SAR Electromagnetic Image Conditioning Using a New Adaptive Particle Swarm Optimization

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Abstract ─ In Synthetic Aperture Radar (SAR) image Objects or region detection is a difficult task because of improper variation of boundary due to speckle noise. So, it creates the problems of human being for the analysis. In fact, this process leads to inaccurate in the detection and measurement of object parameters. In this paper proposes a new automatic detection of objects from SAR images. For detection of objects an effective method is introduced using the variance of Particle Swarm Optimization (PSO) called Adaptive PSO (APSO). In this paper develops the dynamically varying the inertia weight for PSO and tuning the social components, cognitive components. This APSO find the optimal threshold value for making the better segmentation by preprocessing SAR image with effective Filter. The proposed APSO method has also compared with existing methods in terms of detection of object regions and parameter calculations.

Index Terms ─ Preprocessing, SAR Image, segmentation, sensing system, swarm optimization, threshold.

I. INTRODUCTION

Synthetic Aperture Radar (SAR) image analysis makes the difficult for analysis for region extraction or identification because of in cleared visualization due to speckle noise. In general, the lakes at anywhere on the ground surface varies their dimensional nature from season to season. In order to analyze the boundary information and the size of the lakes in SAR image. It requires the proper segmentation methodology for extraction of the lake regions by preprocessing with an isotropic diffusion filter SRAD [1] instead of normal filters [2] which smooth's the image by reducing the speckle noise. The automatic detection and processing system are required to detect the objects and regions. This results basic pointer for diagnosis the object. From the literature study it is observed that only few authors are working on regions or objects in SAR image. Deng et al. invented watershed algorithm and region growing methods for segmentation [3]. Further, the contrast of the de-speckling image can be improved by histogram equalization and to enhance the segmentation process to work on high intensity objects. Objects can be extracted from active contour without edge method. In most cases it is verified that Otsu method is the best technique for image segmentation [4]. Another hybrid technique based on k-means particle swarm optimization introduce by Sepas-Moghaddam [5]. PSO has been used in many other applications which include image de-noising [6], [7], [8], Image analysis and wireless sensor networks. Ali Mohammad Nick Farjam et al. segmented the conical image using Otsu method by which the threshold was optimized by using PSO method. In multilevel thresholding the PSO technique reduces the complexity [9]. To grasp the color objects PSO has been applied to the color image. To remove the speckle various de-speckling filtering techniques are introduced [10], [11]. A novel FO-DPSO is introduced for the remote sensing image segmentation. Image registration, denoising and measuring features is done by various PSO techniques [12]. ShuoLiu, Ali Qusay Al-Faris et al. introduces the MRI image segmentation with Otsu combination with PSO. Effective automatic segmentation methods are suggested in SAR images.

This paper puts the order as follows. Section II describes the proposed modified Otsu method. Section III gives the overview of particle swarm optimization. Section IV gives the detail about the proposed APSO to obtain optimum threshold. The performance evaluation described in Section V and Section VI gives the conclusion of this paper.

II. BACK GROUND OF OTSU METHOD

The challenging task is to find the optimum threshold value for automatic detection of objects in an image sensing and recording system. Otsu method is one of the basic techniques to find the optimum threshold for an image [13]-[15]. In modified Otsu technique iterative method is the basis for finding the initial threshold value. The average threshold value for image histogram is taken at τ. δ_1 and δ_2 represents the mean of the intensity values which is greater than and less than the current threshold respectively.

