FAST GRAPH-BASED SAR IMAGE SEGMENTATION VIA SIMPLE SUPERPIXELS

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ABSTRACT

Graph-based methods have been successfully applied in the field of computer vision for image segmentation. Unfortunately, most of them are not suitable to deal with large-scale SAR image segmentation due to their high computation complexity. A fast and efficient graph-based SAR image segmentation is proposed in this paper through using superpixels to reduce the computation complexity. Firstly, a SAR image is divided into several non-overlapped subdivisions with the same size. Each of the subdivision is processed as a single OpenMP parallel region, which can be processed at the single computing node with multi-core CPU. Secondly, the number of nodes and edges in the graph is reduced by extracting the superpixels other than single pixels based on global information of each subdivision. Finally, an effective rule is proposed to merge two adjacent sub-graphs from two different subdivisions into a new sub-graph.

***Index Terms*—**Synthetic aperture radar (SAR), Image segmentation, Graph-based method, Superpixels.

1. INTRODUCTION

Synthetic aperture radar (SAR) image segmentation [1], as a basic problem in SAR image application, has been attracting more and more attention. The main purpose of SAR image segmentation is to partition an image into regions with different characteristics, which is a challenging task because of the existence of speckle noises in SAR images. Meanwhile, the increasing size of SAR images has also increased the difficulty of SAR image segmentation, which introduces high computational complexity and large memory requirement.

Many researches have been done to solve the problem of SAR image segmentation. In order to reduce the time cost of image segmentation, many fast methods were proposed. F. S. Cohen and D. B. Cooper [2] presented parallel hierarchical and iterative algorithms to segment textured images by adopting strategies maximum likelihood and maximum a posteriori likelihood segmentation. A multi-scale spectral image segmentation algorithm was proposed by T. Cour et al. [3], where the normalized cut graph partitioning framework of image segmentation is used in each scale. The segmentation algorithm can work in parallel across the scales in the graph simultaneously. H. G. Sui et al. [4] gave an implementation of the Markov Random Field (MRF) method on graphics processing units (GPUs) as general purpose computation for SAR image segmentation. S. P. Gou et al. [5] proposed a novel parallel spectral clustering approach by exploiting the distributed computing in MATLAB for SAR image segmentation. The algorithm works quickly and obtains results with high accuracy. However, these methods are not sufficient enough when facing large-scale SAR images (for example, images with size over pixels). It becomes a bottleneck problem in practical application of SAR image segmentation, as the overall time and space complexity reach a very high level. Consequently, the main problems of fast SAR image segmentation can be summarized as follows. Firstly to simplify the image segmentation process, and secondly to build an efficient computation model.

Graph-based methods [6-10] have been successfully used in image segmentation and classification area. However, good performance always comes with high computational complexity and large memory cost. In order to segment images quickly and accurately, many researchers [11-14] have developed several versions of fast implement of graph-based methods which provide efficient tools for SAR image segmentation. The examples above highlight the fact that the graph-based approach is flexible to image processing. It also shows that the performance of segmentation can be improved by applying graph partitioning method under pixel-wise framework. However, these graph-based methods are not suitable to the large-scale SAR images, because the computational costs and the memory requirements are expensive. Firstly, the graph is very large as each pixel is considered as a node of graph at the initial iteration stage. Meanwhile, the number of edges is also determined by the number of pixels in the image, which leads to a huge graph to deal with. Secondly almost all the methods only considered the local information in the image rather than global information which is equally important for image understanding. More specifically, the speckled noise, which always suppresses the performance of SAR image segmentation, is more likely to be introduced through the usage of local information. Nevertheless, the introduction of global information can relatively reduce the effect of speckle noise.

To solve the problems mentioned above, an efficient graph-based SAR image segmentation is proposed by adopting superpixels to reduce the scale of graph. Firstly, the image is divided into several subdivisions with the same size. Each of the subdivision can be processed as a single OpenMP parallel region at the single computing node in the platform of multi-core CPU. Secondly, global information is extracted from each subdivision to reduce the number of nodes and edges in the graph. Finally, an effective merging rule is proposed to merge adjacent sub-graphs of different subdivisions. The proposed graph-based method is suitable for large-scale SAR images, which can reduces the time and space complexity compared with conventional methods.

