IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

Radar Image Segmentation using Particle Swarm and Gravitational Search

Rubbaldeep Kaur
Student, Computer Engineering, PIET Patiala
rubbaldeepkaur@gmail.com

Er. Pooja
Assistant Professor, Computer Engineering, PIET Patiala
rubbalkhaira91@gmail.com

Abstract: **Image segmentation can recognizes the areas of interest in a scene. Due to the presence of speckle noise, segmentation of Synthetic Aperture Radar (SAR) images is still a challenging problem. In this research paper we presented a radar image segmentation using modified particle swarm and gravitational search algorithm (PSO-GSA). In this method, threshold assessment is observed as an exploration process that examines for a suitable value in a continuous grayscale interval. Hence, proposed modified PSO-GSA algorithm is familiar to explore the optimal threshold. In order to provide an efficient fitness function with our proposed modified PSO-GSA algorithm, we assimilate the concept of grey number in Grey theory, maximum provisional entropy to get an enhanced two-dimensional grey entropy. In core, the segmentation speed of our proposed method owes to PSO-GSA algorithm, which has an owing convergence performance. Moreover, the segmentation quality of our proposed method is benefitted from the enhanced two-dimensional grey entropy, which results in mitigation of noise. Experimental results indicate that our method is superior to conventional PSO-GSA, GA based, AFS based and ABC based methods in terms of segmentation time and thresholding.**

Keywords: **Digital image processing, Image Segmentation, SAR images, PSO-GSA, Radar Images, Particle swarm and gravitational search.**

I. INTRODUCTION

Segmentation means dividing an image into its elementary regions or objects. Generally, toughest tasks in digital image processing is independent segmentation. A rugged segmentation process brings the process a long way to effective solution of imaging difficulties that require objects to be documented independently. In general, the more correct the segmentation, the extra likely acknowledgment is to succeed.

The objective of segmentation is to partition an image into regions, In region based segmentation we achieve segmentation by finding boundaries between regions based on discontinuities in gray levels, segmentation was accomplished via thresholds based on the distribution of pixel properties, such as gray-level values or color.

A greyscale image is turned into a binary (black and white) image by first choosing a grey level T in the original image, and then turning every pixel black or white according to whether it's grey [1]

Value is greater than or less than T.

$$\text{A pixel becomes} \begin{cases} \text{White if its grey level is} > T \\ \text{Black if its grey level is} \leq T \end{cases}$$

Thresholding is a vital part of image segmentation, where we wish to isolate objects from the background. It is also an important component of robot vision. The resulting image can then be further processed to find the number, or average size of the grains.

To see how this works, recall that in MATLAB, an operation on a single number, when applied to a matrix, is interpreted as being applied simultaneously to all elements of the matrix. The command $X > T$ Will thus return 1 (for true) for all those pixels for which the grey values are greater than T, and 0 (for false) for all those pixels for which the grey values are less than or equal to T. We thus end up with a matrix of 0's and 1's, which can be viewed as a binary image [2]. Where level is a value between 0 and 1 (inclusive), indicating the fraction of grey values to be turned white. The function automatically scales the value level to a grey value appropriate to the image type, and then performs a thresholding by first method. As well as isolating objects from the background, thresholding provides a very simple way of showing hidden aspects of an image [3].

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

II. Proposed PSOGSA Algorithm

PSOGSA is basically to conglomerate the capability of PSO of social thinking ($gbest$) with the ability of local searching in GSA. So as to conglomerate these algorithms (1), method is proposed as follow:

$$V_i(t+1) = w \times V_i(t) + c_1' \times rand \times ac_i(t) + c_2' \times rand \times (gbest - X_i(t)) \tag{1}$$

Where $V_i(t)$ is the velocity at iteration t of agent i, weighting factor is c_j', weighting function is denoted by w, $rand$ representing random number between 0 and 1, $ac_i(t)$ represents agent i acceleration at iteration t, and $gbest$ denotes best solution so far. The positions of particles are updated in each iteration by:

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

[Step 1] Initialization.

