International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622
International Conference on Humming Bird (01st March 2014)

RESEARCH ARTICLE OPEN ACCESS

Segmentation of Remote Sensing Image Analysis Using Neural Network

Ms.P.P.N Vijila

PG Student
Department of AE
University College of Engineering
Nagercoil-629004 .
vijilanesamani@gmail.com

Ms.R.Femi M.E.,

Teaching Fellow
Department of ECE
University College of Engineering
Nagercoil-629004 .

Abstract:
Segmentation and classification are important task in remote sensing image analysis. Here we use a new segmentation that uses graph Laplacian energy as a measure of segmentation. This method reduces the redundancy in the hierarchy by an order of magnitude with little or low loss of performance. In the classification stage we use local self similarity feature to capture the internal geometric layouts of region in an image. By incorporating neural network segmentation method we can obtain a very clear image and the edges can be clearly segmented whereas by using watershed segmentation we cannot obtain a clear image and oversegmentation also takes place.

Index Terms: graph Laplacian Energy (GLE), local self similarity (LSS) , watershed segmentation , Neural network

I. INTRODUCTION

Sensors used in remote sensing image analysis produce very high spatial resolution **(**VHR**)** images that contain valuable spectral and textural information for land cover classification. It leads to the detection and identification of man made structures such as roads and buildings.

Two approaches are pixel based approach and object based approach. Pixel based approach classify each pixel seperately. Object based approach groups pixels in to regions before the classification stage. Object based image analysis approach receives more attention in analysing remote sensing data. One of the main step in the object based image analysis is the image segmentation. It partitions an image in to nonoverlapping regions so that each region is a homogeneous and neighboring ones as different as possible. Segmentation is the building block for object based analysis.

Here we use a new hierarchical image analysis method that applies the graph Laplacian energy (GLE). This is the generic measure of segmentation. After segmentation we proceed with the classification stage which applies local self similarity algorithm. This is used to incorporate the local contextual and shape information in urban area land cover classification using very high resolution **(**VHR**)** remote sensing images. To obtain spectral and textural feature we employ a new segmentation method known as linear regression method. This method works across different bands in a computationally efficient way and which will accurately localizes the boundaries.

The rest of the paper is organised as follows: In section II, we introduce graph Laplacian energy representation. Section III presents the segmentation algorithm in detail.
Section IV describes region merging. Section V describes the classification method.

II. GRAPH LAPLACIAN ENERGY REPRESENTATION

Energy of a graph G is defined as the sum of the singular values of its adjacency matrix and the Laplacian energy of G is defined as the sum of the distance between Laplacian eigen values and average degree of G. The bounds for the Laplacian energy are given using the first Zagreb index of the graph.

Let G be an (n, m) graph with n vertices and m edges and A be the adjacency matrix. The graph LE is defined as

$$LE(G) = \sum_{i=1}^{n} \left| \lambda_i - \frac{2m}{n} \right| \quad (1)$$

Where λ_i denotes eigenvalues of the Laplacian matrix and $2m/n$ is the average vertex degree.

Eigen Values of the Normalised Laplacian Matrix

Eigen values of the normalized laplacian matrix generally reflect deeper properties of a graph for example

1. The multiplicity of the eigen value zero counts the number of connected components.
2. The largest eigen value is 2 exactly when the graph is bipartite.
3. The third eigen value roughly measures how hard it is to cut the gragh in to distinct pieces.
4. The eigen values of the normalized matrix are also related to behavior of random walks on the graph.

Hierarchial Representation

We compute the nGLE at every level in the hierarchy independently and use the nGLE as a function of level index. In the curve local minima are met when graphs at particular levels exhibit homogeneous node degree, which means that the graphs are close to regular graphs. We choose the highest level partition that gives the local minimum, which breaks the image in to the fewest large components. Thus we will get the main component of a remote sensing image by using graph LE. The first segmentation can produce some main components of the image. In order to classify the image, we need to further segment the existing main components in to finer parts. We find these parts by recursively applying the graph Laplacian method on each component.

