

# Multi-agent Remote Sensing Image Segmentation Algorithm

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**Abstract**—Due to fractal network evolution algorithm (FNEA) in the treatment of the high spatial resolution remote sensing image (HSRI) using a parallel global control strategies which limited when the objects in each cycle by traversal of and not good use the continuity of homogenous area on the space and lead to problems such as bad image segmentation, therefore puts forward the remote sensing image segmentation algorithm based on multi-agent. The algorithm in the merger guidelines, combining the image spectral and shape information, and by using region merging process of multi-agent parallel control integral, its global merger control strategy can ensure algorithm has the advantages of parallel computing and fully considering the regional homogeneity, and continuity. Finally simulation experiment was performed with FNEA algorithms, experimental results show that the proposed algorithm is better than FNEA algorithm in dividing the overall effect, has a good stability.

**Index Terms**—Diffusion; Breed; Agent; Parallel Computation

## I. INTRODUCTION

Multi-agent system is a collection of multiple agents; its goal is to transform large and complex system into small, communication and coordination to each other, easy to management system [1]. Its studies involve the agent's knowledge, goals, skills, planning and how to make the agent to take concerted action to solve problems. Researchers mainly study the interaction communication between the agent, coordination and cooperation, conflict resolution, etc., emphasized cooperation group between multiple-agent, rather than the autonomy and play of individual ability, mainly illustrate how to analyze, design, and integrate multiple agent to constitute cooperation system [3-6].

High spatial resolution remote sensing image (HSRI) has rich texture information and shape information, compared with the low resolution image, can get more sophisticated surface feature information [7-9]. However, with the improvement of spatial resolution images, spectrum distribution of features in images is more complex, and of different feature spectrum overlapping, feature information present highly details, the feature classes internal variance in images increases, variance in different features classes decreases, and these characteristics make computer interpretation way must be

transform from the traditional way of pixels oriented spectrum processing to object oriented multi features approach [10-12]. Object-oriented approach is usually obtained multiple pixel object by spatial adjacent, spectral similar through image segmentation. Image segmentation, on the one hand reduces the feature classes internal variance, on the other hand can provide computer interpretation texture and shape information of object, increase the variance between feature classes, to increase the separable of feature category, and to increase the accuracy of classification and identification [13].

For remote sensing image segmentation algorithms, such as regional growth and watershed algorithm is mostly aimed at SAR (Synthetic Aperture Radar) images and middle and low resolution remote sensing images, such as TM and SPOT images, for high resolution remote sensing image segmentation, the research is relatively small [14]. Along with the development of remote sensing technology, the earth resource satellite place provided remote sensing image has higher spatial resolution, breakthrough m level resolution remote sensing image data, have been able to distinguish clearly the details of the ground characteristics, thus in the agricultural, forest, mining, environmental current situation survey, and other social fields has a broad application market [15]. At present, with high spatial resolution remote sensing image automatic analysis and understanding technology, especially the segmentation technology is still very immature, large amount of information in the images can't get the full application [16].

Commonly used remote sensing image segmentation algorithms are mainly the segmentation method based on edges and the segmentation method based on region. Due to the complexity of remote sensing image feature category, the segmentation method based on the edge tends to has not a closed area, is not conducive to extract HSRI object information. Commonly used segmentation algorithm based on region has split-merge algorithm, based on morphological watershed algorithm and fractal network evolution algorithm. Split-merge algorithm is a kind of high efficiency based on quad-tree segmentation method, but it can't make full use of regional homogeneity, and continuity, for feature complex remote sensing image, segmentation effect is poorer; Based on morphological watershed algorithm makes gradient

amplitude figure of image as a topographic map, pixel gradient amplitude value as a pixel altitude, the affect region of each local gradient amplitude minimum form a reception basin, the boundary of reception basin is watershed, but the watershed algorithm is sensitive to remote sensing image weak edge , easy to produce serious over-segmentation phenomenon, through the pre-processing, notation, post-processing methods improve the usability of the algorithm [17]. FNEA algorithm based on local optimum objects merge criterion, combined with the spectral information and shape information of the object to identify, can get better segmentation result. In addition, with the development of computer science, artificial intelligence, and other fields, a large number of new theories and methods, such as fuzzy sets, neural networks, graph theory and level set, morphological theory, has been introduced into the segmentation, the domestic and foreign scholars put forward many threshold fuzzy automatic segmentation, pulse coupled neural network segmentation, graph theory segmentation based on minimum spanning tree, multidimensional level set segmentation, average drift segmentation, improve HSRI segmentation effect. The above segmentation algorithm, FNEA method has been widely used as HSRI core segmentation algorithms in software processing. However, this method uses a parallel global control strategy that restricts each cycle subject by traversal, can not good use of the continuity of homogenous area on the spatial.

