Image Segmentation using a Refined Comprehensive Learning Particle Swarm Optimizer for Maximum Tsallis Entropy Thresholding

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Abstract— **Thresholding is one of the most important techniques for performing image segmentation. In this paper to compute optimum thresholds for Maximum Tsallis entropy thresholding (MTET) model, a new hybrid algorithm is proposed by integrating the Comprehensive Learning Particle Swarm Optimizer (CPSO) with the Powell's Conjugate Gradient (PCG) method. Here the CPSO will act as the main optimizer for searching the near-optimal thresholds while the PCG method will be used to fine tune the best solutions obtained by the CPSO in every iteration. This new multilevel thresholding technique is called the refined Comprehensive Learning Particle Swarm Optimizer (RCPSO) algorithm for MTET. Experimental results over multiple images with different range of complexities validate the efficiency of the proposed technique with regard to segmentation accuracy, speed, and robustness in comparison with other techniques reported in the literature. The experimental results demonstrate that the proposed RCPSO algorithm can search for multiple thresholds which are very close to the optimal ones examined by the exhaustive search method.**

Keyword- Image Segmentation, Maximum Tsallis entropy thresholding, Comprehensive Learning PSO, Powell's Conjugate Gradient method

I. INTRODUCTION

Image thresholding is widely used as a popular tool in image segmentation. It is useful in separating objects from background, or discriminating objects from objects that have distinct gray levels. Many thresholding techniques have been proposed to solve image segmentation problems and are classified by their differences [1]. For instance, some techniques have been classified as either optimal or property-based , while other methods are identified as either global or local thresholdings based on the role of the intensity value . The difference between global and local thresholdings is that a global thresholding technique cuts the entire image with a single threshold value, whereas a local thresholding technique divides the image into sub-images, and for each a threshold is determined.

Thresholding involves bi-level thresholding and multilevel thresholding. Bi-level thresholding classifies the pixels into two groups, one including those pixels with gray levels above a certain threshold, the other including the rest. Multilevel thresholding divides the pixels into several classes. The pixels belonging to the same class have gray levels within a specific range defined by several thresholds. Both bi-level and multilevel thresholding methods can be classified into parametric and nonparametric approaches [2].

Parametric approaches assume that each group (sub-image or class) has the probability density function (PDF) of a Gaussian distribution and finds an estimate of the parameters of such a distribution which will best fit the given histogram data . Unfortunately, when the desired number of classes is much lower than the number of peaks in the original histogram, the computation time to find the threshold values often becomes expensive.

The nonparametric approach is based on a search of the thresholds optimizing an objective function such as the between-class variance (Otsu's function) [2] and entropy (Kapur's function) [3]. Recent developments in statistical mechanics based on Tsallis entropy have intensified the interest of investigating it as an extension of Shannon's entropy [4]. It appears in order to generalize the Boltzmann/Gibbs' traditional entropy to non-extensive physical systems. In this new theory a system dependent parameter 'q' measuring the degree of non-extensivity is introduced. The q parameter in the Tsallis entropy is used as an adjustable value, which plays an important role as a tuning parameter in the image segmentation. Thus replacing the traditional maximum entropy thresholding (MET) with a maximum Tsallis entropy. This replacement not only improves the effectiveness of the segmentation process by increasing the number of thresholds, but also makes cumbersome in finding the optimum thresholds. Meanwhile, the computation time increases sharply when the number of thresholds increases, so the traditional exhaustive method finds it difficult to identify the optimal thresholds. Thus researchers tend to use meta-heuristics methods to find the optimum threshold values quickly.

The meta-heuristic techniques [5-12] are able to escape from local optima and their use has significantly increased the ability of finding very high-quality solutions in a reasonable time. This is particularly true for large and poorly understood problems. Several different meta-heuristics have been proposed and new ones are under constant development. Among them, Genetic Algorithm (GA) [9] have been widely applied to solve the multilevel thresholding problems, then the DE algorithm is applied to find the optimal threshold values by minimizing the dissimilarity between the input image, likewise Particle Swarm Optimization (PSO) [5] is another latest evolutionary optimization technique, which is used for the multilevel thresholding, similarly the Ant Colony Optimization (ACO) and Simulated Annealing (SA) algorithms are used for multilevel image thresholding .

