A Global Graph Based Segmentation of High-Resolution Remote Sensing Images Employing Edge Weight Factor

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Abstract**-**In remote sensing, segmentation can be defined as a process in which a remotely sensed image is completely divided into non-overlapping segments/regions in the image space. The conventional segmentation methods are variation based. Such techniques check for image content variations in the image and predict the regions based on these variations. Since these variations are very large in high resolution remote sensing images, such methods yield a large number of isolated regions. In such approaches, a large number of regions are detected within a whole region. This piecewise segmentation of image causes inaccurate information processing. In our proposed approach, the limitations of traditional variation based segmentation approaches have been overcome by an improved segmentation technique termed as “Edge Weight Factor” region estimation method which is based on enhanced graph theory terminology and employs a factor for predicting the presence of boundaries between regions in an image based on edge weights. The computational time of this algorithm is linear to the number edges in graph and is also found to be fast. A significant property of this technique is its capability to preserve detail in region with low variability and disregard detail in regions of high variability.

Keywords**-** *Segmentation, Boundaries, Regions, Edge, Edge Weight Factor, Cropping.*

I. INTRODUCTION

Many new applications of remote sensing data require the knowledge of complex spatial and structural relationships between regions/segments within an image. Since this knowledge is hidden in the image’s regions, the regions must be separated to retrieve and recognise meaningful spectral or polarimetric signatures or segments of higher-level abstraction, such as inhabitant, water, vegetation, terrestrial, etc. A segment can be defined as a contiguous set of spectrally similar pixels. Segments form a complete disjoint coverage of an image thereby offering a more appropriate means of analysis. Also segmentation of various land cover of regions in remote sensing images is necessary for the efficient analysis and interpretation. Thus, the application of segmentation is not an option, but a necessity in the efficient analysis and classification of remote sensing images. Developments of image segmentation algorithms for remote sensing imageries have been drastically increased after the availability of high resolution imagery [1]. There are basically two remote sensing image segmentation categorisations namely Image driven approach and Model driven approaches. The image driven approaches [2][3][4][5] operate directly on the image pixels and detect objects solely based on the image features. The model driven methods [6][7][8] analyse the data present in the image and based on this information determines a proper segmentation.

It is found that the image driven approaches often define grouping criteria based on parameters like colour and contrast[3] between the regions or on textural features[2][5]. Model-driven approaches are found to work well on simple scenes. However, they are limited when segmenting complex scenes found in remotely sensed images. In remotely sensed images, it is very difficult to divide an image into regions if some regions are recognised by colour, others by their texture, and some others based on the saturation or the intensity. Apart from this drawback, a limitation found in all of the above techniques is, these methods create the regions depending on variations in image content leading to either over segmentation or under segmentation. The limitations of such piecewise segmentation approaches have been overcome by an improved segmentation technique termed as “Edge Weight Factor” (EWF) region estimation method which is based on enhanced graph theory terminology.

II. PROPOSED APPROACH

In the field of remote sensing image analysis, the graph based segmentation methods[9][10][11][12] are considered as one on the best approaches which result in correct isolation of regions upto great extent and also these methods are time & space efficient. The Global graph theory technique is used for detection and edge-based association, representing the edge segments in the form of a chart and finds the diagram for low-cost paths that correspond to significant edges [13]. However there is always a scope for improving the accuracy of segmentation from previous graph based segmentation methods. In this paper we try to enhance the accuracy of prevailing methods by employing a weight factor on edges which can be used for checking the existence of a boundary between the two regions in an image. As with certain classical graph based segmentation methods [10], [11], [12] our methodology is also based on choosing the edges from a graph in which each pixel corresponds to a node(V) and the neighbouring pixels are connected by the undirected edges(E).

Let $G = (V, E)$ represents an undirected graph in which,

- The vertices $v \in V$, are the group of element (pixels) to be segmented.
- The edges $(v_i, v_j) \in E$ corresponds to the pairs of neighbouring pixels.

- Every edge $(v_i, v_j) \in E$ has an associated non-negative weight $w(v_i, v_j)$ with it, which is used as a dissimilarity criteria between neighbouring vertices *vi* and *vj*.

In our approach, the set of vertices in V are pixels and the criteria for measuring the variations between the two pixels is the weights on the edge that connects these two pixels. This dissimilarity measure is based on intensity, colour and motion of pixels.

In the proposed approach, a segmentation S of an image is defined as a separation of V into regions in such a way that each region $R \in S$ relates to a connected region in the graph $G' = (V, E')$, and $E' \subseteq E$. In other words, the subset of edges in E causes the segmentation.

In the proposed method, two parameters are compared for predicting the presence of a boundary between two regions:

1) In the first one, the intensity differences are estimated across the boundary,
2) In the second part, the intensity differences among neighbouring pixels are estimated within each region.

