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Multidimensional Spatial Analysis of Geo-objects from Unstructured Topographic Points

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ABSTRACT

This paper presents a framework for spatial analysis of multidimensional topographic data from point clouds. We have highlighted the challenges of working with multidimensional data for representing the topographic regions for spatial analysis and explained how spatial morphological methods can become first-hand support for processing unstructured data stored in point clouds. The theoretical model for spatial analysis is supported by experimental work on point cloud data of a random topographic region involving a sparse forest region. Special emphasis is given to computing ground-projected area estimations of geographical features. It is observed that morphological processing is equally useful for unstructured data points for extracting geospatial features including tree crowns and rooftops. This paper also highlights challenges in handling large data sets proposes to use morphology-based for addressing these problems and sets the pointer for future research in spatial analysis. The overall accuracy of 98.7% is obtained for surface object classification and segmentation.

Keywords: *spatial analysis, topography, multidimensional visualization, point cloud, geostatistical analysis*

1. INTRODUCTION

Spatial investigation is now a broader field that uncovers several facts and aspects of our environment. With technological advances in sensing, imaging, and storage, the size and the form of spatial data have also changed. A paradigm shift is seen in the use of image and object-based data in real space. It is now possible to explore the geographical environment including topography, hydrology, and forestry better than ever. Data acquisition, representation, and processing are moving towards higher dimensional space rather than using legacy two-dimensional systems. A major source of spatial information is multidimensional point data acquired from modern imaging sensors including LiDAR. The early 1990s used topographic maps as the primary source of quantitative information on topography. With the use of photogrammetry and the data generated from LiDAR sources, the two-dimensional discrete functions of elevation grew to three-dimensional space and allowed estimating generating terrain models and canopy estimates from elevation models. Some of the current research trends in terrain modeling include

- Analysis of relationships between surface properties and topographic characteristics.
- Exploiting the resulting knowledge for the predictive mapping and analysis of geographical features such as folds, domes, and rooftop-like structures.
- Finding and analyzing structural lies and faults, including their relations with other components in the topographic patch.

Analyzing topographic data involves evaluating local and nonlocal morphometric attributes/variables. A local morphometric attribute is usually used to define the surface geometry in the neighborhood of the given test point. Contrary to the local attribute, the nonlocal topographic attribute describes a relative position of the given point on the surface. Some of the local morphometric attributes include curvature and slope aspects. The non-local morphometric attribute includes catchment and dispersive area estimates.

The study of the spatial distribution of natural and man-made structures has been an active area of interest to geographic professionals and earth explorers. Technology-assisted spatial exploration and analysis have generated much interest in recent times. Description of the scene of object using points in space has been challenging and needs further investigations. One interesting area for spatial investigation and analysis in the forestry region and extraction of tree canopies and manmade buildings.

While there are several approaches to investigate and explore information from these data points, the use of simple geostatistical algorithms together with existing central tendency measures can provide interesting spatial information. These measures of central tendency together with these morphometric attributes can be used for spatial approximation of the objects in the topographic landscape. Such spatial localization and structural estimates find their use in application areas such as target estimation from aircraft, landscape, and city planning, and developing micro-mobility support for cellular handovers. Traditional two-dimensional mapping solutions offer limited knowledge about the subject area and need higher dimensional treatments to uncover more precise facts. The geostatistical approach has well established itself on two-dimensional raster and other cartographic data. Extending them to data defined in multidimensional space is challenging but has more significance.

Some of the known methods to perform spatial analysis from geostatistics includes methods like Inverse Distance Weighted (IDW) and Kriging-based methods[1], [2], Spline approximations, Cluster and Grouping Analysis[3], Correlation and Regression analysis on spatial data. It can be a great tool for exploratory analysis for creating a spatial knowledge base and deriving meta-information for specific applications. Topographic data has several intrinsic information within it which can be explored using spatial analysis. This includes information related to forestry, hydrology, shape profiles, and other interesting aspects. In this paper, we explore the usefulness of geostatistical measures and methods for extracting spatial localization of geographical features including tree crowns, valley profiles, and, catchment areas. We apply simple geostatistical methods on the cluster of points in 3D space which represents returns from geographic features and demonstrate how to explore useful spatial information from it. A hybrid approach involving 3D point processing and projection is used for precise visualization of the spatial distribution of spatial features.

