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Lidar Image Segmentation Using Self Tunning Sepectral Clustering

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Abstract

In this article self-adjusting spectral clustering method is used to segment Lidar images. In experiments four different Lidar images (sea, forest, desert and city) was used to evaluate the performance of the algorithm. In many cases non-linear without pattern on are intertwined each other and in some cases are inseparable that the evaluation criterion is the ability to distinguish the parts of an optical detection. For each image of the test, eigenvalues of matrix similarity chart is displayed and the optimal number of clusters was estimated. According to the approximate numbers of clusters, similarity matrix patterns a number are divided into groups equal to the number of clusters and clustering was performed. The output of the program, including pictures have label for clusters and each cluster separately from other clusters is displayed. The results showed that, in cases of non-linear region of the cluster together and are intertwined; this method is capable of separating and labeling correctly. This method is a semi-supervised method which is involved in the process of selecting and identifying the user.

Keywords

Lidar, Three-Dimensional, Normalization, Spectral Clustering, Self-Regulated

1. Introduction

Lidar image (Light Detection and Ranging) is a powerful system to evaluate laser remote sensing, that is a valuable source to acquire three-dimensional space information with high density and velocity of the earth's surface. Three-dimensional objects and large areas are varied, so extracting spatial information from three-dimensional laser scanner is difficult and time consuming (1). Lidar technology is as an effective tool for gathering data in complex three-dimensional surfaces such as urban residential area. These data are the basis for wide applications such as three-dimensional models of cities, urban management and communication. applications and analyzes have shown the diversity and volume of three-dimensional objects and images communications to requires the use of an organized system of data mining which is closed to each application and it can be very effective and helpful. Several tools have been introduced to extract feature of information from these images, that this tools include segmentation and clustering Lidar data to extract three-dimensional objects of Lidar data in an urban area, as an efficient and convenient method capable of matching the feature space is an issue and can adjust their parameters optimally, spectral clustering method is self-adjusting. This algorithm is efficient since the segmentation and feature extraction and clustering of Lidar data. Self-adjusting spectral clustering algorithm has non-linear patterns in the feature space which is able to distinguish interwoven and non-linear complex clusters. Therefore, if in a picture in different parts are inseparable parts are linearly and distinguish through Euclidean distance-based clustering methods and this is very effective and convenient.

In recent years, the articles associated with the use of Lidar to extract climate information (2-4) and using segmentation methods to diagnosis objects (such as trees and buildings) have been presented (5-7), that in none of the self-adjusting clustering method is used. Therefore, with study the potential of this method of dealing with this issue on feature extraction and objects recognition (or words segmentation for these purposes); we are going to extract the Lidar images through self-adjusting spectral clustering and segmentation.

2. History

Li et al (2013) provided a hybrid method for classification trees in Lidar data with aggregation methods based on the regulatory classification and unsupervised clustering method based on the site. In addition, they suggest a powerful three-dimensional data that overcome the limitations of existing methods for the isolation of buildings from the tree spots. They proposed method for solving the problem of incorrect classification of the buildings and the trees which consists of three steps including:

1) Clustering based on the spatial similarity of coherence,

2) Classification using machine learning methods in monitoring with implementation of a three-dimensional shape feature

3) Improving the classification using unsupervised clustering method. For classification of SVM algorithm, RBF kernel was used. Satisfactory results obtained from a hybrid method of Li et al. (8)

- In 2010, in the thesis which was conducted at the University MIT by McDaniel, a method for modeling and classification of forest cover of Lidar data were presented. In this study, it was stated that the automatically operation of unmanned ground vehicles must be able to detect the levels and obstacles and can predict current measurement techniques for the built environment such as urban areas, streets or define it work. However, the automatic navigation in forest is a new challenge. In the thesis, a new and efficient method for modeling land surfaces and stems of trees in the forest using a three-dimensional point cloud obtained with Lidar data is presented. Identification ground level using a two-step procedure is carried out. In the first stage, a local filter based on height to detect and separate from other parts of the land. Second stage, based on SVM classification tool set of geometric features to identify which of the remaining parts of the land is used. Finally, an unusual triangular lattice is made up of the points to model land surface. Then the main stem is estimated using the results of the earth. Data stem is about 130 mm above the ground on the points that have to be selected. This connection points are then clustered using a clustering technique. Finally, the stems of geometric shapes are Lidar data by fitting a model to be followed. The experimental results from 5 forest environment show that this method is effective for diagnosis. To estimate the overall accuracy of classification of 28/86%, and the average error of the Earth is about 7.4 cm. to estimate the stem, up to 50% of main stems could be modeled to cone with root mean square error of 2.13 (quoting 9).

