ANALYTICAL RESULTS OF CLASSIFYING LIDAR DATA WITH TOPOGRAPHY PRESERVING NON-LINEAR AUTONOMOUS PROCESSING FOR BARE EARTH EXTRACTION

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ABSTRACT:

We present an innovative way to autonomously classify LiDAR points into bare earth, building, vegetation, and other categories. One of the most desired commodities for LiDAR collection is a high resolution bare earth product with the same resolution as the input data. The LiteSite® algorithm automatically extracts buildings and foliage from an urban scene and generates an accurate bare-earth product. Our inpainting algorithms then fill these voids utilizing Computational Fluid Dynamics (CFD) techniques and Partial Differential Equations (PDE) to create an accurate Digital Terrain Model (DTM). Inpainting allows generation of high resolution bare-earth Digital Elevation Models (DEMs) in high frequency terrain for urban 3-D modeling. Moreover, if buildings in the scene are partially obscured by trees, then the LiteSite® algorithm automatically removes these obscurations and inpaints the heights while preserving building edge content where vegetation has been extracted. Inpainting preserves building height contour consistency and edge sharpness of identified inpainted regions. This technology reduces manual editing while being cost effective for large scale global bare earth production. Quantitative analyses are provided using Receiver Operating Characteristics (ROC) curves to show Probability of Detection and False Alarm of ground versus non-ground features. Histograms are shown with sample size metrics. Qualitative results illustrate other benefits such as Terrain Inpainting's unique ability to minimize or eliminate undesirable terrain data artifacts.

1. INTRODUCTION

The purpose of this paper is threefold. The first objective is to demonstrate a method for classifying LiDAR points into two categories, bare earth and non-bare earth points. The second objective is to show qualitative and quantitative improvements to bare earth LiDAR classification using our PDE-based inpainting techniques by comparing with truth data. Further discrimination of points into building and vegetation points is discussed. Finally, a framework is presented for an automated scoring technique to grade performance of LiDAR classification using ROC curves and signal detection theory.

2. BARE EARTH PROCESSING

The objective of bare earth processing is to autonomously reconstruct the bare earth in places where buildings, trees, and other non-bare earth objects have been removed or where data is missing while maintaining continuous height contours. This allows our technique to generate high resolution bare earth DEMs from high frequency terrain.

One of the more common applications of LiteSite's Terrain Inpainting is in the creation of a DTM of an input scene as either a final product or as an intermediate input for further processing (e.g., 3D site model creation or orthomosaic production). During this process, LiteSite® automatically classifies and removes culture and vegetation from the input Digital Surface Model (DSM). LiteSite® is designed to process DSMs created from multiple sources. Primary examples are surface models created from photogrammetry, LIDAR, or IFSAR.

Figure 1a shows a DSM generated from LAS point data. After the completion of the automated bare earth process, we output a model containing only those points that fall on the terrain surface, see Figure 1b. All other points in the input belonging to cultural or vegetation features have been removed. These void areas introduced during bare earth processing must be filled to create a complete DTM. Inpainting attempts to accurately propagate information from extracted building and tree boundaries as shown in Figure 1c. Figure 1d shows the automatic classification of culture and vegetation as a separate output.