Taking into account the advantages of the meta-heuristics to escape from local optima with a reasonable time, some meta- heuristic techniques have been extensively employed to search more fastly the optimal thresholds. As is known, normal global meta- heuristic techniques conduct only one search operation in one iteration, for example the PSO carries out a global search in the beginning stage and a local search in the ending stage. In [4], the authors claimed, that the Artificial Bee Colony (ABC) approach features the advantage that it conducts both global search and local search in each iteration, and as a result the probability of finding the optimal result has significantly increased.

Conversely, this paper proposes a new hybrid technique RCPSO which integrates a Powell’s Conjugate Gradient method [8] with the CPSO [7], to perform both global search and local search in each iteration. This hybrid technique is claimed very powerful compared to ABC, because unlike the local search mechanism in ABC, the Powell’s Conjugate Gradient method of the proposed hybrid technique guarantees a fine-tuning of the (improved) solution obtained by the CPSO part. Thus finding the optimal thresholds at a more reasonable time is guaranteed by the proposed hybrid RCPSO method compared to ABC [4].

The remainder of this paper is organized as follows. In Section 2, the problem of the multilevel thresholding is formulated as an optimization problem and the objective function treated are briefly presented. The Section 3 deals with the proposed hybrid technique and its coding for the multilevel thresholding problem modelled as MTET. Section 4 gives numerical experiments and comparative results of the proposed method with the other techniques reported in the literature. Concluding remarks are given in Section 5.

II. Problem Formulation

The optimal thresholding methods search the thresholds such that the segmented classes on the histogram satisfy the desired property. This is performed by maximizing an objective function which uses the selected thresholds as the parameters. In this paper, Maximum Tsallis entropy thresholding method is used [4].

A. Non-extensive Entropy

The entropy is basically a thermodynamic concept associated with the order of irreversible processes from a traditional point of view. Shannon redefined the entropy concept of Boltzmann/Gibbs as a measure of uncertainty regarding the information content of a system. The Shannon entropy is defined from the probability distribution, where p_i denotes the probability of each state i. Therefore, the Shannon entropy can be described as:

$$S = -\sum_{i=1}^{L} P_i \log_2(\rho_i) \tag{1}$$

where: L denotes the total number of states.

This formalism is restricted to the domain of validity of the Boltzmann-Gibbs-Shannon (BGS) statistics, which only describes Nature when the effective microscopic interactions and the microscopic memory are short ranged. Suppose a physical system can be decomposed into two statistical independent subsystems A and B, the Shannon entropy has the extensive property:

$$S(A+B) = S(A) + S(B) \tag{2}$$

However, for a certain class of physical systems which entail long-range interactions, long time memory, and fractal-type structures, it is necessary to use non extensive entropy. Tsallis has proposed a generalization of BGS statistics, and its form can be depicted as:

$$S_q = \frac{1 - \sum_{i=1}^{q} (\rho_i)^q}{q-1} \tag{3}$$

where: the real number q denotes an entropic index that characterizes the degree of non-extensivity. Above expression will meet the Shannon entropy in the limit q→1. The Tsallis entropy is non-extensive in such a way that for a statistical dependent system. Its entropy is defined with the obey of pseudo additivity rule.

$$S_q(A+B) = S_q(A) + S_q(B) + (1-q) \times S_q(A) \times S_q(B) \tag{4}$$

Three different entropies can be defined with regard to different values of *q*. For q < 1, the Tsallis entropy becomes a sub extensive entropy where $S_q(A + B) < S_q(A) + S_q(B)$; for q = 1, the Tsallis entropy reduces to an standard extensive entropy where $S_q(A + B) = S_q(A) + S_q(B)$; for q >1, the Tsallis entropy becomes a super extensive entropy where $S_q(A + B) > S_q(A) + S_q(B)$.

The parameter q describes the long-range correlation within an image. In fact, the long-range correlation is the overall effect of the object pattern, image size, scene illumination, gray-level contrast and soon. For different images the strength of long-range correlation may not be the same so the proper q values for them should be different. Thus, it is difficult to determine the proper q value for a given image. Nevertheless, the results of the proposed method depend closely on the q values and in this paper the proper value of q is determined by evaluating the misclassification error.

