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A two-dimensional image segmentation method based on genetic algorithm and entropy

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ABSTRACT

Thresholding is a well-known technique for digital image segmentation. A growing number of contributions achieved the thresholding value by maximizing some information theory functions such as entropies. The classical techniques search for the thresholding value by formulating the entropy upon the ordered image gray level distribution. This ordering step does not allow to converge enough to the entropy optimum. In this paper, we propose a novel tow-dimensional image segmentation approach based on the flexible representation of Tsallis and Renyi entropies and employing the Genetic Algorithm (GA). From the information theory point of view, the entropy is used here to measure the amount of information contained in the two-dimensional histogram of the image. The GA is then used to maximize the entropy in order to segment efficiently the image into object and background. The experimental results show that our approach maximizes efficiently the entropy and generates better image segmentation quality compared to the classical thresholding technique.

1. Introduction

In many vision applications, it is useful to be able to separate out the regions of the image corresponding to objects, in which we are interested, from the regions of the image that correspond to background. Thresholding often provides an easy and convenient way to perform this segmentation on the basis of the different intensities or colors in the foreground and background regions of an image. So, many techniques have been proposed for image segmentation including graph-based algorithms, edge detection algorithms, and threshold-based algorithms [1,2]. Image segmentation is an indispensable part of computer vision, which directly influences the quality of feature extraction and classification. In the past few decades, many image segmentation methods have been proposed and applied in different fields [7,3–6]. Thresholding is one of the widely used techniques in image segmentation. The principle of thresholding consists of finding an adequate threshold to segment object from background through certain criteria, such as Otsu thresholding [8], maximum entropy thresholding [9], minimum error thresholding [10], 2D maximum entropy thresholding [11] and Fisher information [12,13]. In the case of segmenting several objects from background, thresholding technique needs to be extended to multilevel thresholding. However, large amount of calculation and long computation time occur when exhaustively searching multilevel thresholds.

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Recently, Genetic Algorithm (GA) has been intensively investigated and applied to many optimization problems. GAs are especially appropriate in optimization of large search spaces, which are unsuitable for exhaustive search procedures. These algorithms effectively and rapidly provide a sufficient solution for a given optimization problem. These algorithms do a trade-off between the explorations of the search space and the exploitation of the best solutions found so far. However, GA only provide near-optimal solutions which are satisfactory in practical applications. In this regard, GA performs different tasks in image processing [14]. For example, Bhandarkar et al. [15] defined a multi-term cost function which is minimized using a GA-evolved edge detection. In their approach to image segmentation, edge detection is formulated as the problem of minimizing an objective cost function over the space of all possible edge configurations and a population of edge images is evolved using specialized operators.

In last years there were new strategies and algorithms proposed to find the solution of multithreshold problem, so several metaheuristics optimal algorithms were applied to multilevel thresholding. Hammouche et al. [16] presented optimal thresholding using genetic algorithms. Recently, Ghamisi et al. [17] developed particle swarm optimization, Darwinian particle swarm optimization, and fractional-order Darwinian particle swarm optimization for determining thresholds. Liang et al. [18] designed an ant colony optimization segmentation algorithm for solving multilevel Otsu problem. Sathya and Kayalvizhi [19] applied bacterial foraging into finding thresholds for maximizing Kapur's and Otsu's objective functions. Cuevas et al. [20] used differential evolution optimization to find multilevel thresholds. Osuna-Enciso et al. [21] presented a comparison of three optimization algorithms for selecting multilevel thresholds. Nevertheless, with the number of thresholds increasing, these metaheuristics cannot find the balance of global search and local search, which would lead to inaccurate results and a slow convergence rate [22,23].

The segmentation problem is formulated as an optimization problem and Genetic Algorithm efficiently locates the global maximum in a search space and solves the problem of parameter selection in image segmentation. A new approach based on GA has been proposed for selection of threshold from the histogram of images [24].

In this work, we focus on the two-dimensional image segmentation using entropy. The entropy allows to measure the amount of information given by the gray levels distribution of an image. Our objective is to segment the image by maximizing the entropy. The optimization task will be accomplished using GA. The Renyi and Tsallis entropies are employed and compared in this paper. Contrary to classical thresholding method, in the proposed method we would not need to order the image intensities in advance. Indeed, the image segmentation problem is seen as a general combinatorial optimization exercise rather than a classical thresholding task. Our main objective is to enhance the entropy maximization in order to improve the image segmentation quality.

