International Journal of Hybrid Information Technology
Vol.8, No.7 (2015), pp.1-10
http://dx.doi.org/10.14257/ijhit.2015.8.7.01

A Three-Level Thresholding Technique based on Nonextensive Entropy and Fuzzy Partition with Artificial Bee Colony Algorithm

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Abstract

In this paper, a new three-level thresholding method for image segmentation is proposed based on nonextensive entropy and fuzzy sets theory. Firstly, the image histogram is transformed from crisp set to fuzzy domain using fuzzy membership function, such as triangular membership function. After that, the nonextensive entropy of each part of fuzzy domain of histogram is computed. The threshold is selected by maximizing the nonextensive fuzzy entropy. However, the search of combination of membership function's parameters is costly. For reduce the computation time, the artificial bee colony algorithm is used to search the optimal combination of the membership function's parameters. The experimental results on tested images demonstrate the success of the proposed approach compared with the competing methods.

Keywords: *image segmentation, histogram thresholding, nonextensive entropy, fuzzy sets, artificial bee colony*

1. Introduction

Image segmentation is a process which partitions an image into some nonoverlapping meaningful homogeneous regions such that the segmented image can be further analyzed and interpreted. It plays an important role in a variety of applications such as object recognition, robot vision, and medical image processing [1]. Among many segmentation approaches, thresholding is a simple and commonly used technique for image segmentation [1]. It is based on the assumption that the objects can be distinguished by their gray levels. The optimal thresholds are those permitting the distinction of different objects from each other or different objects from the background. The automatic fitting of this threshold is one of the main challenges of image segmentation [1, 2].

In nature, the image is a typical physical system with nonextensive characteristics [3]. However, the traditional thresholding methods often neglect the effects of nonextensive information on threshold selection, and thus no good thresholding results can be obtained sometimes. Nonextensive entropy [4] is an effective measure for physical system with nonextensive characteristics. In recent years, some researchers have proposed some thresholding approaches based on nonextensive entropy, and have obtained better results [5, 6]. In addition, for a gray scale image, there are more gray levels and the boundary between any two consecutive gray levels is not distinct. Consequently, thresholding images based on the gray levels are ambiguous in nature [7]. Therefore, all non-fuzzy technologies have limitation in image segmentation, and the nonextensive entropy-based method is no exception. Fuzzy theory can be used to deal with these ambiguity and uncertainty in image thresholding, and many thresholding methods have proposed based on fuzzy set theory in recent years [7-9]. However, the fuzzy methods can not handle the

ISSN: 1738-9968 IJHIT

nonextensivity exist in image, so these methods are sometimes unable to obtain satisfactory results also.In this paper, for handling the ambiguity and nonextensivity in image segmentation, a new three-level image thresholding method is presented based on the fuzzy sets and nonextensive entropy theory. When the histogram of image transformed from crisp set space to fuzzy domain, the new method involves the optimization of the combination of fuzzy membership functions' parameters in thresholding, and this process is very time-consuming. The artificial bee colony (ABC) algorithm [10] is a recently developed powerful evolutionary algorithm proposed by Karaboga and Basturk which is based on the intelligent behavior of honeybee swarms to solve non-convex optimization problem. The convergence performance of ABC is superior to the traditional optimization algorithm, so it has been applied in many engineering fields successfully [11]. In order to reduce the computation time, the ABC algorithm is used in the proposed new approach. The experimental results show that the proposed method is an effective image thresholding method, and the computation time is satisfies the demand of engineering applications.