Initializing all agents randomly. Each agent is deliberated as a candidate solution. After initializing all agents, calculate resultant forces, gravitational constant, and Gravitational force among agents by using below equations.

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

(3)

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

(4)

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

(5)

[Step 2] Updating acceleration

After it, acceleration of particles is defined by (6).The best solution for each iteration should be updated.

$$a_i^d(t) = \frac{F_i^d(t)}{M_{ii}(t)} \tag{6}$$

[Step 3] Calculating acceleration & velocity

Hence by calculating the accelerations and updated best solution, velocities of all agents can be evaluated by using (1).

[Step 4] Updating Positions:

Thereby finally, the positions of all agents are defined as (2). The procedure of updating velocities and positions stops when meets an end criterion as shown in Fig.1.

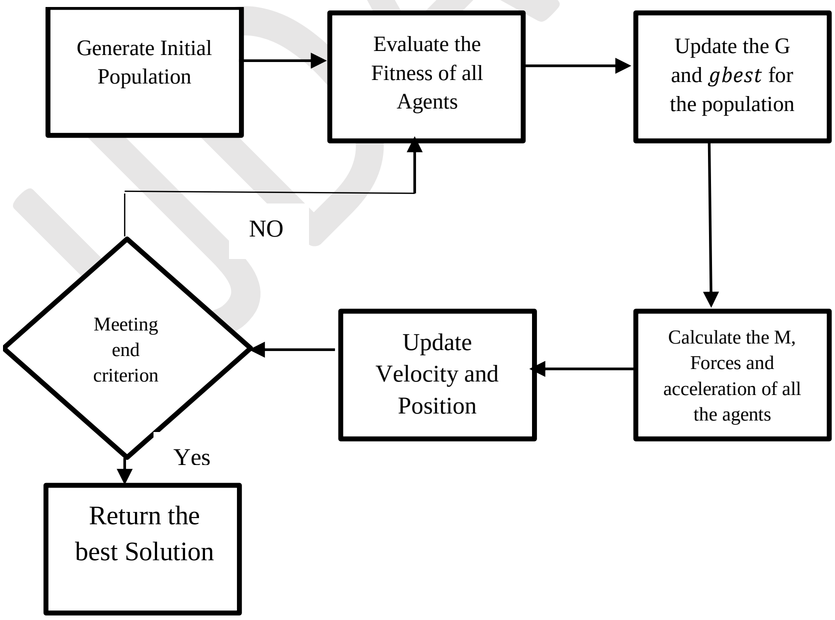

Figure 1: Steps for Modified PSO-GSA

To see how PSOGSA is proficient some observations are noted as follow. In PSOGSA, the quality of solutions i.e. fitness is measured in the updating process. The agents close to good solutions try to fascinate the other agents, exploring the search space. When all agents are close to a good solution, they move gradually slow. $gBest$ helps them to achieve the global best. PSOGSA uses memory to store the best solution

IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

$gBest$ found so far, hence it is available anytime. Each agent can perceive the best solution so far and thereby ends toward it. With amending c_1' and c_2', the capabilities of universal search and local search can be balanced.

In our study, all images are grayscale images. To compare the proficiency of our method with others, segmentation approaches based on PSO-GSA algorithm are used to segment some distinctive images, casing a noise-free optical image, an optical image contaminated by synthetic noise i.e. possessing speckle noise with variance 0.005 noise with density 0.02, and a real SAR image. In this research, for PSO-GSA algorithm, maximum number of iterations is 10, the population size is 10, and the bounded times for abandonment is 10, the lower and upper constraints are 0 and 255 respectively as in grey scale each pixel value is in between 0 to 255.

