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SAR Image Segmentation Based On Hybrid PSOGSA Optimization Algorithm

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ABSTRACT
Image segmentation is useful in many applications. It can identify the regions of interest in a scene or annotate the data. It categorizes the existing segmentation algorithm into region-based segmentation, data clustering, and edge-base segmentation. Region-based segmentation includes the seeded and unseeded region growing algorithms, the JSEG, and the fast scanning algorithm. Due to the presence of speckle noise, segmentation of Synthetic Aperture Radar (SAR) images is still a challenging problem. We proposed a fast SAR image segmentation method based on Particle Swarm Optimization-Gravitational Search Algorithm (PSO-GSA). In this method, threshold estimation is regarded as a search procedure that examinations for an appropriate value in a continuous grayscale interval. Hence, PSO-GSA algorithm is familiarized to search for the optimal threshold. Experimental results indicate that our method is superior to GA based, AFS based and ABC based methods in terms of segmentation accuracy, segmentation time, and Thresholding.

I. INTRODUCTION

An *image* is an artifact that depicts visual perception similar in appearance to some physical object or a person. Images may be two-dimensional (2D), such as screen display, a photograph, etc., or three-dimensional (3D), such as a hologram or a statue. A *digital image* is a numeric representation of a two-dimensional image. An image can be defined as a two-dimensional function $f(x, y)$, where x and y are three-dimensional coordinates, and the amplitude off at any pair of coordinates(x, y) is called the intensity of the digital image at that point.

Image processing is a method of converting an image into *digital* form and performs some operations on it, to get an enhanced image or to extract some useful information from it. It is a form of signal processing in which the input is an image, like photograph frame, and the output may be either an image or a set of characteristics or parameters associated with the image.

Segmentation is a process that divides an image into its basic parts or objects. In general, independent segmentation is one of the toughest tasks in digital image processing. Image segmentation is useful in many applications. It can identify the regions of interest in a scene or annotate the data. It categorizes the existing segmentation algorithm into region-based segmentation, data clustering, and edge-base segmentation. Region-based segmentation includes the seeded and unseeded region growing algorithms, the JSEG, and the fast scanning algorithm.