2. Thresholding Principle Based On Fuzzy Set and Nonextensive Entropy

2.1. Image Transformed From Crisp Set to Fuzzy Set

Let $\boldsymbol{I}=\{f(x,y)\}$ denotes a digital image with size of $M\times N$ and L grayscale levels, where $x=1,\ldots,M$ and $y=1,\ldots,N$. In addition, let $H=\{h(g)|g=0,1,\ldots,L\text{-}1\}$ denotes the normalized gray level histogram, and it can be calculated by $h(g)=n_g/(M\times N)$, where n_g denotes the number of pixels in the image with gray level g. Obviously, image is a crisp set data. The first step of image thresholding based on fuzzy sets theory is to convert the image histogram information to the fuzzy domain. Take into account the computational efficiency and the effectiveness of segmentation results, the following linear functions are used in the new method as the membership functions, for example

$$\mu_A(g)=\begin{cases}1 & g\le a\\ (g-c)/(a-c) & a<g\le c\\ 0 & g>c\end{cases} \tag{1}$$

$$\mu_B(g)=\begin{cases}0 & g\le a\\ (g-a)/(c-a) & a<g\le c\\ 1 & g>c\end{cases} \tag{2}$$

for 2-level thresholding, and

$$\mu_A(g)=\begin{cases}1 & g\le a\\ (g-b)/(a-b) & a<g\le b\\ 0 & g>b\end{cases} \tag{3}$$

$$\mu_B(g)=\begin{cases}0 & g\le a\\ (g-b)/(b-a) & a<g\le b\\ 1 & b<g\le c\\ (g-d)/(c-d) & c<g\le d\\ 0 & g>d\end{cases} \tag{4}$$

$$\mu_C(g)=\begin{cases}0 & g\le c\\ (g-c)/(d-c) & c<g\le d\\ 1 & g>d\end{cases} \tag{5}$$

for 3-level thresholding. Where, A, B and C denote the fuzzy subsets of image fuzzy domain; a, b, c and d denote the parameters of membership functions, and 0<a<c<255 (for 2-level thresholding) and 0<a<b<c<d<255 (for 3-level thresholding). The intersection(s) of the membership functions is (are) selected as the optimal threshold(s), namely, t=(a+c)/2 (2-level thresholding), or t=((a+b)/2,(c+d)/2) (3-level thresholding).

2.2. Thresholding through Nonextensive Fuzzy Entropy

According to the pseudo additivity rule of nonextensive entropy [12], the total nonextensive fuzzy entropy of image about fuzzy subsets can be defined as

$$H(\mathbf{I})=H(\mathbf{A})+H(\mathbf{B})+(1-q)\cdot H(\mathbf{A})\cdot H(\mathbf{B}) \tag{6}$$

for 2-level thresholding, and

$$\begin{aligned}H(\mathbf{I})&=H(\mathbf{A})+H(\mathbf{B})+H(\mathbf{C})+(1-q)\cdot[H(\mathbf{A})\cdot H(\mathbf{B})\\ &\quad+H(\mathbf{A})\cdot H(\mathbf{C})+H(\mathbf{B})\cdot H(\mathbf{C})]\\ &\quad+(1-q)^2\cdot H(\mathbf{A})\cdot H(\mathbf{B})\cdot H(\mathbf{C})\end{aligned} \tag{7}$$

for 3-level thresholding. Where

$$H(\mathbf{X})=\frac{1}{1-q}\left(\sum_{g=0}^{L-1}\left(\mu_{\mathbf{X}}(g)\cdot h(g)/P_{\mathbf{X}}\right)^q-1\right) \tag{8}$$

$$P_{\mathbf{X}}=\sum_{g=0}^{L-1}\mu_{\mathbf{X}}(g)\cdot h(g) \tag{9}$$

Where, the real number q is an entropic index that characterizes the degree of nonextensivity; H(X) denotes the nonextensive entropy of image fuzzy subdomain X, for 2-level thresholding, X=A or B, for 3-level thresholding, X=A, B or C; H(I) denotes the total nonextensive fuzzy entropy of image I. When H(I) is maximized, the optimal threshold(s) can be obtained, namely

$$t^*=\arg\max(H(\mathbf{I})) \tag{10}$$

In the limit q→1, the image fuzzy Tsallis entropy defined in this paper meets the fuzzy entropy defined by Zhao et al in [8].

3. Threshold Selection Using Artificial Bee Colony Algorithm

Since an exhaustive search for all fuzzy membership function parameter combinations is too costly, in this paper artificial bee colony (ABC) algorithm is introduced into maximum nonextensive fuzzy entropy image segmentation to find the best fuzzy parameter combination adaptively.