In order to improve the effect of HSRI segmentation, this paper proposes a high resolution remote sensing image segmentation algorithm based on multi-agent theory (MARSS). Multi-agent theory (multi - agent) has parallel computing ability and high flexibility in the global control , make its more efficient in processing engineering problems, has been successfully applied to image segmentation, communications, medical image processing and other fields.

This paper mainly in the following aspects as the development and innovative work:

(a) According to the fractal network evolution algorithm is used when dealing with high spatial resolution remote sensing image is to restrict objects in each cycle by traversal of a parallel global control strategies and not good use the continuity on the space of homogenous area, resulting in image segmentation result is bad and poor stability, at the same time because of the multi-agent theory in the global control with parallel computing ability and high flexibility, make its more efficient in processing engineering problems, therefore puts forward the remote sensing image segmentation algorithm based on multi-agent. The algorithm in the merger guidelines combine image spectral and shape information, and by using multi-agent parallel control integral region merging process, in its global merger control strategy can ensure algorithm has the advantages of parallel computing and fully considering the regional homogeneity, and continuity.

(b) in order to further validate the correctness and validity of remote sensing image segmentation algorithm

based on multi-agent is proposed in this paper, , a simulation experiment was performed with FNEA algorithms, the contrast evaluation method of high spatial resolution remote sensing image segmentation result adopted the unsupervised evaluation method, the experiment using two groups of data sets of high spatial resolution remote sensing image, a set of Sanya of Hainan province village area, another group is in the Beijing area, the experimental results show that: compared with FNEA, although this algorithm of large difference area of the same material will produces the over-segmentation phenomenon, but algorithms in this paper for small physical differences area, segmentation effect is better. General score (GS)evaluation index taking overall result evaluation to the segmentation results, GS value of this paper is lower than FNEA algorithm, the overall effect is better. Through the intelligent initialization number parameter analysis to this paper's algorithm shows that this algorithm has better stability, and the segmentation result is better than FNEA algorithm as a whole.

## II. PROPOSED ALGORITHM

Agent derived from the concept of people's knowledge of artificial intelligence, has been widely used in physics, biology, computer, social and other fields in complex system simulations. Agent perceive environment, according to the accessed environmental information and their own status, effects on environment, makes there exist very strong interactivity and flexibility in the agent and the environment. At the same time, when many agent working at the same time, there is maintained strong independence between the agents, make the multi-agent has the characteristics of parallel computing in the global control.

Based on the multi-agent system strong interaction with the environment, the advantages of high flexibility, parallel control, using multi-agent diffusion, copy, reproduce, etc. Operator proposed high resolution remote sensing image segmentation method based on multi-agent theory (MARSS). In order to facilitate MARSS methods described, explained for the following variables:

(a) To split HSRI  $e_s = \{r_1, r_2, \dots, r_n\}$  is the working environment of MARSS algorithm,  $r_n$  as the  $n_{th}$  pixel in the image, N is number of image pixels, and when initialization, each pixel  $r_n$  was regarded as a figure spot object;

(b) The figure object collection of high resolution image segmentation is  $o = \{o_1, o_2, \dots, o_t\}$ ,  $o_t$  is the first figure spot  $T$  is the total number of figure spot;

(c) The agent set  $AG = \{Ag_1, Ag_2, \dots, Ag_n\}$ , each agent  $Ag_n$  contains perception  $p_n$ , merger object rules  $r_n$  and  $a_{sn}$  status attribute and behavior collection  $a_{cn}$  4 parts, the specific meaning in the MARSS method as shown in table 1.  $p_n$  and  $a_{sn}$  embodies the strong interactions of agent and image, the setting of  $a_{sn}$  and  $a_{cn}$  makes agent more flexible in the segmentation.

TABLE I. MULTI-AGENT THEORY AND MARSS VARIABLES CORRESPONDING INSTRUCTION

Multi-agent theory	MARSS
Multi-agent set AG	For intelligent AG segmentation
Intelligent individual $Ag_n$	$Ag_n$ Said search the segmentation process executive
Perceptron $p_n$	$p_n$ as Intelligent individual $Ag_n$
Ruler $r_n$	$r_n$ as Intelligent individual $Ag_n$
Status attribute $a_{sn}$	$a_{sn} = (a_r, p_r, p_o, c)$
Action $a_{sn}$	$a_{sn} = \{a_1, a_2, a_3\}, a_1, a_2, a_3$ Representing the diffusion behavior, reproduction, death, for the search, combined with object, state attribute update agent.

