How to Play 21-Questions with your Lidar Data

As many already know, lidar (light detection and ranging) data are becoming the “go to” data source for elevation products including, terrain and surface models, hydrography, and for extracting many surface features, such as buildings and roads. As lidar sensors are constantly improving and collecting ever increasing point densities, the challenge to correctly classifying the returns is increasing. So, this month’s column offers up both a “tip” and a “challenge” to users.

In the airborne lidar industry, following acquisition and calibration, roughly 30-40% of a project’s processing budget is dedicated towards the classification of points. Using ASPRS and USGS Base Lidar Specification standards, points are generally classified into six classes including, Class 1 (Unclassified), Class 2 (bare ground), Class 7 (low noise), Class 9 (water), Class 17 (bridge deck) and Class 18 (high noise). The ASPRS vegetation classes (Class 3 – 5), the building class (Class 6) and others are generally considered for specialized applications. It should be obvious that the lidar-derivative products mentioned above are all depend on the point cloud being classified accurately.

Numerous commercial off-the-shelf (COTS) and open-source software programs are available to automate the classification process; there are even Facebook discussion groups and several YouTube channels for several of the more popular ones. Even with the large and expanding user community, after the initial automated classification, these programs require a knowledgeable analyst to manually comb through the dataset and verify the accuracy of the automated output, and to manually “clean-up” the data as needed. The automated routines are not 100% accurate. So, first the challenge... Are there alternatives to manual clean-up?

The tip... one possible alternative to manual intervention involves Artificial Intelligence/Machine Learning (AI/ML). When tackling a project with AI/ML, there are a host of methods and algorithms from which to pick. In fact, Random Trees and an implementation of UNET are available in the extended Esri ArcGIS Pro software suite. Instructions on how to install these tools can be found at: https://pro.arcgis.com/en/pro-app/2.7/help/analysis/deep-learning/install-deep-learning-frameworks.

Random Forests (decision trees), one of the “machine learning” algorithms, are predictive models that work by taking observations about data, (X, Y, Z, intensity, returns, scan angle) and then use those observations in regression models to gradually work towards a conclusion about the target variable (classification). In other words, the machine learning algorithm is playing “21 questions” with the provided information to focus in on the target.

Decision tree algorithms are preferable to other machine learning or deep learning algorithms for a few reasons, but mostly because they are not resource intensive. Many machine learning programs require powerful GPUs or process servers, while decision trees are designed to work well with CPUs in a desktop environment. For example, on a desktop CPU, these algorithms have been able to train in time frames ranging from 30 seconds to a few minutes per 5000’ x 5000’ tile with approximately 15E6 points. Classification processes in about the same time frame. Along with the speed, decision trees are fairly simple to explain, we can examine each individual classification and see how and why the algorithm came to that classification conclusion.

We have been experimenting with using various decision-tree algorithms to classify small datasets of both topographic and bathymetric lidar that were provided by NOAA and USGS (available on the NOAA Digital Coast and the US National Map). The most promising aspect of our testing so far is that the algorithms use only six parameters (X, Y and Z values, intensity data, return number vs. total number of returns, and scan angle), rather than the multiple datapoints with multiple parameters that are already used by most existing lidar classification programs. The results have been promising with classification accuracies hovering around 98%.

While there is still plenty of research to be done, from the experimenting so far, this seems like a viable solution to the manpower shortages that everyone faces and the timelines that we are always racing.

Please feel free to share your ideas and comments with us. Send your questions, comments, and tips to GISTT@ASPRS.org.

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