III. RESULTS

- **# Case 1**

Figure 2: Original Image # Case 1

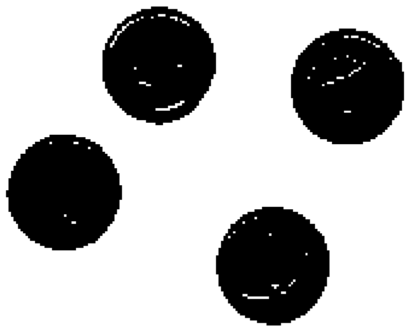

Figure 3: Segmented Image # Case 1

In Order to compare with base paper we take a general purpose image as shown in Figure 2 and evaluate the threshold value (167), Time (0.10), fitness of an image, and by comparing the results with the preceding work taken in the Table below shows the comparison of Genetic, ant colony, Artificial Fish Swarm algorithms and base paper [4]. Fitness of an image is $1.0 \times 10^{3} * 2.5775$.

Table 1: Comparison over different Algorithms using 4.1 image.

Algorithms	Fitness Function	Threshold	Time (s)
Proposed	Variance Grey entropy	167	***0.10***
PSOGSA [4]	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

- **# Case 2**

In Order to compare with base paper we take a general purpose image as shown in Figure 4 and evaluate the threshold value (165), Time (0.112), fitness of an image, and by comparing the results with the preceding work taken in the Table below shows the comparison of Genetic, ant colony, Artificial Fish Swarm algorithms and base paper [4]. Fitness of an image is $1.0 \times 10^{03} * 2.4103$.

IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

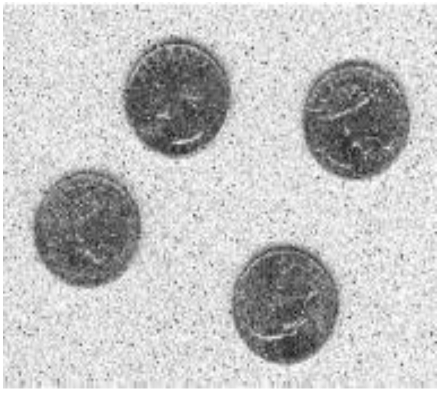

Figure 4: Original Image # Case 2

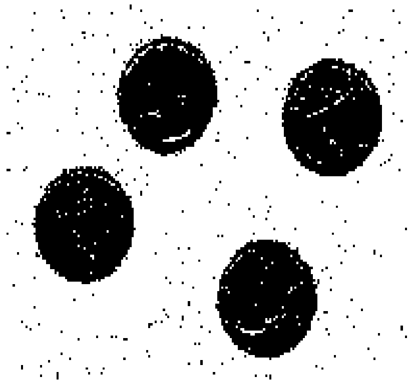

Figure 5: Segmented Image # Case 2

Table 2: Comparison over different Algorithms using Fig.4 image.

Algorithms	Fitness Function	Threshold	Time (s)
Proposed	Variance Grey entropy	165	***0.112***
PSOGSA [4]	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

- **# Case 3**

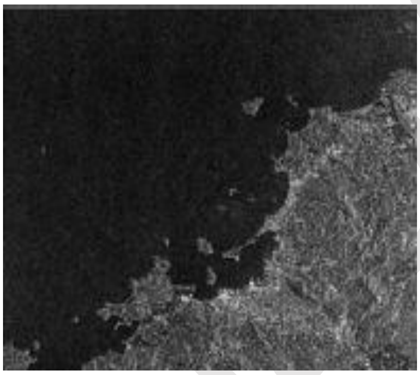

Figure 6: Original Image # Case 3

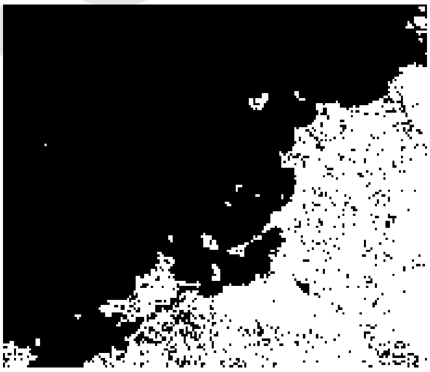

Figure 7: Segmented Image # Case 3

In Order to compare with base paper [4] we take an SAR image Fig.6 and evaluate the threshold value (61), Time (0.101), and an image fitness, and by comparing the results with the preceding work taken in the Table below of Genetic, ant colony, Artificial Fish Swarm algorithms and base paper [4] Fitness of an image is 883.960.

