Image Segmentation using Improved Bacterial Foraging Algorithm

Beenu[1], Sukhwinder Kaur[2]

[1]ECE Department, RIEIT, Railmajra, Ropar, Punjab, India
erbeenu_goyal@yahoo.co.in

[2]ECE Deparment, RIEIT, Railmajra, Ropar, Punjab, India
sukhisembhi@yahoo.co.in

Abstract: ***Bacterial foraging optimization algorithm (BFOA) has been widely accepted as a global optimization algorithm of current interest for distributed optimization and control. BFOA is inspired by the social foraging behavior of Escherichia coli. BFOA has already drawn the attention of researchers because of its efficiency in solving real-world optimization problems arising in several application domains. The underlying biology behind the foraging strategy of Escherichia coli is emulated in an extraordinary manner and used as a simple optimization algorithm. The cross entropy function works well in case of bi-level thresholding problem. However, if there is a need of the multi-thresholding in image processing application, a global and generic objective function is desired so that each threshold could be tested for its best performance statistically. The maxima of the selected threshold is optimized by using the BFO algorithm based on constant chemo taxis length, constant rate of elimination and dispersion of bacteria and constant swim and tumbling of bacteria. The constant rate of swim, tumbling and rate of elimination and dispersion does not provide a natural optimization of the maxima of the threshold level from the given threshold levels.***

Keywords: bacterial foraging optimization algorithm, rate of swim, rate of elimination

1. Introduction

In recent years, bacterial foraging behaviors i.e., bacterial chemotaxis as a rich source of potential engineering applications and computational model have attracted more and more attentions. A few models have been developed to mimic bacterial foraging behaviors and been applied for solving practical problems. Among them, Bacterial Foraging Optimization (BFO) is a population-based numerical optimization algorithm. Until date, BFO has been applied successfully to some engineering problems, such as optimal control, harmonic estimation, transmission loss reduction, and machine learning. However, experimentation with complex optimization problems reveal that the original BFO algorithm possesses a poor convergence behavior compared to other nature-inspired algorithms and its performance also heavily decreases with the growth of the search space dimensionality.

2. Brief Literature Survey

The result of image segmentation is a set of segments (sets of pixels) that collectively cover the entire image. Pixels in the same region are similar with respect to some characteristics or computed properties, such as color, intensity, Adjacent regions are significantly different with respect to the same characteristics. The goal of segmentation is to simplify and/ or change the representation of an image into something that is more meaningful and easier to analyze (Shapiro & Stockman, 2001). The most successful image segmentation algorithm into homogeneous regions is fuzzy c-means algorithm Bezdek, 1981). Experiment results showed that higher segmentation accuracy was obtained using the proposed segmentation method comparing with the fast FCM algorithm and the conventional genetic fuzzy clustering algorithm. Zeng et al. (2008).

3. Image Segmentation

Segmentation is the process of dividing a digital image into multiple segments (sets of pixels, also known as super pixels). Image segmentation is typically used to locate objects and boundaries (lines, curves, etc.) in images. Image segmentation is to classify or cluster an image into several parts (regions) according to the feature of image. Image segmentation is the process of assigning a label to every pixel in an image .The result of image segmentation is a set of segments that collectively cover the entire image, or a set of contours extracted from the image (see edge detection). The segmentation is based on measurements taken from the image and might be grey level, colour, texture, depth or motion. Due to the importance of image segmentation a number of algorithms have been proposed but based on the image that is inputted the algorithm should be chosen to get the best results.

The image segmentation algorithm used for monochrome images mainly used for the property of intensity values of pixels based on the discontinuity and similarity. The most widely used color driven segmentation techniques include clustering, histogram based segmentation, edge detection, region growing, neural networks segmentation, compression based, watershed transformation, multi-scale segmentation, graph partitioning methods. These techniques have the aim to reduce the number of color components from the input image. The main characteristics used as the basis of color image segmentation are color and texture. Color histograms are commonly used in content-based retrieval systems and have proven to be very useful. Various different color spaces have been defined which simply described the colors, or gamut that a camera can see, a printer can print or a monitor can display. An advantage resulting from the choice of color space representation could be taken to enhance the performance of processes such as segmentation and feature matching because of the three fold increase in color signal dimension as compared to black and white images. The allocation of individual pixels into heir corresponding segments based on the color changes largely aims at maximizing the total information and minimizing the differences between the amounts of information contained in the different segments.