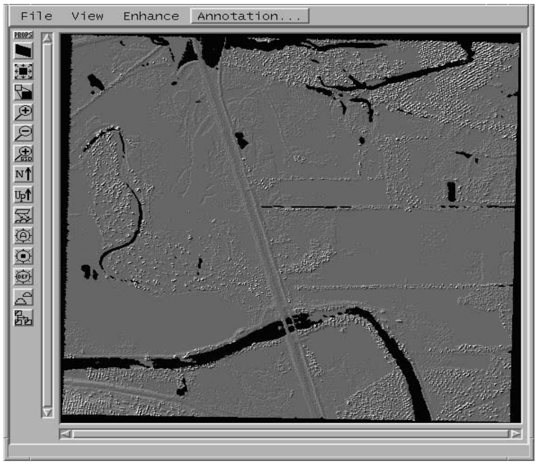


Figure 1a. DSM Created from LAS Points

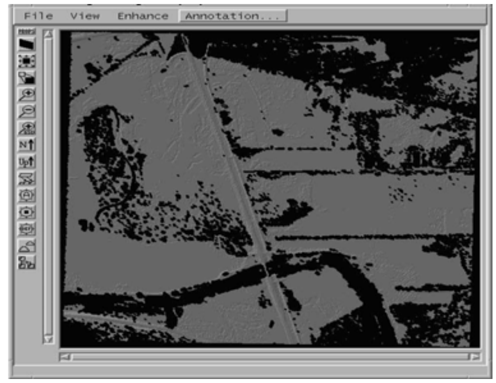


Figure 1b. Ground Points Identified

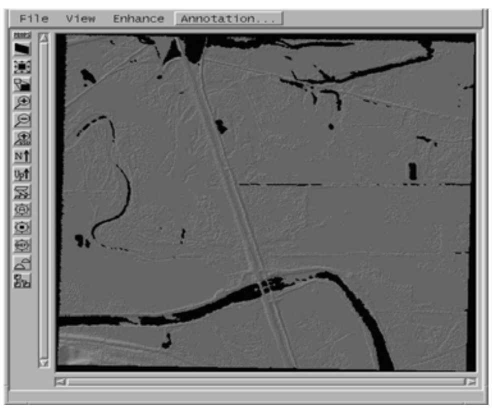


Figure 1c. DTM Voids Filled With Inpainting

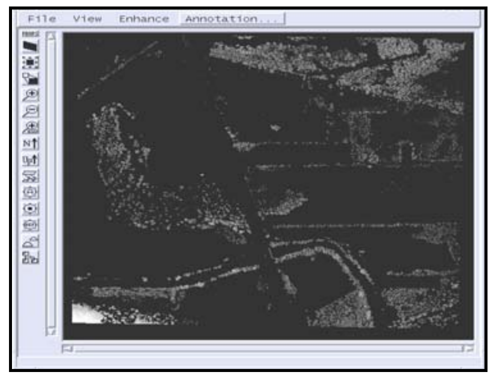


Figure 1d. Building and Tree Points Identified

The LiteSite® software automates the creation of geospatial products including bare earth Digital Terrain Models (DTM) and image-textured 3D site models [1]. Terrain inpainting provides void fill processing for geospatial data production in areas where information is incomplete. Geospatial products created through digital processing can introduce visible artifacts from void fill and other associated processing. Terrain inpainting produces minimal artifacts, and at the same time provides a representation designed to be as accurate as possible with quantifiable accuracy assessment. Quantitative assessment and built-in error estimation are vital for the robustness and applicability of terrain inpainting. We have further improved determination of the bare earth points prior to void filling using principles from the Multi-Directional Ground Filtering (MGF) algorithm by Meng [2].

3. LIDAR CLASSIFICATION

We perform an initial automated classification of the LAS file to a gridded space producing a classified DTM. Our algorithm ingests the original LAS file and DTM, and then outputs a new LAS file with the point classification field set by comparing points to DTM appropriate height values. For each point in the input LAS file, we classify its feature label. Geospatial coordinates are left unaltered. Automated scoring through comparison of the classifications of the input and output is performed. The first step is recording the original classification of the input file. Then each point in the DTM with valid height (i.e., not NaN) has its feature type label classified. The closest index point for each valid post is located in the DTM as the ground point. If the point is within the specified tolerance of the ground surface DTM, we classify it as ground. This threshold is called the ground surface tolerance.

If we are labeling buildings, we make sure the point is non-null in the building DEM and then ensure that the height of the current point (from the LAS file) is above the ground by a specified tolerance. If so, we classify it as building. If we are labeling vegetation, the same process described for buildings is used for vegetation. We identify points that are not in any of the previously checked categories and label them with the other label. An output comparison between the original LAS and reclassified LAS points is performed.