The ABC algorithm introduced by Karaboga and Basturk [10] is a new evolutionary algorithm for application problems, which models the specific intelligent behaviours of honey bee swarms around hive. Due to its simplicity and ease of implementation, the ABC algorithm has captured much attention and has been applied to solve many practical application problems. This algorithm is based on swarm intelligence and social insects. A swarm is a group of multi-agent system such as bees, in which simple agents coordinate their activities to solve the complex problems. In the ABC algorithm, three group bees, i.e., employed bees, onlooker bees and scout bees, are utilized. The ABC algorithm basically consists of four phases: initialization, employed bees, onlooker bees and scout bees steps [10-11].

Let $X_i= (x_{i1}, xi2\ldots xid)$ represent a position (solution) in the food source searched by the ith employed bee or its corresponding onlooker bee, where i=1, 2, M, M denote the number of possible solutions. Here, a position implies a possible solution to the optimization problem and obviously, the number of employed bees is M. Onlooker bees work to search locally around their corresponding employed bees, which means that the number of onlookers is also M. Any employed bee and its corresponding onlooker bee who cannot find any better position in a certain number of iterations will be replaced by a scout bee. The main steps of the ABC algorithm can be outlined as follows:

Step 1 Initialization: In this step, the algorithm randomly generates an initial population $\{X_1, X_2, X_M\}$ with M solutions. Each solution $X_i= (x_{i1},x_{i2},\ldots,x_{id})$ is a d-dimensional vector, and is generated as follows:

$$X_{ij}=x_i^L+r\cdot(x_i^U-x_i^L) \tag{11}$$

where x_i^L and x_I^U are the lower and upper bounds for the dimension j, respectively, i=1,2,…,M, j=1,2,…, d and r~U(0,1), U() is the uniform distribution random function.

Step 2 Employed bees step: Employed bees generate food sources in the neighbourhood of their current positions, the neighbouring food source is generated as follows:

$$V_{ij}=x_{ij}+\varphi\cdot(x_{ij}-x_{kj}) \tag{12}$$

where j is a randomly chosen integer between 1 and d and $k\in\{1,2,\ldots,M\}$ is a randomly chosen food source that must be different from the food source x_i, φ~U(-1,1) is a random number which controls the production of a neighbor food source around x_i. When applying a greedy selection process, if the refreshed position is better than the reference one, the reference position is replaced with the refreshed position.

Step 3 Onlooker bees step: In the onlooker bee step, the ABC algorithm employs the roulette wheel selection where each food source is assigned to a probability as follows:

$$p_i=\frac{\text{fitness}_i}{\sum_{i=1}^{M}\text{fitness}_i} \tag{13}$$

where fitness_i is the fitness value of the ith solution X_i. A random number r~U(0,1) is generated for each food source x_i. If r is less than the probability value p_i, the onlooker bee generates a neighbouring food source by using Equation (12) again. The greedy selection applies to both solutions again. If the food source x_i

does not improve, its counter $count_i$ is increased by 1, otherwise, $count_i$ is reset to 0. This process is repeated for all the onlooker bees in the population.

Step 4 Scout bees step: In the scout bee step, the ABC algorithm decides if any food source will be abandoned through the use of its counter. If the value of the counter $count_i$ is greater than the control parameter *limit*, then the food source x_i is abandoned and replaced with a new food source generated with the Equation (12) providing diversification ability to the ABC algorithm. This abandoning and scouting mechanism assists the algorithm to escape local optimums.

Step 5: The stopping criterion (generally the number of iterations) is checked. If it is satisfied, computation is terminated, and the best harmony which corresponds to the optimal solution of the optimization problem is marked. Otherwise, Step 2, 3 and 4 are repeated.