4. Algorithm

BFO is an evolutionary optimization technique motivated by the foraging behaviour of the Escherichia coli abbreviated as E. Coli bacteria. The biological aspects of the bacterial foraging strategies and their motile behavior as well as their decision-making mechanisms. As a heuristic method, BFO is designed to tackle non-gradient optimization problems and to handle complex and non-differentiable objective functions. Searching the hyperspace is performed through three main operations, namely chemotaxis, reproduction and elimination dispersal activities.

The segmentation using BFA consists of following steps: chemotaxis, swarming, reproduction, elimination and dispersal. Chemotaxis is the activity that bacteria gathering to nutrient-rich areas spontaneously. A cell-to-cell communication mechanism is established to simulate the biological behaviour of bacteria swarming.

An E-coli bacterium can move in two different ways alternatively: tumble and run. A tumble is represented by a unit walk with random direction, a unit walk with the same direction as the previous step indicates a run. A chemotactic process is started by one step of tumble and followed by uncertain steps of run, depending on the variation of the environment.

E-coli bacterium has a specific sensing, actuation and decision-making mechanism. As each bacterium moves, it releases attractant to signal other bacteria to swarm towards it. Meanwhile, each bacterium releases repellent to warn other bacteria to keep a safe distance from it. BFA simulates this social behaviour by representing the combined cell-to-cell attraction and repelling effect.

The proposed objective function is given below:

Say, the No. of Threshold Level = K = {t1, t2, t3, ... tK}, then the objective function H is given by:

$$H_k = -\sum_{i=t_k}^{L-1} \frac{p_i}{\omega_k} \ln \frac{p_i}{\omega_k}$$

$$\omega_k = \sum_{i=t_k}^{L-1} p_i$$

where and Pi is the histogram value of the ith gray level.

The above proposed objective function is a global objective function based on entropy in combination with histogram, and the user can tailor the objective function based on the application. If the no. of threshold levels is 2, then the system becomes binary thresholding based on Otsu method. However, the same algorithm can be extended to multi-level thresholding if the value of K is more than 2.

Later, the maxima of the selected threshold is optimized by using the BFO algorithm based on chemotaxis with random value of length within limit, random rate of elimination and dispersion of bacteria and random swim and tumbling of bacteria. The random rate of swim, tumbling and rate of elimination and dispersion give a better optimization of the maxima of the threshold level from the given threshold levels.

The movement of the ith bacterium is described by

Ps (f + 1, g; u) = Ps (f; g; u) + C (s) x V (f)

where Ps (f; g; u) is the sth location of the bacterium at the fth chemotactic, gth reproductive, and uth elimination steps. C(s) is the length of one walking cycle. Here, it is defined as a small constant value. V(f) is the direction angle of the fth chemotactic step; its default value is set at a range of [0; 2π].

5. MATLAB Implementation

1. A is an image contains N pixels with gray levels from 0 – L-1.
2. Nt is the maximum no. of thresholds, Nt = L-1.
3. T = {tk, k=1,2,3,. . . Nt} is the set of thresholds.
4. S = {x1,x2,. . . xi} is the no. of particles such that xi indicates particle I, with xij ϵ {0.1}. for j=1,2 …Nt, such that, if xij = 1, then the corresponding tk in T has been chosen to be part of the solution proposed by xi. Otherwise, if xij = 0, then the corresponding tk in T is not part of the solution proposed by xi.
5. Nt is the no. of thresholds used by the multi-threshold segmentation solution represented by particle, xi, such that

$$n_i = \sum_{k=1}^{N_t} x_{i,k} \text{ with } n_i \le N_t$$

6. The optimized threshold levels can be tested for their performance by evaluating the standard deviation, class variance, PSNR and entropy of the thresholded images obtained by proposed algorithm and Otsu algorithm.

In the presented modified algorithm, we propose to add the random reproduction and elimination of the bacterium so that the more natural randomness could be added in order to enhance the segmentation process. The random reproduction and elimination is inserted in the step-2 and step-3. Here the for loop is executed in random manner where the incremental operator is incremented by some random number.

6. Performance Measures

In order to evaluate and compare the resultant thresholded image with proposed algorithm with respect to other algorithms, following performance measures are suggested:

PSNR: The peak-signal to noise ratio (PSNR) was used to evaluate the reconstructed image quality. The PSNR is defined as follows:

$$PSNR = 10\log_{10}\frac{255^2}{\frac{1}{N\times N}\sum_{i=0}^{N-1}\sum_{j=0}^{N-1}\left(f(i,j)-\hat{f}(i,j)\right)^2}dB,$$

where N × N is the size of the original image and f(i,j) and ˆf(i,j) are the gray-level pixel values of the original and reconstructed images, respectively.