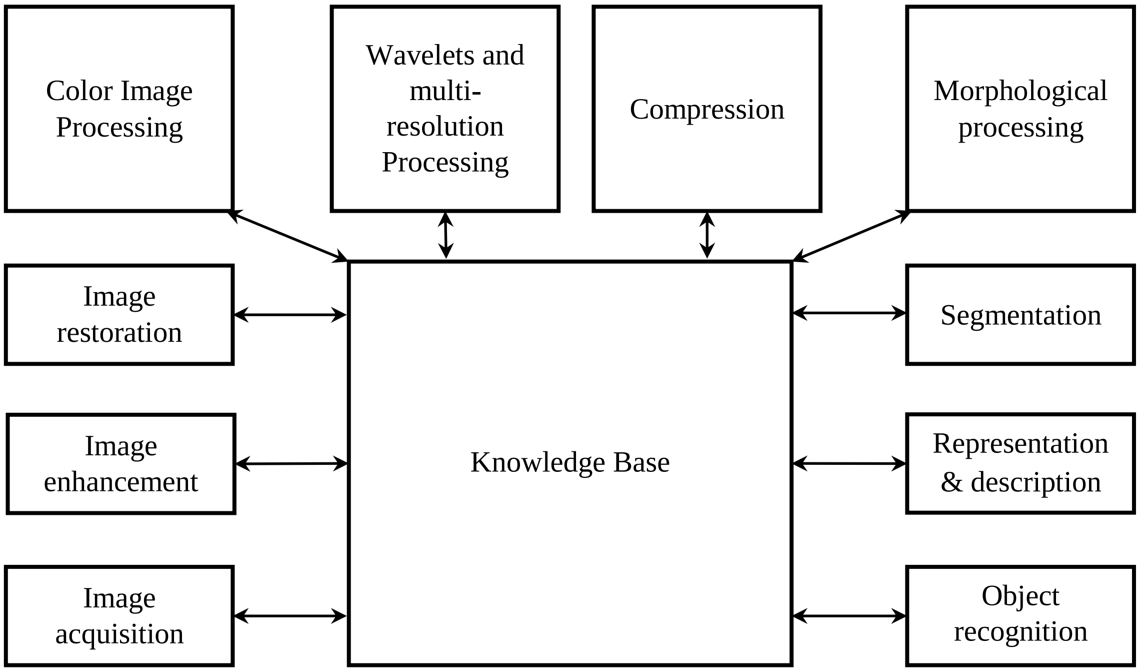

Figure 1: Fundamental steps in digital image processing.

Particle Swarm Optimization (PSO)

Particle Swarm Optimization (PSO) is one of the more recently developed evolutionary techniques, and it is based on a suitable model of social interaction between independent agents (particles) and it uses social knowledge in order to find the global maximum or minimum of a generic function. In the PSO the so called swarm intelligence (i.e. the experience accumulated during the evolution) is used to search the parameter space by controlling the trajectories of a set of particles according to a swarm-like set of rules. The position of each particle is used to compute the value of the function to be optimized. Particles are moved in the domain of the problem with variable speeds and every position they reach represents a particular configuration of the variables set, which is then evaluated in order to get a score [19].

Gravitational Search Algorithm (GSA)

In this section, we introduce our optimization algorithm based on the law of gravity [19]. In the proposed algorithm, agents are considered as objects and their performance is measured by their masses. All these objects attract each other by the gravity force, and this force causes a global movement of all objects towards the objects with heavier masses. Hence, masses cooperate using a direct form of communication, through gravitational force. The heavy masses which correspond to good solutions – move more slowly than lighter ones, this guarantees the exploitation step of the algorithm.

In GSA, each mass (agent) has four specifications: position, inertial mass, active gravitational mass, and passive gravitational mass. The position of the mass corresponds to a solution of the problem, and its gravitational and inertial masses are determined using a fitness function. In other words, each mass presents a solution, and the algorithm is navigated by properly adjusting the gravitational and inertia masses.

SAR Images

Ecological monitoring, earth-resource mapping, and military schemes require broad-area imaging at high resolutions. Many times the imagery must be developed in inclement weather or during night as well as day. Synthetic Aperture Radar (SAR) delivers such a capability. SAR systems take benefit of the long-range propagation characteristics of radar signals and the complex material processing capability of modern digital electronics to provide high resolution imagery. Synthetic aperture radar complements photographic and other optical imaging competences because of the minimum constraints on time-of-day and atmospheric circumstances and because of the unique responses of terrain and cultural targets to radar frequencies [20]. Synthetic aperture radar skill has provided terrain structural information to geologists for mineral examination, oil spill boundaries on water to environmentalists, sea state and ice hazard maps to navigators, and reconnaissance and targeting info to military processes.

II. LITERATURE SURVEY:

S. C. Zhu et al (1996), [12] presented a novel statistical and variational approach to image segmentation based on a new algorithm named region competition. This algorithm was derived by minimizing a generalized Bayes/MDL criterion using the variational principle. They provided theoretical analysis of region competition including accuracy of boundary location, criteria for initial conditions, and the relationship to edge detection using filters.

A. Tsai et al (2001), [15] presented first address the problem of simultaneous image segmentation and smoothing by approaching the Mumford–Shah paradigm from a curve evolution perspective. Various implementations of this algorithm are introduced to increase its speed of convergence. This more general model leads us to a novel PDE-based approach for simultaneous image magnification, segmentation, and smoothing, thereby extending the traditional applications of the Mumford–Shah functional which only considers simultaneous segmentation and smoothing.