The remainder of this paper is organized as follows. Section 2 presents the two-dimensional entropy-based thresholding. The proposed method for image segmentation using GA is described in Section 3. The experimental results are presented and discussed in Section 4. Finally, Section 5 is devoted to some concluding remarks.

2. Two-dimensional thresholding based on Renyi and Tsallis entropies

Entropy is a main tool in information theory. Shannon has used it to measure the amount of information content [25]. In information theory, entropy was used as a quantifier that explains how much randomness is in a signal or in a random event. Entropy allows us to describe how much information is carried out by the signal.

Let us assume that $Z=\{z_1, z_2, z_3, \ldots, z_k\}$ is a source of symbols. The corresponding set of probabilities is $P=\{p_1, p_2, p_3, \ldots, p_k\}$ which satisfy the condition $\sum_{i=1}^{k} p_i = 1, 0 \le p_i \le 1$. The average information per source output can be obtained by Shannon entropy defined as [26]:

$$S_H = -\sum_{i=1}^{k} p_i \log(p_i), \tag{1}$$

where k is the total number of symbols. If we consider that a system can be decomposed in two statistical independent subsystems A and B, the Shannon entropy has the extensive property (additivity) $S(A+B)=S(A)+S(B)$. A simple generalization of Shannon entropy S_H in the case of two-dimensional distribution can be written as:

$$S_H = -\left\{ \sum_{i=0}^{k}\sum_{j=0}^{k} p(i,j) \log p(i,j) \right\}. \tag{2}$$

An important generalization of Shannon entropy is called Renyi's entropy. This entropy is defined as [27,28]:

$$S_\alpha = \frac{1}{1-\alpha} \ln \left(\sum_{i=0}^{k}\sum_{j=0}^{k} p(i,j)^\alpha \right), \tag{3}$$

where α is a real parameter.

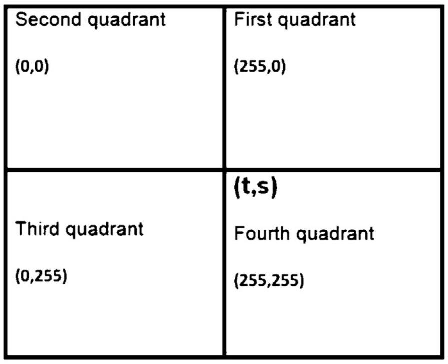

Fig. 1. Quadrants in the 2D histogram due to thresholding at (t;s).

Independently, Tsallis [29] defined another generalized entropic formula in the case of non-extensive systems given by:

$$S_q = \frac{1}{q-1}\left(1 - \sum_{i=1}^{k} p_i^q\right), \tag{4}$$

where the real number q is an entropic index that characterizes the degree of non-extensivity. Tsallis entropy has a non-extensive property for two statistical independent systems, defined by the following rule [30,31]:

$$S_q(A+B) = S_q(A) + S_q(B) + (1-q)\cdot S_q(A)\cdot S_q(B). \tag{5}$$

In image segmentation and edge detection Tsallis entropy can be employed to determine the threshold value through non-additive information content.

Let us consider $f(x, y)$ be the gray value of the pixel located at the point (x, y) in a digital image of size M × N such that $x \in \{1, 2, \ldots, \mathrm{M}\}$ and $y \in \{1, 2, \ldots, \mathrm{N}\}$. Global threshold selection methods are usually based on the gray level histogram of image. The optimal threshold t^* is determined by optimizing a suitable function which is obtained from the gray level distribution and some other features of the image.

We denote the first quadrant by $[0, t] \times [s + 1, 255]$, the second quadrant by $[0, t] \times [0, s]$, the third quadrant by $[t + 1, 255] \times [0, s]$, and the fourth quadrant by $[t+1, 255] \times [s+1, 255]$. The four quadrants of the two-dimensional histogram are displayed in Fig. 1. In image segmentation context the first and third quadrants can be ignored because they contain the information about edges and noise alone, and then we are only interested in posteriori class probabilities $P_2(t, s)$ and $P_4(t, s)$ and hence we further approximate $P_4(t, s)$ as $P_4(t, s) = 1 - P_2(t, s)$ [28].