Figure 2 below shows the LiDAR classification processing flow diagram. The process begins with ingest of LAS formatted LiDAR points, but the process is able to use other formats. The unordered points are gridded and small gaps are filled with a simple nearest neighbor interpolation for a fast void fill. In the case of LiDAR inputs, this process is performed for both the first and last return DSMs. The larger voids are then filled with our PDE inpainting technology for greater accuracy. Building and tree points are further separated through the use of the height difference between first and last DSMs along with a set of additional post-processing classification steps. A slope calculation is performed to help distinguish buildings and trees for inputs where the input DSM only has one reflective surface available. Using the ground point DTM, the building post DSM and the vegetation post DSM our algorithm assigns a classification label to the original points and outputs a labeled LAS formatted file.

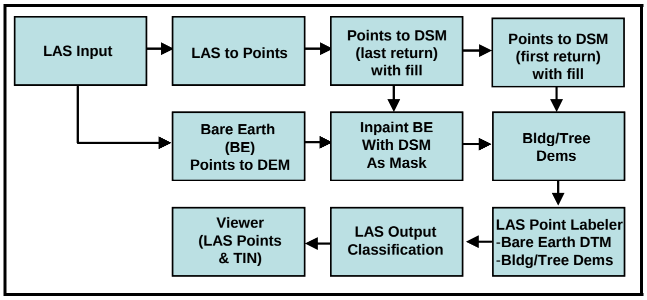
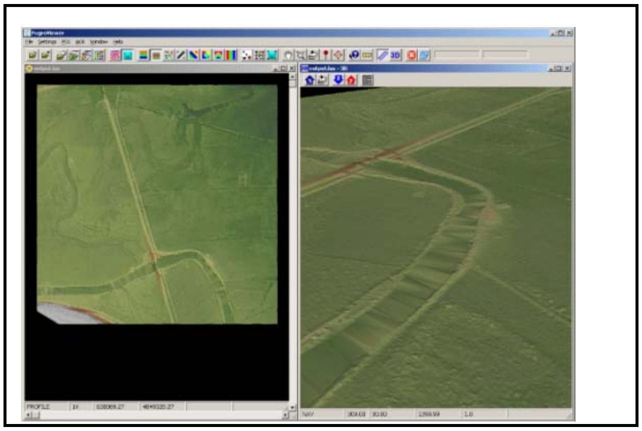


Figure 2. LiteSite® LiDAR Classification Processing Flow Diagram

4. SAMPLE QUALITATIVE RESULTS

Figure 3 shows 3D views of sample data. Hydrographic features are very important for defining any DEM surface and therefore must be retained in LiDAR derived DEMs. Our algorithm strives to ensure that hydrographic features are retained as ground points in the DTM, while a minimal number of noisy or non-ground posts are classified as ground by our algorithm. In a traditional DEM surface, natural depressions exist, bridges may be removed, but road fills with culverts create apparent dams resulting in DEMs that appear to disrupt the natural flow of water [3].



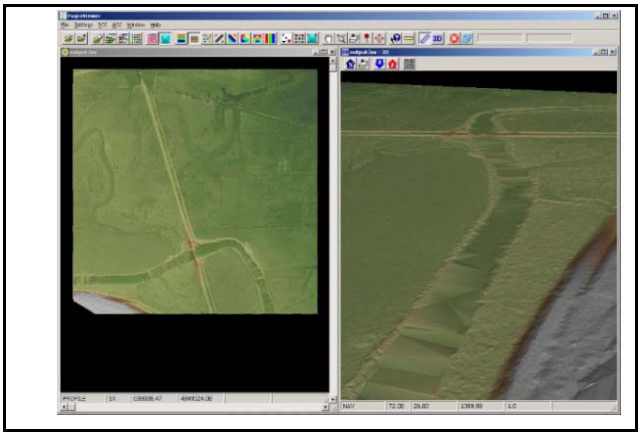


Figure 3. Detail of Hydrographic Features

A useful viewing technique is to look at profiles to see landscape variations in the data. The profile analysis in Figure 4 shows that ground and vegetation points are reasonable. The different colors indicate the assigned classification.