Fig 1. Original image

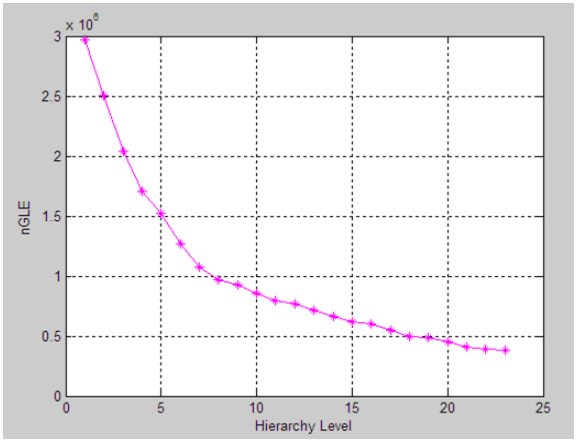


Fig 2. Graph energy as a function of level index The plot is computed using the image in fig 1.

III. SEGMENTATION ALGORITHM

In remote sensing, a segmentation mothod should overcome the advances made in data acquisition, specifically the spectral and spatial resolution capability.

1. Segmentation Using Watershed Algorithm

Watershed Segmentation

The concept of watersheds is based on visualizing an image in three dimensions : two spatial coordinates versus grey levels. In such a topographic interpretation, we consider three types of points:

1. Points belonging to a regional minimum
2. Points at which a drop of water, if placed at the location of any of those points, would fall with certainty to a single minimum
3. Points at which water would be equally like to fall to more than one such minimum

For a particular regional minimum, the set of points satisfying condition (2) is called the catchment basin or watershed at that minimum. The points satisfying the condition (3) form crest lines on the topographic surface and are termed divide lines or watershed lines.

The principal objective of segmentation algorithms based on these concepts is to find the watershed lines. The basic idea is simple: Suppose that a hole is punched in each regional minimum and that the entire topography is flooded from below by letting water rise through the holes at a uniform rate. When the rising water in distinct catchment basins is about to merge, a dam is built to prevent the merging. The flooding will eventually reach a stage when only the tops of the dams are visible above the water line. These dam boundaries correspond to the divide lines of the watersheds. Therefore, they are boundaries extracted by a watershed segmentation algorithm.

Watershed Segmentation Algorithm

Let $M_1, M_2, \ldots, M_R$ be sets denoting the coordinates of the points in the regional minima of an image $g(x,y)$. Let $C(M_i)$ be a set denoting the coordinates of the points in the catchment basin associated with regional minimum M_i. The notation min and max will be used to denote the minimum and maximum values of $g(x,y)$. Finally, let $T[n]$ represent the set of coordinates (s,t) for which $g(s,t) < n$. That is

$$T[n] = \{(s,t) | g(s,t) < n\} \quad (1)$$

Geometrically, $T[n]$ is the set of coordinates of points in $g(x,y)$ lying below the plane $g(x,y) = n$

The topography will be flooded in integer flood increments, from $n = min + 1$ to $n = max + 1$. At any step n of the flooding process, the algorithm needs to know the number of points below the flood depth. Conceptually, suppose that the coordination in $T[n]$ that are below the plane $g(x,y) = n$ are "marked" black and all other coordinates are marked white. Then when we look down on the xy plane at any increment$n$ of flooding, we will see a binary image in which black points correspond to points in the function that are below the plane $g(x,y) = n$.

Let $C_n(M_i)$ denote the set of coordinates of points in the catchment basin associated with minimum M_i that are flooded at stage n. The binary image is given by

$$C_n(M_i) = C(M_i) \cap T[n] \quad (2)$$

In other words, $C_n(M_i) = 1$ at location (x,y) if $(x,y) = C_n(M_i)$ AND $(x,y) \in T[n]$; otherwise $C_n(M_i) = 0$. The geometrical interpretation of this result is straight forward. We are simplily using the AND operator to isolate at stage n of flooding the portion of the binary image in $T[n]$ that is associated with regional minimum M_i.