For the convenience of description of MARSS theory, take picture 1 for an example to describe the algorithm process. In the whole process of image segmentation, an arbitrary agent  $a_{gn}$  in multi-agent system in different environment, through the behavior such as diffusion, reproduction, death search the mutual best merge objects, and with mutual best merger guidelines as object determination criterion for the combining operation, finally achieve the goal of segmentation. Specific as follow:

A. Initialization

When initialization (figure 1 (a)), the multi-agent system uses a certain distribution way (such as uniform distribution) makes multi-agent distributed in figure spot object collection  $o = \{o_1, o_2, \dots, o_t\}$ , initialize each pixel is a spot. At this point, the perception of agent  $Ag_n$ ,  $p_n$  pointing to the corresponding objects o T, at the same time state attribute  $((a_e, p_r, p_o, c) = (0, \text{false}, \text{true}, \text{true}))$ .

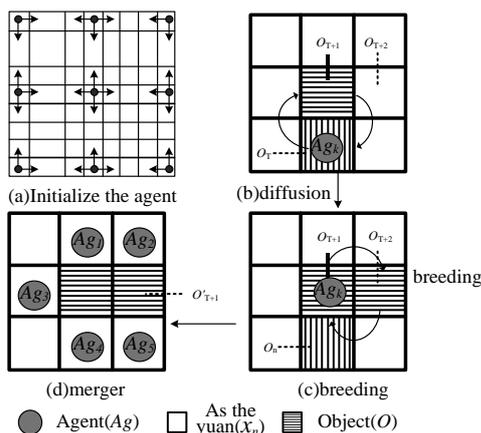


Figure 1. Is a merge strategy controlled by Multi-agent

B. The Behavior of the Multi-agent

After the initialization, MARSS through the agent's behavior such as diffusion, reproduction, death for split operation.

1) Agent Spread

According to  $r_n$ , assuming that  $Ag_n$  find candidates for merging of  $o_i, o_i+1$ , but the candidate merger object of  $o_i+1$  is not  $o_i$  (figure 1 (b)),  $o_i$  and  $o_i+1$

have large heterogeneity,  $Ag_n$  selective diffusion behavior (figure 1 (c)).  $Ag_n$  spread to  $o_i+1$ , namely the  $p_n$  point to  $o_i+1$ ,  $Ag_n$  age increase at the same time, the other properties remain unchanged, the expression as type (1), among them, the  $o_{\min}(o_i)$  represents best combined object identifier

$$b_1 : p(Ag_n) \rightarrow o_i + 1, r_e(Ag_n) \leftarrow r_e(Ag_n) + 1 \quad (1)$$

if  $o_i + 1 = o_{\min}(o_i)$  and  $o_i \neq o_{\min}(o_i + 1)$

2) Agent Spawn

When the candidate merger object that the  $Ag_n$  referred to object  $o_i+1$  is  $o_i+2$ , at the same time  $o_i+2$  is  $o_i+1$  candidates for merging, which can meet the mutual best merger object condition, then the  $Ag_n$  choose reproduction (figure 1 (c)) reproduce offspring agent, and the child agent join to the original agent collection, at the same time  $Ag_n$  merger  $o_i+1$  and  $o_i+2$  (figure 1 (d)), make the  $p_r = \text{true}$ , its expression as shown on the type (2). Among them, the  $\{Ag_n\}_m$  is the offspring intelligence collection that  $Ag_n$  reproduce,  $m$  is the number of objects adjacent with  $Ag_n$ , and  $o_i+1$  as the new object after merge.

$$b_2 : Ag \leftarrow \{Ag_n\}_m, o_i + 1 = \{o_i + 1, o_i + 2\}, p_r = \text{true} \quad (2)$$

if  $o_i + 2 = o_{\min}(o_i + 1)$  and  $o_i + 1 = o_{\min}(o_i + 2)$

3) Agent Death

When  $Ag_n$  that pointing to  $o_i$  to satisfy any of the following four conditions,  $Ag_n$  choose death,  $Ag_n$ s are cleared from the agent collection, its expression as shown in type (3)

$$a_3 : Ag \leftarrow Ag \setminus \{Ag_n\} \quad (3)$$

- (1) Age properties of  $(Ag_n, a)$  exceeds the specified agent age of  $(t_h)$ , namely  $a_e > t_h$ .
- (2)  $Ag_n$  has chosen a reproductive behavior, namely,  $p_r = \text{true}$ .
- (3)  $Ag_n$  could not find the candidates for merging of  $o_i, o_i+1$ , namely  $c = \text{false}$ .
- (4)  $o_i$ , the pointed object of  $Ag_n$  has been incorporated into the other object, namely the  $P_o = \text{false}$ .

