Using k-way Normalized Cuts to Integrate LiDAR and Hyperspectral Imagery for Segmentation

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Abstract: The segmentation of hyperspectral images (HSIs) is being used in many fields from target detection to classification. In this paper, we propose a new affinity matrix for the normalized cuts algorithms that takes into account both the hyperspectral and LiDAR data for segmentation. The affinity matrix uses both the spatial-spectral as well as the elevation information; and our results show that the segmentation is much more accurate and can distinguish objects better than a plain normalized-cuts algorithm. We show the improvement gained by adding the LiDAR data onto the hyperspectral data, and discuss the parameters selection strategies.

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1. Introduction

Hyperspectral images (HSI) measure how much light is reflected from a material. Since materials reflect light differently, these reflections generate a spectral fingerprint for each material. When a large number of bands are considered, material can be detected from a single pixel in HSIs. This important information has been used in many areas including the defence industry, mining, civil engineering and geology.

On the other hand, LiDAR is a remote sensing technique that measures the elevation in a given scene. The elevation information obtained from LiDAR has been complementary to hyperspectral imagery. Using elevation maps, it is possible to distinguish objects of similar material but of different elevation. Therefore, it makes great sense to combine hyperspectral data with the elevation information derived from LiDAR to increase the efficiency of HSI segmentation.

In our previous paper [1] and in [2], the normalized cuts algorithm was extended for the segmentation of hyperspectral images. The affinity matrix of the normalized cuts algorithm was modified such that it uses both the spatial and spectral information; and the results were showed good success in segmentation. However, errors occurred when similar objects whose height were different were also segmented as the same object.

In this paper, we propose to integrate both the LiDAR and HSI data; and we propose a Normalized Cuts method that depends on both the spectral-spatial and the elevation information.

2. Background

A graph G = (V, E) consists of a set of objects called vertices (V) and edges (E) that represent connections between vertices. A graph is weighted if each edge has an associated number $w_{i,j}$. In figure 1, the graph consists of two classes: A and B. Several nodes in the graph are connected each other and weighted based on the similarity between them. If the similarity of two nodes is high, weight on the edge is close to 1, otherwise it is close to 0. We aim to partition the graph into disjoint sets such as A and B. The degree of dissimilarity between two classes can be computed as the total weight of the edges that have been moved away. In graph theory, it is called cut, and is computed as below:

$$cut(A,B) = \sum_{i\in A, j\in B} w_{i,j} \tag{1}$$

The optimal partitioning graph is the one that minimizes this cut value [3,4].

However, the minimum cut criteria favors to cut small sets of isolated nodes. To avoid this problem, equation 1 must be normalized.

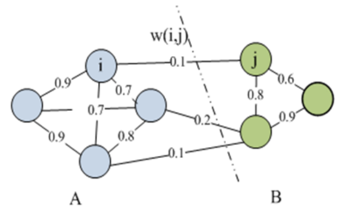

Fig. 1. An example of weighted graph.

Instead of looking at the cut value, the normalized cut compute the cost function as a fraction of the total edge connections between classes to all the nodes in the graph. The normalized cuts (Ncut) is given as follows:

$$Ncut(A,B) = \frac{cut(A,B)}{assoc(A,V)} + \frac{cut(A,B)}{assoc(B,V)} \tag{2}$$

and

$$assoc(A,V) = \sum_{i \in A, j \in V} w_{i,j} \tag{3}$$

Now, we aim to minimize the normalized cut value. The solution of this problem is discrete. If it is relaxed to take on real values, equation 2 can be minimized by solving a general eigenvalue system that is given in equation 4. **W** is similarity matrix whose entries compose of $w_{i,j}$, and **D** is a diagonal matrix with entries that are the sums of connection from one node to all other nodes on its diagonal.

$$(\mathbf{D} - \mathbf{W})\mathbf{y} = \lambda \mathbf{D}\mathbf{y} \tag{4}$$

In this paper, hyperspectral imagery and LiDAR data are combined to construct the similarity matrix. Then, using constructed similarity matrix, we solve relaxed version of equation (4), and we seek a discrete solution closest to the continuous optima in an iterative manner as mentioned in [4]. The discrete eigenvectors of this system correspond to segments of HSI.

3. Proposed Similarity Matrix for HSIs

Designing the similarity matrix is critically important for image segmentation. Firstly, we construct a weighted graph, by taking each pixel as a node, then connecting each pair of pixels by an edge. We use spatial-spectral information and LiDAR data to compute a weight for each pair of pixels. However, all pixel pairs do not connect, therefore, just the closest r pairs are connected for computational complexity. We can define edge weight that connect two nodes as follow:

$$w_{i,j} = e^{-\frac{d_{spectral}(i,j)}{\sigma^2_{spectral}}} * e^{-\frac{d_{LiDAR}(i,j)}{\sigma^2_{LiDAR}}} * \begin{cases} e^{-\frac{d_{spatial}(i,j)}{\sigma^2_{spatial}}} & if \quad d_{spatial}(i,j) < r \\ 0 & otherwise \end{cases} \tag{5}$$

In equation 5, $d_{spectral}(i,j)$, $d_{LiDAR}(i,j)$ and $d_{spatial}(i,j)$ are spectral, LiDAR and spatial Euclidean distance between th nodes i and j, respectively. $\sigma_{spectral}$, σ_{LiDAR} and $\sigma_{spatial}$ control the scale of data similarity measure. In the simulation part, efficiency of HSIs segmentation will be discussed for different r and values.

