Methods for LiDAR point cloud classification using local neighborhood statistics

Conference Paper *in* Proceedings of SPIE - The International Society for Optical Engineering · May 2013

DOI: 10.1117/12.2015709

Methods for LiDAR point cloud classification using local neighborhood statistics

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ABSTRACT

LiDAR data are available in a variety of publicly-accessible forums, providing high-resolution, accurate 3-dimensional information about objects at the Earth's surface. Automatic extraction of information from LiDAR point clouds, however, remains a challenging problem. The focus of this research is to develop methods for point cloud classification and object detection which can be customized for specific applications. The methods presented rely on analysis of statistics of local neighborhoods of LiDAR points. A multi-dimensional vector composed of these statistics can be classified using traditional data classification routines. Local neighborhood statistics are defined, and examples are given of the methods for specific applications such as building extraction and vegetation classification. Results indicate the feasibility of the local neighborhood statistics approach and provide a framework for the design of customized classification or object detection routines for LiDAR point clouds.

Keywords: LiDAR, point cloud, classification, statistics, local neighborhood

1. INTRODUCTION

It is clear from a visual inspection of LiDAR point cloud data that the 3-dimensional arrangement of LiDAR points is useful for distinguishing materials and objects in a scene. Characteristics of the distribution of points such as smoothness, regularity, and vertical scatter may help determine what type of surface or object the points represent. In this work, local neighborhoods of LiDAR points were examined and a series of statistics were defined to quantify these characteristics. Methods for defining local neighborhoods are discussed in Section 4, and a selection of local neighborhood statistics is discussed in Section 5.

The statistical attributes were combined into feature vectors that were then used to segment the point cloud data into classes using traditional data classification routines. Not all attributes were useful for each scene classification task. The utility of individual statistical measures depends upon the characteristics of the particular LiDAR point cloud being examined, and the goal of the classification scheme. To determine which features were most useful for creating separable classes, the histograms of values for each statistic within a training region of interest were examined. Features that maximize the separability of classes were chosen for inclusion in the classification routine (Section 6).

Two methods for classifying the LiDAR feature vectors, one supervised and one unsupervised, are discussed in Section 7. Results using both classification approaches and different combinations of statistical features are compared in Section 8. A summary of results and directions for future work are given in the final two sections (Sections 9 and 10).

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Laser Radar Technology and Applications XVIII, edited by Monte D. Turner, Gary W. Kamerman,
Proc. of SPIE Vol. 8731, 873103 · © 2013 SPIE · CCC code: 0277-786X/13/$18 · doi: 10.1117/12.2015709

2. PREVIOUS WORK

Chehata et al. (2009) present a variety of statistics-based point cloud features and perform feature selection from LiDAR data using a random forests classification.[1] The ISPRS Commission III, Working Group 4, on 3D scene analysis provided a benchmark dataset for comparing methods of urban object classification and 3D building reconstruction. An accompanying report summarizes the success of the participants in classifying buildings and trees.[2] Using the benchmark dataset, Niemeyer et al. (2012) used an approach similar to Chehata et. al (2009), incorporating point cloud statistics, but instead made use of a conditional random field classification scheme to incorporate contextual information.[1,3]

Brodu and Lague (2012) present a multi-scale dimensionality approach for classifying terrestrial laser scanning data.[4] The method relies on calculating the principal components of the matrix of xyz-coordinates of local neighborhoods of points. By analyzing the percentage of variance explained by each principal component, the local neighborhood of points can be classified as being linear, planar, or globular. Looking at the dimensionality over varying spatial scales allows points to be classified.

The approach for classifying LiDAR point cloud data using point cloud statistics based features presented in this paper is a very similar approach to that presented in Chehata et. al (2009) or Niemeyer et. al (2012).[1,3] We use slightly different statistics, however, apply the multi-scale approach of Brodu and Lague (2012) to additional statistics, and use different methods for feature selection and classification.[4]

3. THE STUDY AREA AND LIDAR DATASET

LiDAR data were acquired for selected areas of California during 2010 by the Association of Monterey Bay Area Governments (AMBAG), via a USGS grant through the American Reinvestment and Recovery Act of 2009. The primary dataset used for this paper was collected for a portion of Camp Roberts (near Paso Robles, California) over multiple days in September, 2010, with a point density of $\sim$2.5 points per square meter. Bare-earth Digital Elevation Models (DEMs) with a resolution of 3-meter pixels were delivered with the data.

