Assessing Accuracy of the Vertical Component of Airborne Laser Scanner for 3D Urban Infrastructural Mapping

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Abstract
This study presents two methods used to measure the accuracy of the height component of Airborne Laser Scanning (ALS) data. The objectives are: to assess the accuracy of LiDAR data, to find correlation between the actual and sensor recorded height, and to explore the effectiveness of linear regression model for accuracy assessment. Field observation was carried out with Total Station as reference data and the corresponding data obtained from normalized digital surface model (n-DSM). First, statistical method was used to obtain a Root Mean Square Error (RMSE) value of 0.607 and linear accuracy of 1.18948 at 95% confidence level. Similarly, linear regression function was used to obtain RMSE value of 0.5073 and linear accuracy of 1.10999. The study shows that ALS recorded height is reliable for 3D urban mapping. A resulting correlation coefficient of 0.9919 indicates a very good agreement between the sensor recorded height and the actual height of the object (R^2= 0.9839; $p < 2.2e-16$). The study indicates that linear regression model is effective for assessing the accuracy of ASL data.

1. Introduction

Over the last two decades, airborne laser scanners (ALS) has been widely used as a surveying tool for generating extremely accurate and quick 3D data of the earth's surface that are used in a variety of applications such as urban planning, terrain mapping, forest stand, 3D building model, cartographic visualization, etc. (Cheuk and Yuan, 2009). ALS otherwise called light detection and ranging (LiDAR) system is an active optical remote sensing technology that emits a laser pulse towards the earth surface. The reflected laser signal from surface materials is recorded by the sensor, along with the round-trip travel time (Raber and Cannistra, 2005), to produce accurate 3D components of surface object (Carlberget al., 2009). Progress in ALS technology allows very dense point cloud to be collected for better access to deriving the geometrical properties of the surface material and roughness. Also, the intensity is not affected by shadow, and it is less affected by natural illumination conditions (Rottensteiner and Clode, 2008). Consequently, ALS data and its derived products are becoming a standard component of nations' geospatial database similar to digital orthophoto in the 1990s (Samberg, 2005). Accurate and up-to-date 3D information is very important for morphologically dependent applications like 3D city modeling, transportation planning, topographic analysis and forest management (Ekhtari et al., 2008 and Verma et al., 2006). Inaccuracy in the data will result in faulty decisions that could have dire consequences on the socio-economic and well-being of the citizens. In the light of the widespread applications of ALS data, the need to assess its accuracy becomes even more imperative since aggregation of errors from individual sensor components, target properties, and post-processing activities (Aguilar et al., 2010 and Cheuk and Yuan, 2009) can render the final point cloud less accurate. Accuracy assessment is useful for self-evaluation and improvement, quantitative comparison and analysis of methods, sensors, and algorithm, to guide reliable decision making process. Building detection and 3D modeling have been well researched and, yet, remains an active research interest in remote sensing and computer vision disciplines. Quite a lot of work had been done to automatically reconstruct 3D building for urban

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applications (Alharthy and Bethel, 2004, Alharthy and Bethel, 2002, Chen et al., 2005, Kada and McKinley, 2009, Rottensteiner and Briese, 2002, Sohn and Dowman, 2003, Tse and Dakowicz, 2005 and Verma et al., 2006), however, emphasis is much more focused on developing algorithms than evaluating the height of the model generated. A comprehensive review of methods and algorithms developed for automatic urban 3D building detection and reconstruction is presented in the work of (Haala and Kada, 2010). Despite the high range accuracy provided by ALS, it generally does not guarantee quality results of the model produced due to accumulation of errors from the various sources mentioned earlier. The extensive investigation by (Cheuk and Yuan, 2009) on assessing spatial uncertainty of LiDAR derived 3D model exposed the danger of assuming absolute correctness of such output. Though much had been done on LiDAR vertical accuracy assessment, most are limited to 2.5D terrain surfaces from digital terrain model (Aguilar et al., 2010). According to Van der Sande et al., (2010), accuracy assessment involves relative comparison of remote sensing data with reference data from either field measurement, existing maps or random sampling theoretically assumed to be accurate. According to (Aguilar et al., 2010, Congalton, 2004, Disa et al., 2012, Idris et al., 2012, Raber and Cannistra, 2005, Samberg, 2005; and van der Sande et al., 2010) careful field measurement is better as reference data for evaluation since it does not have inherent propagated error. The need to move beyond the 2.5D terrain data to 3D accuracy assessment of above terrain objects as a prerequisite to evaluating LiDAR derived 3D model have come of age, hence the motivation for this study.

