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An Improved Segmentation Technique of Multispectral Image Using Modified Particle Swarm Optimization Algorithm

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Abstract

The search for optimal solutions to optimization problems often uses meta-heuristic algorithms. This algorithm is generally based on several natural aspects such as biology and physics. One of the advantages of the bioinspired algorithm is its learning capability to handle optimization problems. This algorithm can be used in multilevel thresholding problems which have recently gained a lot of attention for image segmentation. The problem of multispectral image segmentation is still challenging and complicated in many applications. Therefore, to overcome this problem, a new multilevel algorithm based on Particle Swarm Optimization (PSO) is proposed in this study. Standard PSO is modified by adding inertial weights and mutations of position. The experimental results are measured in several parameters, namely computation time (CPU time), Mean Square Error (MSE), Peak Signal to Noise Ratio (PSNR), Structural Similarity Index Measure (SSIM), Variation of Information (VoI), and Probability Rand Index (PRI). The experimental results show that the proposed PSOt outperforms other competitive algorithms in terms of stability and convergence rate, which can be applied to practical problems such as multispectral image segmentation.

***Keywords**: image segmentation**,** multispectral image, particle swarm optimization.*

1 Introduction

The process of dividing an image into different regions based on its homogeneities such as the gray level intensity, texture, position information, and others is called the image segmentation process. Image segmentation techniques are based on similarity and discontinuity. One example of an approach based on similarity is thresholding. Thresholding is divided into two groups, namely bi-level and multilevel thresholding

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(Dhieb & Frikha, 2016). Bilevel thresholding divides the image into two separate classes, while multilevel thresholding divides the image into more than two different classes. Bilevel thresholding can simply solve the problem of image segmentation by only involving two gray levels. This method will experience difficulties when dealing with complex image segmentation problems. Therefore, we need a technique that can overcome the problems, namely the multilevel thresholding technique. These techniques are grouped into two types, namely parametric techniques and non-parametric techniques (Lahmiri & Boukadoum, 2014). In non-parametric techniques, the threshold is determined by calculating several criteria such as between-class variance and entropy.

The search for optimal solutions to optimization problems often uses meta-heuristic algorithms. This algorithm is generally based on several natural aspects such as biology and physics. One of the advantages of the bioinspired algorithm is its learning capability that can handle optimization problems. Some of the meta-heuristic algorithms are particle swarm optimization (PSO) (Eberhart & Shi, 2001), ant colony optimization (ACO) (Dorigo et al., 2006), genetic algorithm (GA) (J. Zhang et al., 2014), gray wolf optimizer (GWO) (Mirjalili et al., 2014), artificial bee colony (ABC) (Li et al., 2015), bacteria foraging optimization (BFO) (Sathya & Kayalvizhi, 2011), etc. One of the widely used is the particle swarm optimization (PSO) algorithm. The PSO algorithm was first introduced by Shi and Eberhart (1995) (Eberhart & Shi, 2001). Previous research in (Charansiriphaisan et al., 2014); (Sun et al., 2013) shows that PSO is more efficient and precise when used to find the optimal threshold in multilevel thresholding problems (Murinto et al., 2022) implemented in gray level image. Although PSO has many advantages, PSO also has weaknesses. One of them is easy to get stuck in the local optima. Likewise, it also suffers from premature convergence when dealing with complex optimization problems. PSO can also be used to perform feature selection in high dimensions (Swesi & Bajer, 2017).

In this paper, a modified Particle Swarm Optimization (PSO) algorithm called Modified Particle Swarm Optimization (PSOt) is proposed to handle two problems, namely being trapped in local minima and slow convergence rate when solving high-dimensional problems. In this study, two strategies are applied to the PSOt algorithm. This paper is organized into several sections. Part 1 is the introduction section which contains the background problem and the proposed solution. In Section 2, the proposed conventional PSO algorithm is briefly explained. Section 3 describes the multilevel thresholding problem based on Otsu's criteria. Section 4 presents the proposed method. Section 5 describes the experiments and results of multispectral image segmentation. Finally, conclusions are given in Section 6.

2 Particle Swarm Optimization

Particle swarm optimization (PSO) is a stochastic optimization technique inspired by the behavior of a flock of birds or the sociological behavior of a group of people. The scenario involves a flock of birds in search of food sources in a certain area. At first, a flock of birds did not know exactly where the food was, but eventually, they would find out how far the food was found. The best strategy used by members of the flock in finding and determining food sources will be followed by the other birds. In addition, the best strategy is also obtained from the previously achieved best position. PSO is built based on the optimization concept through a particle swarm. The PSO algorithm is a multi-agent parallel search technique that maintains a particle swarm. Each particle represents a potential solution in the swarm. All particles fly through the multidimensional search space by adjusting their position based on their own experience and their neighbors.

The PSO algorithm can be written in the form of equations to update velocity and position (Kennedy J, 1995) (Bansal et al., 2011)which are shown in equation (1) and equation (2) respectively.

$$v_{id}^{t+1} = w.v_{id}^{t} + c_1 .r_1.(p_{id}^{t} - x_{id}^{t}) + c_2 .r_2(p_{gd} - x_{id}^{t}) \quad (1)$$

$$x_{ij}^{t+1} = x_{ij}^{t} + v_{ij}^{t+1} \quad (2)$$

where c_1 and c_2 are positive constants, called acceleration coefficients. r_1 and r_2 are two random numbers whose values are in the range [0,1]. w is the inertial weight. A large value of inertial weight will facilitate global exploration while a small value of inertial weight will facilitate local exploitation. The ith particle is represented as $X_i = (x_{i1}, x_{i2}, \dots, x_{iD})$. The best position before the ith particle is stored is represented as $P_i = (p_{i1}, p_{i2}, \dots, p_{iD})$. The position gives the best fitness value. The index of the best particle among all the particles in the population is represented by the symbol g. The rate of change of position or velocity for the ith particle is represented as $V_i = (v_{i1}, v_{i2}, \dots, v_{iD})$. During the update process, the particle's velocity of each dimension is limited to v_{max}. D is the dimension of each search space.

