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ADAPTIVE SCALE SELECTION FOR MULTISCALE SEGMENTATION OF SATELLITE IMAGES

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Abstract- Multiscale image segmentation generates a set of image regions (objects) at hierarchical levels of details, in which the segmentation at a coarser level can be produced by merging regions at finer ones. With dramatically increasing of the spatial resolution of satellite imaging sensors, object-based image analysis (OBIA) has been gaining prominence in remote sensing applications. Multiscale image segmentation is a prerequisite step that splits an image into hierarchical homogeneous segmented objects for OBIA. However, scale selection remains a challenge in multiscale segmentation. We implement this method through definition of segmented object complexity based on inherent features of images and prior knowledge of thematic maps, in the top-down segmentation procedure. In this study, we presented an adaptive approach for defining and estimating the optimal scale in the multiscale segmentation process. Central to our method is the combined use of image features from segmented objects and prior knowledge from historical thematic maps in a top-down segmentation procedure. Our first contribution is a general framework to select the optimal scale for every segmented object (not for the whole scene or local regions in previous studies) in the segmentation procedure (not pre-evaluation or post selection in previous studies). Our second contribution is incorporating prior knowledge from thematic maps for a more appropriate segmentation scale. Then, in the similar manner; complex segmented objects were split into the simplest objects iteratively. Finally, the final segmentation result was obtained and evaluated. We have applied this method on a GF-1 multispectral satellite image and a ZY-3 multispectral satellite image to produce multiscale segmentation maps and further classification maps, compared with the state-of-the-art and the traditional mean shift algorithm. The experimental results illustrate that the proposed method is practically helpful and efficient to produce the appropriate segmented image objects with optimal scales.

Index Terms— Mean-shift segmentation, object-based image analysis (OBIA), object complexity, prior thematic map, scale selection.

I. INTRODUCTION

In high-spatial-resolution satellite images, abundant and detailed geometric information of scene and ground objects are typically presented, which allows for accurate analysis on the matic classification or ground object recognition at fine scales. However, it is difficult to obtain satisfactory results using the traditional pixel-based image analysis methods (using only spectral information of pixels) from these high-spatial-resolution images, in extracting ground object information. To overcome these problems, object-based image analysis (OBIA) technique has been proposed and represents an evolving paradigm, because it can effectively incorporate spatial relations between objects and expert knowledge into the classification and achieve better performance than pixel based classification. Multiscale image segmentation is the prerequisite and most critical procedure for OBIA, in which a satellite image is split into spatially contiguous and homogeneous regions (referred to as segmented object in the rest of this paper). It is the core of object-based analysis. Numerous image segmentation techniques used in remote sensing application are summarized and reviewed. Multiscale image segmentation generates a set of image regions (objects) at hierarchical levels of details, in which the segmentation at a coarser level can be produced by merging regions at finer ones. Such hierarchies can be built by a bottom-up approach or a top-down approach. The bottom-up approach forms objects by combining and merging pixels or regions, whereas the top-down approach moves from splitting the whole image into image objects based on heterogeneity criteria. No matter which method is used, the segmentation process can improve the subsequent analysis and classification if conducted at appropriate scales. However, defining and selecting suitable scales for multiscale image segmentation are challenging and problematic. The appropriate scale is not readily apparent in image segmentation, and there is currently no objective approach to decide the optimal scale for segmentation. So, the selection of segmentation scales is often dependent on subjective trial-and-error methods. They typically utilize measures of the similarity between a segmentation result and a reference segmented map (usually delineated by professional interpreters) in

which the optimal scale parameter is the best match to the reference map.