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The calculated threshold is,

$$\tau[\mathrm{i}] = \frac{\delta_1{}^{(\mathrm{i})} + \delta_2{}^{(\mathrm{i})}}{2}. \tag{1}$$

This threshold value is forwarded to the next iteration. This iteration continuous up to the value where the threshold value converges to $\tau[i] - \tau[i-1]$. At the end of the iteration the new threshold value is calculated as:

$$\tau^{\mathrm{opt}} = \frac{\delta_1{}^{(\mathrm{i})} + \delta_2{}^{(\mathrm{i})}}{2}. \tag{2}$$

This calculated threshold value τ^{opt} is used as an initial threshold value for the conventional Otsu method. Based on this τ^{opt} value image divided in to two groups. The mean of the two groups is represented as:

$$m_{t1}(i) = \sum_{k=1}^{\tau^{opt}} \frac{dP(k)}{\rho_1(i)}, m_{t2}(i) = \sum_{k=\tau^{opt}+1}^{s} \frac{dP(k)}{\rho_2(i)}. \tag{3}$$

For whole image the mean is calculated as:

$$m_t = \sum_{k=1}^{s} dP(k). \tag{4}$$

Here, s represents the number of gray levels. The optimum threshold value is calculated as:

$$t^* = argmax[\rho_1(m_{t1} - m_t)^2 + \rho_2(m_{t2} - m_t)^2], \tag{5}$$

where ρ_1 and ρ_2 are the estimated group probabilities. These values are calculated using:

$$\rho_1 = \sum_{k=1}^{\tau^{opt}} p(k)\, , \rho_2 = \sum_{k=\tau^{opt}+1}^{s} \frac{dP(k)}{\rho_2(i)}, \tag{6}$$

The results of Otsu method and proposed Modified Otsu method are shown in Fig. 1 (c) and Fig. 3 (d). This segmentation is done on the image of preprocessing SAR input image by the SRAD filter shown in Fig. 1 (b). The segmented results of Conventional Otsu and Modified Otsu overlaid on the input SAR image are shown in Fig. 1 (e) and Fig. 1 (f).

The proposed Modified Otsu method is tested under 52 SAR images. From the experimental results it is observed that the proposed Modified Otsu method detects the better lake positions compared to Otsu method and it matches almost matches the segmented regions of human experts. In this paper introduced an idea to optimize the objective function that described by a modified Otsu method using PSO and the proposed APSO. The main problem is to find the optimum threshold for making the proper segmentation. The proposed approach is able to find the optimum set of thresholds with larger between class variance than the other techniques.

III. PARTICLE SWAM OPTIMIZATION FOR SAR IMAGE PROCESSING

It is based on the population based evolutionary technique proposed by Kennedy and Eberhart based on swarm intelligence [18] and other contributions [16], [17], [19] and [20]. For discrete solutions PSO is one of the solutions at the initial stage after it replicates the social behavior of fish and birds in a group for search food. The population of particles flies through the search space looking for an optimal value. Every particle in the search space having its own fitness value accessed by the object function. The population of random particles is initiated by PSO that is looking for a global optimum solution. All through the generations every particle is updated by particle best and global best values [23]-[25]. After getting these two values based on the distance from the best particle of the population and the distance from the own best position, the position and velocity of the particle are updated. By iteratively, it estimates the fitness value, the particle velocities and positions are deliberated by the following standard equations:

$$M_{k,n}{}^{i+1} = W_0 M_{k,n}{}^{i} + \Theta_1 rand_1\left(PBest_{k,n} - P_{k,n}^{i}\right) + \Theta_2 rand_2\left(GlBest_{k,n} - P_{k,n}^{i}\right), \tag{7}$$

$$P_{k,n}^{i+1} = P_{k,n}^{i} + M_{k,n}{}^{i+1}. \tag{8}$$

Here in the Eq. (7) $M_{k,n}{}^{i}$ is the momentum component, n represents the search space, i represents the iteration, $P_{k,n}^{i}$ represents the position of a particle, Θ_1 and Θ_2 are cognitive and social components taken as constant in standard PSO and W_0 is the initial weight. The $rand_1$ and $rand_2$ are the random values, not the same for all the iterations, but in the range of 0 and 1 only. $GlBest$ and $PBest$ are the globally best and particle best values. The effects of social, Inertia weight and cognitive components are obtained by PSO algorithm. The insertion of this inertia weight impacts the history of the velocities on the current history. This inertia weight can be a constant or time varying, where the large and small values have a capability to assist the global and local explorations. In this paper, the inertia weight with constant and dynamically varying values are applied to the SAR image. Initially the constant inertia weight (CIW) is taken as 0.8. In order to get the optimal solution better tuning is significant. For this Eberhart have proposed a new improved PSO concept by means of Dynamically Varying Inertia Weight (DVIW) which is given by:

$$W_0 = W_{max} - (W_{max} - W_{\mathrm{min.}}). Iter/Iter_{max}, \tag{9}$$

where W_{min} and W_{max} values are set at 0.2 and 0.1 respectively. $Iter_{max}$ and $Iter_{max}$ represents the maximum number of iterations and current iteration. The DVIW provides better weight in order to get the optimum solution.

IV. THE PROPOSED ADAPTIVE PARTICAL SWARM OPTIMIZATION

The main problem with this in this PSO process is the most suitable tuning of the social and cognitive components. In order to meet the global optimal solution here proposed a dynamically varying acceleration coefficient in PSO method [21], [22].

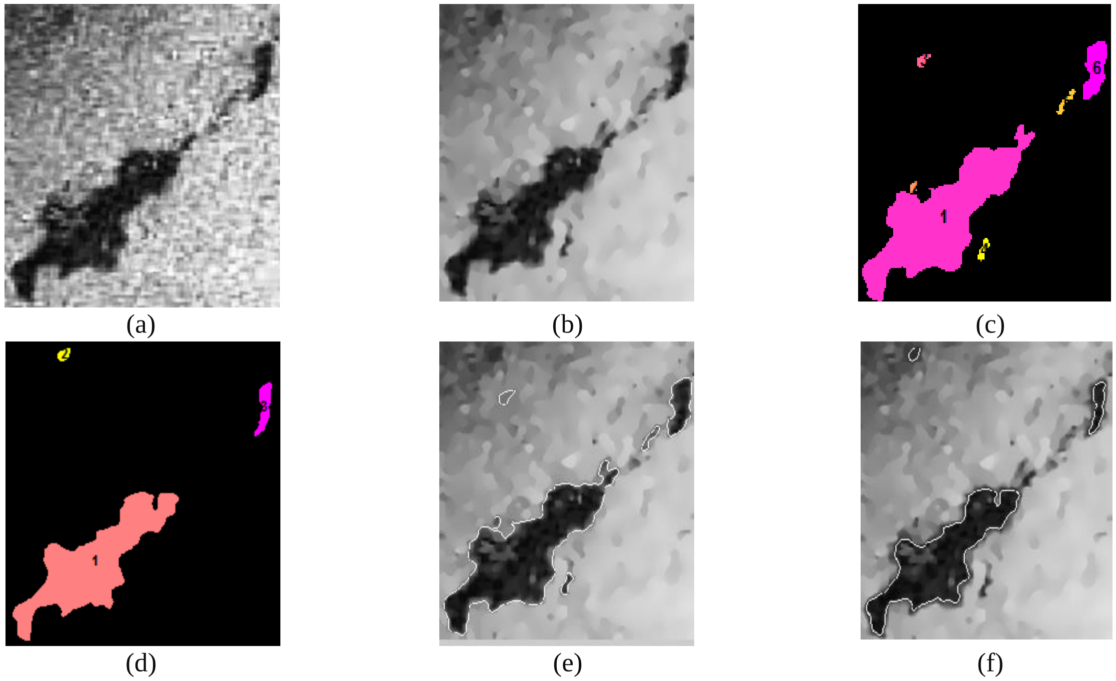

Fig. 1. Segmentation results of Lake Objects in SAR image. (a) Original SAR image, (b) SARD filtered image, (c) Segmented results by Otsu, (d) Segmented results by Modified Otsu, (e) Otsu results overlaid on the original image, and (f) Modified results overlaid on the original image.