When we use ABC algorithm to find a combination of (a, c) (for 2-level thresholding) or (a, b, c, d) (for 3-level thresholding) such that $H(\boldsymbol{I})$ has the maximum value, we chose x=(a, c) or x=(a, b, c, d) as solution vector, where $0 \le a < b < c \le L\text{-}1$. It begins by generating *HMS* harmonies randomly using $x_i^j = g_{min} + r \cdot (g_{max} - g_{min})$, i=1, 2,…, M, j=1,2 or j=1, 2, 3, 4 and $x_i^1 = a$, $x_i^2 = c$ or $x_i^1 = a$, $x_i^2 = b$, $x_i^3 = c$, $x_i^4 = d$ where g_{min} and g_{max} are the minimum and maximum grey level values of image. We use equation (13) to evaluate these harmonies. Notice that it is possible that the randomly generated individuals do not follow the increasing order $0<a<c<L$ (for 2-level thresholding) or $0<a<b<c<d<L$ (for 3-level thresholding). To resolve this problem, the elements of the individual vector are ordered by ascending firstly and then they will be put back the population to participate in iteration.

When the above scheme of ABC algorithm is applied to search the optimal parameters' combination of membership functions, a randomly population with size of M is initialized firstly, then the ABC algorithm is iterated until the algorithm convergence. Finally, the optimal threshold(s) can be computed through the optimal parameters' combination.

4. Experiment Results and Analysis

We implement the proposed method in Matlab language with a Interl(R) Core(TM)2 Duo CPU T8100 2.10GHz and 2GB RAM. To evaluate the performance of the new method for image thresholding, we have implemented the proposed method on a variety of synthetic and real images. The results yielded by the proposed method were compared with those obtained by methods widely used in the literatures, i.e. the maximum entropy method proposed by Kapur *et al*. [2], the fuzzy entropy method proposed by Cheng *et al*. [7], the maximum fuzzy entropy method proposed by Zhao *et al*. [8], and the maximum nonextensive entropy method proposed by Portes *et al*. [5]. In addition, using many images, when q is 0.7 our proposed method produced the best optimal thresholds, so the parameter q is set to 0.7 in this paper. The parameters of ABC used for searching the optimal combination of parameters of membership function in proposed method are set as M=30, $limit$=100, the maximum number of iterations is set as 100.

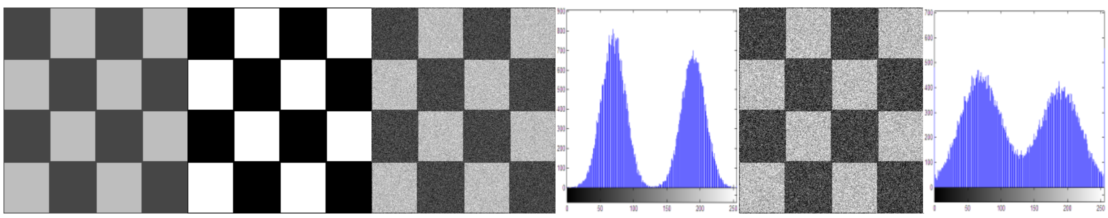
4.1. Performance Evaluation

For evaluating the effectiveness of the different thresholding methods more objectively, we first conducted an experiment on a synthetic image for 2-level thresholding. In this study, we employ misclassification error (ME) measure [13] to evaluate the performances of the competing methods. It regards image segmentation as a pixel classification process. ME reflects the percentage of background pixels wrongly assigned to foreground, and conversely, foreground pixels wrongly assigned to background. For the two-class segmentation problem, ME can be simply expressed as

$$ME = 1 - \frac{|B_o \cap B_T| + |F_O \cap F_T|}{|B_O| + |F_O|} \tag{14}$$

where B_O and F_O denote the background and foreground of the ground truth image, respectively; B_T and F_T indicate the background and foreground pixels in the segmented image, respectively, and |•| is the cardinality of a set •. The value of ME varies from 0 for a perfectly classified image to 1 for a totally wrongly classified image. A lower value of ME means that the quality of the segmentation result is better.