Let $C[n]$ denote the union of the flooded catchment basins portions of stage n.

$$C[n] = \bigcup_{i=1}^{R} C_n(M_i) \quad (3)$$

Then $C[max + 1]$ is the union of all catchment basins:

$$C[max + 1] = \bigcup_{i=1}^{R} C(M_i) \quad (4)$$

The elements in both $C_n(M_i)$ and $T[n]$ are never replaced during execution of the algorithm, and that the number of elements in these two sets either increases or remains the same as n increases. Thus it follows that $C[n-1]$ is a subset of $C[n]$. Also $C[n]$ is a subset of $T[n]$, so it follows that $C[n-1]$ is a subset of $T[n]$. From this we have the important result that each connected component of $C[n-1]$ is contained in exactly one connected component of $T[n]$

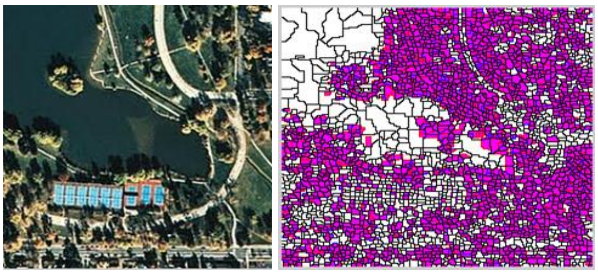


Fig 3. Original image and segmented image

The algorithm for finding the watershed lines is initialized with $C[\min+1] = T[\min+1]$. The algorithm then proceeds recusively, assuming at step n that $C[n-1]$ has been constructed. A procedure for obtaining $C[n]$ from $C[n-1]$ is as follows. Let Q denote the set of connected components in $T[n]$. Then for each connected component $q \in Q[n]$, there are three possibilities:

1. $q \cap C[n-1]$ is empty
2. $q \cap C[n-1]$ contains one connected component of $C[n-1]$.
3. $q \cap C[n-1]$ contains more than one connected component of $C[n-1]$

Construction of $C[n]$ from $C[n-1]$ depends on which of these three conditions holds. Algorithm efficiency is improved by using only values of n that correspond to existing gray level values in $g(x,y)$; we can determine these values, as well as the values of min and max, from the histogram of $g(x,y)$. By using watershed segmentation the edges are not clearly segmented and oversegmentation is also a major drawback, so for overcoming this we are going for another algorithm called Adaline Neural Network Algorithm.

B. Segmentation Using Adaline Neural Network Algorithm

ADALINE (Adaptive Linear Neuron or later Adaptive Linear Element) is a single layer neural network. It consists of a weight, a bias and a summation function. The difference between Adaline and the standard (McCulloch-Pitts) perception is that in the learning phase the weights are adjusted according to the weighted sum of the inputs (the net). In the standard perception, the net is passed to the activation (transfer) function and the function's output is used for adjusting the weights. There also exists an extension known as Madaline. Adaline can be defined as a single layer neural network with multiple nodes where each node accepts multiple inputs and generates one output. Given the following variables:

- x is the input vector
- w is the weight vector
- n is the number of inputs
- θ some constanty is the output

then we find that the output is

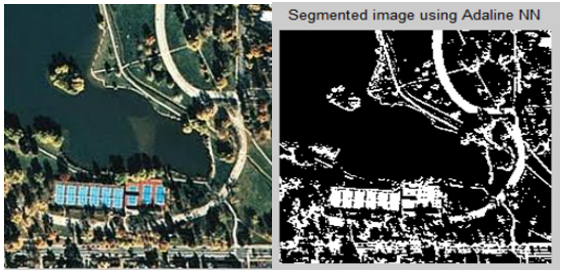
$$y = \sum_{j=1}^{n} x_j w_j + \theta$$

If we further assume that

- $x_{n+1} = 1$
- $w_{n+1} = \theta$

then the output reduces to the dot product of x and

$$w \; y = x_j \cdot w_j$$



IV REGION MERGING

Region merging is used to eliminate false boundaries and spurious regions by merging adjacent regions that belong to the same object. Here we are merging the neighbouring regions from bottom up to create a hierarchial tree description. In each region merging iteration, we merge the most similar pairs of neighbouring regions and treat the newly merged region as the parent nodes. The merging continues until there is only one region left. Each merging iteration generates a higher level of segmentation over the previous one. The merging step should be able to handle regions in arbitrary shape. Statistical properties are used to calculate the average intensity gradient value for disconnecting region.

