

Optimum Multilevel Image Thresholding Based on Tsallis Entropy Method with Bacterial Foraging Algorithm

P.D. Sathya[1] and R. Kayalvizhi[2]

**[1] Research Scholar, Department of Electrical Engineering, Annamalai University
Chidambaram – 608 002, Tamilnadu, INDIA**

**[2] Professor, Department of Instrumentation Engineering, Annamalai University
Chidambaram – 608 002, Tamilnadu, INDIA**

Abstract

Multilevel image thresholding is an important operation in many analyses which is used in many applications. Selecting correct thresholds is a critical issue. In this paper, Bacterial Foraging (BF) algorithm based on Tsallis objective function is presented for multilevel thresholding in image segmentation. Experiments to verify the efficiency of the proposed method and comparison to Genetic Algorithm (GA) is presented. The experiment results show that the proposed method gives the best performance in multilevel thresholding. The method is also computationally efficient, more stable and can be applied to a wide class of computer vision applications, such as character recognition, watermarking technique and segmentation of wide variety of medical images.
Keywords: *Multilevel thresholding, Bacterial foraging algorithm, Tsallis objective function, image segmentation.*

1. Introduction

Image segmentation is a process of dividing an image into different regions such that each region is nearly homogeneous, where the union of any two regions is not. It serves as a key in image analysis and pattern recognition and is a fundamental step toward low-level vision, which is significant for object recognition and tracking, image retrieval, face detection, and other computer-vision-related applications [1]. Many segmentation techniques have been proposed in the literature. Among all the existing techniques, thresholding technique is one of the most popular one due to its simplicity, robustness and accuracy [1-3].

Otsu and Kapur methods were proved to be two best thresholding methods for the uniformity and shape measures [4, 5]. However, it is required to determine threshold levels depending on the scene to obtain consistent segmentation results in many cases. Multilevel thresholding techniques were therefore developed. Most bi-level thresholding methods can easily evolve into multilevel thresholdig methods directly [6]. But, the computational complexity would grow exponentially as the threshold number increases due to their exhaustive searching approach [7, 8], which would limit the multilevel thresholding applications.

Yen et al used a maximum correlation criterion to multilevel thresholding, where the segmentation results are satisfactory and the threshold determination process could be accelerated [7]. Yin proposed algorithm that can determine the number of thresholds automatically as well as save a significant amount of computing time [8]. It appears that approximately all the methods suffered the computational complexity and the segmentation performance instability as the threshold number increases.

To eliminate such problems, evolutionary techniques have been applied in solving multilevel thresholding problem [9, 10]. Peng-Yeng developed a fast scheme multilevel thresholding using genetic algorithms for image segmentation [9]. Shu-Kai et al presented a hybrid optimal estimation algorithm for solving multi-level thresholding problems in image segmentation. The distribution of image intensity is modeled as a random variable, which is approximated by a mixture Gaussian model [10]. However, the method still fails to deal with the common drawback of GAs, the decreasing optimal stability as the convergent speed increases.

Yin proposed particle swarm algorithm based multilevel minimum cross entropy threshold selection procedure [11]. The method uses recursive programming technique which reduces an order of magnitude for computing the minimum cross entropy thresholding (MCET) objective function. Then, a particle swarm optimization (PSO) algorithm is proposed for searching the near-optimal MCET thresholds. However, Ratnaweera et al. state that the lack of population diversity in PSO algorithm is understood to be a factor in their convergence to local optima, which means that it cannot guarantee that the global optima in the search space will be found [12].

This paper proposes the development of a novel optimal multilevel thresholding algorithm, especially suitable for multimodal image histograms, for segmentation of ten benchmarked images, employing bacterial foraging (BF) technique. Bacterial foraging is comparatively a very recent technique that is being used for solving multidimensional global optimization problems [13].

In foraging theory, it is assumed that the objective of the animals is to search for and obtain nutrients in such a fashion that the energy intake per unit time is maximized [13]. This foraging strategy has been formulated as an optimization problem by employing optimal foraging theory. The foraging behavior of *E. Coli* bacteria includes the methods of locating, handling and ingesting food, has been successfully mimicked to propose a new evolutionary optimization algorithm.

