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Optimal Gray Level Mapping for Satellite Image Contrast Enhancement Using Grey Wolf Optimization algorithm

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Abstract: *Enhancing the image quality is a vital phase in every image processing system. The objective is to improve both the visual and the informational quality of distorted images. Contrast enhancement and brightness preservation are essential constraints for many vision based application. Histogram equalization (HE) fails to preserve the brightness while enhancing the contrast due to the abrupt mean shift during the process of equalization. To overcome the deficiency, intelligent approaches are applied for searching a new set of gray levels in such a way to achieve optimum image quality. In this proposed methodology, Grey Wolf Optimization(GWO) algorithm is applied as an optimizer to extract the new set of gray levels of the input image in the search space. The objective is to maximize the quality of the image by replacing the existing gray levels with new set of grey levels having reduced entropy and number of edges. Canny edge detector is applied to evaluate the image quality, entropy and number of edges in every possible solution. Proposed approach is tested on low contrast satellite images which give better performance in terms of PSNR, MSE and SSIM.*
Keywords: *Canny edge detector, Gray level mapping, Grey Wolf Optimization Algorithm, satellite images.*

I. Introduction

Image enhancement is helpful in numerous applications such as in the field of agriculture, geology, forestry, biodiversity conservation, weather forecast, etc. The objective of image enhancement is to improve the interpretability of the information in the input image for individual spectators. An enhancement algorithm is one that achieves an 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 gray levels of the input image into new grey levels which offer better contrast for the image [1]. Histogram equalization is an efficient method for contrast enhancement [2]. It will enhance the level of contrast and reduce noise robustness, white or black stitching and mean brightness preservation. The main drawback of histogram equalization is that the brightness of the image gets changed after applying histogram equalization. Range Limited Bi-Linear Histogram Equalization (RLBHE) divides the input histogram into two independent sub-histograms by a threshold in order to effectively separate the objects from the background [3 & 4]. The main drawback of RLBHE is that divide the image into two sub-images, upper bound or lower bound leads to loss of information in the image. In Average histogram equalization method is a pipelined approach including colour channel stretching, histogram averaging and re-mapping is developed [5]. However it fails to produce natural look, in spite of preserving brightness. Satellite images are low contrast and dark images, which has complete information but is not visible they can be enhanced based on Discrete Wavelet Transform and Singular Value Decomposition [6]. Several histogram methods are developed to enhance an image [7-12]. In this proposed methodology Grey Wolf Optimization (GWO) algorithm [14] has been applied for searching the best alternative set of gray 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 arranged as follows: Section I summarizes the existing approaches, Section II presents the methodology of the proposed work, Section III discusses the problem formulation of gray level mapping and the associated quantitative performance evaluation, Section IV focuses the steps involved in the search process of GWO algorithm, Section V explains GWO implementation for image enhancement, Section VI presents case studies with low contrast satellite images and its results, Section VII concludes the work.

II. Basic Methodology

The set of gray level 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 gray level is searched 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 solution 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 gray levels of the input image, where N is the number of gray levels in the input image. Hence, the population of solutions is a set of integer vectors of dimension N having values in the interval (0; 255) are sorted in ascending order. It is also possible the descendant ordering of solutions can also be used, in this case the mapping will correspond to the descendent order of the input vector.

III. Formulation of Gray Level Mapping

Image enhancement on spatial domain uses a transform function which generates a new intensity value for every pixel. The enhancement process can be modelled as a transformation function which is given by

$$T(G(K)) = C_j\ (K) \tag{1}$$

where T is the function used for generating the new gray levels of the image, G is the gray level array of the input image sorted in ascending order, C_i symbolizes the possible new set of gray levels given by the j^{th} solution and $k=1,2,....n$. where n is the number of gray levels presents in the image. In this methodology, searching the optimal set of gray levels is formulated as a maximization problem for improving the quality of the given image. Changing the prominent gray level intensity values of the image modifies the quality of the image. Image quality is a combinatorial function of entropy, sum of edge intensity values and number of edges.