The Tsallis entropy $S_q(t)$ is parametrically dependent on the threshold value t for the foreground and background. It is formulated as the sum of the corresponding entropies, according to the pseudo-additive property, defined in Eq. (4). Then, we try to maximize the information measure between the two classes (object and background). When $S_q(t)$ is maximized, the luminance level t that maximizes the function is considered to be the optimum threshold value [32].

$$(t^*(q), s^*(q)) = arg_{t\in G} \max \left[S_q^A(t,s) + S_q^B(t,s) + (1-q)\cdot S_q^A(t\cdot s)\cdot S_q^B(t,s)\right]. \tag{6}$$

In the proposed scheme, we construct a binary image by choosing a suitable threshold value using Tsallis or Renyi entropy. The technique consists of treating each pixel of the original image and creating a new image, such that $f_t(x, y) = 0$ if $f_t(x, y) \le t^*(q)$ and $f_t(x, y) = 1$ otherwise for every $x \in \{1, 2, \ldots, M\}$, $y \in \{1, 2, \ldots, N\}$. When $q \to 1$, the threshold value in Eq. (6), equals to the same value found by Shannon's method. Thus, the proposed method includes Shannon's method as a special case.

3. The use of the Genetic Algorithm

In this work, the image segmentation problem is seen as a general combinatorial optimization exercise rather than a classical thresholding task. As a criterion for this, we consider the gray level image histogram as a probability distribution and we apply the Tsallis and the Renyi entropies as a general information theory entropy formalism. Our main objective is to enhance the entropy maximization in hope to improve the image segmentation quality. To do this, we seek to divide the pixels into two groups more efficiently than thresholding do. Conceptually, our problem consists of finding an optimal or an acceptable suboptimal object from a finite set of feasible solutions. In such problems exhaustive search is impossible, so one has to rely on computational intelligence methods. In this paper, we choose to use the Genetic Algorithm to solve our combinatorial optimization problem.

The father of the original Genetic Algorithm (GA) was John Holland [33] who invented it in the early 1960s. Genetic algorithms belong to the larger class of Evolutionary Algorithms (EA), which generate solutions to optimization problems

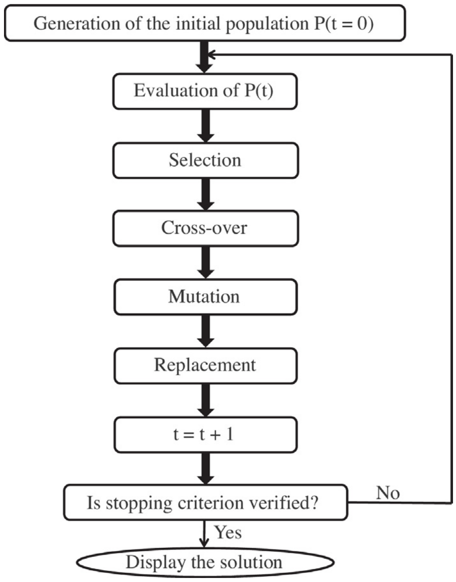

Fig. 2. GA structure.

using techniques inspired by natural evolution. A GA come from the artificial intelligence field and it is an adaptive heuristic search algorithm that mimics some of the processes observed in natural selection.

An implementation of a GA begins with a population of chromosomes (typically random). One then evaluates these structures and allocates reproductive opportunities in such a way that those chromosomes which represent a better solution to the target problem are given more chances to “reproduce” than those chromosomes which are poorer solutions. The “goodness” of a solution is typically defined with respect to the current population [34].

