Volume 5, Issue 9, September 2015 ISSN: 2277 128X

International Journal of Advanced Research in Computer Science and Software Engineering

Research Paper

Available online at: www.ijarcsse.com

Segmentation of Remote Sensing Image Using Fuzzy logic for Dynamic Statistical Region Merging Algorithm

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Abstract: Remote sensing is the acquisition of information about an object or phenomenon without making physical contact with the object. Remote sensing image segmentation is definitely to simplify and/or change the representation of a graphic into something that's more meaningful and better to analyze. Image segmentation is an essential tool in image processing and can serve being an efficient front end to sophisticated algorithms and thereby simplify subsequent processing .It is the process of dividing an image into homogenous and non-overlapping regions, which is an essential step toward higher level image processing such as image analysis ,pattern recognition and automatic image interpretation. This paper presents improved remote sensing image segmentation for dynamic statistical region merging algorithm. The proposed method uses dynamic statistical region merging algorithm by using fuzzy logic in order to automatically select scale value. In previous method the segmentation performance relates closely to the scale but the scale is selected manually which may cause incorrect merging. Thus, to improve the accuracy and correctness dynamic statistical region merging-automatic scale value is used to find the automatic scale values. The performance of the algorithm was measured using the receiver operating characteristics such as accuracy and f-measure. Quantitative analysis suggests that this method can consistently segment remote sensing images with high accuracy and efficiency.

Keywords: Dynamic Statistical Region Merging, Remote Sensing Image, Region Merging, Image Segmentation.

I. INTRODUCTION

Image segmentation is the division of an image into regions or categories, which correspond to different objects or parts of objects. Every pixel in an image is allocated to one of a number of these categories. A good segmentation is typically one in which pixels in the same category have similar grey scale of multivariate values and form a connected region, and the neighbouring pixels which are in different categories have dissimilar values. The prospective of segmentation is definitely to simplify and/or change the representation of a graphic into something that's more meaningful and better to analyze. Image segmentation is usually used to find objects and boundaries (lines, curves, etc.) in images. It's a very important process because it is the first step of the image understanding process, and all others steps, such as feature extraction, classification and recognition, depend heavily on its results. Image segmentation has been the topic of intensive research, and a wide variety of image segmentation techniques have already been reported in the literature. All the pixels in a region are similar regarding some characteristic or computed property, such as color, intensity, or texture**.** Not all the segmentation techniques are feasible for Remote Sensing Image (RSI) because the complexity and redundancy of the RSI increases significantly. The RSI provides more information such as for instance spectral, shape, context and texture. RSI is more seriously disturbed by illuminance, noises and so on. Different classes have inherent features in different scales. For example, at coarse scale we may find urban regions, while at finer scale we might find individual houses or roads. So any single-scale segmentation can barely produce satisfying result. Recently, more and more attention has been paid on multi-scale segmentation. The multi-scale segmentation is applied widely on information extraction from RSI, e.g. change detection, classification and so on. Statistical region merging (SRM) is an algorithm used for image segmentation. The algorithm can be used to judge the values within a regional span and grouped together on the basis of the merging criteria resulting an inferior list. Utilizing the Dynamic Statistical Region Merging-Manual scale value (DSRM-MSV) for remote sensing image segmentation, the effect is unsatisfactory. To improve the segmentation accuracy and the correctness Dynamic Statistical Region Merging- Automatic Scale Value (DSRM-ASV) is introduced. It tries to let probably the most similar regions to be tested first. Initially, it redefines the dissimilarity based-on regions. Then, it dynamically updates the dissimilarity and adjusts the test order during the task of merging. The accuracy of the DSRM-ASV is higher than the DSRM- MSV and its computational complexity is approximately linear. Thus, in this study, DSRM-ASV method which uses remote sensing images to find the automatic scale values by using fuzzy logic is proposed.