Agent behavior need to set up two parameters: the agent age  $t_h$  and agent initialization number n. Among them, choice principles of  $t_h$  for all agents have the ability to traverse the entire image range when diffusion, so  $t_h$  to meet  $4N > N$ , N for image size, when  $t_h$  exceeds a certain value, the effects on the segmentation result is very small. Under a certain distribution, parameter n determines the referents of agent perception  $p_n$ .

C. The Mutual Best Merge Criteria

Agent need according to the appropriate criteria for judging whether the object is the best combination object, MARSS algorithm in three different behaviors in the segmentation process are adopting mutual best merge norms as the agent objects merge rule  $r_n$ . Mutual best merge criteria include two parts: judgments of candidates for merging, determination of mutual best merge objects.

1) Candidates for Merging

In the mutual best merger guidelines, the determination of candidates for merging sees type (4). According to (4) and (5) ~ (9), agent use the spectral information of pattern spot objects (type (6)) and shape information (type (7) - (9)) to find the candidates for merging.

$$o_{\min} = \arg \min \{c(o_i, o_i + j)\}, o_i + j \in N(o_i) \quad (4)$$

$$o_{\min}^* = o_{\min}, \text{ if } c(o_i + j, o_{\min}) \leq \text{scale}^2$$

In the formula, as candidates for merging;  $o_i$  is the object  $p_n$  pointing to;  $o_i + j$  for  $o_i$  adjacent objects; Scale for the scale of segmentation.  $B(o_i, o_i + j)$  for the  $o_i$  and  $o_i + j$ ,  $j$  merger cost, calculation methods as shown in (5). Merger cost function contains spectral information merge costs CCLR ( $o_i, o_i + j$ ) and shape information merging cost CSHP ( $o_i, o_i + j$ ), the calculation formula respectively for type (6) with type (7), WSHP for the shape information weight

$$B(o_i, o_i + j) = \varpi_{shp} c_{shp}(o_i, o_i + j) + o_i, (1 - \varpi_{shp}) c_{shp}(o_i, o_i + j), \varpi_{shp} \in [0, 1] \quad (5)$$

$$c_{clr}(o_i, o_i + 1) = \sum_{j=1}^c \varpi_i (l_{mrk} \theta_i^k - j_i \theta_i^k) \quad (6)$$

$$c_{shp}(o_i, o_i + j) = \varpi_{cmp} c_{cop}(o_i, o_i + 1) + (1 - \varpi_{cmp}) c_{smk}(o_i, o_i + j), \varpi_{cmp} \in [0, 1] \quad (7)$$

Type (6),  $o_i^k, o_{i+j}^k, o_{mrg}^k$  respectively respect  $o_i, o_i + j$  and standard deviation that combined objects o m r g in k band contained pixel;  $n_i, n_i + j, n_{mrg}$  represent the number of pixel in  $o_i, o_i + j, o_{mrg}$ ; B represents the band number of image;  $w_k$  for the weight of the first k band. In type (7), containing the compact degree merger price of the object CCMP ( $o_i, o_i + j$ ) and smoothness combined price CSMH ( $o_i$  and  $o_i + j$ ), calculation formula respectively type (9) and (8), WCMP for compact degrees weight coefficient. In type (8)  $l_i, l_i + j, l_{mrg}$  respectively the perimeter of  $o_i, o_i + j, o_{mrg}$ . In type (9),  $b_i$ , respectively the perimeter of the external rectangle  $o_i, o_i + j, o_{mrg}$ .

$$c_{cmp}(o_i, o_i + j) = n_{mrg} \frac{l_{mrg}}{\sqrt{n_{mrg}}} - n_i \frac{l_i}{\sqrt{n_i}} - n_i + j \quad (8)$$

$$c_{smh}(o_i, o_i + j) = n_{mrg} \frac{l_{mrg}}{b_{mrg}} - n_i \frac{l_i}{b_i} - n_i + j \quad (9)$$

Candidates for merging determine formula of agent at the same time, taking into account the image spectral information and shape information, you need to set up four parameters: the first k band weighting  $w_k$ , shape weight WSHP, compact degree weight WCMP, segmentation scale. In segmentation,  $w_k$  assignment according to the importance of spectrum, a band is important, the weight is heavy. Due to split information is indispensable of the spectra, WSHP value not more than 0.9. WCMP can choose according to feature state, when feature is compact, choose larger value, when features are dispersive, choose smaller value. Scale controls the final figure spot size, larger Scale values; finally get the figure spot correspondingly larger.

2) Determination of Mutual Best Merge Objects

(1) The search for candidate merges objects. For a scale, according to the type (4), if  $o_i$  candidates for merging is  $o_i + 1$ .