- Rottensteiner et al (2002) presented a new method for automatic generation of three-dimensional structural models generated by Lidar sensors. Using interpolation hierarchical method using the error distribution function, the Lidar points on the diagonal on buildings and other objects were separated. It was formed by a model in which the construction of digital and the rest of the height of the main points of a digital surface model was Lidar resolution. As a result, a mask made of construction and polyhedral building models in these candidate regions in a bottom-up process with the use of techniques based on the curvature caused cut. The results of the proposed algorithm on test images on Lidar sites of Vienna in Austria were presented which showed high efficiency of the proposed method (10).

3. Methods

Here, we describe the self-adjusting spectral clustering method for segmentation Lidar image: The proposed method is implemented with MATLAB software. Therefore, this description is proposed of MATLAB algorithm. The developed algorithm is as follows:

Stage 1) Input of this code is Lidar images of various sectors such as forest, deserts, beaches and urban areas. The images are stored in the file directory and name of the image is considered as the input code. This stage image is input to the program.

Stage 2) the self-adjusting spectral clustering method to create the optimal number of clusters based on the similarity matrix and extracted with eigenvalues determined. Therefore, at this stage consists of a similarity matrix of the input image and the eigenvalues of the schedule presented in Appendix. Similarity matrix based on spectral clustering self-adjusting formula exponentially on the distance between the reference samples (pixel color) in the feature space (image) is created. Sigma value (constant similarity function) is adjustable and is selected according to the distance between samples in the feature space.

Stage 3) diagonal matrix D is formed the total array of row similarity matrix. Each diagonal array in diagonal matrix D practically is the similar total amount of each sample to the other samples. Thus, the elements of the row and column i is total similar sample to other samples.

Stage 4) the matrix L, normalized similarity matrix is formed.

Stage 5) for the number of clusters 1, up to maximum value of the parameter C is determined. Eigenvalues of the matrix L is calculated normalized. Output diagram is used for determining the optimum number of clusters. Optimum value is where a curve is broken and converts to straight line which is optimum value usually about 2 to 4 clusters, because the number of regions in the images is the same number.

Stage 6) with determine the optimal number of clusters, the image format of RGB to turned format L * a * b and based on the algorithm, nearest samples or samples with the highest similarity clustering is performed.

Stage 7) coordinates of the center of the cluster and the cluster index is determined. Each of the samples is labeled based on the cluster to which it belongs. Now different samples were separated and each cluster to show other parts of the image becomes is black.

Stage 8) images separated clusters and if not optimal clustering of samples does not belong to any cluster, these samples were identified and displayed. But actually, since the optimal number of clusters, based on the arrangement of the eigenvalues of the normalized similarity matrix is determined, this sample is neglected and is a small percentage of the sample.

4. Findings

Four Lidar samples were taken for testing is and segmentation of images using the proposed method will be described later. Sample images are displayed in Figure 1.

