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Color and Texture based Satellite Image Segmentation using Texture based Superpixels Technique

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***Abstract*—In the field of remote sensing, image segmentation methods becomes more and more important to analyze the images. From the images, Image Segmentation extracts the similar features based on their color, intensity. Then using different segmentation techniques groups them together. The consideration of the segmentation quality is of great significance. This paper presents a technique to segment the satellite images into different regions based on the properties of color and texture present in the image. In this technique, the implicit integration of color attributes and texture attributes are performed separately and combined them during the segmentation process. The Texture superpixels method improves the superpixels decomposition approach and locally set the spatial regularity of superpixels, to automatically adapt the image contents, thus improving the accuracy of segmentation.**

***Index Terms*— High Resolution, Image Segmentation, Remote Sensing, Spatial Resolution.**

I. INTRODUCTION

In digital image processing, segmentation means the grouping of neighbouring picture elements (pixels) into pixel groups (regions, segments, picture primitives) based on similarity criteria (spectral signature, texture). In contrast to classification and clustering, segmentation is to be understood as methods that do not summarize the pixels based on their similarity in the feature space, but in the image itself (location space). It deals with not just a combination of spectrally similar pixels, but at the same time the spatial context is taken into account. Segmentation approaches thus integrate an important property of image understanding, which is also of great importance for visual interpretation.

Image segmentation plays the role as a preprocessing step in image processing. The segmentation of various land cover areas in a satellite image is a complicated task. Generally, such kind of images carry out insignificant illumination feature, and are essential because of numerous kinds of environmental distributions. Typically, satellite images contain various objects or regions, e.g., vegetation, water bodies, concrete structures, open spaces etc. These areas are not very well separated because of having low spatial resolution. Satellite images include information over a large range of scales. Therefore, for satellite image study, it is very essential to recognize how information varies over the different scales of imagery. The main concern of the Segmentation consists in the correct mapping of region boundaries and the creation of homogeneous segments in order to eliminate the noise. When images are analyzed or classified, this usually requires accurate segmentation.

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II. LITERATURE REVIEW

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

For incorporating the textural and spectral properties of the objects which are to be detected, a new region-merging segmentation technique was developed by Gamanya R, De Maeyer P, and De Dapper M in 2007. At different stages of scale, the object's different size and behaviour were detected by this technique [1].

To segment the remotely sensed images based on Artificial Neural Networks and Genetic algorithm, a multi-component image segmentation algorithm was demonstrated by Awad M, Chehdi K, Nasri A. in 2007 [2].

A segmentation algorithm was implemented by Saha S, Bandyopadhyay S. in 2008 with the use of symmetry-based cluster validity index [3]. If it is symmetric, the presence clusters are indicated by the index value. For optimization of index value and make the segments of clusters in an image, genetic algorithm is utilized.

For remote sensing images, boundary constrained multi scale segmentation was proposed by Zhang X, Xiao P, Song X, She J. in 2013. Based on the strategy of local best region growing, the aggregation of adjacent pixels is done to cause the initial segmentation [4]. This process of initial segmentation is established the Region Adjacency Graph (RAG). In order to generate multi-scale segmentation results, the strategy of local mutual best region merging is implemented to RAG finally.

Some different segmentation techniques were proposed by Wang C, Shi AY, Wang X, Wu FM, Huang FC, and Xu LZ in 2014 for various applications of remote sensing [5]. However, the applications are involved a novel multi-scale segmentation algorithm according to the wavelet transform which is developed as JSEG algorithm, Wavelet JSEG (WJSEG); for high resolution remote sensing image segmentation

Vibha L, Shenoy P D, Venugopal K R, Patnaik L M in 2009 have proposed a technique of genetic algorithm based segmentation and presented an automatic image segmentation algorithm for the satellite images [6].

A hybrid method was framed by Zheng L, Shi D, and Zhang J. in 2010for crop image segmentation [7]. This method is formed by combining the Fisher Linear Discriminant (FLD) and Mean Shift techniques. At the stage of the FLD, a point-line-distance-based strategy has been adopted by this technique for weighting training data.

A fast and accurate segmentation procedure was developed by Chen Q, Zhou C, Luo J, Ming D, in 2005 and it has been incorporated in the watershed transformation to gain the satellite images' initial segments, based on the textures of high spatial resolution remotely sensed data [8].

The procedure was improved and deployed the watershed segmentation by Wang Z, Song C, Wu Z, Chen X in 2005 [9].

To segment the areas which contain soil and vegetation, physics-based reflection models were designed by Onyango CM, Marchant JA, in 2001. The areas of vegetation and land were segmented by using color images [10]. Based on mean and standard deviation parameters, the reflectance based segmentation results were analyzed and validated. Only three bands are involved in this segmentation such as Red, Green, and Blue and this is the main limitation.

