Multifeature Based Satellite Image Segmentation of High Spatial Resolution Remote Sensing Images

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Abstract. With the continuous development of remote sensing technology, the spatial resolution of the image is getting higher and higher and the characteristic information contained in the image is more abundant. High spatial resolution data provides detailed information about the ground for various applications. Methods of Image segmentation become more and more important in the field of remote sensing image analysis. The structural features and texture information are more obvious. The traditional segmentation method based on a single feature of the image can no longer meet the high requirements. In this work, an efficient algorithm is introduced for evaluating segmentation quality. Multifeature based Satellite image segmentation algorithm is proposed to segment the HSR satellite images into different regions based on the properties of multiple features such as color and texture present in the image. The combination of Multifeature information helps to improve an accuracy of segmentation.

Keywords: High Spatial Resolution · Satellite Image Segmentation · Remote Sensing

1 Introduction

Image Segmentation is very primary and critical task in satellite image processing. Segmentation is a technique of dividing an image into a set of different classes whose characteristics such as intensity, color, texture, etc. are similar. Segmentation is a method that summarizes the pixels based on their similarity in the feature space, but in the image itself (location space). It is a combination of spectrally similar pixels, but at the same time the spatial context is also considered. A segmentation technique thus collects important properties of image understanding, thereby having a great importance for visual interpretation.

High Resolution images have the characteristics of abundant geometric and detail information and have been widely used in many applications. The segmentation of various land cover areas in a satellite image is a complicated task. Generally, this kind of images carry out insignificant illumination feature, and are essential because of various

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kinds of environmental distributions. Typically, satellite images contain various objects or regions, i.e. vegetation, water bodies, concrete structures, open spaces etc. These areas are not very well differentiated because of the low spatial resolution. Satellite images contain information over a wide range of scales. Therefore, to study satellite images, it is very important to understand how information differentiates over the different scales of imagery. The main goal of the Segmentation consists in the correct mapping of the boundaries of region and the creation of homogeneous segments in order to eliminate the noise. To analyze or classify images, accurate segmentation is usually needed.

Many research scholars have been done a lot of research on the problems of multiple features fusion, multiscale and multitemporal high resolution remote sensing image segmentation.

Image Clustering is done using the segmented regions, instead of the image pixels in "Color image segmentation based on mean shift and normalized cuts" by W. Tao, H. Jin, and Y. Zhang. This work reduces the sensitivity to noise & results in enhanced image segmentation performance. But it is difficult to divide a natural image into important regions to represent different scenes [1].

To perform MultiScale Segmentation for High Resolution Remote Sensing Imagery Based on Statistical Region Merging and Minimum Heterogeneity Rule, the SRMMHR Method was implemented by Haitao et al. There are many other issues that require further investigation, including the improvement of sort function & merge predicate, the study of evaluation index for estimating segmentation results, the determination of parameters for various classes [2].

To perform Per-pixel vs. object-based classification of urban land cover extraction using high spatial resolution imagery, Object –based Methods were implemented by S. Myint et al. In this work, solved the problem of salt and pepper noise [3].

A novel segmentation framework based on bipartite graph partitioning was implemented by Z. Li et al. In this work, author was able to aggregate multi-layer superpixels in a principled & very effective manner but here is scope of future work to the selection of super pixels more systematically & the incorporation of high level cues [4].

A Scale-Synthesis Method was implemented by Lina Yi, Guifeng Zhang, Zhaocong Wu. This method is highly flexible to be adjusted to meet the segmentation requirements of varying image analysis tasks but it is less effective regarding optimal scale selection [5].

For Unsupervised multispectral satellite image segmentation, Region based normalized cut method was implemented by B. Banerjee, S. Varma, and K. M. Buddhiraju. The strategy taken in this method of region based NCuts is usually based on a region adjacency graph, which is actually a single scale graph; therefore the result is heavily dependent on presegmentation process. To make the result more robust, multiple super pixels can be used [6].

Multiscale Object Accuracy Measure and the measure of Bidirectional Consistency Error Method was proposed by Xueliang Zhang et al. in "Toward Evaluating Multiscale Segmentations of High Spatial Resolution Remote Sensing Images". In this work, author presented two discrepancy measures to determine the manner in which geographic objects are delineated by Multiscale segmentation [7].

A conditional random field classification alg. Was proposed by J. Zhao et al. to perform High Resolution Image Classification by integrating spectral spatial location cues by conditional random fields. Here is future scope of presenting more potentially useful details & the use of spatial location cues in other Remote Sensing techniques [8].