II. LITERATURE SURVEY

Jorge E. Patino et al. [6] discussed the applications of satellite remote sensing to regional science research in urban settings. The most common applications found in the literature are the detection of urban deprivation hot spots, quality of life index assessment, urban growth analysis, house value estimation, urban population estimation and urban social vulnerability assessment. The satellite remote sensing imagery used in these applications has medium, high or very high spatial resolution, such as images from Landsat MSS, Landsat TM and ETM+, SPOT, ASTER, IRS, Ikonos and Quick Bird. Calderero et al. [15] proposed an unsupervised region merging techniques providing a set of the most relevant region-based explanations of image at different levels. These techniques were characterized by general and non parametric region models, with neither color nor texture homogeneity assumptions, nor a set of innovative merging criteria, based on information theory statistical measures. Maire, M. et al. [14] the author investigated two fundamental problems in computer vision: contour detection and image segmentation. Present state-of-the-art algorithms for both of these tasks. Their contour detector combines multiple local cues into a globalization framework based on spectral clustering. Their segmentation algorithm consists of generic machinery for transforming the output of any contour detector into a hierarchical region tree. In this manner, they reduce the problem of image segmentation to that of contour detection. Extensive experimental evaluation demonstrates that both their contour detection and segmentation methods significantly outperform competing algorithms. Jianyu Chen et al. [16] the author has proposed a new approach to multi scale segmentation of satellite multispectral imagery using edge information. The Canny edge detector was applied to perform multispectral edge detection. The detected edge features were then utilized in a multi scale segmentation loop, and the merge procedure for adjacent image objects has been controlled by a separability criterion that combines edge information with segmentation scale. A.K. Bhandari et al. [17] a modified artificial bee colony (MABC) algorithm based satellite image segmentation using different objective function has been proposed to find the optimal multilevel thresholds. Three different methods were compared with this proposed method such as ABC, particle swarm optimization (PSO) and genetic algorithm (GA) using Kapur's, Otsu and Tsallis objective function for optimal multilevel thresholding. Ting Liu et al. [18] author analyzed urban land changes in Atlanta metropolitan area through the combined use of satellite imagery, geographic information systems (GIS), and landscape metrics. The study site was a fast-growing large metropolis in the United States, which contains a mosaic of complex landscape types. Their method consisted of two major components: remote sensing-based land classification and GIS-based land change analysis. Specifically, author adopted a stratified image classification strategy combined with a GIS-based spatial reclassification procedure to map land classes from Landsat Thematic Mapper (TM) scenes acquired in two different years.

III. SEGMENTATION TECHNIQUES

The various segmentation techniques used in this proposed framework are listed below:

Region Growing: It can be classified as a pixel-based image segmentation method as it involves the choice of initial seed points. This method starts with initial "seed points" and then examines neighboring pixels (using either 4-connectivity or 8-connectivity) to find out perhaps the pixel neighbors ought to be added with the region. The method is iterated on, in the exact same manner as general data clustering algorithms. The region growing algorithm is described as: (i) select several seed points. Seed point selection is dependent on some user criterion (for example, pixels in a particular gray-level range, pixels evenly spaced on a grid, etc.). The first region begins as the complete precise location of the seeds. (ii) The regions are then grown from these seed points to adjacent points according to a location membership criterion. The criterion could be pixel intensity, gray level texture or color. Due to the fact the regions are grown on the building blocks of the criterion, the image information itself is important. For instance, if the criterion were pixel intensity, examine the adjacent pixels of seed points. If they've the same intensity value with the seed points, classify them to the seed points. It is surely an iterated process until there's no change in two successive iterative stages. The suitable choice of seed points is just a significant issue.

Statistical Region Merging: Statistical region merging (SRM) is an algorithm used for image segmentation. The algorithm can be used to judge the values within a regional span and grouped together based on the merging criteria resulting a smaller list. Using the Statistical Region Merging (SRM) for remote sensing image segmentation, the result is unsatisfactory. To improve the segmentation accuracy and the correctness Dynamic Statistical Region Merging (DSRM) is introduced. It tries to let probably the most similar regions to be tested first. Initially, it redefines the dissimilarity based-on regions. Then, it dynamically updates the dissimilarity and adjusts the test order during the task of merging. The accuracy of the DSRM is higher than the SRM and its computational complexity is approximately linear.