3. Multilevel Thresholding Multispectral Image

Segmentation of 3-band multispectral images (color images) is a process to find more than two thresholds. This threshold will be used to segment the three bands namely R-band, G-band, and B-band. In optimization problems, the main objective is to find extreme values. This value depends on the problem at hand, it can be a maximum or minimum value which later will be used to optimize the fitness function based on certain limitations (Ghamisi et al., 2014). The multilevel thresholding problem can be considered an optimization problem which is obtained by optimizing the objective function. The between Otsu's classes difference is a widely used thresholding technique. The Otsu technique is a non-parametric technique for segmentation by dividing the entire image into classes so that the variance of the different classes is maximized. In a 3-band multispectral image, each band component consists of N pixels and L gray levels. Threshold values are obtained in the range of [0, L-1], where L is considered to be 256 and each gray level is associated with a histogram that represents the frequency of the gray level pixels used by the $f(x, y)$ image. It is assumed that the m-1 threshold is the threshold vector $T = [t_1, t_2, .., t_{M-1}]$ that divide the image into m classes, as shown in equation (3).

$$\begin{cases} K_1 = \{(x,y) | 0 \le f(x,y) \le t_1 - 1\} \\ K_2 = \{(x,y) | t_1 \le f(x,y) \le t_2 - 1\} \\ \vdots \\ K_m = \{(x,y) | t_k - 1 \le f(x,y) \le L - 1\} \end{cases} \quad (3)$$

Next, an image histogram $\{f_0, f_1, .., f_{L-1}\}$ is computed, where f_i is the frequency of the ith gray level. While the probability of the ith gray level can be defined as equation (4).

$$p_i = \frac{f_i}{\sum_{i=0}^{L-1} f_i}, \quad \sum_{i=0}^{L-1} p_i = 1 \quad (4)$$

For each K_m class, the cumulative probability ω_m and the average gray level μ_m in each region can be defined as equation (5).

$$\omega_m = \sum_{i \in K_m} p_i, \quad \mu_m = \sum_{i \in K_m} \frac{i.p_i}{\omega_m} \tag{5}$$

The optimal multilevel threshold is obtained by maximizing the variance between class functions, which is written as equation (6).

$$\sigma_B^2 = \sum_{m=0}^{M} \omega_m.(\mu_m - \mu_T)^2, \quad \mu_T = \sum_{i=0}^{L-1} i\,.\,p_i \tag{6}$$

where μ_T is the average gray intensity of the image. The optimal threshold vector is written as equation (7).

$$T^* = argmax(\sigma_B^2) \tag{7}$$

By maximizing the Otsu function (Otsu, 2010) in equation (7), the optimal threshold can be obtained from the corresponding solution.

3 The Proposed Method

In this study, multilevel thresholding image segmentation uses the Modified PSO (PSOt) algorithm to obtain the optimal threshold. The general steps of the PSOt algorithm to solve multispectral image segmentation problems are explained as follows:

Step 1: Initialize the PSOt parameters

1.1. Initialize the coefficient of inertial weight (w), the initial particles in the swarm (N), the minimum (Nmin) and maximum (Nmax) values of the particles in each swarm, the maximum number of threshold levels, and the total number of iterations.

1.2. Initialize the positions of all the particles in the swarm $0 \le x_i^s[0] \le L-1$.

1.3. Initialize the local best $\widetilde{(x_i^s)}$ and global best $\widetilde{(g_i^s)}$ of all swarm particles.

Step 2: Calculate the probability distribution of the image using equations (3) and (4).

Step 3: Estimate each ith particle in the swarm *s*.

Evaluate the values of the particles using an objective function on the RGB image component.

3.1. Det ermine the final Pbest and Gbest by using the inertial weight (w), updating the velocity. and position using equations (1), (2), and (3), as well as position mutation to get optimal fitness.

3.2. Cal culate the values from equations (5) and (7) based on the initial threshold defined in $x_i^s[t+1]$.

3.3. Co mpute the between classes variance (solution of each ith particle in swarm *s*) (6).

If $\sigma_{iB}^{K^2} > \sigma_{ibestB}^{K^2}$ then $\sigma_{nbestB}^{K^2} = \sigma_B^{K^2}$ and $\widetilde{x_i^s} = x_i^s[t+1]$

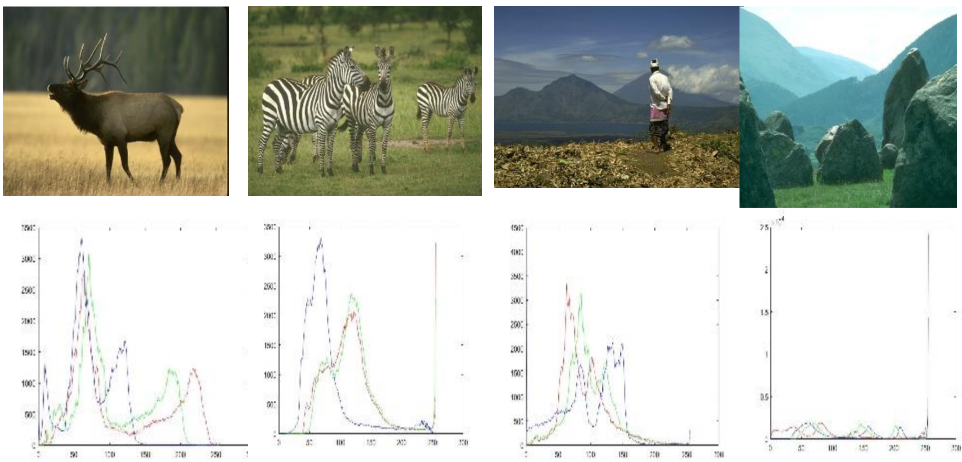
If $max\ \sigma_{sB}^{K^2} > \phi^K$ then $\phi^K = max\ \sigma_{sB}^{K^2} = \sigma_B^{K^2}$ and $\widetilde{g_i^s} = x_i^s[t+1]$

Step 4: End.

4. The Experiment Result and Discussion

This section describes the experimental settings for the proposed modified PSO algorithm. The image data used to test the performance of the proposed algorithm is multispectral images (3 bands). The test images are obtained from https://www2.eecs.berkeley.edu/Research/Projects/CS/vision/bsds/. Multispectral

images (3 bands RGB) and their histograms used in this experiment are shown in Figure 1. The four test images are named as follows: Test01, Test02, Test 03, and Test04. The proposed PSO namely Modified PSO is compared to the other metaheuristic algorithms, namely: Standard PSO (Eberhart and Kennedy, 1995) Harmonic Search Algorithm (HSA) (Y. Zhang et al., 2015) and IPSO (Madhava Rajaa et al., 2015). In this study, the same maximum number of iterations was used, namely 1500, while the initial population size was 30.
Experiments were carried out on test images with a low threshold. The low thresholds are 4, 6, and 8. The reason for choosing these thresholds is to measure the performance of each algorithm on multilevel thresholding problems. Because the optimization algorithm has random and stochastic characteristics, in this study each experiment was carried out 30 times for each RGB image and each threshold level, and all results were based on the average value. The quality of the segmented image as the result of applying those algorithms is evaluated for each threshold level. The performance evaluation uses Computational Time (CPU Time), Mean Value To Reach (MVTR), Standard Deviation (SD), Peak Signal to Noise Ratio (PSNR), Mean Square Error (MSE), Structural Similarity Index Measure (SSIM), Features Similarity Index Measure (FSIM), Probability Rand Index (PRI), and Variation of Information (VOI).



