ALTERNATIVE METHODOLOGIES FOR THE QUALITY CONTROL OF LIDAR SYSTEMS

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ABSTRACT

The ever improving capabilities of the direct geo-referencing technology (GNSS/INS) is having a positive impact on the widespread adoption of LIDAR systems for the acquisition of dense and accurate surface models over extended areas. Unlike photogrammetric techniques, derived footprints from a LIDAR system are not based on redundant measurements, which are manipulated in an adjustment procedure. Consequently, we do not have the associated measures (e.g., variance component of unit weight and variance-covariance matrices of the derived parameters), which can be used to evaluate the quality of the final product. In this regard, LIDAR systems are usually viewed as a black box that lacks a well defined set of quality control procedures. This paper introduces alternative procedures for evaluating the quality of LIDAR data. The main premise of the proposed methodologies is that overlapping LIDAR strips will represent the same surface if and only if there are no biases in the derived surfaces. Therefore, we will use the quality of coincidence of conjugate surface elements in overlapping strips as the basis for deriving the quality control measures. The paper starts with an analysis of error sources in a LIDAR system and its impact on the resulting surface. This analysis will be followed by several procedures to derive quantitative measures for evaluating the quality of the LIDAR data. These methodologies include the manipulation of range and intensity images generated from the irregular LIDAR data. Then, we will introduce methodologies, which are based on extracted linear features and areal patches from overlapping strips. The last approach is based on the manipulation of the irregular LIDAR points in a surface matching procedure to evaluate the quality of coincidence between conjugate surface elements in overlapping LIDAR strips. The paper will evaluate the performance of these procedures using real datasets. The paper will conclude by a comparative analysis that evaluates the pros and cons of the proposed methodologies in terms of complexity, validity, and the accuracy of the derived measures.

Keywords: LIDAR, quality control, system biases, linear features, areal features, surface matching.

INTRODUCTION

A typical LIDAR system consists of three main components, a GPS system to provide position information, an INS unit for attitude determination, and a LASER system to provide range (distance) information between the LASER firing point and the ground point. In addition to range data, modern LIDAR systems can capture intensity images over the mapped area. Therefore, LIDAR is being more extensively used in mapping and GIS applications. Figure 1 shows an example of a schematic diagram of a LIDAR system together with the involved coordinate systems. Equation 1 is the basic model that incorporates the LIDAR measurements for deriving positional information (El-Sheimy et al., 2005). This equation relates four coordinate systems, which include the ground coordinate system, the inertial measurement unit (IMU) body frame coordinate system, the laser unit coordinate system, and the laser beam coordinate system. This equation is simply the result of three vectors summation; $\vec{X}_o$ is the vector from the origin of the ground coordinate system to the GPS antenna phase center, $\vec{P}_G$ is the offset between the laser unit and the GPS phase center with respect to the laser unit coordinate system, and ρ is the measured distance between the laser beam firing point and the target point. The summation of these three vectors after applying the appropriate rotations ($R_{\omega,\phi,\kappa}$, $R_{\Delta\omega,\Delta\phi,\Delta\kappa}$, $R_{\alpha,\beta}$) will yield the vector $\vec{X}_G$, which represents the ground coordinates of the object point under consideration. The quality of the derived surface depends on the accuracy of the involved sub-systems (i.e., laser, GPS, and INS) and the calibration parameters relating these components (i.e., bore-sighting parameters). LIDAR calibration procedures remain to be a proprietary procedure that is only available to the system manufacturer.

As it can be seen in Equation 1, the derived coordinates of the laser footprint is not based on an adjustment procedure. In other words, the derived positional information is not accompanied by statistical measures (e.g., posteriori variance component and the variance-covariance matrix of derived point cloud), which can be used as a means for the quality control of the system performance. Therefore, this paper is dedicated to introducing alternative measures for the quality control of LIDAR systems. A common Quality Control procedure is based on the manipulation of range and/or intensity images. When using range measurements, the data from two overlapping strips are interpolated onto a regular grid to create two range images. Image differencing is then performed, and the resulting image shows the deviations between the two range images. These deviations can be used as a measure of data quality; the smaller the deviations, the higher the quality of the datasets. As an example,

Figure 2 shows two interpolated range images and their difference image. The main disadvantage of this procedure is that the interpolation techniques might lead to pessimistic deviations at the vicinity of object space discontinuities (refer to the large differences at the building boundaries in Figure 2-c). Moreover, this procedure does not provide measures for evaluating the horizontal discrepancies between the strips.

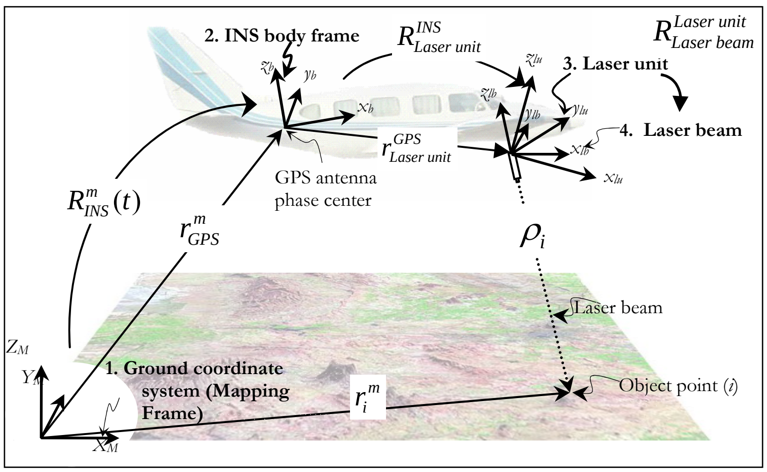
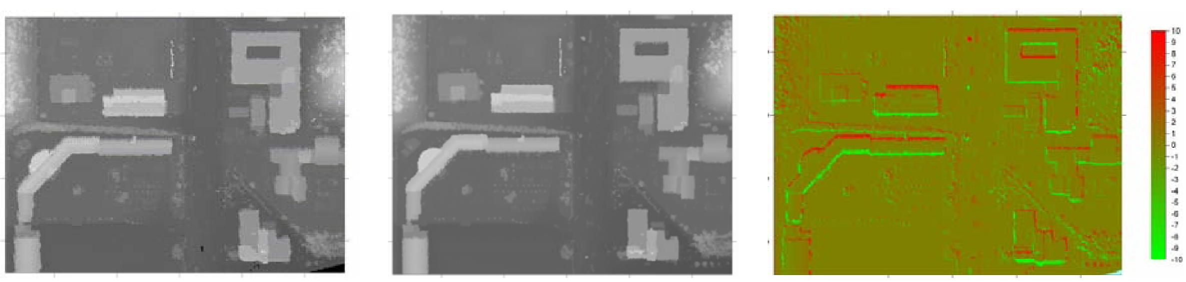