Let R represent the entire image region and select a predicate P. One approach for segmenting R is to subdivide it successively in to smaller and smaller quadrant regions so that, for any region R_i,$P(R_i)$= TRUE. We start with the entire region. If $P(R)$ =FALSE, we divide the image in to quadrants. If P is FALSE for any quadrant, we subdivide that quadrant in to sub quadrants, and so on. This particular splitting technique has a convenient representation in the form of a so called quadtree. The root of the tree corresponds to the entire image and that each node corresponds to a subdivision. In this case, only R_4 was subdivided further

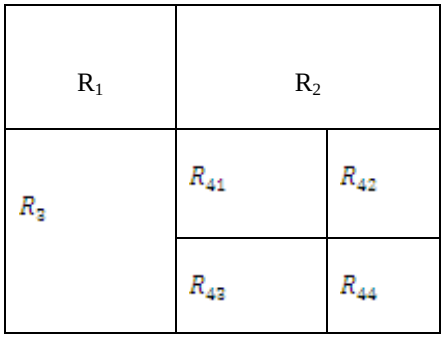


Fig:4. Partitioned Image

If only splitting were used, the final partition likely would contain adjacent regions with identical properties. Tis drawback may be remedied by allowing merging, as well as splitting. Satisfying the constraints this requires merging only adjacent regions whose combined pixels satisfy the predicate P. That is, two adjacent regions R_j and R_k are merged only if $P(R_j \cup R_k)$ =TRUE

Steps Used In Region Merging

1. Form initial region in the image
2. Build regions adjacency graph RAG
3. For each region do:
   3.1 Consider its adjacency region and test to see if they are similar
   3.2 For regions that are similar merge them and modify
4. Repeat step 3 until no regions are merged

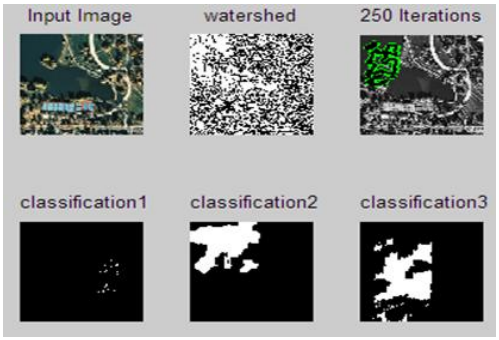
.

IV CLASSIFICATION

For classification process Local Self Similarity (LSS) algorithm is used. To extract features from each segmented parts, the LSS method is used. The LSS describes the similarity between a patch and its neighbouring region in an image. It offers a single unified way to describe the internal relations in an image. The process of extracting the LSS is computed as follows.

1. Calculate an N×N correlation surface ζ_p of an $\omega \times \omega$ patch t_p with the surrounding N×N region R_p using sum of squared differences (SSD) method. Here both R_p and t_p are centered at p. $\zeta_p(x)$ is the correlation of t_p with an $\omega \times \omega$ patch t_x centered at x:$\zeta_p(x) = exp\left(-\left(SSD\left(t_p, t_x\right)/\delta\right)\right)$, where δ represents the maximal variance of the difference between all patches within a small neighbourhood of p and the patch centered at p.

2. Discrete the correlation surface ζ_p on a log polar grid and store the maximal value of ζ_p within each grid bin $d_p(p,d) = max_{x \in BIN(p,d)}\{\zeta_p(x)\}$
3. Normalise the binned log polar vector by linearly stretching its values to the range $[0,1]$.



CONCLUSION

We can get a sensible semantic interpretation in terms of object and object parts which helps to achieve more robust classification. Here LSS is introduced for urban area land cover classification in remote sensing images. This method has achieved performance on satellite image analysis that is better than those from other methods. By this method we can obtain both the textural and spectral feature of an image.

REFERENCES

[1] L.Wang,W. P. Sousa, and P. Gong, (2004) "Integration of object-based and pixelbased classification for mapping mangroves with IKONOS imagery," Int. J. Remote Sens., vol. 25, no. 24, pp. 5655–5668.

[2] T. Blaschke, S. Lang, and G. J. Hay, (2008) Object-Based Image Analysis. New York: Springer-Verlag.

[3] J. M. Duarte-Carvajalino, G. Sapiro, M. Vélez-Reyes, and P. E. Castillo, (2008) "Multiscale representation and segmentation of hyperspectral imagery using geometric partial differential equations and algebraic multigrid methods," *IEEE Trans.* Geosci. Remote Sens., vol. 46, no. 8, pp. 2418–2434.

