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Alternate PSO-Based Adaptive Interval Type-2 Intuitionistic Fuzzy C-Means Clustering Algorithm for Color Image Segmentation

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ABSTRACT Interval type-2 fuzzy c-means (IT2FCM) clustering algorithm can describe more uncertainty than fuzzy c-means (FCM) clustering algorithm by using two fuzzifiers to construct a more inclusive boundary. How to obtain appropriate fuzzifiers and initialize cluster centers are essential tasks for the IT2FCM. To effectively solve these problems, this paper proposes an alternate particle swarm optimization-based adaptive interval type-2 intuitionistic fuzzy c-means clustering algorithm (A-PSO-IT2IFCM) and applies this proposed method to color image segmentation. First, in order to further deal with the uncertainty, a novel interval type-2 fuzzy clustering objective function is constructed by utilizing the intuitionistic fuzzy information extracted from images. Then an alternate particle swarm optimization (PSO) scheme is designed to optimize fuzzifiers and cluster centers alternatively. In addition, a multiscale update strategy for the positions of particles is introduced into the A-PSO-IT2IFCM to increase the diversity of swarm and boost the convergence of optimization. The color image segmentation experiments on Berkeley and UC Merced Land Use datasets show that the proposed algorithm can adaptively determine fuzzifiers and cluster centers and achieve good segmentation results.

INDEX TERMS Image segmentation, interval type-2 fuzzy clustering, intuitionistic fuzzy set, particle swarm optimization, alternate optimization.

I. INTRODUCTION

Fuzzy set theory was first proposed by Zadeh in 1965 [1]. Some improved fuzzy sets, such as type-2 fuzzy set [2], interval type-2 fuzzy set [3] and intuitionistic fuzzy set [4] have been proposed successively over the years. These extended fuzzy sets can deal with more uncertainty than fuzzy set and have been widely used in data analysis, pattern recognition, image processing and so on [5]–[7].

Fuzzy c-means (FCM) [8] algorithm is a classical clustering method which introduces fuzzy set into clustering problems. To consider more uncertainty than FCM, type-2 fuzzy c-means (T2FCM) clustering algorithm is proposed based on type-2 fuzzy set. It can effectively cluster data with different volume or density [9]. However, T2FCM is computationally expensive. To reduce the complexity, interval type-2 fuzzy c-means (IT2FCM) clustering algorithm is proposed based on interval type-2 fuzzy set [10]. However, there are still some problems for IT2FCM: 1) How to adaptively select the fuzzifiers which determine the degree of fuzziness of the partitions. 2) How to effectively initialize appropriate cluster centers.

It is known that the fuzzifier m is an important parameter for FCM. When m is 1, FCM becomes K-means clustering algorithm [11]. In Ref. [3], m was suggested to be assigned in the range [1.1, 5]. Given the number N of data, m should be larger than $N/(N\text{-}2)$ according to Ref. [12]. Later, some researchers proposed that the value of m should be in the interval [1.25, 1.75] [13], while others thought that it should be in the range [1.5, 2.5] [14]. It is not supposed to use the same

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fuzzifier m for all the data. It should be selected according to the characteristics of data. Huang and Xia [15] presented a theoretical approach which utilizes the behavior of membership function on two special data points to determine m. For IT2FCM, there are two different fuzzifiers m_1 and m_2 used to construct the upper and lower boundaries of membership degree function to deal with more uncertainty. These two fuzzifiers have a great influence on the performance of IT2FCM. Memon [16] extracted the information from individual data points and proposed a histogram approach to determine the fuzzifier values of IT2FCM. There have been few relevant researches about the selection of fuzzifiers m_1 and m_2 for IT2FCM at present. How to obtain the fuzzifiers for IT2FCM by a simple and effective method has become an essential task.

To solve the initialization of cluster centers, several methods [17]–[21] are proposed. For example, Zhang and Wang [17] proposed a method in which initialized cluster centers are constituted by the main peaks of gray histogram by using peak detection and interval analysis. Qiu and Xiao [18] utilized the centroids calculated from multi-feature patterns to obtain the initialized cluster centers. Considering the advantages of simple implementation and parallel search in the solution space, particle swarm optimization (PSO) was introduced into clustering problems, in which cluster centers are automatically searched in the feasible region [19].

Aiming to determine appropriate cluster centers and fuzzifiers in IT2FCM simultaneously, an alternate particle swarm optimization-based adaptive interval type-2 intuitionistic fuzzy c-means (A-PSO-IT2IFCM) clustering algorithm is proposed and applied to color image segmentation in this paper. In order to fully process the uncertainty in images, an objective function with intuitionistic fuzzy information is first defined in this paper which takes the compactness of partitions and the separation of each class into consideration. Then a novel alternate optimization scheme based on PSO is presented to obtain the appropriate cluster centers and fuzzifiers alternatively. Moreover, considering that PSO is prone to fall into local optimization, a multiscale update strategy for the positions of particles is utilized in A-PSO-IT2IFCM to obtain the diverse swarm and improve the optimization efficiency. Experimental results reveal that the proposed method can obtain appropriate cluster centers and fuzzifiers, which bring satisfactory segmentation results.

The remainder of this paper is organized in four sections. Section II describes the theory of IT2FCM and PSO. Section III introduces the proposed A-PSO-IT2IFCM in detail. Section IV shows experimental results on Berkeley and UC Merced Land Use Datasets. Finally, the whole article is concluded in Section V.

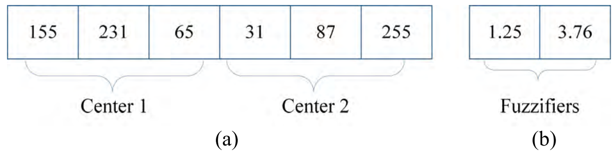

FIGURE 1. **Particle representation: (a) the particle of cluster centers; (b) the particle of fuzzifiers.**

II. PREVIOUS WORK

A. INTERVAL TYPE-2 FUZZY C-MEANS CLUSTERING ALGORITHM

IT2FCM is an extension of FCM and can handle more uncertainty in data than FCM [10], [22], [23]. In IT2FCM, the objective functions are constructed by using two different fuzzifiers m_1 and m_2 which represent different fuzzy degrees. They are defined as

$$\begin{cases} J_1(u,v) = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m_1}(x_i) d^2(x_i, v_j) \\ J_2(u,v) = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij}^{m_2}(x_i) d^2(x_i, v_j) \end{cases} \tag{1}$$

where N represents the number of data $X = \{x_1, x_2, \cdots, x_N\}$ and c is the number of clusters. $u_{ij}(x_i)$ represents the membership of the i^{th} pattern belonging to the j^{th} cluster. $d(x_i, v_j)$ denotes the Euclidean distance between the i^{th} pattern and the j^{th} cluster center. The upper and lower membership functions are expressed as (2), as shown at the bottom of this page.