The presented MTET model is derived the traditional entropic form based on Shannon theory can be generalized by an additional nonextensive parameter and it is named ‘‘Tsallis entropy’’, of order q [4]. The notable advantage of the proposed method is that the Tsallis entropy uses global and objective property of the image histogram and is easily optimized for thresholds.

The Tsallis entropy can be extended to the fields of image processing, because of the presence of the correlation between pixels of the same object in a given image. The correlations can be regarded as the long-range correlations that present pixels strongly correlated in luminance levels and space fulfilling.

B. Thresholding Model

Your Assume that an image can be represented by *L* gray levels. The probabilities of pixels at level *i* is denoted by p_i; so $p_i \geq 0$ and $p_1 + p_2 + \ldots p_L = 1$. If the image is divided into two classes, $C_A$and $C_B$by a threshold at level t, where class $C_A$consists of gray levels from 1 to tand C_B contains the rest gray levels from t + 1 to L, the cumulative probabilities can be defined as:

$$\omega_A = \sum_{i=1}^{t} \rho_i , \sum_{i=t+1}^{L} \rho_i \tag{5}$$

Therefore, the normalization of probabilities p^A and p^B can be defined as:

$$P^A = \frac{\{P_1, P_2 ....., P_t,\}}{\omega_A}. \tag{6}$$

$$P^B = \frac{\{P_{t+1}, P_{t+22} ....., P_L,\}}{\omega_B}. \tag{7}$$

Now, Tsallis entropy for each individual class is defined as:

$$S_q^A(t) = \frac{1 - \sum_{i=1}^{t} (\rho_i^A)^q}{q-1} \tag{8}$$

$$S_q^B(t) = \frac{1 - \sum_{i=t+1}^{L} \left(\rho_i^B\right)^q}{q-1} \qquad (9)$$

The Tsallis entropy Sq(t) of each individual class is dependent on the threshold t. The total Tsallis entropy of the image is written as:

$$S_q(t) = S_q^A(t) + S_q^B(t) + (1-q) * S_q^A(t) * S_q^B(t) = \qquad (10)$$

$$1 - \frac{1 - \sum_{i=1}^{t} \left(\rho_i^A\right)^q}{q-1} + 1 - \frac{1 - \sum_{i=t+1}^{L} \left(\rho_i^B\right)^q}{q-1} + (1-q) * \frac{1 - \sum_{i=1}^{t} \left(\rho_i^A\right)^q}{q-1} * \frac{1 - \sum_{i=t+1}^{L} \left(\rho_i^B\right)^q}{q-1}$$

The task is to maximize the total Tsallis entropy between class $C_A$and C_B. When the value of $S_q(t)$ is maximized, the corresponding gray-level t* is regarded as the optimum threshold value:

$$\mathrm{t} = \arg\max\left(\mathrm{S_q(t)}\right) \qquad (11)$$

For bi-level thresholding, the best threshold can be obtained by a cheap computation effort, however, for multi-level thresholding (suppose the number of class is *m*), the problems will encounter following two challenges: 1) The optimization functions become more complicated. This causes little trouble since computers can calculate the function rapidly. 2) The parametric space is enlarged exponentially.

The optimal multilevel thresholding problem is configured as an m-dimensional optimization problem. Interestingly, 'm' optimal thresholds $[T_1, T_2, \ldots, T_m]$ for a given image can be determined by maximizing the objective function:

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$$[T_1, T_2, \ldots, T_m] = \arg\max\ [\, S_q^1(t) + S_q^2(t) + \cdots + S_q^M(t) +$$

$$(1-q).\, S_q^1(t).\, S_q^2(t) \ldots S_q^M(t)] \qquad (12)$$

Where,

$$S_q^1(t) = \frac{1 - \sum_{i=1}^{t_1} (p_i/p^1)^q}{q-1}, \qquad S_q^2(t) = \frac{1 - \sum_{i=t_1+1}^{t_2} (p_i/p^2)^q}{q-1}$$

and

$$S_q^M(t) = \frac{1 - \sum_{i=t_{m-1}}^{G} (p_i/p^M)^q}{q-1}, \qquad \mathrm{M=m+1}$$

The number of $S_q(t)$ calculated is equal to:

$$S_q(t) = (L-1) * (L-2) \ldots\ldots * (L-1) * \frac{(L-m+1)}{1*2*\ldots.*(m-1)} \qquad (13)$$

It indicates the number of function calculated also increase from 255 to 3.6×10^{11} if the value of m ranges from 2 to 7. Therefore, the exhaustive search algorithm finds very expensive computation for multi-level thresholding, to overcome this, a refined CPSO method is proposed in this research for finding optimum thresholds and discussed in the next section.

