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Revised Progressive Morphological Method for Ground Point Classification of Airborne LiDAR Data

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ABSTRACT

Airborne Light Detection and Ranging (LiDAR) has been very effectively used in collecting terrain information over different scales of area. Inevitably, filtering the non-ground returns is the major step of digital terrain model (DTM) generation and this step poses the greatest challenge especially for tropical forest environment which consists of steep undulating terrain and mostly covered by a relatively thick canopy density. The aim of this research is to assess the performance of the Progressive Morphological (PM) algorithm after the implementation of local slope value in the ground filtering process. The improvement on the PM filtering method was done by employing local slope values obtained either using initial filtering of airborne LiDAR data or ground survey data. The filtering process has been performed with recursive mode and it stops after the results of the filtering does not show any improvement and the DTM error larger than the previous iteration. The revised PM filtering method has decreasing pattern of DTM error with increasing filtering iterations with minimum ±0.520 m of RMSE value. The results also suggest that spatially distributed slope value applied in PM filtering algorithm either from LiDAR ground points or ground survey data is capable in preserving discontinuities of terrain and correctly remove non-terrain points especially in steep area.

Keywords: Airborne LiDAR, LiDAR Filtering, Progressive Morphology, Slope, Tropical Area

1. Introduction

Light Detection and Ranging (LiDAR) is an active remote sensing technique that is able to map various activities of the earth's surface and features such as vegetation and building, which also provides digital terrain model (DTM) with up to sub-meter vertical accuracy (Bater & Coops, 2009; Lin et al., 2013; Ismail et al., 2015). LiDAR with high resolution data can be used in generating the DTM and digital surface model (DSM) which is important to support wide range of applications such as engineering projects, hydrology and floodplain management, corridor mapping. By applying suitable processing technique, a high quality of DTM can be generated from LiDAR data (Cui et al., 2013; Andersen et al., 2016; Rahmayudi & Rizaldy, 2016). Hence, an effective of LiDAR data processing is important to all applications. However, the classification of point cloud also known as LiDAR data filtering which focusing on the ground and non-ground points separation are very crucial to most of the applications (Liu, 2008; Cui, 2013; Li et al., 2014). LiDAR data filtering becomes more challenging especially at high relief area or hybrid geographic features (Li, 2013) and complex configuration with geometrical similarities of ground and objects points (Sithole & Vosselman, 2004; Zhang & Whitman, 2005; Silván-Cardenás & Wang, 2006; Li, 2013; Li et al., 2014).

Although dozens of filtering algorithms have been developed to separate ground points from the land features, the difficulties in ground points extraction still exist where most of the algorithms need specific condition to produce good results (Meng et al., 2010; Uysal & Polat, 2014). The performance of LiDAR ground filtering methods is variable at different areas and terrain surface (Meng et al., 2010; Zhang et al., 2016). This study focuses on the development of revised Progressive Morphology (PM) algorithm which used spatially distributed slope value as one of the parameter for ground point extraction.

2. Methodology

2.1 Description of Study Area

The study area are generally characterized by tropical vegetated region (Figure 1 and Figure 2). It is located at Simpang Pelangai, Bentong (3°10'32.1"N 102°11'35.1"E) in Pahang which characterized by complex and rough terrain surface. This study area contains about 1.39 ha of rubber trees. The terrain characteristics at Simpang Pelangai are also significant to this research where the slope ranges between 0° to 20°. All these characteristics support the selection of this study area in conducting this study.

Figure 1 Map of Study Area

Figure 2 Photos taken over study area

2.2 Data Collection

Two (2) main types of data have been used in this study. First, airborne LiDAR data that has been acquired in ASCII format comprised of *x, y, z* coordinates and intensity values in Rectified Skew Orthomorphic (RSO) Malaya coordinate system. The second data used in this study is ground surveyed data that came from ground survey technique by using total station. Airborne LiDAR data was collected on January 2013 utilizing REIGL laser scanner which mounted on a British Nomad aircraft. The data was conveyed in LAS format with average point density about 2.15 points per meter square. Table 1 shows the description of airborne LiDAR data.