For finding the presence of a boundary between two regions of an image, a Weight Factor is employed as described below.

2.1) Region Estimation Weight Factor

For finding whether or not there exists a boundary between two regions of an remotely sensed image, a Weight Factor is employed in the segmentation process. This factor is used for estimating the variation difference between the pixels present at the boundary of two neighbouring regions relative to a measure of difference between neighbouring pixels within each of the two regions. Thus the factor evaluates and compares the inter-region dissimilarity to within the region dissimilarities and is found to be adaptive with regard to the local features of the data.

The internal dissimilarity of a region $R \subseteq V$ is defined as the largest weight in the minimum spanning tree of the region, $MST(R, E)$ as given below,

$$Int(R) = max_{e \epsilon MST(R,E)} \; w(e) \qquad (1)$$

One perception with regard to this measure is that, any region R remains connected only when the edges having weight at least $Int(R)$ are taken. The difference between two regions $R_1, R_2 \subseteq V$ can be defined to indicate the minimum weight edge connecting the two regions as given below,

$$Dif(R_1, R_2) = min_{v_i \epsilon R_1, v_j \epsilon R_2, (v_i, v_i) \epsilon E} \; w(v_i, v_j) \qquad (2)$$

The $Dif(R_1,R_2) = \infty$ is taken when $R1$ and $R2$ don't have an edge connection. This estimate of dissimilarity can cause problems because only the smallest edge weight across the two regions is given by it.

The Edge Weight Factor calculates if there is an evidence of a boundary between the two regions by evaluating the dissimilarity across the regions, $Dif(R_1,R_2)$ with the internal dissimilarity in at least one of the regions, $Int(R_1)$ and $Int(R_2)$.

A threshold parameter is utilised for controlling the level at which the dissimilarity among regions must be larger than minimum internal dissimilarity. The Edge Weight Factor $D(R_1,R_2)$ can then be stated as,

$$D(R_1, R_2) = \begin{cases} \text{true} & \text{if } Dif(R_1, R_2) > MInt(R_1, R_2) \\ \text{false} & \text{otherwise} \end{cases} \qquad (3)$$

The minimum within dissimilarity, *MInt*, is given as,

$$MInt(R_1, R_2) = \min \; (Int(R_1) + \tau(R_1), Int(R_2) + \tau(R_2)) \qquad (4)$$

The range to which the difference among a pair of regions must be larger than their within difference in order to have the presence of a boundary (i.e. D to be true) is described by a threshold function τ. $Int(R)$ is not a good measure of estimate for the local characteristics of the data for small regions. In the severe case, $Int(R) = 0$ when $|R| = 1$.

Thus, a threshold function is taken based on the region's size as,

$$\tau(\mathrm{R}) = k/|\mathrm{R}| \qquad (5)$$

Where $|R|$ represents the size of R and k is taken as a constant.

Thus, it is desired to have a strong proof of the boundary for small regions. k can be used as a range of observation, such that the greater value of k leads to the choice for larger regions, however, the value of k should not be thought as the minimum region size. The smaller regions are permitted only when there exists an enough difference among the adjacent regions.

Without varying the algorithmic results in (3), τ can be used for any single region with a non negative function. As an example, the segmentation algorithms can be allowed to create regions depending on some shapes by defining the τ which can be large if the region does not fit certain indicated shape and τ will be small if region fit the shape. This will lead the segmentation method to combine regions that does not fit the desired shape which in turn will cause incorrect segmentation.

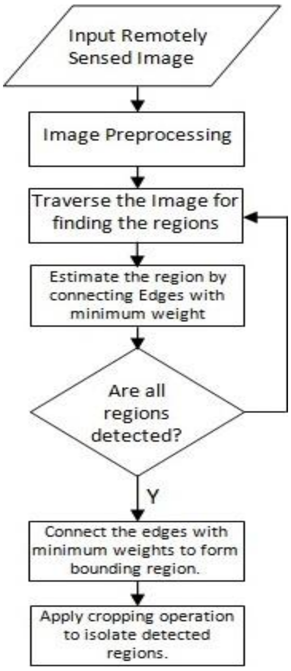


Fig 1: Flow chart of the proposed image segmentation approach.

The figure 1 depicts the flow chart of the proposed segmentation method. The remotely sensed image is first subjected to preprocessing for converting it to binary image for efficient computation. The approach predicts the regions from image by checking the weight assigned to each edge element and with respect to the highest threshold value of the image. The boundaries of the regions are declared by connecting the minimum weight edge elements. The minimum weight edges together form a bounding region for each distinct region of the remotely sensed image. The predicted bounding regions of the remotely sensed image are then isolated using image cropping operation performed on the specified location coordinates.

