Control Point Statistics in TerraScan

TerraScan, versions 002.001 and above

GeoCue Group Support
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Introduction

Terrasolid software offers a variety of ways to gauge the accuracy of LIDAR and imagery data. From using control points to determine the vertical accuracy of a ground surface, tie lines to measure and correct the mismatch between overlapping flight lines, and tie points to correct aerial imagery positions, each of these tools provide the us with values such as 'average mismatch' and 'RMS'. How are these values arrived at, and what do they mean for the users of our software? This article is the first in a series that will begin to address these questions and provide meaning to this type of information. We will conduct a brief review of the relevant statistics and discuss how these principles are applied to the use of control points.

When all is said and done, we wish to have a dataset that represents the real world as accurately as possible, given the tools we have to work with and inherent error and uncertainty that can be introduced. We could choose to use subjective, qualitative terms like 'good', 'well', or 'bad' to describe the accuracy of our data or 'better/worse' to compare one dataset to another, but this approach lacks precision and meaning especially in communicating data accuracy within our production teams, and from vendors to customers. TerraScan gives us the ability to quantify the accuracy of the data with meaningful numbers that help to remove ambiguous interpretation of the data quality and prove that it meets the ASPRS Positional Accuracy Standards.

This quantification is rooted in evaluating how close a prediction is to is real world observation. In the context of LIDAR and this article, laser returns are our prediction of the position and elevation of the ground surface and control points (Known Points) are our observation of the real world (or ground truth). We can use descriptive statistics to describe how close the predictions are to reality.

Descriptive Statistics

While everyone knows what 'average' means (pun intended) and use it in our everyday life, lets quickly discuss the concept and (importantly) define this term.

"The Arithmetic Mean of a sequence (or set) of measurements $x_1, x_2, x_3, \ldots, x_n$ is equal to the sum of measurements divided by the number of measurements in the sequence." (Ericson and Harlin 1994)

There are many different ways to communicate this equation and here is one of them:

$$\mu = \frac{x_1 + x_2 + x_3 + \ldots x_n}{n}$$

Where µ is the mean of the dataset, x_n are individual observations, and n is the number of observations.

Let us apply this equation to the two sets of predictions in Figure 1. Both sets contain LIDAR returns on a ground surface with varying degrees of error. The ground has an elevation of 10m. The elevations of Set A’s returns are 9m and 11m. The elevations of Set B’s returns are 9.65m and 10.02m. The average elevation value for Set A is 10m and the average for Set B is 9.835m. If we used the average values to determine which predictive set is better, then Set A would be chosen with a mean value closest to the truth. However, by visually comparing these two sets we can subjectively determine that Set B is the better one. How would we go about quantifying what our eyes are seeing?

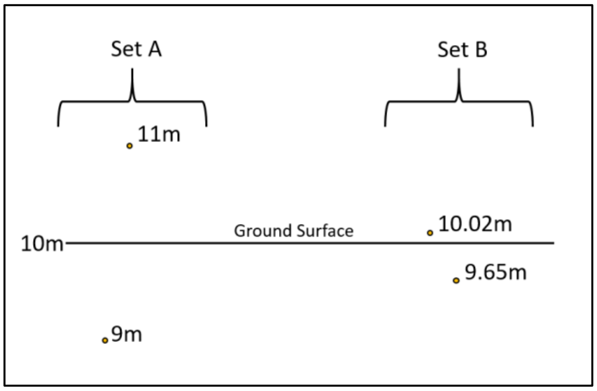


Figure 1: shows two datasets attempting to predict the position of the Ground surface

While the mean is technically used to measure central tendency, it is not necessarily a good gauge of accuracy. There is, however, a way to directly measure the accuracy of predictions that yields a single, positive, and unambiguous value that describes the magnitude of the difference between observed and predicted values. This can be accomplished by using RMSE.

While the use of mean is ubiquitous in everyday life, the use of RMSE is not. Called RMSE (Root-mean-square-error) or RMSD (Root-Mean-Square-Deviation) it is used to quantify the differences between values predicted versus values observed. This is calculated by squaring the differences of known and unknown pairs, adding the squares together, dividing by the number of unknown points, and finally taking the square root.

