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Segmentation of Natural Calamity Images

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ABSTRACT

The digital image processing has been proved to be an effective tool for analysis in various fields and applications in engineering. Among the segmentation methods, image thresholding technique is one of the most well known methods due to its simplicity, robustness, and high precision. In this paper an attempt is made for an efficient segmentation of Natural calamity images by Healthy Bacteria Foraging Optimization Algorithm.

Introduction

Extraction of very minute details from Natural Calamity (NC) images is a challenging task for meteorological department of the Government. The current research attempts to investigate better method for segmentation of NC images and hopeful results has been obtained by Healthy Bacterial Foraging Optimization Algorithm (H-BFOA). For experimentation we have procured NC Images of the calamity that took place in Jammu and Kashmir of India in the month of September 2014. Extraction of color segmentation over gray level segmentation gives very faithful results towards the required information [1][2]. A unique idea of segmentation of NC images with H-BFOA for the extraction of information is explained in the following sections. In image analysis, image segmentation is the most important which divides the image into distinct and self-similar pixel groups is the most important prospect [3][4].

Color Image Segmentation

Colour Image segmentation process is a different task, and for the past two decades huge research went was done by aspirant researchers in this field. To extract information from color image, it has to be decomposed into identifiable items using color image processing techniques plus gray image processing techniques. In the visible electromagnetic spectrum, colour is a perceptual phenomenon related to human response to different wavelengths [5]. Colour is the most well-known feature of any image and using vision algorithms information can be extracted from the respective image. The gray scale image has less information compared to colour image [6]. Besides many Image segmentation algorithms with BFOA [7], Fuzzy set and Fuzzy Logic [8] also have been used for segmenting colour images [9].

Bacterial Foraging Optimization Algorithm

BFOA, a global optimization algorithm was proposed by Passino in 2002. Its efficiency uses in solving real-world optimization problems and several application domains. The life cycle of BFOA is explained below [10]:

1. Chemotaxis
2. Swarming
3. Reproduction
4. Elimination and Dispersal

During foraging, a bacterium can exhibit two different actions: tumbling or swimming [11]. The tumble action modifies the orientation of the bacterium. Swimming is the chemotaxis step, the bacterium will move in its current direction. Chemotaxis movement is continued until a bacterium goes in the direction of positive-nutrient gradient. After a certain number of complete swims, the best half of the population undergoes the reproduction and elimination of the rest of the population. In order to escape local optima, an elimination dispersion event is carried out where some bacteria are liquidated at random with a very small probability and the new replacements are initialized at random locations of the search space. Considering the foraging behaviour of E. coli, it has a common type of bacteria with a diameter of 1μ*m* and a length of about 2μ*m* and under appropriate circumstances it can reproduce in 20 min. The ability to move comes from a set of up to six rigid 100–200 rps spinning flagella, each driven by a biological motor. The E. coli bacterium alternates between running (at 10–20 μ*m* sec, but they cannot swim straight) and tumbling (changing the flagella). When the flagella rotate clockwise, they operate as propellers and hence an E. Coli bacteria may run or tumble. In elimination-dispersal event, the gradual or unexpected changes in the local environment where a bacterium population lives, may occur due to various reasons such as a significant local rise of temperature that may kill a group of bacteria that are currently in a region with a high concentration of nutrient gradients. BFO has various applications like Option Model calibration [12], image processing [13], RFID Network scheduling [14].

Proposed Method

The Proposed algorithm can be explained with the following steps:

1. I is an image that contains N pixels with gray levels from 0_L-1.
2. Input image into RGB planes.
3. Initialize TR=0, TG=0, TB=0.
4. Bacterial search area of a Red component image size into [m n].

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5. Nc=1, Ns=1 i.e, Chemotactic and Swim length is one.
6. By using image histogram, calculate the health status H(i+1) of all image pixels. The health status of $H_i(i+1)$ is given by: H(i+1)/(m*n).
7. Calculate the Euclidean Distance(ED), between adjacent pixels x & y.
8. If Ed < some threshold, replace first pixel with adjacent pixel.
9. Calculate the health status of new pixels and varying the health status of Bacteria. A small local rise of temperature which keeps the bacteria in warm condition by varying health status results in quick and potential growth.
10. Calculating the difference of Health status of adjacent pixels, if it is less than threshold health status, then they are the unpopular colours and can be removed to produce a new colour.
11. Adding the colour value to TR, TG, TB, and move the pixel over the entire image.
12. Do the same for Green and Blue images.
13. Individual thresholds as given by:

TR=T(1)/(m*n)

TG=T(2)/(m*n)

TB=T(3)/(m*n).

14. Final Threshold :TH=(TR+TG+TB)/3.
15. Compute the performance indices as PSNR, Standard Deviation (SD), Entropy and Class Variance and compare these values with Otsu method.