Full classification of LiDAR points for non bare earth points is desirable. Figure 5 shows non-ground LiDAR points further classified as vegetation and building posts. We have previously shown that inpainting can be a useful method for enhancing building posts in a DSM prior to extraction of building vectors [4]. This automated application of classifying all LiDAR points saves manual labor editing time.

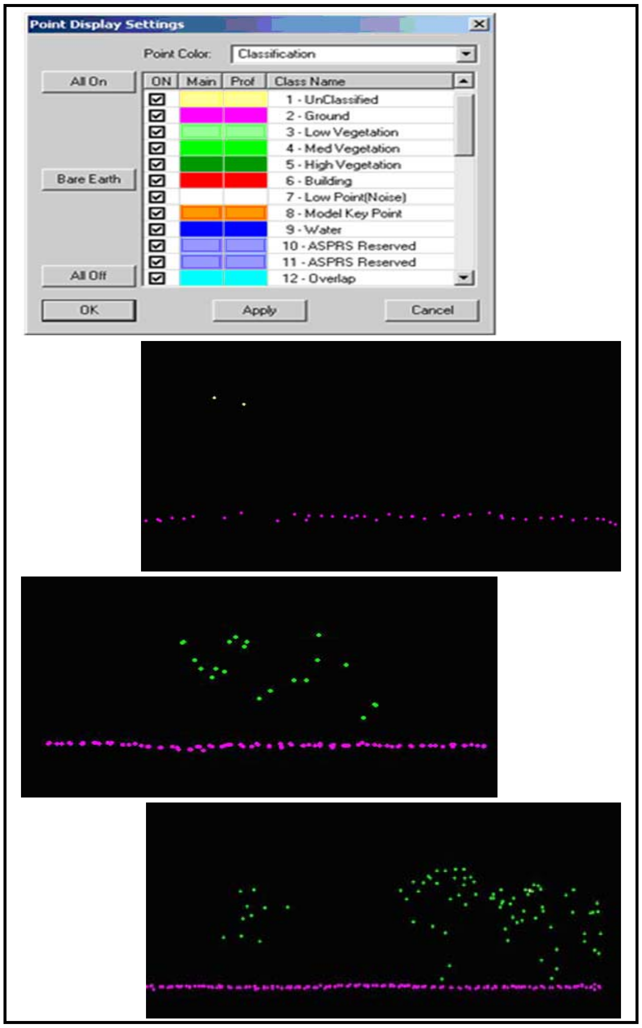


Figure 4. Profile Analysis Illustrating Ground and Vegetation Classification

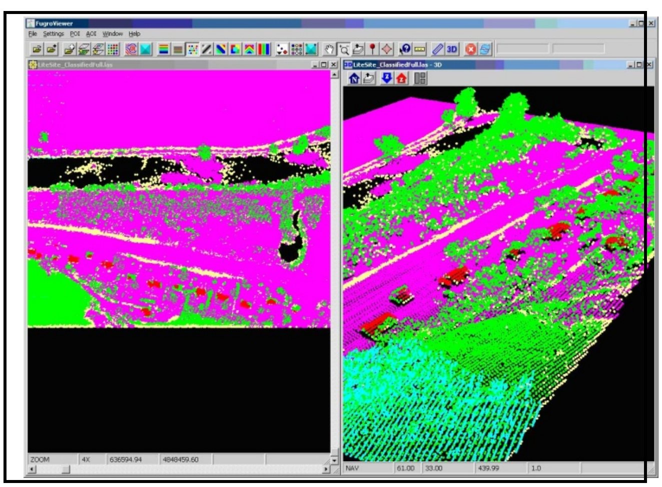


Figure 5. Full Classification of LiDAR Points

5.0 SAMPLE QUANTITATIVE ANALYSES

There are many opportunities in the process to look at optimal decision making to determine the best threshold for a parameter. This section focuses on one of the parameters at the very end of the processing flow, namely the ground surface tolerance. The value of the ground surface tolerance serves as the horizontal axis of the histograms.

