An Optimizing Multilevel Thresholding for Image Segmentation Based on Hybrid Swarm Computation Optimization

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Abstract. This paper suggests a solution for the image segmentation (IS) problem with the multilevel thresholding based on one of the latest hybrid swarm computation optimization algorithms, particle swarms, and gravitational search (PSGA). The experimental results are comparable with other state-of-the-art algorithms that show that the PSGA on selected images is better than the competitors.

Keywords: Cross-entropy thresholding · Image segmentation · Particle warms · And gravitational search

1 Introduction

Image threshold segmentation is one of the most effective, and real-time methods that have received widespread attention in image processing [1]. Multi-threshold image segmentation is considered as an extension of threshold segmentation that can distinguish background and multiple goals, but the disadvantage is that the calculation is complicated and takes a long consumption time. Many biological heuristics is the promising ways of applying successfully to deal with IS problems, e.g., genetic evolution, swarm behavior [2]. For example, the gravity search algorithm (GSA) [3] was taken inspiration based on the theory of Newtonian physics as the gravity law and mass interactions; the FA algorithm was taken inspiration from Firefly insect [4]; the CS algorithm was mimicked from Cuckoo search [5]. Some applications in image processing as segmentation issues have used these algorithms, e.g., a threshold selection criterion solved by GSA

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[6], the multi-threshold calculated by FA [7], and the multi-threshold optimized by CS [8]. These applications show advantages of computational time, but they still have a drawback of local search capabilities that is easy to fall into the defect of local optimum. This issue causes IS unexpectedly accurate.

The hybrid swarm computation optimization algorithms is one of the proper ways to deal with this issue of drop trap local optimal [9]. The hybrid algorithm is the idea of mixed algorithms by adding or combining the advantages of different algorithms for enhancing both of global exploration and local mining capabilities [10, 11]. The PSGA [12] is one of the latest metaheuristic algorithms that is a hybrid algorithm of particle swarm (PSO) [2] and gravitational search (GSA) [3] by combining the agents' group to the optimization algorithm.

In this paper, we consider a solution problem of the multi-threshold segmentation of color images with adjusting PSGA to avoid a single algorithm's weak local search ability and easy local optimum for causing inaccurate segmentation. Multi-threshold Otsu's rule [13] is used as an IS evaluation function to perform multi-threshold segmentation on multi-target images.

2 Hybrid Particle Swarm and Gravitational Search (PSGA)

The PSGA algorithm is a combined the global search ability of the PSO algorithm and the local mining ability of the GSA algorithm [12].

2.1 Standard Particle Swarm Optimization Algorithm

In PSO [2], each particle represents a feasible solution, and each moment has its own speed and position. Let the position and velocity of the tth particle in the d dimension at the tth iteration be $X_i^d(t)$ and $V_i^d(t)$, where $d = 1, 2, \ldots, D$, and D are the search space dimensions. In each iteration, the optimal solution of the individual particle is $p\text{best}_i^d$, and the optimal solution of the group is $g\text{best}^d$. Then the particle updates its speed and position according to Eqs. (1) and (2) during each iteration:

$$V_i^d(t+1) = \omega V_i^d(t) + c_1 \cdot \text{rand}_1 \cdot \left(p\text{best}_i^d - X_i^d(t)\right) + c_2 \cdot \text{rand}_2 \cdot \left(g\text{best}^d - X_i^d(t)\right) \tag{1}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{2}$$

In the formula: ω is the inertia weight of the particle; c_1 and c_2 are the acceleration factors; rand_1 and rand_2 are random numbers of [0, 1] respectively. The first part ωV_i^t in Formula (1) reflects the mining ability of the particle swarm optimization algorithm, and the second and third parts $c_1 \cdot \text{rand}_1 \cdot \left(p\text{best}_i^d - X_i^d(t)\right)$, $c_2 \cdot \text{rand}_2 \cdot \left(g\text{best}^d - X_i^d(t)\right)$, respectively, reflect the particle Ability to think independently and communicate with groups.

2.2 Standard Gravity Search Algorithm(GSA)

The particles in GSA [3] are attracted to each other by gravity, and the particle's motion follows Newton's law of motion. Gravitational force causes particles to move toward larger mass particles, while the largest mass particles occupy the optimal position. According to this principle, the optimal solution of the optimization problem can be obtained.