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

Figure 1. Multispectral images (3-band RGB) and its Histogram (a) Test01 (b) Test02 (c) Test03 (d) Test04.

The proposed modified particle swarm optimization (PSOt) algorithm is applied to multispectral image segmentation. Suppose there is a gray-level image consisting of N pixels that are distributed as objects and backgrounds. If L is an intensity level in each image component, where the level is within the range of $\{0,1,2,\ldots,\mathrm{L}-1\}$, then searching for a multilevel threshold can be considered as searching for the threshold set T(i), where i=1, 2,…, L. From the thresholding results, the initial image will be transformed into a new image that has an L+1 level. If T(i), where i=1,2,…,L is the threshold value, $T(1) < T(2), \ldots, < T(L)$ and if $f(x,y)$ is an image function that gives the grayscale values of the pixels with coordinates (x,y), then the resulting image, i.e. $g(x,y)$ can be written as equation (8).

$$g(x,y) = \begin{cases} 0, \ if \ f(x,y) \leq T(1) \\ 1, \ if \ T(1) < f(x,y) \leq T(2) \\ \dots\dots\dots \\ \dots\dots.. \\ L, \ if \ f(x,y) > T(L) \end{cases} \quad (8)$$

The problem of multilevel thresholding can be considered an optimization problem. The final goal is to find a threshold value that can maximize the fitness function ϕ of the grayscale components. Thresholds are used to ensure that the histogram of the resulting image meets the criteria based on the between-classes variance. If the optimal threshold is obtained by maximizing the between-classes variance, then the fitness function can be written as equation (9).

$$\phi = arg\, max \left(\sum_{i=0}^{m} \sigma_i\right) \quad (9)$$

where ϕ is the fitness function based on the criteria of between-classes variance, σ_i is the i-th variance, with i=1, 2…, m.

The multilevel thresholding problem in multispectral RGB band images can be explained as follows: If L represents an intensity level in each band, for example, 3-band RGB where the level is within the range of $\{0,1,2,\dots,\mathrm{L}-1\}$, then it can be defined in equations (10) and (11):

$$prob_i^K = \frac{h_i^K}{N} \quad (10)$$

$$\sum_{i=0}^{L-1} prob_i^K = 1 \quad (11)$$

where *i* represents a certain intensity level, namely $0 \leq i \leq L-1$, K represents the image component, namely, $K = \{R,G,B\}$ for RGB band images, N represents the total number of pixels in the image and h_i^K is the number of pixels for the ith intensity level corresponding to the K component. h_i^K is an image histogram for each K component, which can be normalized and considered a probability distribution $prob_i^K$.

The combination of the average (mean) of each component is the total mean of each image component which can be calculated using equation (12):

$$\mu_T^K = \sum_{i=0}^{L} i * prob_i^K \quad (12)$$

Furthermore, if the thresholding level is *m*, it will give the result of the *m-1* threshold level T_j^K, $j = 1,2,\dots,m-1$ and can be written as equation (13).

$$g^K(x,y) = \begin{cases} 0, \ \text{if}\ (x,y) \leq T_1^K \\ \frac{1}{2}(T_1^K + T_2^K), \ \text{if}\ T_1^K < f^K(x,y) \leq T_2^K \\ \dots\dots\dots\dots\dots\dots\dots \\ \dots\dots\dots\dots\dots\dots\dots \\ \dots\dots\dots\dots\dots\dots.. \\ \frac{1}{2}(T_{m-2}^K + T_{m-1}^K), \ \text{if}\ T_{m-2}^K < f^K(x,y) \leq T_{m-1}^K \\ L, \ \text{if}\ (x,y) > T_{m-1}^K \end{cases} \quad (13)$$

Where *x* and *y* are the width (L) and length (P) of pixels of an image with size L x P denoted by $f^K(x,y)$ with an intensity level of L for each component. Here the pixels will be divided into *m* classes, namely $M_{1,}^K M_2^K,\dots,M_{m,}^K$, which represent several objects or features. One of the methods to obtain the optimal threshold is to maximize the between-classes variance (Otsu criteria) of each component, which can be written as equation (14).

$$\sigma_B^{K^2} = \sum_{K=\{R,G,B\}}^{n} {}_{j=1} \; w_j^K \left(\mu_j^K - \mu_T^K\right)^2 \quad (14)$$

Where j represents a particular class such that w_j^K and μ_j^K are the probabilities of occurrence and the mean of class j, respectively. The probability of the event w_j^K of class $M_1^K, M_2^K, \dots, M_m^K$, is defined as equation (15).

$$w_j^K = \begin{cases} \sum_{i=1}^{T_j^K} prob_i^K, \; j = 1 \\ \sum_{i=T_{j-1}^K+1}^{T_j^K} prob_i^K, \; 1 < j < m \\ \sum_{i=T_{j-1}^K+1}^{L} prob_i^K, \; j = m \end{cases} \tag{15}$$

The mean of each class μ_j^K is calculated using equation (16).

$$\mu_j^K = \begin{cases} \sum_{i=1}^{T_j^K} \frac{i * prob_i^K}{w_j^K}, \; j = 1 \\ \sum_{i=T_{j-1}^K+1}^{T_j^K} \frac{i * prob_i^K}{w_j^K}, \; 1 < j < m \\ \sum_{i=T_{j-1}^K+1}^{L} \frac{i * prob_i^K}{w_j^K}, \; j = m \end{cases} \tag{16}$$

The *m*-level thresholding problem is reduced to an optimization problem to find a threshold T_j^K that maximizes the fitness function of each K image component and can be written as equation (17).

$$\phi^K = \max_{1<T_1^K<\dots<T_{m-1}^K<L} \sigma_B^{K^2}(T_j^K) \tag{17}$$

Where ϕ^K s the fitness function of Otsu's criteria, K is one of the RGB band components, $K = \{R, G, B\}$ for RGB band images, and $\sigma_B^{K^2}$ is the between-classes variance of each component which is defined as equation (18).

$$\sigma_B^{K^2} = \sum_{j=1}^{m} w_j^K (\mu_j^K - \mu_T^K)^2 \tag{18}$$

Where j is a particular class such that w_j^K and μ_j^K respectively represent the probability of occurrence and the mean of class K.