The proposed BF method is used to maximize Tsallis objective function. The method has been compared with particle swarm optimization (PSO) and genetic algorithm (GA) algorithms. The results show that the proposed algorithm can outperform the other two methods both from the point of view of maximizing the objective function as well as maximizing the Peak signal to Noise Ratio (PSNR) value.

2. The proposed Tsallis multilevel thresholding method

In this section, a new thresholding method is proposed based on the entropy concept. This method is similar to the maximum entropy sum method of Kapur et al [3]; however the Tsallis non-extensive entropy concept is used for customizing information theory.

Let there be L gray levels in a given image and these gray levels are in the range {0, 1, 2,………,(L-1)}. Then one can define Pi = h(i)/N, $(0 \leq i \leq (L-1))$ where h(i) denotes number of pixels for the corresponding gray-level L and N denotes total number of pixels in the image which is equal to $\sum_{i=0}^{L-1} h(i)$.

Tsallis bi-level thresholding can be described as

$$f(t) = \arg\max[S_q^A(t) + S_q^B(t) + (1-q).S_q^A(t).S_q^B(t)] \quad (1)$$

where

q is an entropic index

$$S_q^A(t) = \frac{1 - \sum_{i=0}^{t-1} \left(\frac{Pi}{P^A}\right)^q}{q-1}, \quad P^A = \sum_{i=0}^{t-1} Pi$$

$$S_q^B(t) = \frac{1 - \sum_{i=t}^{L-1} \left(\frac{Pi}{P^B}\right)^q}{q-1}, \quad P^B = \sum_{i=t}^{L-1} Pi\,.$$

The information measures between the two classes (object and background) are maximized. When $S_q^A(t)$ is maximized, the luminance level t is considered to be the optimum threshold value. This can be achieved by a cheap computational effort.

This Tsallis entropy criterion method can also be extended to multilevel thresholding and it is described as follows:

$$f(t) = \arg\max[S_q^A(t) + S_q^B(t) + S_q^C(t) + \ldots + S_q^m(t) + (1-q).S_q^A(t).S_q^B(t).S_q^C(t)\ldots.S_q^m(t)] \quad (2)$$

where

$$S_q^A(t) = \frac{1 - \sum_{i=0}^{t_1-1} \left(\frac{Pi}{P^A}\right)^q}{q-1}, \quad P^A = \sum_{i=0}^{t_1-1} Pi$$

$$S_q^B(t) = \frac{1 - \sum_{i=t_1}^{t_2-1} \left(\frac{Pi}{P^B}\right)^q}{q-1}, \quad P^B = \sum_{i=t_1}^{t_2-1} Pi$$

$$S_q^C(t) = \frac{1 - \sum_{i=t_2}^{t_3-1} \left(\frac{Pi}{P^C}\right)^q}{q-1}, \quad P^C = \sum_{i=t_2}^{t_3-1} Pi \ldots.$$

$$S_q^m(t) = \frac{1 - \sum_{i=t_m}^{L-1} \left(\frac{Pi}{P^m}\right)^q}{q-1}, \quad P^m = \sum_{i=t_m}^{L-1} Pi\,.$$

The aim of this proposed PSO algorithm is to maximize the Tsallis objective function using equation (2).

3. Bacterial Foraging Algorithm

3.1 A Brief Overview

It is the law of nature that species with good foraging strategies survive while those with poor searching ability are either eliminated or shaped into good ones. This is because the former is more likely to enjoy reproductive success by producing better species in future generations. This activity of foraging led the researchers to use it as an optimization process. The foraging behavior of *E. Coli* (bacteria present in intestines) can be explained by four processes namely, chemotaxix, swarming, reproduction, elimination and dispersal which are described below.

a) Chemotaxis: An *E. coli* bacterium can move in two different ways: it can swim or it can tumble. The bacterium moves in a specified direction during swimming and during tumbling it does not have a set direction of movement and there is little displacement. Generally, the bacterium alternates between these two modes of operation in its entire lifetime. This alternation between the two modes enables the bacteria to move in random directions and search for nutrients.