2. Material and Methods

The following data were used in this study (i) Riegl LiDAR data and (ii) survey data as described the study area and data description section. Again, detail procedures for data processing, field measurement, analysis and methods of validation were discussed.

2.1 Study area and Data Description

ALS data collected with Riegl LMS-Q560 sensor over Universiti Putra Malaysia (UPM) campus in 2009 was used in this study. The sensor uses the line scan mode with pulse length of 4.0ns and an average range resolution of 0.2cm. It was mounted on-board aircraft, flown at an altitude of approximately 5000m above mean sea level with average point density of 2.3points/m^2. The vicinity around UPM main library is a good choice because it has a combination of high and low buildings, typical of the urban setting. This enables different building heights to be observed.

2.2 ALS Data Processing

Two basic LiDAR products, digital terrain model (DTM) and digital surface model (DSM) are important when height of objects above the Earth's surface is required. Here, ALS data processing step involved two stages. First, the LiDAR point cloud was processed in E3De3.0 software. E3De is a powerful tool developed by ITT Visual Information Solution to provide automatic solution for airborne LiDAR data processing (ITT, 2011). The package is focused on producing realistic 3D model from large quantity of data in a short period of time. Again, E3De can generate DTM, DSM, and SHP files to represent objects like buildings, trees, power line, etc. in the mapped area. E3De is efficient for transforming georeferenced point clouds into GIS layers that can be integrated with other geodatabase. In E3De, the point clouds were morphologically filtered (Tse and Dakowicz, 2005) and classified into terrain and above terrain XYZ point files. The terrain points contain the laser returns from the bare earth (use for generating the DTM), while the above terrain points represent those backscattered from the surface (called DSM) to include trees, building, power-line etc. recorded by the sensor (Figure 1).