Performance Measures

To calculate and compare the resultant threshold of an image with the proposed algorithm and OTSU method, following performance measures are considered:

a) PSNR: Peak Signal to Noise Ratio (PSNR) is calculated by using the Eq.1.

$$PSVR = 10\log_{10}\frac{R^2}{\frac{1}{N\times N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-L}\left(f(i,j)-(i,j)\right)^2}\alpha\beta \quad ..\text{Eq.1}$$

Where N × N is the size of the input image

f(i,j)=gray-level pixel values of the input and

f(i,j)=gray level pixel values of the reconstructed images.

Generally, PSNR is used to analyze quality of image, sound and video files in dB (decibels). PSNR calculation of two images, one input and an altered image, describes how far two images are equal.

In the Eq.1, ‘R’ is the maximum fluctuation in the input image. If the input image has a double-precision floating-point data type, R is1 that we considered with proposed algorithm H-BFOA for the segmentation of NC images. But in case of Otsu method, R value considered is 255, and hence better PSNR values are expected with H-BFOA, compared to Otsu method.

b) Standard Deviation (SD): The Standard Deviation of an image is given by the Eq.**2**.

$$\hat{\sigma} = \frac{1}{n\times n}\sum_{j=1}^{n}\sum_{i=1}^{m}\left(x_{ij}\ \hat{\mu}\right)^2 \quad \ldots\ldots\text{Eq.2}$$

This corresponds to the degree of deviation between the gray levels and its mean value, for the overall image.

c) Entropy E: The expression of the information entropy of an image is given by the equation (3).

$$E = -\sum_{i=0}^{L-1} P_i \ln P_i \quad \ldots\ldots\ldots\text{Eq.3}$$

Where L= the number of gray level, pi equals the ratio between the number of pixels whose gray value equals i (0 to L - 1) and the total pixel number contained in an image. The information entropy measures the richness of information in an image. If pi is the constant for an arbitrary gray level, it can be proved that the entropy will reach its maximum.

d) Class Variance: Class variance of the segmented image is computed by the following computation method: If the histogram is divided into two classes by the gray-level intensity t (threshold), then the probabilities of the respective classes can be expressed by the following Eq.**4.a** and Eq.**4.b**

$$P_1(t) = \sum_{i=0}^{t} P(i) \quad \text{---------------- Eq.}\mathbf{4.a}$$

and

$$P_2(t) = \sum_{i=t+1}^{N-1} P(i) \quad \text{---------------- Eq.}\mathbf{4.b}$$

Also, the class means m1 and m2 are given by the equation 5.(a) and 5.(b).

$$m1(t) = \sum_{i=0}^{t} {i_p(i)}/{p_1(t)} \quad \text{-------------------Eq.5.a}$$

$$m2(t) = \sum_{i=0}^{t} {i_p(i)}/{p_2(t)} \quad \text{---------------- Eq.}\mathbf{5.b}$$

The two class variances are given by the equations Eq.6**.a** and Eq.**6.b**

$$\sigma_1^2(t) = \sum_{i=0}^{t}(i-m1)(i-m1)\,P_i/p1(t) \quad \text{----- ------- Eq.6}\mathbf{.a}$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{N-1}(i-m2)(i-m2)\,P_i/P_2(t) \quad \text{-----------Eq.6}\mathbf{.b}$$

The total class variance (σ_T) is given by Eq.7:

$$\sigma_T^2 = \sigma_B^2 + \sigma_w^2 \quad \text{------------------- Eq.}\mathbf{7}$$

Where σ_B^2 = between class variance and

σ_w^2 = within class variance

Equations for class variance and within class variance are given by following the equations Eq.8.a, and Eq.8.b

$$\sigma w^2(t) = p_1(t)\sigma_1^2(t) + p_2(t)\sigma_2^2(t) \quad \text{--------------- Eq.8.a}$$

$$\sigma^2 B(t) = P_1(t).P_2(t)\{m_1(t)-m_2(t)\}^2 \quad \text{-------------- Eq.8.b}$$

Experimental results

The proposed algorithm H-BFOA is used to segment NC images. The input images Figs. 1, 4, 7, 10, 13 are taken from Google images and are shown in Fig.0.0. The health status of adjacent pixels is equal to 0.005 on H-BFOA then, figures 2, 5, 8, 11, 14 are the H-BFOA outputs. Figures 3, 6, 9, 12, 15 are the OTSU output images. The result images infer clearly that the colour images have more information than gray level images. More specifically, with H-BFOA for NC images we could distinguish colour shades over water. The proposed H-BFOA is compared with OTSU method and results are tabulated. Tables.1, 2, 3 and 4 depict the performance indices for all the images. Peak Signal Noise Ratio (PSNR), Entropy, Standard Deviation (SD), and Class Variance (CV) are compared with the OTSU method and tabulated.

Conclusions

H-BFOA method is proved to be efficient, particularly when segmentation is done for NC images and very firm information could be extracted through a proper thresholding process. The performance indicator values PSNR, Entropy, SD, and CV are significant with the proposed algorithm and the same is proved to be efficient. In future the work can be extended with a scale area depth of location for a specific type of NC images.