2. THE PROPOSED METHOD

2.1. Simple superpixels extraction

For SAR images, one pixel represents a region on the earth. If the size of the superpixels is too larger, some detailed information will be ignored. A simple superpixels extraction method based on intensity and spatial constraint is developed in this paper by considering the tradeoff between the speed of segmentation and the detail-preservation for SAR image. The main motivation of the proposed algorithm is that the pixels which have similarity in intensity and spatial information can be merged into a superpixel. Superpixels [15] are roughly homogeneous in size and shape just like pixels. G. Mori [16] also demonstrated the efficiency and accuracy of image processing models can be improved by using superpixels.

As shown in Fig. 1, each dot represents a pixel in an image. The black one represents the current pixel which is going to be merged with others. The blue ones represent a certain space constraint. To form a superpixel, the current pixel can only be merged with its neighbor pixels represented by blue dots. We calculate the intensity difference between the current pixel i and its neighbors for each pixel in an image. In this paper, the difference is defined as $Dif_{sp}(i, j)=|D(i) - D(j)|$, where $D(i)$ and $D(j)$ represent the intensities of the pixel i and j, respectively. The predication that determines whether the pixels i and j should be merged together or not is defined as follows:

$$D_{sp}(i,j)=\begin{cases} true & if \quad Dif_{sp}(i,j)<T_{sp} \\ false & otherwise \end{cases} \tag{1}$$

where the threshold $T_{sp}>0$ is considered to be proportional to the resolution of SAR image. When $D_{sp}(i,j)=ture$, the pixels i and j will be merged. Superpixels with different sizes will be constructed after processing all pixels in the image.

The size of the superpixels is determined as a rhombus which is made up of the blue dots in Fig. 1. The length of the rhombus is denoted as L which is also positively related to the scale and resolution of SAR images. Large size of superpixels will be generated while dealing with large images, which can reduce the computation complexity by reducing the number of edges in the graph. Small size of superpixels is adopted for low resolution SAR image in which a pixel represents a large region in the ground, which can preserve more detailed image information.

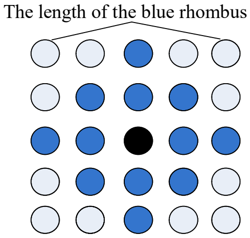

Fig.1. Each dot represents a pixel. The black dot represents the current pixel to be merged, and the blue ones represent a certain space constraint.

2.2. Fast graph-based segmentation

As mentioned above, the proposed superpixels based initial segmentation can reduce the computation complexity to some extent. However, the time cost is still very high while dealing with large-scale SAR images. Another strategy is designed to reduce the computation complexity further. The whole SAR image will be divided into many subdivisions before constructing the superpixels and each subdivision will be segmented as it has been described in Fig. 2. Thus, the classical single pixel can be replaced with the extracted superpixels and the subdivisions can be segmented quickly via the traditional graph-based segmentation methods. The subdivisions can be processed in parallel by using OpenMP compiler-directed statement as all of the subdivisions are independent to others. The result of each subdivision can be obtained by fast SAR image segmentation model described in Fig. 2. To obtain the result of the whole image we need to design an effective rule that can determine whether two adjacent subgraphs should be merged or not.

An improved graph-based predication is proposed in this paper. The predication is based on the difference of intensity at the boundary of different subdivisions. After segmenting the subdivisions by the graph-based method the pixels from two different sub-graphs should be merged if they have similar properties. Therefore, if the sub-graphs at the boundary of different subdivisions are merged, they will be merged into a graph that represents the merged subdivisions.