Standard Deviation (SD): The standard variation of an image is given by:

$$\hat{\sigma}^2 = \frac{1}{n\times n}\sum_{j=1}^{n}\sum_{i=1}^{m}(x_{i,j}-\hat{\mu})^2,$$

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

Entropy E: The expression of the information entropy of an image is given by:

$$H = -\sum_{i=0}^{L-1} p_i \ln p_i,$$

Where L denotes 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 const for an arbitrary gray level, it can be proved that the entropy will reach its maximum. Below given figures shows the results of the segmentation obtained by Ostu algorithm and proposed algorithm. Fig. 1 is the original image, while fig. 2 and 3 shows the segmented image obtained after applying the Otsu and modified proposed algorithm.

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 as:

$$p_1(t) = \sum_{i=0}^{t} p(i) \quad \text{and} \quad p_2(t) = \sum_{i=t+1}^{N-1} p(i)$$

Also, the class means m1 and m2 are given by:

$$m_1(t) = \sum_{i=0}^{t} ip(i)/p_1(t)$$

$$m_2(t) = \sum_{i=t+1}^{N-1} ip(i)/p_2(t)$$

The two class variances are given by:

$$\sigma_1^2(t) = \sum_{i=0}^{t}(i-m_1)^2\frac{p(i)}{p_1(t)}$$

$$\sigma_2^2(t) = \sum_{i=t+1}^{N-1}(i-m_2)^2\frac{p(i)}{p_2(t)}$$

The total class variance (σ_T) is given by:

$$\sigma^2_T = \sigma_2^{B} + \sigma^2_W$$

Where σ^2_B is the between class variance and σ^2_W is the within class variance and given by following equations.

$$\sigma^2_W(t) = p_1(t)\,\sigma_1^2(t) + p_2(t)\,\sigma^2_2(t)$$

$$\sigma^2_B(t) = p_1(t).p_2(t)\,\{m1(t) - m2(t)\}^2$$

Fig. 1
(Original Image)

Fig. 2
Segmentation with Ostu Algorithm

Fig. 3
Segmentation with Modified BFO

Fig. 4

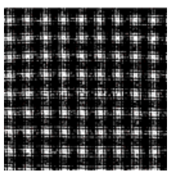

Fig. 5

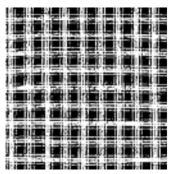

Fig. 6

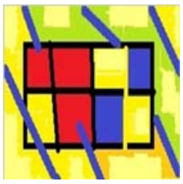
Fig. 7
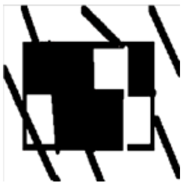
Fig. 8
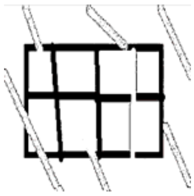
Fig. 9

Fig. 10

Fig. 11

Fig. 12

Fig. 13
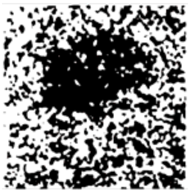
Fig. 14
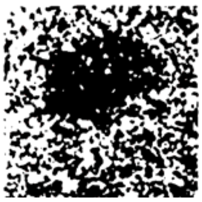
Fig. 15

Fig. 16

Fig. 17

Fig. 18

Fig. 19

Fig. 20

Fig. 21

(Original Image) Segmentation with Ostu Algorithm Segmentation with Modified BFO

7. Results

The results of the proposed modified BFA algorithm are shown in image from 1 to 21. The results are deduced using the original gray-scale image patterns. Parametric results are displayed in Tables 1 – 6.

