Journal of Basic and Applied Engineering Research
p-ISSN: 2350-0077; e-ISSN: 2350-0255; Volume 3, Issue 10; July-September, 2016, pp. 865-869

http://www.krishisanskriti.org/Publication.html

Segmentation of SAR Images Based on Representative Features, DSRM and Fuzzy Logic

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Abstract—*Image classification, which can be defined as identification of objects in a scene captured by a vision system, is one of the important tasks for remote sensing images. For complex SAR images existing segmentation techniques fails to produce accurate results. This paper proposes an image segmentation method based on similarity of representative features, dynamic statistical region merging (DSRM) and fuzzy logic. Segmentation based on representative features produces oversegmented results. The segmented results are refined based on a dynamic statistical region growing method and uses fuzzy logic for calculating membership grades of pixels to classify pixels into appropriate segments Segmentation results on natural images demonstrate that the presented algorithm produces more robust results than existing techniques*

1. INTRODUCTION

In general an image segmentation is defined as a process of partitioning an image into similar groups such that each region is similar but the union of two adjacent regions is different. For different applications image segmentation has been interpreted differently. For example, it is viewed as a bridge between low level and high level vision subsystems in machine vision applications and as a tool to delineate anatomical structure in medical imaging.

Segmentation is depends on different criteria. One of the criterion is the scale parameter, which is an abstract value to determine the maximum change of difference caused by combining different objects. It is dependent on the size of the object. Small scale number results in small objects and large scale number results in large objects, which points into multi resolution image segmentation. The color is the second criteria which is actually the pixel value. Shape is the next criteria which includes smoothness, which describes the similarity between image object borders and compactness and a perfect square, which describes the closeness of pixels clustered in an object by comparing it to a circle .Neighborhood function is the last criterion, which compares image object grown with adjacent pixels.

2. RELATED WORK

Geographic object based image analysis (GEOBIA) [1] has received tremendous attention in analyzing remote sensing images. GEOBIA is based upon two major concepts a) dividing images b) allowing for multiple scales when organizing and utilizing the segmented objects.[2]Reviewed various segmentation techniques. Measurement space guided clustering involves separating images based on histogram peaks to define classes in the image. This type of segmentation is most likely to avoid errors through poor region merges. It doesn't provide spatially contiguous regions and which may result in salt and pepper effect. Single linkage algorithms involving individual pixel linkage to create regions. Hybrid linkage avoid this problem through using neighborhood characteristic. In centroid based algorithm region means are recomputed as regions are merged. Texture can be thought of as the spatial patterns in an image.

Remote sensing radiometers which produces multispectral images, provide much enhanced capabilities of characterizing ground objects. Both spectral and texture information are expected to use in the remote sensing segmentation techniques. Automatic segmentation using region based method and feature distribution [3] consists of three steps 1) Hierarchical splitting 2) agglomerative merging 3) Pixel-wise refining .This method doesn't require a priori knowledge. Texture is very difficult to characterize .A multiscale texture analysis procedure for improved forest stand classification [4] utilized two different approaches: local variance and second order statistics. Local image variance is a measure of deviation from the mean within the processing neighborhood. This procedure results in a dataset which contains the variance values for all spectral bands. The maximum size of the processing window was set using range values. The next approach is the second order statistics. This method uses three second order texture measures: angular second moment, entropy and contrast. Angular second moment measures homogeneity. Entropy is a measure of the amount of the order and repeatability and contrast is the measure of the degree of spread of the values in the matrix. Watershed method is one of the traditional segmentation method. It is a mathematical approach. A novel texture preceded segmentation algorithm for high resolution imagery [5] uses a texture preceded algorithm for segmentation. Fast node merging can be achieved by region adjacency graph depending on a global optimum. The similarity between nodes in the graph is established by a combined distance, composed of texture, spectral and shape features. Then the final segmentation can be obtained iteratively by fast merging. This algorithm can also detect the real object boundaries.