Figure 1. Coordinates and parameters involved in a LIDAR acquisition system.

$$\vec{X}_G = \vec{X}_o + R_{\omega,\phi,\kappa}\, R_{\Delta\omega,\Delta\phi,\Delta\kappa}\, \vec{P}_G + R_{\omega,\phi,\kappa}\, R_{\Delta\omega,\Delta\phi,\Delta\kappa}\, R_{\alpha,\beta} \begin{bmatrix} 0 \\ 0 \\ -\rho \end{bmatrix} \tag{1}$$



a) b) c)

Figure 2. Image differencing of interpolated range images generated from overlapping strips: a) interpolated range image from first strip, b) interpolated range image from second strip, c) difference image.

Similarly, intensity measurements can also be interpolated onto a grid to obtain two overlapping intensity images of an area. Conjugate features in these images are then identified and their horizontal coordinates are measured. The corresponding elevation data can be retrieved from the respective range images. Finally, the derived coordinates can be compared. Differences that exceed the expected noise level in the data indicate the presence of biases in the LIDAR system. Unfortunately, this procedure is time consuming, and sometimes it is hard to identify conjugate features in the intensity images. Moreover, the results are still prone to artifacts introduced by the interpolation technique. To avoid the above limitations, alternative procedures can be developed by evaluating the degree of coincidence of conjugate surface elements (linear and areal features), which can be accurately derived from the irregular LIDAR point cloud. In such approaches, conjugate surface elements are manually extracted. Alternatively, automated procedures can be used to determine corresponding surface elements while evaluating their degree of coincidence. These techniques will be discussed in the Quality Control section of this paper.

The need for establishing standards and specifications for the quality control of LIDAR data is being recognized by the research and mapping organizations. For example, The Canadian British Columbia Base Mapping and Geomatic Services (BMGS) established a Community of Practice involving experts from academia, mapping, current users, and LIDAR data capture and system design organizations to develop a set of specifications and procedures that would realize the objective of evaluating the quality of LIDAR data and products (BMGS, 2006). Similar initiatives are taking place in the United States under the auspices of the United States Geological Survey (USGS), the American Society of Photogrammetry and Remote Sensing (ASPRS), and Federal Emergency Management Agency (FEMA). The presented work in this paper is the result of the joint cooperation between the Digital Photogrammetry Research Group of the University of Calgary and the BMGS. In the next section, we will introduce the error budget associated with a LIDAR system. In this section, the effect of measurement noise and biases in the system calibration parameters (bore-sighting) will be analyzed. After that, we will emphasize some quality control methods, which will be followed by experimental results from real data and concluding remarks.

ERROR BUDGET IN LIDAR SYSTEMS

As mentioned before, the error in the LIDAR-derived coordinates is affected by errors in the components of the LIDAR equation. These components, or input parameters, can either be estimated or measured from a system calibration procedure. In this section, we are interested in analyzing the effect of random noise and systematic biases in the measurements from the various LIDAR components on the final product. The purpose of such analysis is to allow for the estimation of the quality of the final product in terms of the quality of the system's measurement. Moreover, knowing the expected accuracy of the final product, one might be able to interpret the outcome of the quality control procedure as being acceptable or as an indication of the presence of systematic biases in the data acquisition system. Finally, by analyzing the effect of systematic biases, one might be able to offer some diagnostic tips about the origin of identified discrepancies from the proposed quality control procedures.

For any point measured by the LIDAR system, error propagation can be used to determine the error in the LIDAR-derived coordinates given the errors in the LIDAR input parameters. It should be noted that the error budget does not consider the effect of LIDAR interaction with different terrain and ground cover types. In other words, the error budget assumes a relatively flat solid surface. To facilitate the estimation of the contribution of error sources in various LIDAR components to the final accuracy of the derived point cloud, an error propagation calculator has been devised. The calculator allows the user to specify values for each of the system input parameters for a certain LIDAR footprint, and to enter the noise level for each of the parameters. The calculator then determines the accuracy of the ground coordinates of the point. Conversely, if the user requires specific accuracy for the final ground coordinates, the calculator can be used to determine the accuracies that would be required for the input components through a trial and error process. Figure 3 shows the calculator's user interface. In this figure, typical values for the LIDAR input parameters have been entered along with the sigma values. The output box gives the variance-covariance matrix of the final ground coordinates of the point in question, followed by the respective standard deviations. Using such a calculator, one can answer the following questions:

- What is the error budget for each source component in the LIDAR equation?
- What is the best possible achievable accuracy for a given LIDAR component configuration based on the manufacturer's standard deviation?