Table 3: Comparison over different Algorithms using Fig.6image.

Algorithms	Fitness Function	Threshold	Time (s)
Proposed	Variance Grey entropy	61	***0.101***
PSOGSA [4]	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

IJDACR
ISSN: 2319-4863

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

- **# Case 4**

In Order to compare with base paper [4] we take an SAR image Fig.8 and evaluate the threshold value (79), Time (0.171), and an image fitness 1.4368×10^3.

Figure 8: Original Image # Case 4

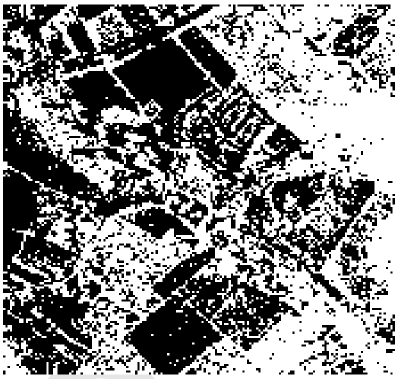

Figure 9: Segmented Image # Case 4

Table 4: Comparison over different Algorithms using Fig.8 image.

Algorithms	Fitness Function	Threshold	Time (s)
Proposed	Variance Grey entropy	79	***0.171***
PSOGSA [4]	Variance Grey entropy	79	0.184

- **# Case 5**

In Order to compare with base paper [4] we take an SAR image in Fig.10 and evaluate the threshold value (53), Time (0.111), and an image fitness 1.44×10^3.

Figure 10: Original Image # Case 5

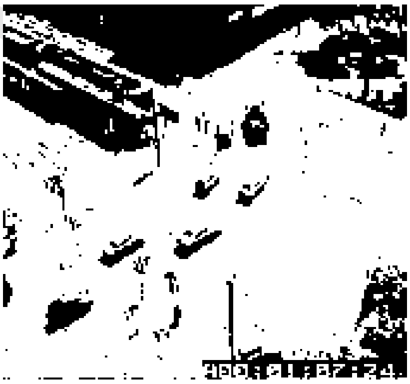

Figure 11: Segmented Image# Case 5

Table 5: Comparison over different Algorithms using Fig.10 image.

Algorithms	Fitness Function	Threshold	Time (s)
Proposed	Variance Grey entropy	53	***0.111***
PSOGSA [4]	Variance Grey entropy	53	0.127

Comparison of nature-inspired algorithms

The above experimental results indicate that our method outperforms the methods in [PSO-GSA, GA, ABS, and AFS]. To compare the convergence performance of modified PSO-GSA algorithm, PSO-GSA algorithm, GA, and AFS algorithm, this group of experiments run with the same settings, comprising the fitness functions (improved two-dimensional grey entropy), the maximal iterations (10), the population size (10) with the same initial population distribution, over the 10 runs. The traces of fitness and thresholds are given. Moreover, ABC algorithm converges very quickly, especially at initial part. Sometimes the threshold does not change for several iterations, but dramatically changes at some iterations.

IJDACR
ISSN: 2319-4863

IJDACR
International Journal Of Digital Application & Contemporary Research

International Journal of Digital Application & Contemporary Research
Website: www.ijdacr.com (Volume 4, Issue 2, September 2015)

Comparisons of segmentation time

Some experimental results are listed in Tables 1–5, in which the best results are in bold. The comparative results in Tables 1–5 indicate that our method is significantly faster than the other three methods. The segmenting time of the methods tested here is ordered as our method < the method in ACS < the method in AFS < the method in GA < the method in GA.