b) Swarming: Once one of the bacteria reaches the desired food location, it should attract other bacteria so that they converge at the desired location. To achieve this, a penalty function based upon the relative distances of each bacterium from the fittest bacterium is added to the original objective function. Finally, when all the bacteria have merged into the solution point the penalty function becomes zero. The effect of swarming is to make the bacteria congregate into groups and move as concentric patterns with high bacterial density.

c) Reproduction: The original set of bacteria after several chemotaxis stages undergoes the reproduction stage where the bacteria are split into two groups. The least healthy bacteria die and the other healthiest bacteria split into two at the same location thus ensuring that the population of the bacteria remains constant.

d) Elimination and Dispersal: An unforeseen event may cause the elimination of a set of bacteria and/or disperse them to a new environment. This helps in reducing the probability of being getting trapped in local minima.

3.2 The BF Algorithm

The algorithm is discussed here in brief.
Step1: Initialization

i. Number of bacteria (S) to be used for finding the minima.
ii. Number of parameters (p) to be optimized.
iii. Specifying the location of the initial set of bacteria.
iv. N_c is the number of chemotactic steps taken by each bacterium before reproduction.
v. N_s is the maximum number of steps taken by each bacterium when it moves from low nutrient area to high nutrient area.
vi. N_{re} and N_{ed} are the number of reproduction and elimination dispersal events.
vii. P_{ed} is the probability of elimination and dispersal.
viii. Random swim direction vector Δ(i) and run length vector C(i).

Step2: Iterative algorithm for optimization

The algorithm begins with the calculation of objective value using equation (2) for the initial bacterial population inside the innermost chemotaxis loop. Any i^{th} bacteria at the j^{th} chemotactic, k^{th} reproduction and l^{th} elimination stage is $\theta^i(j,k,l)$ and its corresponding objective value is given by $J_1(i,j,k,l)$. The algorithm works as follows:

1. Starting of the Elimination-dispersal loop
2. Starting of the Reproduction loop
3. Starting of the chemotaxis loop

a) i = 1, 2, ...S, calculate $J_1(i, j, k, l)$

b) $J_1(i, j, k, l)$ is served as J_{1last} so as to compare with other J_1 values.

c) Tumble: Generate a random vector $\Delta(i)$ with each element $\Delta n(i)$, m = 1,2, … , P, a random number on [-1, 1].

d) Move: $\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\dfrac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$

This results in a step size C(i) in the direction of the tumble for i^{th} bacterium.

e) Calculate $J_1(i, j+1, k, l)$

f) Swim

Let n = 0 (counter for swim length)
While $n<N_s$
n=n+1;
If $J_1(i, j+1, k, l) < J_{1last}$ then $J_{1last} = J_1(i, j+1, k, l)$ and

$$\theta^i(j+1,k,l) = \theta^i(j,k,l) + C(i)\frac{\Delta(i)}{\sqrt{\Delta^T(i)\Delta(i)}}$$

This $\theta^i(j+1,k,l)$ is used to calculate new $J_1(i, j+1, k, l)$.

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Else $n = N_s$

g) Go to the next bacterium (i+1) till all the bacteria undergo chemotaxis.

4. If $j<N_c$, go to step 3 and continue chemotaxis since the life of bacteria is not over else go to the reproduction stage.

5. Reproduction:

a) For the given k and l, and for each i = 1, 2, 3, ... S, let $J^{i}_{health} = \sum_{j=1}^{N_c+1} J(i,j,k,l)$ be the health of ith bacterium. The bacteria are stored according to ascending order of J^{i}_{health}.

b) The bacteria with the highest J^{i}_{health} values die and other bacteria with minimum values split and the copies that are made are placed at the same location as their parent.

6. If $k < N_{re}$, go to step 2 to start the next generation in the chemotactic loop else go to step 7.

7. Elimination - dispersal: For i = 1, 2, ... S a random number (rand) is generated and if rand $\leq P_{ed}$, then that bacterium gets eliminated and dispersed to a new random location, else the bacterium remains at its original location.