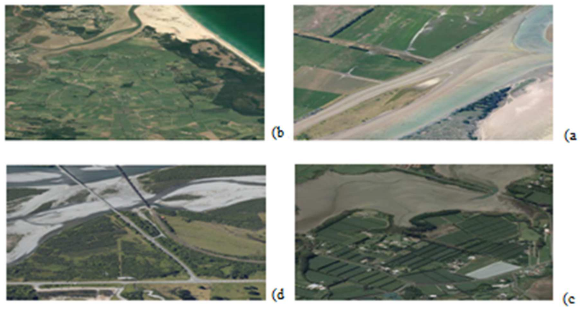

Figure 1. *Sample images of Lidar.*

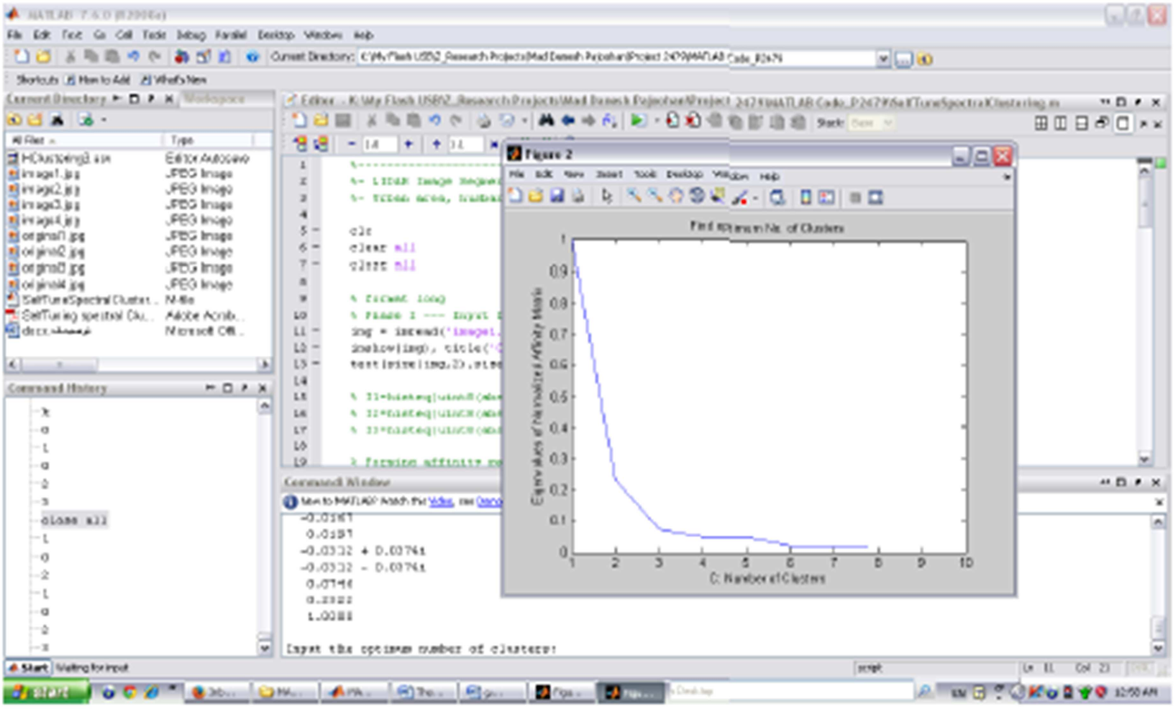

Figure 2. *The appearance of the program after the run along the graph similarity normalized eigenvalues matrix to determine the optimal number of clusters.*

Figure 2 shows the appearance of the proposed algorithm, which after entering the name of the input image and implementation of image similarity matrix of the eigenvalues of the graph will be displayed. It shows a bearish chart that increasing the number of clusters for a similarity matrix of the eigenvalues of the matrix decreases. The optimal number of clusters is determined based on the graph and usually break point of the charts is the optimal point. Eigenvalues of the graph can be used as a carpet, two straight lines on the graph, which charts the early starts and the other ends. Point are fitted where this two lines together to an intermediate point on the graph, which is typically in the range of 2 to 4 clusters.

According to Figure 3, the failure of this diagram is almost at point 3. Therefore, the optimal cluster number is three. By entering the number 3 as the number of clusters in the next step, a similarity matrix is separated to three regions and each part separately is shown a distinct color. The output image is shown in Figure 4. In this figure, the image labeled sections (Fig. 4 Part A.) and the image of each of the sectors, with the elimination of other sectors is shown. Original image indicate the different resolution, proper selection is the number of clusters.