III. SOLUTION METHODOLOGY

To find the optimal thresholds using the Maximum Tsallis entropy model, this research integrates two efficient techniques, one is to thoroughly search the solution space and the other is to fine-tune the solution and its region obtained by the former technique. The global optimizer is the Comprehensive Learning Particle Swarm Optimizer and the fine-tuning algorithm used is the PCG- method.

A. Comprehensive Learning Particle Swarm Optimizer

Particle Swarm Optimization (PSO) technique, inspired by the swarming behaviour of animals as bird flocking, was introduced by Kennedy and Eberhart (1995). A particle swarm is a population of particles, where each particle is a moving object that 'flies' through the search space and is attracted to previously visited locations with high fitness. In contrast to the individuals in evolutionary computation, particles neither reproduce nor get replaced by other particles.

Although there are numerous variants for the PSO, premature convergence when solving multimodal problems is still the main deficiency of the PSO. In the original PSO, each particle learns from its $pbest$ and $gbest$ simultaneously. Restricting the social learning aspect to only the $gbest$ makes the original PSO converge fast. However, because all particles in the swarm learn from the $gbest$ even if the current $gbest$ is far from the global optimum, particles may easily be attracted to the $gbest$ region and get trapped in a local optimum if the search environment is complex with numerous local solutions. To overcome this, a learning strategy called comprehensive learning was proposed [7].

In this learning strategy, the following velocity updating equation is used:

$$V_i^d = w * V_i^d + c * rand_i^d * \left(pbest_{fi(d)}^d - x_i^d\right) \tag{14}$$

Where $f_i = [f_i(1), f_i(2), \ldots\ldots f_i(D)]$ defines which particles' $pbest$ the particle should follow. $pbest_{fi(d)}^d$ can be the corresponding dimension of any particle's $pbest$ including its own $pbest$, and the decision depends on probability P_c, referred to as the learning probability, which can take different values for different particles. For each dimension of particle i, we generate a random number. If this random number is larger than P_{c_i} , the corresponding dimension will learn from its own $pbest$; otherwise it will learn from another particle's $pbest$. The comprehensive learning is specifically employed to combat the ''curse of dimensionality'', by splitting a composite high-dimensional swarm into several smaller-dimensional swarms, which cooperate with each other by exchanging information to determine composite fitness of the entire system.

B. Powell's conjugate gradient method

Powell's conjugate direction method, is an algorithm proposed by Michael J. D. Powell for finding a local minimum of a function. Conjugate gradient (CG) methods comprise a class of unconstrained optimization algorithms which are characterized by low memory requirements and strong local and global convergence properties. The function need not be differentiable, and no derivatives are taken.

Conjugate gradient methods are widely used for unconstrained optimization, especially large scale problems. Most of conjugate gradient methods don't always generate a descent search direction, rather in a direction that preserves the minimization achieved in the previous step called conjugate direction. The function must be a real-valued function of a fixed number of real-valued inputs. The caller passes in the initial point. The caller also passes in a set of initial search vectors. Typically N search vectors are passed in which are simply the N normals aligned to each axis.

Powell demonstrated that the N vectors produced in successive cycles are mutually conjugate, so that the minimum point of a quadratic surface is reached in exactly n cycles. In practice, the merit function is seldom quadratic, but as long as it can be approximated locally by Powell's method will work. Of course, it takes more than n cycles to arrive at the minimum of a non-quadratic function. The algorithm iterates an arbitrary number of times until no significant improvement is made. The PCG algorithm is given in Figure 1.