There are many different ways to communicate this equation and here is one of them:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(\hat{y}_i - y_i)^2}{n}}$$

Where $\hat{y}_i$ is the predicted values, y_i is the observed values, and n is the number of prediction and observation pairs.

By applying the RMSE to the situation in Figure 1 (above), we can determine which set makes a better prediction of the position of the ground surface. Set A has an RMSE of 1.0m and Set B has an RMSE of 0.248m. This clearly shows that the predictions in Set B are more accurate than those of Set A.

Note: Terrasolid reports use the term RMS for RMSE.

Another descriptive statistic that we will see when working in Terrasolid is the Standard Deviation. This can be represented by 'SD' or the Greek letter σ. This value is used to describe the amount of variation (dispersion) of the data about the mean (Devore et al. 1995). The smaller the SD, the more the data tends to be close to the mean. While a larger SD indicated that the data is more spread out. This can be used to describe the precision of the predictions.

Control Report

TerraScan allows us to create a report that quantifies the differences between laser points and ground control points. Statistically speaking, the control points (known points) are the observed elevation values of the ground surface and the LIDAR points are the predicted values for the ground surface.

Using the Output Control Report, TerraScan determines the change in the Z axis (dz) between the control points and the LIDAR returns in preparation for analysis. So, how does it go about making these measurements?

There is likely not a LIDAR return that exists on the exact XY location of each known point, so a surface needs to be interpolated using the Lidar returns in the vicinity of the known points. This ensures that there is a point of comparison between the returns and the control. This surface is created using a TIN (Triangulated Irregular Network). This will create a surface that connects three LIDAR returns in the vicinity. To determine which three points to use, there are three user defined settings: Max Triangle, Max Slope, and Z Tolerance.

The Max Triangle setting defines the maximum length of a triangle edge. If the Triangle edge length exceeds the given value, then the control point is not used for the output report due to the uncertainty of the measurement. The Max Slope setting defines the maximum terrain slope, or the maximum slope of an allowed triangle. This ensures that the slope of the surface does not exceed that of the real-world location and inadvertently skew the measurement. The Z Tolerance allows for the noise level (normal elevation variation) of the laser points to be accounted, much the same as one would intuitively do when visually fitting a line of best fit to data.

Once the surface is created, a plumb probe will be created from the control point to the surface. The location where the probe breaks the surface then becomes the XYZ location of the point of comparison. Once this is accomplished the dz between them is measured. See Figure 2.

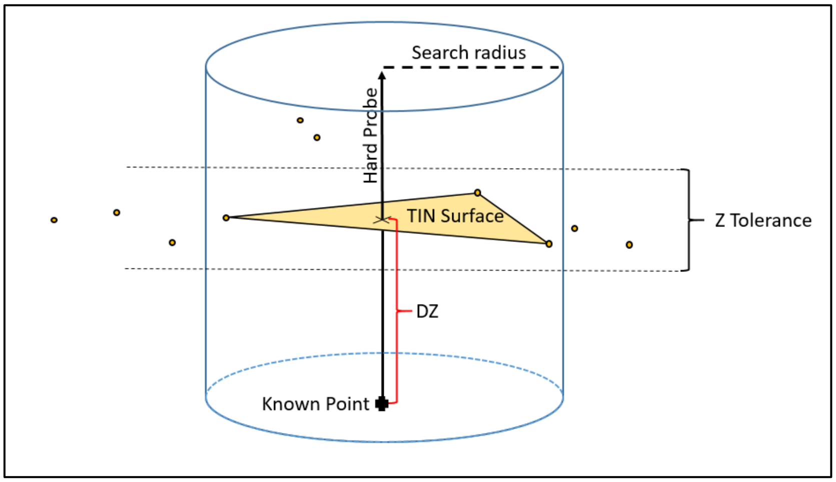
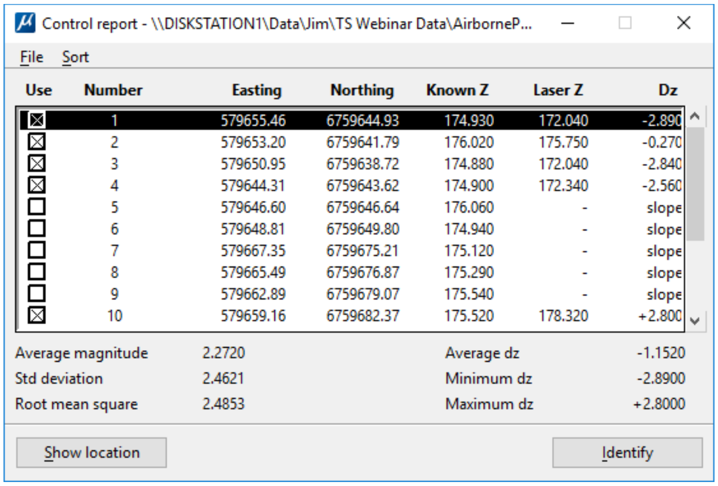