Regions of interest were selected in 3D-space using the open source CloudCompare utility developed by Daniel Girardeau-Montaut.[5] This tool enables selection of “tree” points, while excluding LiDAR returns from ground underneath the tree. Similarly, the “building” ROI only contains rooftop points. Returns that may have come from the side of the building were excluded (Figure 1).

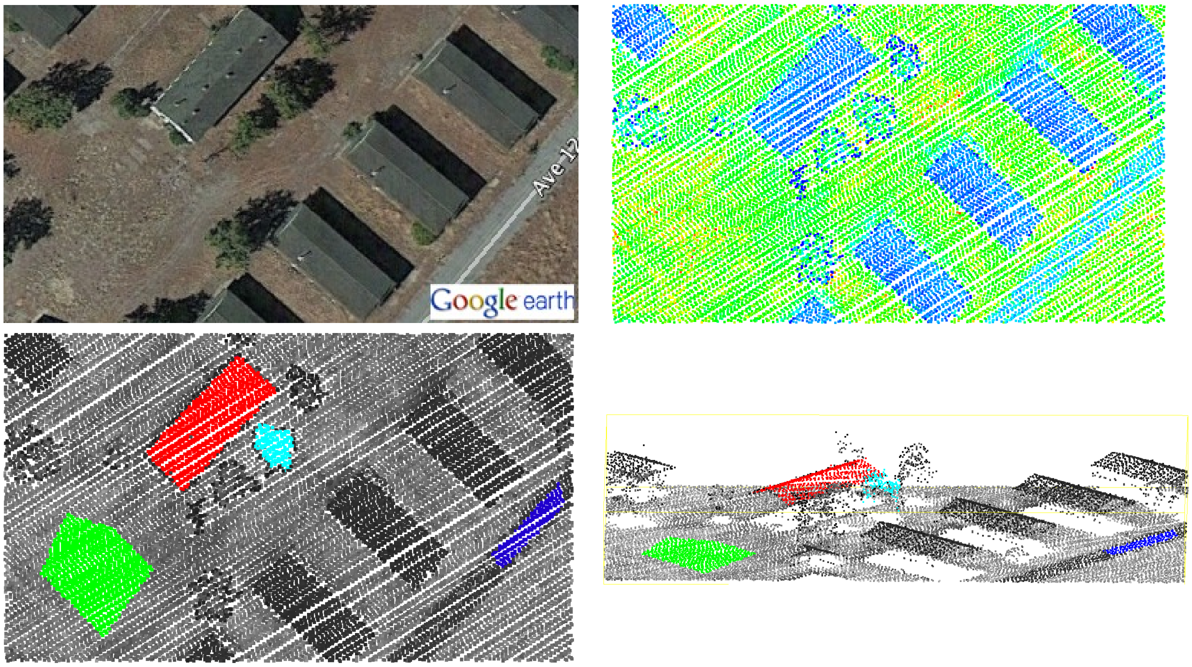

Figure 1. The sample dataset of a portion of Camp Roberts, California used in this research. The Google Earth image (Top Left) shows the approximate area covered by the LiDAR data. (Top Right) The LiDAR data colored according to point intensity (darker regions are shown in blue; brighter regions in green). (Bottom) A grayscale display of the LiDAR data with regions of interest points in color: building (red), tree (cyan), road (blue), and grass (green). Regions of interest were defined in 3D-space using the open source CloudCompare utility.[5]

4. LOCAL NEIGHBORHOODS

One of the challenges of working with LiDAR point cloud data is the irregularly-gridded nature of the data. In this work, we made use of a fast nearest neighbor searching algorithm provided by Merkwirth et. al.[6] This tool enables the rapid determination of local neighborhoods of points without requiring the data to be gridded. This approach maintains the accuracy of the original point cloud, and avoids the introduction of interpolation errors that must occur if the point cloud data is gridded into a traditional raster-type image.

Two approaches were used for defining local neighborhoods of points. The first approach defines the neighborhood based on a set number of nearest neighbors. A minimum of three points is required for each neighborhood to ensure the local surface planar orientation can be calculated. Increasing the number of points included in the nearest neighbor search increases the computation time. In the results presented in this paper, we restricted the number of nearest neighbors to three.

The second approach for defining a local neighborhood depends upon a user-defined radial distance. The radius defines a circular area in the x-y plane, and the neighborhood incorporates the vertical column of points at all heights. The radius must be large enough to incorporate a sufficient number of points for calculation of meaningful statistics, but not so large that spatial details are lost. In this work, with an average point density of 2.5 points per square meter, we considered multiple sizes of neighborhoods with the radii ranging from 1.2 to 3.7 meters.