2. LITERATURE AND RELATED WORK

Spatial analysis of topographic data relies on morphometric attributes and discrete point locations within it. The last two decades have seen a growing interest of researchers which has extended the spatial analysis from two-dimensional image processing to higher-dimensional space. The scope of spatial image analysis including those for data obtained from laser scanning [4] and LiDAR sensors for applications in diverse areas has increased. Spatial analysis of natural landscapes, vegetation, and manmade structures provides an open opportunity for researchers. Ground [5] and non-ground [6], [7] classification is the first step in LiDAR Processing.

Processing of airborne LiDAR for estimation of tree crowns discussed in [8] demonstrates the use of spatial investigation on natural and unstructured formations. It used the voxel-based technique to determine and approximate the density distribution of possible tree crowns in the given area. A similar application was discussed for the estimation of treetop and spatial localization of possible missing trees using a k-nearest neighbor technique in [9]. It relied on computing the average of the k reconstructed height values of the trees having the most similar crown properties for the estimation. Besides, trees, the land parcel also contains man-made houses and buildings. Detection of buildings and rooftops have also equal importance in topographic analysis.

Detection of tree crowns has been a key aspect of spatial analysis of topography. Tree detection in urban areas [10] highlights the usefulness of region growing approach for detecting objects. It requires to use of weighted SVM to control the misclassifications. While this method in its original form can detect and approximate the building structures, the performance is limited for natural objects such as trees. Voxel-based method [8] is yet another approach for detecting surface objects by evaluating the density distribution. It highlighted that airborne LiDAR gives better estimates of tree crowns than terrestrial LiDAR samples. The approach of perspective density [4] can also be used to compute the crown volume for diverse types of trees. A more intuitive approach based on graph-based segmentation [11] can help to determine the topological structure and use the bottom-up approach for extracting the crown from the point cloud obtained from aerial sensors. Gaussian filter and energy function minimization-based approach [12] can be used when crowns obscure and overlap. If multispectral airborne LiDAR is available, then the mean shift segmentation method can be used. It can take the benefit of both spatial domain and multispectral domain to deal with the under segmentation of crown segments.

Building and rooftop detection and segmentation are also an important part of point cloud classification, especially in urban regions. The segmentation-based approach [13] has been used in many commercial and free tools to identify rooftops and building structures. Euclidean distance-based segmentation is widely used for segmenting planar surfaces. [14] and [15] highlight the usefulness of Euclidean based clustering method and RANSAC algorithms for rooftop identification. The method used in [16] also highlights the use of a region-growing approach for detecting rooftops and can detect multiple buildings situated distance apart.

Several attempts have been done to extract the non-ground objects including tree crowns and buildings. When both trees and building structures coexist in the region, spatial analysis of the LiDAR returns for detecting and classifying trees and buildings becomes challenging. A hybrid approach to detecting the tree crown and rooftops can be used. Properties like slope variance, curvature continuity, height filters can be combined to achieve the required classification. This paper presents the single framework for classifying tree crowns and rooftops from the aerial LiDAR data set.

3. DATA DESCRIPTION AND EXPERIMENTAL SETUP

To discover the spatial distribution of points, an airborne point cloud describing the topographical region encompassing trees and artificial man-made structures from Wekiwa Springs State Park, Florida is used. The data sample stores the unstructured set of 291,725 points in 3D space as records of x, y, and z coordinates having horizontal coordinates: UTM z17 N NAD83 (CORS96) [EPSG: 26917] and vertical coordinates: NAVD88 (GEOID09) [EPSG: 5703]. Other attributes attached to the points include scan_angle, intensity, and return number, respectively. The data selection coordinates are Xmin: 451238.934, Xmax: 451469.419, Ymin: 3176118.909 and Ymax: 3176358.703 respectively. The data set contain points in the defined region with 30m resolution and

The selected region is defined by returns stored as a point cloud. Geospatial features such as small and large tree canopies are distributed over the region besides several man-

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made buildings/houses. The data set also contains returns from the ground including roads and water bodies. Clusters of points are likely to define the geo-objects such as tree canopy and rooftops based on point distribution in 3D space. The 3D aerial view of the regions is shown in Figure 1. The 3D visualization of the point cloud with elevation is shown in Figure 2. It gives the general idea of non-ground objects which need further processing for classification into tree ground points, crowns, and rooftops.