Table No. 1 Depicting Low Threshold for PSO

Image ID	*Image Size*	*Threshold*		
		PSO	*Otsu*	*BFA*
Leena	512x512	0.4502	0.4549	0.4688
	256x256	0.4843	0.4549	0.4648
	96x96	0.4344	0.4549	0.4570
BW Pattern	512x512	0.3451	0.3882	0.6055
	256x256	0.3907	0.4000	0.5156
	96x96	0.3342	0.3843	0.4844
Colored pattern	512x512	0.5981	0.5569	0.3164
	256x256	0.5346	0.5529	0.3164
	96x96	0.5098	0.5549	0.3125
Hunter man	512x512	0.3421	0.3137	0.3828
	256x256	0.3234	0.3137	0.3906
	96x96	0.3702	0.3176	0.3915
Dotted Pattern	512x512	0.4577	0.4941	0.5234
	256x256	0.4235	0.4941	0.5195
	96x96	0.4356	0.4941	0.5078
Aeroplane	512x512	0.5709	0.6039	0.6250
	256x256	0.5462	0.6000	0.5938
	96x96	0.5567	0.5961	0.6016
Thumb Print	512x512	0.3341	0.3705	0.6636
	256x256	0.3012	0.3765	0.6836
	96x96	0.3209	0.5176	0.6055
Fruits	512x512	0.4453	0.4824	0.3398
	256x256	0.4320	0.4824	0.3394
	96x96	0.4431	0.4824	0.3320

Table No. 2 Entropy between Otsu and BFA

Image ID	*Image Size*	*Entropy*	
		Otsu	*BFA*
Leena	512x512	0.9778	0.9859
	256x256	0.9782	0.9834
	96x96	0.9801	0.9801
BW Pattern	512x512	0.9997	0.7467
	256x256	0.9967	0.9409
	96x96	0.9998	0.9174
Colored pattern	512x512	0.9823	0.6024
	256x256	0.9826	0.6258
	96x96	0.9827	0.6590
Hunter man	512x512	0.9994	0.9827
	256x256	0.9994	0.9801
	96x96	0.9984	0.9821
Dotted pattern	512x512	1.000	0.9901
	256x256	1.000	0.9922
	96x96	0.999	0.9975
Aeroplane	512x512	0.7969	0.8159
	256x256	0.7915	0.7830
	96x96	0.7820	0.7859
Thumbprint	512x512	0.5312	0.9989
	256x256	0.6312	0.9789
	96x96	0.8714	0.9452
Fruits	512x512	0.9997	0.7934
	256x256	0.9997	0.7903
	96x96	0.9993	0.7837

Table No. 3 Standard deviation between Otsu and BFA

Image ID	*Image Size*	*Standard Deviation*	
		Otsu	*BFA*
Leena	512x512	0.4923	0.4951
	256x256	0.4924	0.4942
	96x96	0.4931	0.4931
BW Pattern	512x512	0.4999	0.4093
	256x256	0.4988	0.4794
	96x96	0.5000	0.4711
Colored pattern	512x512	0.4939	0.3541
	256x256	0.4940	0.3633
	96x96	0.4940	0.3762
Hunter man	512x512	0.4998	0.4940
	256x256	0.4998	0.4931
	96x96	0.4995	0.4935
Dotted pattern	512x512	0.5000	0.4966
	256x256	0.5000	0.4973
	96x96	0.5000	0.4991
Aeroplane	512x512	0.4278	0.4347
	256x256	0.4258	0.4227
	96x96	0.4223	0.4238
Thumbprint	512x512	0.3654	0.3327
	256x256	0.3654	0.4927
	96x96	0.4548	0.4809
Fruits	512x512	0.4999	0.4265
	256x256	0.4999	0.4254
	96x96	0.4998	0.4229

Table No. 4 Class variance between Otsu and BFA

Image ID	*Image Size*	*Class variance*	
		Otsu	*BFA*
Leena	512x512	0.0014	0.0014
	256x256	0.0058	0.0057
	96x96	0.0430	0.0427
BW Pattern	512x512	0.0022	0.0054
	256x256	0.0097	0.0128
	96x96	0.0608	0.0778
Colored pattern	512x512	0.0014	0.0111
	256x256	0.0058	0.0431
	96x96	0.0382	0.2883
Hunter man	512x512	0.0013	0.0015
	256x256	0.0053	0.0064
	96x96	0.0373	0.0356
Dotted pattern	512x512	0.0012	0.0012
	256x256	0.0049	0.0050
	96x96	0.0382	0.0383
Aeroplane	512x512	0.0006	0.0006
	256x256	0.0028	0.0029
	96x96	0.0228	0.0225
Thumbprint	512x512	0.0230	0.0160
	256x256	0.0231	0.0162
	96x96	0.0803	0.0753
Fruits	512x512	0.0014	0.0032
	256x256	0.0060	0.0133
	96x96	0.0424	0.0966