Initialize the starting point X_1, independent vectors
$d_i = e_i (i = 1, 2, . . . , D)$, the tolerance for stop criteria ε, set
$f(1) = f(X_1)$, $X_c(1) = X_1$, $k=1$.
While (stopping criterion is not met, namely
$|\Delta f| > \varepsilon$) **do**
For i = 1 to D **do**
If ($k \geq 2$) **then**
$d_i = d_{i+1}$
End If
$X_{i+1} = X_i + \lambda_i d_i, \lambda_i$ is determined by Minimizing
$f(X_{i+1})$
End For
$d_{i+1} = \sum_1^D \lambda_i^* d_i = X_{D+1} - X_D, X_c(k+1) = X_{D+1} + \lambda_k d_{i+1}$,
$f(k + 1) = f(X_c(k + 1))$
$k = k + 1$, $X_1 = X_c(k)$, $\Delta f = f(k) - f(k-1)$
End While

Fig.1. Pseudo-code of the PCG method

By integrating both these CPSO and PCG algorithm a new hybrid algorithm called RCPSO for finding optimum thresholds using MTET for image segmentation is proposed in this paper. The pseudo-code of the proposed RCPSO algorithm is shown in Figure 2.

1. Initialize population pop "create population from randomly chosen threshold values"
2. Evaluate population pop "evaluate all candidate solutions".
3. Store the best solution T^* with its fitness in a separate location.
4. Update particle memories

   For a fixed number of iterations

   For all individual j in population pop

   For all candidate solutions parameters k in T

   "Update velocity"

$$\varphi = rand\ (\varphi_{min}, \varphi_{max})$$

$$\mathrm{pop}_{\mathrm{v_k}} = \mathrm{w}^* \mathrm{pop}_{\mathrm{v_k}} + \mathrm{C} * \varphi(t_k^* - pop\_fi^*)$$

% velocity update using Comprehensive Learning%

"Constrain particle velocity to [v_{min}, v_{max}]"

if pop(j)_v_k>v_{max} then pop(j)_v_k=v_{max}

if pop(j)_v_k<v_{max} then pop(j)_v_k=v_{min}

"Update velocity"

pop(j)_t_k = pop(j)_t_k + pop(j)_v_k

"Constrain particle position to [g_{min}, g_{max}]"

if pop(j)_t_k<g_{min} then pop(j)_t_k = g_{min}

if pop(j)_t_k>g_{min} then pop(j)_t_k = g_{max}

endfor //k

endfor //j

Evaluate population pop "evaluate all candidate solutions"

"Update Particle Memories"

For each particle j, if its fitness is better than that of the same particle in the bestpop

then $bestpop(j)_{t_k}$ = pop(j)_t_k

5. Compare the best individual T of the pop with T^*. If T has a fitness value poorer than T^*, Go to Step 7
6. If T has a fitness value better than T^*,

   %Fine-tuning using PCG method%

   then invoke PCG method and use T as the starting point X_o.

   Find the final solution X_F of the Powell's Conjugate Gradient method,

   replace T^* with X_F.
7. endfor // iteration
8. Output best recording solution T^*

Fig.2. Pseudo-code of the proposed RCPSO

IV. EXPERIMENTAL RESULTS AND COMPARISON

Five images named ‘‘LENA’’ ‘‘PEPPER’’ ‘‘CAMERAMAN’’ ‘‘BUTTERFLY’’ and ‘‘BABOON’’ are used for conducting our experiments. These original test images are adopted from [4].

The Tsalli’s index ‘q’ is a real number to state the nonextensivity of the systems. In image processing, ‘q’ is effective to evaluate the pixels’ long-range correlations so its value is adjustable and can play as a tuning factor in the segmentation process. In this research the value of q=0.7 is estimated based on the procedure followed in [11].