II. EXISTING SYSTEM

Segmentation separates an image into its component parts or objects. The level to which the separation is carried depends on the problem being solved. When the objects of interest in an application have been inaccessible the segmentation must stop. Segmentation algorithms for images generally based on the discontinuity and similarity of image intensity values. Discontinuity approach is to partition an image based on abrupt changes in intensity and similarity is based on partitioning an image into regions that are similar according to a set of predefined criteria. Thus the choice of image segmentation technique is depends on the problem being considered. Edge detection is a part of image segmentation. The effectiveness of many image processing also computer vision tasks depends on the perfection of detecting meaningful edges. It is one of the techniques for detecting intensity discontinuities in a digital image. The process of classifying and placing sharp discontinuities in an image is called the edge detection.

Image Segmentation is the process of partitioning a digital image into multiple regions or sets of pixels. Essentially, in image partitions are different objects which have the same texture or color. The image segmentation results are a set of regions that cover the entire image together and a set of contours extracted from the image. All of the pixels in a region are similar with respect to some characteristics such as color, intensity, or texture. Adjacent regions are considerably different with respect to the same individuality. The different approaches are (i) by finding boundaries between regions based on discontinuities in intensity levels, (ii) thresholds based on the distribution of pixel properties, such as intensity values, and (iii) based on finding the regions directly. Thus the choice of image segmentation technique is depends on the problem being considered. Region based methods are based on continuity. These techniques divide the entire image into sub regions depending on some rules like all the pixels in one region must have the same gray level.

A. EDGE DETECTION TECHNIQUES:

The edge representation of an image significantly reduces the quantity of data to be processed, yet it retains essential information regarding the shapes of objects in the scene. This explanation of an image is easy to incorporate into a large amount of object recognition algorithms used in computer vision along with other image processing applications. The major property of the edge detection technique is its ability to extract the exact edge line with good orientation as well as more literature about edge detection has been available in the past three decades. On the other hand, there is not yet any common performance directory to judge the performance of the edge detection techniques.

B. SELECTED PROBLEMS IN MULTISPECTRAL IMAGE ANALYSIS

- Image Segmentation
- Texture Analysis – fractal/Radon transform based
- Edge /line Detection – morphological/neural
- Image Classification
- Neural Network Classification
- Genetic Algorithm Pre-processing / Contextual Postprocessing
- Fuzzy Integration for ensemble classifier Combination

Fig.1. IRS1B Image

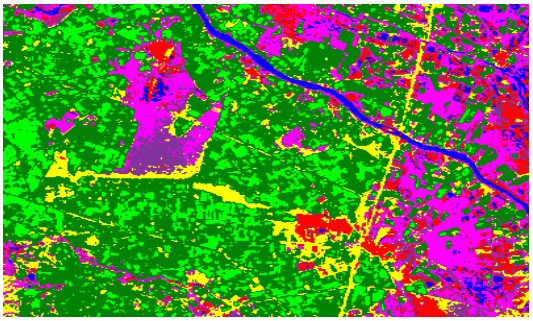


Fig.2. Genetic-Neural-Classification

Fig.3. IRS1C PAN Image

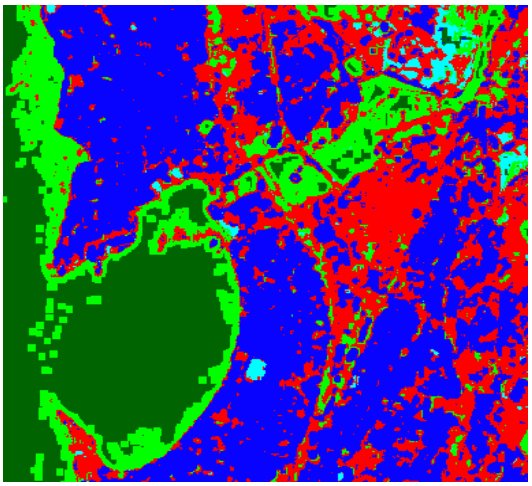


Fig.4. Fractal Textural Classification

Fig.5. Linear features mixed with building

C. OUTLINESSELECTED PROBLEMS

- Image Compression
- Rate constrained JPEG for custom rate of compression
- Change Detection
- Super-pixel approach
- Texture based approach