4. Result and Discussion

The experiment results of the modified PSO algorithm implementation on test images were analyzed at different threshold levels (m = 4, 6, 8). The results of segmentation are shown in Figure 2, Figure 3, and Figure 4 which displays 3 of the 4 multispectral test images. The performance of the proposed PSOt algorithm is qualitatively represented at different segmentation levels. It can be seen from Figure 2, Figure 3, and Figure 4 that the proposed algorithm produces satisfactory results, especially for natural images.

Quantitatively, the performance of the modified PSO proposed in this study is shown in comparison with other techniques, namely PSO, Iterative Particle Swarm Optimization (IPSO), and (Autonomous Groups Particles Swarm Omptimization (AGPSO). Table 1 shows a comparison of PSNR and MSE values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8, while Table 2 shows a comparison of SSIM and FSIM values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8. PSOt has a slight superiority compared to PSO, APGSO, and IPSO when implemented on natural images taken from the Berkeley image dataset. Therefore, it is clear that PSOt has a higher mean fitness which indicates higher accuracy than other algorithms.

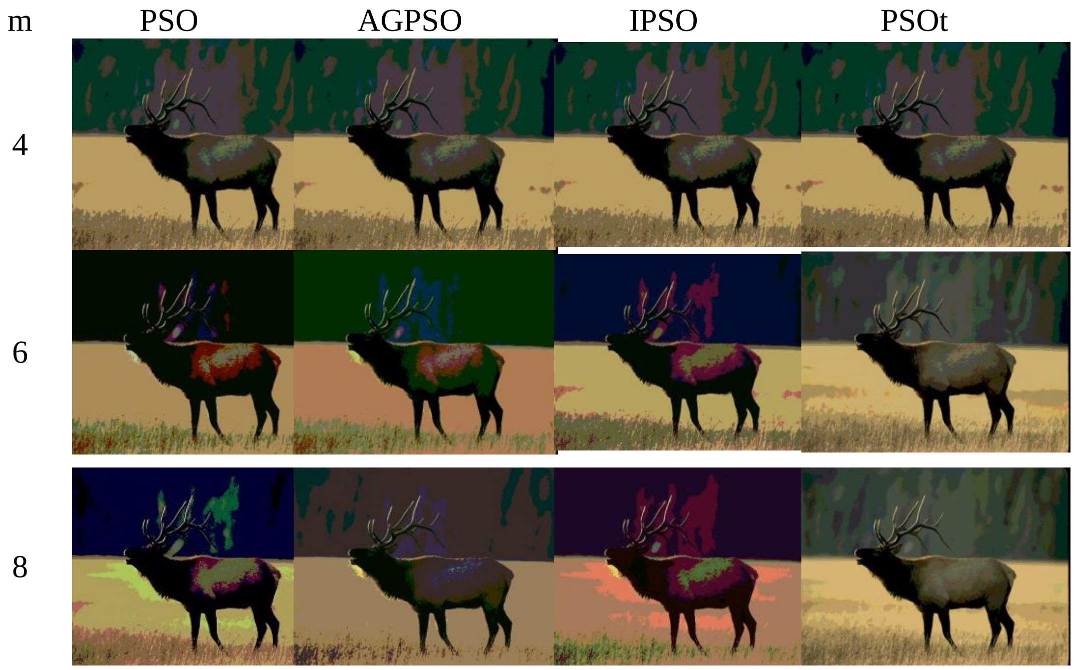


Figure 2. The image segmentation result of Test01 using PSO, AGPSO, IPSO, PSOt at levels 4,6,8

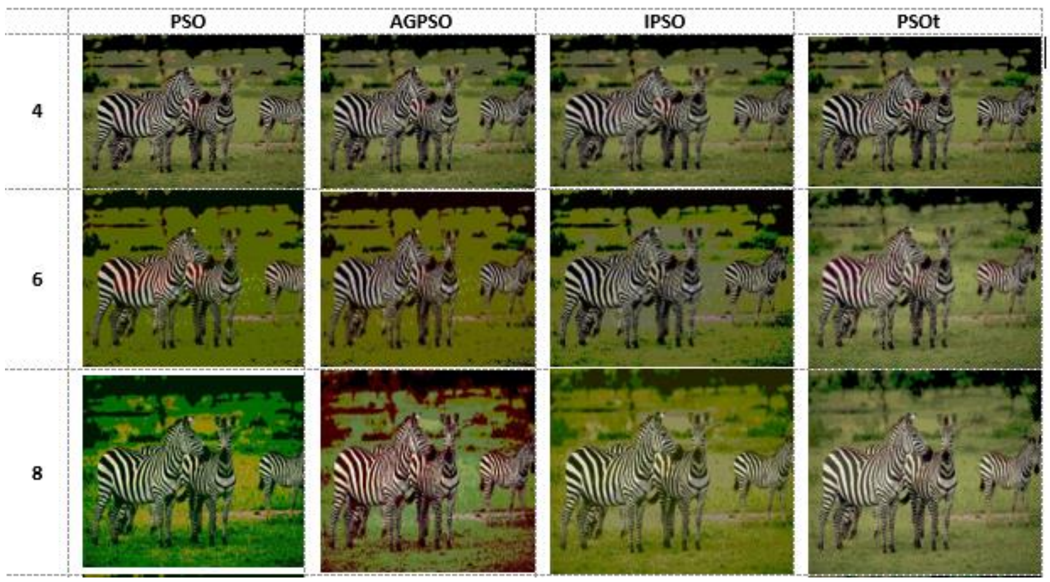


Figure 3. The image segmentation result of Test02 using PSO, AGPSO, IPSO, PSOt at levels 4,6,8

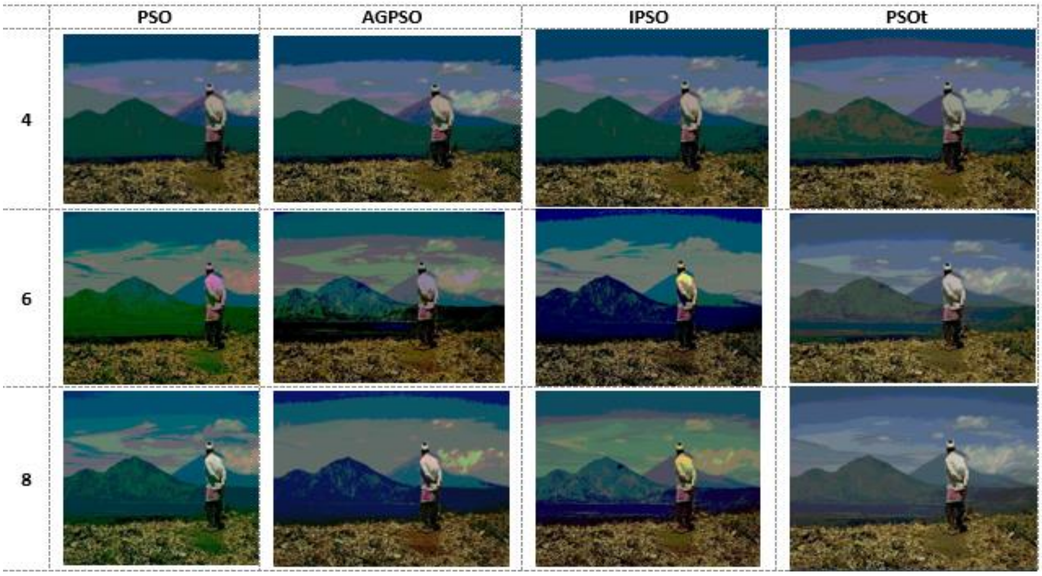


Figure 4. The image segmentation result of Test03 using PSO, AGPSO, IPSO, PSOt at levels 4,6,8

