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A Two-Dimensional Image Segmentation Method Based on Hybrid Genetic Algorithm with Particle Swarm Optimization and Entropy

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Abstract

For segmentation of digital images, thresholding is a popular approach. Through increasing few data theory functions like entropies, an increasing contribution accomplished the thresholding rate. The conventional methods finds for thresholding rate through composing the entropy over the prearranged image gray level distribution. To merge into optimal entropy, this prearrangement phase does not allow. Depending on the Renyi entropies, Tsallis flexible representation and hybrid genetic algorithm with particle swarm optimization (GA_PSO), we project a new method of two-dimensional image segmentation in this paper. The entropy is employed to measure the sum of data composed in image two-dimensional histogram from the view of data theory. With a view to effectively segment the image to object from the background, GA_PSO is employed to entropy maximization. The simulation outcomes show that the method enhances the entropy proficiently and produces enhanced quality of image segmentation when comparing with conventional thresholding method.

Keywords: Particle Swarm Optimization (PSO); Genetic Algorithm (GA); Entropy; Segmentation.

1. INTRODUCTION

The principle of thresholding consists of finding an adequate threshold to segment object[1,2] from background through certain criteria, such as Otsu thresholding [3], maximum entropy thresholding, minimum error thresholding, 2D maximum entropy thresholding and Fisher information. 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. GA has been examined and used to numerous optimization issues at present times. GAs is suitable mainly for huge search spaces optimization that is inappropriate for comprehensive search process. For a applied optimization issue, the method rapidly and efficiently offer a adequate solution. A trade-off is offered by the method among the exploitation and exploration of the search space. GA offers close optimal solution that are acceptable for real time applications. Accordingly, in image processing GA carry out various tasks [4]. A multi-term cost function is described through [5] that is reduced by employing detection of GA-evolved edge. Edge detection is formed as reduction problem as main cost function to image segmentation in this method on space of entire probable edge setup and edge images population is developed by employing specific operators.

There were several method and techniques projected to search the multithreshold solution, hence various metaheuristic optimal method were used towards multilevel thresholding. By employing GA, [6] projected an optimal thresholding. For deciding the thresholds, fractional-order Darwinian particle swarm optimization (PSO) and Darwinian PSO and PSO are modeled by [7]. A segmentation method of ant colony optimization (ACO) is modeled as for resolving the problem of multilevel Otsu. In searching the thresholds for Kapur's and Otsu's maximizing main functions, used bacterial foraging. To search multilevel thresholds, differential evolution optimization procedure is employed. For choosing multilevel thresholds, three optimization method were projected through [8]. The metaheuristic is not capable to search the management of local and global search with the increment in thresholds that might tend to imprecise outcomes and slower rate of convergence.

One of the optimization problems is segmentation and in image segmentation, GA effectively evaluates the global maxima within the search space and resolves the parameter selection problem. For threshold selection from image histogram, a novel technique depending on GA had been projected. By employing entropy in this work, we aim at 2-D image segmentation. The entropy is used to measure the data amounts applied through the image gray levels dispersion. Through entropy maximization, the aim is image segmentation. By employing GA_PSO, the optimization can be done. In this paper, Tsallis and Renyi entropies are compared and used. When compared to the conventional thresholding technique, the projected method does not require to organize intensities of image in advance. When compared to the conventional thresholding approach, the problem of image segmentation is a common combinatorial optimization task. To improve the entropy maximization and to enhance the quality of image segmentation is the major aim.

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_PSO 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

In data theory, entropy is the major tool. To measure the sum of data content, Shannon has employed it. Entropy is employed as quantifier in data theory which demonstrates how far the randomness of event and signal. The sum of data performed through the signal is computed through entropy. Here, $Z = \{z1, z2, z3, \ldots, zk\}$ refers symbols source. $P = \{p1, p2, p3, \ldots, pk\}$ is the respective probability set in that satisfy the criteria $\sum_{i=1}^{k} P_i = 1, 0 \leq pi \leq 1$. Through Shannon entropy, the average data for each source output might be gained [26]:

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

The sum of symbols is denoted through k. The Shannon entropy comprises of the wide feature $S(A + B) = S(A) + S(B)$ when we assume the decomposition of system of A and B statistical independent subsystems. The simpler Shannon entropy SH generalization is 2-D distribution that can be represented as