Recent improvements related to the laser detection and ranging that reduced the effort and time to make a model. The objects' surface is reported by P.Gong and T. Saagawa in 2005. The spectral data can be complemented by this information but poor in spectral terms [11]. The spectral data is provided by remote sensing sensors. As urban scenes are very complex geometrically, the laser scanner data is required for urban applications. The compatibility of laser scanner data's spatial resolution is with the available satellite imagery's spatial resolution but the characteristic of information is varied. The altitude of the pixels is computed by this data and a new approach is given for segmentation and detection. The issue of mixed pixel is decreased by using the high spatial resolution sensing data but the disadvantage is that the noise and internal variability with the land-use classes still at increasing phase. As the per-pixel based techniques are not efficient due to the inability of acquiring the reflectance change, it's difficult to the extract the information from high resolution remote sensing imagery. To achieve the requirements of the object-oriented classification, the approach must be followed by the region based methods. Hence, the study of image segmentation algorithm is gaining higher attention under such circumstances.

III. Existing Techniques

A. MeanShift Segmentation

The Mean Shift algorithm is an iterative nonparametric estimation method for estimating the modes of a probability density. It is based on a rise in the gradient of the estimated probability density. The Mean Shift procedure can be summarized as follows:

Either a set of data$\{x_i\}, i \in \{1..n\}$ in $R^d$the multidimensional density estimator at any point is given by (1):

$$\nabla\hat{f}(x) = \frac{c_{k,d}}{nh^d}\sum_{i=1}^{n} k\left(\|\frac{x-x_i}{h}\|^2\right) \quad (1)$$

Where *k* is the profile of the kernel function *K* and *h* is the width of this kernel.

Determining the modes using the Mean Shift method amounts to cancelling the gradient of the probability density estimator, that is, $\nabla\hat{f}(x) = 0$. After some simplifications and substitutions in (3), cancelling the gradient amounts to cancelling the quantity$M_h(x)$ given by (2):

$$M_h(x) = \frac{\sum_{i-1}^{n} x_i g(\|\frac{x-x_i}{h}\|^2)}{\sum_{i=1}^{n} g(\|\frac{x-x_i}{h}\|)} - x \quad (2)$$

$M_h(x)$ denotes the vector Mean Shift and g the derivative of the profile function *k*.

The Mean Shift algorithm is given as follows:

1. Initialize h,ε and the merge threshold.
2. Conversion of RGB color systems to Lab
3. Construct a set of hyper spheres of radius h over the entire image. Each centre the hyper sphere is considered a mode.
4. For each hyper sphere:
   4.1 Calculate the vector $M_h(x)$
   4.2 $x \leftarrow x + M_h(x)$
   4.3 As long as$x^{\varepsilon+1} - x^t > \varepsilon$ going to 4.1
5. Eliminate modes whose difference is less than the melting threshold.
6. Associate each pixel of the image with the associated mode according to the criterion of nearest neighbours to color sense.

Note that the pass band *h* is composed of two pass bands, the first spatial, which we will noteh_s, and the second spectral, which we denote byh_r.

B. Superpixels Segmentation

The SLIC (Simple Linear Iterative Clustering) algorithm makes it possible to segment an image into K regions called superpixels according to the content of the image. The segmentation into superpixels is very useful for detecting objects, for cutting out images and for reducing the amount of data to be processed. Rather than doing a simple decimation on the image to reduce the amount of information, segmenting into superpixels allows us to have a set of regions of interest to process, without reducing the amount of raw information in the image. Specific algorithms can then be applied to these regions based on their content. The following sections present the SLIC algorithm, as well as the connectivity algorithm applied in post-processing. This algorithm is necessary since SLIC does not guarantee regions included in a single block. The images below show the result of segmentation with SLIC before and after post-processing.

The algorithm can be summarized with the following steps:

1) Initialization of the centres of the superpixels. The centres are equidistant (distance S) and are in 5 dimensions (x, y, L, a, b) for their spatial coordinates and the color of the pixel in LAB space.
2) Initialization of the Superpixel map and the distance map. The distances are initialized to infinity and the pixels are assigned to the Superpixel 0.
3) For each centre, the distance of the pixels lying within a radius of 2S to the centre is calculated. If the distance is less than that in memory for the pixel, it is modified in memory and the pixel is now part of the Superpixel.

4) The positions of the centres (5 dimensions) of the superpixels are updated according to the average value of all the pixels of the Superpixel.
5) Steps 2 and 3 are re-performed until the algorithm converges, that is to say, the average displacement of the centres between two iterations is less than a certain threshold.

IV. Proposed Technique

This section presents the proposed color and texture based image segmentation**.** Like color, texture is a fundamental factor in perception of the environment and the recognition of its objects. Unlike color, the texture remains difficult to define in a precise and generic way. The definition of texture is the "spatial repetition of the same pattern in different directions of space ".

A. Color and Texture Based Satellite Image Segmentation

Image segmentation methods using color and texture together allow an image to be partitioned while being closer to human perception than those using color or texture alone.
In general, the combination of color and texture information is interesting in that it helps to improve the results of segmentation compared to using one of the two sources alone. In the technique of color and texture segmentation, we can distinguish three categories of together use of color and texture.

1) The implicit integration of color attributes and texture attributes.
2) The methods which extract color and texture information Cascade.
3) The approaches which extract the color attribute and the texture attributes separately and combines them during the segmentation process.