To flock the optimum global solution social practical with large value and cognitive with small values is allowed. Tuning of these parameters is done as describing the following equation,

$$M_{k,n}{}^{i+1} = W_0 M_{k,n}{}^{i} + \Theta_1 rand_1\left(PBest_{k,n} - P_{k,n}^{i}\right) + \Theta_2 rand_2\left(GlBest_{k,n} - P_{k,n}^{i}\right)$$

$$\text{Where } \Theta_1 = (\Theta_{1S} - \Theta_{1i}) * \frac{1}{Iter_{max}} + \Theta_{1i}$$

$$\Theta_2 = (\Theta_{2S} - \Theta_{2i}) * \frac{1}{Iter_{max}} + \Theta_{2i}. \quad (10)$$

Here the $\Theta_{1S}, \Theta_{1i}, \Theta_{2S}$ *and* Θ_{2i} are constants, $Iter_{max}$ is the maximum number of iterations. In this paper Θ_{1S} *and* Θ_{2S} are taken as 0.5, Θ_{1i} and Θ_{2i} are taken as 2.65.

A. Methodology of proposed APSO for SAR image analysis

The automatic object detection system in this paper proposed APSO method to maximize the between class variance. The frame work is developed based on several contributions presented in [26]-[32]. From the Fig. 2 initial velocity and position are allocated to each particle randomly. The fitness of all the particles is computed using Eq. (5) and particle positions and velocities are updated according to Eqs. (7) and (8). In each iteration particle identifies the better position and those locations are stored.

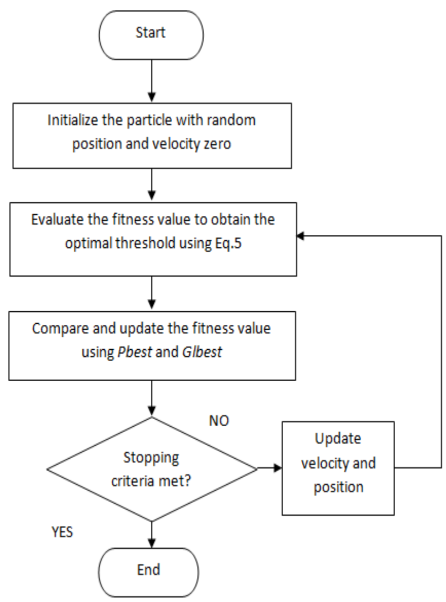

Fig. 2. Proposed APSO method operating flow chart.

The optimal threshold value can be calculated using proposed APSO algorithm described as below:

Step 1. Initialization: At initial the population size is arranged between the ranges of 0 to 255. The correct threshold value is identified by modifying Otsu method to detect the objects views of the lakes in the SAR images.

Step 2. Evaluation of Objective Function: The object function is specified in Eq. (5). Every particle in the SAR image gives the optimal value based on this function. The obtained optimal threshold value maximizes the between class variance of the foreground and background pixels.

Step 3. Updating the swarm: In this step the updated object values and positions are calculated using object function. The determined new value is assigned to *Pbest.* Like wise best of *Pbest* is assigned to *GlBest.* Based on this *Pbest* and *GlBest* the position of the new particle is updated for every iteration.

Step 4. Stopping Criteria: This Iteration process continues up to the maximum number of iterations. *GlBest* is the position of particle optimum threshold value.