W. Tao et al (2007), [18] developed a novel approach that provides effective and robust segmentation of color images. By incorporating the advantages of the mean shift (MS) segmentation and the normalized cut (Ncut) partitioning methods, the proposed method requires low computational complexity and is therefore very feasible for real-time image segmentation processing. Because the number of the segmented regions is much smaller than that of the image pixels, the proposed method allows a low-dimensional image clustering with significant reduction of the complexity compared to conventional graph-partitioning methods that are directly applied to the image pixels. The superiority of that method was examined and demonstrated through a large number of experiments using color natural scene images.

S. Mirjalili et al (2010), [19] proposed a hybrid population-based algorithm (PSOGSA) is with the combination of Particle Swarm Optimization (PSO) and Gravitational Search Algorithm (GSA). The main idea is to integrate the ability of exploitation in PSO with the ability of exploration in GSA to synthesize both algorithms strength. The results show the hybrid algorithm possesses a better capability to escape from local optimums with faster convergence than the standard PSO and GSA.

M. Miao et.al. (2011), [20] proposed a fast SAR image segmentation method based on Artificial Bee Colony (ABC) algorithm using threshold estimation as a search procedure that searches for an appropriate value in a continuous grayscale interval.ABC algorithm is used to search for the optimal threshold. Experimental results indicate that the proposed method is superior to Genetic Algorithm (GA) based and Artificial Fish Swarm (AFS) based segmentation methods in terms of segmentation accuracy and segmentation time.

C. Liu et al(2013), [22] presented a novel variational framework for multiphase synthetic aperture radar (SAR)image segmentation based on the fuzzy region competition method. A new energy functional is proposed to integrate the Gamma model and the edge detector based on the ratio of exponentially weighted averages (ROEWA) operator within the optimization process.

III. PROPOSED WORK

In the proposed work, Segmentation subdivides an image into its constituent regions or objects. The level to which the subdivision is carried depends on the problem being solved. That is, segmentation should stop when the objects of interest in an application have been isolated. To compare the efficiency of our method with others, segmentation methods based on PSO-GSA algorithm are used to segment some typical images, covering a noise-free optical image, an optical image polluted by synthetic noise (composed of Gaussian noise with mean 0 and variance 0.01, speckle noise with variance 0.005, and salt and pepper noise with density 0.02), and a real SAR image.

In this experiment, for PSO-GSA algorithm, the population size is 10, the fixed maximum number of iterations is 10, and the limit times for abandonment is 10, the lower and upper bounds are 0 and 255 respectively, because in grey scale each pixel value is between 0 to 255, there are 265 levels in grey scale images so we take the bounds between 0 to 255

PSO Algorithm

[Step 1] Initialization.

Initialize positions and associate velocity to all particles (potential solutions) in the population randomly in the D-dimension space.

[Step 2] Evolution:

Evaluate the fitness value of all particles.

[Step 3] Compute the personal best:

Compare the personal best (p_{best}) of every particle with its current fitness value. If the current fitness value is better, then assign the current fitness value to p_{best} and assign the current coordinates to p_{best} coordinates.

[Step 4] Determine the current best fitness value:

Determine the current best fitness value in the whole population and its coordinates. If the current best fitness value is better than global best (g_{best}), then assign the current best fitness value to g_{best} and assign the current coordinates to g_{best} coordinates.

[Step 5] Calculate accelerations of the agents:

Update velocity (V_{id}^t) and position (X_{id}^t) of the d-th dimension of the *i*-th particle using the following equations:

$$V_{id}^t = \omega(t) * V_{id}^{t-1} + c_1(t) \times rand1_{id}^t \times (pbest_{id}^{t-1} - X_{id}^{t-1} + c_2(t)$$

$$\times (1 - rand1_{id}^t) \times (gbest_d^{t-1} - X_{id}^{t-1})$$

$$V_{id}^t > V_{max}^d \, or V_{id}^t < V_{min}^d, then V_{id}^t = U(V_{min}^d, U_{max}^d)$$

$$X_{id}^t = rand2_{id}^t \times X_{id}^{t-1} + (1 - rand2_{id}^t) \times V_{id}^t$$