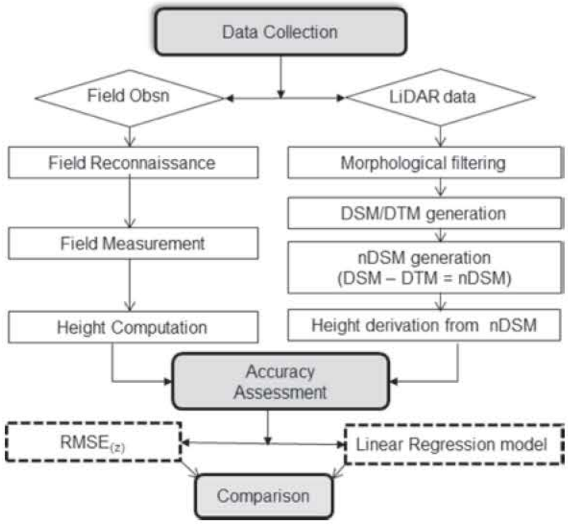

Figure 1: Methodical workflow of ALS accuracy assessment

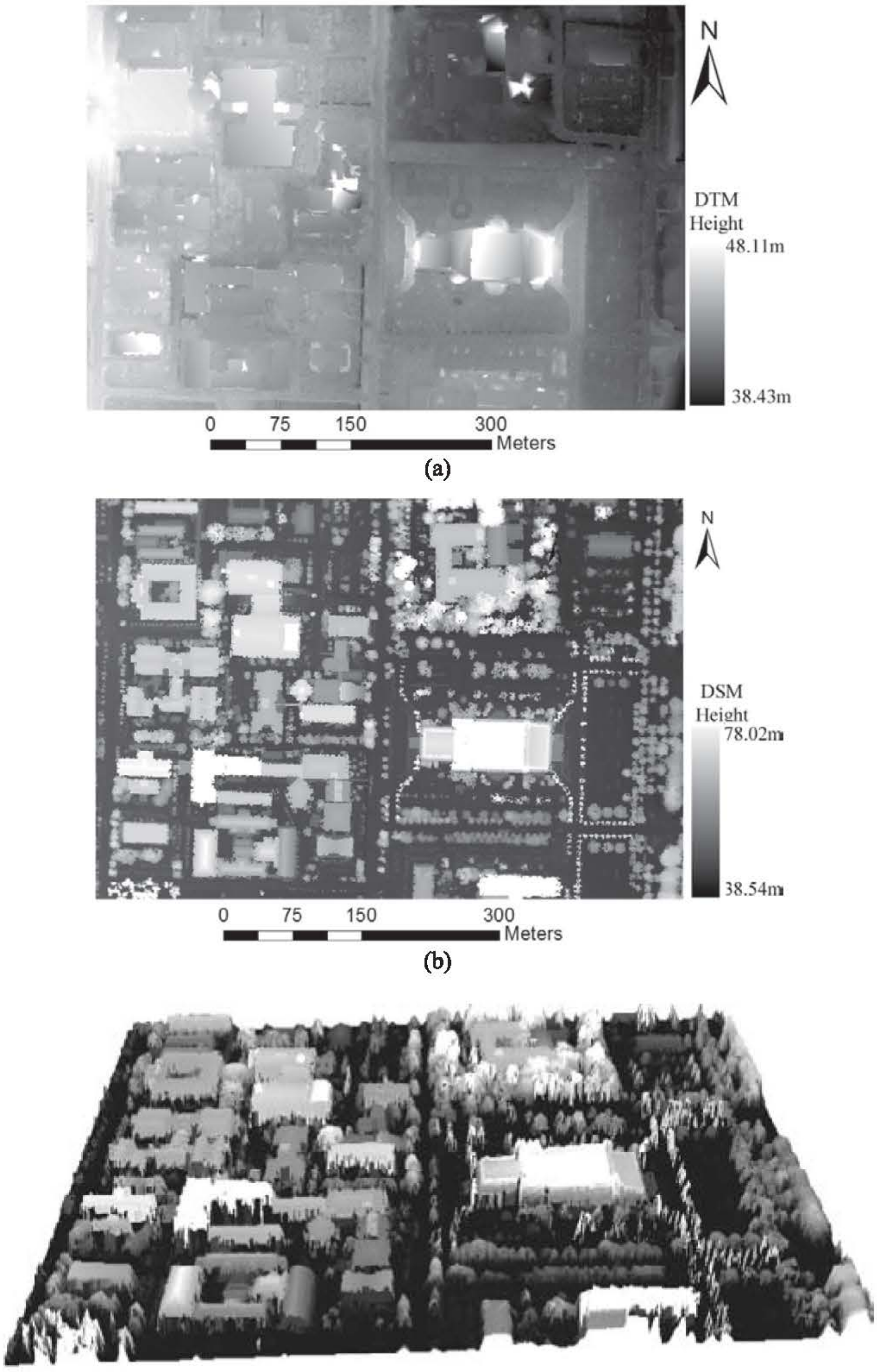

Figure 2: Figure showing data derived from LiDAR point cloud (a) Digital Terrain Model of the study area (b) Digital Surface Model and(c) Normalized DSM

Also, building footprints were obtained from E3De in shape file for 3D building model. Second, the two xyz point files (bare ground points and surface feature points) were input into ArcGIS9.3 to generate triangulated irregular network (TIN) for each data file. The TIN files were further converted to raster data as DTM and DSM, and both resampled to one meter resolution to enable pixel to pixel correspondence. Then normalized DSM (nDSM) was derived by subtracting the DTM from the DSM using ArcGIS Spatial Analyst Raster Calculator tool as presented in figure 2a-c. According to (Rottensteiner et al., 2007) the difference in height ΔH between the two (DSM and DTM) is a useful means to obtain height of objects above the terrain. Since the height above terrain surface is significant to this study, we choose to use nDSM where height value can directly be derived from LiDAR data. Thus, the height of corresponding building points computed from field observation were derived from nDSM and used for the analysis.