(2) Determine the mutual best merge object. According to (4), if the ( $o_i + 1$ ) candidate merger object is  $o_i, o_i$  and  $o_i + 1$  are the mutual best combined object.

D. Segmentation Algorithm

MARSS algorithm process is shown in figure 2.

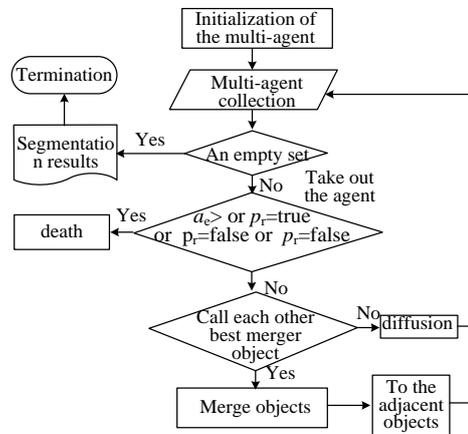


Figure 2. MARSS algorithm flow chart

(a) Initialization. Each pixel  $x \in N$ , initialized to a figure spot  $o_n$ , get set  $O = \{o_1, o_2, \dots, o_n\}$ , m agent consisting of a collection  $Ag = \{A_{gn}\}$  m, attributes  $A_{gn} = (a_e, pr, Po, c) = (0, false, true, true)$ , the  $p_n$  point to  $o_n$ .

(b) If the  $Ag = \theta$ , output segmentation results  $o = \{o_1, o_2, \dots, o_i\}$ , or execute Step (3).

(c) From the  $Ag$  take the  $A_{gn}$ . Determine  $A_{gn}$  status, if the  $A_{gn}$  has executed reproduction ( $pr = true$ ), age more than threshold ( $a_e > t_h$ ),  $A_{gn}$  can not find candidates for merging ( $c = false$ ), or  $A_{gn}$  pointing to the object  $o_i$  has been merged into other objects ( $Po =$

false), the  $A_{gn}$  death is cleared out agent set  $Ag$ , execute step (2), otherwise execute the step (4).

(d) Looking for mutual best merge object,  $A_{gn}$  calculate the candidate merge object of  $o_t$  for  $o_t + 1$ , the candidate object  $o_t + 1$  to find is  $o_t$ ,  $A_{gn}$  to reproduce, or  $A_{gn}$  diffuse. Take Step (2).

### III. EXPERIMENTAL RESULTS

In current remote sensing image segmentation software e Cognition software multi-scale segmentation, namely FNEA segmentation algorithm, shows excellent performance. In order to check the MARSS calculation method have effectiveness, use HSRI two groups of data sets, and were analyzed compared to FNEA test results . HSRI segmentation result contrast evaluation method uses unsupervised evaluation method.

#### A. Segmentation Result Evaluation Method

Evaluation method of image segmentation algorithms can be divided into three categories: visual evaluation, supervision evaluation and non-supervision evaluation. In the supervision and evaluation, access to segmentation reference image with very strong subjectivity, very time consuming, taking high quality reference image of complex remote sensing image is difficulty. In order to quantitatively evaluate the overall effect of the Segmentation results of remote sensing Image, this paper adopted the n0n-supervision Evaluation method that JOHNSON. B mentioned in Unsupervised Image Segmentation Evaluation and Refinement Using a Multi-scale Approach

$$GS = Var_{norm} + MI_{norm} \tag{10}$$

$$Var = \frac{1}{c} \sum_{i=1}^b \frac{1}{h} \sum_{j=1}^h h_i (\sigma_j^i)^2 \tag{11}$$

$$MI = \frac{1}{c} \sum_{j=1}^b \frac{h \sum_{i=1}^h \sum_{k=1}^k n_i (\theta_j^k)^2}{\sum_k (y_i - y_j)^2 \left( \sum_{i=1}^h \sum_{j=1}^h \sigma_{ij} \right)} \tag{12}$$

In type (10), the  $Var_{norm}$  and  $mi_{norm}$  respectively the values of  $Var$  and MI after normalized, the normalized formula as shown in type (13); X as a variable ( $Var$  or MI),  $x_{min}$  and  $x_{max}$  respectively the minimum and maximum value of variable,  $x_{norm}$  for normalized variable values

$$x_{norm} = (x - x_{min}) / (x_{max} - x_{min}) \tag{13}$$

Equation (11), for the standard deviation of first t figure spot the first k band;  $N_t$  said t figure spot object pixel number; N for spot number; B for the band. In type (12),  $y_{tk}$  for wave degree average of figure spot t; mean to image the first k wave degree average; WTT 'shows

that object t and t' of the adjacent relation, if the object t, t 'adjacent, the WTT' = 1, otherwise the WTT' = 0.