Another related issue to the LIDAR error analysis is the nature of resulting errors from random errors in the input system measurements. Usually, it is expected that random noise will lead to random errors in the derived point cloud. Moreover, it is commonly believed that random noise will not affect the relative accuracy. However, this is not the case for LIDAR systems. In other words, some of the random errors might affect the relative accuracy of the derived point cloud. Depending on the considered parameter, the relative effect of the corresponding noise level might not be the same. As an illustration, Figure 4 shows that a given attitude noise in the INS derived orientation will affect the nadir region of the flight trajectory less significantly than off nadir regions. Thus, the INS error will affect the relative accuracy of LIDAR derived point cloud. The following list gives some diagnostic hints about the impact of noise in the system measurements on the derived point cloud.

- GPS noise: It will lead to similar noise level in the derived point cloud. Moreover, the effect is independent of the system parameters (flying height, look angle, and flying direction).
- Angular noise (IMU or mirror angles): For this type of noise, the horizontal coordinates are affected more than the vertical coordinates. In addition, the effect is dependent on the system parameters (flying height, look angle, and flying direction).
- Range noise: It mainly affects the vertical component. The effect is independent of the system flying height. However, the impact is dependent on the system look angle and flying direction.

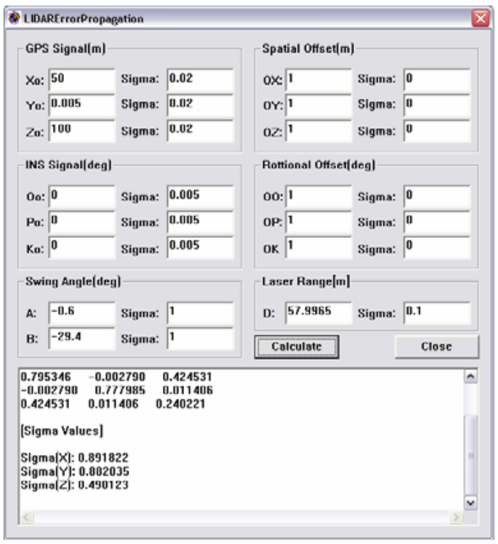


Figure 3. Error propagation calculator.

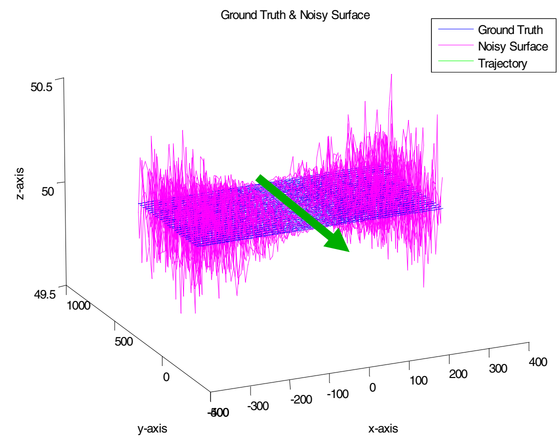


Figure 4. The effect of attitude error on a simulated horizontal surface.

Systematic biases in the system measurements (e.g. GPS/INS measurements, mirror angle measurements, measured ranges) and calibration parameters (e.g. bore-sighting parameters relating the system components) will lead to systematic errors in the derived point cloud. Table 1 provides a summary of the various systematic biases and their impact on the derived LIDR coordinates.

Table 1. Systematic biases and their impact on the derived surface*.

	Flying Height	Flying Direction	Look Angle
Bore-sighting Offset Bias	Effect is independent of the Flying Height	Effect is dependent on the Flying Direction (Except ΔZ)	Effect is independent of the Look Angle
Bore-sighting Angular Bias	Effect Increases with the Flying Height	Effect Changes with the Flying Direction	Effect Changes with the Look Angle (Except ΔX)
Laser Beam Range Bias	Effect is independent of the Flying Height	Effect is independent of the Flying Direction	Effect Depends on the Look Angle (Except ΔY)
Laser Beam Angular Bias	Effect Increases with the Flying Height	Effect Changes with the Flying Direction (Except ΔY)	Effect Changes with the Look Angle (Except ΔX)

* The above table assumes a linear scanner flying over a flat horizontal terrain along a straight-line trajectory with constant attitude along the y-direction

QUALITY CONTROL: ALTERNATIVE METHODOLOGIES

This section provides alternative methodologies for evaluating the quality of LIDAR data. The conceptual basis of these approaches is that conjugate surface elements, which can be identified in overlapping strips, should coincide with each other as well as possible. Deviations between conjugate elements in overlapping strips, beyond the range defined by the expected system accuracy, signify a problem in the data acquisition and processing steps. Explicitly, the methods utilize conjugate surface elements to derive the parameters of a conformal transformation (rotations, scale, and shifts) to assure the best coincidence of these features. Theoretically, the estimated shifts, rotations, and scale should be zero, zero, and unity, respectively, for a well-calibrated system. Therefore, significant deviations from these optimum values can be used as the quality control measure. In other words, deviations with a magnitude that exceeds the noise level in the LIDAR data can be used as an indication of existing biases in the system components. In the following subsections, we will present several approaches that are based on conjugate linear and areal features. In addition, we will present an automated procedure for identifying corresponding surface elements while evaluating their degree of coincidence.

Quality Control by Checking the Coincidence of Conjugate Straight Lines in Overlapping Strips

As mentioned before, extracted linear features from overlapping strips can be used to evaluate an estimate of the conformal transformation parameters that are needed for the co-alignment of such features. Before getting into the mathematical details for using linear features, which are represented by non-conjugate end points in overlapping strips for parameter estimation, we will start by the established procedure for their extraction. Using intensity images, we developed an interface that extracts the LIDAR point cloud in the vicinity of selected points (i.e., extract the LIDAR points within a given radius from the identified points in the intensity image). The extracted point cloud usually corresponds to buildings that contain linear features. Using an automated segmentation procedure, planar patches are identified in the extracted point cloud. Then, neighboring patches are intersected to produce infinite line segments. Then, using the segmented patches, the infinite line, and a given buffer, we can define the end points for the line of intersection. More specifically, LIDAR points within the segmented patches that lie within the given buffer are projected to the line of intersection. Extreme points along the line of intersection are used to define the end points of that line. We repeat the same procedure for the other overlapping strip. In this section, we will introduce two alternative approaches that are based on linear features. It should be noted that both methods do not require lines that have conjugate end-points in the two LIDAR strips and, depending on the nature of the overlap, conjugate lines may arise from quite different parts of the same object.