Figure 2: diagram of a plumb probe method of measuring the difference between control and a laser surface

After this process is repeated for each of the known points, then the statistical analysis begins. The resulting values are then presented in the Output Control Report (Figure 3). This lists each control point's number, position, the corresponding Z value for comparison with the TIN surface, and the dz between them. It also provides useful statistics on the dz values in the bottom portion of the report, which interactively update as a user turns on and off points to be used from the list above.



Use	Number	Easting	Northing	Known Z	Laser Z	Dz
☒	1	579655.46	6759644.93	174.930	172.040	-2.890
☒	2	579653.20	6759641.79	176.020	175.750	-0.270
☒	3	579650.95	6759638.72	174.880	172.040	-2.840
☒	4	579644.31	6759643.62	174.900	172.340	-2.560
☐	5	579646.60	6759646.64	176.060	-	slope
☐	6	579648.81	6759649.80	174.940	-	slope
☐	7	579667.35	6759675.21	175.120	-	slope
☐	8	579665.49	6759676.87	175.290	-	slope
☐	9	579662.89	6759679.07	175.540	-	slope
☒	10	579659.16	6759682.37	175.520	178.320	+2.800

Average magnitude	2.2720	Average dz	-1.1520
Std deviation	2.4621	Minimum dz	-2.8900
Root mean square	2.4853	Maximum dz	+2.8000

Figure 3: Output Control Report Dialog

From this example Output Control Report, what can we say about the relationship between the LIDAR data and the control points? Well, to begin, an Average dz of -1.152m tells us that, in general, the points fall below the control. We can see that the dz went from 2.89m below the surface to 2.8m above the surface with a range of 5.69m. The standard deviation tells us that 68.27% of the predictions are within 2.4621m of the mean and that 95.45% of the predictions are within 4.9242m of the mean when the dz errors are Gaussian. And finally, a Root Mean Square (Error) of 2.4853m which could then be used to describe the accuracy of the data, again when the errors are Gaussian.

This statistical report information can help users decide whether to correct the vertical bias in data and by how much as well as to evaluate the non-vegetated vertical accuracy (NVA) at the 95% confidence level. The exportable nature of this report to an ASCII text format allows it to be easily incorporated into project reports to be sent to the customer to inform them about the provided data and how it meets required ASPRS Positional Accuracy Standards for Digital Geospatial Data. Likewise, data recipients may use this report to help determine if the data they are receiving meets their requirements, and data users may verify the data meets their needs by evaluating check points before using the data. In the next articles in this series we'll similarly look at statistical information derived for tie lines and tie points and how they can be used to evaluate data positioning and calibration and reporting on further adherence to the ASPRS Positional Accuracy Standards.

References

Devore, J. L., Eltinge, E. M., & Devore, J. L. (1995). *Student solutions manual for Probability and statistics for engineering and the sciences, fourth edition*. Belmont, CA: Duxbury.

Earickson, R., & Harlin, J. (1994). *Geographic measurement and quantitative analysis*. New York: Macmillan College