[4] Y.Wu, K. Ji,W. Yu, and Y. Su, (2008) "Region-based classification of polarimetricSAR images using Wishart MRF," *IEEE* Geosci. Remote Sens. Lett., vol. 5, no. 4, pp. 668–672t.

[5] H. G. Akçay and S. Aksoy, (2008) "Automatic detection of geospatial objects using multiple hierarchical segmentations," *IEEE* Trans. Geosci. Remote Sens., vol. 46, no. 7, pp. 2097–2111.

[6] G. Ons and R. Tebourbi, (2009) "Object oriented hierarchical classification of high resolution remote sensing images," in Proc. 16th *IEEE ICIP*, Nov. 7–10, pp. 1681–1684.

[7] R. Gaetano, G. Scarpa, and G. Poggi,(2009) "Hierarchical texture-based segmentationof multiresolution remote-sensing images," IEEE Trans. Geosci. Remote Sens., vol. 47, no. 7, pp. 2129–2141.

[8] C. Kurtz, N. Passat, P. Gançarski, and A. Puissant, (2012) "Extraction of complexpatterns from multiresolution remote sensing images: A hierarchical top-down methodology," Pattern Recognit., vol. 45, no. 2, pp. 685–706.

[9] E. Shechtman and M. Irani, (2007) "Matching local self-similarities across images and videos," in Proc. IEEE CVPR, Jun. 17–22, pp. 1–8.

[10] I. Gutman and B. Zhou,(2006) "Laplacian energy of a graph," Linear Algebra Appl., vol. 414, no. 1, pp. 29–37.

[11] J. M. Gauch, (1999) "Image segmentation and analysis via multiscale gradient watershed hierarchies," *IEEE* Trans. Image Process., vol. 8, no. 1, pp. 69–79.

[12] J. Shi and J. Malik, (2000) "Normalized cuts and image segmentation," IEEE Trans. Pattern Anal. Mach. Intell., vol. 22, no. 8, pp. 888–905.

[13] D. Comaniciu and P.Meer, (2002) "Mean shift: A robust approach toward feature space analysis," IEEE Trans. Pattern Anal. Mach. Intell., vol. 24, no. 5, pp. 603–619.

[14] D. G. Lowe, (2004) "Distinctive image features from scale-invariant keypoints," Int. J. Comput. Vis., vol. 60, no. 2, pp. 91–110.

[15] C.-C. Chang and C.-J.Lin (2011, Apr.). LIBSVM: A library for support vector machines. ACM Trans. Intell.Syst. Technol.[Online].*2(3)*, pp. 27:1–27:27.

[16] R. M. Haralick, K. Shanmugam, and I. H. Dinstein,(1973) "Textural features for image classification," IEEE Trans. Syst., Man Cybern., vol. SMC-3, no. 6, pp. 610–621.

[17] R. O. Duda, P. E. Hart, and D. G. Stork,(2000) Pattern Classification and Scene Analysis, 2nd ed. New York: Wiley.

[18] L. Fei-Fei, R. Fergus, and A. Torralba, (2007) "Recognizing and learning object categories," in Proc. CVPR Short Course.

[19] T. Blaschke, "Object based image analysis for remote sensing," *ISPRS J. Photogramm. Remote Sens.*, vol. 65, no. 1, pp. 2–16, Jan. 2010.

[20] S. Ryherd and C. Woodcock, "Combining spectral and texture data in the segmentation of remotely sensed images," *Photogramm. Eng. Remote Sens.*, vol. 62, no. 2, pp. 181–194, Feb. 1996.

[21] M. Kim, M. Madden, and B. Xu, "GEOBIA vegetation mapping in Great Smoky Mountains National Park with spectral and non-spectral ancillary information," *Photogramm. Eng. Remote Sens.*, vol. 76, no. 2, pp. 137–149, 2010.

[22] X. Hu, C. V. Tao, and B. Prenzel, "Automatic segmentation of high-resolution satellite imagery by integrating texture, intensity and color features," *Photogramm. Eng. Remote Sens.*, vol. 71, no. 12, pp. 1399–1406, 2005.

[23] R. Trias-Sanz, G. Stamon, and J. Louchet, "Using colour, texture, and hierarchical segmentation for high-resolution remote sensing," *ISPRS J. Photogramm. Remote Sens.*, vol. 63, no. 2, pp. 156–168, Mar. 2008.