$c_1(t)$, $c_2(t)$ = time-varying acceleration coefficients with $c_1(t)$ decreasing linearly from 2.5 to 0.5 and $c_2(t)$ increasing linearly from 0.5 to 2.5 over the full range of the search, and w(t) = time-varying inertia weight changing randomly between U(0:4 ; 0:9) with iterations, $rand1$, $rand2$, are uniform random numbers between 0 and 1, having different values in different dimension, t is the current generation number.

The above equation has been introduced to clamp the velocity along each dimension to uniformly distributed random value between V_{min}^d and V_{max}^d if they try to cross the desired domain of interest. These clipping techniques are sometimes necessary to prevent particles from explosion. The maximum velocity is set to the upper limit of the dynamic range of the search ($V_{max}^d = X_{max}^d$) and the minimum velocity (V_{min}^d) is set to (X_{min}^d).

However, position-clipping technique is avoided in modified PSO algorithm. Moreover, the fitness function evaluations of errant particles (positions outside the domain of interest) are skipped to improve the speed of the algorithm.

[Step 6] Repeat from Steps 2 to 5 until iterations reaches their maximum limit:

Repeat Steps 2 to 5 until a stop criterion is satisfied or a pre-specified number of iteration is completed, usually when there is no further update of best fitness value.

GSA Algorithm

[Step 1] Initialize of the agents.

Initialize the positions of the N number of agents randomly within the given search interval as below:

$$X_i = x_i^1, \ldots\ldots x_i^d, \ldots\ldots x_i^n \; for \; i = 1,2, \ldots\ldots, N$$

Where, x_i^d represents the positions of the *i*-th agent in the d-th dimension and N is the space dimension.

[Step 2] Fitness evolution and best fitness computation for each agents:

Perform the fitness evolution for all agents at each iteration and also compute the best and worst fitness at each iteration defined as below (for minimization problems):

$$best(t) = \min_{j\epsilon\{1,\ldots,N\}} fit_j(t)$$

$$worst(t) = \max_{j\epsilon\{1,\ldots,N\}} fit_j(t)$$

Where, $fit_j(t)$ represents the fitness of the j-th agent at $iteration\ t, best(t)\ and\ worst(t)$ represents the best and worst fitness at generation t.

[Step 3] Compute gravitational constant G:

Compute gravitational constant G at iteration t using the following equation:

$$G(t) = G_o^{(-\alpha t/T)}$$

In this problem, G_0 is set to 100, α is set to 20 and T is the total number of iterations.

[Step 4] Calculate the mass of the agents:

Calculate gravitational and inertia masses for each agents at iteration t by the following equations:

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

$$m_i(t) = \frac{fit_i(t) - worst_i(t)}{best(t) - worst(t)}$$

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

Where, M_{ai} is the active gravitational mass of the *i*-th agent, M_{pi} is the passive gravitational mass of the *i*-th agent, M_{ii} is the inertia mass of the *i*-th agent.

[Step 5] Calculate accelerations of the agents:

Compute the acceleration of the *i*-th agents at iteration t as below:

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)}$$

Where, $F_i^d(t)$ is the total force acting on *i*-th agent calculated as,

$$F_i^d(t) = \sum_{j\epsilon Kbest\ ,j\neq i} rand_j F_{ij}^d(t)$$

K_{best} is the set of first K agents with the best fitness value and biggest mass. K_{best} is computed in such a manner that it decreases linearly with time and at last iteration the value of K_{best} becomes 2% of the initial number of agents. $F_{ij}^d(t)$ is the force acting on agent '*i*' from agent '*j*' at *d*-th dimension and t-th iteration is computed as below:

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

Where, $R_{ij}(t)$ is the Euclidian distance between two agents '*i*' and '*j*' at iteration t and $G(t)$ is the computed gravitational constant at the same iteration. ε is a small constant

[Step 6] Update velocity and positions of the agents:

Compute velocity and the position of the agents at next iteration (t + 1) using the following equations:

$$v_i^d(t+1) = rand_i \times v_i^d(t) + a_i^d(t)$$
$$x_i^d(t) = x_i^d(t) + v_i^d(t+1)$$

[Step 7] Repeat from Steps 2 to 6 until iterations reaches their maximum limit.