2.3 Field Survey Measurement

Field survey operation was carried out to obtain height of buildings using Topcon (GTS-239N) Total Station. The instrument incorporates electronic theodolite with coded scales of horizontal and vertical circle, and an in-built electronic distance measurement (EDM) unit, so angles and distances can be measured simultaneously and displayed digitally. The vertical circle with a very accurate clinometer makes calculating height difference at centimeters accuracy possible. Prior to field observation, the Total Station functionalities were carefully checked and the vertical axis tested.

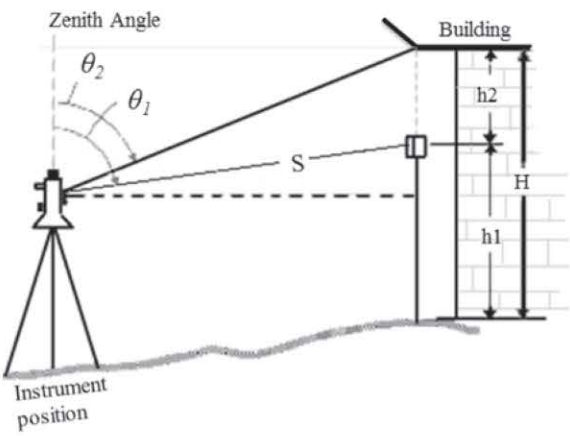

Figure 3: Instrument setup for field measurements

Figure 3 describes the general field procedure with the three parameters required to calculate height of the building: 1) slope distance between the instrument and the building, 2) angular difference between the reflector and the top the building, and 3) height of the reflector. Meanwhile the vertical circle setting of the instrument was configured to read zenith angle for ease of computation. With the instrument set and leveled some distance away from the corner of building such that the vertical angle is greater than 45^0, the reflector was placed on the ground vertically against the corner of the building and the height *h1*recorded. The reflector was sighted with the telescope to measure and record the slope distance *S* and vertical angle θ_1 of the reflector. The vertical clamp was of the instrument was unlock to sight the top of the building corner and the vertical angle θ_2 recorded. In order to increase the accuracy readings were taken on both faces and the mean vertical angle recorded. The same procedure was repeated for every other corner. Flat top building corners with good observation view, and less tree canopy cover were randomly selected. After the field data collection, height *h2* was computed using trigonometric function (Sine rule),and subsequently height, *H* of the buildings were obtained by adding the result to the respective height of reflector *h1* as described in equations (1) and (2).

$$H = h1 + h2$$

Equation 1

h1 in equation (1) is the height of reflector which varies as 1.5m or 2.0m for ease of observation.

$$h2 = \left(\frac{S * \sin(\theta 1 - \theta 2)}{\sin \theta 2}\right)$$

Equation 2

Taking the parameters of point 1 as an example: **S** = 75.671m, θ_1= 89⁰ 41' 00", θ_2 =73⁰ 17' 20", (θ_1 - θ_2) = 16⁰ 23' 40",**h1** = 1.5m

Then:

$$h2 = \left(\frac{75.671 * \sin(16\ 23\ 40)}{\sin(73\ 17\ 20)}\right) = 22.29982\text{m}$$

Therefore, height, H, of the building is computed thus: h1 + h2 = 22.29982 + 1.5 = 23.79989 (23.8 approx.)