The speed and position of particles in GSA are updated according to Eqs. (3)–(5) during each iteration:

$$V_i^d(t+1) = \text{rand} \cdot V_i^d(t) + a_i^d(t) \tag{3}$$

$$X_i^d(t+1) = X_i^d(t) + V_i^d(t+1) \tag{4}$$

$$a_i^d(t+1) = F_i^d(t)/M_i^d(t) \tag{5}$$

where: $X_i^d(t)$, $V_i^d(t)$, $a_i^d(t)$, $F_i^d(t)$, $M_i^d(t)$, respectively, represent the position, velocity, acceleration, and position of the tth particle in the $d-$dimension during the tth iteration. The magnitude of the resultant force and the mass of inertia.

The calculation of the resultant force is shown in Eqs. (6) and (7):

$$F_{ij}^d(t) = \left[\frac{G(t) \cdot M_i(t) \cdot M_j(t)}{R_{ij}(t) + \varepsilon}\right] \cdot \left[X_j^d(t) - X_i^d(t)\right] \tag{6}$$

$$F_i^d(t) = \sum_{j=1, j \neq i}^{N} \text{rand}_j \cdot F_{ij}^d(t) \tag{7}$$

In the formula: N is the total number of particles; $F_{ij}^d(t)$ represents the gravitational force of particle j to particle i; rand_j is a random number of [0, 1]; $R_{ij}(t)$ is the Euclidean distance between particle i and particle j; ε is a A constant with a small value; $G(t)$ is the gravitational constant. The calculation formula is shown in Eq. (8):

$$G(t) = G_0 \cdot \exp(-\alpha \cdot t/\max t) \tag{8}$$

Among them: G_0 and α are constants; t is the current number of iterations; $\max t$ is the maximum number of iterations. The inertial mass of the particles in Eq. (6) can be obtained from Eqs. (9) and (10):

$$m_i(t) = \frac{\text{fit}_i(t) - \text{worst}(t)}{\text{best}(t) - \text{worst}(t)} \tag{9}$$

$$M_i(t) = m_i(t) / \sum_{j=1}^{N} m_j(t) \tag{10}$$

where: $\text{fit}_i(t)$ represents the fitness value of the tth particle at the tth iteration. For the image multi-threshold segmentation problem for which the maximum value is obtained, $\text{best}(t)$ and $\text{worst}(t)$ are obtained from equations as follows.

$$\text{best}(t) = \max \text{fit}_j(t), j \in \{1, 2, \ldots, N\} \tag{11}$$

$$worst(t) = \min fit_j(t), j \in \{1, 2, \ldots, N\} \tag{12}$$

2.3 Hybrid Particle Swarm and Gravitational Search

Whenever the GSA updates the agent's position, it only considers the effect of the particle's current position and does not consider the global memory of the particle. PSGA combines the group communication ability ($g$best) in PSO with the local search ability of GSA so that the particle movement follows. Due to the law of movement, the ability of group information exchange has been enhanced. The new particle velocity update formulas as follows.

$$V_i^d(t+1) = \omega V_i^d(t) + c_1' \cdot \text{rand}_1 \cdot a_i^d(t) + c_2' \cdot \text{rand}_2 \cdot \left(g\text{best}^d - X_i^d(t)\right) \tag{13}$$

By adjusting the values of $c_1^{'}$ and $c_2^{'}$, the influence of gravitational attraction between particles and the exchange of global information on optimal value search can be balanced.

3 Optimizing Multi-threshold for Image Segmentation by PSGA

3.1 Generalized Inverse Learning Strategy

The main idea for a feasible solution is to calculate and evaluate its inverse solution at the same time and choose the better solution as the next generation individual [12]. In the D-dimensional search space, X_d is a feasible solution, and X_d^* is its inverse solution. The definition of the generalized inverse learning strategy is shown in the following equation.

$$X_d^* = \Delta - X_d \tag{14}$$

where d is set $1, 2, \ldots, D$. In the problem of obtaining the global optimal (GO) value of image multi-threshold segmentation, considering the roundedness of the image threshold solution $X_d \in [a_d, b_d]$, let $\Delta = k(a_d + b_d)$, then generalized reverse in image multi-threshold segmentation The definition of learning strategy is shown in Formula (15):

$$\begin{cases} X_d^* = k(a_d + b_d) - X_d \\ X_d^* = a_d, \ \text{if}\ X_d^* < a_d \\ X_d^* = b_d, \ \text{if}\ X_d^* < b_d \end{cases} \tag{15}$$

where k is a random number of [0,1].