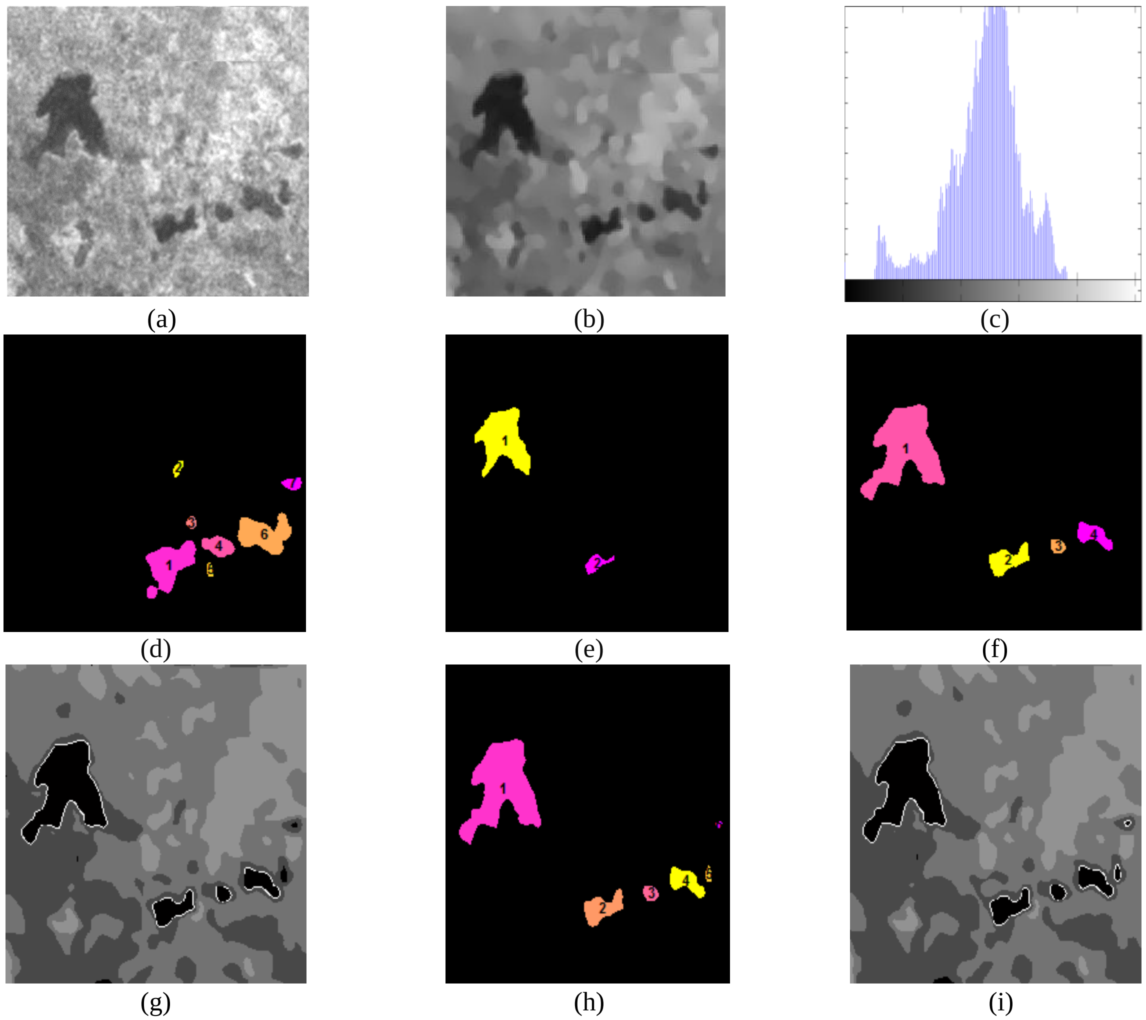

Fig. 3. Comparative results of proposed APSO + Modified Otsu with existing methods. (a) Original image, (b) SRAD filtered image, (c) Histogram of SAR image, (d) Segmented results by the Otsu method, (e) Segmented results by Modified Otsu, (f) Segmented results of PSO with Modified Otsu, (g) Segmented results of PSO with Modified Otsu overlaid on the original image, (h) Segmented results of proposed APSO with Modified Otsu, and (i) Segmented results of proposed APSO with Modified Otsu overlaid on the original image.

V. EXPERIMENTAL RESULTS

This work describes the automatic detection of the lakes in SAR image using proposed APSO method. The SAR image strips obtained from NASA/JPL during Titan-flyby. The experiments have been executed on the HP with Intel Core 2 Duo CPU@2GHz with 4 GB RAM running on a windows 7 operating system. The proposed APSO method implemented in MATLAB 2012a software. The performance measures of PSO and proposed APSO methods are shown in Tables 1, 2, 3 and 4.

