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UC Davis Institute for Data Analysis and Visualization

Extraction of Features from High-resolution 3D LiDaR Point-cloud

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Abstract

Airborne and tripod-based LiDaR (light detection and ranging) scans are capable of producing new insight into geologic features by providing high-quality 3D measurements of the landscape. High-resolution LiDaR is a promising method for studying a range of processes that alter the landscape, such as slip on faults, erosion/deposition, flooding, or human activities. LiDaR scans can contain up to several billion individual point returns associated with the reflection of a laser from natural and engineered surfaces. These point clouds are typically gridded and then used to derive a high-resolution digital elevation model (DEM). Currently, there exist only few methods that support direct analysis of the ungridded point cloud data at their full resolution and in their natural 3D perspective. To address this problem, we are developing new algorithms for extracting features from LiDaR data. Here we present a method for working directly with the individual point returns of a scan to determine feature values within a LiDaR data set. Computing feature values such as curvature enables us to rapidly and automatically identify key features such as ridge-lines, stream beds, and edges of terraces.

1 Our Goals

* Identify and extract regions in LiDaR data sets matching individual structural characteristics (e.g., ridge-lines).

* Be able to automatically differentiate between natural and man-made objects (e.g., trees and buildings) from raw LiDaR data (point clouds).

* Detecting and joining objects corresponding to similar structural classes.

2 Octree-based Data Management and Level-of-detail (LOD) Visualization

To be able to deal with this huge amount of data we organize the points into an octree-based voxel structure. We modify the point sets of each octree level to match a level-specific resolution and store them on disc. This approach allows us to dynamically reload point sets of a certain resolution if necessary. This way, when visualizing the point cloud we have the possibility to adapt the resolution of the points to be high at regions where the user is interested in and to be low outside his focus. Figure 1(a) and Figure 1(b) show some examples concerning the efficient data management with LOD supported visualization allowing the exploration of huge point cloud data sets (over 100 million points).

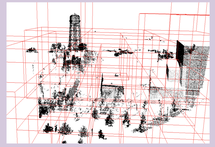

Figure 1 (a)

Point cloud and corresponding voxel grid of an environmental scan of the UC Davis water tower (consisting of 4.8 million points) at a low resolution level.

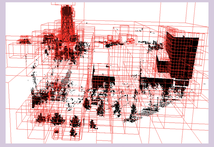

Figure 1 (b)

Point cloud and corresponding voxel grid of an environmental scan of the UC Davis water tower (consisting of 4.8 million points) at a high resolution level.

3 Point Classification

Classification of points depending whether they are part of a surface, a curve or a junction of either one. This is accomplished by collecting all points lying within a pre-specified local environment of a point p and by analysing the neighborhood shape using Principle Component Analysis (PCA).

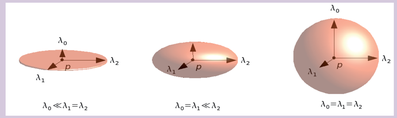

Figure 2 (a) Figure 2 (b) Figure 2 (c)

Figure 2 shows the three principle neighborhood shapes: (a) planar, (b) cylindrical and (c) spherical.

Figure 3 (a) Figure 3 (b) Figure 3 (c)

Figure 3(a) shows all points of a water tower scan colored from blue to red according to how flat the shape of their local neighborhood is (red = planar, blue = non-planar). Figure 3(b) shows the points identified as points having cylindrical shaped neighborhood in red against what others are drawn blue. Figure 3 (c) shows the points which are assumed to have a spherical neighborhood colored red. Those points which have no spherical neighborhood are colored blue. The color bar at the left encodes this scheme in colors reaching from blue (low shape similarity) to red (high shape similarity).

4 Extraction of Ridge-lines

1. Using points with planar shaped neighborhood.

2. Fitting polynomial surface patches to the local point neighborhood of each point using a technique called Moving Least Squares (MLS).

3. Computing the Root Mean Squared RMS) curvature from the fitted surface patches. Curvature in general is the amount by which a geometric object deviates from beeing flat.

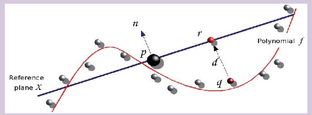

Figure 4

Figure 4 illustrates the basic principle of fitting surfaces via MLS on the basis of a 1-dimensional example.