Region Splitting and Merging: The split-and-merge algorithm is composed by two steps. First, the method subdivides the entire image into smaller regions following a dissimilarity criterion. To divide the image, different strategies can be adopted such as a quad tree partition (where each region is subdivided into four equal regions) and a binary space partition (BSP) (where an optimal partition is selected to divide the region). Second, the neighbor regions obtained from the splitting step are merged if they verify a similarity criterion. These similarity and dissimilarity criteria can be based on an intensity range, gradient, contrast, region statistics, or texture. The combination of splitting and merging steps allows for the segmentation of arbitrary shapes, which are not constrained to vertical or horizontal lines, as occurs if only the splitting step is considered. Region splitting and merging subdivide an image initially into a set of arbitrary, disjoint regions and then merge and/or split the regions in an attempt to satisfy the necessary conditions.

Dynamic statistical region merging algorithm- Automatic Scale Value (DSRM-ASV)

The SRM can also be used for multi-scale segmentation by construct a hierarchical structure. It is able to capture the main structural components of image using a simple but effective statistical analysis, and it has the ability to cope with significant noise corruption, handle occlusions. However, the SRM has some problems on the order followed to test the merging of regions. It only uses gray difference of adjacent pixels to define the Dissimilarity, according to which the testing order is decided. The order is determined at the beginning, and does not change during the procedure of region merging. This static testing order may cause incorrect merging. To reduce this incorrect merging, a dynamic strategy is proposed. The Dynamic Statistical Region Merging (DSRM-ASV) tries to test the most similar regions first. At first, the Dissimilarity is redefined as the difference of the regions, to which each pixel belongs. Then, it dynamically updates the dissimilarity and adjusts the test order during the procedure of merging. So, it barely causes incorrect merging. In (DSRM-MSV) the problem of manual scale selection occurs. To remove the problem of manual scale selection, this dissertation will use fuzzy logic in order to automatically select the scale value.

IV. RESULTS AND DISCUSSIONS

In this paper, the performance of DSRM-ASV to find the automatic scale value from remote sensing images was analyzed. The remote sensing images were collected for experimental purpose. The implementation of the framework is done in MATLAB. The performance metrics like F-Measure and Accuracy are computed for quantitative comparison.

For qualitative analysis, output images of the implemented framework are shown in Fig 1(a)-(e). The images show the original image, and then fuzzy logic is applied to the image to find the scale value. Then DSRM algorithm is applied to the image to improve the accuracy and correctness of the image. After applying the DSRM algorithm we evaluate the parameters.

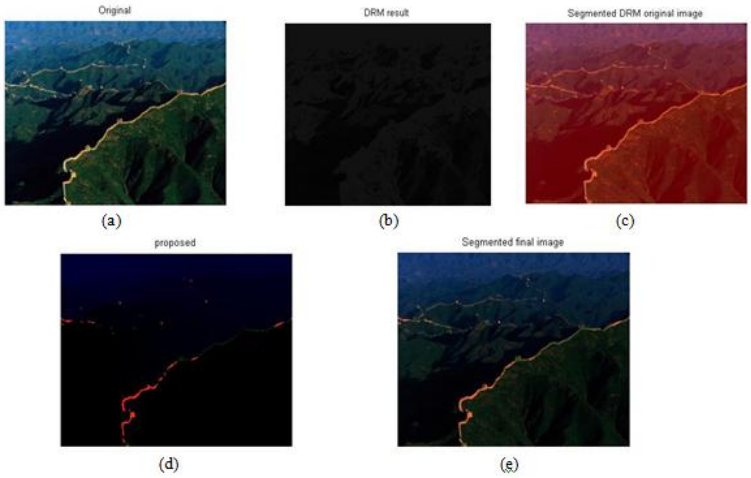

Fig 1: (a) original remote sensing image, (b) showing DSRM image after applying fuzzy logic, (c) image showing the segmented DSRM original image, (d) image showing the proposed image after applying DSRM-ASV algorithm, (e) Final segmented image after applying fuzzy logic and DSRM algorithm.