Each LiDAR point serves as a trial point in the histogram. COTS processing followed by manual editing is considered "truth data" for this data set. Thus, we assume these to be the points which should be categorized as ground and those which should be categorized as non-ground. Our framework for scoring performance of LiDAR classification consists of the following automated processing stages:

1. Input the target LAS voxel space for evaluation [classified by our algorithm]

2. Compare the target LAS voxel space with original LAS truth data.

    - For each point in the target LAS voxel space, assign a classification hypothesis according to a measured threshold distance to the corresponding nearest bare earth surface point in the gridded version (DTM) of the truth data; compute histograms of hypotheses, as ground or non-ground points, for a range of threshold distance values.

3. Generate ROC (Pd, Pfa) curve using the histograms.

4. Measure the area under the ROC curve.

5. The area is the measure of confidence in detection, ranging between 0.5 (chance diagonal) and 1.0.

Correct Rejection is defined as those points labeled non-ground in truth data and determined to be non-ground by our algorithm. False Alarm is defined as those points labeled non-ground in truth data and determined to be ground by our algorithm. A miss is defined as those points labeled ground in truth data and determined to be non-ground by our algorithm. A hit is defined as those points labeled ground in truth data and determined to be ground by our algorithm.

Following sample data histograms in Figure 6 show distributions for non-ground (Hypothesis 0) and ground (Hypothesis 1). The number of samples (LiDAR points) in the non-ground truth histogram is 637,196. The number of samples in the ground truth histogram is 1,293,384.

Data shows that in some locations our bare earth extraction may follow the DSM too closely and erroneously includes points that belong to the non-ground points, which are most likely low vegetation posts. Data also suggests that truth data may contain points which are labeled non-ground, but are really ground points. Subsequent ROC curves given the above histograms are shown in Figure 7. The last bin contains points where the DTM and the LiDAR points have no difference

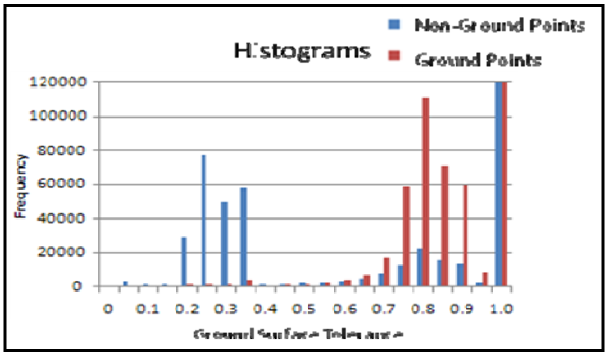


Figure 6. Histograms

In height. This is the reason for a portion of the Figure 7a curve looking nearly like the chance diagonal. Figure 7b shows the portion of the ROC curve without the last histogram bin. ROC curves are shown because they are a widely accepted means of evaluating test results. Higher performance tests contain curves near the upper left portion of the graph. The ROC curve graphically displays the entire range of the test performance thresholds with respect to error analysis.