3. Accuracy Assessment and Result

3.1 Statistical Analysis

In order to minimize error in picking corresponding building point on the n-DSM, corners and intersection of the building were observed. At few locations where measurements were taken at the center of the building, distance from the corner to the point of observation were recorded to guide in point selection. Figure 4 is the plot of the selected points on the n-DSM image of the study area. The computed height from field survey and their corresponding derived elevation from n-DSM were tabulated in Table 1 for statistical analysis. For this study, we employed statistical approach recommended by ASPRS LiDAR committee as contained in the NSSDA (National Standard for Spatial Data Accuracy) for determining and report elevation data collected with ALS (Rottensteiner et al., 2007). RMSE and Radial Accuracy are the two NSSDA published statistical testing methods widely used (Guo et al., 2010). RMSE is the square root of the average of a set of squared differences between a dataset values and values from an independent identical point of higher accuracy. RMSE is mathematically expressed as:

$$RMSE_z = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Z_l - Z_o)^2}$$

Equation 3

Where Z_l, Zo are height of the point from LiDAR data and the corresponding measure data from field observation respectively and n is the total number of points. Accuracy_z is a measure of a radius of uncertainty in a way that the actual or theoretical value of a point is within that circle 95% of time. Provided that systematic errors have been resolved as much as possible and that vertical error is normally distributed, the factor 1.9600 (FGDC, 1998) is applied to the RMSE value to calculate the linear error at 95% confidence limit. Thus the vertical accuracy is computed as in equation 2. Table 1 presents the height of building points from ALS data and identical field observations with the computed RMSE of 0.60687 and vertical accuracy of 1.18948.

$$\text{Accuracy}_z = RMSE * 1.9600$$

Equation 4

3.2 Regression Analysis

Linear regression analysis is a powerful tool that provides a means of validating the statistical analysis. A linear model is one in which all the parameters appear linearly as shown in the First-order polynomial model in equation 5. Linear model uses method of least squares to estimate parameters and produce accurate result. For this reason, it is widely used in the field of education, medicine, industry, and agriculture (Prajneshu, 1984). However, once polynomial model is fitted to data using linear regression, there is a need to estimate parameters all over again if extra term is to be added to the model later on.