High Spatial Resolution Image Analysis

- Development of a Generic Framework
- Complete System to address requirements of high spatialresolution image analysis
- Development of tools
- Segmentation
- Component Labeling
- Feature Computation
- Classification

Hyperspectral Image Analysis

- Development of a Generic Framework
- System to address requirements of high spatial resolutionimage analysis
- Development of selected tools
- Dimensionality Reduction
- Classification
- Ongoing work
- Search Techniques for Feature Selection

Super-resolution

III. PROPOSED SYSTEM

We propose an adaptive approach for scale selection in multiscale segmentation of satellite image, as illustrated in Fig. 4.1.It is an iterative procedure, including six steps as follows:

1) The first step is data preparation and preprocessing, including geometrical registration between satellite images and thematic maps, class merging of the matic maps, construction of segmentation scale sequence S =($s0$, $s1$, . . . ,sn), and parameter settings.

2) The whole image is taken as a segmented object to be placed into a collection $\boldsymbol{Y}$ of segmented objects, whichwould be split in the next iteration.

3) An object $\boldsymbol{B}$ with scale $si-1$ fetched from the collection $\boldsymbol{Y}$, was split into multiple segmented objects ($\boldsymbol{b}1$,$\boldsymbol{b}2$, . . . , $\boldsymbol{b}m$) with scale si . And several features, including spectral features, textural features, geometry features, and edge features, were extracted.

4) Utilizing image features and thematic maps, complexity of a segmented object $\boldsymbol{bj}$ was analyzed and calculated, to determine whether this object needs to further be split with scale si+1 in the next iteration. If yes (complexity>threshold), the process flow turned to step 5), if no(complexity <threshold), this object was inserted into a hierarchical collection $\boldsymbol{N}$ of objects without more iterative segmentation, and turn to step 3).

5) This object $\boldsymbol{bj}$ was placed into collection $\boldsymbol{Y}$, and turn to step 3).

6) When the collection $\boldsymbol{Y}$ is empty, the multiscale segmentation result was produced in collection $\boldsymbol{N}$, organized in a hierarchical structure.

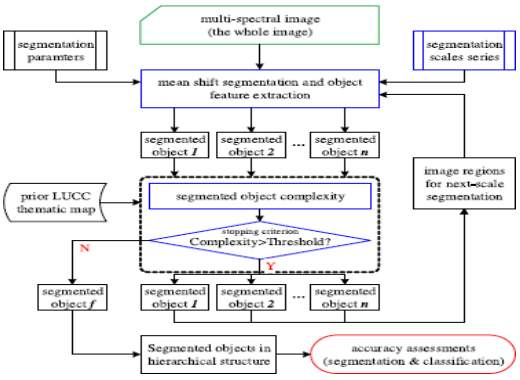


Fig.6. Flow diagram of adaptive scale selection in multiscale segmentation.

A. MEAN-SHIFT SEGMENTATION AND FEATURE EXTRACTION

Mean shift is a nonparametric feature-space analysis technique for locating the maxima of a density function and is used for image segmentation, visual tracking, and mode seeking. For mean-shift image segmentation, images were first filtered in the spatial–spectral domain to generate initial clustering regions (referred to as

mean-shift filtering). Then, adjacent regions with similar spectral features merge together, to produce the final segmentation results (referred to as mean-shift merging). In mean-shift merging, a transitive closure algorithm is first utilized to merge the spatially adjacent modes (segmented regions) with a similar mode and weak edge strength in the joint feature space, to produce larger regions. Then, small spatial regions containing too few pixels are merged into their nearest neighbor in spatial space, to improve segmentation results. After the mean-shift segmentation, we extract three spectral features (including standard deviation, heterogeneous, and entropy), five textural features (including energy, contrast, entropy, inverse difference moment, and correlation), and two shape features (including smoothness and shape compactness) from segmented regions for further analysis and classification.