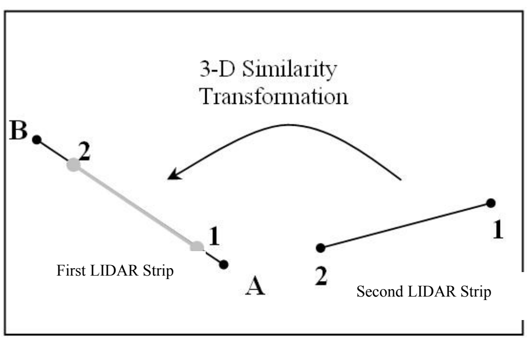


Figure 5. Conceptual basis for using linear features in a line-based approach for the determination of the conformal transformation parameters between two 3D datasets.

The objective of the first approach is to introduce the necessary constraints to describe the fact that the line segment from the first strip (12) coincides with the conjugate segment from the overlapping strip (AB) after applying the transformation, Figure 5. For these points, the constraint equations can be written as in Equations 2.

$$\begin{bmatrix} X_T \\ Y_T \\ Z_T \end{bmatrix} + S\ R_{(\Omega,\ \Phi,\ K)} \begin{bmatrix} X_1 \\ Y_1 \\ Z_1 \end{bmatrix} = \begin{bmatrix} X_A \\ Y_A \\ Z_A \end{bmatrix} + \lambda_1 \begin{bmatrix} X_B - X_A \\ Y_B - Y_A \\ Z_B - Z_A \end{bmatrix} \quad (2a)$$

$$\begin{bmatrix} X_T \\ Y_T \\ Z_T \end{bmatrix} + S\ R_{(\Omega,\,\Phi,\,K)} \begin{bmatrix} X_2 \\ Y_2 \\ Z_2 \end{bmatrix} = \begin{bmatrix} X_A \\ Y_A \\ Z_A \end{bmatrix} + \lambda_2 \begin{bmatrix} X_B - X_A \\ Y_B - Y_A \\ Z_B - Z_A \end{bmatrix} \quad (2b)$$

where:

$(X_T\ Y_T\ Z_T)^T$ is the translation vector between the strips
$R_{(\Omega,\Phi,K)}$ is the required rotation matrix for the co-alignment of the strips, and
S, λ_1, and λ_2 are scale factors.

Through subtraction of equation (2a) from (2b), and the elimination of the scale factors, the equations in (3) can be written to relate the rotation elements of the transformation to the coordinates of the points defining the line segments.

$$\frac{(X_B - X_A)}{(Z_B - Z_A)} = \frac{R_{11}\,(X_2 - X_1) + R_{12}\,(Y_2 - Y_1) + R_{13}\,(Z_2 - Z_1)}{R_{31}\,(X_2 - X_1) + R_{32}\,(Y_2 - Y_1) + R_{33}\,(Z_2 - Z_1)}$$

$$\frac{(Y_B - Y_A)}{(Z_B - Z_A)} = \frac{R_{21}\,(X_2 - X_1) + R_{22}\,(Y_2 - Y_1) + R_{23}\,(Z_2 - Z_1)}{R_{31}\,(X_2 - X_1) + R_{32}\,(Y_2 - Y_1) + R_{33}\,(Z_2 - Z_1)} \quad (3)$$

These equations can be written for each pair of conjugate line segments giving two equations, which contribute towards the estimation of the two rotation angles, azimuth and pitch angle, along the line. On the other hand, the roll angle across the line cannot be estimated. Hence, a minimum of two non-parallel lines is needed to recover the three elements of the rotation matrix (Ω,Φ, K). To allow for the estimation of the translation parameters and the scale factor, Equations (4) below can be derived by rearranging the terms in Equations (2a) and (2b) and by eliminating the scale factors λ_1 and λ_2. A minimum of two non-coplanar lines are required to recover the scale and translation parameters. Overall, to recover all seven parameters of the transformation function, a minimum of two non-coplanar line segments is required. For more details related to this approach, interested readers can refer to Habib et al., 2004. We will denote the above transformation method as the line-based incorporation of linear features.

$$\frac{(X_T + S\ x_1 - X_A)}{(Z_T + S\ z_1 - Z_A)} = \frac{(X_T + S\ x_2 - X_A)}{(Z_T + S\ z_2 - Z_A)}$$

$$\frac{(Y_T + S\ y_1 - Y_A)}{(Z_T + S\ z_1 - Z_A)} = \frac{(Y_T + S\ y_2 - Y_A)}{(Z_T + S\ z_2 - Z_A)} \quad (4)$$

where:

$$\begin{bmatrix} x_1 \\ y_1 \\ z_1 \end{bmatrix} = R_{(\Omega,\,\Phi,\,K)} \begin{bmatrix} X_1 \\ Y_1 \\ Z_1 \end{bmatrix} \quad \text{and,} \quad \begin{bmatrix} x_2 \\ y_2 \\ z_2 \end{bmatrix} = R_{(\Omega,\,\Phi,\,K)} \begin{bmatrix} X_2 \\ Y_2 \\ Z_2 \end{bmatrix}$$