Return the best fitness computed at final iteration as a global fitness of the problem and the positions of the corresponding agent at specified dimensions as the global solution of that problem.

IV. SIMULATION RESULTS

Figure 2: Original Image

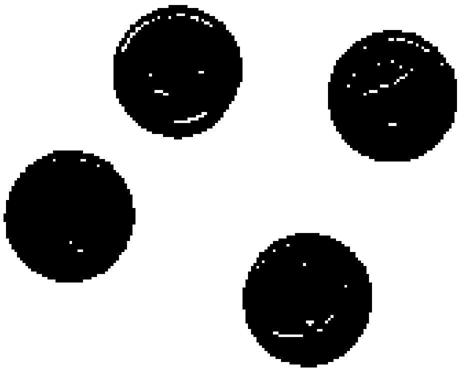

Figure 3 : Segmented Image

We take a general purpose image shown in figure 2 for comparison to base paper images and calculate the threshold value (167), Time (0.119), and fitness of an image, and compare the results with the previous work taken in the Table below show the comparison of ant colony, Genetic, Artificial Fish Swarm algorithms. Image Fitness is 1.0×10^3 *2.5775.

Table 1: Comparison over different Algorithms using image (figure 2)

Algorithms	Fitness Function	Threshold	Time (s)
PSO-GSA	Variance Grey entropy	167	0.119
ACS	Improved two-dimensional grey entropy	205	5.821
GA	Two-dimensional entropy	207	14.391
GA	Two-dimensional grey entropy	206	17.640
AFS	Two-dimensional entropy	187	12.015

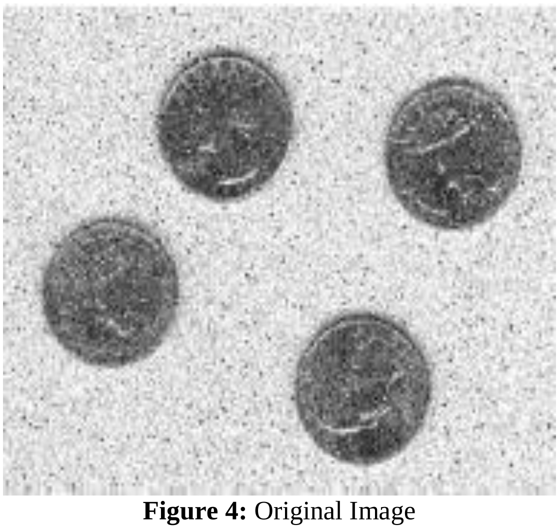

Figure 4: Original Image

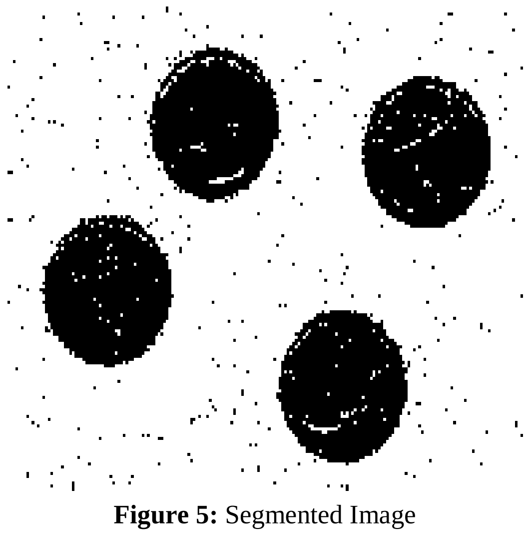

Figure 5: Segmented Image

We take a general purpose image shown in figure 4 for comparison to base paper images and calculate the threshold value (165), Time (0.123), and fitness of an image, and compare the results with the previous work taken in the Table below show the comparison of ant colony, Genetic, Artificial Fish Swarm algorithms. Image Fitness is 1.0×10^{03} *2.4103.