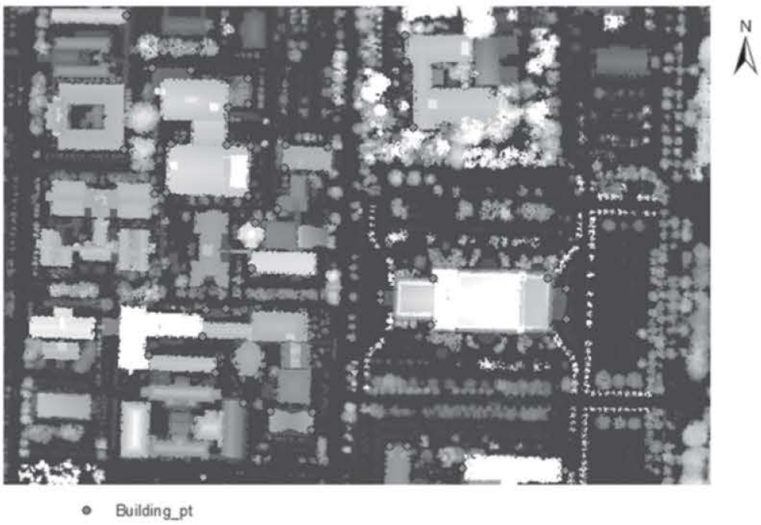

Figure 4: Plot of building corner points on nDSM image

Table 1: Field observed height and ALS derived height and their residuals

SN	LiDAR Hgt	Obsv. Bldg_hgt	Diff. in height	Square Diff	Accuracy Assessment
1	24.1	23.8	0.3	0.09	
2	5.61	6.121	-0.511	0.261121	
3	5.97	6.105	-0.135	0.018225	
4	22.109	23.837	-1.728	2.985984	
5	15.39	15.227	0.163	0.026569	$RMSE_z = \sqrt{\frac{1}{N}\sum_{i=1}^{n}(Z_i - Z_o)^2}$
6	5.638	6.104	-0.466	0.217156	
7	5.58	6.132	-0.552	0.304704	
8	23.73	24.657	-0.927	0.859329	= √14.73206/40
9	23.454	24.68	-1.226	1.503076	
10	8.443	9.022	-0.579	0.335241	= 0.606878
11	9.483	9.809	-0.326	0.106276	
12	10.893	10.995	-0.102	0.010404	**RMSE = 0.607**
13	10.859	11.069	-0.21	0.0441	
14	6.013	6.232	-0.219	0.047961	Linear accuracy at 95% confidence limit for
15	10.609	10.726	-0.117	0.013689	normally distributed error, the factor 1.9600
16	12.09	12.174	-0.084	0.007056	(bandwidth) is applied to the RMSE.
17	11.779	12.343	-0.564	0.318096	
18	19.799	19.086	0.713	0.508369	i.e RMSE x 1.9600
19	16.44	16.782	-0.342	0.116964	
20	3.48	2.248	1.232	1.517824	= 0.606878 x 1.9600
21	3.41	3.393	0.017	0.000289	
22	14.847	15.155	-0.308	0.094864	= 1.189482
23	8.37	8.898	-0.528	0.278784	
24	14.85	15.33	-0.48	0.2304	**Accuracy = 1.190m**
25	13.99	14.953	-0.963	0.927369	
26	11.79	11.958	-0.168	0.028224	
27	11.87	11.901	-0.031	0.000961	
28	11.59	11.934	-0.344	0.118336	
29	12.91	14.279	-1.369	1.874161	
30	13.557	14.438	-0.881	0.776161	
31	14.76	14.967	-0.207	0.042849	
32	14.48	14.903	-0.423	0.178929	
33	13.233	13.162	0.071	0.005041	
34	10.29	10.469	-0.179	0.032041	
35	5.23	5.418	-0.188	0.035344	
36	5.075	5.193	-0.118	0.013924	
37	11.522	11.127	0.395	0.156025	
38	12.42	12.62	-0.2	0.04	
39	12.919	13.672	-0.753	0.567009	
40	12.324	12.522	-0.198	0.039204	
		Sum of Square of the residual		**14.73206**	

Nonlinear models which describes growth behavior over time (i.e. population biology), was not considered for this study, because the parameters involved are not of natural processes. Again, the facts that the least-squares estimators of nonlinear parameters do not possess the desirable properties of linear regression models make them unsuitable. The weakness of nonlinear models include excess variance above the minimum, they are known for skewed distribution, no closed-form expression for the best fitting parameter, and are not unbiased (Ratkowsky, 1993). This analysis describes the relationship between two variables (X and Y) as a straight line, usually modeling Y as a linear function of X to generate the random error, residual, and the correlation coefficient, Theoretically, given that X as LiDAR derived data set and Y as the observed dataset, the regression Y on X is given in equation 5:

$$Y_i = b_0 + b_1 X_i + \varepsilon_i$$

Equation 5

Where i = 1, …n, b_0 is the intercept, b_1 is the slope, and Random Error $\varepsilon_i \sim N(0,\sigma^2)$. This means that the residual is normal with zero mean and a constant variance. To compute the residual, the analysis use the linear function (equation 6) to produce a line that "best" fit the data as:

$$\hat{y} = b_0 + b_1 X_i = E(Y/X = x_i)$$

Equation 6

The difference between the observed values yi and the fitted value $\hat{y}_i$ give the residual $e_i$as in equation 7.

$$e_i = y_i - \hat{y}_i$$

Equation 7

The data was processed in R programming for the linear regression analysis. A maximum accuracy of 1.10999, standard error of 0.5073, and correlation coefficient of 0.9919 was obtained from the regression analysis. Figure 5 is the histogram plot of RMSEs estimated from the two methods compared with the industry range accuracy standard specification of 0.15m to 0.3m in clear urban area (Toth, 2009).