Figure 1. Aerial View of Wekiwa Springs State Park, Florida

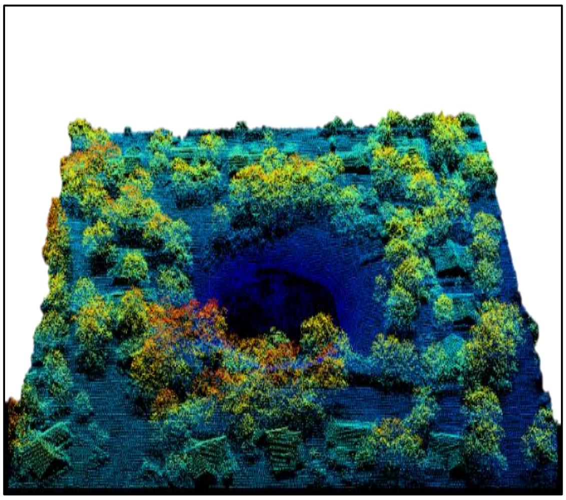

Figure 2. Visualization of Point Cloud Data based on Elevation

4. FRAMEWORK FOR SPATIAL ANALYSIS

The experimental data used in this work comprises clusters of dense and sparse points returns obtained from the airborne LiDAR data. The data comprises returns from tree canopies, buildings, streets, lake regions, and open land. The framework for spatial analysis is divided into four stages. The general framework for the geostatistical analysis is shown in Figure 3. At the initial stages of processing, the system is provided with a set of surface point returns organized as point clouds. This point cloud undergoes classification into the set of points into ground and non-ground points. The set comprising of non-ground points denotes the surface objects and features including small plants, bushes, tree canopies, and rooftops. These non-ground points are further processed separately for detections of tree crowns and rooftops.

Ground Point Classification

The ground plane estimation is done based on a local greedy approach that uses a height-based filter [5], [17] and a multiscale curvature filter [18] to optimize the results. Points on the Ground plane are more likely to be distributed uniformly and thus can be evaluated as a grid with elevation at each location. A height filter $H \in R^3$ is applied to all points in the point cloud to filter out those points that are within the median height of the neighbor points and also show small curvature variations compared to their neighbors or points within the proximity. The height filter H is a constraint by the distance from the imaginary zero-plane where all elevation values are zero across the plane. This plane matches the minimum mean elevation from the dataset. The height filter evaluates the elevation at each (i, j) and determines its possibility to be ground point together with curvature. Curvature is computed at point p_{ij} and a tolerance threshold t_θ is augmented to it. If the curvature is within the threshold limit, then the point is the possible candidate for the ground plane.