In the computational sense, the main operators of a GA are selection, crossover and mutation. Given a clearly defined problem to be solved and a bit-string representation for candidate solutions, the simple GA works as follows:

1. Start with a randomly generated population of N L-bit chromosomes (candidate solutions to a problem).
2. Calculate the fitness $f(x)$ of each chromosome x in the population.
3. Repeat the following steps (a)–(c) until N offspring have been created:
   (a) Select a pair of parent chromosomes from the current population, with the probability of selection being an increasing function of fitness. Selection is done “with replacement,” meaning that the same chromosome can be selected more than once to become a parent.
   (b) With probability pc (the crossover probability), cross over the pair at a randomly chosen point (chosen with uniform probability) to form two offspring. If no crossover takes place, form two offspring that are exact copies of their respective parents.
   (c) Mutate the two offspring at each locus with probability pm (the mutation probability), and place the resulting chromosomes in the new population.
4. Replace the current population with the new population.
5. Go to step 2.

The folwchart of the used GA is given in Fig.2. The main advantages of GA are as follows:

- It is derivative-free technique.
- It can be used for both continuous and discrete optimization problems.
- It uses stochastic operators instead of deterministic rules to search for an optimum solution. It consider many points in the search space simultaneously, not a single point. Thus, there is a reduced chance of converging to local minima.
- It works directly with binary strings of characters representing the parameter set (population, solution set), but not the parameters themselves.

In our image segmentation problem we aim at dividing the pixels into two groups that maximizes the Tsallis and Renyi entropies which are employed as fitness functions. Contrary to the classical thresholding method, this will be done without ordering the gray levels intensities in advance. The objective is to maximize the amount of information measured by the entropy from the image.

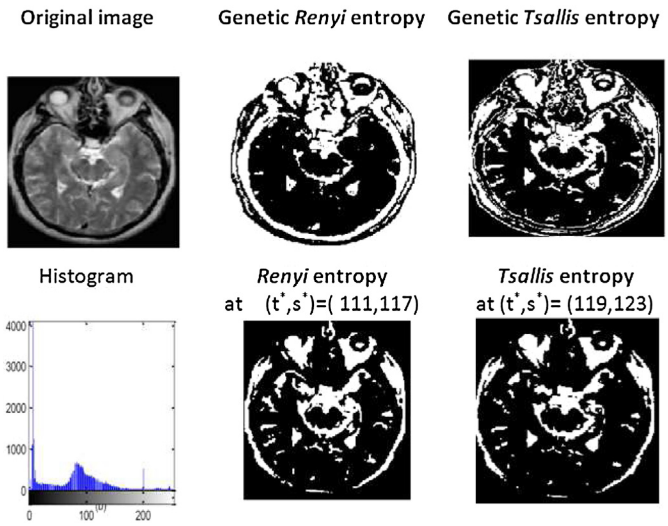

Fig. 3. Brain (A).

4. Experimental results and discussion

In this section, we compare our segmentation method with the classical thresholding approach using Renyi and Tsallis entropies. The competitive methods are applied to a sample of medical and real world images displaying different histograms and sizes.

The obtained results will be compared visually and quantitatively by using the Peak Signal to Noise Ratio (PSNR). It is the ratio between the highest possible signal power and noise power corrupted which affects the fidelity of its representation [35]. It is the logarithmic function of the peak value of the image to the root mean square error defined as:

$$\mathrm{PSNR} = 20\log_{10}\left(\frac{255}{\sqrt{\mathrm{MSE}}}\right), \tag{7}$$

where MSE is the mean square error defined by:

$$\mathrm{MSE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N}(I(i,j) - S(i,j))^2}{\mathrm{MN}}, \tag{8}$$

with I and S are input and output images of size $M \times N$, respectively.

The PSNR index is used to measure the segmentation quality. For the better segmentation the value of the PSNR measure should be higher.

We recall that the GA is controlled by two main parameters; the population size p and the chromosome length m. The stopping condition is based on the maximal number of generations. In our experiments we have taken $p = 30$, $m = 50$ and the maximal number of generations was set to 300.

The first interesting result of our experiments is the significant increase achieved on the entropies when using the GA. Indeed, the entropy value has been increased by at least 10%, for all the tested images, compared to the classical thresholding approach.

Figs. 3–10 show the original image, its histogram and the segmented images obtained by the different approaches. The pairs of the thresholding values (t^*, s^*) are provided when using the classical two-dimensional thresholding method. We recall that our approach based on GA does not give rise to thresholding values but it searches for dividing the image set of pixels into two homogeneous groups without ordering the intensities in advance.