In IT2FCM, Karnik-Mendel iterative algorithm is used to estimate the maximum value v_j^R and minimum valuev_j^L of the j^{th} cluster center [24]. When the iterative algorithm is performed, the left memberships $u_{ij}^L(x_i)$ and right memberships $u_{ij}^R(x_i)$ are computed according to each feature for a pattern. They are calculated as

$$u_{ij}^L(x_i) = \frac{\sum_{l=1}^{M} u_{il}}{M}, \quad u_{il} = \begin{cases} \bar{u}_{ij}(x_i), & \text{if } x_{il} \text{ uses } \bar{u}_{ij}(x_i) \text{ for } v_j^L \\ \underline{u}_{ij}(x_i), & \text{Otherwise} \end{cases} \tag{3}$$

$$u_{ij}^R(x_i) = \frac{\sum_{l=1}^{M} u_{il}}{M}, \quad u_{il} = \begin{cases} \bar{u}_{ij}(x_i), & \text{if } x_{il} \text{ uses } \bar{u}_{ij}(x_i) \text{ for } v_j^R \\ \underline{u}_{ij}(x_i), & \text{Otherwise} \end{cases} \tag{4}$$

$$\begin{cases} \bar{u}_{ij}(x_i) = \max\left\{ \left[\sum_{k=1}^{c}\left(\frac{d(x_i,v_j)}{d(x_i,v_k)}\right)^{\frac{2}{m_1-1}}\right]^{-1}, \left[\sum_{k=1}^{c}\left(\frac{d(x_i,v_j)}{d(x_i,v_k)}\right)^{\frac{2}{m_2-1}}\right]^{-1} \right\} \\ \underline{u}_{ij}(x_i) = \min\left\{ \left[\sum_{k=1}^{c}\left(\frac{d(x_i,v_j)}{d(x_i,v_k)}\right)^{\frac{2}{m_1-1}}\right]^{-1}, \left[\sum_{k=1}^{c}\left(\frac{d(x_i,v_j)}{d(x_i,v_k)}\right)^{\frac{2}{m_2-1}}\right]^{-1} \right\} \end{cases} \tag{2}$$

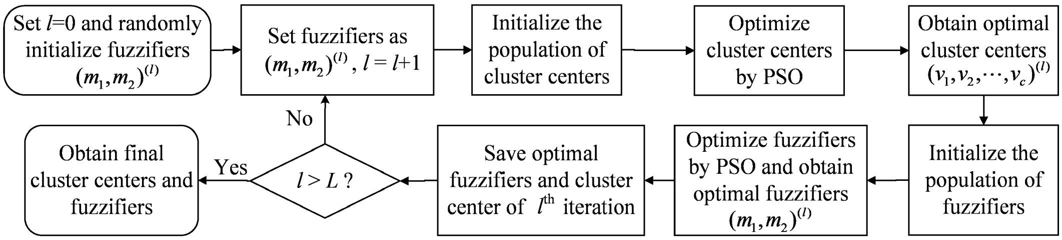

FIGURE 2. Cluster centers and fuzzifiers updating by using alternate particle swarm optimization.

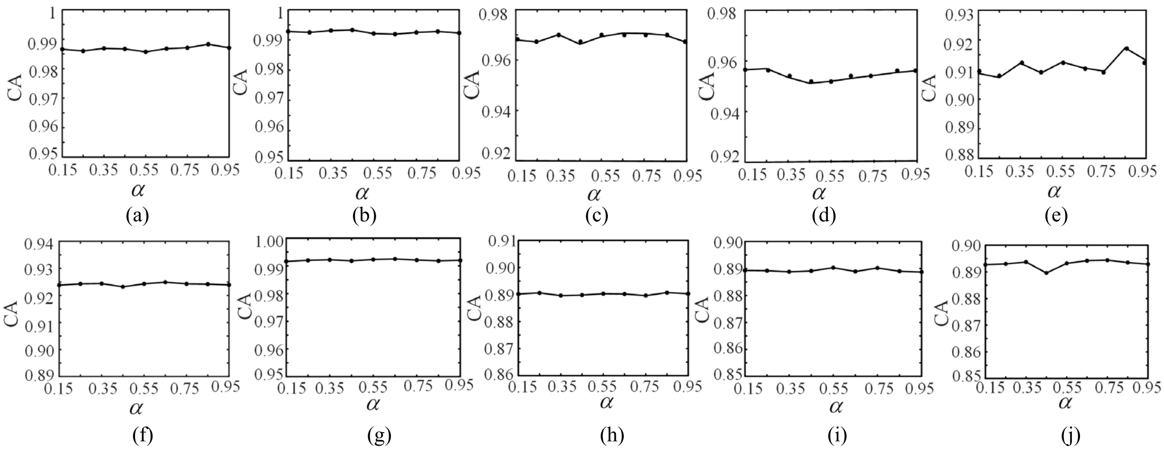

FIGURE 3. Changing trends of CA against the factor α on berkeley images: (a) #3096; (b) #3063; (c) #24063; (d) #238011; (e) #241004; (f) #15088; (g) #8068; (h) #135069; (i) #101027; (j) #113016.

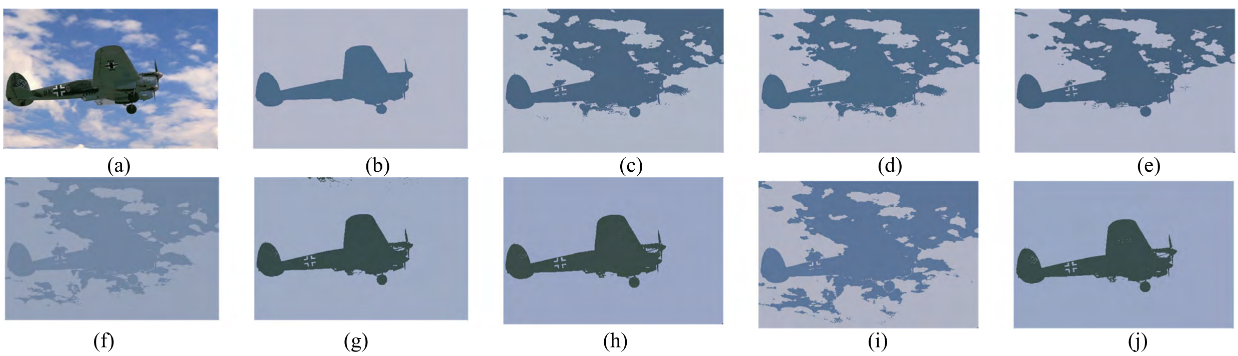

FIGURE 4. Segmentation results on berkeley #3063: (a) original image; (b) benchmark image; (c) FCM ($m = 2.00$); (d) IFCM ($m = 2.00$); (e) IT2FCMB^B ($m_1 = 1.10, m_2 = 2.00$); (f) IT2FCMW^W ($m_1 = 3.00, m_2 = 5.00$); (g) PSO-FCM ($m = 2.00$); (h) PSO-IT2IFCMB^B ($m_1 = 1.50, m_2 = 3.00$); (i) PSO-IT2IFCMW^W ($m_1 = 2.50, m_2 = 3.50$); (j) A-PSO-IT2IFCM.

where M denotes the number of features of a pattern. Then the crisp centroids and membership matrix can be obtained by type-reduction and defuzzification methods.

$$v_j = \frac{v_j^L + v_j^R}{2} \tag{5}$$

$$u_{ij}(x_i) = \frac{u_{ij}^R(x_i) + u_{ij}^L(x_i)}{2} \tag{6}$$

B. PARTICLE SWARM OPTIMIZATION

PSO is a classical optimization method proposed by Eberhart and Kennedy [25], [26]. In PSO, particles search around in the feasible solution space until all particles converge to the optimal solution. During this process, both the experimental knowledge of the particles and socially exchanged information from the particles' neighborhood are taken into consideration [27]. The search strategy can be expressed as

$$\begin{aligned} V_i(t+1) &= w \times V_i(t) + c_1 rand_1 \times (Pbest_i(t) - p_i(t)) \\ &\quad + c_2 rand_2 \times (gbest(t) - p_i(t)) \end{aligned} \tag{7}$$

$$p_i(t+1) = p_i(t) + V_i(t+1) \tag{8}$$

where V_i and p_i denote the velocity vector and position vector of the particle i, respectively. w is a weight factor, c_1 and c_2 are the acceleration coefficients, and t is the iteration counter. $rand_1$ and $rand_2$ represent two random numbers between 0 and 1. $Pbest_i$ denotes the best personal position of the particle i found so far and $gbest$ is the global optimal