5. POINT CLOUD ATTRIBUTES

A series of LiDAR point attributes were examined, including the inherent LiDAR properties of intensity and height above ground level, and a set of statistics was designed to characterize the 3-dimensional arrangement of local neighborhoods of LiDAR points. Each of the individual attributes was recorded for all LiDAR point neighborhoods and then normalized so that each of the attribute had the same "weight" in the classification scheme.

5.1 Height Above Ground Level and Intensity

It is straightforward to make use of the height above ground level and return intensity values to classify LiDAR point cloud data. While the return intensity values are not typically normalized between flight lines, the relative intensity of points may be useful in distinguishing different materials.

A DEM or some other estimate of the bare earth surface is required to determine a point's height above ground level. In this work, we made use of the 3-meter resolution DEMs that were delivered by the vendor. The fast nearest neighbor searching algorithm of Merkwirth et. al. was used to determine nearest DEM pixels to each LiDAR point.[6] The elevation of the nearest DEM pixel was subtracted from the elevation of the LiDAR point to determine the height above ground level of each point.

5.2 Differences of Elevations

This statistic captures the average differences in elevations of neighborhoods of points. The statistic is calculated by subtracting the minimum elevation within the neighborhood from the mean of elevations of all points within a neighborhood.

5.3 Standard Deviations of Elevations

This statistic is a useful measure of "smoothness". This statistic is simply the standard deviation of elevations of all points within a neighborhood.

5.4 Standard Deviations of Intensity Values

This statistic gives a measure of visual texture, and is calculated by finding the standard deviation of intensity values of all points within a neighborhood.

5.5 Angle of Planar Surface Normal

In this paper, this statistic was only calculated for neighborhoods defined using a point's three nearest neighbors. The three nearest neighbors of each LiDAR point were used to define a plane. The deviation of the surface normal of the plane from vertical is recorded.

5.6 Principal Component Percentage of Variance

This statistic is adapted from Brodu and Lague (2012).[4] For each neighborhood of points, the principal components of the matrix of xyz-coordinates is calculated. The percentage of the total variance explained by each principal component gives an indication of the "dimensionality" of the object. For example, to explain the location of a point on a linear object (such as a telephone wire), only a single measurement is needed. The distance in the direction of the axis aligned with the telephone wire is sufficient for defining the point's location. Therefore, a set of points representing a linear feature will have most of the variance in its xyz-coordinates explained by the first principal component. A planar surface, where points are spread in two dimensions, will require two components to define the location of points. The first two principal components will be necessary for explaining most of the variance in the data. Finally, if all three principal components are needed to represent a significant percentage of the variance, the object is 3-dimensional. Figures 2 and 3 show an example point cloud created to demonstrate this concept.

The dimensionality of an object also depends upon the spatial scale at which it is examined. An object that looks planar close up (at a small spatial scale) may be 3-dimensional at a larger spatial scale. Further, this multi-scale behavior will vary for different materials. Calculating this statistic at multiple spatial scales is useful for distinguishing different types of materials.

5.7 Point Density

The point density is determined by dividing the total number of points in a neighborhood by the square of the neighborhood radius.

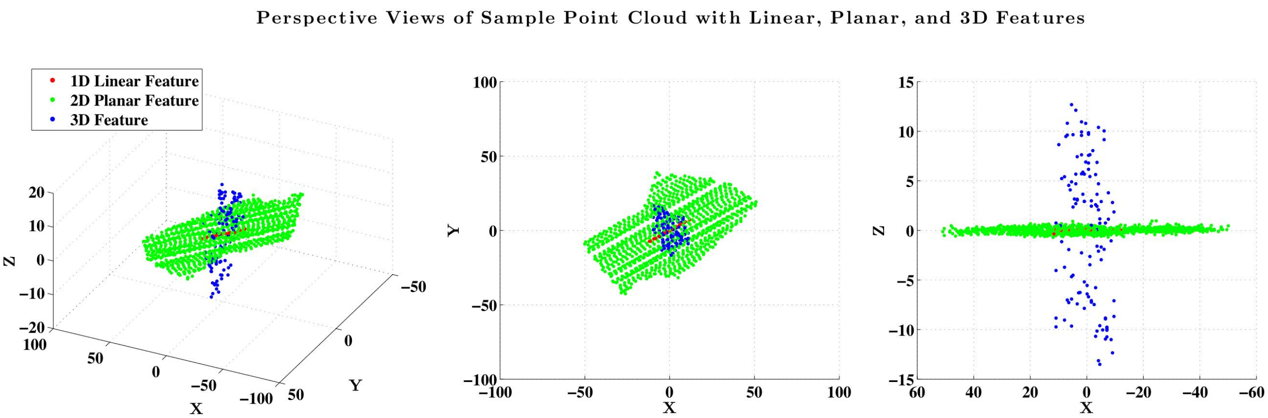

Figure 2. An example point cloud with linear (red), planar (green), and 3D objects (blue).