The objective function of the optimal gray level mapping is given by

Maximize

$$\text{F(z)} = log(log(E(I(Z)))) * \frac{NE(I(Z))}{nh*nv} * H(I(Z)) \tag{2}$$

Sum of the edge intensity of the enhanced image is evaluated by

$$E\big(I(z)\big) = \sum_{x=1}^{nh}\sum_{y=1}^{nv}\sqrt{\delta h(x,y)^2 + \delta v(x,y)^2} \tag{3}$$

where

$$\delta h(x,y) = g(x+1,y-1) + 2g(x+1,y) + g(x+1,y+1) - g(x-1,y-1) - 2g(x-1,y) - g(x-1,y+1)$$

$$\delta v(x,y) = g(x-1,y+1) + 2g(x,y+1) + g(x+1,y+1) - g(x-1,y-1) - 2g(x,y-1) - g(x+1,y-1)$$

The term $g(x,y)$ denotes the gray level intensity value of the enhanced image $I(Z)$ at coordinates (x,y). The variables δh and δv represents maximum number of x coordinate in horizontal axis and maximum number of y coordinate in vertical axis.

Edge detection is an image processing technique for finding the boundaries of objects within the image. It works by detecting discontinuity in brightness. The Canny edge detector used in this proposed method as an edge detection operator for evaluating the number of edges in the resulting image $NE(I(Z))$ by multistage algorithm to detect a wide range of edges in an image.

Entropy is a statistical measure of randomness that can be used to characterize the texture of the input image. It can be found for the image with maximum intensity of L_{max} and probability of occurrence of i^{th} pixel $p(i)$ is given by

$$H\big(I(Z)\big) = -\sum_{i=0}^{L_{max}-1} p(i)log_2(p(i)) \tag{4}$$

IV. Grey Wolf Optimization

Grey wolf optimizer (GWO) is a population based meta-heuristics optimizing algorithm that simulates the leadership hierarchy and hunting mechanism of grey wolves for searching the best possible solution [14]. 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 organized pack.

1 The Hierarchical Ranks

1.1 Alpha

Alpha wolves are the leaders of the group that can be male wolves and/or female wolves. The dominant alphas are mostly responsible for making decisions about hunting, sleeping place, time to wake, and so on. The alpha's decisions are dictated to the pack.

1.2 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.

1.3 Omega

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

1.4 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.

2. Algorithmic Model

In order to mathematically model the social hierarchy of wolves while designing GWO algorithm, we consider the best fitness solution as 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.

2.1 Encircling the Prey

Grey wolves encircle their prey during the hunting process. The following equations represent the encircling behaviour of the wolves

$$D = |C . X_p(t) - A . X(t)| \tag{5}$$

$$X(t+1) = X_p(t) - A . D \tag{6}$$

where *t* is the current iteration, *A* and *C* are coefficient vectors, X_p 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:

$$A = 2a * r1 - a \tag{8}$$

$$C = 2 * r2 \tag{9}$$

where *a* is linearly decreased from 2 to 0 over the course of iterations and *r1*, *r2* are random vectors in the range of [0, 1]. So a grey wolf can update its position inside the problem space around the prey in any random position.

2.2 Hunting

Grey wolves have the ability to recognize the position 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.