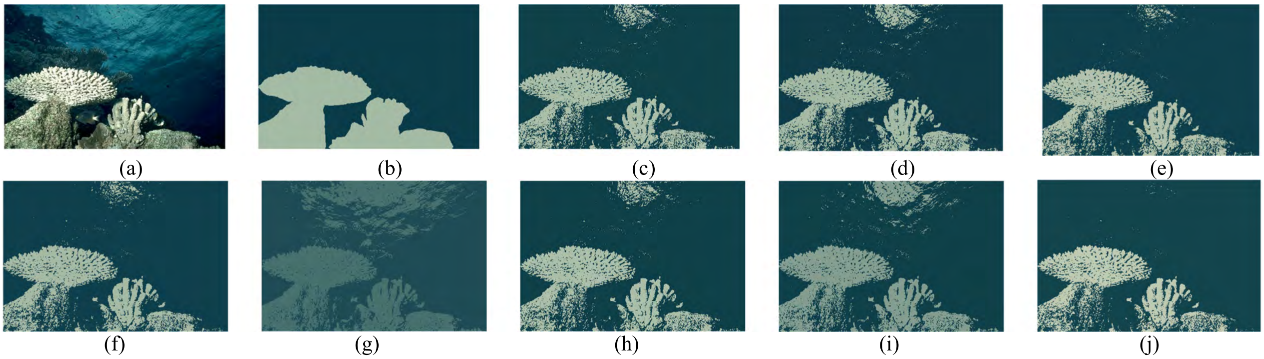

FIGURE 5. Segmentation results on berkeley #101027: (a) original image; (b) benchmark image; (c) FCM ($m = 2.00$); (d) IFCM ($m = 2.00$); (e) IT2FCMB^B ($m_1 = 1.10, m_2 = 2.00$); (f) IT2FCMW^W ($m_1 = 3.00, m_2 = 5.00$); (g) PSO-FCM ($m = 2.00$); (h) PSO-IT2IFCMB^B ($m_1 = 1.50, m_2 = 3.00$); (i) PSO-IT2IFCMW^W ($m_1 = 2.50, m_2 = 3.50$); (j) A-PSO-IT2IFCM.

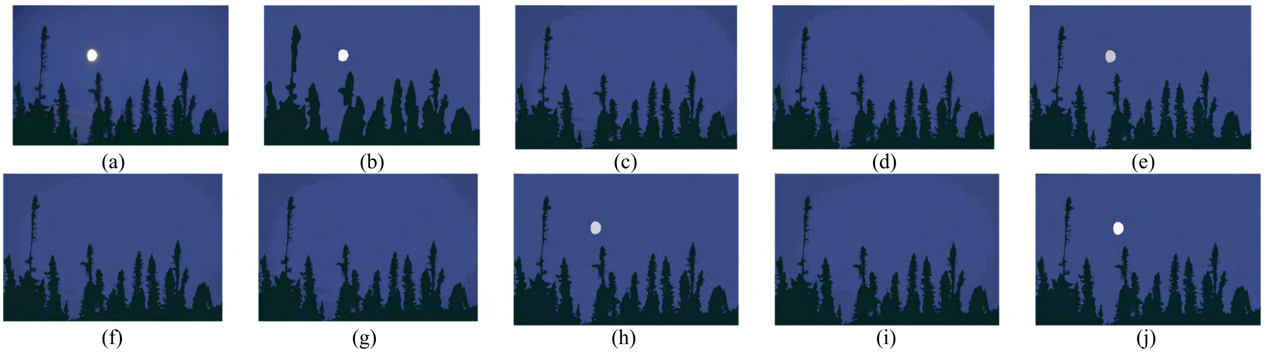

FIGURE 6. Segmentation results on berkeley #238011: (a) original image; (b) benchmark image; (c) FCM ($m = 2.00$); (d) IFCM ($m = 2.00$); (e) IT2FCM^B ($m_1 = 1.50, m_2 = 3.00$); (f) IT2FCM^W ($m_1 = 2.00, m_2 = 4.00$); (g) PSO-FCM ($m = 2.00$); (h) PSO-IT2IFCM^B ($m_1 = 1.50, m_2 = 3.00$); (i) PSO-IT2IFCM^W ($m_1 = 2.50, m_2 = 3.50$); (j) A-PSO-IT2IFCM.

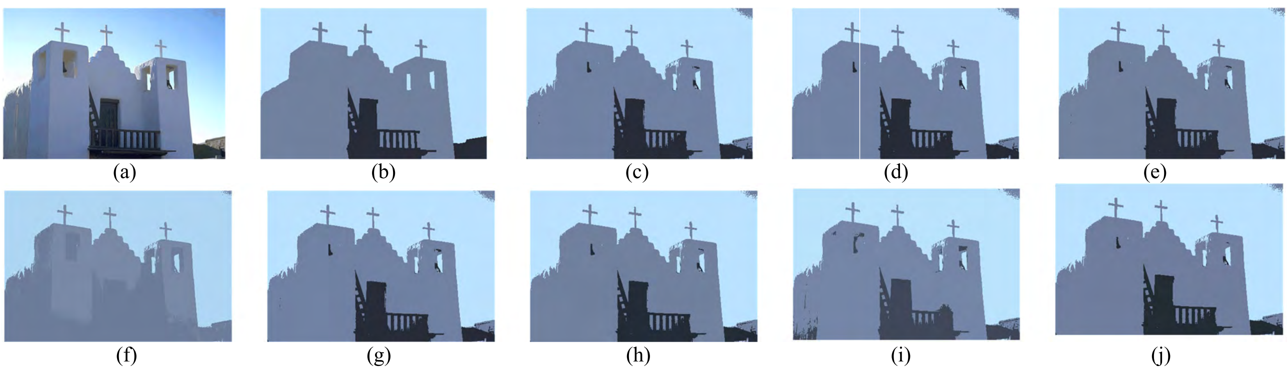

FIGURE 7. Segmentation results on berkeley #24063: (a) original image; (b) benchmark image; (c) FCM ($m = 2.00$); (d) IFCM ($m = 2.00$); (e) IT2FCM^B ($m_1 = 1.10, m_2 = 2.00$); (f) IT2FCM^W ($m_1 = 3.00, m_2 = 5.00$); (g) PSO-FCM ($m = 2.00$); (h) PSO-IT2IFCM^B ($m_1 = 1.10, m_2 = 2.00$); (i) PSO-IT2IFCM^W ($m_1 = 2.00, m_2 = 4.00$); (j) A-PSO-IT2IFCM.

position among the whole population. Considering the maximum problems, *Pbest* and *gbest* can be updated according to the following scheme:

$$\begin{aligned} &\text{If } Fit(p_i(t+1)) > Fit(Pbest_i(t)), \\ &\qquad \text{then } Pbest_i(t+1) = p_i(t+1); \\ &\text{If Fit}(p_i(t+1)) > Fit(gbest(t)), \\ &\qquad \text{then } gbest(t+1) = p_i(t+1). \end{aligned}$$

where $Fit(\cdot)$ represents the fitness function which is used to evaluate the positions of particles. The algorithm terminates after the difference in fitness values of $gbest(t)$ and $gbest(t+1)$ is less than a minimum threshold or a finite number of steps.