8. If $l < N_{ed}$ go to step 1 else stop.

4. Experimental Results and Analysis

In this section, the performances of the following methods are evaluated: Tsallis based BF, PSO and GA methods. All the experiments were performed on a P4 3GHz with 2GHz RAM. Benchmark images namely Lenna, Pepper, Baboon, Hunter, Cameraman, Airplane, Map, Living room, House and butterfly used for the experiment are gathered in Figure 1 with their histograms.

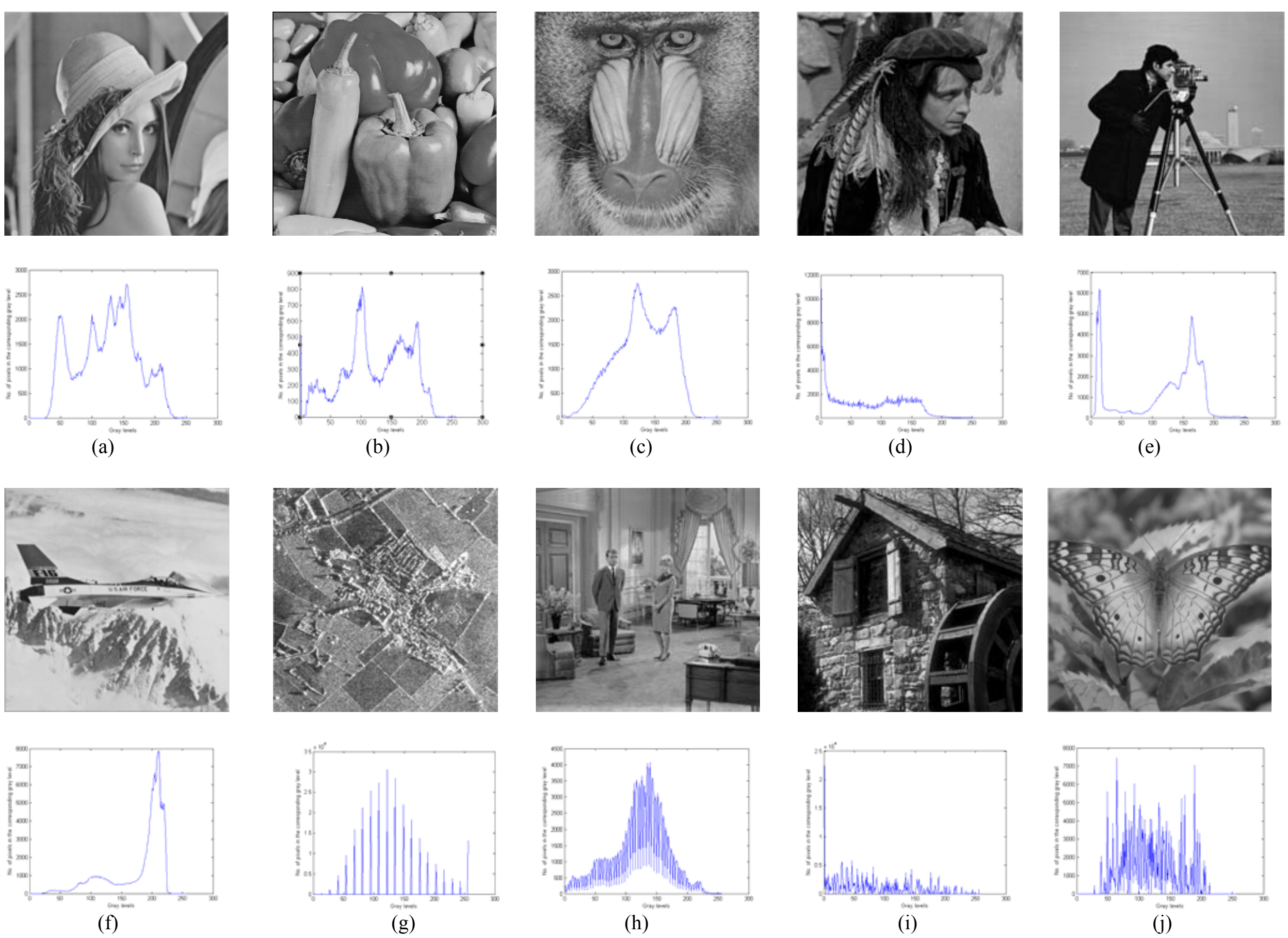
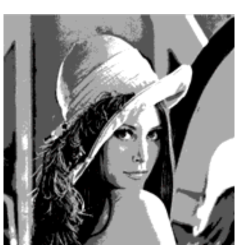