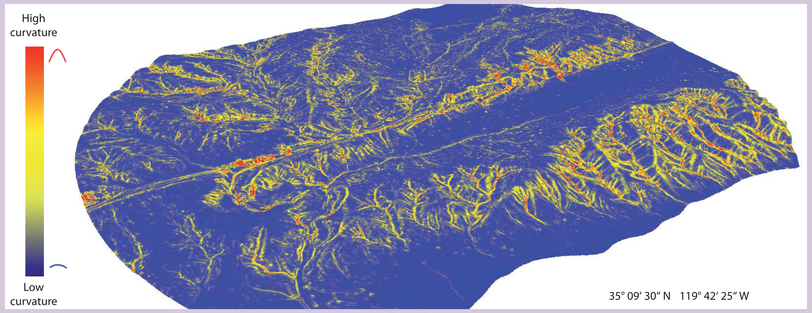

Figure 5 (a)

Figure 5(a) shows an airborne LiDaR scan of a portion of the San Andreas fault in the Carrizo plain, California, showing interactions of stream channels and the active fault trace. The image spans a reach of the fault that is ~1.9 km long. The point cloud contains ~1.6 million points, which are colored from blue to red depending on whether a point represents a ridgeline or not. Specifically, blue points represent smooth areas, with yellow and red points representing ridgelines as identified by our algorithm. The color values represent Root Mean Squared (RMS) curvature values of polynomial surface patches fitted to the local neighborhood of a point by using a technique called Moving Least Squares (MLS). Data from GeoEarthScope (http://www.unavco.org/geoearthscope/).

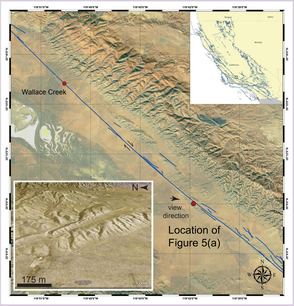

Figure 5 (b)

Figure 5(b) shows the southern San Andreas fault and locations of the area shown in Figure 5(a) and Wallace Creek. Inset in lower left shows terrain view in Google Earth (2x vertical exaggeration), taken from approximately the same look direction as seen in Figure 5(a). Inset in upper right is active fault map.

5 Feature Graph Extraction

1. Definition of seed nodes and critical nodes. Seed nodes are given by all points whose neighborhood is of planar (cylindrical) shape and whose curvature (feature) values are above a given threshold (see Figure 6(a)). Critical nodes are given by points possessing a spherical neighborhood.

2. Establishing edges between seed nodes (see Figure 6(b)).

3. Connecting critical nodes (see Figure 6(c)).

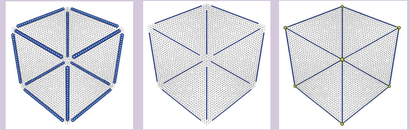

Figure 6 (a) Figure 6 (b) Figure 6 (c)

Figure 6(a)-(c) illustrate the principal stages of creating a feature graph by using a simple cube example. Figure 6(a) shows the identified seed nodes (as blue points) corresponding to points assumed to have a cylindrical neighborhood. Figure 6(b) shows the established edges connecting the seed nodes. Figure 6 (c) shows the final graph after connecting the critical nodes (shown as green points).

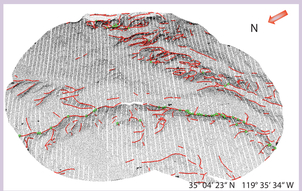

Figure 7 (a)

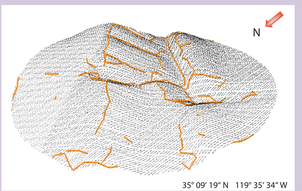

Figure 7 (b)

Figure 7(a) shows an environmental LiDaR scan performed airborne consisting of about 6.5 million points (0.96 km long). The picture also shows the extracted feature graphs depicted as red lines. The green points represent the critical nodes corresponding to very strong features like tapering ridge-lines. Figure 7(b) shows a more detailed view of a feature graph extracted from a smaller data set (about 50K points, 0.15 km long).

Figure 8 (a) Figure 8 (b) Figure 8 (c)

Figure 8(a) shows the original point cloud representing a water tower structure. Figure 8(b) presents the feature values delivered by our algorithm. The points are colored from blue to red depending on the strength of the underlying line-like features. We are able to distinguish between points lying on a surface (blue) and points corresponding to line-like features (yellow and red). Figure 8(c) shows the extracted feature graph corresponding to the highlighted points of Figure 8(b).

6 Conclusions

We have introduced a novel approach for extracting and visualizing features from LiDaR data sets. Our examples demonstrate the benefits of this method for extracting feature graphs from point clouds representing surface components like ridges and creases as well as curve-like components. As our method was designed as an interactive, user-controlled method offering also a high degree of automation, one specific strength is the ability for a user to influence the analysis process and obtain instant visual feedback. This work is fundamental for future research, for example to detect and measure deformation of environmental structures such as buildings and bridges exposed to terrestrial influences.

Acknowledgements

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