The process of connecting subdivisions A and B is shown in Fig. 3. The sub-graph C_1 is in subdivision A and a sub-graph C_2 is in subdivision B. It is assumed that sub-graph C_1 consists of four pixels which are represented by four blue dots, and the sub-graph C_2 consists of six pixels which are represented by six black dots. When the pixels in sub-graph

C_1 are near to the pixels in sub-graph C_2, we will calculate the difference of intensities between the pixels which are connected by the red lines which represent the edges between two sub-graphs. The set of the edges represented by redlines is denoted by E_{sd}. Then, a minimum difference of the differences are defined as follows,

$$Dif_{sd}(C_1, C_2) = \min_{v_i \in C_1, v_j \in C_2, (v_i, v_j) \in E_{sd}} w((v_i, v_j)) \tag{2}$$

Then, we calculate the predication $D_{sd}(C_1, C_2)$ that determines whether sub-graphs C_1 and C_2 should be merged or not as described in the following,

$$D_{sd}(C_1, C_2) = \begin{cases} true & if \quad Dif_{sd}(C_1, C_2) < MInt(C_1, C_2) \\ false & otherwise \end{cases} \tag{3}$$

When $D_{sd}(C_1, C_2) = ture$, we merge sub-graphs C_1 and C_2 into a new sub-graph. After processing all the sub-graphs at the boundary from different subdivisions, a graph that represents the whole image is obtained.

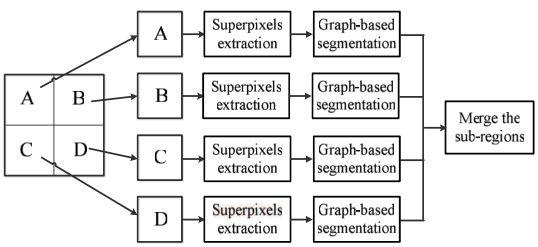

Fig.2. The fast SAR image segmentation model. The large square represents the whole image, and the small squares represent the subdivisions with the same size.

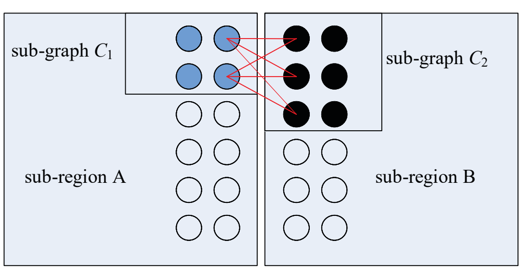

Fig.3. Subdivisions merging. Each dot represents a pixel. The set of blue circles represents a sub-graph C_1 belong to subdivision A. The set of black dots represent a sub-graph C_2 belonged to subdivision B. The red lines represent the edges between sub-graph C_1 and C_2.

3. EXPERIMENTS

In this section, real SAR images are used to evaluate the performance of the proposed method. All the experiments are performed on an Intel® Xeon® Processor E3-1230 v2 (8M Cache, 3.30 GHz), and the code is written with OpenMP® in Microsoft® Visual Studio 2010 development environment. The proposed method is compared with traditional graph-based method in [6].

3.1. Experiment 1—validating the effectiveness

The first image is a real SAR image (746×1020, near Xi'an, China, 3-look intensity, 1m resolution, shown in Fig.4(a)), which consists of three types of land-cover: airport runway, land and village. The results obtained by the method in [6] and our method are presented in Fig. 4(b) and Fig. 4(c), respectively. It can be easily observed that the airport runway (inside red circle of Fig. 4(b)) is not correctly segmented by the original graph-based segmentation method, while our method can effectively restore the main structure of the image, as shown in Fig. 4(c). In addition, the proposed method improves the uniformity of homogeneous regions.

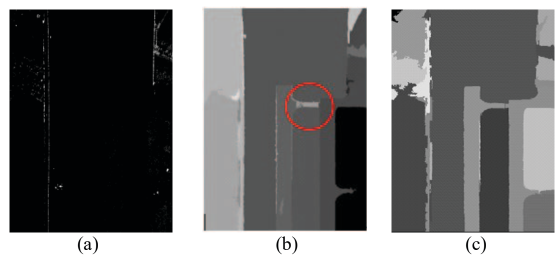

Fig.4. Results with different methods. (a) Near Xi'an, China. (b) is the result with the method in [6]. (c) is the result obtained by the proposed method.