Table 2: Comparison over different Algorithms using image (figure 4)

Algorithms	**Fitness Function**	**Threshold**	**Time (s)**
PSO-GSA	Variance Grey entropy	165	0.123
ACS	Improved two-dimensional grey entropy	204	6.669
GA	Two-dimensional entropy	163	15.358
GA	Two-dimensional grey entropy	207	19.152
AFS	Two-dimensional entropy	162	12.546

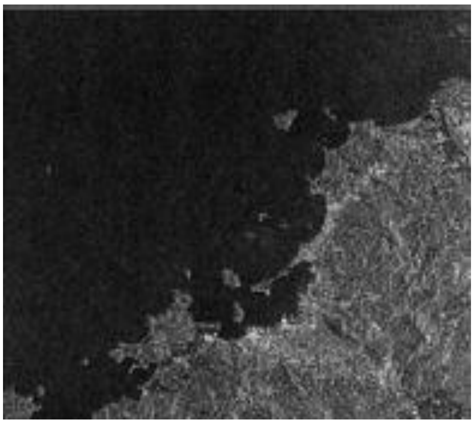

Figure 6: Original Image# Case 3

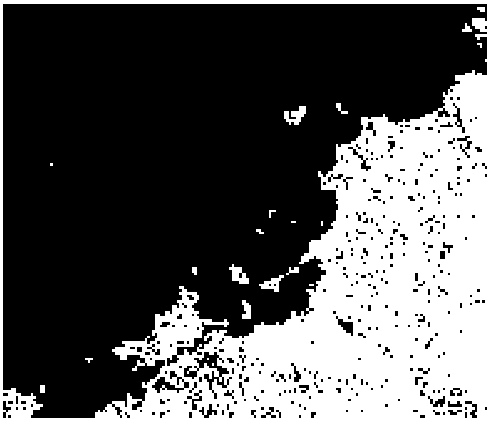

Figure 7: Segmented Image# Case 3

We take an SAR image 5.4 and calculate the threshold value (61), Time (0.115), and fitness of an image, and compare the results with the previous work taken in the Table below show the comparison of ant colony, Genetic, Artificial Fish Swarm algorithms. Image Fitness is 883.960.

Table 3: Comparison over different Algorithms using image (figure 6)

Algorithms	**Fitness Function**	**Threshold**	**Time (s)**
PSO-GSA	Variance Grey entropy	61	0.115
ACS	Improved two-dimensional grey entropy	95	4.835
GA	Two-dimensional entropy	131	13.460
GA	Two-dimensional grey entropy	94	17.740
AFS	Two-dimensional entropy	62	6.441

V. CONCLUSION

We proposed a fast segmentation method on SAR images. The technique regards threshold estimation as a search process and employs PSO-GSA algorithm to optimize it. In order to provide PSO-GSA algorithm with an efficient fitness function, we integrate the concept of grey number in Grey theory, maximum conditional entropy to get improved two-dimensional grey entropy. In essence, the fast segmentation speed of our method owes to PSO-GSA algorithm, which has an outstanding convergence performance. On the other hand, the segmentation quality of our method is benefit from the improved two-dimensional grey entropy, for the fact that noise almost completely disappears. Experimental results indicate that our method is superior to GA based, AFS based and ABC based methods in terms of segmentation accuracy, segmentation time, and Thresholding.

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