A Hybrid Genetic Algorithm and Gravitational Search Algorithm for Image Segmentation Using Multilevel Thresholding

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Abstract. This paper presents a novel optimal multilevel thresholding algorithm for histogram-based image segmentation. The proposed algorithm presents an improved variant of the gravitational search algorithm (GSA), a relatively recently introduced stochastic optimization strategy. To strengthen its ability to achieve generation jumping when getting stuck at local optima, this paper proposes a novel algorithm, GA-GSA (genetic algorithm-based gravitational search algorithm) for image segmentation. In this paper, the proposed method employs both GA and GSA and the maximum entropy criterion as the objective function for achieve multilevel thresholding. To demonstrate the ability of the proposed algorithm, the novel method is employed on two benchmark images, and the performances obtained outperform results obtained using two other stochastic optimization methods, i.e., PSO (Particle Swarm Optimization) and GSA. The experimental results illustrate that the proposed algorithm could significantly enhance performance compared to other popular contemporary methods.

Keywords: Genetic algorithm, Gravitational search algorithm, GA-GSA, Image segmentation, Multilevel thresholding.

1 Introduction

Image segmentation is an important technology for image processing [1]. It is useful for separating objects from backgrounds or discriminating objects from objects with distinct gray-levels. Image thresholding is often used in image segmentation. Thresholding techniques can be classified into two types: optimal thresholding methods [2] and property-based thresholding methods [3]. Optimal thresholding methods search for the optimal thresholds by optimizing an objective function based on an image gray-level histogram. Researchers have proposed several algorithms to determine the functions, including maximizing entropy to measure the homogeneity of segmented classes, maximizing the separability measure based on between-class variance, and minimizing of Bayesian error. However, these methods all have a same problem: segmentation accuracy is reducing with the Image complexity rises. Researchers have developed several

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algorithms to solve this type of optimization problems, including branch-and-bound, met-heuristic, and gradient-based methods. Among them, meta-heuristic-based methods, i.e., heuristic algorithms, have become increasingly popular. J. Holland introduced the genetic algorithm (GA) in the 1970s [4]. GA is an adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetics which prevents the algorithm from falling into local optima effectively. Rashedi et al. propose the gravitational search algorithm (GSA) [5]. GSA is one of the newest heuristic algorithms inspired by the law of gravity and mass interactions. Although GSA easy to achieve convergence, it is more likely becomes inactive. Some studies have examined improved algorithms [6]. This paper uses GA to prevent GSA from getting 'stuck' in local optima. Taking advantage of the compensatory properties of GA and GSA, we propose a new algorithm that combines their evolutionary natures (GA-GSA). The experimental results illustrate that the proposed algorithm could significantly enhance performance compared to other popular contemporary methods.

2 Hybrid Image Segmentation Algorithm

Assume that an unconstrained D-dimensional optimization problem must be solved by maximizing the objective or fitness function $f(X)$ given thus:

$$f(X) = f([x_1, x_x, \ldots, x_D]) = H_0 + H_1 + H_2 + \ldots + H_D \tag{1}$$

where D denotes the number of parameters to be optimized. In the proposed segmentation algorithm, $f(X)$ is an entropy criterion formula and X is a set of segmentation threshold.

2.1 Genetic Algorithm

GA is an adaptive method that can be used to solve search and optimization problems. It is based on the genetic process of biological organisms. This operation has two processing steps. In the first step, a given number of crossing sites are uniformly selected, and the parent individual is randomly selected. In the second step, two new individuals are formed by exchanging alternate selection pairs between the selected sites. Mutation is a random alteration of some gene values in an individual. The allele of each gene is a candidate for mutation, and the mutation probability determines its function [7]. In the new generation, the population is more adapted to the environment than the previous generation, and the evolution continues until meeting an optimization criterion.Therefore, although GA would lose some chromosome information in selection, it is capable of global optimization and effectively avoids falling into local optima.

2.2 Gravitational Search Algorithm

In GSA, agents sets, called masses, are introduced to find the optimum solution by simulating the Newtonian laws of gravity and motion. All objects attract

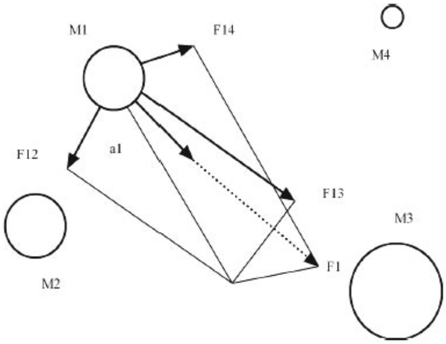


Fig. 1. Example twig query and documents

each other with gravity, and this force causes a global movement of all objects towards objects with heavier masses (Fig. 1). Masses thus communicate with others through the gravitational force. Heavy masses, which correspond to good solutions, move more slowly than light ones. This guarantees the ex-ploitation step in the algorithm. By lapse of time, we expect the heaviest mass to attract the other masses. This mass can present an optimum solution in the search space. At a specific time t, the force acting on mass i from mass j is:

$$F_{ij}^{d}(t) = G\left(t\right) \frac{M_{pi}\left(t\right) M_{aj}\left(t\right)}{R_{ij}\left(t\right) + \epsilon} \left(x_j^d\left(t\right) - x_i^d\left(t\right)\right) \tag{2}$$

where M_{aj} is the active gravitational mass related to agent j, M_{pi} is the passive gravitational mass related to agent i, $G(t)$ is gravitational constant at time t, is a small constant, and $R_{ij}(t)$ is the Euclidian distance between agents i and j. Assuming the gravitational and inertial masses are equal, their values are calculated using the fitness map. The gravitational and inertial masses are updated thus:

$$M_{ai} = M_{pi} = M_{ii} = M_i, i = 1, 2, \ldots, N \tag{3}$$

The detailed calculations of gravitational constant, mass, position, and velocity of agent i can be found in [5]. As gravitational force helps all masses achieve convergence quickly, GSA is thus a potentially attractive choice for local optimism.

2.3 Hybrid GA-GSA (HGA-GSA)

According to the analysis above, GSAs behavior enhances the search for an optimal solution, while GA is better at reaching a global region. Therefore, the proposed algorithm employs GA for generation jumping to avoid GSA getting stuck in the local optima problem. GA-GSA integrates GAs global optimization and GSAs fast convergence by unifying the GA crossover and mutation operator and the GSA speed-displacement formula to solve optimization problems more efficiently and effectively. At the same time, the search accuracy improves. We

use real-coding in this paper to avoid the encoding and decoding process and improve computational efficiency. The GA-GSA steps include the followings:
Step 1: Population-based initializing (pop, size N).
Step 2: Evaluating fitness of each agent.
Step 3: (GA method) Performing GA selection, crossover and mutation operations to generate new population.
Step 4: Updating G(t), best(t), worst(t) and Mi(t).for i=1, 2, . . ., N; t is the current number of iterations.
Step 5: Calculating the total force in different directions of each agent.
Step 6: Calculating acceleration and velocity of each agent.
Step 7: Updating agents positions.
Step 8: Repeating steps 2 to 7 until the stopping criterion is met (e.g. a maximum iteration).
Fig. 2. shows the GA-GSA principle.

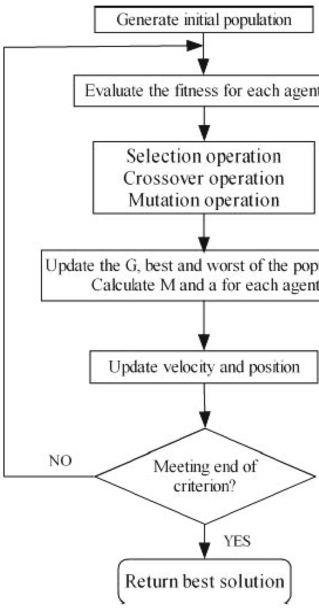


Fig. 2. The GA-GSA principle

3 Performance Evaluation

We evaluate the proposed algorithm's performance by comparing its results with other sto-chastic optimization methods, including PSO [8] and GSA. Pictures Lenna and Pepper (each is 256*256) are chosen to present comparative results. Fig. 3 presents the original images. In all cases, the population size is set to 40 and maximum iteration to 100 for the functions in Tables 1 and 2.

(a) (b)

Fig. 3. The (a) Lenna and (b) Pepper

Table 1. A comparative study of optimal GA-GSA, GSA, and PSO thresholds

Images	c	GA-GSA		GSA		PSO	
		Optimal thresholds	Objective values	Optimal thresholds	Objective values	Optimal thresholds	Objective values
Lenna	2	86,157	12.590	90,158	12.308	91,157	12.287
	3	67,114,175	15.294	76,120,170	15.292	74,119,169	15.270
	4	60,123,169,185	18.013	59,91,131,173	17.985	58,90,130,170	17.533
	5	49,90,139,163,196	20.601	56,87,123,158,189	20.583	56,87,120,157,185	20.240
Pepper	2	76,150	112.691	175,146	112.666	175,146	112.660
	3	54,113,169	115.788	160,113,167	115.780	154,107,159	115.760
	4	52,103,153,195	18.708	155,109,153,196	118.701	153,102,147,194	118.683
	5	45,74,106,147,198	21.504	140,75,115,158,195	121.482	142,77,111,151,194	121.281

Table 2. A comparative study of uniformity values for GA-GSA, GSA, and PSO

Images	c	Uniformity		
		GA-GSA	GSA	PSO
Lenna	2	0.8166	0.8067	0.7967
	3	0.8785	0.8476	0.8374
	4	0.8810	0.8486	0.8439
	5	0.9180	0.8744	0.8615
Pepper	2	0.8061	0.7865	0.7865
	3	0.8742	0.8561	0.8086
	4	0.9657	0.9636	0.9619
	5	0.9716	0.9667	0.9627