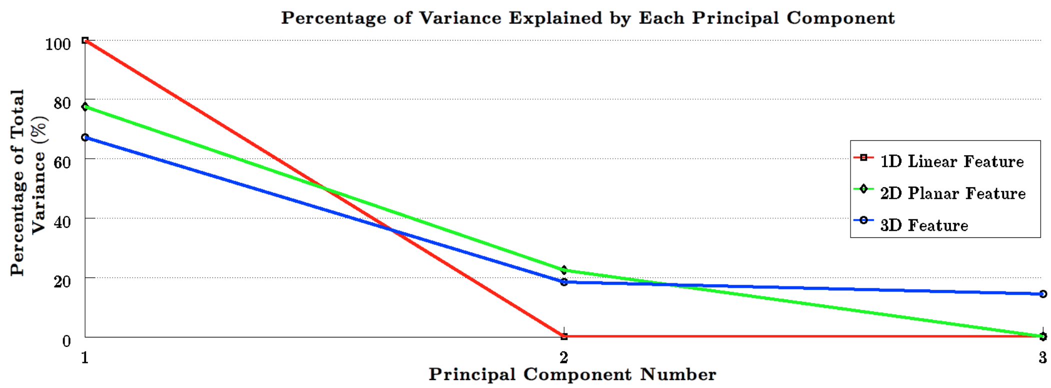

Figure 3. The percentage of variance explained by each principal component for a linear (red), planar (green), and 3D object (blue). The linear feature requires only one principal component to explain all of the variance in the xyz-coordinates.

6. FEATURE SELECTION

Many of the features described in Section 5 are similar for multiple classes of materials. In Figure 4, the shaded regions represent the variability in the feature vectors for each of the four regions of interest. This figure illustrates that the intraclass variability often exceeds the differences between classes. It is therefore necessary to choose a subset of features that maximize the class separability.

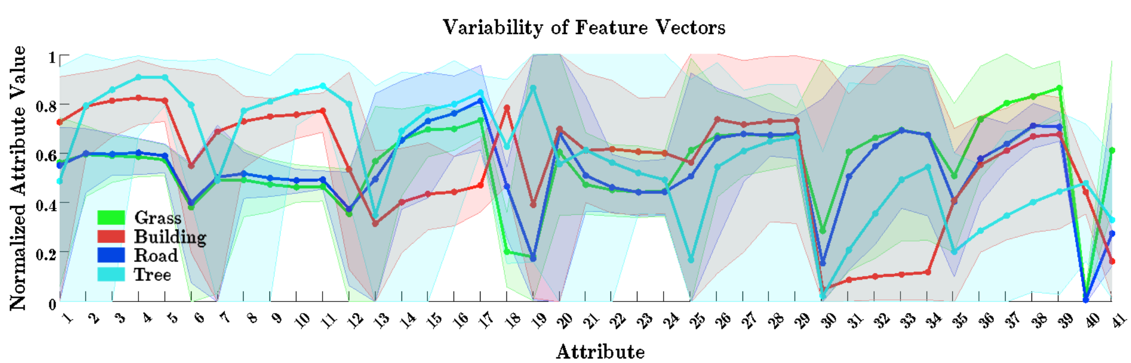

Figure 4. The mean feature vectors for each region of interest, with the variability of each class represented by the shaded region. The intraclass variability of the features often exceeds the differences between classes.

The features as plotted in Figure 4 are as follows:

1. Differences of elevations (1.2-m neighborhood)
2. Differences of elevations (1.8-m neighborhood)
3. Differences of elevations (2.4-m neighborhood)
4. Differences of elevations (3-m neighborhood)
5. Differences of elevations (3.7-m neighborhood)
6. Differences of elevations (3-nearest neighbors)
7. Standard deviation of elevations (1.2-m)
8. Standard deviation of elevations (1.8-m)
9. Standard deviation of elevations (2.4-m)
10. Standard deviation of elevations (3-m)
11. Standard deviation of elevations (3.7-m)
12. Standard deviation of elevations (3-nearest neighbors)
13. Standard deviation of intensities (1.2-m)
14. Standard deviation of intensities (1.8-m)
15. Standard deviation of intensities (2.4-m)
16. Standard deviation of intensities (3-m)
17. Standard deviation of intensities (3.7-m)
18. Standard deviation of intensities (3-nearest neighbors)
19. Angle (3-nearest neighbors)
20. Percentage of variance - 1st Principal Component (PC) (1.2-m)
21. Percentage of variance - 1st PC (1.8-m)
22. Percentage of variance - 1st PC (2.4-m)
23. Percentage of variance - 1st PC (3-m)
24. Percentage of variance - 1st PC (3.7-m)
25. Percentage of variance - 2nd PC (1.2-m)
26. Percentage of variance - 2nd PC (1.8-m)
27. Percentage of variance - 2nd PC (2.4-m)
28. Percentage of variance - 2nd PC (3-m)
29. Percentage of variance - 2nd PC (3.7-m)
30. Percentage of variance - 3rd PC (1.2-m)
31. Percentage of variance - 3rd PC (1.8-m)
32. Percentage of variance - 3rd PC (2.4-m)
33. Percentage of variance - 3rd PC (3-m)
34. Percentage of variance - 3rd PC (3.7-m)
35. Point density (1.2-m)
36. Point density (1.8-m)
37. Point density (2.4-m)
38. Point density (3-m)
39. Point density (3.7-m)
40. Height above ground level
41. Intensity

To select the most useful features for scene classification, the average distance between class means and the average standard deviation of values were measured for each attribute. The most useful attributes were chosen as those for which the average distance between class means exceeds the average standard deviation. For the sample dataset used in this paper, the attributes meeting this criterium are the following:

- 4 and 5: Differences of elevations (3-m and 3.7-m radius neighborhoods)
- 9 - 11: Standard deviation of elevations (2.4, 3, and 3.7-m radius neighborhoods)
- 16 - 18: Standard deviation of intensity values (3 and 3.7-m radius neighborhoods and 3-nearest neighbors neighborhood)
- 37 - 39: Point density (2.4, 3, 3.7-m radius neighborhoods)
- 41: Intensity

Although in this case the point density features meet the criteria for being useful for separating the classes, it is unlikely that these features would be useful for scene classification, as the point density has more to do with collection geometry than any characteristic of the materials in the scene. A second subset of features was chosen using all of the separable features except for the point density features (statistics 4, 5, 9-11, 16-18 and 41). A third subset of features was defined subjectively by choosing features that appear to have distinct class means (statistics 4, 5, 8-11, 13, 15-18, 22, 25, 31, 32 and 41). Classification results using these subsets are compared to results of classification based on only the height above ground level and intensity information, and classification using all available features in Section 7.

7. CLASSIFICATION METHODS

Statistics of local neighborhoods were used to define a series of attributes for each LiDAR point. These attributes comprise a feature vector for each LiDAR point. The feature vectors were classified using traditional data processing techniques.[7] Both a supervised "Spectral Angle Mapper (SAM)" and an unsupervised "KMEANS" classification method were considered here.

For the supervised SAM classification technique, training regions of interest (as shown in Figure 1) are used to design classification decision criteria. The SAM classifier assigns feature vectors to a class based on minimizing the angle between the feature vector and the mean feature vector of the training class.[8] The angle between vectors is calculated using the well known formula:

$$Angle = \arccos\left(\frac{\mathbf{A}\cdot\mathbf{B}}{||\mathbf{A}||\,||\mathbf{B}||}\right) \tag{1}$$

A minimum angle threshold can be defined so that points that are not close to any of the training classes remain unclassified. A threshold of 0.05 radians was used for the work presented in this paper.

For the unsupervised KMEANS classification method, the user must define the number of clusters to be used. Four clusters were used for this paper. The KMEANS algorithm randomly chooses cluster centers, and then assigns vectors to the nearest cluster center. The cluster centers are then updated, and the process is repeated until cluster centers stabilize, or a certain number of iterations have been completed. Because the initial cluster centers are randomly assigned, running the classifier more than once may produce different results.[9]

8. COMPARISON OF RESULTS

The KMEANS classifier is an unsupervised routine, with classes being randomly assigned. In the figures showing KMEANS classification results below, the colors do not necessarily correspond to particular classes, although some effort was made to match the KMEANS class colors to the SAM classes for purposes of visual comparison. For the SAM classifier, class colors correspond to the regions of interest as shown in Figure 1. Unclassified points are shown in black.

8.1 Classification Using Height Above Ground Level and Intensity

It is a fairly standard practice to classify LiDAR data using the height above ground level and intensity information. Results of a supervised SAM classification and an unsupervised KMEANS classification are shown in Figure 5. The SAM classification results are very poor. The KMEANS method does a slightly better job of distinguishing the road from the dry grass covered ground, but trees and buildings are confused.