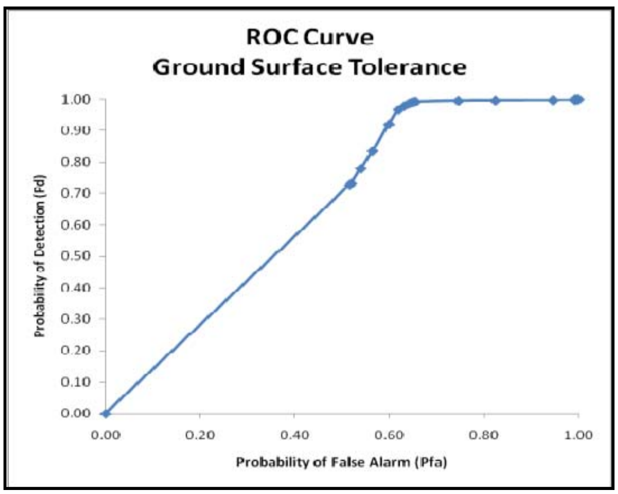


Figure 7a. ROC Curves Showing All Bins

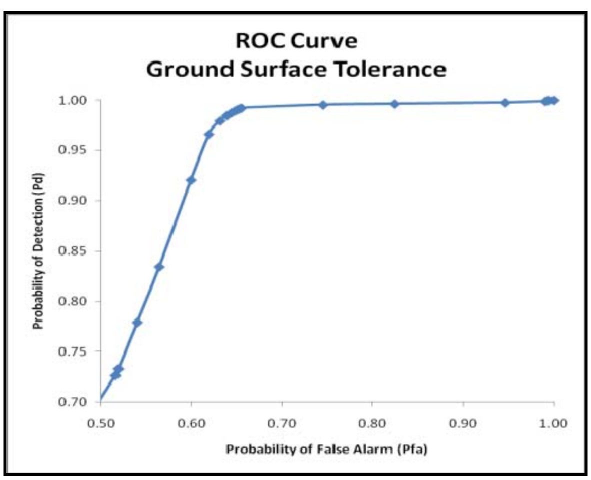


Figure 7b. ROC Curve Not Showing Last Bin

Figure 8 shows the four sample states based on a chosen threshold. This threshold represents a good choice for satisfying product specifications for probability of detection and false alarm.

The horizontal axis of the histograms depicts the ground surface tolerance. A lower ground surface tolerance corresponds to a higher vertical difference between LAS point and DTM post. A higher ground surface tolerance is based on a very low vertical difference between the computed DTM surface and a given LiDAR point.

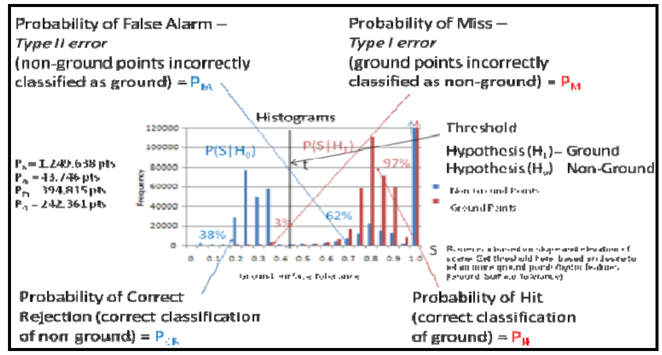


Figure 8. Error Analysis

Figure 9a shows 3% missed points as our algorithm sees these as high frequency details. Our algorithm considers these points to look like buildings or vegetation non-bare earth (type II errors). Figure 9b shows 62% false positive (type I errors). The reason for so many type I errors may be that COTS software used to generate truth mostly includes the lowest point per square area as the ground for data thinning (even if only slight height difference, as shown in Figure 10). Too many ground points classified as non–ground results in a loss of hydro features. Too many non-ground points classified as ground results in a noisy DTM.