B. SEGMENTATION SCALE SEQUENCE

In mean-shift segmentation, there are three important parameters (***hs***, ***hr***, ***S***) to control the segmentation performance. In image filtering, spatial bandwidth ***hs*** indicates the spatial size of moving windows and spectral bandwidth ***hr*** represents the allowable spectral difference between pixels. The mean-shift algorithm filters the image by grouping together all pixels that are closer than ***hs*** in the spatial domain and ***hr*** in the spectral domain. And in the merging step, segmented region containing less than ***S*** pixels was merged into nearest neighbor in spatial domain and spectral domain. In multiscale segmentation applications, a common practice is to fix the spatial bandwidth ***hs*** and the spectral bandwidth ***hr*** and apply a sequence of decreasing scales ***S*** = ($s0$, $s1$, . . . ,sn) to produce multiscale segmentation results. Following the decimation ratio between adjacent two layers in the image pyramid model [38], [39], we also set the decimation ratio 2 for the segmentation scale sequence (si= 2× si+1).First, we set $s0$ to be n, then $s1$ to be half of $s0$, and so on, until sn is less than a threshold value ***Ts*** . Here, n and ***Ts*** are image-based and application-based parameters. Parameter n should be larger than the possible biggest segmented object in the image, which ensures that the biggest object is not over segmented with the largest scale. In our study, we found that setting n to be 2560 works well for satellite images with spatial resolutions ranging from 2 to 30 m. So, we set the scale sequence to be (2560, 1280, 640, 320, 160, 80, 40, 20) in the following experiments.

C. SEGMENTED OBJECT COMPLEXITY

In the procedure of top-down segmentation, a segmented region (object) with a higher complexity needs to be further split into simpler regions in the next iterative segmentation. In our study, we analyzed and calculated the complexity of a segmented object from both inherent features of image regions and land plot knowledge of prior thematic maps.

1) Complexity From Image Features: Variances on spectral values, shapes, and textures reflect the complexity of a segmented region. So, the measures for object complexity are based on feature variances, comprising spectral value, texture, shape, size, and temporal inside segmented objects.

2) Complexity From Prior LUCC Thematic Maps: Land the matic maps record the land attributes and geometrical edges of ground plots, which are potential references for further remote sensing applications. For image segmentation, the prior the matic map may not be the primary measure, but it has the potential of improving the performance of segmentation, including feature extraction, scale selection, and parameter optimization. For example, it is our prior thematic map, which generally says that built-up areas indicate smaller scale and segmented objects, while forest lands mean larger scale and segmented objects in satellite images. So, we briefly analyzed the land plots in the local region around a segmented object to define four complexity metrics for scale selection.

a) Number of land plots within a segmented object: In the prior thematic map, the number of land plots within the spatial extent of a segmented object *NP* indicates the actual scale of ground objects in local region. The more the land plots are, the smaller the scale for ground objects is in the local regions, and more iterative segmentation is needed in the top down procedure, and vice versa.

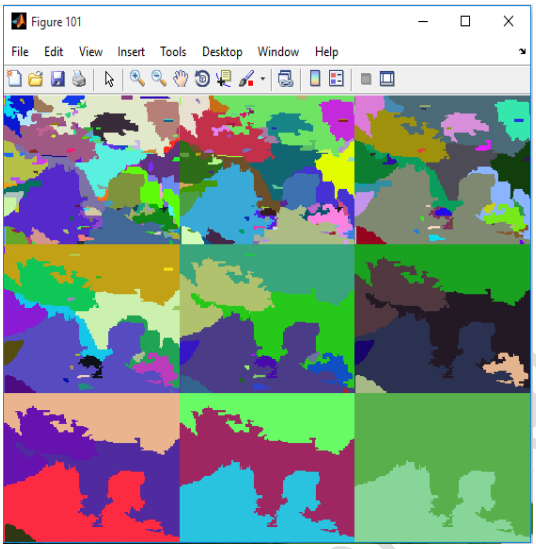
b) Number of land classes within a segmented object: In the prior thematic map, the number of land classes within the spatial extent of a segmented object *NT* also indicates the actual scale of ground objects in local region. The more the land classes are, the smaller the scale for ground objects is in the local regions, and more iterative segmentation is needed in the top down procedure, and vice versa.

c) Area ratio of the largest land plot within a segmented object: In the thematic map, the ratio of the largest land plot area within a segmented object to the area of this segmented object is *RP*. The greater the ratio is, the smaller the complexity of the segmented object is, and the less the possibility of the next iterative segmentation is, and vice versa.