Input NC IMAGES	H-BFOA Output	OTSU Output

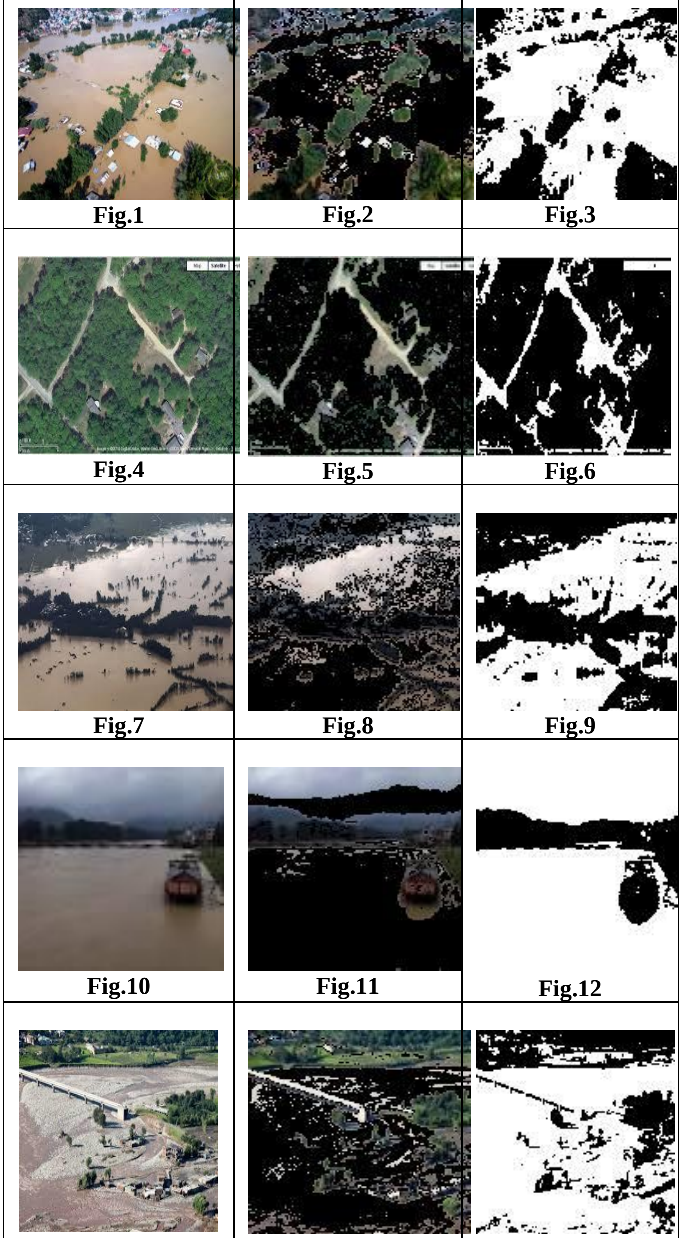

Fig.1 Fig.2 Fig.3
Fig.4 Fig.5 Fig.6
Fig.7 Fig.8 Fig.9
Fig.10 Fig.11 Fig.12
Fig.13 Fig.14 Fig.15

Figure.0.0. Input and Output result images

Table No.1 entropy Comparison: h-bfoa & otsu

S.No	PERFORMANCE MEASURES		
	ENTROPY	***H-BFOA***	***OTSU***
1	IMAGE 1	0.9954	0.9219
2	IMAGE 2	0.8839	0.7220
3	IMAGE 3	0.9961	0.9934
4	IMAGE 4	0.9492	0.7447
5	IMAGE 5	0.9912	0.8845

Table No.2 SD Comparison:: H-bfoa & otsu

S.NO	PERFORMANCE MEASURES		
	SD	***H-BFOA***	***OTSU***
1	IMAGE 1	0.4984	0.4727
2	IMAGE 2	0.4592	0.4000
3	IMAGE 3	0.4987	0.4977
4	IMAGE 4	0.4823	0.4085
5	IMAGE 5	0.4970	0.4594

Table No.3 CV Comparison:: H-bfoa & otsu

S.NO	PERFORMANCE MEASURES		
	CV	***H-BFOA***	***OTSU***
1	IMAGE 1	0.0025	0.0022
2	IMAGE 2	0.0021	0.0016
3	IMAGE 3	0.0025	0.0025
4	IMAGE 4	0.0023	0.0017
5	IMAGE 5	0.0025	0.0021

Table No.4 Psnr Comparison:: H-bfoa & otsu

S.NO	PERFORMANCE MEASURES		
	PSNR	***H-BFOA***	***OTSU***
1	IMAGE 1	60.4397	53.2975
2	IMAGE 2	55.9701	49.4018
3	IMAGE 3	57.0629	51.0116
4	IMAGE 4	57.9642	31.8375
5	IMAGE 5	60.5905	51.8821

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