$Var$  value is small, which indicates that high homogeneity within the overall segmentation image spot, the segmentation effect is good in figure spot;  $Var$  value is large, it shows that in the overall segmentation image spot, the homogeneity is low, the segmentation effect is poor in figure spot, owe segmentation degree is high. MI value is small, shows high heterogeneity between segmentation image blocks, segmentation effect is good between the figure spot; MI value is big, show that the heterogeneity between segmentation image is low, segmentation effect is poor between the figure spot, splitting degree is high. Global score is small, indicating that the overall segmentation effect is good, low degree of owe segmentation and over-segmentation.

#### B. Split Test

Experiment 1 image for Sanya village area of Hainan province in 2012 size of 400 pixels by 400 pixels, QUICKBIRD image of resolution of 2.4 m 4 band, as shown in figure 3 (a)). Trial FNEA algorithm and MARSS algorithm parameter is set to scale = 50, band weight  $w_k = 1$  a/b, shape weight  $WSHP = 0.1$  and the compact degree  $WCMP = 0.5$ , b for the image band. MARSS algorithm is initialized by uniform distribution, the initial agent number is 2000, and under the distribution for a given initialization number of imaging agent determines the agent referents. FNEA algorithm and MARSS algorithm segmentation results, respectively, as shown in figure 3 (b), (c).

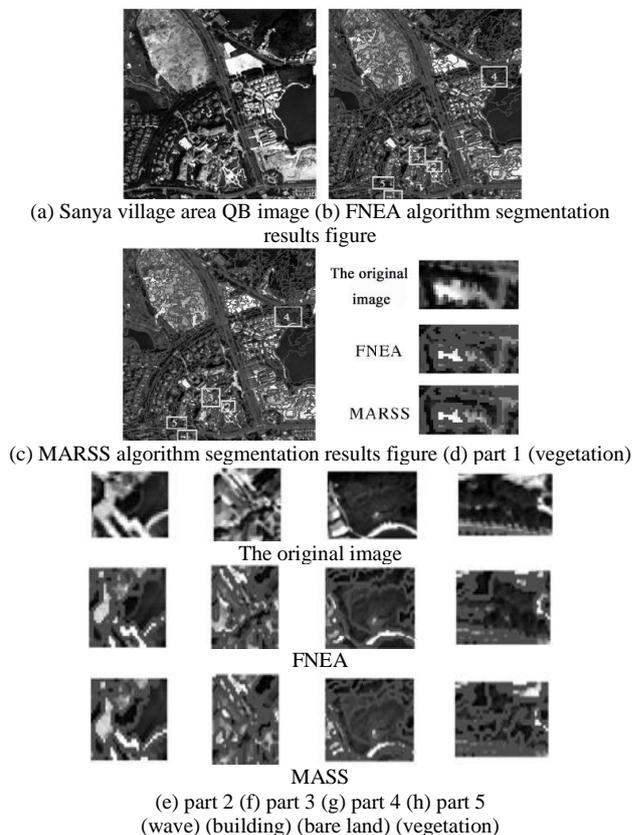
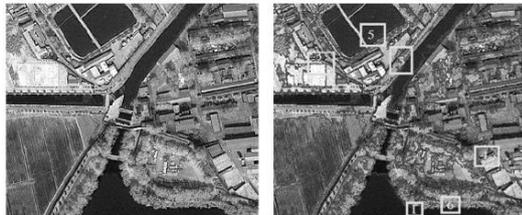
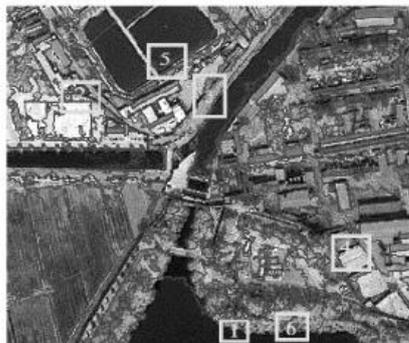


Figure 3. Sanya village region QB image segmentation result

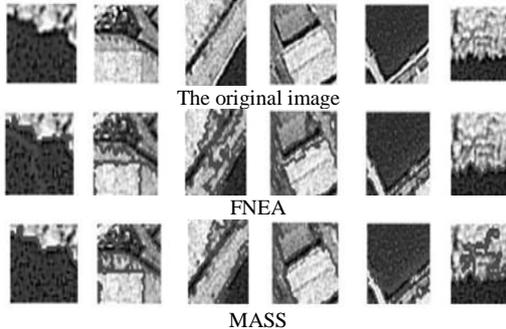
Test 2 data is the QUICKBIRD image in Beijing area 548 pixels by 463 pixels resolution of 2.4 m (as shown in figure 4 (a)). Wave band weighting  $w_k$ , shape weight WSHP and a compact WCMP parameter is respectively set to  $1/b$ , 0.1 and 0.5,  $b$  for the image band. Initial agent for 2000 MARSS, and segmentation results of FNEA in scale of 50, as shown in figure 4 (b) (c).