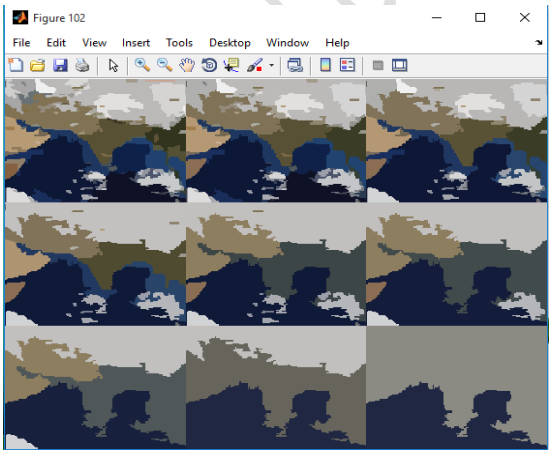
d) Area ratio of the largest land class within a segmented object: In the thematic map, the ratio of the largest land class area within a segmented object to the area of this segmented object is *RT*. The greater ratio, the smaller complexity of the segmented object, and the less possibility of the next iterative segmentation, and vice versa.

IV. RESULTS

Fig: input image



Fig(a)



Fig(b)

Fig: images with multi level segmentation

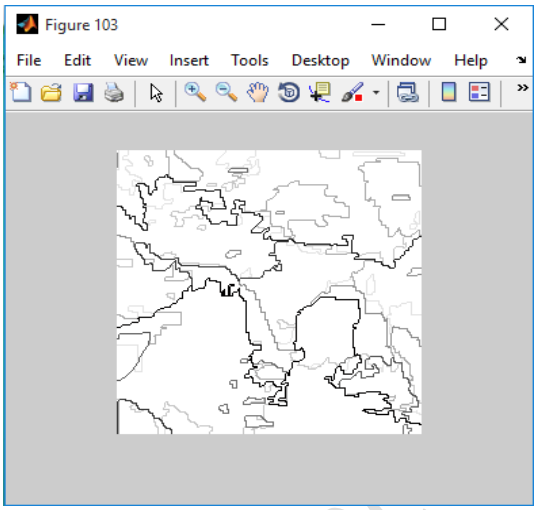


Fig: final segmented regions

CONCLUSION

Scale selection in multiscale segmentation is an important and challenging step for object-based remote sensing applications. We have proposed an adaptive scale selection method (ASMS) for the top-down multiscale segmentation based on combined use of inherent features of segmented objects and prior knowledge from thematic maps, to improve performance of image segmentation and even further classification. This methodology has been applied to produce multiscale segmentation maps of a GF-1 multispectral image in Heilongjiang Province, China and a ZY-3 multispectral image in Huangyan, Zhejiang Province, China. We compared the segmentation performance of this proposed method with the J-X method and the T-MS method, based on qualitative visual interpretation, unsupervised segmentation evaluation, and supervised classification evaluation. The experimental results showed that our approach could identify the appropriate segmentation scale for each segmented object accurately, and achieve better segmentation results for further image classification. Despite these encouraging results, more work is needed to further evaluate and improve the proposed method, including the following:

1) Several parameters are set based on empirical attempt, and more robust approaches are needed to find suitable values.

2) Deep analysis is carried on to test and evaluate the contribution of prior thematic maps for improving the performance of scale selection.

3) We would extract more information and knowledge (such as spatial context relationships and spatial scenes) from prior thematic map and evaluate their importance for scale selection.

4) The idea of segmented object complexity can be further extended into the bottom-up image segmentation.

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