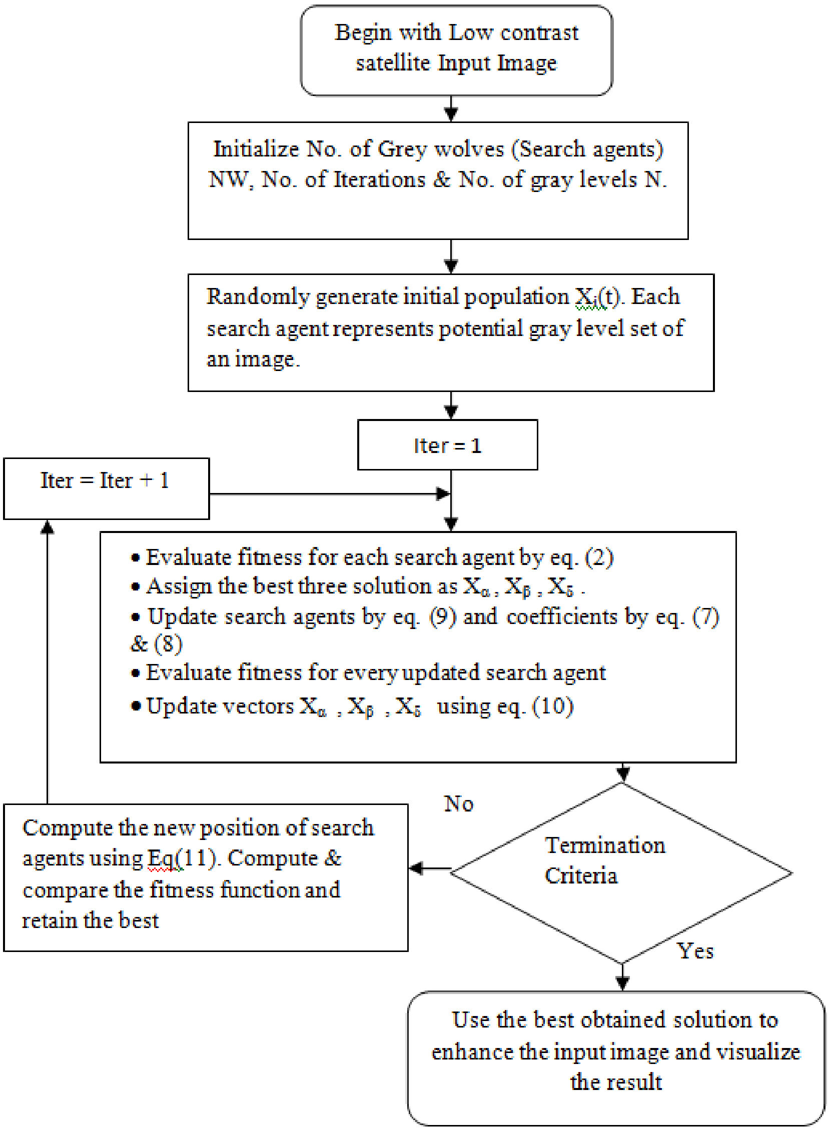
$$\left.\begin{aligned} D_\alpha &= |C_1 * X_\alpha - X| \\ D_\beta &= |C_2 * X_\beta - X| \\ D_\delta &= |C_3 * X_\delta - X| \end{aligned}\right\} \tag{9}$$

$$\left.\begin{aligned} X_1 &= X_\alpha - A_1 * (D_\alpha) \\ X_2 &= X_\beta - A_2 * (D_\beta) \\ X_3 &= X_\delta - A_3 * (D_\delta) \end{aligned}\right\} \tag{10}$$

$$X(t+1) = \frac{(X_1 + X_2 + X_3)}{3} \tag{11}$$

2.3 Exploitation: Attacking the prey

The grey wolf kills the hunt by attacking the prey when it stop moving. The vector A is a random value in interval [-2*a, 2*a], 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. These operators allow GWO search agents to update their position based on the position of the alpha, beta & delta and attack towards the prey.



2.4 Exploration: Search for prey

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.

V. GWO Implementation for Image Contrast Enhancement

In this approach, GWO algorithm is used as an optimizer to search the optimal grey level for the best mapping that maximizes the quality of the image. The following steps need to be applied to enhance the image.

1. Initialization

Random initial population of solutions is generated. It consists of ascending ordered integer vectors having values in the interval [0,255], NW 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.

2. Assigning Best Solution

1. Generate an initial population Xi(t) randomly.
2. Evaluate fitness function for each search agent f(xi)
3. Assign the first, second & third best values as X_α, X_β, X_δ respectively.

3. Solution Updation
1. Update each search agent in the population by using Eq.(6)
2. Decrease the parameter a from 2 to 0.
3. Update the co-efficient A and C using Eqn.(7) and (8) respectively.
4. Evaluate the fitness function of each search agent f(xi).
5. Update the vectors X_α , X_β , X_δ using Eqn.(10).
6. Compute for next iteration using Eqn.(11).

4. Termination Criteria
In this work, the stop condition has been chosen to be predefined number of iterations reached.

VI. Simulation And Results

The proposed approach is applied to low contrast satellite images for the validation of the GWO based approach for image contrast enhancement. The GWO parameters are initialized by setting the number of grey wolves as 40, Number of generations as 100, Number of grey levels of the image chosen to be 10 which is the unknown design variable in GWO.