(a) Beijing area QB images (b) FNEA algorithm segmentation results figure



(c) MARSS algorithm segmentation results figure



(d) part 1(e) part 2(f) part 3 (g) part 4 (h) part 5 (i) part 6 (wave) (vegetation) (road) (building) (wave) (vegetation)

Figure 4. Beijing area QB image segmentation results

In order to clearly contrast the segmentation results of two methods on visual, the test 1 and 2 respectively choose five and six children regions enlarge to compare and analysis, the chosen area contains water, vegetation, roads, construction and other typical feature categories, as shown in figure 3 (d) ~ (h). From figure 3 shows that, compared with MARSS, FNEA in the region that same material differences are large, the segmentation results are good, as shown in figure 3 (h) the vegetation area difference is big, FNEA segmentation result is complete; Compared with FNEA, MARSS algorithm in different material difference smaller region, segmentation effect is better, as shown in figure 3 (d) the vegetation and roads, water and vegetation of figure 3 (e), figure 3 (f) of building with different roof, figure 3 (g) bare land border with the plant light spectrum difference is relatively small, MARSS can also accurately partition it, ensure the

correctness of the follow-up processing (e.g., classification). Also, figure 4 (d) to (g) segmentation result is shown in different material differences is smaller region, MARSS algorithm compared FNEA algorithm segmentation result is better; In figure 4 (h), (I) shown water vegetation in the same material in regions with large differences, MARSS algorithm segmentation results relatively FNEA algorithm is more fragile.

In order to more accurately and objectively evaluate the segmentation results of MARSS algorithm with FNEA algorithm, take section 3.1 GS indicators for quantitative evaluation of the segmentation results of two kinds of algorithm, the result of experiment 1 and experiment 2 as shown in table 2.

TABLE II. STATISTICS OF MARSS ALGORITHM WITH FNEA ALGORITHM SEGMENTATION

	Segmentation method	MI <sub>nom</sub>	Var <sub>nom</sub>	GS
test 1	FNEA	0.234	0.566	0.801
	MARSS	0.216	0.551	0.767
test 2	FNEA	0.233	0.613	0.847
	MARSS	0.153	0.618	0.771

According to the results of Table 2, in experiment 1 and experiment 2, M I norm index of MARSS calculate method were 0.216 and 0.153, respectively, less than FNEA algorithm 0.234 and 0.233, shows that overall MARSS algorithm segmentation effect is good in FNEA algorithm. Experiment 1 MARSS algorithm  $Var_{nom}$  index is 0.551 less than the 0.566 of FNEA algorithm, illustrate MARSS algorithm compared to FNEA algorithm whole owe segmentation effect is better; And test 2 MARSS algorithm  $Var_{nom}$  index 0.613 large than FNEA algorithm, illustrate MARSS algorithm under segmentation effect compared to FNEA algorithm is poorer. But MARSS algorithm in experiment 1 and experiment 2 GS global index were 0.767 and 0.767, lower than FNEA algorithm 0.801 and 0.847, MARSS algorithm in the over segmentation and under segmentation effect is better than FNEA algorithm

From theory and experiment analysis we can see, the article MARSS algorithm of overall segmentation is better than FNEA algorithm because of MARSS algorithm in global objects merge strategy wipe our FNEA all the objects in each cycle can be traversed only one time, can better use the spatial continuity on homogenous area. To illustrate the advantages of MARSS, take 5 as an example to illustrate. As shown in figure 5 (a), in one loop that FNEA algorithm global control, set object o1, o2, o3 for the same feature, o4 is another feature. According to the mutual best merger guidelines, object o1 and o2 as the mutual best merge, the object o1 can be traversed only once, o3 is no longer considered object o1, may exist object o4 was identified as the object of o3 mutual best merge, in the final merged result, object o3 was mistakenly merger with o4 (as shown in figure 5 (b)). As the global control loops, FNEA algorithm in o3 and o4 combined error will be continuously enlarged. For MARSS, as shown in figure 5 (c), (d), the method canceled the constraints of traversal

times, Agent  $A_{gn}$  find the mutual best merger object  $o_1$  and  $o_2$  through diffusion behavior, will perform reproduction,  $o_1$  and  $o_2$  combined object is  $o'1$ , breeding progeny agent  $Ag_2$  will make perception  $P_2$  pointing to objects,  $o_3$ , and search for the mutual best object  $o'1$ , and will eventually solvated object  $o_3$ ,  $o'1$  (as shown in figure 5 (e)). Therefore, the MARSS algorithm more flexible global control can take account of homogenous area on the space continuity, improve the segmentation effect of different substances on a smaller area (e.g., bare land and vegetation area). And MARSS algorithm take account of the space continuity on homogenous area at the same time, easy to create over segmentation effect in the region of large difference of same material (e.g., vegetation), but on the whole segmentation effect, MARSS algorithm can realize the global optimization control and improve the high resolution image segmentation results.