The cues of contour and texture differences are exploited simultaneously because natural images contain both textured and untextured regions. Contour and texture analysis for image segmentation [6] uses algorithm which partitions grayscale images into disjoint regions of coherent brightness and texture. Contours are treated in the intervening contour framework, while texture is analyzed during textons. [7]Used local spectral histogram representation, which consists of histograms of filter responses in a local window. This representation provides an effective feature to capture both spectral and texture information. The performance of existing method can degrade when choosing a large segment number to deal with a complex scene. The reason is that with more representative features, the least squares solution is more sensitive to noise, and the estimated. Combination weights might not correspond to actual coverage fractions.

3. METHODOLOGY

The architecture of the proposed system is as follows

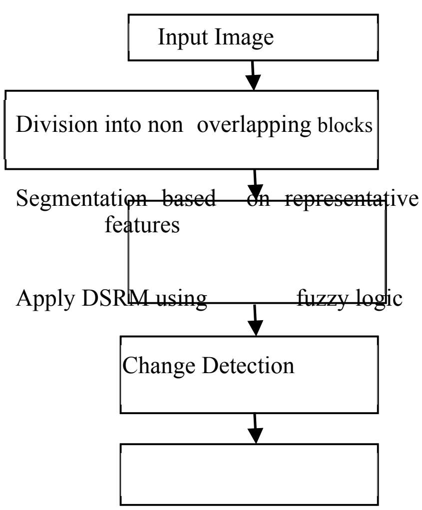

Fig. 1: Architecture of Proposed Segmentation Method

3.1 Proposed Algorithm

Step 1: Select input image

Step 2: Segmentation Based On Similarity of

Representative Features

i. Divide image into non overlapping blocks. ii. Apply bank of filters iii. Perform SVD analysis iv. Perform K means clustering Step 3: Apply Dynamic Statistical Region Merging and Fuzzy Logic.

3.2. Segmentation Based on Similarity of Representative Features

This segmentation method utilizes the spectral and texture representative features for segmentation. Here, we use local spectral histograms to generate combined spectraltexture features.Given an input image window W and a bank of filters{F^{α}, α = 1,2, … K}, we can compute a sub band image $W^{(\alpha)}$ for each filter $F^{(\alpha)}$ through convolution. For$^{(\alpha)}$, we have the corresponding histogram, which is denoted by $H_W^{(\alpha)}$ .For each filter response here there are used 11 equal width bins .Concatenation of the histograms of different filter responses is called as a spectral

histogram, i.e.,

$$H_W = \frac{1}{|W|}\left(H_W^1, H_W^2, \dots\dots\dots H_W^K\right) \qquad (1)$$

Where |. |denotes cardinality.

The spectral histogram is a normalized feature statistic, which can compare image windows of different sizes. For each pixel location, the local spectral histogram is computed over the window centered at the pixel. The size of the window is called integration scale. When the filters are selected properly, the spectral histogram is sufficient to capture texture appearance

Because spectral histograms can characterize image appearance, we assume that spectral histograms within a homogeneous region are approximately constant. For each homogeneous region in an image, we define a representative feature, which should be equal to the constant spectral histogram of the region. The feature of each pixel can be regarded as the linear combination of all the representative features weighted by the corresponding area coverage.

Given an image with N pixels, M-dimensional features at each pixel, and L representative features, we use a multivariate linear regression model to associate each feature to the representative features, which is expressed as

$$Y=Z\beta+\varepsilon \qquad (2)$$

Where Y is an M × N matrix with each column representing a feature at a pixel location, Z is an M × L matrix containing L representative features, β is an L × N matrix containing combination weights for N pixels, and ε is an M × N matrix representing noise.

Representative features can be computed by manually selecting seeds within each region. Given the feature matrix Y and the representative feature set Z. The connection between the feature matrix and the representative features can be estimated by computing β.