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

Renyi's entropy is known as the significant Shannon entropy generalization. This entropy is described as

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

Let α refers real parameter and other generalized entropic expression given by Tsallis [9] is represented as

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

Let in an entropic index q be the real number which characterizes the non-extensivity degree. For systems that are statistically independent, Tsallis entropy comprise a non-extensive feature described through

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

To decide the threshold rate by non-additive data content in edge detection and image segmentation, Tsallis entropy can be used. In a $M \times N$ sized digital image, at the point (x, y), the gray value is denoted thorugh $f(x, y)$ in the way that $y \in \{1, 2, \ldots, N\}$ and $x \in \{1, 2, \ldots, M\}$. The selection of global threshold approaches depends always over the image gray level histogram. Through appropriate function optimization, the best threshold $t*$ is computed that is derived by the distribution at gray level and few other image features. We determine through $[0, t] \times [s + 1, 255]$, the primary quadrant, through $[0, t] \times [0, s]$, the secondary quadrant, through $[t + 1, 255] \times [0, s]$, the next quadrant and through $[t + 1, 255] \times [s + 1, 255]$, the last quadrant. Fig. 1 demonstrates the 2D four quadrants histogram. The third and first quadrants might be avoided in image segmentation as it comprise the edge data and noise only and $P_4(t, s)$ and $P_2(t, s)$ are the posteriori class probabilities and therefore we additionally approximate the $P_4(t, s)\ as\ P_4(t, s) = 1 - P_2(t, s)$.

Over the threshold rate t, the Tsallis entropy $S_q(t)$ is based parametrically for background and foreground. In order to the pseudo-additive feature, it is formed as total of respective entropies. We attempt to extend the data measure among the two classes. The optimum threshold rate is one, luminance level t which enhances the function if the $S_q(t)$ is maximized.

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

By employing Renyi or Tsallis entropy, we build a binary image in the projected method through selecting a appropriate rate of threshold. The method comprise of assuming every actual image pixel and producing a novel image $f_t(x, y) = 0\ if\ f_t(x, y) \leq t*(q)$ and $f_t(x, y) = 1$ or for each $x \in \{1, 2, \ldots, M\}, y \in \{1, 2, \ldots, N\}$. The threshold rate is similar to the Shannon's technique. Therefore, the projected technique employs Shannon's approach as main case.

3. HYBRIDIZATION OF GENETIC ALGORITHM AND PARTICLE SWARM OPTIMIZATION

By employing entropy in this work, we aim at 2-D image segmentation. The entropy is used to measure the data amounts applied through the image gray levels dispersion. Through entropy maximization, the aim is image segmentation. By employing GA, the optimization can be done. In this paper, Tsallis and Renyi entropies are compared and used. When compared to the conventional thresholding technique, the projected method does not require to organize intensities of image in advance. When compared to the conventional thresholding approach, the problem of image segmentation is a common combinatorial optimization task. To improve the entropy maximization and to enhance the quality of image segmentation is the major aim.

John Holland [10] is the father of actual GA who developed in 1960s. By employing natual motivating approaches, towards the huge Evolutionary Algorithms (EA) class, the GA depends to produce best solution for optimization issues. GA is evolved through AI domain and it is a method of adaptive heuristic search which resembles few procedures of natural selection. With taking into account the chromosome population, the GA execution starts. These frameworks are examined and assign a reproductive choices in a manner which the chromosomes demonstrate a optimal solution to the goal issues are assigned high choice to "reproduce" when compared to the poor solutions chromosomes. The solution "goodness" is described specifically in order to the present population [11].Fig. 1 shows the overall structure of GA. The major GA operators are crossover, mutation and selection in the estimation purview. The simple GA working flow is given below when applied with a bit-string representation.

1. Begin with the arbitrarily procedure N population of L-bit chromosomes.
2. Estimate every chromosome x fitness f(x) within the population.
3. Until the offspring has been produced repeat the steps.
   I. From the present population, choose a parent chromosomes pair with the selection probability as enhancing fitness function. “with replacement,” the selection of chromosomes are done and similar one might be chosen higher than one time to be a parent.
   II. The pair cross over is done with the probability pc to formulate the two offspring at a arbitrarily selected point. Produce two offspring which are precise parent copies, when no crossover occurs.
   III. With probability pm, at every locus, mutate the two offspring and adopt the resultant chromosomes in fresh population.
4. With fresh population, replace the present.