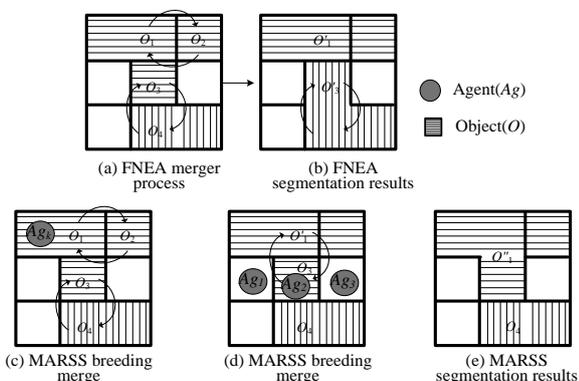


Figure 5. Global merger control comparison diagram of the MARSS and FNEA algorithm

C. Parameter Analysis

Agent initialization number and segmentation scale two parameters influence MARSS algorithm segmentation results a lot. This section studies the influence of agent initialization number and scale of MARSS algorithm segmentation. When testing, agent initial choose the number of 1000, 2000, 3000, 2000 (respectively write as MARSS1000, MARSS2000, MARSS3000, MARSS4000), scale chose 10 to 100, step length of 10 multiple values. Test results as shown in figure 6.

Test 1 results (figure 6 (a)) shows the initial agent number for 1000, 2000, 4000, of the global index GS that MARSS algorithm on different scale segmentation results were superior to FNEA algorithm. When the initial agent number is 3000, relatively FNEA algorithm, MARSS algorithm except in 90 and 100 two scales of segmentation effect is poor performance, GS in eight other scales value better than FNEA GS of the segmentation results. Comprehended the above test results, to initialize agent number 1000, 2000, 3000, 2000, the segmentation results of scale degrees of 10 to 100, and MARSS algorithm overall segmentation effect is better than FNEA algorithm, and has good stability. Due to the different distribution of features, different HSRI

optimal segmentation scale is different, MARSS algorithm in low dimension and scale is too high, can't get the optimal segmentation result, choosing the right segmentation scale according to the actual image. For experiment 1 and experiment 2 images, MARSS algorithm and FNEA algorithm are similar for images optimal segmentation scale, about 40 or 30.

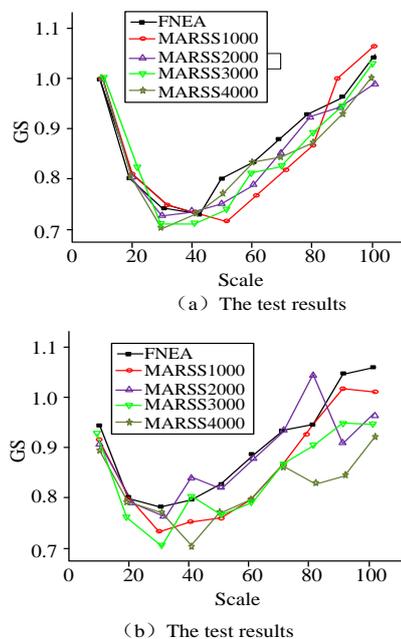


Figure 6. The influence of agent initialization number and segmentation scale parameters to MARSS algorithm segmentation

IV. CONCLUSION

By using multi-agent and image environment strong interactivity, the advantages of high flexibility, parallel computing, this paper proposes a multi-agent based theory of high spatial resolution remote sensing image segmentation algorithm. The algorithm in the merger guidelines, combining image spectral and shape information, and by using multi-agent parallel control integral region merging process, its global merger control strategy can ensure algorithm has the advantages of parallel computing and fully considering the regional homogeneity, and continuity. Split test results show that, compared with FNEA, although this algorithm for the same material exist large difference area produces the over-segmentation phenomenon, but in this paper, algorithms for small physical differences of different region, segmentation effect is better. using all scored evaluation indexes take overall segmentation result evaluation to the segmentation results, this paper algorithm of GS value lower than FNEA algorithm, which split overall effect is better. Through intelligent initialization number parameter analysis, shows that this algorithm has better stability, and the segmentation result is better than FNEA algorithm as a whole.

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