This can be easily solved by the least squares estimation, i.e.

$$\beta = (Z^T Z)^{-1} Z^T Y \quad (3)$$

The segmentation result is immediately given by β, where the largest value in each column shows the segment ownership of the corresponding pixel. It is worth noting that in the solution, all the dimensions of the features are involved to estimate the weights, i.e., to produce segmentation all bands are taken to account. If the representative features are not given, to ensure a unique solution in (3), Z needs to have the full column rank so that

$(Z^T Z)^{-1}$is not singular. Hence, representative features have to be linearly independent.

Since each feature is a linear combination of representative features, the rank of feature matrix Y and the rank of Z should the same, i.e., the number of representative features. However, Y tends to be of full rank because of image noise. Due to the Eckart–Young theorem, we can estimate the underlying feature matrix with the expected rank. Singular value decomposition (SVD) is the basis of low rank approximation. To the features in the subspace, we can apply K-means clustering where cluster centers corresponds to representative features. By projecting the cluster centers back to the original space, easily obtain the representative feature. When performing k-means clustering a problem can occur. The features near boundaries can form small clusters, which results in clustering very sensitive to initialization. To tackle this problem, measure edgeness for each pixel and neglect the features of pixels with high edgeness before clustering. For the pixel location (x,y), we compute the feature distance between pixel locations (x+d,y) and (x-d,y) and that between (x,y+d)and (x,y−d), where d is half of the side length of W. Edgeness is the sum of these two distances.

3.2. Apply Dynamic Statistical Region Merging (DSRM) using Fuzzy Logic

In fuzzy clustering, the centroid of each sub class are estimated adaptively in order to minimize the cost function. One of the popular fuzzy clustering algorithm, fuzzy C means is been used here. Fuzzy C means utilizes a membership function to estimate the degree of membership of m^{th} object to the nth cluster.

The Fuzzy C Means (FCM) algorithm assigns pixels to each segment by using fuzzy memberships. Let X=(x_1, x_2,., x_N) denotes an image with N pixels to be partitioned into c clusters, where xi represents multispectral (features) data. The algorithm is an iterative optimization that minimizes the cost function defined as

$$J=\sum_{j=1}^{N}\sum_{i=1}^{C} U_{ij}^{m}\left\|x_i - z_j\right\|$$

Where uij represents the membership of pixel xj in the ith cluster, z_i is the ith cluster center, || || is a norm metric, and m is a constant. The parameter m controls the fuzziness of the resulting partition. The cost function is minimized when pixels close to the centroid of their clusters are assigned high membership values, and low membership values are assigned to pixels with data far away from centroid. The membership function represents the probability that a pixel belongs to a specific cluster. In the FCM algorithm, the probability is dependent solely on the distance between the pixel and each individual cluster center in the feature domain. The membership functions and cluster centers are updated by the following:

$$U_{ij}=\frac{1}{\sum_{K=1}^{C}\frac{\left\|x_j-x_i\right\|}{\left\|x_j-z_k\right\|}^{\frac{2}{m-1}}}$$

And

$$Z_i = \frac{\sum_{j=1}^{N} {U_{ij}}^{m} X_j}{\sum_{j=1}^{N} {U_{ij}}^{m}}$$

The proposed method uses dynamic statistical region merging algorithm by using fuzzy logic in order to automatically select scale value. The above method results in an oversegmented image which if further refined by using the DSRM combined with fuzzy logic. The algorithm for DSRM using fuzzy logic is as follows,

Start

Step 1: Compute the image gradient

Step 2: Sort the image pixels.

Step 3: Build the pixels pairs C1 and C2.