Table 1 Description of airborne LiDAR data

Characteristics	Description
Area (hectare)	1.39
Number of points	27991 points
Average Point density (per m^2)	2.15
LiDAR system	RIEGL LMS-Q560
Flying Height	1,000 m from Mean Sea Level
Flying Date	January 2013
Coordinate system	RSO Malaya Meters
File format	ASCII format (x,y, and z coordinates)
Sources	Jurukur Teraju

Ground control points (GCP) was collected by using field survey technique. The instrument used is Nikon Total Station with an optical levelling capability. The total number of GCPs collected is 126 points. Most of the GCPs gathered were under forested canopy and slope area. This is important in order to avoid bias from undesirable conditions or environments such as flat area open area, etc. Further description of ground survey data as shown in Table 2.

Table 2 Description of ground survey data

Characteristics	Description
Number of points	126 points
Instrument	Topcon total station
Date of data acquisition	2 April 2013
Sources	Cadastral Surveying & Engineering Laboratory, FGHT, UTM
Coordinate system	RSO Malaya Meters
File format	ASCII format (x,y, and z coordinates)

Airborne LiDAR data was directly used in data processing which discussed in the next section. Aerial photograph that was obtained during airborne LiDAR data collection by capturing the image of scanning area. This data in Tagged Image File (TIF) format is important as a reference to show the land cover of the study area. All the data are vital to accomplish the aim and objective of this study.

2.3 Airborne LiDAR Filtering

At this stage, an existing PM filtering algorithm has been enhanced and adapted to filter airborne LiDAR data over tropical area. The improvement considers the effect of slope towards the performance of the algorithm. The parameter of slope has been used as a constant be replaced with spatially distributed slope value. Generally, PM algorithm requires some input values; i) cell size (c); ii) slope (s), iii) initial elevation difference threshold (dh_o), iv) maximum elevation threshold (dh_{max}), v) window base (b), and vi) iteration (k). All these parameters have their significant role in filtering LiDAR data.

Slope value is important in deriving the difference elevation threshold (dh_T) value for ground filtering procedure. This value used in determining LiDAR point clouds for each grid cell either belong to ground points or non-ground points (see equation 1). Therefore, the local slope value should be used in order to make sure the filtering process produce accurately filtering results. Hence, equation (1) has been replaced with the individual or spatially distributed slope value of each point as shown in equation (2).

$$dh_T = s(w_k - w_{k-1})c + dh_o \quad (1)$$

$$dh_{T_{ij}} = s_{ij}(w_k - w_{k-1})c + dh_o \quad (2)$$

where;
dh_T = elevation difference threshold;
dh_{Tij} = elevation difference threshold for specific grid;
s = slope;
s_{ij} = spatially distributed slope;
w_k = window size;
c = cell size; and
dh_o = initial elevation difference threshold.

The filtering process was performed iteratively. Each process needs to include the slope value that generated from each iteration until the lowest error of LiDAR-derived DTM obtained. Figure 3 describes the procedure of employing spatially-distributed slope value into PM algorithm.