4. Data Set and Results

4.1. Data Set Description

MUUFL Gulfport Hyperspectral and LiDAR Airborne data set is used for simulation. Data were collected using a Gemini LiDAR and CASI-1500 flown in a single plane simultaneously [6].

4.2. Results

First, we compute the similarity matrix **W** as given equation 5. Parameters in this equation are chosen experimentally as follows: $\sigma_{spectral} = 0.3$, $\sigma_{LiDAR} = 2$ and $\sigma_{spatial} = 5$ and $r = 6$. Second, equation 4 is solved for 14 eigenvalues and corresponding eigenvectors. The number of eigenvectors are also chosen experimentally for better segmentation. These eigenvectors are the solution of relaxed problem. We use the method given in [5] and obtain the discrete eigenvectors. Some of this discrete eigenvectors are given in figure 2. These eigenvectors partition the image into disjoint sets as we have seen in figure 2. Then, discrete eigenvectors are merged and segments of HSIs are obtained. In figure 3, HSIs' segments that compose of 14 discrete eigenvector are shown. There are two segmented image in figure 3. Figure 3(b) is segmented by using spatial and spectral information. However, figure 3(c) is segmented by using LiDAR data beside spatial and spectral information. By using LiDAR data, segmentation results have been improved. When LiDAR is used, some group of trees, some individual trees and one extra object are also segmented as seen in the figure 3(c).

We will discuss segmentation solution for different σs, different r and different number of eigenvector, and results these parameters will be given.

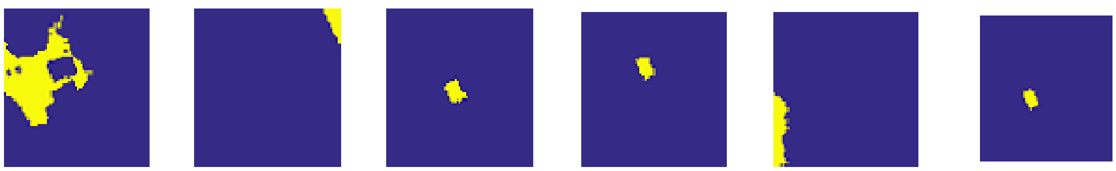

Fig. 2. Six discrete eigenvectors

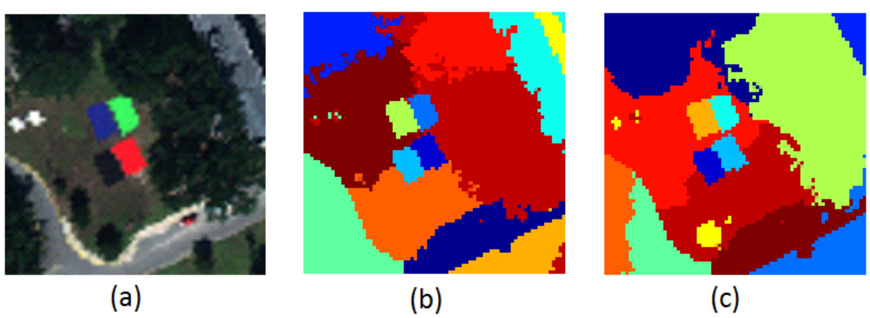

Fig. 3. (a) false RGB, (b) segments of HSI without using LiDAR, (c) segments of HSI with using LiDAR

References

1. Orhan Torun, S. Esen Yuksel, "Hyperspectral Image Segmentation Using Normalized Cuts," SIU, 2016.
2. Gillis, David B., and Jeffrey H. Bowles. "Hyperspectral image segmentation using spatial-spectral graphs." SPIE Defense, Security, and Sensing. International Society for Optics and Photonics, 2012.
3. Z. Wu and R. Leahy, "An Optimal Graph Theoretic Approach to Data Clustering: Theory and Its Application to Image Segmentation", IEEE Trans. Pattern Analysis and Machine Intelligence, vol. 15, no. 11, pp. 1,101-1,113, Nov. 1993.
4. J. Shi, J. Malik, "Normalized cuts and image segmentation", PAMI 22(8) (2000) 888-905.
5. S. X. Yu and J. Shi,"Multiclass spectral clustering", In International Confererence on Computer Vision,2003.
6. P. Gader, A. Zare, R. Close, J. Aitken, G. Tuell, "MUUFL Gulfport Hyperspectral and LiDAR Airborne Data Set", University of Florida, Gainesville, FL, Tech. Rep. REP-2013-570, Oct. 2013.