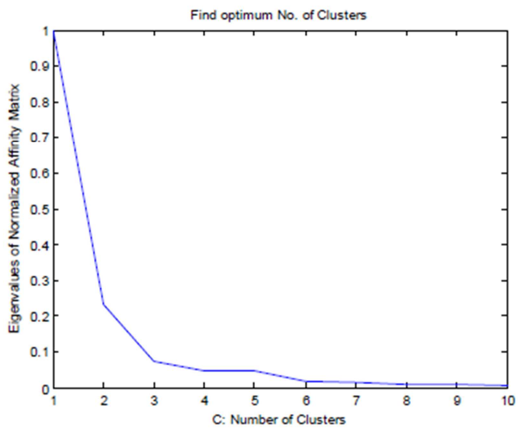

Figure 3. *Graphs of the eigenvalues of the normalized similarity matrix to determine the optimal number of clusters for the image shown in Figure 1 (a).*

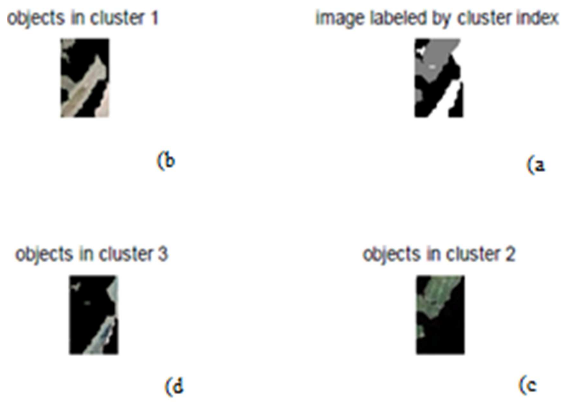

Figure 4. *The output program for the image Figure 1 (a).*

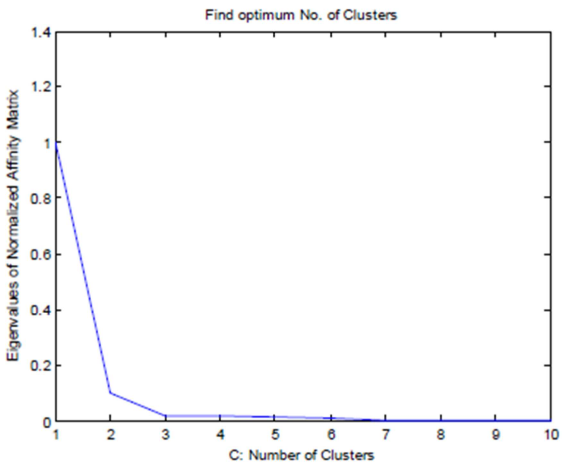

Figure 5. *The graph eigenvalues normalized similarity matrix to determine the optimal number of clusters for the image Figure 1 (b).*

According to Figure 5, the failure of this diagram is almost at point 3. Therefore, the optimal cluster number is three. By entering the number 3 as the number of clusters in the next step, a similarity matrix is separated to three regions and each part separately is shown a distinct color. The output image is shown in Figure 6. In this figure, the image labeled sections (Fig. 6 Part A.) and the image of each of the sectors, with the elimination of other sectors is shown. Original image indicate the different resolution, proper selection is the number of clusters.

Figure 6. *The program output for the image Figure 1 (b).*

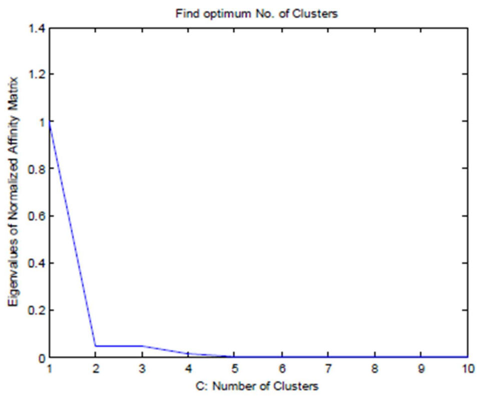

Figure 7. *The graph eigenvalues normalized similarity matrix to determine the optimal number of clusters for the image Figure 1 (c).*