Tait et al., 2007, proposed an alternative procedure for estimating the transformation parameters using linear features while using the existing point-based approach for conformal transformation. In this procedure, the standard ellipsoids of the endpoints are artificially extended along the line direction, Figure 6. To do this extension, we need to identify two coordinate systems (XYZ and KLM). The XYZ-coordinate system is the ground reference frame. On the other hand, the KLM-coordinate system is defined with the K-axis aligned along the line in question. For a given point, the variance-covariance matrix can be described by Equation 5. The variance-covariance matrix of this point relative to the KLM-coordinate system can be defined through the law of error propagation as in Equation 6 (Where R is the rotation matrix relating the XYZ and KLM-coordinate systems). To compensate for the fact that the end points for corresponding lines are not conjugate, we need to artificially expand the variance along the line direction, Equation 7, where W is an arbitrary large value. Finally, the modified variance-covariance matrix in the XYZ-coordinate system can be defined through the law of error propagation, Equation 8. The main advantage of this approach is that existing point-based conformal transformation techniques can be used while using linear features that are not represented by conjugate end points. This approach will be referred to as the point-based incorporation of linear features.

$$\Sigma_{XYZ} = \begin{bmatrix} \sigma_X^2 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 \\ 0 & 0 & \sigma_Z^2 \end{bmatrix} \quad (5)$$

$$\Sigma_{KLM} = R \begin{bmatrix} \sigma_X^2 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 \\ 0 & 0 & \sigma_Z^2 \end{bmatrix} R^T \quad (6)$$

$$\Sigma'_{KLM} = R \begin{bmatrix} \sigma_X^2 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 \\ 0 & 0 & \sigma_Z^2 \end{bmatrix} R^T + \begin{bmatrix} W & 0 & 0 \\ 0 & 0 & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (7)$$

$$\Sigma'_{XYZ} = R^T \ \Sigma'_{KLM} \ R \quad (8)$$

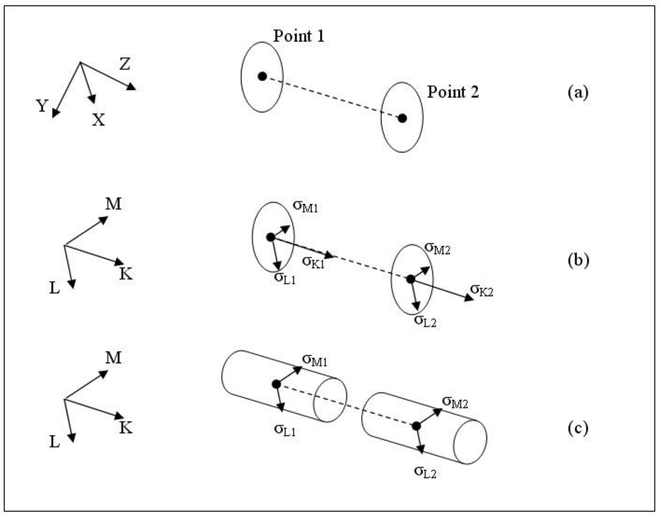
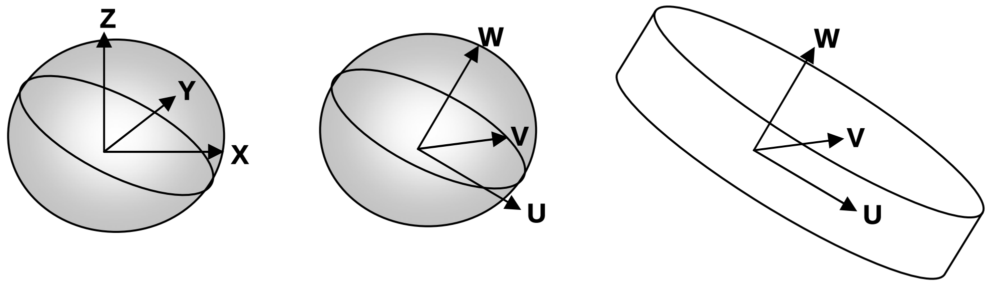


Figure 6. Conceptual basis for using linear features in a point-based approach for the determination of the conformal transformation parameters between two 3D datasets.

Quality Control by Checking the Coplanarity of Conjugate Planar Patches in Overlapping Strips

Instead of using linear features, one can incorporate conjugate planar patches in a point-based approach for the estimation of the conformal transformation parameters. Similar to the point-based procedure for the incorporation of linear features, we can use points along planar patches after expanding the variance-covariance matrix in the plane direction, Figure 7. The expansion can be carried out as shown in Equation 9, where R is the rotation matrix between the original XYZ-coordinate system and the UVW-coordinate system, which is defined with the UV-axes aligned along the plane (i.e., the W-axis is aligned along the normal to the plane). It should be noted that W and N in Equation 9 refer to arbitrarily chosen large numbers.

$$\Sigma'_{UVW} = R \begin{bmatrix} \sigma_X^2 & 0 & 0 \\ 0 & \sigma_Y^2 & 0 \\ 0 & 0 & \sigma_Z^2 \end{bmatrix} R^T + \begin{bmatrix} W & 0 & 0 \\ 0 & N & 0 \\ 0 & 0 & 0 \end{bmatrix} \quad (8)$$

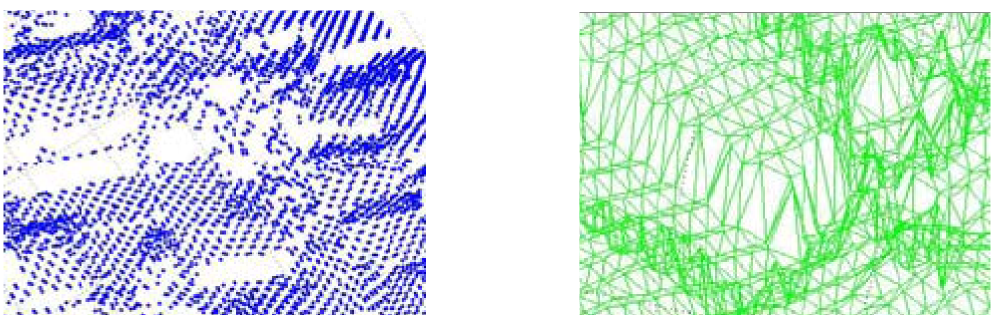


a b c

Figure 7. Conceptual basis for using planar patches in a point-based approach for the determination of the conformal transformation parameters between two 3D datasets.