Table 1: Comparison of PSNR and MSE values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

image		PSNR				MSE			
	m	**PSO**	**AGPSO**	**IPSO**	**PSOt**	**PSO**	**AGPSO**	**IPSO**	**PSOt**
	4	18,3444	16,0898	17,7589	18,3639	961,2048	1600,179	1163,2743	947,787
Test01	**6**	14,5825	15,254	15,296	22,673	2301,6968	2002,992	1956,7964	351,406
	8	14,3318	17,4589	16,323	25,0051	2215,8886	1584,068	1612,7272	215,4253
	4	15,6049	15,6479	15,604	15,5677	1401,4633	1771,295	1793,3177	1804,356
Test02	**6**	14,3565	14,8059	16,896	18,7674	1119,0017	2411,518	2298,0588	863,7309
	8	14,4210	15,6467	17,056	21,1134	805,3037	1859,607	1351,6924	528,6371
	4	19,0804	18,9436	18,973	19,1015	702,5733	850,2099	836,295	799,7088
Test03	**6**	16,5603	16,8244	17,076	22,7373	1774,4989	1359,455	128,6368	346,2229
	8	17,3134	18,0225	19,261	25,0521	2414,6247	1059,659	788,3255	203,5984
	4	19,8070	19,8035	19,784	19,8034	2547,0473	680,3392	683,3349	686,2423
Test04	**6**	17,4608	17,8387	17,549	23,3553	1480,6304	1075,578	1150,166	303,1636
	8	18,2490	19,1946	17,923	25,7821	1112,84882	809,7345	1075,087	171,743

Table 2: Comparison of SSIM and FSIM values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

image	m	SSIM				FSIM			
		PSO	**AGPSO**	**IPSO**	**PSOt**	**PSO**	**AGPSO**	**IPSO**	**PSOt**
	4	0,6385	0,7257	0,6147	0,6451	0,8165	0,9234	0,8157	0,8165
Test01	**6**	0,444	0,6621	0,5062	0,7562	0,8138	0,8726	0,8156	0,8624
	8	0,4385	0,6860	0,5822	0,7962	0,7869	0,8918	0,8272	0,9010

	4	0,5378	0,5390	0,5369	0,5346	0,8031	0,8016	0,8016	0,8008
Test02	**6**	0,5505	0,4638	0,4743	0,7038	0,7764	0,7811	0,7756	0,8503
	8	0,4722	0,5390	0,6207	0,7862	0,8241	0,8367	0,8472	0,8911
	4	0,5580	0,5526	0,5558	0,5567	0,8143	0,8127	0,8128	0,8129
Test03	**6**	0,4877	0,5025	0,4991	0,6737	0,774	0,7842	0,7973	0,8804
	8	0,5133	0,5189	0,5802	0,7229	0,8103	0,8190	0,8342	0,9116
	4	0,7242	0,7242	0,723	0,7241	0,8568	0,8563	0,8567	0,8563
Test04	**6**	0,5756	0,6075	0,5932	0,8543	0,7971	0,8100	0,8063	0,9263
	8	0,6050	0,6674	0,6022	0,9079	0,8495	0,8750	0,8281	0,9558

PSNR and MSE values of the four RGB test images at levels m=4,6,8 are shown in Table 1. SSIM and FSIM values of the four RGB test images at levels m=4,6,8 are shown in Table 2. Based on Table 1, it can be seen that in m=4 the algorithm has smaller PSNR and MSE than at a higher threshold level. Likewise, smaller FSIM and SSIM values are obtained at the low threshold level m=4. Higher PSNR values and lower MSE indicate that the quality of segmentation results is good. Meanwhile, higher FSIM and SSIM values indicate better segmentation results. Figure 5 and Figure 6 show a comparison graph of the PSNR and MSE values of PSO, AGPSO, IPSO, and PSOt at m=4,6,8 respectively.

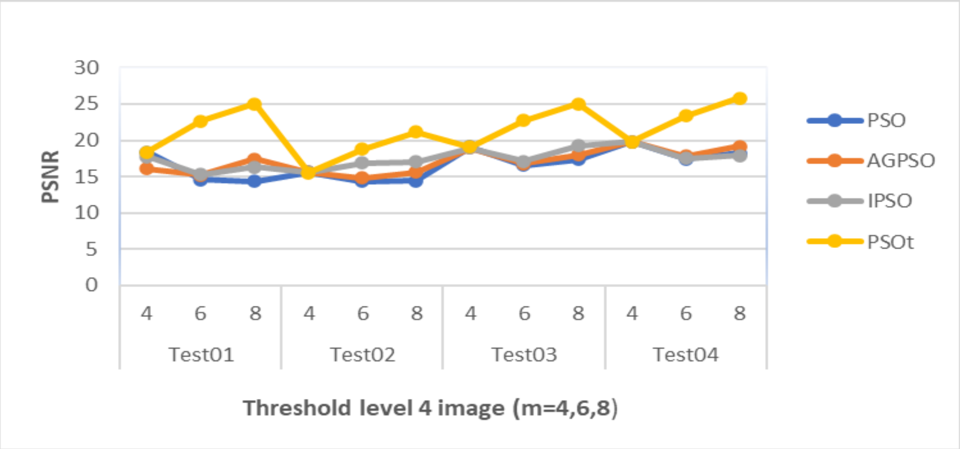


Figure 5. Comparison graph of PSNR values of PSO, AGPSO, IPSO, and PSOt at level m=4,6,8