Table No. 5 Peak signal to noise ratio

Image ID	*Image Size*	*PSNR*
		Otsu vs BFA
Leena	512x512	65.659
	256x256	67.704
	96x96	67.703
BW Pattern	512x512	53.695
	256x256	57.792
	96x96	56.106
Colored pattern	512x512	53.740
	256x256	53.881
	96x96	54.114
Hunter man	512x512	60.147
	256x256	59.779
	96x96	59.396
Dotted pattern	512x512	60.362
	256x256	61.080
	96x96	64.596
Aeroplane	512x512	67.390
	256x256	71.177
	96x96	74.554
Thumbprint	512x512	59.235
	256x256	59.049
	96x96	59.620
Fruits	512x512	53.768
	256x256	53.857
	96x96	53.613

Table No. 6 PRT between PSO, Otsu and BFA

Image ID	*Image Size*	*PRT(in secs)*		
		PSO	*Otsu*	*BFA*
Leena	512x512	10.94	0.0703	0.2013
	256x256	10.34	0.0827	0.1808
	96x96	9.921	0.0682	0.1899
BW Pattern	512x512		0.0727	0.1887
	256x256		0.0701	0.1757
	96x96		0.0686	0.1742
Colored pattern	512x512		0.0709	0.1874
	256x256		0.0672	0.1795
	96x96		0.0740	0.1717
Hunter man	512x512	12.81	0.0744	0.1834
	256x256	11.70	0.0749	0.1831
	96x96	10.90	0.0675	0.1715
Dotted Pattern	512x512		0.0824	0.1970
	256x256		0.0675	0.1798
	96x96		0.0712	0.1880
Aeroplane	512x512	12.85	0.0733	0.1882
	256x256	11.87	0.0642	0.1739
	96x96	10.96	0.0704	0.1619
Thumb Print	512x512		0.0728	0.1982
	256x256		0.0691	0.1714
	96x96		0.0660	0.1759
Fruits	512x512	11.06	0.0704	0.1872
	256x256	10.43	0.0648	0.1736
	96x96	9.60	0.0681	0.1806

8. Conclusion

One important concern in image segmentation is the effectiveness in thresholding. According to the segmented results, the proposed method has demonstrated satisfactory results. However, it is somewhat difficult to compare quantitatively the performance of global thresholding results. Three common performance evaluation criteria, the Peak to Signal Noise Ratio (PSNR), entropy and standard deviation measure, are employed to evaluate the thresholding methods. As all the optimization algorithms are stochastic and random searching one, the results of experiments are not absolutely the same in each run of the algorithm. Hence, it is necessary to analyze the stability of all the algorithms. This comparison is utilized to find which algorithm is more stable than others.

References

[1] M. Maitra, and A. Chatterjee, "A hybrid cooperative comprehensive learning based PSO algorithm for image segmentation using multilevel thresholding", Expert Systems with Applications, Vol. 34, 1341-1350, 2008.

[2] S. Mishra, "A hybrid least square-fuzzy bacteria foraging strategy for harmonic estimation," IEEE Trans. Evol. Comput., 9(1), pp. 61-73, 2005.

[3] M. Tripathy, and S. Mishra, "Bacterial foraging based solution to optimize both real power and voltage stability limit," IEEE Transactions, Power Syst., 22(1), pp. 240-248, 2007.

[4] W. Lin, and P.X. Liu, "Hammerstein model identification based on bacterial foraging," IEE Electronics Letters, 42(23), pp. 1332-1334, 2006.

[5] P. K. Sahoo, S Soltani, and A. K. C. Wong, "A survey of thresholding techniques, Computer Vision, Graphics and Image Processing, vol. 41(2), pp. 233-260, 1988.

[6] C.A. Glasbey, "An analysis of histogram based thresholding algorithms," CVGIP: Graphical Models and Image Processing, Vol. 55, pp. 532-537, 1993.

[7] J. S. Weszka, "A survey of threshold selection techniques, Computer Vision Graphics Image Processing", Vol. 7, 259-265, 1979.

[8] N. Otsu, "A threshold selection method from gray level histograms," IEEE Transaction on Systems, Man and Cybernetics, SMC-9(1), pp.62-66, 1979.

Author Profile

Beenu is serving Rayat Polytechnic College as lecturer since December 2009. Rayat Polytechnic College is a premier institute of India, located in Punjab State. Teaching is not just her job but a passion and she would love to do it for whole life as she believes that imparting education is the best way to serve mankind. She is studying Master of Technology in Electronics and Communication from Rayat Institute of Engineering & Information Technology (Rail Majra, Nawanshahar, Punjab, India). She believes that an Image has so many hidden aspects that our normal eyes cannot capture and logical representation of Information hidden behind an Image is the most interesting subject. She has spent years of quality time in this domain and has obtained expertise in the same. But still believes that its exploration is endless.