According to Figure 7, the failure of this diagram is almost at point 2. Therefore, the optimal cluster number is two. By entering the number 3 as the number of clusters in the next step, a similarity matrix is separated to two regions and each part separately is shown a distinct color. The output image is shown in Figure 8. In this figure, the image labeled sections (Fig. 8 Part A.) and the image of each of the sectors, with the elimination of other sectors is shown. Original image indicate the different resolution, proper selection is the number of clusters.

Figure 8. *The program output of the image Figure 1 (c).*

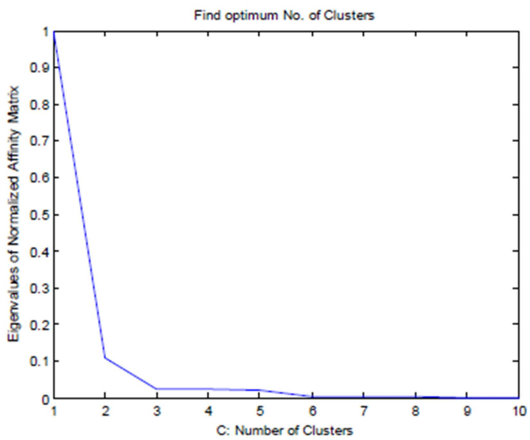

Figure 9. *The graph eigenvalues normalized similarity matrix to determine the optimal number of clusters for the image Figure 1 (d).*

According to Figure 9, the failure of this diagram is almost at point 3. Therefore, the optimal cluster number is three. By entering the number 3 as the number of clusters in the next step, a similarity matrix is separated to three regions and each part separately is shown a distinct color. The output image is shown in Figure 10. In this figure, the image labeled sections (Fig. 10 Part A.) and the image of each of the sectors, with the elimination of other sectors is shown. Original image indicate the different resolution, proper selection is the number of clusters.

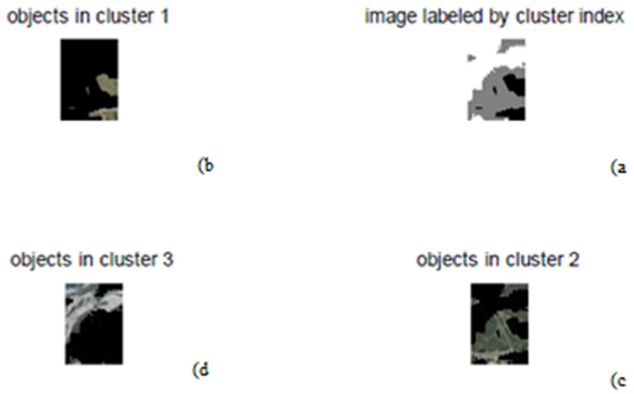

Figure 10. *The program output of the image Figure 1 (d).*

5. Conclusions

In the experiments, the four Lidar images with a number of different areas (water, forest, desert and city) algorithm was used to assess the performance and the criteria was ability to distinguish the parts of a visual diagnosis. For each image, eigenvalues of matrix similarity is displayed and the optimal number of clusters was estimated. Based on the number of clusters approximate similarity matrix, patterns divided into a number of groups equal to the number of clusters and clustering was performed. The output of the program, which includes images related to each cluster to cluster separately from other clusters displayed. It can be concluded that self-adjust spectral clustering algorithm is suitable and efficient to segment Lidar images. Because in these pictures, linear areas - was not separated and in comparison with other clustering methods, Euclidean distance based clustering patterns in space will be much better. For future research are proposed as follows: Using spectral clustering with self-adjusting similarity matrix, based on different criteria of similarity between patterns, the optimal number of cluster detection algorithm, based on the eigenvalues of diagram defined evaluation parameters to evaluate and compare the results of clustering and also to determine the optimal number of clusters, the clusters based on the optimization of the parameters evaluation quantity.

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