TABLE I
Comparison of Optimum threshold values

Test image	m	Optimum threshold values			
		RCPSO	**ABC**	**PSO**	**GA**
Lena	2	98,172	120,164	120,164	120,164
	3	79,118,169	81,124,178	110,149,187	98,159, 181
	4	73,103,129,185	85,124,161,193	85,118,164,200	86,120, 151,205
	5	56,106,153,175,215	76,108,136,164,193	86,117,142,166,196	95,130, 152,173,200
Pepper	2	51,161	82,154	82,154	82,154
	3	109,158,218	86,118,190	93,133,179	75,103, 182
	4	47,61,83,147	71,121,161,197	73,121,141,176	73,109,141,193
	5	51,90,124,171,203	70,109,139,169,197	78,111,141,169,198	78,105,139,168,200
Camera man	2	72,153	120,154	120,154	120,154
	3	36,67,145	78,128,178	78,121,173	81,143,170
	4	45,88,104,160	91,123,156,211	82,122,154,201	76,116,148,202
	5	51,98,133,171,202	70,107,134,158,200	78,110,133,159,199	88,118,143,169,205
Butterfly	2	78,150	97,136	97,136	97,136
	3	84,115,167	99,135,197	100,135,185	89,124,169
	4	63,94,150,210	95,120,144,189	89,122,143,178	94,121,141,179
	5	50,90,132,165,196	89,114,141,170,213	70,107,134,162,189	70,119,140,170,214
Baboon	2	62,125	91,147	91,147	91,147
	3	60,132,147	111,148,188	108,155,181	111,136,193
	4	59,99,124,186	75,114,146,175	62,115,144,174	94,125,152,177
	5	57,68,123,156,198	78,106,136,157,179	84,110,132,153,175	90,116,139,159,180

The RCPSO and other three multilevel thresholding methods that are ABC, PSO, and GA are implemented for the purpose of comparisons. Table 1 summarizes the optimum thresholds of the five test images. This result reveals that the segmentation results depend heavily on the objective function that is selected. Similarly, all test images reveal the fact that thresholding results determined by proposed method found qualitatively better compared to other techniques. It is also found that thresholding results are better qualitatively when the number of thresholds increased.As the steps enumerated above, the PCG method will be invoked (Step 6) if and when: T^* of the CPSO phase in the present iteration should be less than the previous. Thereby the individual associated with the T^* will be deterministically guided by the PCG method using the gradient information to fine-tune the currently best-explored region. The termination is done when there is no improvement in T^* for a preset number of iterations.

The popular performance indicator, peak signal to noise ratio (PSNR), is used to compare the segmentation results using the proposed and other threshold techniques of this paper. For the sake of completeness we define PSNR, measured in decibel (dB) as

$$PSNR(in\ dB) = 20log_{10}(\frac{255}{RMSE}) \qquad (16)$$

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

and M, N are the size of image, I is the original image and I is the thresholded image at a particular level.

Table 2 summarizes the PSNR values for all the four techniques used in this paper. A higher value of PSNR indicates a better quality of thresholding. For all the test images, the proposed method proves to be better than ABC, PSO and GA methods.

Similarly, the standard deviation σ is given by,

$$\sigma = \sqrt{\frac{1}{t}\sum_{i=1}^{t}\left(s_i - \mu\right)^2} \tag{17}$$

TABLE II
Comparison of PSNR values for different methods

Test Image	m	PSNR (dB)			
		RCPSO	ABC	PSO	GA
Lena	2	18.4215	15.2419	15.2419	15.2419
	3	21.2332	17.4715	17.1425	16.9455
	4	22.1332	19.5070	19.4324	19.0207
	5	23.2841	20.9916	20.5637	19.8703
Pepper	2	18.9114	12.9108	12.9108	12.9108
	3	19.6412	16.6563	16.0269	15.5628
	4	21.7087	19.2433	16.7109	16.3735
	5	22.2012	20.4910	20.2089	19.7642
Cameraman	2	18.8389	10.6258	10.6258	10.6258
	3	21.2321	15.6856	14.9951	14.5900
	4	22.2612	16.7835	15.9187	14.9756
	5	24.8512	17.8802	17.2393	16.6026
Butterfly	2	16.8115	13.0516	13.0516	13.0516
	3	19.1106	18.1337	17.8316	17.2964
	4	21.4774	20.0356	18.9792	18.8382
	5	23.7354	21.9096	21.4406	20.2055
Baboon	2	18.6184	13.1404	13.1404	13.1404
	3	19.5185	18.1076	17.0809	16.7728
	4	20.4310	17.5204	17.1462	17.1583
	5	21.0652	18.7616	18.2718	17.2903