3.2 The Mutation Strategy of the Optimal Solution

In PSGA, the GO particle $g\text{best}^d$ plays an important role. Once $g\text{best}^d$ is trapped in the local optimum, it cannot jump out, and the remaining particles will move closer to it, causing the algorithm to prematurely converge and fail to obtain the optimal solution of the segmentation threshold. Cauchy Mutation [13] is used to mutate global superior particles, and expanded the neighborhood search space. The Cauchy variation is shown in the following equation.

$$g\text{best}_d^* = g\text{best}_d + \text{cauchy}() \tag{16}$$

where $g\text{best}_d$ is the component of the optimal particle in the $d-$dimension, cauchy () is a random number following the standard Cauchy distribution, and $g\text{best}_d^*$ is the optimal particle after mutation. Experiments show that the mutation strategy works well only on some test functions and has certain limitations.

A normal mutation strategy (NM) is introduced in this paper as a suitable variable for image threshold optimization. It is combined with the particle motion speed in PSOSA, perturbing $g$best in a small range during each iteration, thereby expanding the GO position. Search the area, so that the GO particle $g$best can jump out in time when it falls into the local optimal. The specific implementation is shown in the following equations.

$$W_d(t) = \left(\sum_{i=1}^{\text{Popsize}} V_i^d(t)/\text{PopSize} \right) \tag{17}$$

$$g\text{best}_d^*(t) = g\text{best}_d(t) + W_d(t) \cdot N(0, 1) \tag{18}$$

In the formula: PopSize represents the total number of particles; $N(0, 1)$ is the standard normal distribution function; the probability density function and the distribution function are shown in Eqs. (19) and (20), respectively:

$$\varphi(x) = \frac{1}{\sqrt{2\pi}} e^{-x^2/2} \tag{19}$$

$$\Phi(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{x} e^{-t^2/2} \mathrm{d}t \tag{20}$$

3.3 Threshold Image Segmentation

The generalized backward learning strategy in the image threshold optimization process is introduced in this paper that combines the typical mutation strategy of the optimal global solution to expand the search space of the population and the optimal comprehensive solution. The optimal solution of the multilevel image threshold segmentation with the evaluation function is obtained by applying the PSGA. Figure 1 shows the multi-threshold IS process.

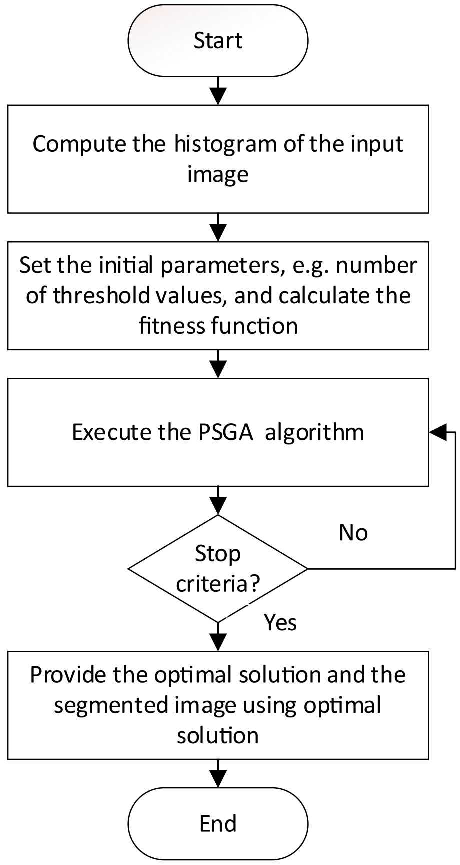


Fig. 1. Flowchart of multi-threshold image segmentation using PSGA

Otsu algorithm [13] is used as the fitness function for IS evaluation criterion to perform multi-threshold segmentation on complex multi-target images. The multi-threshold Otsu is expressed as follows.