Step 4: Compute the merging predicate: The proposed predicate is based on measuring the dissimilarity between pixels along the boundary of two regions. We obtain the dissimilarity between two neighboring regions R1, R2 ⊆ V as the minimum weight edge connecting them. Since the merging predicate will decide whether there is an evidence of merging between the pair of regions .It involves two aspects: a dissimilarity measure which is used to determine the candidate region for merging, and the consistency property which checks if the regions are homogeneous. We define the following region merging predicate P: P(R1,R2)=

$$\begin{cases} true & if \begin{array}{c}(a) S(R1,R2)=\min_{R_1\in\Omega_1} S(R_1,R_1)=\min_{R_2\in\Omega_2} S(R_2,R_2); and \\ (b) R_1\ and\ R_2\ are\ consistent\end{array} \\ false & otherwise \end{cases}$$

WhereΩ_1 and Ω_2 are the neighborhood sets of R_1 and R_2, respectively.

Step 5: Update the membership function of the pixels using the fuzzy logic.

End

3.3. Change detection

One of the most important application of SAR images is to perform change detection. Change detection refers to the process of determining whether any change has been occurred to the study site using the pre event and post event images of the site. In this paper the segmented output of both pre and post event images are used to perform correlation based change detection.

In this method after segmentation, the correlation between the corresponding segments are calculated. If the correlation is high, then no change has occurred otherwise a change is noted and a change map is generated. In the change map, the red pixels corresponds to the area with change and green pixels denote the no change area.

4. RESULTS AND DISCUSSION

The proposed method was applied to some of the study sites and the results obtained were very accurate when compared to the existing method. Fig. 2 shows the results of applying the existing and proposed segmentation

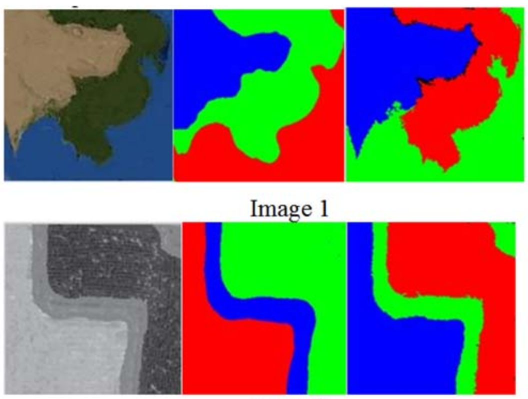

Figure 2. Segmentation using existing and proposed methods.

The accuracy of the proposed segmentation method is analyzed using the four parameters such as dice coefficient, RMS error, PSNR and Hausdorff distance.

Table I: Performance Analysis

Image	Parameters	Existing System	Proposed System
Image 1	Dice coefficient	0.01	0.05
	RMS Error	0.06	0.01
	PSNR	49.7	65.4
	Hausdorff distance	11.4	4.5
Image 2	Dice coefficient	0.08	0.09
	RMS Error	0.06	0.01
	PSNR	50.4	75.4
	Hausdorff distance	10.4	.8

It is evident from the table that the efficiency of the proposed segmentation method is better than the existing method.

Fig. 3 shows the results of applying the change detection using the segmented results of pre event and post event image.

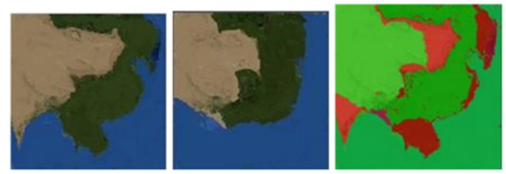

Figure 3: Change detection

Accuracy of change detection is obtained by plotting the confusion matrix and it is found that this change detection method produced 85% accuracy.

5. CONCLUSION

We have presented a new method for segmenting remote sensing images based on similarity of representative features followed by DSRM using fuzzy logic. DSRM lets 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 procedure of merging, followed by updating the membership function using fuzzy logic. Experiments demonstrate that the accuracy of the proposed method is higher than the existing techniques.

6. ACKNOWLEDGEMENT

First of all, we thank almighty for giving us strength and courage for taking a relevant area and to do research on that. We thank everyone, who directly or indirectly helped us for doing the thesis.

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