III. ALTERNATE PAERICLE SWARM OPTIMIZATION-BASED ADAPTIVE INTERVAL TYPE-2 INTUITIONISTIC FUZZY C-MEANS CLUSTERING ALGORITHM

How to initialize cluster centers and select the appropriate fuzzifiers are important tasks for IT2FCM. In this paper, an alternate particle swarm optimization-based adaptive interval type-2 intuitionistic fuzzy c-means clustering algorithm

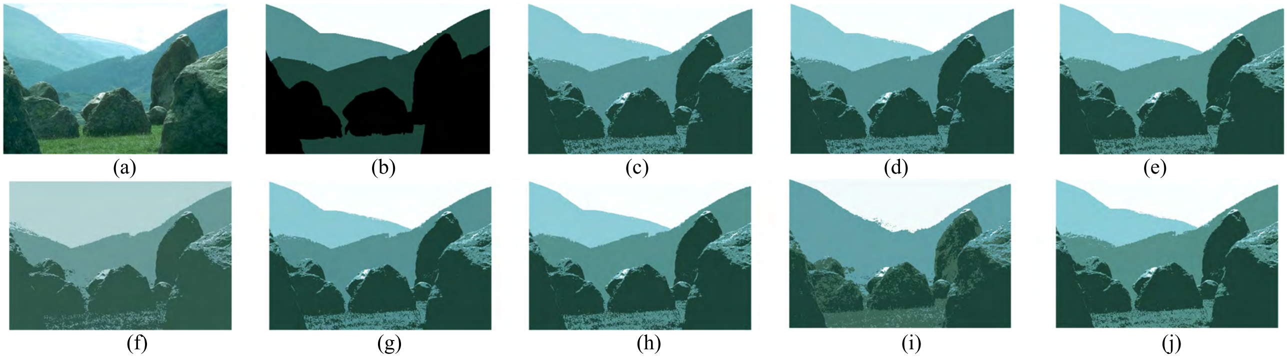

FIGURE 8. Segmentation results on berkeley #241004: (a) original image; (b) benchmark image; (c) FCM (m= 2.00); (d) IFCM (m= 2.00); (e) IT2FCM^{B} (m_1= 1.10, m_2= 2.00); (f) IT2FCM^{W} (m_1= 3.00, m_2= 5.00); (g) PSO-FCM (m= 2.00); (h) PSO-IT2IFCM^{B} (m_1= 1.10, m_2= 2.00); (i) PSO-IT2IFCM^{W} (m_1= 2.50, m_2= 3.50); (j) A-PSO-IT2IFCM.

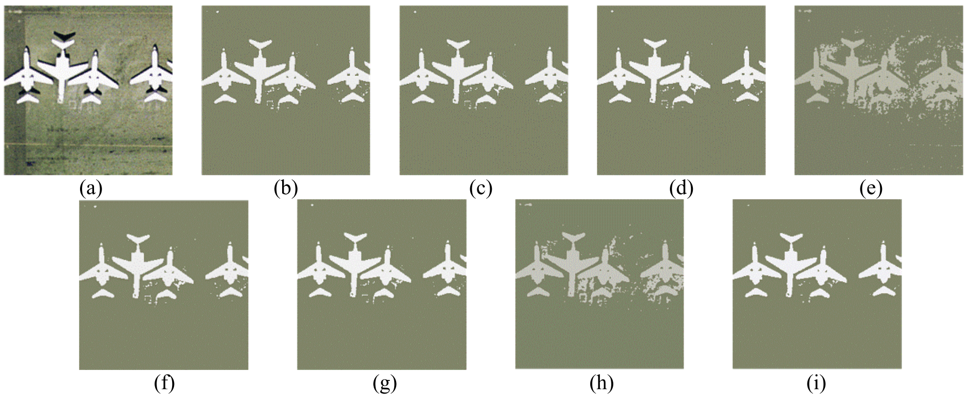

FIGURE 9. Segmentation results on #airplane39: (a) original image; (b) FCM (m= 2.00); (c) IFCM (m= 2.00); (d) IT2FCM^{B} (m_1= 1.10, m_2= 2.00); (e) IT2FCM^{W} (m_1= 3.00, m_2= 5.00); (f) PSO-FCM (m= 2.00); (g) PSO-IT2IFCM^{B} (m_1= 1.50, m_2= 3.00); (h) PSO-IT2IFCM^{W} (m_1= 2.00, m_2= 4.00); (i) A-PSO-IT2IFCM.

TABLE 1. Methods and the correspond parameter settings.

Method	Input Parameters	Appearance in
FCM	$m=2, T=100$	R. Ceylan et al. [8]
IFCM	$m=2, T=100, \alpha=0.85$	P. H. Thong et al. [33]
IT2FCM	m_1, m_2, T=100	C. Hwang et al. [10]
PSO-FCM	m=2, T=100, $pop=30$, $w=0.5$, $c_1=c_2=2, k=1$	L. Li et al. [34]
PSO-IT2IFCM	m_1, m_2, T=100, $pop=30$, $w=0.5$, $c_1=c_2=2$	Proposed in this paper
A-PSO-IT2IFCM	$T=10, L=10, pop=10, w=0.5$ $c_1=c_2=2, \alpha$	Proposed in this paper

(A-PSO-IT2IFCM) is proposed to solve these two problems. In this method, a novel alternate PSO-based scheme with the objective function with intuitionistic fuzzy information is designed to find the appropriate cluster centers and fuzzifiers in IT2FCM.

A. PARTICLE REPRESENTATION AND INITIALIZATION

In the proposed method, cluster centers and fuzzifiers are encoded as particles, respectively. For image segmentation, the cluster center particles are composed of real pixel values in an image and the fuzzifiers particles are random numbers in the range (1, 5]. For instance, Figure 1 shows a particle encoding cluster centers and fuzzifiers. The particle in Fig. 1(a) represents two cluster centers in the RGB space. {155, 231, 65} is cluster center 1 and {31, 87, 255} is cluster center 2. The particle in Fig. 1(b) is fuzzifiers combination. {1.25, 3.76} denotes $m_1 = 1.25$ and $m_2 = 3.76$. After decoding particles, fitness functions can be computed under above fuzzifiers and cluster centers.

B. FITNESS FUNCTION CONSTRUCTION

Let $X = \{x_1, x_2, \cdots, x_N\}$ denote an image. To deal with more uncertainty in the image, a novel interval type-2 fuzzy clustering fitness function with intuitionistic fuzzy information is designed as

$$f_{API} = (\frac{1}{c} \times \frac{E_1}{E_c} \times D_{\max})^2 \tag{9}$$

where c denotes the number of clusters. E_c denotes the interval type-2 fuzzy compactness of the partition. E_1 is the special case of E_c when c is equal to 1 and actually represents the difference between each pixel value and the pixel mean.

TABLE 2. CA and NMI of A-PSO-IT2IFCM and compared algorithms on berkeley images.