The visual comparison of the segmented images leads to conclude that our approach outperforms the classical thresholding one. Indeed, the GA-based segmentation achieves a good balance between preserving image details and robustness to different types of images. This remarkable improvement is due to the entropy increase achieved by means of the GA. On the other hand, we can see that the Renyi entropy leads to slightly better results than the Tsallis entropy.

Table 1 gives the PSNR values obtained on the 8 images for the GA-based segementation when using Tsallis and Renyi entropies. For each test image, the best result is written in bold. It is clear that the Renyi entropy outperforms the Tsallis entropy for the purpose of image segmentation by using the GA. This result can be explained by the fact that the Tsallis-based fitness function is more complex in optimization than that using the Renyi entropy.

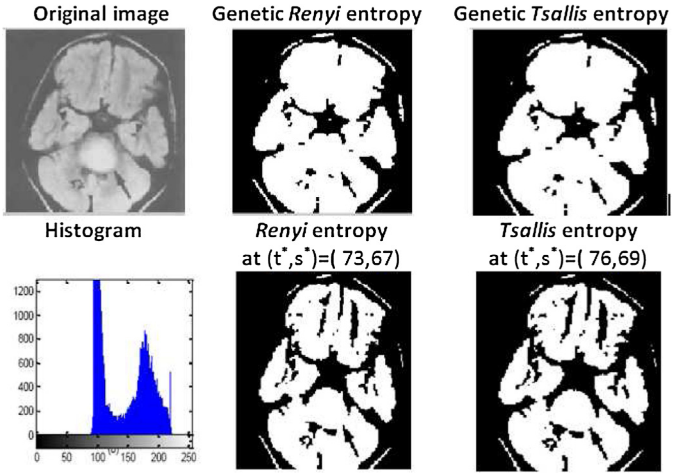

Fig. 4. Brain (B).

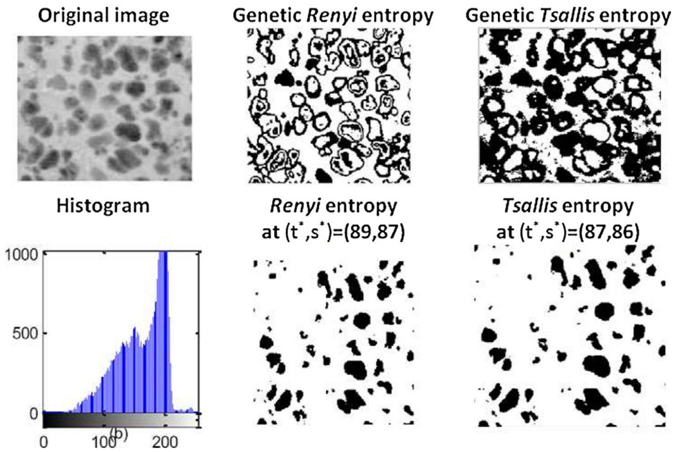

Fig. 5. Light microscopy.

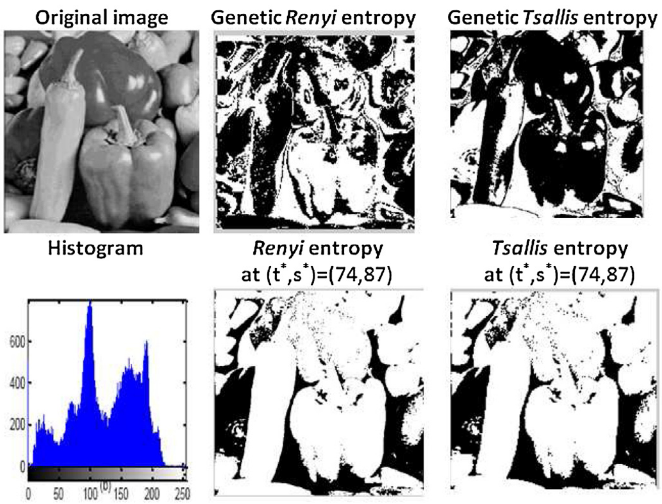

Fig. 6. Peppers.