Performance Measures

For evaluating the performance of the proposed algorithm, the following significant fidelity metrics are considered. Image distortion and sharpness of the resultant image are the two important characteristics assessed to judge the efficiency of enhancement algorithms. Mean Square Error (MSE) is a very frequently used distortion (error) measurement parameter, which need to be minimized for a better enhancement approach. Likewise, PSNR quantify the quality of an image that takes a higher value for an image with less noise content. Thus, it eventually evaluates the similarity measure between the original and processed image based on the MSE values computed over every pixel which is depicted as

$$MSE = \frac{\sum_{x,y}[I_o(i,j)-I_e(i,j)]^2}{xy} \tag{12}$$

$$PSNR = 10\,log_{10}\left(\frac{(L_{max}-1)^2}{MSE}\right) \tag{13}$$

Where $I_o(i, j)$ is the intensity of the original image and $I_e(i, j)$ is the intensity of the enhanced image. Here, x and y are the number of rows and columns in the image. L_{max} is the maximum possible pixel value of the image.

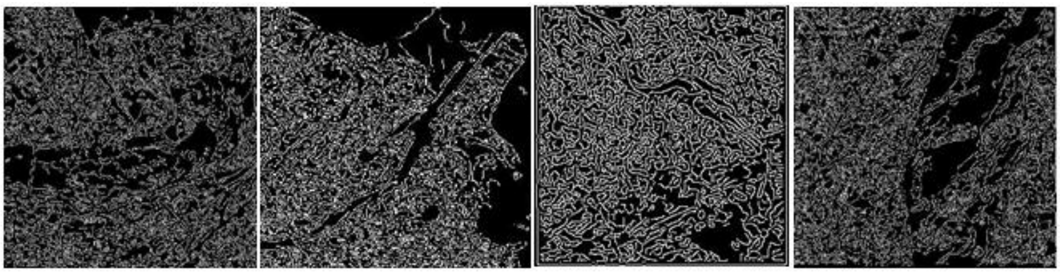
Structure similarity index (SSIM) gives the measure of edge information content in the processed image. It is measured by evaluating the similarity in the high frequency content i.e edge information of enhanced and original image. A higher value of SSIM indicates a better performance of the enhancement algorithm.

$$SSIM(x,y) = \frac{(\mu_o\mu_e + C_1)(2\sigma_{oe}+C_2)}{(\mu_o^2+\mu_e^2+C_1)(\sigma_o^2+\sigma_e^2+C_2)} \tag{14}$$

where, μ_o and μ_e stands for mean intensity of original image and enhanced image respectively, σ_o and σ_e indicates the standard deviations of original and enhanced respectively, σ_{oe} is the covariance between original and enhanced image. C_1 and C_2 are the constants, and are included to avoid instability when μ^2_o and μ^2_e are very close to zero.

A1 B1 C1 D1

A2 B2 C2 D2



A3 B3 C3 D3

Fig.2. A1–D1: Low contrast satellite input images (https://www.satimagingcorp.com/gallery/), A2–D2: Enhanced images using proposed GWO methodology, A3–D3: Edges of the enhanced images.

Performance metrics	**Enhanced Satellite Images**			
	A2	**B2**	**C2**	**D2**
MSE	18.2945	28.7643	22.4328	29.6322
PSNR	36.8721	33.9055	35.7695	34.2179
SSIM	0.9581	0.9138	0.9406	0.9391

Table-1: Performance Measures

It is found from table-1 image-A has a low MSE of 18.2945 that due to its ability to converge an optimal gray level for low contrast input satellite image. Qualitative and numerical measures of the output images also vindicate the effectiveness of the proposed GWO algorithm for searching the optimal value. Degradation of structural information such as SSIM is an important criterion for analyzing the performance of the image enhancement techniques. It is from table-1, SSIM index of the enhanced images based on the proposed approach is nearer to one. It implies that the structure of the original image is preserved in the proposed enhancement methodology. Visual and performance measures proved the suitability of the proposed GWO based methodology for contrast enhancement of satellite images.

VII. Conclusion

Grey Wolf Optimization based methodology for image contrast enhancement especially when input image has low dynamic range has been presented. The gray levels of the input image are replaced by a new set of gray levels which is effectively searched by GWO algorithm. To analyze the method performance, four low contrast satellite images were selected and the proposed method was applied on them. The simulation results were satisfactory. Image enhancement based on GWO seems to be a promising approach for multi spectral satellite images.

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