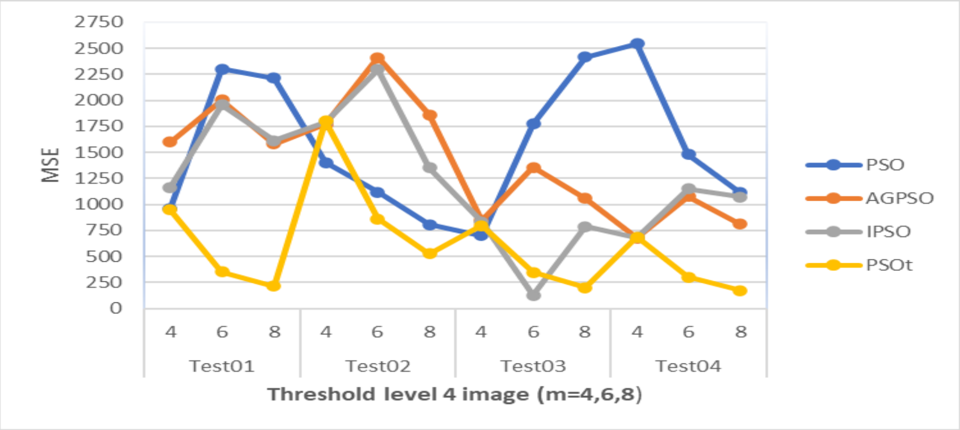


Figure 6. Comparison graph of MSE values of PSO, AGPSO, IPSO, and PSOt at level m=4,6,8

Based on Table 2, the higher threshold levels produce SSIM and FSIM values that are close to the good segmentation category. This means that the segmentation performance increases as the threshold levels increased. Higher SSIM and FSIM values indicate that the segmentation result is better and more accurate. From Table 2, it can be seen that PSOt produces better values for both lower and higher threshold levels. In addition, the SSIM and FSIM values also increase significantly at higher threshold levels. Figure 7 and Figure 8 respectively show a comparison graph of SSIM and FSIM images using PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8.

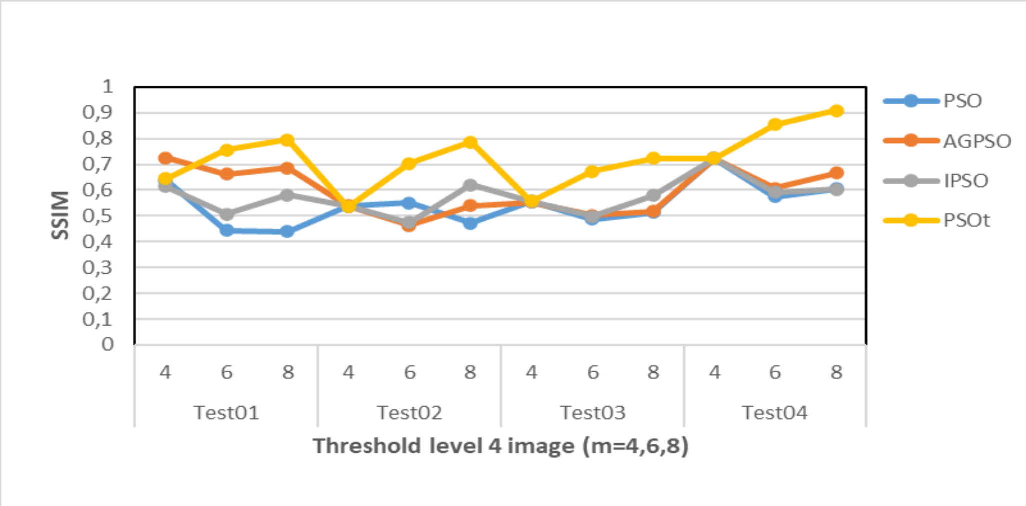


Figure 7. Comparison graph of SSIM values of PSO, AGPSO, IPSO, and PSOt at level m=4,6,8

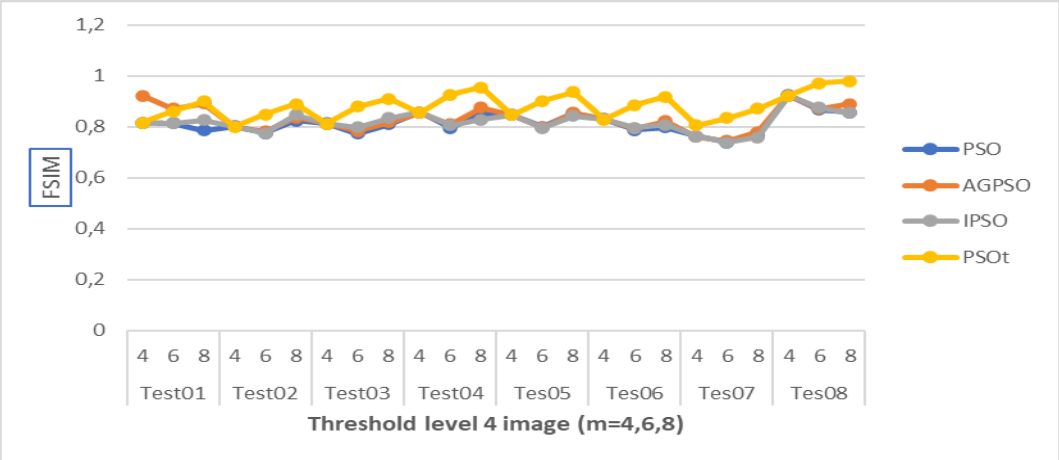


Figure 8. Comparison graph of FSIM values of PSO, AGPSO, IPSO, and PSOt at level m=4,6,8

The PRI and VoI values of the four RGB images at levels m=4,6,8 are shown in Table 3. The PRI and VoI indices are special measurements of image segmentation. A high PRI value and a lower VoI value indicate that the segmentation quality is better. Based on Table 3, PSOt produces the most number of best scores in the two indices.

This shows the superiority and robustness of the PSOt algorithm. Figure 9 shows a comparison graph of PRI values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8.

Table 3: Comparison of PRI and VoI values of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

image	m	PRI				VOI			
		PSO	AGPSO	IPSO	PSOt	PSO	AGPSO	IPSO	PSOt
Test01	4	0,60501	0,59651	0,59651	0,59651	2,8571	2,8948	2,8948	2,8948
	6	0,6081	0,59268	0,59268	0,59268	2,8583	2,9069	2,9069	2,9069
	8	0,61144	0,58962	0,58962	0,58962	2,8792	2,9166	2,9166	2,9166
Test02	4	0,58325	0,57928	0,57928	0,59651	2,9368	2,9457	2,9494	2,8948
	6	0,58174	0,57826	0,57826	0,59268	2,9416	2,9526	2,9526	2,9069
	8	0,58043	0,57736	0,57736	0,58962	2,9457	2,9555	2,9555	2,9166
Test03	4	0,57517	0,57403	0,57353	0,57928	2,9624	2,9662	2,9676	2,9494
	6	0,57458	0,57353	0,57307	0,57826	2,9643	2,9676	2,9691	2,9526
	8	0,57403	0,57307	0,57265	0,57736	2,9662	2,9690	2,9704	2,9555
Test04	4	0,57155	0,57066	0,57066	0,57517	2,9739	2,9767	2,9767	2,9624
	6	0,57123	0,57042	0,57066	0,57458	2,9749	2,9775	2,9775	2,9643
	8	0,57094	0,57265	0,5704	0,57403	2,9758	2,9704	2,9783	2,9662