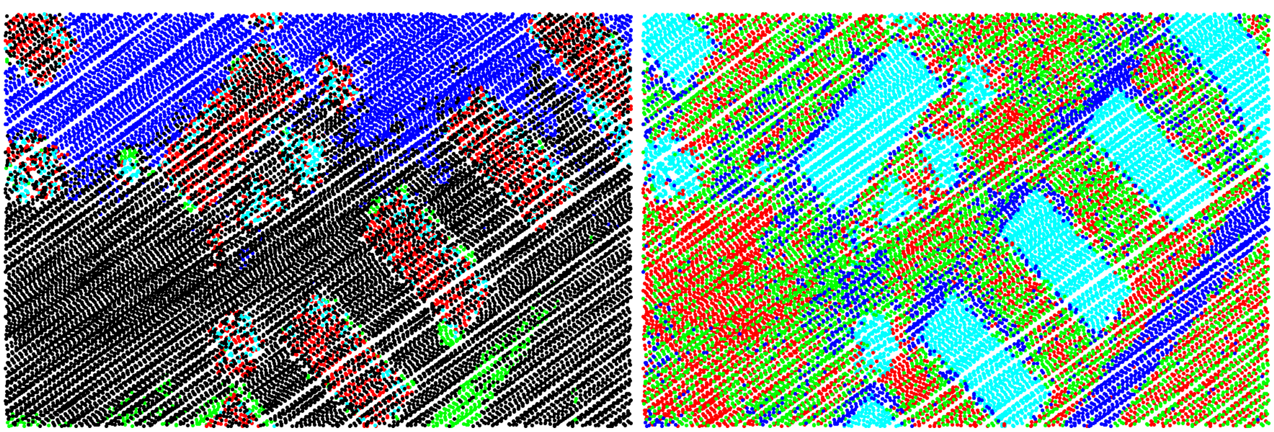

Figure 5. Spectral angle mapper (SAM) supervised classification results (L) and KMEANS unsupervised classification results (R) using only height above ground level and return intensity information.

8.2 Classification Using All Available Attributes

Results of the classification using all of the available LiDAR point attributes - statistical measures based on neighborhoods of points, along with the height above ground level and intensity information - are shown in Figure 6. In this case, the SAM and KMEANS classifier produce similar results, with a slightly cleaner result from the SAM classifier. For both classification methods, there is some confusion in the grass and road classes. Also, while buildings are mostly classified correctly, the edges of the buildings are confused with the tree class.

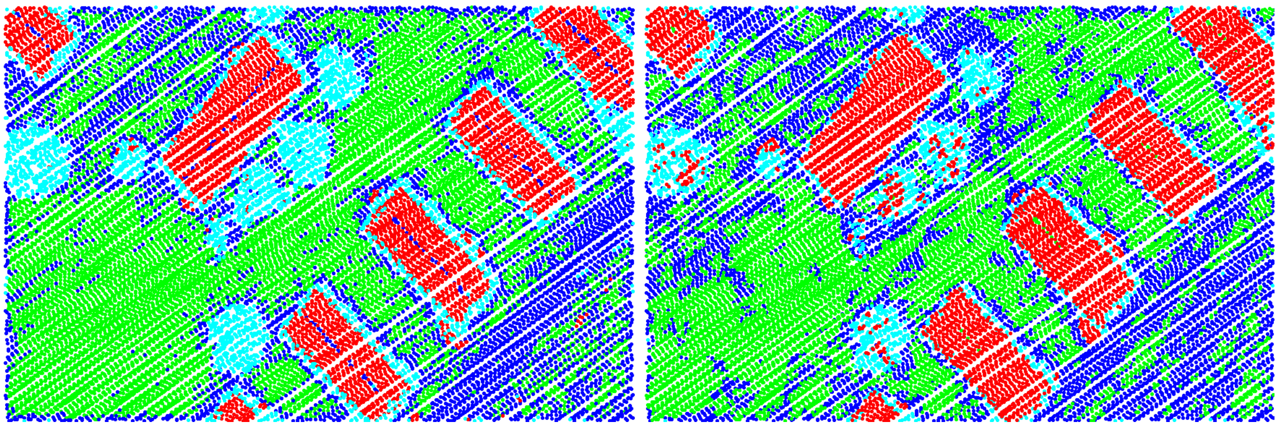

Figure 6. Spectral angle mapper (SAM) supervised classification results (L) and KMEANS unsupervised classification results (R) using all available local neighborhood statistics, height above ground level, and return intensity information.