Tables 1 shows the optimal thresholds (with c=2, 3, 4 and 5) and the corresponding objective function values (Maximum entropy) obtained using GA-GSA, GSA, and PSO respectively. The objective function value results are averaged over 30 runs, and Table 1 presents the thresholds in the last iteration. In each case, GA-GSA comfortably outperforms the other algorithms. To qualitatively judge the segmentation procedure that produced thresholded images, we employ

(a) (b) (c) (d)

Fig. 4. (a) 3-level thresholds, (b) 5-level thresholds, (c) 3-level threshold,s and (d) 5-level thresholds

Table 3. Performance measures for the Gray21 image obtained b using the GA-GSA algorithm

Image	c	Thresholds	Objective values	Uniformity
Gray21	2	90,193	6.0682	0.9182
	3	49,116,182	6.5790	0.9520
	5	46,106,149,193	7.2721	0.9593
	6	44,81,125,174,216	7.4543	0.9676

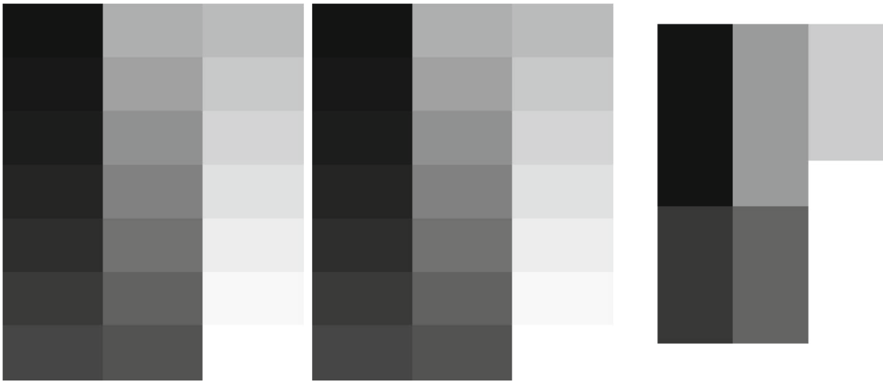
the popular uniformity measure [9], which has also been employed by Yin [10] to provide an effective performance comparison. The uniformity measure is:

$$\mu = 1 - 2c\frac{\sum_{j=0}^{c}\sum_{i\in R_j}(f_i - \mu_j)^2}{N(fmax - fmin)^2} \tag{4}$$

Where c is number of thresholds; R_j is the jth segmented region; N is the total number of pixels in the given image; f_i is gray level of pixel i; μ_j is mean gray level of pixels in jth region; $fmax$ is maximum gray level of pixels in the given image; $fmin$ is minimum gray level of pixels in the given image. Typically, $u \in [0, 1]$; a μ increases in value, the thresholded image quality also improves. Table 2 shows a comparative study of the uniformity measures obtained using two methods for the same Lenna and Pepper images. The uniformity results are also averaged over 30 runs.

The results in Table 2 show that, in all cases, GSA performs better than the PSO-based segmentation method, and the GA-GSA method performers are the best. The proposed GA-GSA can achieve significantly better segmentation results, demonstrated by higher μ values in each case. The results from the Lenna image can achieve a μ value in the range of 0.82-0.92, while other methods fail to reach a μ value of 0.88. For a visual GA-GSA interpretation of the segmentation results, Figs. 4 presents the segmented Lenna and Pepper images with $c = 3$ and $c = 5$, in respectively.

Furthermore, we present sample results, tested on an analog image a Gray21 image using the proposed multilevel thresholding method. This image is selected because it contains 21 rectangles of different gray shades and produces



(a) (a) (b) (a) (c) (b)

Fig. 5. The (a) Gray21 image, (b) the thresholded image using 3-level thresholds, and (c) 5-level thresholds

a unique histogram with 21 distinct peaks, which is strikingly different from the histograms produced by the Lenna and the Pepper images. Fig. 5 presents the original image and the segmented image with $c = 3$ and $c = 5$. Table 3 presents the optimal thresholds, objective function values and uniformity measures obtained for this image. We can achieve a maximum u of 0.9676 for $c = 5$. The experimental results show that GA-GSA is effective for multi-threshold segmentation.

4 Conclusions

In this paper, we have presented a novel optimal multilevel thresholding algorithm for histo-gram-based image segmentation employing an improved GSA variant, called GA-GSA (genetic algorithm-based gravitational search algorithm). In the existing GSA, only the gravitational force guides masses, because the algorithm is constructed based on the laws of gravity and mass interactions. Though GSA is a powerful global search tool, it is not effective enough for more complicated problem: segmentation accuracy is reducing with the Image complexity rises. Conversely, GA is an adaptive heuristic search algorithm premised on the evolutionary ideas of natural selection and genetics. Combining the two can improve existing algorithms. The hybrid GA-GSA thus combines GA global optimization with GSA fast local search, enriches search behavior, and enhances search capabilities. The proposed algorithm can therefore effectively and efficiently achieve image segmentation using multilevel thresholding. To evaluate our algorithm, GA-GSA is employed on two benchmark images and an analog image; the results are compared to PSO and GSA. The performance obtained by GA-GSA provides superior results, which are comparable with PSO and GSA in all cases.

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