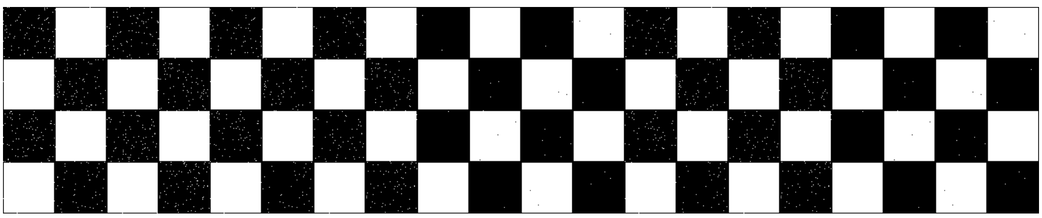
The first image is shown in Figure 1(a), which is a simple synthetic image with 256×256 pixels and shows two parts, one with gray level 70, other part with gray level 190. Ideal segmentation is shown in Figure 1(b). Gaussian noise is added to the original image. Figure 1(c) is an image that is added Gaussian noise with zeros mean and variance 0.005 on original and its histogram is shown in Figure 1(d), Figure 1(e) is an image that is added Gaussian noise with zeros mean and variance 0.015 on original and its histogram is shown in Figure 1(f).



(a) (b) (c) (d) (e) (f)

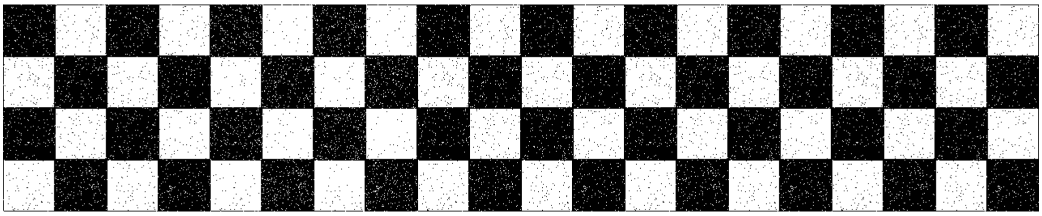
Figure 1. Synthetic Image. (a)Original Synthetic Image, (b)Ground Truth Image of (a), (c)Noise Image 1, (d)Histogram of (c), (e)Noise Image 2, (f)Histogram of (e)

The segmented results obtained by the competing methods corresponding to Figure 1(c) and Figure 1(e) are shown in Figure 2 and 3. From the Figure 2 and 3, we can see that the results obtained by maximum fuzzy entropy (Figure 2(c), 3(c)) and the proposed method (Figure 2(e), 3(e)) are better than others results. The results obtained by Cheng *et al*'s fuzzy method (Figure 2(b), 3(b)) are bad. There are more noise points in the results obtained by Kapur *et al*'s method (Figure 2(a), 3(a)), and the Portes *et al*'s method (Figure 2(d), 3(d)).



(a) Kapur (b) Cheng (c) Zhao (d) Portes (e) Proposed

Figure 2. Thresholding Results of Synthetic Noisy Image 1 by Different Methods



(a) Kapur (b) Cheng (c) Zhao (d) Portes (e) Proposed

Figure 3. Thresholding Results of Synthetic Noisy Image 2 by Different Methods

Table 1 and 2 show the optimal thresholds, misclassified pixels, and ME values obtained by competing methods. From Table 1 and 2, we can see that the number of misclassified pixels and the ME value obtained by proposed method is less than the results obtained by other competing methods.

Table 1. Performance Comparison of Segmentation on Synthetic Noisy Image1

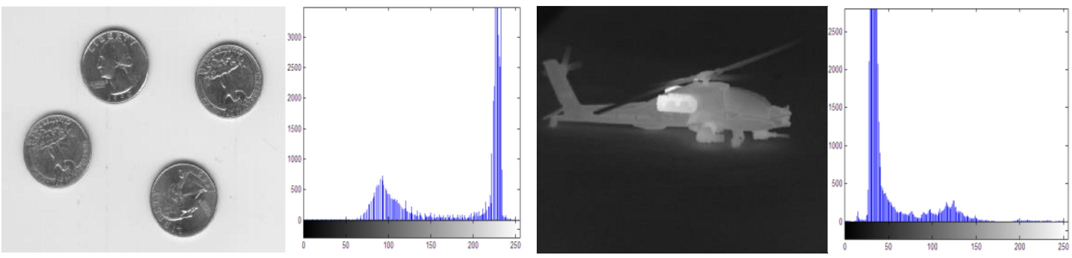
Method	Kapur	Cheng	Zhao	Portes	Proposed
Threshold	107	109	127	110	127
Misclassified pixels	658	855	31	434	31
ME	0.0100	0.0130	0.0047	0.0066	0.0047