Quantitative Analysis:

The quantitative results are presented in tables which gives the comparison between the existing and proposed technique on basis of F-Measure and Accuracy. The existing technique uses DSRM-MSV algorithm whereas the proposed technique uses DSRM-ASV algorithm using the fuzzy logic.

F-Measure Analysis:

Table1 shows the comparative output of the existing and proposed technique on basis of f-measure. The results were taken on fifteen remote sensing images.

Image No.	Existing (DSRM-MSV)	Proposed (DSRM-ASV)
1.	0.86	0.91
2.	0.77	0.90
3.	0.92	0.94
4.	0.42	0.85
5.	0.45	0.93
6.	0.97	0.98
7.	0.80	0.96
8.	0.86	0.92
9.	0.53	0.81
10.	0.64	0.88
11.	0.98	0.99
12.	0.51	0.91
13.	0.74	0.96
14.	0.77	0.96
15.	0.86	0.95

The figure below shows the graphical implementation of the above table. The graph clearly depicts that the results of the proposed technique are much better than those obtained from the existing technique.

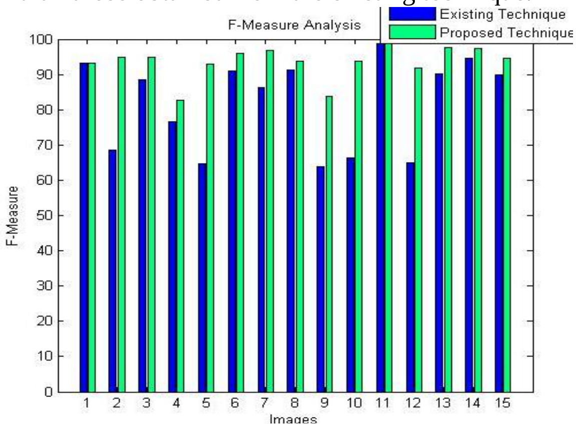

Fig 2: Graphical representation of existing and proposed technique in terms of F-measure.

Accuracy Analysis:

Table 2 shows the comparative output of the existing and proposed technique on basis of accuracy. The results were taken on fifteen remote sensing images.

Image No.	Existing (DSRM-MSV)	Proposed (DSRM-ASV)
1.	93.3%	93.3%
2.	68.57	95%
3.	88.49	94.8
4.	76.7	82.6
5.	64.8	92.9
6.	91.1	95.9
7.	86.4	96.9
8.	91.2	93.9
9.	63.8	83.7
10.	66.3	93.9
11.	98.8	98.9
12.	64.9	91.8
13.	90.1	97.6
14.	94.5	97.4
15.	89.9	94.7

The figure below shows the graphical implementation of the above table. The graph clearly depicts that the results of the proposed technique are much better than those obtained from the existing technique.

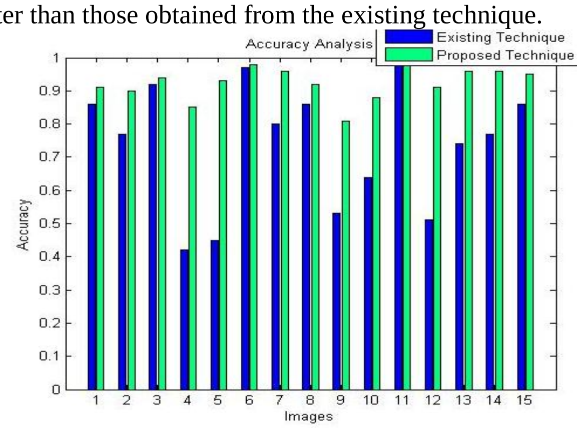

Fig 3: Graphical representation of existing and proposed technique in terms of Accuracy.

V. CONCLUSION AND FUTURE SCOPE

In this paper, the performance of DSRM-MSV, and proposed DSRM-ASV was evaluated on a number of remote sensing images in order to find the automatic scale value by applying fuzzy logic which helps to improve the accuracy and correctness of the image and bring exciting improvement in the proposed work. Further, this technique can be used on multiple scales to find the best scale selection for the remote sensing images to improve the segmentation accuracy.

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