Image	Index	FCM	IFCM	IT2FCM^{B}	IT2FCM^{W}	PSO-FCM	PSO-IT2IFCM^{B}	PSO-IT2IFCM^{W}	A-PSO-IT2IFCM
#3063	CA	0.7291	0.7234	0. 7544	0.6666	0.9917	**0.9928**	0.6012	0.9923
	NMI	0.2510	0.2460	0.2727	0.2043	0.8935	**0.9068**	0.0665	0.9011
#3096	CA	0.9859	0.9863	0.9864	0.7625	0.9859	0.9873	0.9474	**0.9883**
	NMI	0.7231	0.7326	0.7322	0.1605	0.7231	0.7467	0.4512	**0.7481**
#15088	CA	0.9208	0.9235	0.9217	0.7832	0.9208	0.9232	0.9084	**0.9242**
	NMI	0.3406	0.3408	**0.3411**	0.1758	0.3406	0.3401	0.3225	0.3402
#135069	CA	0.7346	0.7261	**0.9918**	0.6504	0.7346	0.9916	0.7243	**0.9918**
	NMI	0.1224	0.1180	0.8121	0.0891	0.1224	0.8096	0.1191	**0.8122**
#8068	CA	0.8547	0.8622	0.8795	0.8545	0.8547	0.8632	0.8526	**0.8907**
	NMI	0.4528	0.4585	0.5079	0.4522	0.4528	0.4579	0.4463	**0.6154**
#67079	CA	0.8273	0.8308	0.8303	0.8273	0.8164	0.8307	0.8242	**0.8308**
	NMI	0.4467	0.4482	**0.4535**	0.4461	0.4469	0.4479	0.4457	0.4509
#86016	CA	0.8394	0.8518	0.8438	0.7651	0.8394	0.8653	0.8524	**0.8835**
	NMI	0.3927	0.4124	0.3994	0.3008	0.3927	0.4385	0.4143	**0.4692**
#100007	CA	0.8184	0.8248	0.8183	0.7651	0.8184	**0.8273**	0.8069	0.8248
	NMI	0.1454	0.1490	0.1453	0.1171	0.1454	**0.1496**	0.1407	0.1489
#101027	CA	0.8839	0.8847	0.8867	0.8218	0.8839	0.8867	0.8753	**0.8890**
	NMI	0.4351	0.4262	**0.4618**	0.2930	0.4351	0.4532	0.3870	0.4597
#113016	CA	0.8164	0.8475	0.8621	0.6880	0.8164	0.8677	0.5131	**0.8935**
	NMI	0.2786	0.3244	0.3509	0.1554	0.2786	0.3428	0.0781	**0.4235**
#238011	CA	0.8093	0.8245	0.9567	0.7982	0.8093	**0.9578**	0.7324	0.9554
	NMI	0.5600	0.5679	0.7327	0.5551	0.5600	**0.7342**	0.5304	0.7283
#118035	CA	0.9342	0.9355	0.9329	0.9268	0.9342	**0.9355**	0.9328	0.9351
	NMI	0.7572	0.7168	0.7628	0.7530	0.7572	0.7635	0.7569	**0.7647**
#24063	CA	0.9675	0.9679	0.9695	0.7357	0.9675	**0.9699**	0.9526	**0.9699**
	NMI	0.8393	0.8404	0.8490	0.6568	0.8393	0.8413	0.8041	**0.8497**
#241004	CA	0.9096	0.9104	0.9111	0.7326	0.9096	0.9108	0.9012	**0.9187**
	NMI	0.7618	0.7628	0.7659	0.6028	0.7618	0.7653	0.7422	**0.7667**
#42049	CA	0.9687	0.9684	0.9689	0.9680	0.9687	0.9686	0.9681	**0.9693**
	NMI	0.7295	0.7243	**0.7311**	0.7270	0.7295	0.7293	0.7268	0.7301
#167062	CA	0.9721	0.9243	0.9666	0.9602	0.9773	0.9320	0.8383	**0.9856**
	NMI	0.8835	0.8080	0.8719	0.8592	0.8951	0.8168	0.7397	**0.9072**
#181021	CA	0.9189	0.9207	0.9201	0.9139	0.9203	0.9200	0.9137	**0.9207**
	NMI	0.4430	0.4570	0.4536	0.4497	0.4522	0.4527	0.4485	**0.4572**
#147091	CA	0.9316	0.9286	0.9316	0.9290	0.9316	0.9316	0.9304	**0.9316**
	NMI	0.6312	0.6198	0.6442	0.6281	0.6438	0.6442	0.6296	**0.6472**

$D_{\max}$ measures the maximum fuzzy separation of the partition. E_c and $D_{\max}$ can be defined as

$$E_c = \sum_{i=1}^{N}\sum_{j=1}^{c} u_{ij} d_{IFS}^2(x_i, v_j) \tag{10}$$

$$D_{\max} = \max_{p,q=1}^{c} d_{IFS}^2(v_p, v_q) \tag{11}$$

where $d_{IFS}(x_i, v_j)$ is the intuitionistic fuzzy distance between x_i and v_j which can be calculated by

$$d_{IFS}(x_i, v_j) = sqrt((t(x_i) - t(v_j))^2 + (r(x_i) - r(v_j))^2 + (\pi(x_i) - \pi(v_j))^2) \tag{12}$$

where $t(\cdot)$, $r(\cdot)$ and $\pi(\cdot)$ denote the membership degree, non-membership degree and hesitation degree, respectively. In A-PSO-IT2IFCM, $t(x_i)$ is computed as the normalized value of x_i and $r(x_i)$ is computed by using Yager's function [28]

$$r(x_i) = (1 - t(x_i)^{\alpha})^{1/\alpha}, \quad 0 < \alpha < \infty \tag{13}$$

$\pi(x_i)$ can be obtained by

$$\pi(x_i) = 1 - t(x_i) - r(x_i) \tag{14}$$

The fuzzy membership degree u_{ij} can be obtained by type-reduction and defuzzification methods introduced in section II.A. In A-PSO-IT2IFCM, the upper and lower memberships under the intuitionistic fuzzy distance are calculated as (15), as shown at the bottom of next page.

C. ALTERNATE PARTICLE SWARM OPTIMIZATION OF CENTERS AND FUZZIFIERS

In A-PSO-IT2IFCM, a novel alternate optimization scheme based on PSO is presented to obtain cluster centers and fuzzifiers. The flowchart of this strategy is shown in Fig. 2. Firstly, two fuzzifiers $\{m_1, m_2\}$ are randomly initialized within the range of (1, 5]. Then the optimal cluster centers $v = \{v_1, v_1, \ldots, v_c\}$ are obtained by PSO-based optimization. Utilizing the obtained optimal cluster centers, the optimal fuzzifiers $m = \{m_1, m_2\}$ are further computed by PSO-based optimization method. This alternate PSO-based optimization process continues until reaching the maximum number T of iterations. This strategy can not only ensure the effect of the fuzzifiers in IT2FCM, but also find the appropriate combinations of fuzzifiers and cluster centers.

TABLE 3. The fuzzifiers obtained by A-PSO-IT2IFCM and compared algorithms on berkeley images.