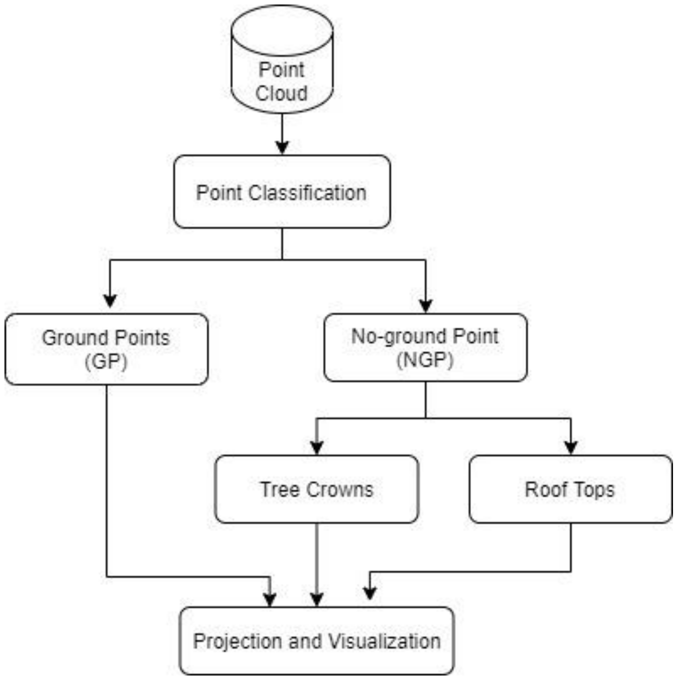

Figure 3. Framework for Analyzing Unstructured Point Cloud

The use of the median eliminates the outlier points and thus overcomes the problem of incorrect classification. The estimated plane further computes the orthogonal distance and minimizes it using principal component analysis. For a point p_{ij} with height z_{ij}, the normal n, it is computed as

$$d = min \sum^{N} \left((p_{ij} - \bar{p}) \cdot n \right)^2$$

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where, $n \in R^3$ is the normal vector and the z component of the normal is used to compute relatively flat ground surface. The z component is computed as $n \cdot (0,0,1)$. The points that do not satisfy the height variance and curvature tolerance are classified as non-ground points. The surface is then interpolated using a thin-plate spline for ground plane approximation. The dual conditions of median height and curvature keep the ground plane estimate more controlled and exhibit surface continuity. Optionally, the streets and roads can be determined by a set of connected points that have the same elevation and exhibit uniform returns with no or minimal height variation.

Non-ground Classification

The non-ground points obtained as a result of the above process is further processed for detecting tree crown and rooftops. Tree crowns denote the points that are dense but exhibit random and high variations in height. Rooftops on the other hand are relatively flat and thus height variation in the rooftop points will be minimal. The variations in height values if any will be contiguous and gradual in some direction.

As a next step, the rooftops are estimated. To estimate the rooftops, the point cloud is projected to obtain a 2D grid of height maps. Two criteria that help to classify rooftops include the gradient change in height across the surface and contour. The rooftop height will be continuous in slope with small variance and maintain spatial continuity. The rooftop is found to have similar normal across the surface. The points on the rooftop surface are computed by computing the orthogonal regression and fitting them to each point within k-neighbors. The standard deviation across the surface should be small for good orthogonal fitting and hence it is used to verify the planar structure of the rooftop. The set of identified points is associated with the rooftop. The contour is by computing the centroid of the cluster and computing the farthest point in the cluster inside out in all radial directions. A close shape approximation requires more points on the contour and hence small increments are desired. Final contour approximation is done by interpolating the points using the spline function for a closed figure.

Once the rooftops are classified, the rest of the points are processed in three-dimensional space. To detect the crown, we use the region growing algorithm [19] for determining the members of the tree crown. The crown radius is empirically determined through curvature continuity. The seed points are determined and points are classified to belong to the tree crown controlled by the search radius and nearest neighbor described by the region growing algorithm. The results can be further improved using a hybrid approach that used region growing and additionally used valley profiles to segment adjacent tree crowns. This is needed especially when tree crowns penetrate or shadow the other crown. The region of steep change in the curvature helps to segment the crown adjacent to each other. Morphology-based detection of valley profiles[20] was used to find the discontinuities between overlapping crowns and used to detect the contour profile for the tree crowns. Those points that are neither classified as ground plane nor surface objects are treated as noise and removed.

As a next step, the classified points are augmented with color attributes. All ground points are associated with a single color and non-ground objects like trees crowns and building rooftops with a distinct color. Each of these classified points helps in the segmentation of the surface features and thereby allows processing them independently. Further, for better visualization, progressive color mapping is done on the points in each class with height and curvature. This can be rendered in 3D space and enables interactive visualization from different perspectives. Finally, the segmented and classified points are projected onto a two-dimensional intensity map for use with cartographic applications and generating topo sheets.

5. OBSERVATIONS AND DISCUSSIONS

The point cloud is processed using the proposed hybrid framework. The points are segmented into 1,66,798 ground and 1,24,927 non-ground points respectively. Ground points are interpolated to fill the region with sparse points. The non-ground points are further processed to segment rooftops and tree crowns. The spatial distribution of identified tree counts and the crown diameter is shown in Figure 4. The observation suggests that the height of the majority of the trees is between 3m and 8m.