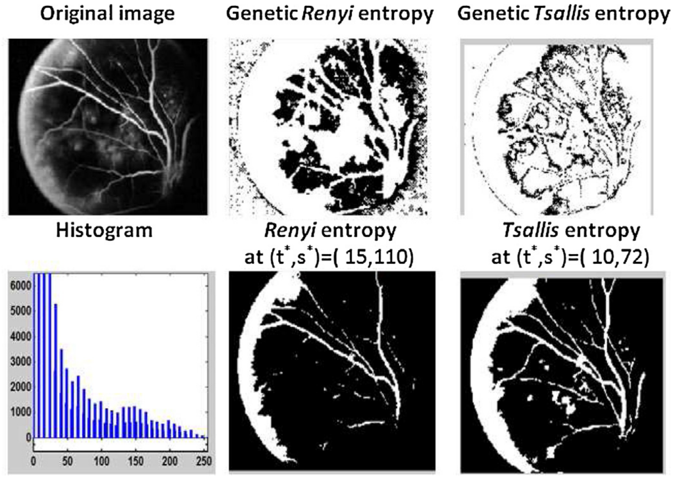

Fig. 7. Retina.

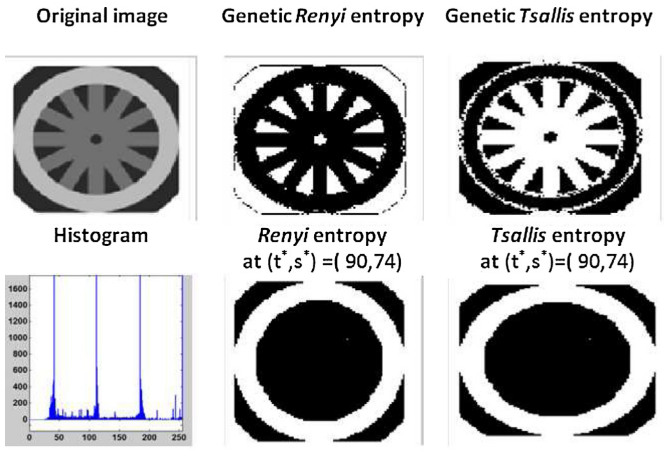

Fig. 8. Tire.

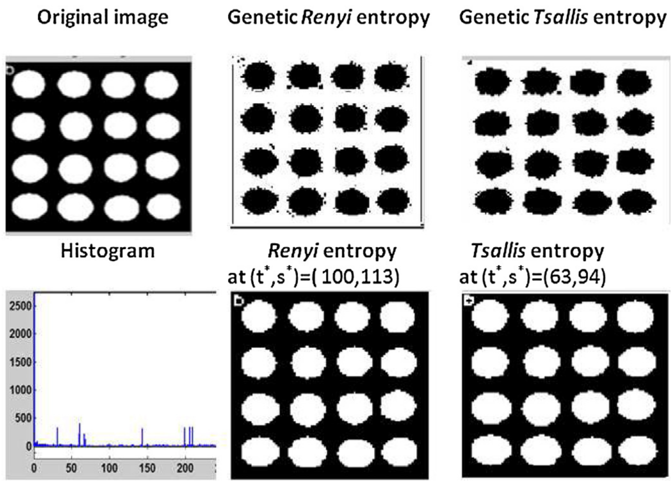

Fig. 9. Cells.

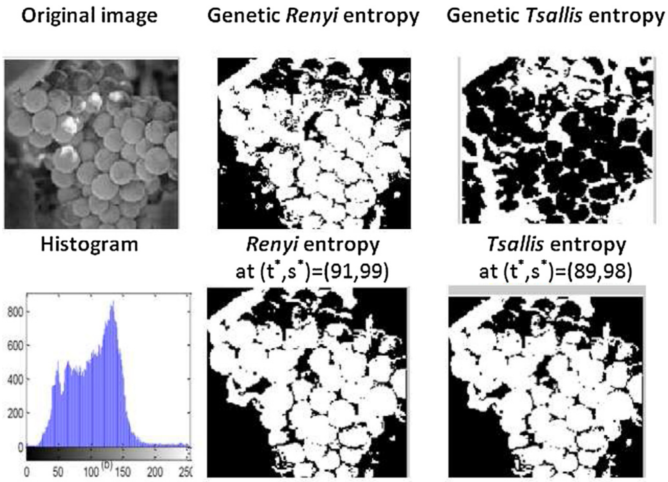

Fig. 10. Grape.