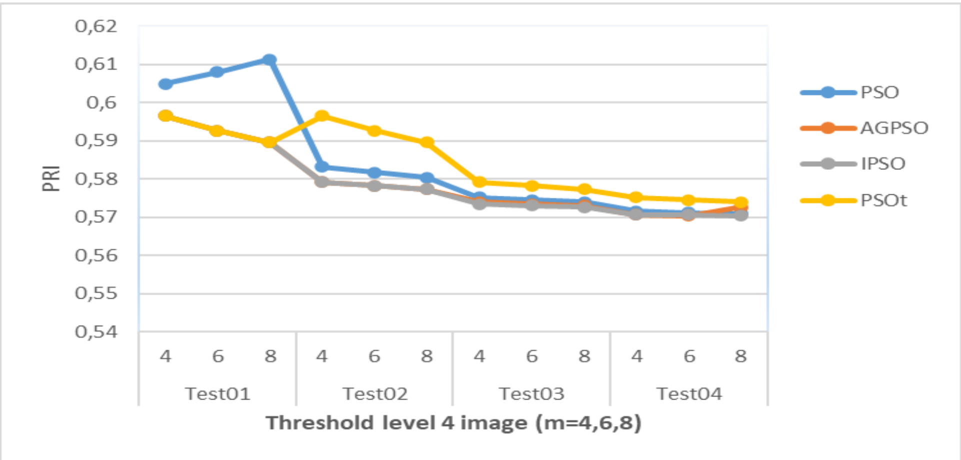


Figure 9. Comparison graph of PRI values of PSO, AGPSO, IPSO, and PSOt at level m=4,6,8

The average processing time of the four RGB images at level m=4,6,8 is shown in Table 4. The processing time of PSOt is longer than PSO, IPSO, and AGPSO. However, the PSOt convergence rate is faster than the other algorithms. As shown in Table 4, the computational speed (CPU time) will increase when the threshold level increases. Table 5 shows the optimal threshold values calculated using IPSO, PSO, AGPSO, and PSOt on four RGB images at levels m=4,6,8. Figure 10 shows a comparison graph of the CPU time of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8.

Table 4: Computational time comparison of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

image	m	PSO	AGPSO	IPSO	PSOm
Test01	4	3,2897	1,7286	2,3323	12,8777
	6	3,8718	2,2816	2,9053	12,6155
	8	4,5684	3,0048	3,5066	7,9319
Test02	4	1,9062	2,0589	2,9081	4,0279
	6	2,5266	2,5555	3,7178	5,9272
	8	3,0021	3,0929	4,4652	7,596
Test03	4	2,1859	2,0555	4,3256	4,0213
	6	2,634	2,7812	5,1482	5,5162
	8	3,0922	3,0914	7,7048	6,8315
Test04	4	1,9103	1,9933	1,9769	4,2683
	6	2,4636	2,5376	2,5511	5,2093
	8	6,4781	3,8221	3,1253	6,5149

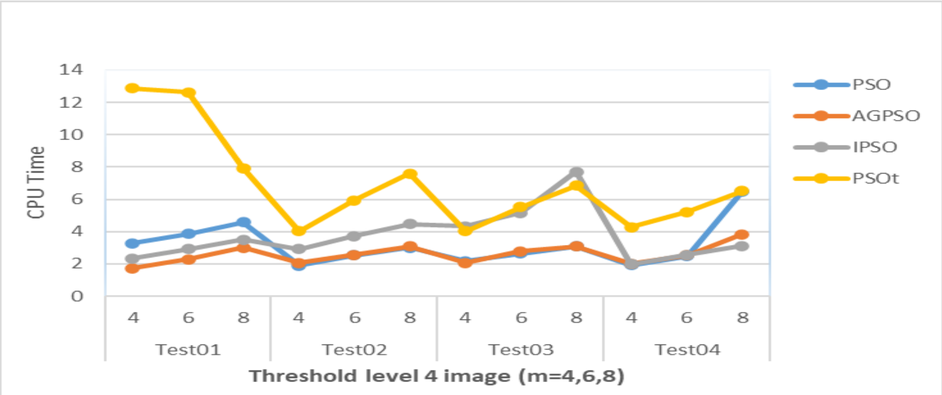


Figure 10. Comparison graph of the CPU time of PSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

Table 6 shows the statistical analysis results of the Wilcoxon Sum Test for 30 runs from 56 experimental samples of PSO, AGPSO, IPSO, and PSOt algorithms. The significance level is 5% of the PSNR data taken from Table 1 corresponding to the threshold levels of 4,6,8. The value of *p* is a statistical probability, h=1 means that the null hypothesis can be rejected at the 5% significance level. Whereas h=0 indicates the null hypothesis cannot be rejected (acceptable). If the value of *p* is less than 0.05 (5% significance level), this indicates that it is proven to be strong against the null hypothesis. The better value of the objective function which is achieved by the best algorithm in each problem is statistically significant and does not occur by chance. In this experiment, PSOt was used as a control algorithm and compared with the PSO algorithm in terms of PSNR values. Table 6 shows that the results of PSOt are not only faster but can also obtain better results than other algorithms. Based on Table 6, almost all values of *p* produced by the Wilcoxon test when comparing PSOt with PSO, IPSO, and AGPSO are less than 0.05 (5% significance level). This shows that the PSNR value of PSOt is statistically better and does not occur by chance.