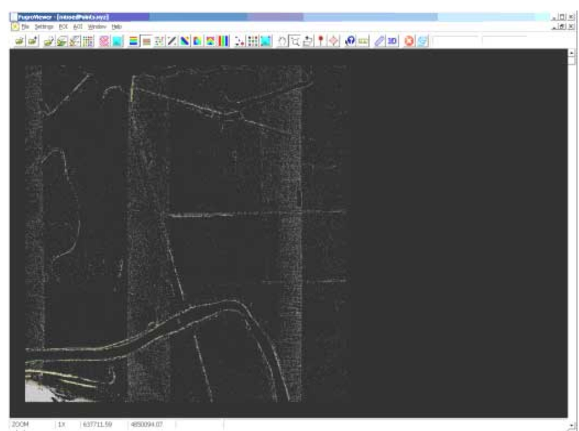


Figure 9a. Type II errors – Missed Points

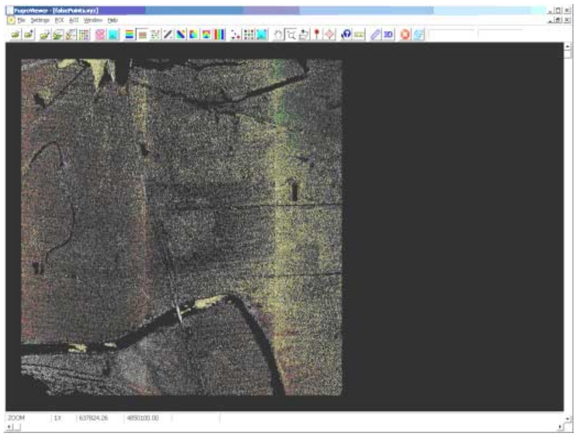


Figure 9b. Type I errors – False Alarms

Figure 10a shows an example of a profile from truth data which may suggest that some points should have been classified as ground using COTS software. Figure 10b shows a profile from the same area with our algorithm's results.

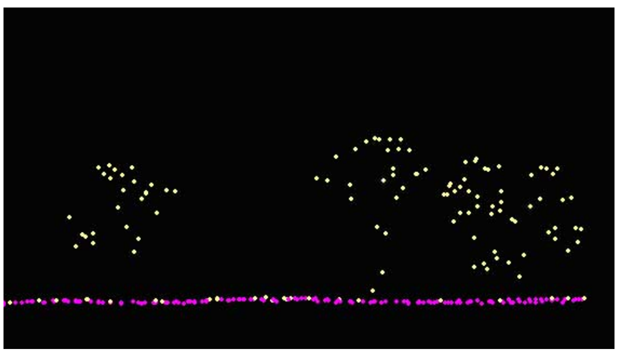


Figure 10a. Profiles of Truth Data from COTS Software

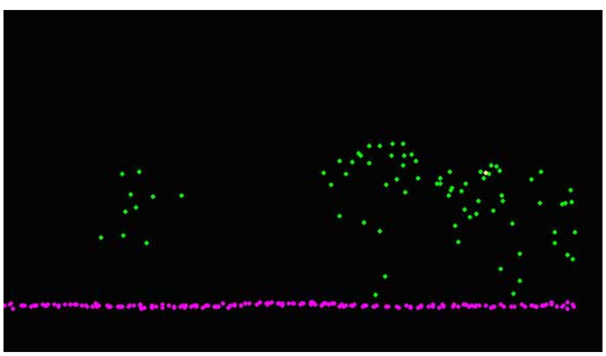


Figure 10b. Profile of LiteSite Classification

6. CONCLUSIONS

In this paper we discussed terrain inpainting for voids introduced during processing, such as for bare earth DTM generation. The production processing flow presented displays terrain inpainting's ability to automatically fill voids using only the original source data at hand and in a way that both mitigates and quantifies error, and creates minimal processing artifacts. The application of this technology is beneficial in improving LiDAR classification of ground vs non-ground LiDAR points. We demonstrated a method for classifying LiDAR points into bare earth and non-bare earth points. The presented method demonstrates an automated scoring technique framework which may be used in making best decision on how to tune or calibrate a LiDAR sensor to a known test range. This framework may also be used to evaluate multiple systems capabilities in a comparative sense.

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