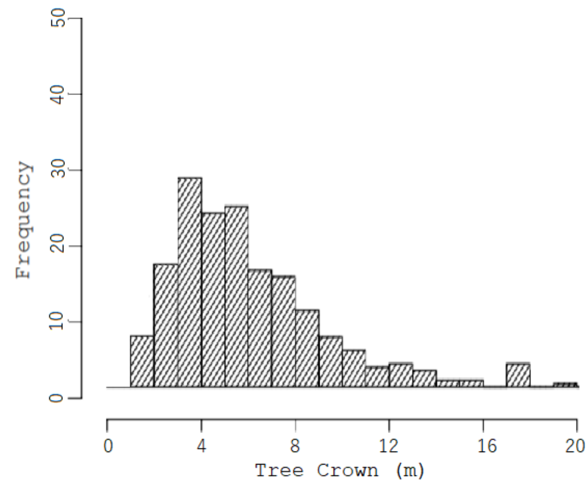

Figure. 4. Tree Crown Spatial Distribution

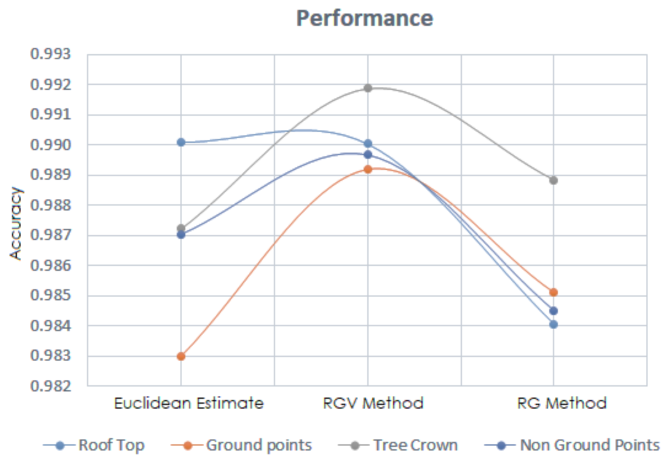

Figure 5. Performance of Spatial Clustering

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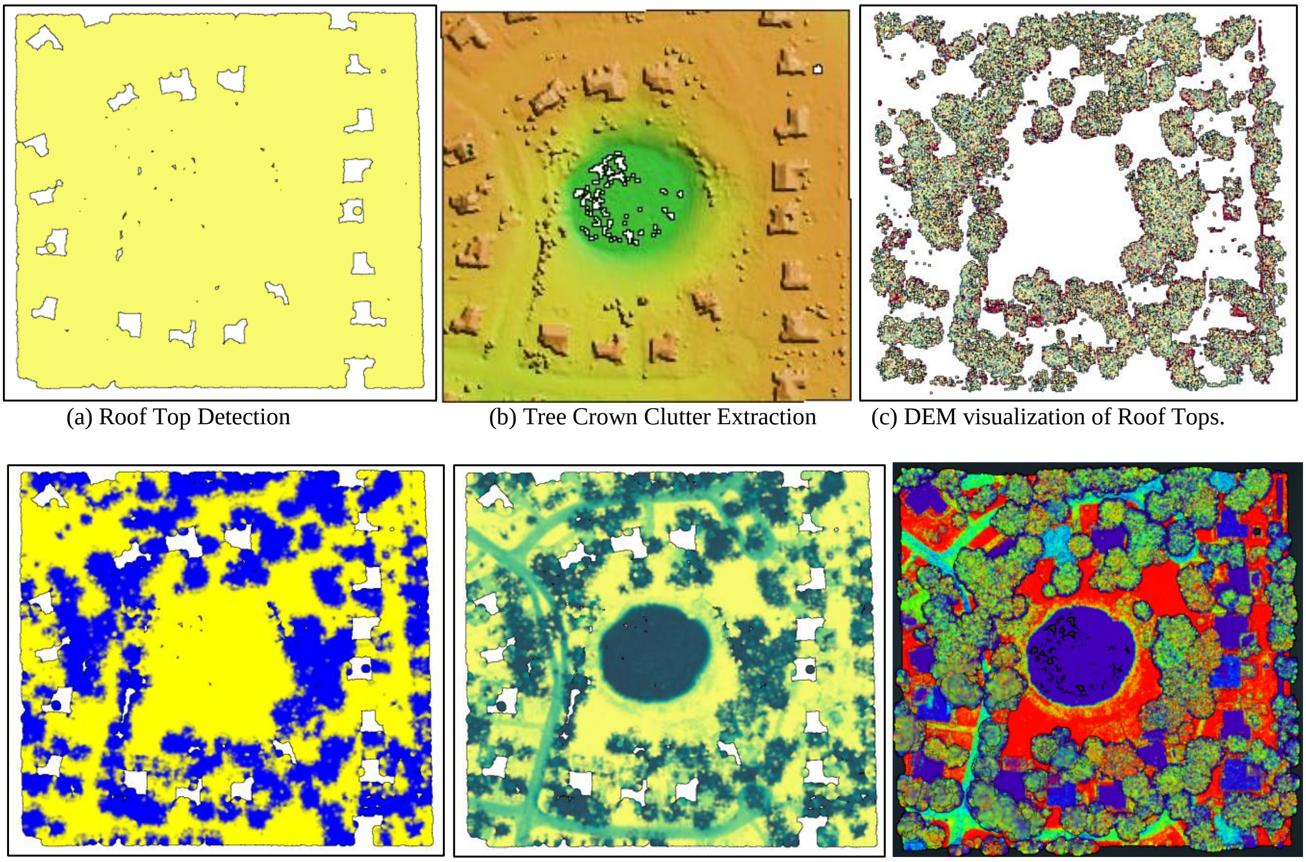