Fig. 1 Test Images and their histograms

(a) [(a) Lena, (b) Pepper, (c) Baboon, (d) Hunter, (e) Cameraman, (f) Airplane, (g) Map, (h) Living Room, (i) House, (j) Butterfly]

Table 1: Objective values and their optimal threshold values by using BF, PSO and GA methods

Test Images	m	Objective values			Optimal threshold values		
		BF	PSO	GA	BF	PSO	GA
LENNA	2	0.8889	0.8889	0.8889	120,164	120,164	120,164
	3	1.296278	1.296268	1.296247	81,124,178	110,149,187	98,159,181
	4	1.654271	1.654255	1.654208	85,124,161,193	85,118,164,200	86,120,151,205
	5	1.995787	1.995773	1.995717	76,108,136,164,193	86,117,142,166,196	95,130,152,173,200
PEPPER	2	0.8889	0.8889	0.8889	82,154	82,154	82,154
	3	1.296278	1.296274	1.296262	86,118,190	93,133,179	75,103,182
	4	1.654264	1.654248	1.654225	71,121,161,197	73,121,141,176	73,109,141,193
	5	1.995771	1.995766	1.995739	70,109,139,169,197	78,111,141,169,198	78,105,139,168,200
BABOON	2	0.8889	0.8889	0.8889	91,147	91,147	91,147
	3	1.296284	1.296274	1.296202	111,148,188	108,155,181	111,136,193
	4	1.654266	1.654262	1.654241	75,114,146,175	62,115,144,174	94,125,152,177
	5	1.995744	1.995737	1.995708	78,106,136,157,179	84,110,132,153,175	90,116,139,159,180
HUNTER	2	0.8889	0.8889	0.8889	94,137	94,137	94,137
	3	1.296270	1.296267	1.296227	82,118,171	83,143,174	87,147,173
	4	1.654258	1.654255	1.654240	71,110,142,182	78,109,143,187	90,119,150,191
	5	1.995766	1.995720	1.995713	65,93,123,150,182	70,103,139,174,198	79,114,144,174,198
CAMERA MAN	2	0.8889	0.8889	0.8889	120,154	120,154	120,154
	3	1.296189	1.296180	1.296141	78,128,178	78,121,173	81,143,170
	4	1.654190	1.654183	1.654177	91,123,156,211	82,122,154,201	76,116,148,202
	5	1.995674	1.995669	1.995663	70,107,134,158,200	78,110,133,159,199	88,118,143,169,205
AIRPLANE	2	0.8889	0.8889	0.8889	72,153	72,153	72,153
	3	1.296223	1.296204	1.296180	99,143,193	98,134,192	89,148,172
	4	1.654277	1.654262	1.654243	68,103,135,182	85,117,153,180	79,111,153,173
	5	1.995795	1.995784	1.995768	61,94,121,150,185	75,107,134,157,185	73,98,131,162,192
MAP	2	0.881206	0.881206	0.881206	114,176	114,176	114,176
	3	1.273982	1.267481	1.232429	84,142,198	90,131,183	80,145,172
	4	1.587902	1.585544	1.579716	73,113,156,203	78,121,158,189	80,117,157,199
	5	1.828422	1.818369	1.788800	75,112,147,174,206	79,113,142,170,191	91,118,144,174,206
LIVING ROOM	2	0.888881	0.888881	0.888881	81,144	81,144	81,144
	3	1.296281	1.296275	1.296255	89,143,197	91,137,198	88,117,178
	4	1.654263	1.654247	1.654244	67,107,145,186	87,126,165,200	90,126,158,199
	5	1.995743	1.995701	1.995627	72,111,139,164,199	71,125,150,176,205	69,126,157,182,204
HOUSE	2	0.888761	0.888761	0.888761	87,145	87,145	87,145
	3	1.296092	1.296090	1.296052	88,133,199	90,133,199	82,123,177
	4	1.653630	1.653586	1.653581	67,105,146,189	70,112,152,189	73,111,151,189
	5	1.994217	1.993744	1.993426	66,95,121,155,200	70,104,134,160,212	60,99,114,158,198
BUTTERFLY	2	0.888825	0.888825	0.888825	97,136	97,136	97,136
	3	1.296202	1.296190	1.296168	99,135,197	100,135,185	89,124,169
	4	1.653424	1.652617	1.652564	95,120,144,189	89,122,143,178	94,121,141,179
	5	1.994823	1.991453	1.989359	89,114,141,170,213	70,107,134,162,189	70,119,140,170,214