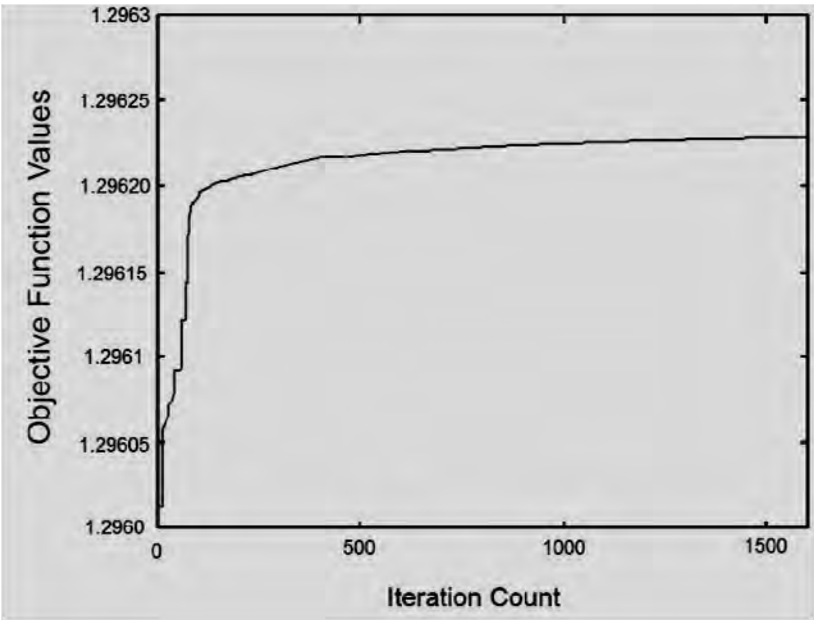

Fig. 3. Convergence plot of the RCPSO

where‘t’ is the number of runs for each algorithm and in this research it is 50. Note that ‘S_i’ is the best objective value obtained by the i-th run of the algorithm and μ is the mean. Both best objective function value and standard deviation are summarized in Table 3. A lower value of σ indicates a better quality of thresholding. From σ values listed in Table 3, it is evident that the proposed method outperforms other methods, which shows a better stability of the proposed method.

Finally, the convergence plot of the proposed RCPSO method for the test image ‘Butterfly’ with m=3 alone is shown in Fig 3. The plots are similar for other cases also. In general, the fitness values of selected thresholds using RCPSO algorithm appears the fact that the selected thresholds can effectively find the adequate solutions based on the maximum entropy criterion.

TABLE III
Comparison of RCPSO and ABC algorithms for best Objective function and Standard Deviation

Test image	m	Best objective function value		Standard Deviation	
		RCPSO	ABC	RCPSO	ABC
Lena	2	0.885012	0.888888	0.0000	0.0000
	3	1.223113	1.296294	0.0000	1.68e-006
	4	1.656062	1.654319	0.0000	2.13e−006
	5	1.991421	1.995881	0.0000	3.43e-006
Pepper	2	0.887743	0.888888	0.0000	0.0000
	3	1.295984	1.296295	0.0000	1.70e−006
	4	1.654319	1.654308	0.0000	2.65e−005
	5	1.995874	1.995864	4.0605e−008	4.12e−004
Cameraman	2	0.878760	0.888950	0.0000	0.0000
	3	1.293324	1.296289	1.2303e−009	3.69e−006
	4	1.651214	1.654290	1.6831e−008	5.66e−005
	5	1.984512	1.995774	2.727e−007	7.68e−005
Butterfly	2	0.887741	0.888888	0.0000	0.0000
	3	1.295414	1.296286	0.0000	1.68e−006
	4	1.653312	1.654319	0.0000	1.85e−005
	5	1.988451	1.995883	2.6223e−008	6.74e−005
Baboon	2	0.887745	0.888906	0.0000	0.0000
	3	1.295412	1.296286	0.0000	2.80e−006
	4	1.653321	1.654260	1.0904e−010	3.69e−006
	5	1.994547	1.995784	2.9953e−008	9.63e−006

V. CONCLUSION

This article presents an extensive study on the application of a hybrid algorithm integrating a metaheuristic with a deterministic technique for multilevel thresholding for image segmentation problem. As seen from the experimental results, non-extensive entropy based MTET image thresholding using Hybrid RCPSO algorithm is effective for image segmentation applications. The proposed hybrid method yielded a near optimum (compared to exhaustive search) threshold value for q=0.7, the segmentation results are promising. It is demonstrated that the simulation results obtained using the hybrid RCPSO method are superior to that of ABC, PSO and GA methods in terms of producing quality thresholds.

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