8.3 Classification Using Selected Subsets of Attributes

It is more efficient, and with an appropriate selection - more accurate, to use a subset of attributes. As discussed in Section 6, an automated method of choosing a feature subset is to select those attributes for which the average distance between class means is greater than the average standard deviation of the class. Using this automated attribute selection method, twelve features were selected (4, 5, 9-11, 16-18, and 37-40). These features include attributes based on the differences in elevations, the standard deviation of elevations, standard deviation of intensity values, point density, and height above ground level. Results of classification using this subset of attributes are shown in Figure 7.

While the point density attributes meet the criteria for the automated feature selection, they are not expected to be useful for scene classification in general, since the point density is dependent upon sensor collection geometry more than on any material characteristics. By comparing classification results incorporating the point density features (Figure 7), and classification results excluding these features (Figure 8), we can see that for this sample dataset, inclusion of the point density attributes improved the distinction of buildings and trees, but caused confusion among the road and grass classes.

The automated method used for feature selection in this paper is very simple and not overly successful. A subjective choice of a subset of attributes that appear to have distinct class means produced better results (Figure 9). The subset includes statistics 4, 5, 8-11, 13, 15-18, 22, 25, 31, 32, and 41. These features include attributes based on differences in elevations, standard deviation of elevations, standard deviation of intensities, return intensity, and some of the principal component based features. In this case, the SAM routine successfully distinguished the four classes. Some confusion remained along the edges of buildings, with these points being incorrectly classified as belonging to the tree class. The KMEANS routine was also successful in distinguishing buildings from trees, but did a much poorer job of separating the road and grass classes.

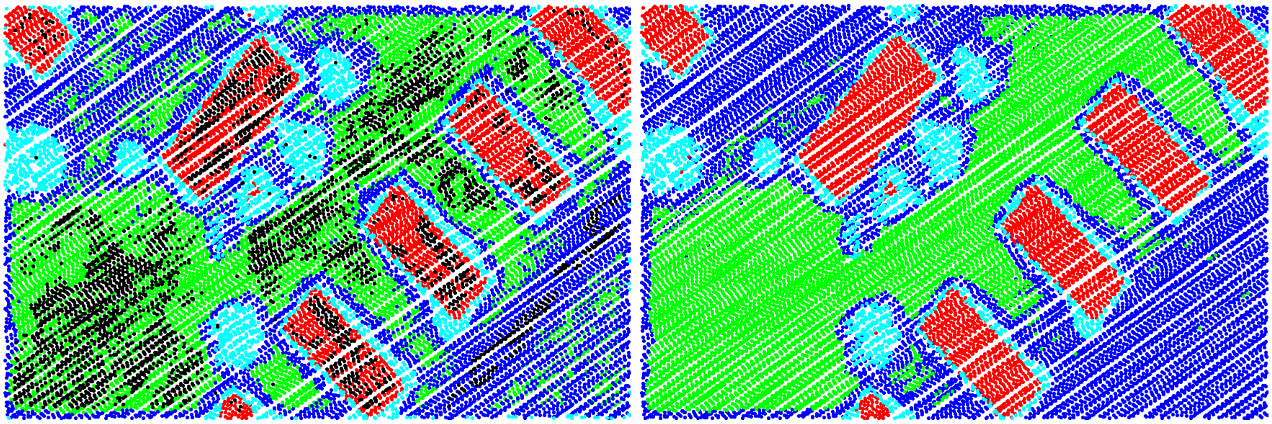

Figure 7. Spectral angle mapper (SAM) supervised classification results (L) and KMEANS unsupervised classification results (R) using attributes chosen by automatic threshold, including some attributes based on point density.