Table 1: Optimized parameter values for constant inertia weight

Parameter Description	Parameter Value
Population	50
Iteration	150
W_0	1.2
θ_1	0.8
θ_2	0.8

Table 2: Optimized parameter values for particle swarm optimization

Parameter Description	Parameter Value
Population	50
Iteration	150
W_{MIN}	0.1
W_{MAX}	1.5
θ_1	0.8
θ_2	0.8

Table 3: Optimized parameter values for proposed adaptive particle swarm optimization

Parameter Description	Parameter Value
Population	50
Iteration	150
W_0	1.2
θ_{1S}, θ_{2S}	0.5
θ_{1i}, θ_{1i}	2.65

Table 4: Feature information of the identified objects by proposed APSO with modified Otsu method

Method	Extent	Circularity	Tortuosity
APSO + Modified Otsu	0.485609	0.341809	0.250798
	0.494286	0.494776	0.352329
	0.733728	0.955424	0.351079
	0.525333	0.569329	0.389926
	0.692308	0.75906	0.411692
	0.760000	1.280154	0.390931
No. of Objects:6			

Here is the optimal threshold value is getting from the proposed APSO method. For analysis, SAR input image Fig. 3 (a) is taken. It is preprocessed by the SRAD filter for smooth image shown in Fig. 3 (b). Figure 3 (c) represents the corresponding histogram for input image. Figures 3 (d), (e) show the segmented results for Otsu and Modified Otsu. Figures 3 (f)-(i) show the segmented results for PSO and proposed APSO with modified Otsu, which extracts the lake objects from the SAR input image. From this, the size and shape of the objects are extracted to identify the proper objects. Extracts the boundary of the lake objects and overlaid on the input SAR image for analysis. This gives the better identification and accurate detection of the unclear objects.

The Object shape and features like Perimeter, Area, Eccentricity, Minor axis, Major axis, Circularity, Extent and Tortuosity are extracted from segmented image. From the Circularity, Extent and Tortuosity range, it is possible accurately identifying the object appearance. Figures 4, 5 and 6 compares the Object features information about the proposed APSO method with existing methods. From these figures the conventional Otsu method detects the 10 objects among them, 5 are matched with the real objects. The proposed modified Otsu detects the 2 objects are detected without any false objects, but it does not cover all the lakes in the image. PSO is intrigued to optimize the class variance for improving the performance of Modified Otsu. Modified Otsu with PSO method detects the 4 out of 6 objects that reduce the false detection rate compared to Conventional Otsu. Further, using proposed APSO with Modified Otsu produces the segmented results that detect the all the objects combatively verified with the lake areas identified by human experts. The feature extraction information due to various methods is given in Tables 5, 6 and 7; the comparison of various techniques is presented in Table 8.

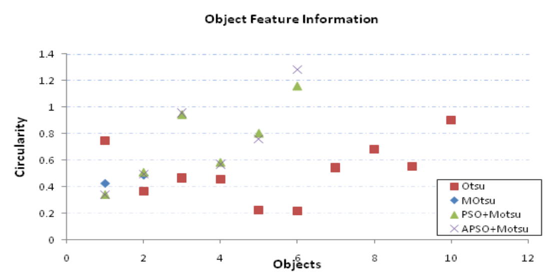

Fig. 4. Comparison of Circularity of identified objects.

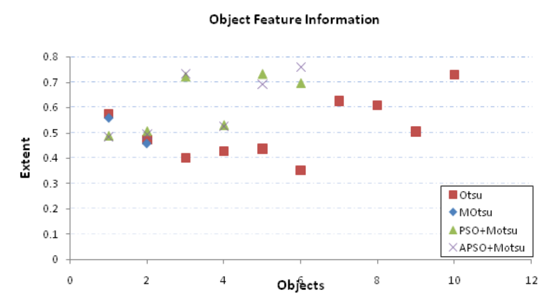

Fig. 5. Comparison of Extent of identifying objects.