Table 2. Performance Comparison of Segmentation on Synthetic Noisy Image2

Method	Kapur	Cheng	Zhao	Portes	Proposed
Threshold	125	117	127	125	127
Misclassified pixels	1878	2384	1818	1878	1818
ME	0.0287	0.0364	0.0277	0.0287	0.0277

4.2. Experiments on Real Images

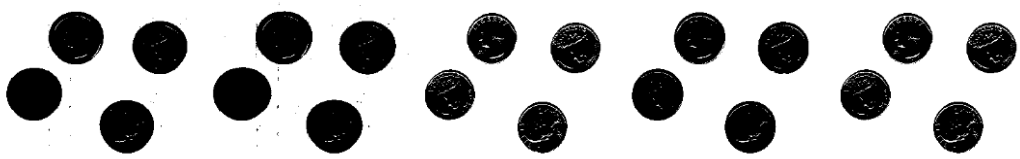
To test the performance of proposed method on real images, we carried out a large number of experiments. For the limitation of space, the only two experimental results are listed. Figure 4 shows the real test images and their histograms. Figure 4(a) shows an ‘eight.tif’ image with size 308×242 and its histogram is showed in Figure 4(b). Figure 4(c) is an ‘infrared-plane.tif’ image with size 320×240 and its histogram is showed in Figure 4(d). From the histograms of the test images, we can see that the target in ‘eight.tif’ image can be separated by 2-level thresholding, while the object in the ‘infrared-plane.tif’ image can be separated by 3-level thresholding.



(a) eight (b) histogram of (a) (c) infrared-plane (d) histogram of (c)

Figure 4. Real Images and Their Histograms

Figure 5 shows the segmented results of the ‘eight.tif’ image by all competing method. From Figure 5, we can see that the results by the Zhao’s method (Figure 5(c)) and the proposed method (Figure 5(e)) are better than the results by other methods.



(a) Kapur (b) Cheng (c) Zhao (d) Portes (e) Proposed

Figure 5. 2-Level Segmented Results of Eight Image by Different Methods

Figure 6 shows the results of the ‘infrared-plane.tif’ image. From the Figure 6, we can see that the result by the proposed method (Figure 6(e)) is better than the results by other methods.

(a) Kapur (b) Cheng (c) Zhao (d) Portes (e) Proposed

Figure 6. 3-Level Thresholding Results of Infrared-Plane Image by Different Methods

Table 3 lists the thresholds and the running times by the different methods on real test images. Comparison of the histograms of real test images shown in the Figure 4 and the threshold(s) obtained by different thresholding methods in Table 2, we can see that the threshold(s) obtained by proposed method matched the valley of histogram better, while the threshold(s) obtained by other methods have more or less deviation. For the running time, the results of Kapur et al’s method, and Portes et al’s method are less than other methods on 2-level thresholding, while in the 3-level thresholding, the running time of the proposed method is less than that of other methods obviously, and it satisfies the requirement of engineering applications.

Table 3. Performance Comparison of Segmentation on Real Test Images

Method		Kapur	Cheng	Zhao	Portes	Proposed
Eight.tif	threshold	210	214	145	181	146
	time (s)	0.0892	0.3546	0.3201	0.0911	0.2941
Infrared-plane.tif	threshold	[57,151]	[33,38]	[73,182]	[65,153]	[76,186]
	time (s)	11.8880	1.8850	1.8786	12.7848	1.2835

From the above experimental results, we can see that the propose method is an effective method for image segmentaion.