(a)


(b)


(c)


(d)


(e)

(f) (g) (h) (i) (j)

Fig. 2 Segmented images of multilevel thresholding for m = 3
[(a) Lena, (b) Pepper, (c) Baboon, (d) Hunter, (e) Cameraman, (f) Airplane, (g) Map, (h) Living Room, (i) House, (j) Butterfly]

Table 2: PSNR value, CPU time and standard deviation value obtained by BF, PSO and GA methods

Test Images	m	PSNR (db)			CPU Time			Standard Deviation		
		BF	PSO	GA	BF	PSO	GA	BF	PSO	GA
LENNA	2	15.2419	15.2419	15.2419	3.0218	3.6810	3.9219	0.0000	0.0000	0.0000
	3	17.4715	17.1425	16.9455	3.5327	4.0357	4.3906	1.6827e-006	2.5418e-006	3.8999e-006
	4	19.5070	19.4324	19.0207	4.0310	4.7523	4.8438	3.4304e-006	1.3306e-005	1.9104e-005
	5	20.9916	20.5637	19.8703	4.5275	4.9900	5.2854	4.5355e-006	1.6797e-005	2.7208e-005
PEPPER	2	12.9108	12.9108	12.9108	3.0531	3.5394	3.9844	0.0000	0.0000	0.0000
	3	16.6563	16.0269	15.5628	3.2310	3.5473	3.9919	2.8014e-006	7.3578e-006	2.0199e-005
	4	19.2433	16.7109	16.3735	4.1089	4.4063	5.0938	1.6217e-005	7.0094e-005	1.7406e-004
	5	20.4910	20.2089	19.7642	4.5213	4.8484	5.2314	2.0208e-004	6.3010e-004	1.1678e-003
BABOON	2	13.1404	13.1404	13.1404	3.1028	3.5021	3.8906	0.0000	0.0000	0.0000
	3	18.1076	17.0809	16.7728	3.7452	4.2591	4.4422	2.9078e-006	9.3397e-006	1.2993e-005
	4	17.5204	17.1462	17.1583	3.9303	4.3365	4.5156	3.4997e-006	7.2225e-006	1.3714e-005
	5	18.7616	18.2718	17.2903	4.8614	5.4188	5.8281	9.7325e-006	1.1321e-005	1.8993e-005
HUNTER	2	11.3848	11.3848	11.3848	3.0106	3.6970	3.9797	0.0000	0.0000	0.0000
	3	14.5772	14.5135	14.0724	3.5624	4.0130	4.3906	4.6660e-007	1.8965e-006	1.0060e-005
	4	16.2874	15.4496	14.1926	4.1200	4.6875	4.7031	1.8203e-006	4.2172e-006	1.0886e-005
	5	17.3380	16.6426	15.6197	4.4226	5.0009	5.4688	5.4613e-005	1.2255e-004	9.3619e-004
CAMERAMAN	2	10.6258	10.6258	10.6258	2.5690	3.0021	3.6482	0.0000	0.0000	0.0000