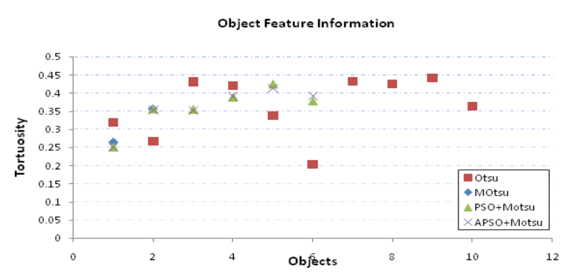

Fig. 6. Comparison of Tortuosity of identifying objects.

Table 5: Feature information of the identified objects by proposed PSO with modified Otsu method

Method	Extent	Circularity	Tortuosity
PSO + Modified Otsu	0.486607	0.339503	0.250904
	0.504762	0.507405	0.35651
	0.71978	0.942214	0.35533
	0.529032	0.582062	0.389345
	0.730769	0.80123	0.425641
	0.694444	1.155998	0.378359
No. of Objects: 6			

Table 6: Feature information of the identified objects by proposed modified Otsu method

Method	Extent	Circularity	Tortuosity
Modified Otsu	0.560333	0.425186	0.264153
	0.459276	0.486309	0.355806
No. of Objects: 2			

Table 7: Feature information of the identified objects by Otsu method

Method	Extent	Circularity	Tortuosity
PSO + Modified Otsu	0.573427	0.744097	0.318594
	0.470588	0.364074	0.265996
	0.400000	0.463283	0.431508
	0.425926	0.455406	0.420552
	0.435537	0.2229	0.337682
	0.350538	0.216019	0.202886
	0.624339	0.542438	0.433129
	0.607143	0.678756	0.425554
	0.503497	0.552815	0.441658
	0.727273	0.899488	0.363988
No. of Objects: 10			

Table 8: Comparison of proposed method with various methods based on experimental results

Methods		Number of Objects Identified from SAR Image I-Identified, O-Objects, NO-Not Objects		
		Image 1	Image 2	Image 3
APSO + Modified Otsu	I	1	6	3
	O	1	6	3
	NO	-	-	-
PSO + Modified Otsu	I	4	6	6
	O	1	4	3
	NO	3	2	3
Modified Otsu	I	4	2	3
	O	1	2	2
	NO	3	-	1
Otsu	I	4	10	6
	O	1	5	2
	NO	3	5	4
Manual Expert		1	6	3

This method has been tested on 78 images, it necessitates the modification of the PSO for good performance. The proposed APSO with Modified Otsu offers maximize fitness function. This method detects all the objects. A visual assessment is made with the segment's results of the Conventional Otsu, Modified Otsu, PSO + Modified Otsu and APSO + Modified Otsu are presented on the Fig. 3. All the algorithms give the best results by preprocessing the image with SRAD filter. In this paper evaluate the threshold value of the proposed APSO method and the performance of the successive rate should be analyzed using Table 8. Among all these algorithms the only proposed APSO with Modified Otsu segmented object matches with the objects identified by human experts. Moreover, it is the more proficient automatic detection and precise algorithm for identifying the objects from the SAR image.

VI. CONCLUSION

In this paper automatic object detection system is proposed to detect the regions of SAR image. The proposed method applies the PSO technique to avoid the problem in the manual detection in SAR images. Due to the simplicity and effectiveness of PSO technique, it is used in many applications to optimize the complex problems. The proposed APSO method detects the optimized threshold. This method is implemented by the combination of Modified Otsu method which gives the effective segmentation results. Here are the results which show the better comparative results of the proposed method with all existed methods by making the calculation of effective fitness value. But these segmentation methods gave the better segmentation by preprocesses the original SAR image with SRAD filter instead of all other de-speckled filter techniques Lee, Frost, Adaptive Frost etc. This APSO out performs the measurement parameters in terms of accuracy.

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