$$\text{Fitness}\ (\sigma^2) = \sum_{k=1}^{j} \omega_k (\mu_k - \mu_t)^2 \tag{21}$$

The specific steps of the method of the optimal segmentation threshold are as follows:

Step1: Initialized parameters of the PSGA: total number of particles N; learning factors $c1$, $c2$; inertia weight ω; reverse probability p_0; maximum number of iterations Maxgen, and random generate the initial positions of all particles.
Step2: If $\text{rand}(0, 1) < p_0$, go to Step3, otherwise go to Step4.
Step3: Calculate the reverse species according to Eq. (15), and calculate the fitness value of the particles between the current population and the reverse population. Select N optimal particles to form a new population; transfer to Step5.
Step4: Calculate the fitness value of the current population, according to Eq. (21)
Step5: Update the best particle in the whole according to the fitness value; mutate it according to Formula (18); compare its fitness value with the mutated particle; take the larger fitness value particle as the new particle GO particle.

Step6: If the current number of iterations exceeds the maximum number of iterations, stop iteration and output the GO particle position as the IS threshold; otherwise, update the speed and position of the population particles according to Eqs. (13) and (4), and transfer to step2.

4 Experimental Results and Analysis

The proposed approach based on minimum cross-entropy as a fitness function optimizes the multilevel thresholding segmentation of color images. Six color images are chosen to test the efficiency of the proposed scheme for segmentation of multilevel thresholds [6] [7]. Threshold values for the three (RGB) channels are (2, 5, 8). Figure 2 lists the selected image color with different bands (RGB) for each color image with it being a multidimensional, multimodal model.

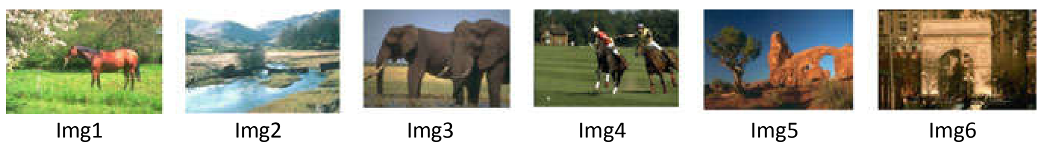
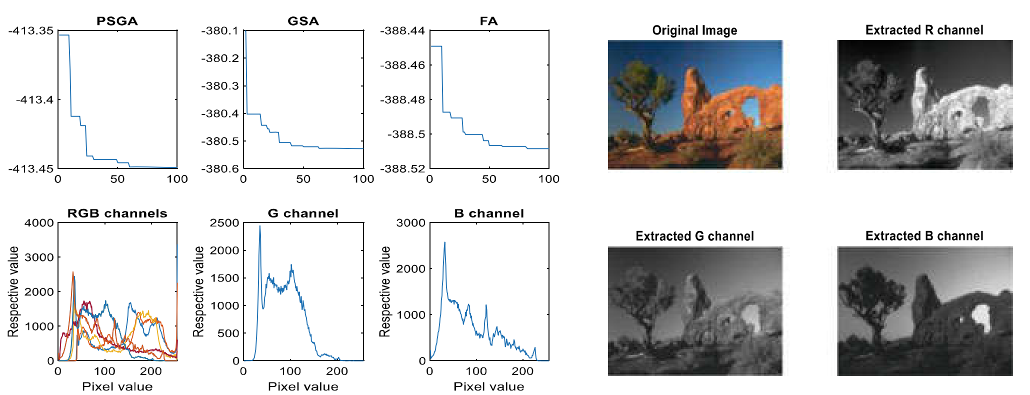


Fig. 2. The selected image color with a multidimensional and multimodal model

The obtained results of the proposed PSGA method for image feature extraction are compared with the gravity search algorithm (GSA) [6], and the firefly algorithm (FA) [7] methods, respectively. The parameter setting for algorithms is listed as follows. $c_1 = 0.5$, $c_2 = 1.5$, inertia weight $\omega = 1.2$, particle velocity $V \in [-5, 5]$; the number of particles/fireflies of the three algorithms is set to $N = 50$, and the maximum number of iterations is Maxgen $= 100$. In FA, the initial $\beta_0 = 1$, and the step factor $\alpha = 0.5$. m is the number of thresholds (m 03, 5, 8) (Fig. 3).



a) Comparison convergence of the PSGA scheme with the GSA and FA methods

b) Visually obtained three channels (RGB) for image 01.