Quality Control by Automated Matching of the Raw LIDAR Data in Overlapping Strips

All of the above approaches to LIDAR quality control require post-processing of the raw LIDAR data. Therefore, the validity of the derived measures depends on the amount of error introduced in the processing steps. To mitigate this dependency, an alternative quality control approach can be based on surface matching and registration of the raw LIDAR data in overlapping strips to identify biases in the data acquisition system without the need for interpolation or segmentation. One way of doing this is to perform automated registration of two overlapping LIDAR strips while checking for consistent deviations between them; these deviations are a measure of internal quality control. The registration is undertaken via a surface matching procedure in which one surface is represented by points and the other surface is represented by triangular patches, as shown in Figure 8. The matching criterion is that the points of the first surface must be coplanar with the corresponding patches of the second surface. For more detail regarding this approach, interested readers can refer to Habib et al., 2001 and Habib and Cheng, 2006.



a) **b)**

Figure 8. The representation of two surfaces to be co-registered: a) using points (surface 1) and b) using triangular patches (surface 2).

EXPERIMENTAL RESULTS

To validate the feasibility and applicability of the above methodologies, a multi-strip LIDAR coverage was collected using the OPTECH ALTM 2070 with an average point density of 2.67 point/m^2 from an altitude of 975m. Four experiments are presented here for comparative analysis of the presented methods. First, the Quality Control is evaluated by checking the coincidence of conjugate points measured from intensity images in overlapping strips. Second, the Quality Control is performed by checking the coincidence of conjugate straight lines in overlapping strips. Third, the analysis is performed while checking the coplanarity of conjugate planar patches in overlapping strips. Finally, Quality Control is established by automated matching of the raw LIDAR data in overlapping strips.

Experiment 1: Checking the Coincidence of Conjugate Points Measured from the Intensity Images

To test this approach, we extracted 100 points in overlapping LIDAR strips. Figure 9 shows a sample of the measured points, the difference in the XYZ coordinates for this point is 0.79, -0.22, -0.05 meters, respectively. The average and standard deviation for all the points is shown in Table 2. The standard deviation of the estimated shifts is significantly large, which can be explained by the fact that identifying conjugate points in overlapping intensity images is sometimes difficult. Moreover, the interpolation technique is another factor. For further illustration, Figure 10 shows another point where the estimated differences in the XYZ directions are 1.65, 1.11, and -0.63 meters, respectively. Therefore, one can conclude that the performance of the Quality control procedure, which is based on the manipulation of intensity images, is not reliable and quite subjective to the interpretation ability of the involved intensity images.

Table 2. The average and standard deviations of the estimated discrepancies between overlapping strips using 100 points

	Average (m)	Standard deviation (m)
X	0.45	0.36
Y	0.50	0.37
Z	0.22	0.28

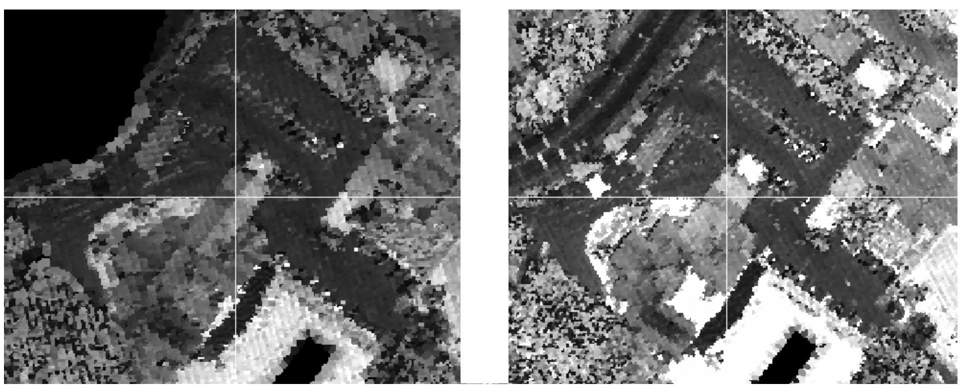


Figure 9. A sample of identified conjugate points in overlapping strips.

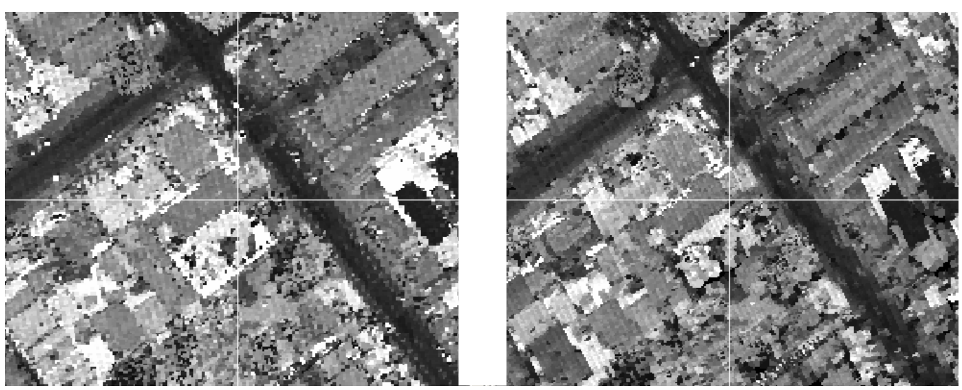


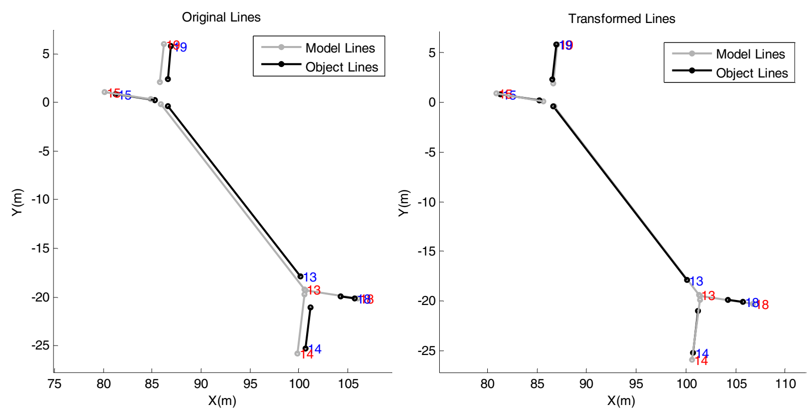
Figure 10. Another sample of identified conjugate points in overlapping strips.