Fine Registration Approach was proposed by Youkyung Han, Francesca Bovolo, Lorenzo Bruzzone. The goal of this approach is to estimate& correct the residual local misalignment which affects Multitemporal VHR images after standard registration & improves registration accuracy. But it become less effective when scenes show very tall elements captured with large off nadir angles. Here is scope to design an approach to mitigate the impact of heterogeneous segments& to improve the robustness of the proposed method to use with multi sensor images [9].

To perform Multi-Scale Segmentation of High Resolution Remote Sensing Images by integrating Multiple Features, The Normalized Cuts Method was proposed by Y. Di et al. The method combined with a variety of features for image segmentation but is not yet implemented fully automatic segmentation feature fusion. Future scope is to implement a method to obtain high segmentation accuracy, fast speed of operation & automatic segmentation [10].

Hence the work must be followed by the region based methods. Hence, the study of image segmentation algorithm is gaining more attention under such circumstances.

2 Proposed Technique

This section presents the proposed Multifeature based satellite image segmentation**.** Multiple features considered in this work are color and texture. The definition of texture is the "spatial repetition of the same pattern in different directions of space ".

2.1 Multifeature Based Satellite Image Segmentation

Image segmentation methods including Multifeature such as color and texture together allow an image to be partitioned while being closer to human perception than those using color or texture separately. In general, the combination of Multifeature such as color and texture information helps to improve the results of segmentation as compared to using one of the two sources alone.

The Texture superpixels technique improves the superpixels decomposition approach and set locally the spatial regularity of superpixels, in order to automatically adapt to the image content. Finally, we introduce a new pixel to superpixels texture homogeneity in order to measure group pixels in terms of texture. The implementation of the proposed algorithm starts with finding the color difference between the adjacent pixel values (x_a, y_a) and (x_i, y_i) is given by Eq. 2.

$$\mathrm{d_{RGB}}=\sqrt{(\mathrm{R_a}-R_i)^2+(G_a-G_i)^2+(B_a-B_i)^2} \tag{1}$$

The distance between the pixels is given by Eq. 5

$$\mathrm{d_{xy}}=\sqrt{(\mathrm{x_a}-x_i)^2+(y_a-y_i)^2} \tag{2}$$

The energy and contrast features are calculated as below:
Energy formula is presented in Eqs. 3, 4 and 5 for the color planes R, G, B respectively.

$$E\frac{R}{n} = \sum\nolimits_{i,j=0}^{N-1} \left(R_{ij}\right)^2 \tag{3}$$

$$E\frac{G}{n} = \sum\nolimits_{i,j=0}^{N-1} \left(G_{ij}\right)^2 \tag{4}$$

$$E\frac{B}{n} = \sum\nolimits_{i,j=0}^{N-1} \left(B_{ij}\right)^2 \tag{5}$$

The combined energy equation is presented in Eq. 6.

$$E_n = E_n^R + E_n^G + E_n^B \tag{6}$$

The contrast for the R, G and B planes is presented in Eqs. 7, 8 and 9.

$$Contrast_R = \sum\nolimits_{i,j=0}^{N-1} R_{ij}(i-j)^2 \tag{7}$$

$$Contrast_G = \sum\nolimits_{i,j=0}^{N-1} G_{ij}(i-j)^2 \tag{8}$$

$$Contrast_B = \sum\nolimits_{i,j=0}^{N-1} B_{ij}(i-j)^2 \tag{9}$$

The combined contrast equation is presented in Eq. 10.

$$\mathrm{contrast} = \mathrm{Contrast_R} + \mathrm{Contrast_G} + \mathrm{Contrast_B} \tag{10}$$

The parameterD_s, known as super pixel distance is defined as

$$\mathrm{D_s} = \mathrm{d_{RGB}} + \mathrm{E_n} + \mathrm{Contrast} + \mathrm{m/s\ d_{xy}} \tag{11}$$

S is the distance between the centres and is given by $\sqrt{\frac{N}{a}}$ the number of image pixels is denoted by N and number of superpixels is denoted by a. ‘m’ is the parameter influencing the spatial disstance.

2.2 Algorithm

Step 1: Determine the cluster centre C_a, For every pixel in the image that consists of the RGB pixel values and the position in the image.

$$\mathrm{C_a} = [\mathrm{R_{a,}} \mathrm{G_{a,}} \mathrm{B_{a,}} \mathrm{x_{a,}} \mathrm{y_a}]^{\mathrm{T}} \tag{12}$$

Step 2: Define a neighborhood of size 2S x 2S, for each centre of the cluster.

Step3: Find out the similar pixels in the neighborhood and update the cluster centre until stability is gain by grouping similar pixels in color and texture.

Step 4: Now with all the clusters, create a dataset D.

Step 5: For every unvisited cluster P, if the numbers of pixels in the cluster are less than minimum threshold, then merge the cluster with a neighboring cluster with the closest color and texture matching pair.