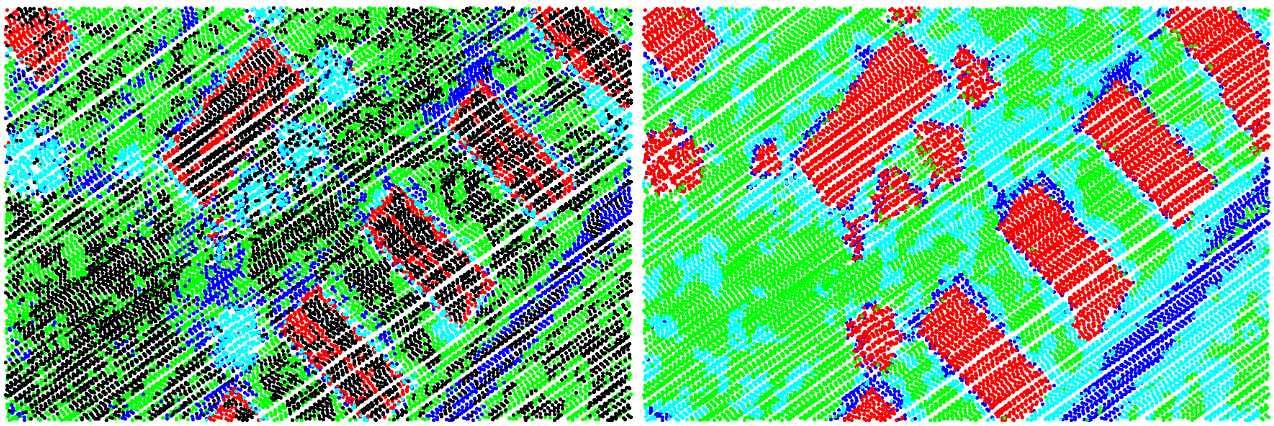

Figure 8. Spectral angle mapper (SAM) supervised classification results (L) and KMEANS unsupervised classification results (R) using attributes chosen by automatic threshold without any point density attributes.

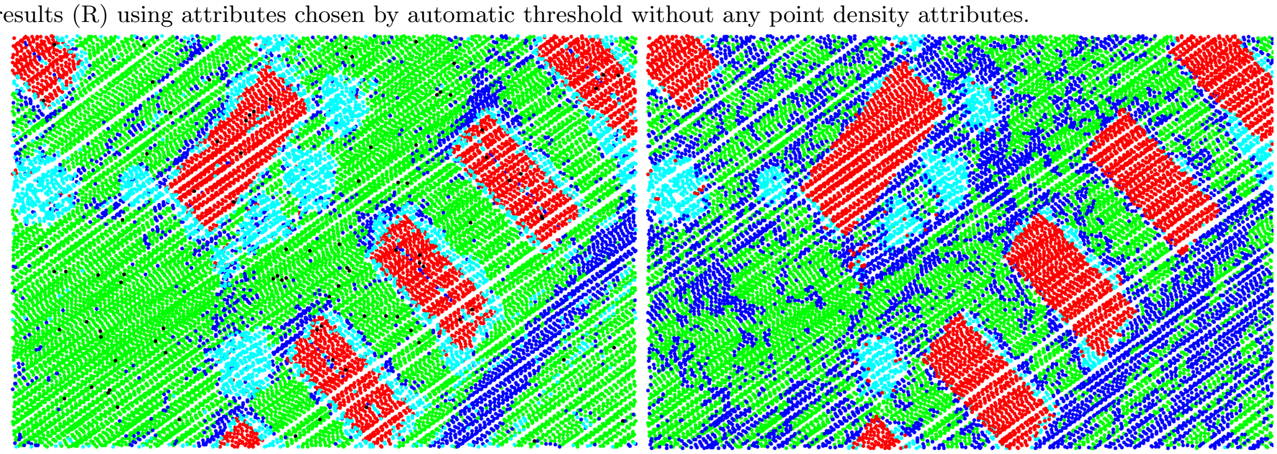

Figure 9. Spectral angle mapper (SAM) supervised classification results (L) and KMEANS unsupervised classification results (R) using a subjective choice of attributes that appear to have distinct class means.

9. SUMMARY AND CONCLUSIONS

A series of LiDAR point cloud attributes based on statistics of local neighborhoods of points were presented. These attributes were combined into feature vectors for each LiDAR point. The feature vectors were then classified using traditional image processing techniques, including a supervised spectral angle mapper (SAM) classification and an unsupervised KMEANS classification.

A simple method was presented for automated feature selection based on finding features that have an average distance between class means greater than the average standard deviation of the classes. This simple method of feature selection does not lead to a very successful classification result. A subjectively chosen subset of features based on choosing features that appear to have distinct class means was found to provide the best classification result.

Results indicate that inclusion of the local neighborhood statistical attributes leads to an improved discrimination of materials over a classification using only height above ground level and intensity information.

10. FUTURE WORK

The methods presented here are sensitive to local neighborhood size. The best method for choosing an appropriate neighborhood size is an ongoing area of research. It is dependent upon the size of the features to be distinguished, the density of the LiDAR point cloud, and the desired speed of processing.

Feature selection affects the efficiency of processing and the accuracy of the classification result. Subjectively choosing the features which had the most distinct training class means worked well in this case, but an automated method for feature selection would be preferable.

Application of the methods presented here to a dataset with ground truth, such as the benchmark dataset provided by the ISPRS Commission III, Working Group 4, will allow for a quantitative assessment of the method.[2]

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