Fig. 3. Comparison convergence of the proposed scheme of PSGA with the GSA and FA methods and the visually extracted three channels (RGB) for image 5 with thresholds set to 5

A metric of the signal-to-noise ratio (PSNR), the calculation time, and the standard deviation σ of the Otsu function value obtained from 30 consecutive runs are used to evaluate the segmentation performance and stability of the algorithms. The signal-to-noise ratio is calculated as $\mathrm{PSNR(dB)} = 20\lg\left(\frac{255}{\mathrm{RMSE}}\right)$, where $\mathrm{RMSE} = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=1}^{N}\left[I(i,j) - \tilde{I}(i,j)\right]^2}$, I and $\tilde{I}$ is the original image and the divided image with size $M \times N$. The standard deviation of the value of the Otsu function is calculated as $\sigma = \sqrt{\frac{1}{k-1}\sum_{i=1}^{k}\left(f_i - \overline{\overline{f}}\right)^2}$ the best one in comparison algorithms, where $k = 30$ is the number of continuous operations, and f_i and $\overline{\overline{f}}$ respectively represent the $i-$th Otsu function value and k is average value of the Otsu function after two consecutive runs. Figure 2 show the comparison convergence of the proposed scheme of PSGA with the GSA and FA methods and the visually extracted three channels (RGB) for image 5 with thresholds set to 5.

Table 1 shows the comparison of the obtained results of the optimization of the proposed PSGA with the PSO and FA methods for multilevel IS based on a metric of the PSNR and Otsu values. The best values are highlighted in Table 1. From the data values, we can see that the number highlight of the achieve identical segmented effects in six color images belongs to the proposed scheme.

5 Conclusions

In this paper, we proposed a solution to multi-threshold IS by adjusting one of the latest hybrid swarm computation algorithms, particle swarms, and gravitational search (PSGA). Combining the global search ability of particle swarm and the local mining ability of gravity search has been implemented to avoid the problem of weak local searchability in the single optimization algorithms. The experimental results are comparable with other state-of-the-art algorithms, e.g., gravity search algorithm (GSA) and the firefly algorithm (FA) schemes. Compared results show that the PSGA on selected images are better than the competitors.

Table 1. Compare the proposed scheme optimization obtained results with PSO and FA schemes for multilevel IS based on a metric of the PSNR and Otsu values

Images		PSGA	PSO	FA	PSGA	PSO	FA	Images		PSGA	PSO	FA	PSGA	PSO	FA
		–PSNR–			*–Otsu value–*					*–PSNR–*			*–Otsu value–*		
Img 1	3	**27.6274**	27.1679	27.1017	1.951	1.951	1.951	Img 4	3	29.0437	29.0453	**28.9791**	1.748	1.747	1.748
	5	**30.7858**	30.6051	30.5365	2.118	2.110	2.118		5	32.2280	31.9321	32.0852	1.817	1.802	1.816
	8	32.3599	**32.8774**	32.9917	2.181	2.158	2.181		8	**34.8932**	34.7236	34.6497	1.860	1.857	1.860
Img 2	3	**28.9463**	28.9479	28.8817	2.206	2.165	2.205	Img 5	3	**29.5754**	29.5889	29.5227	2.176	2.176	2.186
	5	**32.0381**	32.3785	32.1840	2.059	2.059	2.059		5	32.5991	**32.1922**	32.3998	2.283	2.283	2.273
	8	35.4308	**34.6370**	34.0295	2.210	2.209	2.210		8	34.5938	34.8060	**34.9665**	2.328	2.324	2.344
Img 3	3	28.3154	28.3170	**28.3508**	2.285	2.279	2.285	Img 6	3	**27.4589**	27.4486	27.3789	3.350	2.339	2.349
	5	**31.7368**	31.6987	31.5815	2.321	2.306	2.318		5	**30.4249**	30.5891	30.5811	3.283	2.283	2.286
	8	**33.7523**	34.0358	34.2557	1.616	1.616	1.616		8	33.2312	**33.0941**	32.7881	2.328	2.324	2.324

Bold indicates the best one in comparison algorithms

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