The second image is also a real SAR image (8786×6056,Yellow River Estuary in China, 3-look amplitude, 3m resolution, shown in Fig. 5(a)), which consists of three types of land-cover: water area, village, and crops. Fig. 5(b) shows the result obtained by the method in [6], obviously, the region of the village presented by a red circle in Fig. 5(b) is segmented into wrong class. The result obtained by our method is shown in Fig. 5(c), which improves the uniformity in the area of village and the detail information can be preserved effectively.

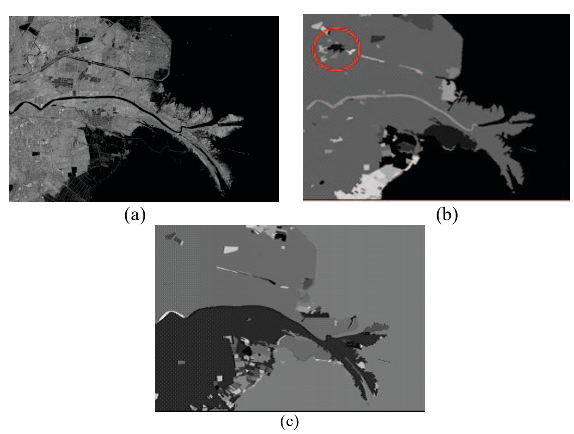

Fig.5. Results with different methods. (a) Yellow River Estuary, China. (b) is the result with the method in [6]. (c) is the result obtained by the proposed method.

3.2. Experiment 2—validating the efficiency

For comparing the efficiency and the speed, number of regions, number of edges and time cost are used to evaluate the performance of different methods. In the first experiment, 4 real SAR images are segmented into the same number of regions by the graph-based and our method (numbers of sub-graphs are the same). Table I shows the running time. Obviously, our proposed method is much faster than the original one with the same numbers of regions. In the second experiment, other 15 SAR images with different sizes are segmented by two methods. Table II shows running time and number of edges. It shows that the proposed method not only decreases the number of edges is by 2.4 times in average, but also reduces the time cost is by 4 times compared with the traditional graph-based method.

TABLE I RUNNING TIME AND NUMBER OF REGION FOR ORIGINAL GRAPH-BASED AND PROPOSED METHODS

SAR Images		Traditional method		Our method	
No.	Number of pixels	Number of regions	Time (ms)	Number of regions	Time (ms)
1	256×256	5000	46	5000	15
2	1100×1000	5000	947	5000	127
3	2500×2500	5000	5876	5000	476
4	5200×5200	5000	21536	5000	1640

TABLE II IMAGE SIZE, NUMBER OF EDGES AND RUNNING TIME FOR ORIGINAL GRAPH-BASED AND PROPOSED METHODS

SAR Images		Traditional method		Our method	
No.	Number of pixels	Number of edges	Time (ms)	Number of edges	Time (ms)
1	1100×1000	4393702	1025	1429582	516
2	1032×1020	4204406	1081	1439692	433
3	1228×1128	5533670	1409	1872036	616
4	2000×2000	15988002	4414	5524446	1140
5	2000×2000	15988002	4433	5196225	1086
6	1000×1000	3994002	1019	1318548	571
7	5200×5200	108128802	29947	35353261	5510
8	2500×2500	24985002	6688	8268217	1772
9	2500×3000	29983502	8411	11033173	2104
10	2250×2000	17987252	4909	6056192	1251
11	2200×2200	19346780	5231	6515906	1232
12	2500×2500	24985002	6783	8579054	1729
13	2500×2500	24985002	6772	7995234	1488
14	2500×2500	24985002	6642	8070696	1728
15	8786×6056	212787540	62205	118970789	16280
Average		35885045	10065	15174870	2497

4. CONCLUSION

This paper proposed an efficient graph-based SAR image segmentation method, which aims at reducing the computational complexity of dealing with large-scale images. A multi-core parallel process in the stand-alone system by OpenMP is used to accelerate the subdivision algorithm. Superpixels replace single pixels to preserving global information and further decrease the complexity, and a new merging rule is proposed to effectively merge two adjacent sub-graphs from two different subdivisions. The proposed method can not only reduce the number of edges, but also decrease the time cost.

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