy of input image is 7.75, GWO it is around 6.78 while GA have higher entropy 7.15. Thus the quality of the input image is 36.72, by using GA[1] quality is 48.31 and the GWO achieves 67.80.

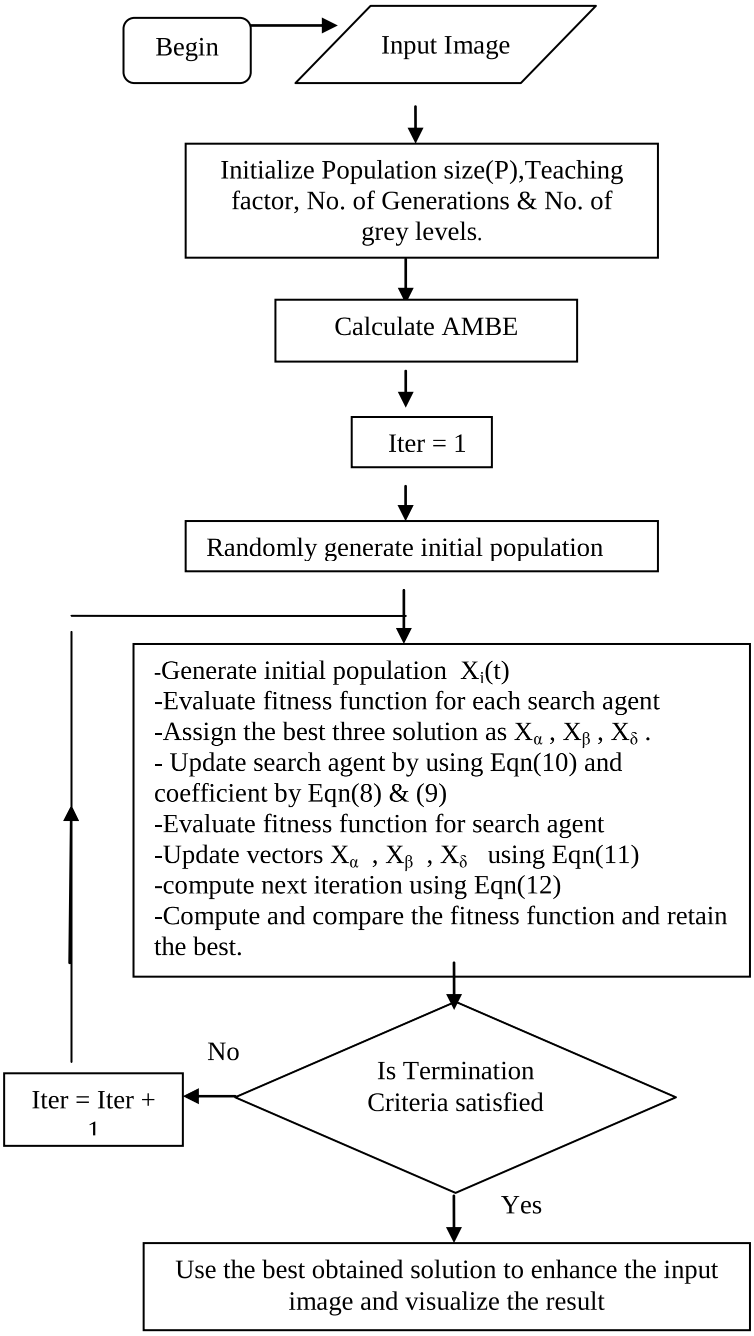

Figure 1 Flow chart for GWO implementation

Case-2 Pepper

Figure 2 (a) Input image (b) Edge (Enhanced) (c) Enhanced image

Table 2 Comparison of image parameters(2-pepper.jpg)

Parameters	Input Image	GA[1]	Proposed GWO
Entropy	9.25	8.26	7.75
Edges	1325	1126	925
PSNR(db)	21.32	15.64	14.62
Quality	45.76	73	91.5(1.818e+4)
STD	14.68	13.94	12.78

In case 2 the number of edges in input image is found to be 1325 which is reduced to 1126 in GA and by proposed GWO it reduces to 925.Peak Signal to Noise Ratio (PSNR) is found to be higher in case of input image 21.32 and it is reduced to 15.64 and 14.23 in GA and proposed GWO method respectively. Entropy of input image is 4.76, GWO it is around 5.74 while GA have higher entropy 6.53. Thus the quality of the input image is 45.6 by using GA [1] quality is 73 and the GWO achieves 91.5. Thus the image parameters such as Entropy, Number of edges, PSNR, Quality of input and enhanced image achieved by proposed GWO method along with GA [1] results. It is found from the table 1 and 2 that the proposed approach achieves better quality, PSNR and entropy values.

Conclusion

This paper, proposed a Grey Wolf Optimization based methodology for image contrast enhancement especially when input image has low dynamic range. The grey levels of the input image are replaced by a new set of grey levels which is effectively searched by GWO algorithm. To analyze the method performance, two standard bench mark images were selected and the proposed method was applied on them. The simulation results were satisfactory. Also, to compare the proposed method with other related ones, three different criteria have been used: number of detected edges, PSNR and visual assessment which includes the brightness preservation constraint. Besides, simulated results demonstrated that the enhanced images are suitable for applications such as consumer electronic products.

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