Experiment 2: Checking the Coincidence of Conjugate Straight Lines in Overlapping Strips

To test this procedure, we manually collected 36 conjugate lines in two overlapping strips. Table 3 summarizes the conformal transformation parameters that have been estimated together with the average normal distance between conjugate linear features before and after applying the transformation for line-based and point-based approaches. Figure 11 shows a sample of conjugate linear features in overlapping strips before and after the application of the conformal transformation parameters. As it can be seen in this table, both approaches produce compatible results. In addition, the reported discrepancies are quite different from those derived using the intensity images. Finally, it is quite evident that the degree of coincidence among conjugate features is significantly improved after applying the estimated transformation parameters (refer to the last two rows in Table 3 and Figure 11-b).

Table 3. Estimated transformation parameters using conjugate linear features in overlapping strips together with the normal distances between the linear features before and after applying the transformation.

	Line-Based Approach	Point-Based Approach
Scale Factor	1.0006	0.9998
X_T (m)	0.75	0.77
Y_T (m)	-0.17	-0.17
Z_T (m)	0.05	0.06
Ω (°)	-0.0386	-0.0421
Φ (°)	-0.0125	-0.0048
K (°)	-0.0145	-0.0134
Normal Distance, m (Before)	0.49 ± 0.24	0.49 ± 0.24
Normal Distance, m (After)	0.18 ± 0.18	0.18 ± 0.19



(a) (b)

Figure 11. Sample of conjugate linear features in overlapping strips before (a) and after (b) applying the estimated conformal transformation parameters in Table 3.

Experiment 3: Checking the Coplanarity of Conjugate Planar Patches in Overlapping Strips

As mentioned before, instead of using conjugate linear features, one can check the quality of the LIDAR data by checking the coplanarity of conjugate planar patches in overlapping strips. The coplanarity of these patches can be checked by estimating the conformal transformation parameters (shifts, rotations, and scale) that need to be applied to one strip to ensure the co-alignment of the two strips. To test this procedure, we manually collected 5 conjugate patches in two overlapping strips (Figure 12). These patches correspond to the roof of a building that appears in overlapping LIDAR strips. Table 4 summarizes the estimated conformal transformation parameters using the extracted planar patches. A visual comparison of the reported results in Tables 3 and 4 shows that the estimated parameters from the line and patch procedures are quite compatible. However, the utilization of the planar patches eliminates the need for the intersection of neighboring ones to derive the linear features and thus saving some processing time.

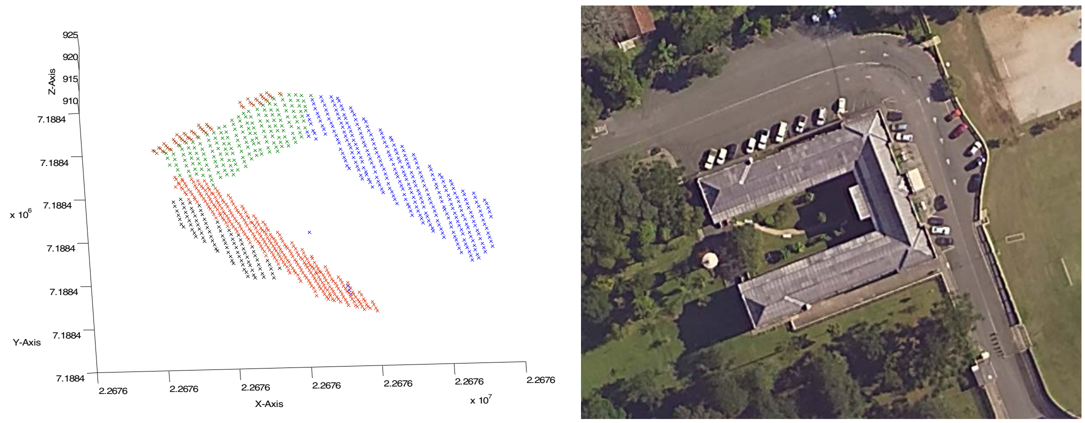


Figure 12. Extracted planar patches from a LIDAR strip.

Table 4. Estimated transformation parameters using conjugate planar in overlapping strips.

Transformation parameter	Line-Based Approach
Scale Factor	0.9985
X_T (m)	0.75
Y_T (m)	-0.11
Z_T (m)	0.13
Ω (°)	-0.0305
Φ (°)	0.0391
K (°)	0.1950

Experiment 4: Automated Matching of the Raw LIDAR Data in Overlapping Strips

To test this approach, we extracted several areas in overlapping LIDAR strips. The estimated parameters together with the average normal distance between conjugate surface elements are shown in Table 5. In this case, we checked the performance by using different number of selected regions; one area at the vicinity of a building, three areas around three buildings, and seven areas around seven buildings (the results are shown in the second, third, and fourth columns in Table 5, respectively). The numbers in the header line of Table 5 indicates the used building numbers for the various tests, refer to Figure 13. The table also shows the average normal distance between conjugate surface elements after the application of the estimated conformal transformation parameters. Based on a comparison of tables 3, 4, and 5, it is clear that the proposed approaches yield comparable results. Moreover, the estimated discrepancies are almost of the same range of the average point density. Such biases could not be recovered using the intensity images.