Table 1
PSNR values: comparison between Tsallis and Renyi entropies for the GA-based segmentation.

PSNR	GA Tsallis	GA Renyi
Brain (A)	3.54	**7.25**
Brain (B)	6.18	**6.40**
Light microscopy	5.12	**5.14**
Peppers	9.11	9.11
Retina	2.06	**2.92**
Tire	4.93	**8.70**
Cells	2.45	**2.64**
Grape	**7.25**	6.60

5. Conclusion

In this work, we proposed a novel approach for image segmentation based on GA and entropy. The entropy measures the amount of information contained in image grey levels distribution. However, the entropy is not sufficiently maximized by the classical thresholding method. This is due to the ordering step applied to the gray levels beforehand. The proposed approach aims at maximizing the entropy by using the GA in order to improve the image segmentation quality. Moreover, the Tsallis and Renyi entropies are used and compared.

The numerical results demonstrated the effectiveness of the proposed method because of the gain in amount of information achieved by the GA. Moreover, it was found that the Renyi entropy provides better image segmentation quality. However, the segmentation quality improvement was not visually as important as expected in spite of the significant increase gained in the entropy value when using GA.

Finally, this work can be broadened by considering other entropies and a large sample of real-world and synthetic images for segmentation and edge detection.

References

[1] S. Lakshmi, V. Sankaranarayanan, A study of edge detection techniques for segmentation computing approaches, Comput. Aided Soft Comput. Tech. Imaging Biomed. Appl. CASCT (2010) 35–40 (IJCA Special Issue).
[2] M.A. El-Sayed, S.F. Bahgat, S. Abdel-Khalek, Novel approach of edges detection for digital images based on hybrid types of entropy, Appl. Math. Inf. Sci. 7 (2013) 1809–1817.
[3] K. Hanbay, M.F. Talu, Segmentation of SAR images using improved artificial bee colony algorithm and neutrosophic set, Appl. Soft Comput. J. 21 (2014) 433–443.
[4] J. Li, X. Rao, F. Wang, W. Wu, Y. Ying, Automatic detection of common surface defects on oranges using combined lighting transform and image ratio methods, Postharvest Biol. Technol. 82 (2013) 59–69.
[5] Z.A. Abo-Eleneen, Gamil Abdel-Azim, An improved image segmentation algorithm based on MET method, IJCSI Int. J. Comput. Sci. 9 (2012) 346–351.
[6] S. Sadek, S. Abdel-Khalek, Generalized α-entropy based medical image segmentation, J. Softw. Eng. Appl. 7 (2013) 62–67.
[7] J.W. Funck, Y. Zhong, D.A. Butler, C.C. Brunner, J.B. Forrer, Image segmentation algorithms applied to wood defect detection, Comput. Electron. Agric. 41 (2003) 157–179.
[8] N. Otsu, A threshold selection method from gray-level histograms, Automatica 11 (1975) 23–27.
[9] J.N. Kapur, P.K. Sahoo, A.K.C. Wong, A new method for gray-level picture thresholding using the entropy of the histogram, Comput. Vis. Graph. Image Process. 29 (1985) 273–285.
[10] J. Kittler, J. Illingworth, Minimum error thresholding, Pattern Recognit. 19 (1986) 41–47.