Table 5: The optimal threshold value computed using IPSO, AGPSO, IPSO, and PSOt at levels m=4,6,8

Citra	m	PSO			AGPSO			IPSO			PSOt		
		R	G	B	R	G	B	R	G	B	R	G	B
Tes01	4	70 123 187	56 105 159	35 65 94	69 123 187	57 105 159	35 66 96	69 123 187	56 105 159	18 19 247	69 123 187	56 105 159	35 66 96
	6	31 31 98 147 231	0 0 65 85 133	0 0 73 78 177	0 0 89 106 175	65 116 116 122 215	5 5 88 89 171	25 25 112 113 228	0 0 76 94 126	40 83 95 95 152	51 77 118 166 203	49 77 107 144 176	30 54 69 89 112
	8	0 0 90 145 167 167 225	0 0 0 0 86 94 115	0 0 34 84 91 129 255	0 0 76 145 145 162 239	0 0 0 0 75 77 96	0 0 60 80 92 92 188	0 0 0 70 100 120 184	10 10 28 28 128 137 230	0 0 43 55 93 98 124	48 69 95 130 163 190 214	42 64 80 101 129 156 181	28 51 64 80 98 115 147
Test02	4	92 133 197	96 134 192	64 106 170	90 129 191	96 134 194	63 105 174	90 129 191	96 134 194	63 105 174	90 129 191	97 135 195	64 106 175
	6	32 32 94 102 176	0 0 99 102 178	74 143 143 154 248	3 3 91 98 180	100 167 167 179 255	64 129 129 133 255	3 3 91 100 175	9 9 99 108 178	96 155 155 157 254	73 99 123 152 206	82 106 128 155 207	53 71 94 134 191
	8	100 122 122 196 196 202 255	100 119 119 135 181 219 255	52 84 84 97 158 173 254	15 15 75 100 101 144 211	86 132 166 166 203 217 255	68 108 108 139 153 204 255	0 0 78 94 117 146 193	0 0 94 100 125 157 197	0 0 57 73 78 119 179	66 88 106 123 144 176 222	74 94 112 129 150 181 224	49 64 78 97 126 165 207
Tes03	4	75 120 185	50 107 169	30 60 95	59 118 176	48 98 146	35 80 129	59 117 176	48 98 145	5 80 129	59 118 177	48 98 146	36 81 130
	6	0 0 77 78 160	0 0 55 56 118	4 4 55 63 200	0 0 62 68 156	0 0 48 52 122	44 87 87 91 204	90 159 159 177 248	63 124 124 124 205	7 97 97 155 186	43 86 124 163 204	29 60 90 120 156	20 46 74 102 140
	8	0 0 57 119 192 192 244	0 0 53 77 100 115 200	76 83 83 87 87 173 184	0 0 46 67 104 106 178	0 0 43 48 87 119 255	0 0 18 61 77 149 188	45 126 131 131 171 187 255	47 109 109 112 133 206 255	0 0 26 64 64 97 180	36 70 99 126 153 181 212	25 51 75 98 120 144 170	15 34 54 73 94 116 146
Tes04	4	54 93 141	58 95 139	31 63 106	54 92 139	59 97 141	32 65 107	55 92 139	60 98 141	32 65 106	55 93 140	60 98 142	32 65 107
	6	0 0 59 60 110	0 0 68 71 125	37 76 83 83 220	72 105 105 108 238	6 6 65 71 124	40 79 79 82 255	70 119 119 134 255	0 0 71 72 120	33 70 87 87 216	40 67 93 122 162	46 74 100 128 165	22 44 66 93 129
	8	0 0 0 0 55 60 94	0 0 0 0 66 69 91	64 68 68 77 77 177 193	0 0 19 19 59 60 82	4 4 76 94 110 141 189	0 0 47 58 59 100 173	0 0 71 97 119 119 255	0 0 63 86 100 110 200	67 78 78 90 90 162 191	31 52 71 90 112 139 176	37 60 80 100 121 145 180	17 33 49 66 86 111 144

Table 6 Statistical analysis of Wilcoxon Rank Sum Test for 30 runs from 56 experimental samples of PSO, AGPSO, IPSO, and PSOt

Citra	m	PSOt vs PSO		PSOt vs AGPSO		PSOt vs IPSO	
		p	h	p	h	p	h
Tes01	4	1,9980E-03	1	3,5770E-02	1	3,3220E-04	1
	6	1,7480E-04	1	4,0030E-04	1	1,0320E-03	1
	8	1,1550E-03	1	4,1050E-03	1	1,8940E-03	1
	12	2,2470E-02	1	3,5340E-03	1	1,2520E-04	1
	16	8,8960E-02	1	1,0920E-03	1	5,1090E-04	1
	20	4,7890E-02	1	6,1980E-04	1	3,1390E-04	1
	24	5,7800E-02	0	5,1580E-04	1	4,1290E-04	1
Tes02	4	1,5510E-02	1	4,5250E-04	1	6,7630E-02	0
	6	1,8330E-02	1	1,0210E-04	1	3,7730E-03	1
	8	5,4260E-04	1	2,1270E-04	1	4,7870E-05	1
	12	0.0005426	1	2,0500E-06	1	1,0880E-03	1
	16	3,7730E-03	1	8,6910E-04	1	1,0040E-02	1
	20	5,7700E-03	1	6,0510E-03	1	0.0001636	1
	24	3,1770E-03	1	5,5120E-02	0	4,6450E-04	1
Tes03	4	7,3760E-03	1	2,7490E-04	1	3,1940E-02	1
	6	1,4310E-03	1	9,9170E-04	1	0.0001093	1
	8	1,7730E-02	1	1,3264E-01	0	1,3264E-01	0
	12	1,5310E-04	1	1,9100E-02	1	4,1090E-03	1
	16	2,8830E-03	1	0.0004525	1	8,4700E-09	1
	20	3,7750E-02	1	2,0690E-02	1	7,3000E-04	1
	24	5,7700E-03	1	3,5060E-02	1	9,1810E-03	1
Tes04	4	1,9930E-04	1	2,6330E-02	1	2,5710E-04	1
	6	2,5320E-02	1	1,4430E-03	1	1,5170E-02	1
	8	6,4890E-04	1	3,9060E-03	1	1,8670E-04	1
	12	3,3220E-04	1	2,4680E-03	1	1,4430E-03	1
	16	4,6450E-04	1	2,7380E-03	1	2,2690E-04	1
	20	3,0350E-03	1	1,1930E-03	1	1,6100E-03	1
	24	7,3760E-03	1	4,3710E-02	1	1,1060E-02	1

5. **Conclusions**

In this paper, modified particle swarm optimization is used to solve optimization problems. One of the optimization problems is multilevel thresholding in multispectral image segmentation, where Otsu's criteria are used as the objective function of the optimization problem. The modified particle swarm optimization algorithm is used to improve the ability to perform image segmentation. The inertial weights are introduced into the standard PSO equation. The resulting Modified PSO was tested on four multispectral images using Otsu at different levels (m=4,6,8). In addition, the proposed approach is compared with other algorithms, namely: PSO, IPSO, and AGPSO. The performance of the proposed approach is evaluated through PSNR, MSE, SSIM, FSIM, PRI, VOI, and CPU Time. The experimental results show that PSOt has advantages in terms of stability, efficiency, and convergence rate. The results of the Sum Rank statistical test show that PSOt has a difference and is better than PSO. In the future, the application of hyperspectral images become important because of the high dimensions and complexity of these images.

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