Table 5. Estimated transformation parameters using automated matching of conjugate surface elements in overlapping strips.

	One Building (1)	Three Building Areas (1,2,3)	Seven Building Areas
Scale Factor	0.9997	0.9998	0.9998
X_T (m)	0.85	0.56	0.75
Y_T (m)	-0.07	-0.26	-0.13
Z_T (m)	0.15	0.09	0.12
Ω (°)	-0.0218	-0.0200	-0.0267
Φ (°)	-0.0201	-0.0034	-0.0088
K (°)	0.1239	-0.0189	-0.0003
Average Normal Distance, m	0.10	0.09	0.09

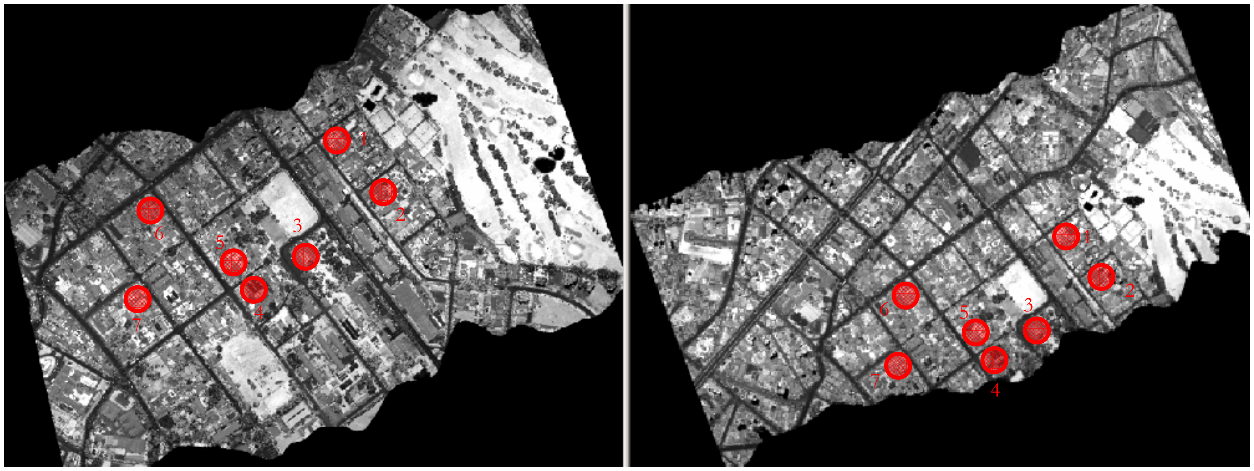


Figure 13. Locations of selected areas for the registration and automated matching of conjugate surface elements in two overlapping strips.

CONCLUSIONS AND RECOMMENDATIONS

This paper presents alternative procedures for the quality control of LIDAR data. In general, quality control is an essential procedure to ensure that the derived data from a given system meets the users' requirements. For LIDAR, quality control is critical since the users' role in the quality assurance process is very limited due to the non-transparent nature of current LIDAR systems. The proposed procedures are based on evaluating the conformal transformation parameters, which are needed for the co-alignment of conjugate surface elements in overlapping LIDAR strips. Deviations in the estimated transformation parameters from the theoretical ones (zero rotations and translations and unit scale factor) are used as quality control measures to inspect the presence of biases in the data acquisition system. When dealing with overlapping LIDAR strips, the deviations are considered as an internal quality control. On the other hand, external (absolute) quality control measures can be derived by comparing the LIDAR surface with another version of the surface that has been independently and accurately acquired.

More specifically, we introduced one approach that utilizes linear features with non-conjugate end points. In this approach, we presented line-based and point-based procedures. Alternatively, we introduced another approach that utilizes conjugate planar patches that are represented by non-conjugate points. To compensate for the non-correspondence of the selected points along the planar patches, we artificially expanded the respective variance-covariance matrix in the plane direction. Finally, we introduced an automated approach that is based on identifying conjugate surface elements while estimating the transformation parameters. Experimental results with real data have showed the feasibility of the proposed algorithms in detecting biases in the horizontal directions between two overlapping LIDAR strips. These errors are speculated to be due to angular bore-sighting biases. Moreover, the alternative approaches have been shown to produce comparable results. Compared to the traditional quality control techniques (e.g., the utilization of intensity images), the proposed approaches delivered more reliable estimates even though the detected biases are within the range defined by the LIDAR point density. Moreover, the last two approaches can be applied for any coverage areas with no requirements of having LIDAR targets or structures with linear features (e.g., urban areas).

It should be noted that in current specifications, only the vertical accuracy is carefully verified by the data provider with precisely surveyed check surfaces. On the other hand, horizontal accuracies are more difficult to verify due to the lack of distinct topographic features for testing. In addition, no specific regulations and verification requirements are defined by the photogrammetric and mapping societies for reporting horizontal accuracies of LIDAR data, ASPRS 2004. However, both horizontal and vertical accuracies should be assessed for quality control since errors in both directions can greatly affect the accuracy of mapping products generated from LIDAR (e.g., digital elevation models). This is especially important for applications such as marine navigation and floodplain management where highly accurate mapping products are needed. The presented methodologies constitute an effective and economic tool for checking the quality of derived LIDAR surfaces.

In the future, the algorithms can be applied for external quality control, where the co-alignment is performed between a LIDAR strip and a control surface of the coverage area. Another extension is to implement the proposed approaches in multiple sub-sections of the LIDAR surface to check if the detected biases are consistent throughout the entire dataset. The identification of biases is the first step to quality control. In the future, the research will be extended to allow for the justification and compensation for detected biases.

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