Image	IT2FCM^{B}	IT2FCM^{W}	PSO-IT2IFCM^{B}	PSO-IT2IFCM^{W}	A-PSO-IT2IFCM
#3063	(1.10,2.00)	(3.00,5.00)	(1.50,3.00)	(2.50,3.50)	(1.32,1.58)
#3096	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.12,1.97)
#15088	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.24,1.94)
#135069	(1.10,2.00)	(3.00,5.00)	(1.50,3.00)	(3.00,5.00)	(1.02,1.96)
#8068	(2.50,3.50)	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(1.00,2.11)
#67079	(3.00,5.00)	(1.10,2.00)	(1.50,3.00)	(2.00,4.00)	(1.34,1.38)
#86016	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.50,3.50)	(1.36,1.45)
#100007	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.10,1.44)
#101027	(1.10,2.00)	(3.00,5.00)	(1.50,3.00)	(2.50,3.50)	(1.19,1.42)
#113016	(1.10,2.00)	(3.00,5.00)	(2.00,4.00)	(1.10,2.00)	(1.52,1.78)
#238011	(1.50,3.00)	(2.50,3.50)	(1.50,3.00)	(2.50,3.50)	(1.36,2.01)
#118035	(1.50,3.00)	(3.00,5.00)	(3.00,5.00)	(1.10,2.00)	(1.06,1.15)
#24063	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.13,1.25)
#241004	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.50,3.50)	(1.18,1.34)
#42049	(1.10,2.00)	(2.00,4.00)	(1.50,3.00)	(2.00,4.00)	(1.25,3.16)
#167062	(1.50,3.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.19,2.63)
#181021	(1.50,3.00)	(2.50,3.50)	(1.10,2.00)	(2.00,4.00)	(1.25,1.61)
#147091	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.59,1.71)

D. PSO BASED MULTISCALE INTERACTIVE LEARNING SCHEME

To improve the searching efficiency of alternate PSO-based strategy, a multiscale interactive learning scheme [29], [30] is introduced in A-PSO-IT2IFCM. Firstly, a learning factor η is used to change the step size according to the iteration number, and it is defined as

$$\eta(t) = e^{-2\tau} \times \cos(2\pi\theta) \times (1 - \frac{t}{T}) \tag{16}$$

where τ and θ are the Gaussian random numbers generated in [0, 1], t represents the current number of iteration and T denotes the maximum number of iterations in PSO method. In the early stage of search, the step size is large and particles search globally to avoid premature convergence. As the iteration number increases, the value of $\eta(t)$ decreases and particles converge near the optimal solution. The new position of the particle $p_i(t)$ is updated by

$$p_i(t+1) = p_i(t) + \eta(t) \times V_i(t+1) \tag{17}$$

It should be noticed that though the small value of $\eta(t)$ helps speeding up convergence, it easily reduces the diversity of swarm. This scheme adds weight information of other positions to improve $gbest$. It is defined as

$$gbest(t+1) = gbest(t) + \eta(t)(gbest(\chi) - gbest(t)) \tag{18}$$

where $gbest(t)$ is the best position of the swarm that has been found so far. $gbest(\chi)$ is the information from historical $gbest$ where χ is a randomly selected positive integer in $[1,\ t-1]$.

The introduction of multiscale update scheme can increase the diversity of swarm and promote fault tolerance of PSO. The framework of PSO based multiscale interactive learning scheme is given in Algorithm 1.

E. FRAMEWORK OF A-PSO-IT2IFCM

In this section, the framework of A-PSO-IT2IFCM is presented in Algorithm 2.

$$\begin{cases} \bar{u}_{ij}(x_i) = \max\left\{ \left[\sum_{k=1}^{c} \left(\frac{d_{IFS}(x_i, v_j)}{d_{IFS}(x_i, v_k)} \right)^{\frac{2}{m_1-1}} \right]^{-1}, \left[\sum_{k=1}^{c} \left(\frac{d_{IFS}(x_i, v_j)}{d_{IFS}(x_i, v_k)} \right)^{\frac{2}{m_2-1}} \right]^{-1} \right\} \\ \underline{u}_{ij}(x_i) = \min\left\{ \left[\sum_{k=1}^{c} \left(\frac{d_{IFS}(x_i, v_j)}{d_{IFS}(x_i, v_k)} \right)^{\frac{2}{m_1-1}} \right]^{-1}, \left[\sum_{k=1}^{c} \left(\frac{d_{IFS}(x_i, v_j)}{d_{IFS}(x_i, v_k)} \right)^{\frac{2}{m_2-1}} \right]^{-1} \right\} \end{cases} \tag{15}$$

TABLE 4. V_{pc} and V_{pe} of A-PSO-IT2IFCM and compared algorithms on UC merced land dataset.

Image	Index	FCM	IFCM	IT2FCM^B	IT2FCM^W	PSO-FCM	PSO-IT2IFCM^B	PSO-IT2IFCM^W	A-PSO-IT2IFCM
#airplane32	V_{pc}	0.9540	0.9493	0.9741	0.6933	0.9540	0.9412	0.3399	**0.9916**
	V_{pe}	0.1309	0.1405	0.0807	0.9174	0.1309	0.1832	1.5649	**0.0215**
# airplane35	V_{pc}	0.8187	0.8178	0.7046	0.5558	0.8187	0.8225	0.7247	**0.9442**
	V_{pe}	0.4868	0.4894	0.7379	1.0809	0.4868	0.4247	0.6213	**0.1427**
# airplane39	V_{pc}	0.9202	0.9204	0.8354	0.5230	0.9202	0.5407	0.5230	**0.9951**
	V_{pe}	0.2212	0.2205	0.4127	0.9618	0.2212	0.9086	0.9618	**0.0159**
# airplane42	V_{pc}	0.9742	0.9590	0.9860	0.7189	0.9742	0.9862	0.5489	**0.9921**
	V_{pe}	0.0839	0.1274	0.0501	0.6701	0.0839	0.0493	0.9175	**0.0271**
# airplane58	V_{pc}	0.7521	0.7549	0.6202	0.4235	0.7521	0.6356	0.3454	**0.8896**
	V_{pe}	0.6277	0.6134	0.8939	1.3719	0.6277	0.8566	1.5506	**0.3392**
#baseballdiamond07	V_{pc}	0.9145	0.8919	0.8410	0.7268	0.9145	0.8492	0.5210	**0.9691**
	V_{pe}	0.2247	0.2778	0.3949	0.6205	0.2247	0.3777	0.9654	**0.0779**
#baseballdiAmond11	V_{pc}	0.8244	0.8241	0.6435	0.5307	0.8244	0.5594	0.5074	**0.9538**
	V_{pe}	0.4178	0.4183	0.7634	0.9478	0.4178	0.9068	0.9880	**0.1259**
#golfcourse88	V_{pc}	0.9540	0.9476	0.8844	0.7560	0.9540	0.8923	0.5118	**0.9944**
	V_{pe}	0.1346	0.1505	0.3085	0.5484	0.1346	0.2907	0.9793	**0.0144**
#golfcourse89	V_{pc}	0.9687	0.9660	0.7911	0.6156	0.9687	0.8099	0.5027	**0.9925**
	V_{pe}	0.0962	0.1044	0.4830	0.8067	0.0962	0.4626	0.9946	**0.0192**
#harbor10	V_{pc}	0.9424	0.9155	0.9638	0.8204	0.9424	0.9536	0.7260	**0.9607**
	V_{pe}	0.1408	0.2283	0.0959	0.4283	0.1408	0.0964	0.6140	**0.0950**
#harbor53	V_{pc}	0.9312	0.9258	0.8825	0.6736	0.9312	0.8835	0.6927	**0.9603**
	V_{pe}	0.1725	0.1870	0.2963	0.7119	0.1725	0.2961	0.6733	**0.1012**
#beach18	V_{pc}	0.9483	0.9460	0.9716	0.6512	0.9483	0.9716	0.6705	**0.9970**
	V_{pe}	0.1504	0.1564	0.0920	0.7447	0.1504	0.0918	0.7120	**0.0084**
#beach25	V_{pc}	0.9248	0.9227	0.9570	0.6368	0.9248	0.9570	0.6603	**0.9768**
	V_{pe}	0.1983	0.2037	0.1263	0.7670	0.1983	0.1262	0.7268	**0.0643**
#river89	V_{pc}	0.8764	0.7037	0.9257	0.5629	0.8764	0.8120	0.5219	**0.9705**
	V_{pe}	0.3056	0.7082	0.2007	0.8947	0.3056	0.4489	0.9599	**0.0778**
#river90	V_{pc}	0.8395	0.8395	0.9003	0.5485	0.8395	0.9003	0.5485	**0.9150**
	V_{pe}	0.3880	0.3880	0.2611	0.9173	0.3880	0.2611	0.9173	**0.2217**