III. SEGMENTATION ALGORITHM

The input consists of an image indicating an undirected graph given as $G = (V, E)$, consisting of n vertices and m edges.

The outputs are regions ($R_1, \ldots, R_r$) created by a segmentation S.

1. Sort out the edges E into $\pi = (O_1, \ldots, O_m)$, base on the edge weight value.
2. Begin the segmentation process S^0, with every vertex v_i *present* in its own region.
3. The step 4 has to be repeated for values of $q = 1, \ldots, m$.
4. Build S^q having S^{q-1} in the following way.

Let v_i and v_j represents the vertices linked by the q-th edge in the sequence of, $o_q = (v_i, v_j)$. If the vertices v_i and v_j are present in the disjoint regions of S^{q-1} and if $w(o_q)$ is small as compared with the internal difference of these two regions, merge these two regions, otherwise don't do anything. Thus more precisely, let R^{q-1} denote the region of S^{q-1} containing v_i and R^{q-1} the region containing v_j. If $R_i^{q-1} \neq R_j^{q-1}$ and $w(o_q) \leq MInt(R_i^{q-1}, R_j^{q-1})$ then S^q may be achieved from S^{q-1} by merging R_i^{q-1} *and* R_j^{q-1}. Else $S^q = S^{q-1}$.

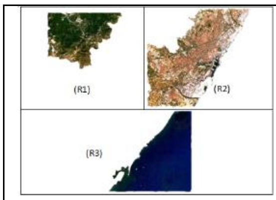
5. Return $S = Sm$.

From the above algorithm it is established that the segmentation S formed by it by employing the Edge Weight Factor D mentioned in section (3) follows the global properties of being neither too fine nor too coarse. That is, even though the algorithm is found to make greedy decisions yet it is found to yield the segmentation that fulfils the global properties. Additionally, it is shown that the Step 1 of the algorithm results in the same segmentation for the chosen possible non-decreasing weight edge sequencing.

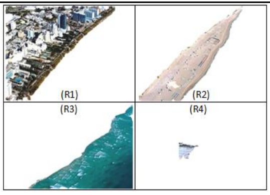
IV. RESULTS AND DISCUSSIONS

The remotely sensed images are first transformed into monochrome images. For finding the different regions present in the image, an undirected graph $G = (V, E)$ is defined, in which each image pixel p_i has a associated vertex $v_i \in V$. The set of edge elements E is generated by connecting pairs of vertices (pixels) which are neighbours in an 8-connected fashion. This process yield a graph where $m = O(n)$, such that the time complexity of the algorithm becomes $O(n \log n)$ for the n image pixels. The algorithm traverses around the image to find paths with low weights that correspond to significant edges. These edges connected together build a bounding region for every distinct region present in the remotely sensed image. The boundaries of the regions are determined by connecting the minimum weight edge elements. The predicted bounding regions of the remotely sensed image are then isolated using image cropping operation performed on the specified location coordinates.

 Input Image 1	 Input image 2
 Detected regions	 Detected regions



Segmented distinct regions of Input Image 1



Segmented distinct regions of Input Image 2

Fig 2: Input images and obtained segmented regions using proposed approach.

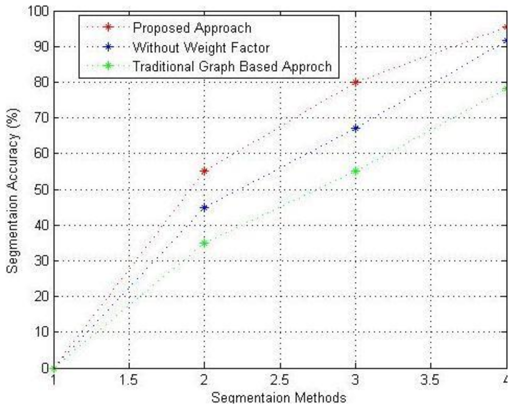


Fig 3: Comparative Segmentation Accuracy of the Proposed Approach

V. CONCLUSION

In this paper an improved graph based algorithm employing for the dynamic segmentation of remotely sensed images is presented. The pair wise Edge Weight Factor is utilised which takes the minimum weight edge across the two regions for estimating the difference between them. Therefore, this algorithm will merge two regions even a low weight edge is present between them there by overcoming the over segmentation problem frequently found in remote sensing image analysis. This algorithm is unique, in the sense that it is both extremely efficient and also overcomes the internal variation problem in regions. The algorithm runs in $O(m \log m)$ time for m edges of the graph and is fast in processing, normally executing in a fraction of second. We have experimentally demonstrated this technique on remotely sensed images and the results reveal that the approach provides a unique, quality solution that is robust to weak region boundaries and also to large variations within the regions.

VI. REFERENCES

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