On the other hand, significantly our algorithm better than the thresholds of GA and AFS based methods. Particularly, Tables 1 and 2 and 3 and 4 and 5 show that our method is robust to noise pollution for the fact that the segmentation threshold (167) of the optical image polluted by synthetic noise is so close to the segmentation threshold (165) of the noise-free optical image and the segmentation threshold in third case is (61).

IV. Conclusion

We proposed a segmentation method on Radar images. The method esteems threshold assessment as a search procedure and employs modified PSO-GSA algorithm to improve it. So as to provide modified PSO-GSA algorithm with a proficient fitness function, we assimilate the idea of grey number in Grey theory, maximum provisional entropy to get an enriched two-dimensional grey entropy. Basically, the fast segmentation speed of our technique owes to PSO-GSA algorithm, which has an outstanding convergence performance. Conversely, the segmentation quality of our technique is advantage from the improved 2-D grey entropy, for the fact that noise nearly vanishes. Experimental results specifies that our technique is superior to PSO-GSA [4], ABC based and AFS based approaches in relations of segmentation time, Thresholding, and segmentation accuracy.

References

[1] L. Zhang and Q. Ji, “A Bayesian Network Model for Automatic and Interactive Image Segmentation,” *Image Processing, IEEE Transactions on,* vol. 20, no. 9, pp. 2582-2593, Sept 2011.

[2] J. Tang, “A color image segmentation algorithm based on region growing,” in *Computer Engineering and Technology (ICCET), 2010 2nd International Conference on*, 2010.

[3] S. Wang and J. Siskind, “Image segmentation with ratio cut,” *Pattern Analysis and Machine Intelligence, IEEE Transactions on,* vol. 25, no. 6, pp. 675-690, June 2003.

[4] A. Kaur, C. Singh and A. S. Bhandari, “SAR Image Segmentation Based On Hybrid PSOGSA Optimization Algorithm,” *Int. Journal of Engineering Research and Applications,* vol. 4, no. 9, pp. 05-11, September 2014.

[5] R. Wilson and M. Spann, Image segmentation and uncertainty, John Wiley \& Sons, Inc., 1988.

[6] A. R. Weeks, Fundamentals of electronic image processing, SPIE Optical Engineering Press Bellingham, 1996.

[7] E. R. Dougherty, R. A. Lotufo and T. I. S. for Optical Engineering SPIE, Hands-on morphological image processing, vol. 71, SPIE press Bellingham, 2003.

[8] Y.-J. Zhang, Advances in image and video segmentation, IGI Global, 2006.

[9] W. Tao, H. Jin and Y. Zhang, "Color Image Segmentation Based on Mean Shift and Normalized Cuts," Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, vol. 37, no. 5, pp. 1382-1389, Oct 2007.

[10] Y.-C. Lin, Y.-P. Tsai, Y.-P. Hung and Z.-C. Shih, "Comparison between immersion-based and toboggan-based watershed image segmentation," Image Processing, IEEE Transactions on, vol. 15, no. 3, pp. 632-640, March 2006.

[11] O. Schwartz and E. P. Simoncelli, "Natural signal statistics and sensory gain control,” Nature," Neuroscience, vol. 4, pp. 819-825, 2001.

[12] M. Cadik and P. Slavik, "Evaluation of two principal approaches to objective image quality assessment," in Information Visualisation, 2004. IV 2004. Proceedings. Eighth International Conference on, 2004.

[13] J. Wang and M. Cohen, "An iterative optimization approach for unified image segmentation and matting," in Computer Vision, 2005. ICCV 2005. Tenth IEEE International Conference on, 2005.

[14] P. C. Teo and D. J. Heeger, "Perceptual image distortion," in in Proc. SPIE, 1994.