IV. EXPERIMENTAL STUDY

The experiments are conducted on real color images from Berkeley Segmentation Dataset [31] and Synthetic Aperture Radar (SAR) images from UC Merced Land Use Dataset [32]. In order to assess the effectiveness of the proposed A-PSO-IT2IFCM, FCM [8], intuitionistic fuzzy c-means (IFCM) clustering algorithm [33], IT2FCM [10], PSO-FCM [34] are adopted as comparison algorithms. In addition, in order to verify the effect of fuzzifiers obtained in the proposed method, the optimization steps of fuzzifiers is removed in the alternation particle swarm optimization strategy and this degradation version of A-PSO-IT2IFCM is called as PSO-IT2IFCM. Since FCM, IFCM, and IT2FCM are not based on swarm intelligent method, cluster centers are randomly initialized by user. In IT2FCM and PSO-IT2IFCM algorithms, some fixed combinations of fuzzifiers {(1.10, 2.00), (1.50, 3.00), (2.50, 3.50), (2.00, 4.00), (3.00, 5.00)} are used and the best and the worst results are presented in the experiments. Other parameters setting of all comparative methods are shown in Table 1.

Algorithm 1 PSO Based Multiscale Interactive Learning Scheme

Input: the size n of population, weight factor w, learning factor c_1 and c_2, maximum iteration T, initialize populations $P = (p_1, p_2, \cdots, p_n)$ and velocities $V = (V_1, V_2, \cdots, V_n)$.
Step 1. Calculate the objective function value of each p_i.
Step 2. Initialize $Pbest(0) = P$ and Set $t = 0$.
Step 3. $gbest(0) = p_i$, where p_i has the maximum value of objective function.
Step 4. While $t \leq T$
(a) Update particle velocities by using (7),
(b) Update positions by using (17) and calculate the objective function values of them,
(c) If $Fit(p_i(t+1)) > Fit(Pbest(t))$
$Pbest(t+1) = p_i(t+1)$
else $Pbest(t+1) = Pbest(t)$
If $Fit(p_i(t+1)) > Fit(gbest(t))$
$gbest(t+1) = p_i(t+1)$
else $gbest(t+1) = gbest(t)$
(d) Update $gbest$ by using (18) and $t = t + 1$
Output: The best position $gbest$ of the swarm.

Algorithm 2 Alternate PSO-Based Adaptive Interval Type-2 Intuitionistic Fuzzy c-Means Clustering Algorithm (A-PSO-IT2IFCM)

Input: Initialize parameters: population size n, weight factor w, learning factor c_1 and c_2, maximum iteration L.
Step 1. Randomly initialize fuzzifiers $(m_1, m_2)^{(0)} \in (1, 5]$ and set $l = 0$.
Step 2. Obtain the optimize cluster centers $(v_1, v_2, \cdots, v_c)^{(l)}$ by using Algorithm I under fuzzifiers $(m_1, m_2)^{(l)}$.
Step 3. Obtain the optimize fuzzifiers $(m_1, m_2)^{(l)}$ by using Algorithm I under above cluster centers $(v_1, v_2, \cdots, v_c)^{(l)}$.
Step 4. Save the optimal cluster centers $(v_1, v_2, \cdots, v_c)^{(l)}$ and fuzzifiers $(m_1, m_2)^{(l)}$ as a combination in archive and $l = l + 1$.
Step 5. If $l > L$, goto Step 6. Otherwise, goto Step 2.
Step 6. Obtain the optimal combination of cluster centers and fuzzifiers with the maximum value of objective function.
Output: Obtain the final segmentation result under the optimal combination.

A. PARAMETER ANALYSIS AND DISCUSSION

In the proposed method, the parameter α is used to construct the non-membership degree in the intuitionistic fuzzy information of each pixel. In this section, in order to discuss the effect of parameter α on the performance of A-PSO-IT2IFCM, the clustering accuracy (CA) [35] is utilized as the evaluation index and the parameter α is tested from 0.15 to 0.95 with the increment 0.1. CA measures the degree of similarity between the benchmark b and the obtained clustering r. It is defined as follows:

$$CA = \sum\nolimits_{i=1}^{N} \delta(b_i, map(r_i)) \big/ N \tag{19}$$

where N is the number of data, and b_i and r_i denote the true clustering label and the obtained clustering label of the i^{th} pattern, respectively. $map(\cdot)$ is the permutation relationship between a clustering label and a category label, and the maximum of $\delta(b_i, map(r_i))$ is selected.

Figure 3 shows the CA curves of A-PSO-IT2IFCM with the variations of α on ten Berkeley images. It can be found from these curves that the parameter α has no obvious influence on the final segmentation performance of the proposed method. In the following experiments, the parameter α is assigned to 0.85.

B. SEGMENTATION EXPERIMENTS ON BERKELEY IMAGES

In this section, A-PSO-IT2IFCM and other comparative methods are applied to segment Berkeley images. In order to assess the performance of these algorithms, two performance indices, CA and normalized mutual information (NMI) are adopted. NMI reflects the mutual information between the benchmark b and the obtained clustering r [36]. It is defined by

$$NMI = \frac{2MI(b; r)}{E(b) + E(r)} \tag{20}$$

where $MI(b;r)$ is the mutual information of b and r, $E(b)$ and $E(r)$ are the entropy of b and r, respectively.

The CA and NMI values of these algorithms are shown in Table 2. IT2FCM^{B} and $\text{PSO-IT2IFCM}^{\text{B}}$ are best segmentation results and IT2FCM^{W} and $\text{PSO-IT2IFCM}^{\text{W}}$ are worst segmentation results under different fuzzifiers combinations. Table 2 reveals that A-PSO-IT2IFCM outperforms other methods on most images. The fuzzifiers automatically obtained by A-PSO-IT2IFCM and the fuzzifiers corresponding to the best and worst results of IT2FCM and PSO-IT2IFCM are presented in Table 3. It is shown that the proposed method can automatically obtain effective and different fuzzifiers combinations for different images.

In order to further highlight the visual segmentation performance of all comparative methods, the segmentation results of #3063, #101027, #238011, #24063, and #241004 are shown in Figs. 4-8. It is easy to see that the proposed approach can obtain better performance on images with more complex background. As shown in Figs. 4 and 5, FCM, IFCM, IT2FCM and PSO-IT2IFCM with inappropriate fuzzifiers cannot segment the airplane and coral from images. PSO-FCM misclassifies some pixels at the top of the image. A-PSO-IT2IFCM and PSO-IT2IFCM with appropriate fuzzifiers can well segment the object and produce fewest misclassified pixels in the background. For #238011, only A-PSO-IT2IFCM and IT2FCM^{B} can well segment the moon and tree from this image. The segmentation performance of all comparison methods are almost the same (shown in Figs. 7 and 8).