5. Conclusion

Considering the nonextensivity and ambiguity of image system, we presented an effective image thresholding method based on nonextensive entropy and fuzzy sets theory. In order to reduce the computation time for search the optimal combination of parameters of fuzzy membership function, the artificial bee colony algorithm is used in the new method. The experiments on both synthetic and real images are illustrated to show that the proposed method can get ideal segmentation result with less computation cost. Further research is to be carried out to test the feasibility of the proposed method for various types of image processing application, such as target detection, medical image processing etc.

Acknowledgements

The author would like to thank all the anonymous reviewers for their valuable comments and thoughtful suggestions which improved the quality of the presented work. This work is partially supported by the Science and Technology Planning Project of Hunan Province, China (Grant No. 2014NK3125), the Scientific Research Fund of Hunan Provincial Education Department, China (Grant No. 14B124), the Doctor Scientific Research Startup Project Foundation of Hunan University of Arts and Science, China, and the Construct Program of the Key Discipline in Hunan University of Arts and Science, China.

References

[1] Y. Wang, "A new image threshold segmentation based on fuzzy entropy and improved intelligent optimization algorithm", Journal of Multimedia, vol. 9, no. 4, **(2014)**, pp. 499-505.
[2] J. N. Kapur, P. K. Sahoo, and A. K. C. Wong, "A new method for gray-level picture thresholding using the entropy of the histogram," Computer Vision, Graphics, and Image Processing, vol. 29, no. 3, **(1985)**, pp. 273-285.
[3] I.Kilic, and O. Kayacan, "A new nonlinear quantizer for image processing within nonextensive statistics," Physica A, vol. 381, **(2007)**, pp. 420-430.
[4] C. Tsallis, "Possible generalization of Boltzmann-Gibbs statistics," Journal of Statistical Physics, vol. 52, no. 1-2, **(1988)**, pp. 479-487.
[5] M. Portes de Albuquerque, I. A. Esquef, A.R. Gesualdi Mello, and M. Portes de Albuquerque, "Image thresholding using Tsallis entropy," Pattern Recognition Letters, vol. 25, no. 9, **(2004)**, pp. 1059-1065.
[6] P. K. Sahoo, and G. Arora, "Image thresholding using two-dimensional Tsallis-Havrda-Charvat entropy," Pattern Recognition Letters, vol. 27, no. 6, **(2006)**, pp. 520-528.
[7] H. D. Cheng, J. R. Chen, and J. Li, "Threshold selection based on fuzzy c-partition entropy approach," Pattern Recognition, vol. 31, no. 7, **(1998)**, pp. 857-870.
[8] M. Zhao, A. M. N. Fu, and H. Yan, "A technique of three-level thresholding based on probability partition and fuzzy 3-partition," IEEE Transactions on Fuzzy Systems, vol. 9, no. 3, **(2001)**, pp. 469-479.
[9] S. Benabdelkader, and M. Boulemden, "Recursive algorithm based on fuzzy 2-partition entropy for 2-level image thresholding," Pattern Recognition, vol. 38, no. 8, **(2005)**, pp. 1289-1294.Table
[10] D. Karaboga, and B. Basturk, "A powerful and efficient algorithm for numerical function optimization: artificial bee colony (ABC) algorithm," Journal of Global Optimization, vol. 39, no. 3, **(2007)**, pp. 459-471.
[11] M. Rani, H. Garg, and S. P. Sharma, "Cost minimization of butter-oil processing plant using artificial bee colony technique," Mathematics and Computers in Simulation, vol. 97, **(2014)**, pp. 94-107.
[12] M. Mathai, and H. J. Haubold, "On generalized entropy measures and pathways," Physica A: Statistical Mechanics and its Applications, vol. 385, no. 2, **(2007)**, pp. 493-500.
[13] S. T. Wang, F. L. Chung, and F. S. Xiong, "A novel image thresholding method based on Parzen window estimate," Pattern Recognition, vol. 41, no. 1, **(2008)**, pp. 117-129.