(a) Roof Top Detection (b) Tree Crown Clutter Extraction (c) DEM visualization of Roof Tops.

(d) Overlapped Roof Top and Tree Crowns (e) 2D Georeferenced Intensity Map (f) 3D Progressive Color based Plot

Figure 6. Tree Crown and Building Extraction from Unstructured Point Cloud

The performance of classification and segmentation is noted for Region-growing (RG) based segmentation and also after additionally using Region-growing with valley(RGV) point contour estimation. Both results are compared to Euclidean-based clustering results. It is found that while the region growing-based approach gives good results, the segmentation result is further improved by adding valley estimation in RG method when applied to unstructured points. The results show higher performance especially for estimating tree crown. The performance of segmentation is shown in Figure 5. The results of applying the framework for extracting tree crowns and rooftops are shown in Figure 6. The spatial approximation of the rooftop and building structure is shown in Figure 6a and Figure 6b respectively. Segmented tree crowns are shown in Figure 6c. Tree crowns are segmented and shown in Figure 6b. Overlay visualization of tree crown and rooftops are visualized in Figure 6d and Figure 6d and Figure 6f respectively. Figure 6f shows the spatial visualization with color mapping for visual understanding and discrimination. Streets are also identified and visualized as contact green shade on the classified ground points.

The performance of the framework in analyzing and spatially detecting surface objects are presented in Table 1. The true positive rate (TPR) and True Negative Rate(TNR) are close to 99%. The overall accuracy percentage is also between 98.85 and 99.0. The F score for the obtained result is close to 98.7%. The Precision or Positive Predictive Value is between 98.7 and 99.2 percent.

Table 1: Classification Performance (%)

Score	Roof Top	Tree Crown	Other Objects
TPR	0.990	0.984	0.990
TNR	0.983	0.985	0.989
PPV	0.987	0.989	0.992
ACC	0.987	0.985	0.990

6. CONCLUSION

In this work, a framework for multiclass classification and segmentation from unstructured point cloud data is implemented. Multiobject detection is obtained using region-growing and implementing height filters. The use of valley point detection improves the segmentation process significantly. The use of curvature continuity helps to determine the tree cron envelop and thus determines the diameter and also discriminates one from the other. The height filter with a slow varying slope is found useful for detecting ground points but for detecting tree crowns, curvature continuity is important. Overall accuracy close to 98.7% is obtained from surface objects. The spatial analysis from the point cloud gives better visualization of surface features and interactions. The framework can be further extended to determine the volume of the crown and spatial occupancy in the given region.

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