TABLE 5. The fuzzifiers obtained by A-PSO-IT2IFCM and compared algorithms on UC merced land dataset.

Image	IT2FCM^B	IT2FCM^W	PSO-IT2IFCM^B	PSO-IT2IFCM^W	A-PSO-IT2IFCM
#airplane32	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.32,1.58)
#airplane35	(1.50,3.00)	(2.00,4.00)	(1.50,3.00)	(2.50,3.50)	(1.12,1.97)
#airplane39	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(2.00,4.00)	(1.24,1.94)
#airplane42	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.02,1.96)
#airplane58	(1.50,3.00)	(2.00,4.00)	(1.50,3.00)	(2.00,4.00)	(1.01,2.11)
#baseballdiamond07	(1.50,3.00)	(2.00,4.00)	(1.50,3.00)	(2.00,4.00)	(1.34,1.38)
#baseballdiamond11	(2.50,3.50)	(3.00,5.00)	(2.50,3.50)	(3.00,5.00)	(1.40,1.45)
#golfcourse88	(1.50,3.00)	(2.00,4.00)	(1.50,3.00)	(3.00,5.00)	(1.10,1.44)
#golfcourse89	(2.00,4.00)	(3.00,5.00)	(2.00,4.00)	(3.00,5.00)	(1.19,1.42)
#harbor10	(1.10,2.00)	(2.00,4.00)	(1.10,3.00)	(3.00,5.00)	(1.52,1.78)
#harbor53	(1.50,3.00)	(3.00,5.00)	(1.50,3.00)	(3.00,5.00)	(1.36,2.01)
#beach18	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.06,1.15)
#beach25	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.13,1.25)
#river89	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.18,1.34)
#river90	(1.10,2.00)	(3.00,5.00)	(1.10,2.00)	(3.00,5.00)	(1.09,1.46)

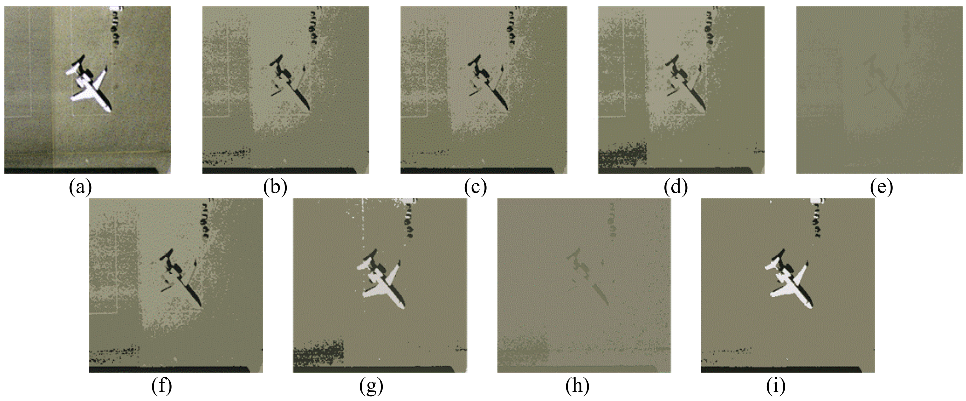

FIGURE 10. Segmentation results on #airplane58: (a) original image; (b) FCM (m= 2.00); (c) IFCM (m= 2.00); (d) IT2FCM^B (m_1= 1.50, m_2= 3.00); (e) IT2FCM^W (m_1= 2.00, m_2= 4.00); (f) PSO-FCM (m= 2.00); (g) PSO-IT2IFCM^B (m_1= 1.50, m_2= 3.00); (h) PSO-IT2IFCM^W (m_1= 2.00, m_2= 4.00); (i) A-PSO-IT2IFCM.

The results of color images clearly prove that the proposed A-PSO-IT2IFCM approach can not only adaptively obtain the appropriate fuzzifiers but also outperforms FCM, IFCM, IT2FCM, PSO-FCM, and PSO-IT2IFCM approaches in terms of evaluation indexes and segmentation results.

C. SEGMENTATION EXPERIMENTS ON SAR IMAGES

In this section, 15 SAR images selected from UC Merced Land Use Dataset are used to testify the performance of A-PSO-IT2IFCM and other comparative algorithms. UC Merced Land Use Dataset is a 21 class land use image dataset meant for research purposes. There are 100 images for each class [32]. Because there are no benchmark images, the unsupervised evaluation indexes partition coefficient (V_{pc}) and partition entropy (V_{pe}) [37] are utilized to evaluate the segmentation results. They are defined as:

$$V_{pc} = \frac{\sum_i^N \sum_j^c u_{ij}^2}{N} \tag{21}$$

$$V_{pe} = \frac{-\sum_i^N \sum_j^c [u_{ij} \log u_{ij}]}{N} \tag{22}$$

where u_{ij} is the membership degree value. Partitions with the maximum of V_{pc} and minimum of V_{pe} represent that the corresponding result is satisfying. Because larger fuzzifiers will lead to smaller V_{pc} and larger V_{pe}, so these two indexes are not suitable for IT2FCM and PSO-IT2IFCM to select fuzzifiers. In this section, the fuzzifiers combinations are still {(1.10, 2.00); (1.50, 3.00); (2.50, 3.50); (2.00, 4.00); (3.00, 5.00)}. The best and worst fuzzifiers of IT2FCM and PSO-IT2IFCM are selected according to visual segmentation results. V_{pc} and V_{pe} values of A-PSO-IT2IFCM and comparison algorithms on SAR images are presented in Table 4. Moreover, fuzzifiers combinations for SAR images obtained by the proposed method and compared methods are shown in Table 5. As shown in Table 4, A-PSO-IT2IFCM outperforms other methods in terms of fuzzy partition coefficient and partition entropy on these images.

The segmentation results of #airplane39 and #airplane58 are selected to present the visual results and are shown in Figs. 9-10. In Fig. 9, all comparative methods can segment four airplanes from the image and only A-PSO-IT2IFCM can remove more noise around the airplane. In Fig. 10, FCM, IFCM, IT2FCM, and PSO-FCM misclassify some parts of the airplane. Although PSO-IT2IFCM segment the airplane well, its result still contain some noisy pixels. Among all comparison algorithms, A-PSO-IT2IFCM obtains the most satisfying segmentation result.

V. CONCLUSION AND REMARKS

The settings of appropriate fuzzifiers and cluster centers are essential tasks for IT2FCM. To effectively solve these problems, an alternate particle swarm optimization-based adaptive interval type-2 intuitionistic fuzzy c-means clustering algorithm (A-PSO-IT2IFCM) is proposed for color image segmentation. Firstly, in order to further deal with the uncertain information in images, a novel interval type-2 intuitionistic fuzzy clustering objective function is defined in A-PSO-IT2IFCM by extracting the intuitionistic fuzzy information from the image. Then, an alternate particle swarm optimization strategy is designed in A-PSO-IT2IFCM to adaptively obtain the appropriate cluster centers and fuzzifiers. Meanwhile, the introduction of multiscale interactive learning scheme in A-PSO-IT2IFCM can guarantee the swarm diversity and avoid premature convergence. Experimental results on images from Berkeley Segmentation and UC Merced Land Use Datasets show that A-PSO-IT2IFCM can adaptively determine the cluster centers and fuzzifiers and obtain good segmentation results.

Actually, most images are complicated and contain noise. How to avoid the influence of noise is a very important task for our proposed method. Moreover, in order to deal with more complex images, the multi-objective optimization method can be introduced into our algorithm in the future work.

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