	3	15.6856	14.9951	14.5900	3.1250	3.7658	4.3906	4.7916e-006	5.4543e-006	8.4892e-006
	4	16.7835	15.9187	14.9756	3.9253	4.6188	4.8594	3.6715e-005	7.5181e-005	1.1024e-004
	5	17.8802	17.2393	16.6026	4.3906	5.1343	5.6026	6.6163e-005	1.0319e-004	7.7199e-004
AIRPLANE	2	13.7290	13.7290	13.7290	2.9632	3.3159	3.8921	0.0000	0.0000	0.0000
	3	15.8742	15.5913	14.6681	3.3310	3.7625	4.1358	8.3154e-007	3.1114e-006	6.9412e-006
	4	16.3276	15.6294	14.9701	3.9259	4.8750	5.2656	9.5166e-007	2.6305e-006	9.2004e-006
	5	17.6049	17.6077	16.1579	4.7410	5.2813	5.6077	5.1122e-006	3.3007e-005	6.3861e-005
MAP	2	16.6045	16.6045	16.6045	2.7942	3.3221	3.6563	0.0000	0.0000	0.0000
	3	18.4286	18.0419	16.2161	3.2771	3.7969	4.1563	5.6090e-007	1.0167e-006	4.6714e-006
	4	20.6499	19.7997	19.7340	3.6104	4.0213	4.5744	5.0556e-004	1.1493e-003	3.9730e-003
	5	22.1638	21.8968	21.5746	3.9885	4.5873	4.9810	6.5988e-004	8.1623e-003	1.6169e-002
LIVING ROOM	2	13.1208	13.1208	13.1208	3.1406	3.6250	3.9531	0.0000	0.0000	0.0000
	3	17.1198	16.9810	16.5873	3.5769	3.9139	4.3417	1.6980e-006	6.9103e-005	7.0160e-004
	4	19.2320	18.8655	18.5189	3.9139	4.3964	4.7602	4.3245e-006	8.4404e-006	2.2951e-005
	5	21.3385	20.9931	20.5597	4.0251	4.6421	5.1715	4.3515e-005	9.3293e-005	1.8187e-004
HOUSE	2	12.9865	12.9865	12.9865	2.9117	3.2563	3.7656	0.0000	0.0000	0.0000
	3	14.0213	13.8104	13.6918	3.3437	3.8884	4.2736	2.5025e-006	4.3646e-005	6.9786e-005
	4	16.8884	16.4428	16.1794	3.8074	4.4620	4.8655	3.7689e-006	8.7702e-005	1.1385e-004
	5	17.5635	16.7719	16.5772	4.5114	4.9437	5.4353	7.5181e-005	9.5166e-005	1.2255e-004
BUTTERFLY	2	13.0516	13.0516	13.0516	3.1406	3.7344	4.1406	0.0000	0.0000	0.0000
	3	18.1337	17.8316	17.2964	3.5746	4.1980	4.5607	1.4899e-006	4.8520e-005	8.5774e-004
	4	20.0356	18.9792	18.8382	4.0356	4.6370	5.0254	1.9529e-005	6.7992e-004	1.3908e-005
	5	21.9096	21.4406	20.2055	4.5154	5.0291	5.5607	6.4439e-005	9.1016e-004	5.1122e-003