Step 6: For each unvisited cluster P, if the numbers of pixels in the cluster are more than minimum threshold, then proceed to the next cluster.

The proposed algorithm is implemented in MATLAB R2018a on real-time Google earth images.

3 Results

3.1 Experimental Analysis on Real-Time High Spatial Resolution Google Earth Satellite Image

The real-time image is collected using Google earth pro software. The resolution of the image is 1920 x 1080. The image is captured from the following coordinates:

19°53′55.65"N, 75°18′52.29"E elev 1906ft eye alt 933ft.

The image is of Dr. BAMU Campus in Aurangabad, India.

The proposed method performs better as compared to the existing techniques. This is proved by the comparison Table 1 provided as.

The proposed technique produced better segmentation result as compared to existing segmentation results. The Segmentation Quality of proposed technique is improved.

Fig. 1. The real-time high spatial resolution google earth input image 1.

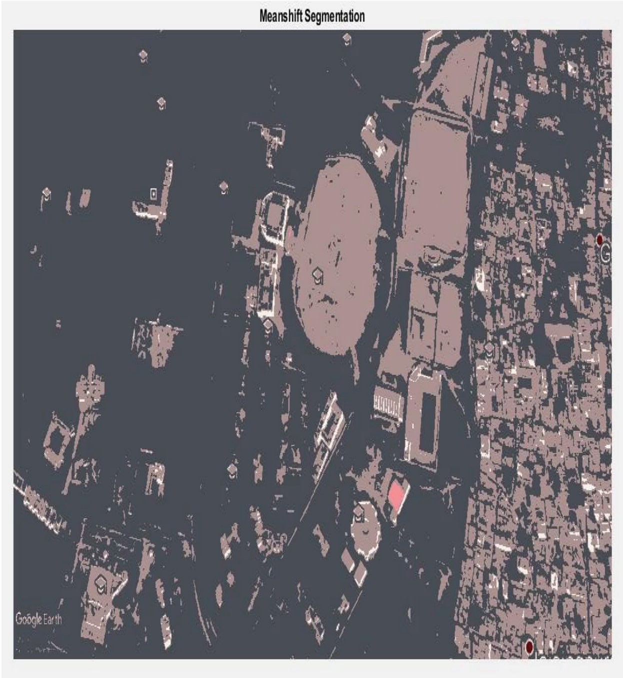

Fig. 2. Mean-Shift segmentation result of input image 1

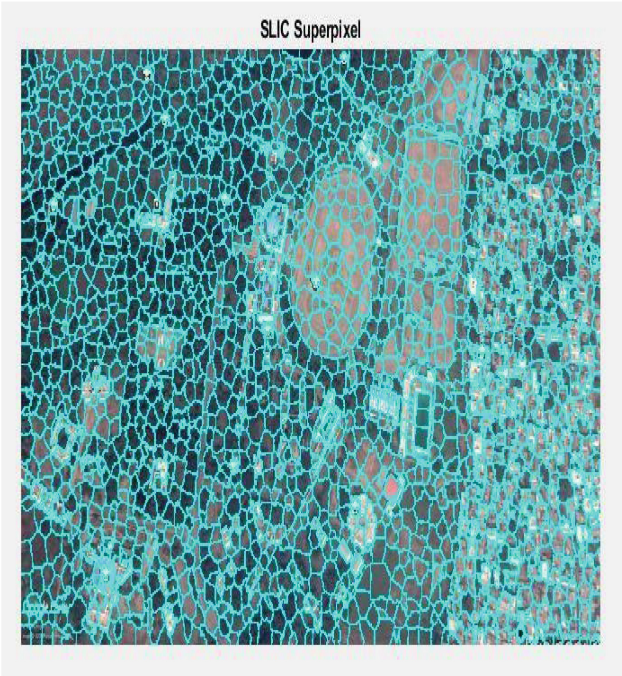

Fig. 3. SLIC-Superpixel segmentation result of input image.

Fig. 4. Multifeature based satellite image segmentation result of input image

Table 1. Comparison Results

Algorithm	Mean Value	Average Deviation from mean value	Entropy	Elapsed time
Mean Shift Segmentation	127.890717	296715.515404	0.288686	470.35
Superpixel Segmentation	112.293302	3223.247003	0.006162	260.172
Proposed Multi feature Based Segmentation Technique (Color and Texture Based)	110.985766	3987.014261	0.002316	1240.073

4 Conclusion

Accurate segmentation of High Spatial Resolution Remote Sensing Imagery identify various patterns, objects, damage assessment due to environmental disasters. This is done by a technique using combination of multifeature information i.e. color and texture. When images are analysed, analysis requires correct segmentation. Color and Texture features information together improves accuracy of segmentation.

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