[11] A. Abutaleb, A. Eloteifi, Automatic thresholding of gray level pictures using 2-D entropy, in: Proceedings of the 31st Annual Technical Symposium, Applications of Digital Image Processing X, vol. 829 of Proceedings of SPIE, International Society for Optics and Photonics, San Diego, CA, USA, 1988, pp. 29–35.
[12] S. Chen, Y. Lin, Y. Liu, Z. Lu, Image segmentation by multi-threshold based on fisher function and histogram algorithm, in: International Conference on Computer Application and System Modeling, 2010.
[13] Z.A. Abo-Eleneen, Gamil Abdel-Azim, A novel approach for MRI brain images segmentation, Int. J. Image Graph. Signal Process. 3 (2013) 10–18.
[14] M. Sahu, K.M. Bhurchandi, Color image segmentation using genetic algorithm, Int. J. Comput. Appl. 140 (2016) 15–20.
[15] S. Bhandarkar, Y. Zhang, W. Potter, An edge detection technique using genetic algorithm-based optimization, Pattern Recognit. 27 (1994) 1159–1180.
[16] K. Hammouche, M. Diaf, P. Siarry, A multilevel automatic thresholding method based on a genetic algorithm for a fast image segmentation, Comput. Vis. Image Underst. 109 (2008) 163–175.
[17] P. Ghamisi, M.S. Couceiro, J.A. Benediktsson, N.M.F. Ferreira, An efficient method for segmentation of images based on fractional calculus and natural selection, Expert Syst. Appl. 39 (2012) 12407–12417.
[18] Y.-C. Liang, A.H.-L. Chen, C.-C. Chyu, Application of a hybrid ant colony optimization for the multilevel thresholding in image processing, in: Neural Information Processing, vol. 4233 of Lecture Notes in Computer Science, Springer, Berlin, Germany, 2006, pp. 1183–1192.
[19] P.D. Sathya, R. Kayalvizhi, Optimal multilevel thresholding using bacterial foraging algorithm, Expert Syst. Appl. 38 (2011) 15549–15564.
[20] E. Cuevas, D. Zaldivar, M. Perez-Cisneros, A novel multithreshold segmentation approach based on differential evolution optimization, Expert Syst. Appl. 37 (2010) 5265–5271.
[21] V. Osuna-Enciso, E. Cuevas, H. Sossa, A comparison of nature inspired algorithms for multi-threshold image segmentation, Expert Syst. Appl. 40 (2013) 1213–1219.
[22] J. Zhang, H. Li, Z. Tang, Q. Lu, X. Zheng, J. Zhou, An improved quantum-inspired genetic algorithm for image multilevel thresholding segmentation, Math. Probl. Eng. 2014 (2014), Article ID 295402, 12 pp.
[23] J.-Y. Li, Y.-D. Zhao, J.-H. Li, X.-J. Liu, Artificial bee colony optimizer with bee-to-bee communication and multipopulation coevolution for multilevel threshold image segmentation, Math. Probl. Eng. (2015), Article ID 272947, 23 pp.
[24] D. Maru1, B. Shah, Image segmentation techniques and genetic algorithm, Int. J. Adv. Res. Comput. Eng. Technol. 2 (2013) 1483–1487.
[25] C.E. Shannon, A mathematical theory of communication, Int. J. Bell Syst. Tech. 27 (1948) 379–423.
[26] M.P. de Albuquerque, I.A. Esquef, A.R. Gesualdi Mello, Image thresholding using Tsallis entropy, Pattern Recognit. Lett. 25 (2004) 1059–1065.
[27] A. Renyi, On measures of entropy and information, in: Proceedings of the Fourth Berkeley Symposium on Math. Statist. Prob., vol. 1, 1960, University of California Press, Berkeley, 1961, pp. 547–561.
[28] P.K. Sahooa, A. Gurdial, A thresholding method based on two-dimensional Renyi's entropy, Pattern Recognit. 37 (2004) 1149–1161.
[29] C. Tsallis, Possible generalization of Boltzmann–Gibbs statistics, J. Stat. Phys. 52 (1988) 479–487.
[30] K. Prasanna Sahoo, G. Arora, Image thresholding using two-dimensional Tsallis–Havrda–Charvat entropy, Pattern Recognit. Lett. 27 (2006) 520–528.
[31] C.A.B. Mello, L.A. Schuler, Thresholding images of historical documents using a Tsallis-entropy based algorithm, J. Softw. 3 (2008) 29–36.
[32] B. Singh, A.P. Singh, Edge detection in gray level images based on the Shannon entropy, J. Comput. Sci. 4 (2008) 186–191.
[33] J.H. Holland, Adaptation in Natural and Artificial Systems, 2nd ed., MIT Press, Cambridge, MA, 1975 (first edition).
[34] J.H. Holland, Genetic Algorithms, Scientific American, 1992, pp. 114–116.
[35] S. Jayaraman, S. Esakkirajan, T. Veerakumar, Digital Image Processing, 7th ed., Tata McGraw Hill Education Ptd. Ltd, New Delhi, 2012, pp. 368–393.