3.3Building Block 3D Model

3D Building block model (figure 6) was constructed over LiDAR intensity image using the foot prints and height derived from LiDAR. Since the objective of the study is accuracy assessment, and not building reconstruction, building block was considered sufficient for visualization purpose. Also, height at sampled points in the study area was displayed in 3D to see if significant variation exists between the two data sets. Building roof shape reconstruction is still an active research area (Alharthy and Bethel, 2002, Kada and McKinley, 2009 and Verma et al., 2006). The red "pole" like feature is the sampled points around the building corners. It can be observed that both the measured and derived height tally confirming the appropriateness of ALS recorded height for 3D city model. However for most urban applications, accurate roof shape is a requirement (Carlberg et al., 2009 and Haala and Kada, 2010) which at present only laser scanning systems provide the most accurate source of data supply for use.

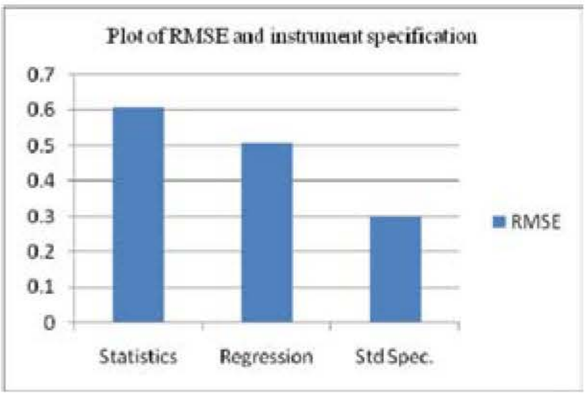

Figure 5: Histogram plot of the RMSEs

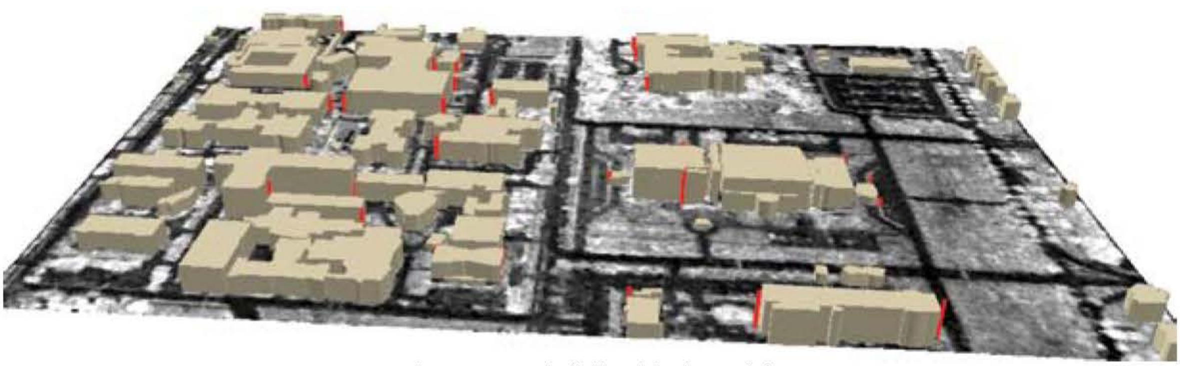

Figure 6: 3D building block models

4. Discussion

In this study, building height values calculated from field observation was used as reference data to assess the accuracy of the vertical component of ALS data. The assumption of using the observation method is that, height derived from n-DSM can give approximate values with the measured values since it provides information about the height of objects above the terrain surface. The important feature in our study is that we shift from the general vertical assessment based on 2.5D to third dimension (height) that makes up a full 3D dataset which (Rottensteiner, 2010) suggests should be taken into account in LiDAR data processing. However, it should be stated clearly that the final measure of accuracy that can be achieved from ALS 3D positional data depends on several factors. On the sensor side (Toth, 2009) identified sensor calibration, scan angle, flying height, and georeferencing elements as primary sources of error. While inherent errors in reference data due to human, instrument and data processing activities (Congalton, 2004) inevitably combined can affect the ultimate accuracy computed. With all these basic fundamentals in mind, our study reveals that the vertical component of ALS data is reliable for urban 3D mapping. We obtained RMSE values of 0.607 from statistical computation and 0.507 from linear regression model, in comparison to the quoted standard range resolution of between 0.15 and 0.3 under an ideal situation (figure 5). An average difference of about 0.25 suggests impacted error from other sources in agreement with the study conducted by (Toth, 2009). Similarly, the statistical estimation produced a linear accuracy of 1.19 at 95% confidence level, while the regression model estimates an accuracy of 1.12. Two obvious factors significantly affect the resultant measure of accuracy in this study. First is the variation in topography around the base of the buildings. In most cases the base of the buildings and the immediate environment