5. Go to step 2.

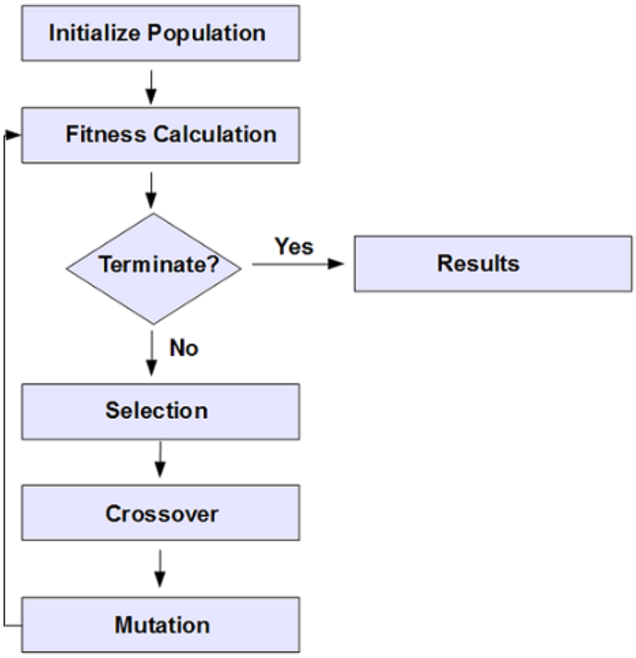

Fig. 1. GA structure

PSO is a metaheuristic as it makes few or no assumptions about the problem being optimized and can search very large spaces of candidate solutions. However, metaheuristic such as PSO do not guarantee an optimal solution is ever found. Also, PSO does not use the gradient of the problem being optimized, which means PSO does not require that the optimization problem be differentiable as is required by classic optimization methods such as gradient descent and quasi-newton methods. Basic variant of the PSO algorithm works by having a population (called a swarm) of candidate solutions (called particles). These particles are moved around in the search-space according to a few simple formulae [9]. The movements of the particles are guided by their own best known position in the search-space as well as the entire swarm's best known position. When improved positions are being discovered these will then come to guide the movements of the swarm. The process is repeated and by doing so it is hoped, but not guaranteed, that a satisfactory solution will eventually be discovered. We focus to segment the pixels in the problem of image segmentation which maximizes of Renyi and Tsallis that are used as fitness functions. This might be performed in comparing with conventional thresholding technique without gray levels intensities ordering. From the image, the goal is to sum of data maximization.

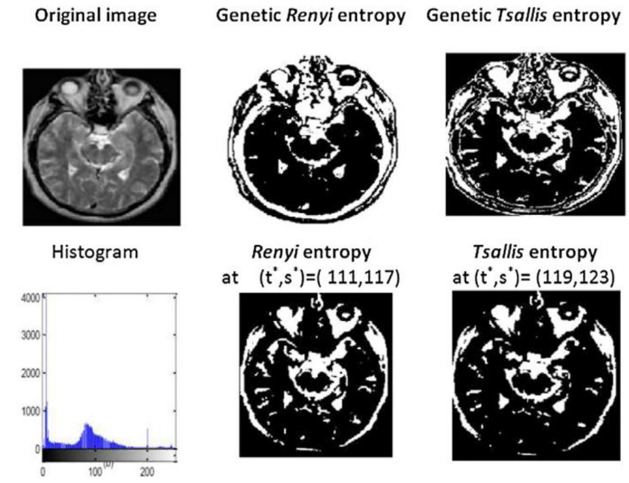

Fig. 2. Sample medical image dataset Brain (A)

4. EXPERIMENTAL RESULTS AND DISCUSSION

With the conventional thresholding methods, we compare the approaches of segmentation by employing Tsallis and Renyi entropies in this part. To practical and medical image samples, the techniques are applied by demonstrating various sizes and histograms. The sample images are shown in Fig. 2. Through the use of Peak Signal to Noise Ratio (PSNR), the derived outcomes are compared quantitatively and visually. It is the proportion among the noise power corrupted and huge probable signal power that impact the representation fidelity [12]. For the image peak value towards the root mean square error, it is logarithmic function and expressed through:

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

Let MSE refers the mean square error described through:

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

With the input and output images are I and S are of M × N size, correspondingly. To measure the quality of segmentation, the PSNR index is employed. The PSNR measure rate must be high for the enhanced segmentation. Through two major features, GA is managed; m is the length of chromosome and p is the size of population. The end

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criteria depend on the maximum generation counts. The m = 50, p = 30 are the values that are taken and the maximum generation count is configured as 300. Fig. 2 demonstrates the actual image, segmented images and histogram through various methods. The thresholding rate pairs (t*, s*) are given while employing conventional approaches of 2D thresholding. The comparison in visual form tends to conclude that the proposed method accomplishes best optimal results in image segmentation. The primary motivational simulation outcomes is the major increase attain through the entropies by employing GA. Through the rate 10%, when comparing with conventional thresholding technique, the rate of entropy has been enhanced for entire sample images.

Table 1: PSNR values: comparison between conventional and proposed entropies for the GA-PSO based segmentation.

PSNR	GATsallis	GARenyi	Proposed
Brain(A)	3.54	7.25	8.01
Brain(B)	6.18	6.40	7.25
Light microscopy	5.12	5.14	6.18
Peppers	9.11	9.11	9.89
Retina	2.06	2.92	4.57
Tire	4.93	8.70	9.58
Cells	2.45	2.64	5.84
Grape	7.25	6.60	8.52

For various image kinds, the GA-based segmentation attains superior maintenance in details and robustness of the image. The considerable enhance is because of the implication of GA and PSO. The GARenyi entropy attains little superior outcomes when comparing with Tsallis entropy. For the entire medical images as shown in Fig. 3, GATsallis is the poor performer, and its worst case is 2.06 when segmenting the Retinal dataset. GARenyi somewhat manages to perform well over the above method where it gives worst case PSNR rate of 2.64. It gives maximum PSNR rate of 9.11 when segmenting the pepper medical image dataset. For GA and PSO based image segmentation, table 1 demonstrates the obtained PSNR rates of given images while employing GARenyi and GATsallis entropies. For image segmentation using GA and PSO, GARenyi entropy exhibits enhanced results. The GATsallis-based fitness function is highly composite that employing the entropy of GARenyi. The projected method gives superior performances over the other methods, as it gives, 4.57 as worst case in segmenting the Retinal dataset and 9.89 when segmenting the pepper medical image dataset. Therefore the proposed GA and PSO based segmentation is highly appropriate in segmenting the medical image dataset.

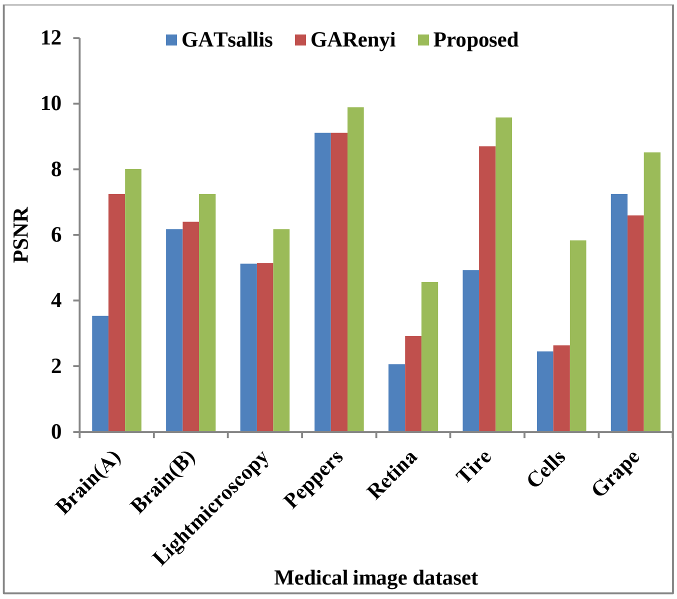

Fig. 3. Comparison of conventional and proposed entropies by means of PSNR

5. CONCLUSION

A new technique for segmenting the images was projected in this paper depending GA and PSO. With the implication of GA and PSO, the quality of image segmentation is enhanced. The entropies Renyi and Tsallis are compared and employed with the proposed method. The numerical outcomes exhibit the efficiency of the projected technique due to the data gain attained through GA. Even though, the Renyi entropy gives enhanced image segmentation, the projected method outperforms it, as it is included with the PSO method.

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