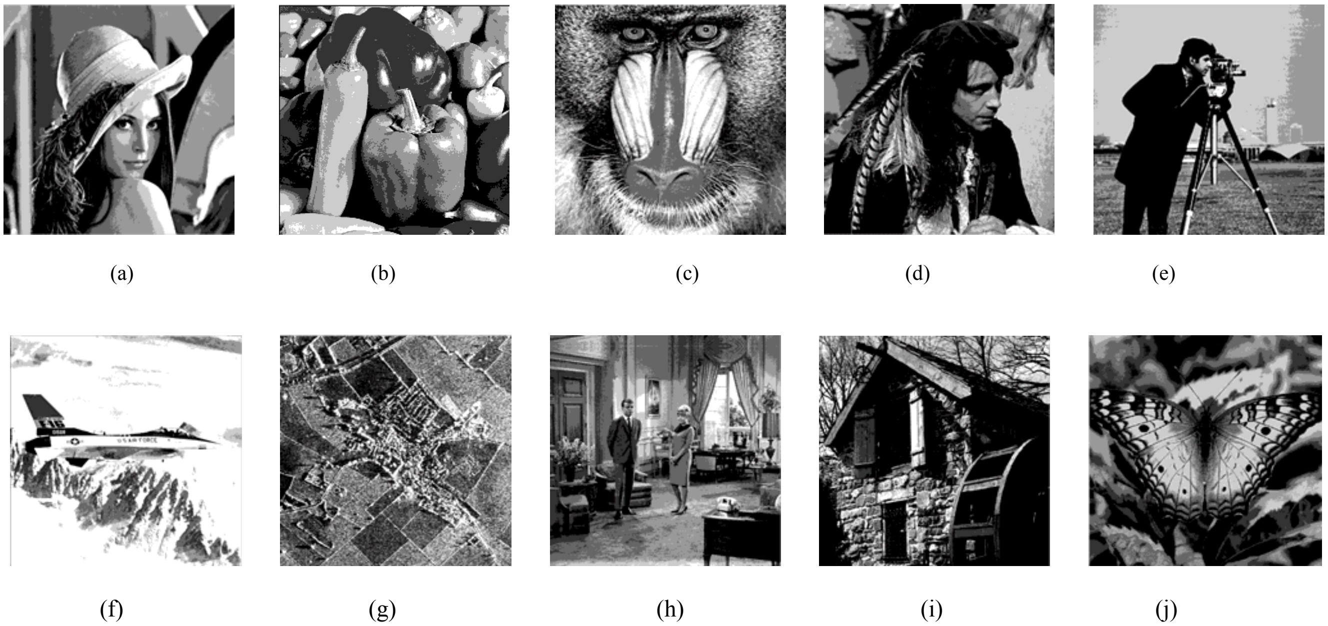


Fig. 3 Segmented images of multilevel thresholding for m = 5
[(a) Lena, (b) Pepper, (c) Baboon, (d) Hunter, (e) Cameraman, (f) Airplane, (g) Map, (h) Living Room, (i) House, (j) Butterfly]

The proposed multilevel thresholding technique using BF is implemented with the following parameters: Number of bacterium (s): 20, Number of chemotatic steps (N_c): 10, Swimming length (N_s): 10, Number of reproduction steps (N_{re}): 4, Number of elimination of dispersal events (N_{ed}): 2, In Tsallis objective function, the parameter q is chosen as 4.

Several aspects would be tested: (1) the multilevel thresholding results of different methods (2) the objective values for different methods (3) the stability of different methods (4) Peak to Signal Ratio (PSNR) value.

The multilevel thresholding is applied to methods aforementioned to experiment their respective effects. Objective values and their thresholds obtained by different methods are listed in Table 1. Multilevel thresholding segmentation results depend on the objective function selected. The higher value of objective function indicated the better segmentation. It is observed that the results by the proposed method are better than others.

Segmented images of Tsallis-BF by m = 3 and 5 are shown in Figures 2 and 3 respectively. The segmentation is better when m = 5 is chosen than by choosing m = 3.

The PSNR value, CPU time and the standard deviation value obtained by different methods are listed in Table 2. PSNR value is calculated as follows:

$$PSNR = 20\log_{10}\left(\frac{255}{RMSE}\right)$$

where

$$RMSE = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}[I(i,j) - \hat{I}(i,j)]^2}$$

The higher value of PSNR means that the quality of the thresholded image is better. For all the images, the performance of the proposed method is better than the PSO and GA, since their objective value and PSNR measure are higher. It is also observed from the table that compared with PSO and GA methods, the BF method shorten the CPU time significantly. The standard deviation value obtained by the proposed method is lower than the other two methods which show the stability of the proposed method.

5. Conclusion

Non-extensive entropy image thresholding is a powerful technique for image segmentation. In this paper, Bacterial Foraging (BF) algorithm based on Tsallis objective function has been proposed to perform multilevel thresholding and the method has been compared with PSO and GA methods. All the techniques have been applied to ten standard test images and the segmentation results are superior to those obtained by applying the Tsallis-BF algorithm. Experimental results show that the BF algorithm converges faster than the PSO and GA and provides better stability. In addition, the new algorithm provides better quality in visualization by obtaining maximum PSNR value. Furthermore, the proposed method is also suitable for other types of images.

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