has significant change in elevation. In this case both the measured height in the field and the derived elevation from the LiDAR derivatives are at variance. In a similar study conducted by (Cheuk and Yuan, 2009) and (Guo et al., 2010) they observed that topographic variability have significant impact on LiDAR generated terrain elevation. Second, LiDAR point density and the resulting interpolation error due to laser pulse discontinuity (Yong and Huayi, 2008). In a situation like this the interpolation algorithm may produce error that is significant enough to affect the elevation value of the building points selected on the n-DSM and in turn the accuracy computed. Figure 7 gives the plot of the correlation between the observed data and the derived data from LiDAR. The two data sets indicate a positive relationship with a correlation coefficient of 0.9919 which indicated a very strong relationship. The interpretation of this is that, the height recorded with ALS system represents the height of the object in reality. This result further buttress the works of (Razak et al., 2011; Streutker and Glenn, 2006) using the same method to determine height of trees. In essence, the practical component through this work signpost a very good agreement between the test and measured datasets ($R^2 = 0.9839$; $p < 2.2e\text{-}16$). This confirms by 98% that the elevation values recorded by the sensor represent the actual elevation of the buildings, whereas the remaining 2% represent the uncertainty resulting from error sources. Also, with the P-value less than the significant level, it is evidence that the assumption that the sensor record the actual height of the building is further affirmed.

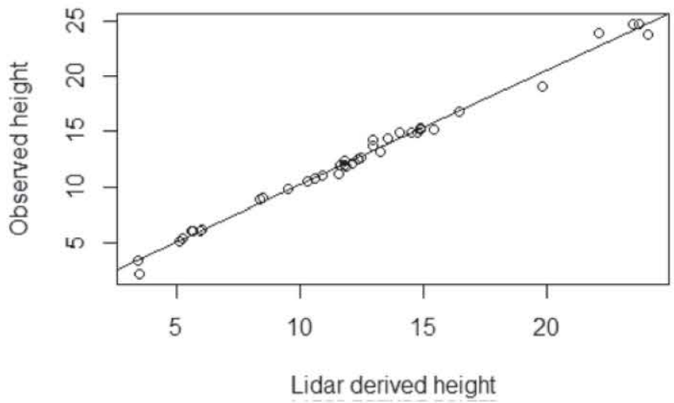

Figure 7: Plot of correlation between observed and LiDAR derived heights

5. Conclusion

This paper described the procedure employed in assessing the accuracy of the height component of ASL data. The two approaches adopted yield positive result that explains reasonable consonance in determining the reliability of ALS data for 3D urban mapping. Clustered points around the fitted regression line provide a visual appraisal of the relationship between the two datasets. With an average RMSE value of 0.5, it is clear that ALS is a reliable surveying technology that can deliver better and fast turnaround mapping project. However, the following factors may affect the quality of result obtained in this study. The LiDAR data used is of low spatial resolution with average point density of less than 2.3points/m^2. This can significantly affect the quality of the result as the accuracy of interpolation algorithms also depends on point density. Again, closeness of buildings, tree canopy, and error in manually selecting corresponding observation points on nDSM are weaknesses that cannot be underestimated. With denser point cloud, careful observation and procedure, the level of overall accuracy of height components will improve. Future research will focus on testing different LiDAR data with varying point density so as to investigate the influence of point density on measure of accuracy.

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