The Texture superpixels technique improves the superpixels decomposition approach & locally set the spatial regularity of superpixels, to automatically adapt to the image content. Finally, we introduce a new pixel to superpixels texture homogeneity to measure group pixels in terms of texture. The implementation of the proposed algorithm begins with finding of the color difference between the adjacent pixel values (x_k, y_k) and (x_i, y_i) is given by (4).

$$d_{RGB} = \sqrt{(R_k - R_i)^2 + (G_k - G_i)^2 + (B_k - B_i)^2} \quad (3)$$

The distance between the pixels is given by (5).

$$d_{xy} = \sqrt{(x_k - x_i)^2 + (y_k - y_i)^2} \quad (4)$$

The energy and contrast features are calculated as follows:
Energy formula is presented in (5), (6) and (7) for the colour planes R, G, B respectively.

$$E_n^R = \sum_{i,j=0}^{N-1} \left(R_{ij}\right)^2 \quad (5)$$

$$E_n^G = \sum_{i,j=0}^{N-1} \left(G_{ij}\right)^2 \quad (6)$$

$$E_n^B = \sum_{i,j=0}^{N-1} \left(B_{ij}\right)^2 \quad (7)$$

The combined energy equation is presented in (8).

$$E_n = E_n^R + E_n^G + E_n^B \quad (8)$$

The contrast for the R, G and B planes is presented in (10), (11) and (12).

$$Contrast_R = \sum_{i,j=0}^{N-1} R_{ij}(i-j)^2 \quad (9)$$

$$Contrast_G = \sum_{i,j=0}^{N-1} G_{ij}(i-j)^2 \quad (10)$$

$$Contrast_B = \sum_{i,j=0}^{N-1} B_{ij}(i-j)^2 \quad (11)$$

The combined contrast equation is presented in (12).

$$Contrast = Contrast_R + Contrast_G + Contrast_B \quad (12)$$

The parameterD_s, known as super pixel distance is defined as

$$D_s = d_{RGB} + E_n + Contrast + \frac{m}{S} d_{xy} \quad (13)$$

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

B. Color and Texture Based Satellite Image Segmentation Algorithm

Step 1: For every pixel in the image, compute the cluster centre C_k consists of the RGB pixel values and the position in the image.

$$C_k = [R_k, G_k, B_k, x_k, y_k]^T$$

Step 2: For each cluster centre define a neighbourhood of size 2S x 2S.
Step 3: Find the similar pixels in the neighbourhood and update the cluster centre until stability is achieved by grouping similar pixels in colour and texture.
Step 4: Create a dataset D with all the clusters.
Step 5: For each unvisited cluster P, if the number of pixels in the cluster are less than minimum threshold, merge the cluster with a neighbouring cluster with the closest color and texture matching.
Step 6: For each unvisited cluster P, if the number of pixels in the cluster are more than minimum threshold, proceed to the next cluster.
The proposed algorithm is implemented in MATLAB R2018a on real-time Google earth images.

V. RESULTS

A. Experimental Analysis on Real-Time High Spatial Resolution Remote Sensing 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°52'47.18"N, 75°21'25.75"E elev 2006ft eye alt 2591ft
The image is of JNEC, CIDCO in Aurangabad, India.

Fig. 1 Real-Time High Spatial Resolution Remote Sensing Satellite Input Image

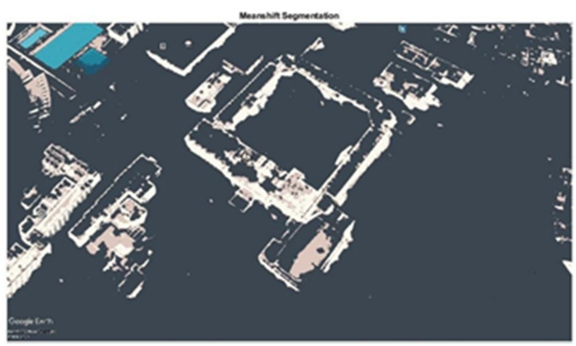

Fig. 2 Mean Shift Segmentation Result of Input Image

Fig. 3 SLIC Superpixel Segmentation Result of Input Image

Fig.4 Color and Texture Based Satellite Image Segmentation Result of Input Image

The proposed method performs better when compared to the existing techniques. This is proved by the comparison provided in Table I.

TABLE I. COMPARISON RESULTS

Algorithm	Mean value	Average Deviation from Mean value	Entropy	Elapsed time (Sec)
Mean Shift Segmentation	135.228661	618791.090970	0.135940	1499.863791
Superpixel Segmentation	144.149662	12201.387571	0.06101	1563.50645
Proposed Segmentation Technique (Color and Texture Based)	113.097259	4777.852174	0.003000	1209.767

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

VI. CONCLUSION

The goal of image segmentation is to split a (digital) image into several areas. High Spatial resolution satellite image segmentation is probably one of the most important areas of image processing. This is done by a technique using combination of color and texture features with superpixels segmentation. When images are analysed, this usually requires correct segmentation. The combination of color and texture features with superpixels segmentation technique improves the superpixels decomposition approach and locally set the spatial regularity of superpixels. The experimental results shows that the proposed technique performs better when compared to the existing techniques.

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