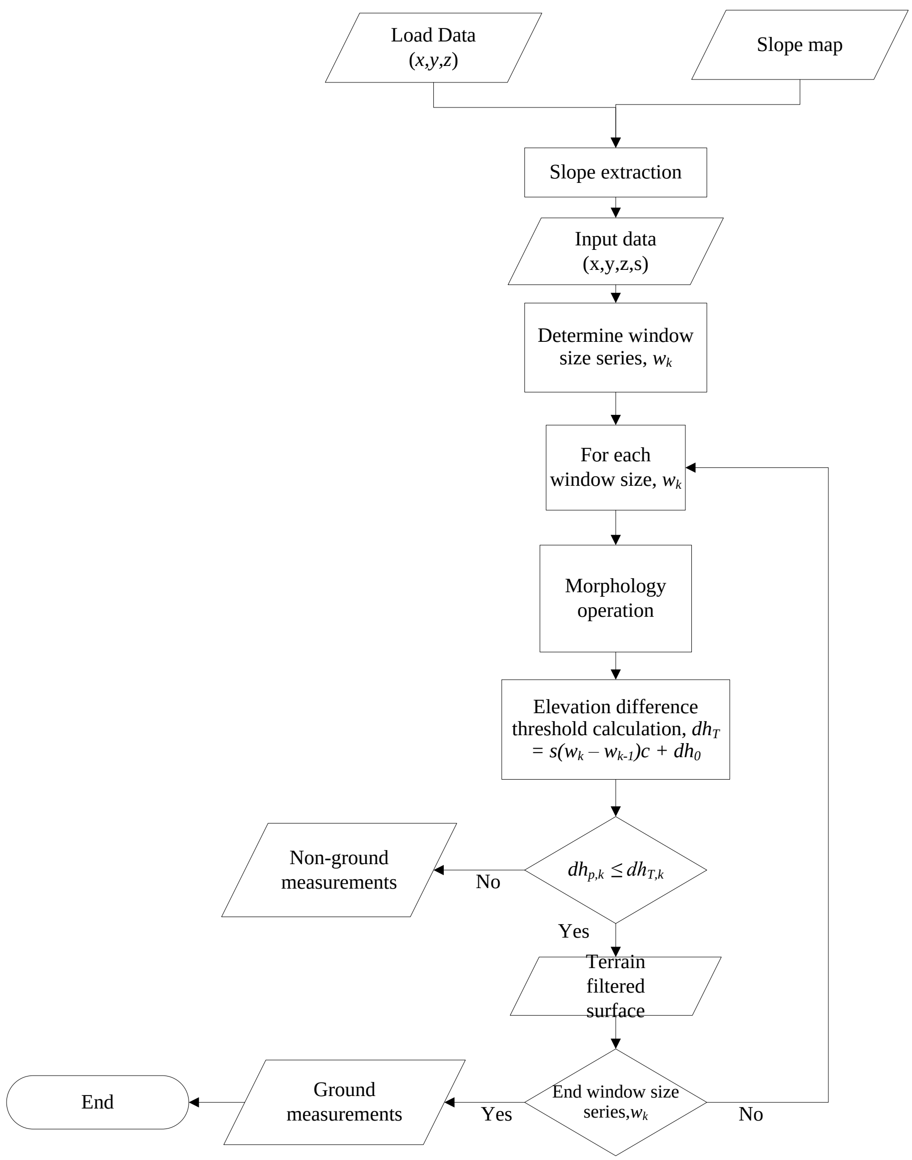

Figure 3 Procedure of employing spatially-distributed slope value into PM algorithm

According to Figure 3, the process is initiated by loading the airborne LiDAR data and producing slope map from ground survey data. This procedure continues with extraction of slope value into raw LiDAR point clouds. Finally, each point clouds should consist of *x,y*, and *z* coordinates couple with slope value. Next, the filtering process continues with determination of window size series (*wk*). This window size series is important in order to gradually increase the window size in removing object points and preserving ground points. Then, for each window size morphology opening operation is applied to the filtered surface to produce smoothed surface. This opening operation with gradually increasing the window size is able to remove object points effectively. Elevation difference threshold utilized to avoid removal of ground points. Any elevation difference of LiDAR points (dh_p) lower than elevation difference threshold (dh_T) considered as ground measurements and vice versa. The dh_T value was determined using spatially distributed slope value which consider local and realistic terrain condition. The implementation of the algorithm in this study is explained as follows:

1. Slope map generation (*rise/ run*).
2. Extraction of slope value into LiDAR points.
3. Create a 2-D array *A[m, n]* for LIDAR points, *p*(*x, y, z, s*)
4. Determine series of *wk* using (4) or (5), where *wk* ≤ maximum window size.
5. $dh_T = dh_0$
6. for each window size *wk*
7. *Pi* = *A[i;]* (*A[i;]* represents a row of points at row *i* in *A* and *Pi* is a 1-D array)
8. *Z* ← *Pi* (Assign elevation values from *P* to a 1-D elevation array *Z*)
9. *Zf* = erosion(*Z;wk*)
10. *Zf* = dilation(*Zf;wk*)
11. *Pf* ← *Zf* (Replace *z* values of *Pi* with the values from *Zf*)
12. *A[i;]* = *Pi* (Put the filtered row of points *Pi* back to row *i* of array *A*)
13. $dh_T = s(wk - wk\text{-}1)c + dh_0$ [*s* represents a spatially distributed slope value]
14. end for window size loop
15. for *i* = *1* to *m*
16. for *j* = *1* to *n*
17. if (*B[i;j]*(x) > 0 and *B[i;j]*(*y*) > 0)
18. if (flag*[i;j]* = 0)
19. *B[i;j]* is a ground point
20. else
21. *B[i;j]* is a non-ground point
22. end for *j* loop
23. end for *i* loop

This approach continues with the generating of slope map that further used in the next iteration until the lowest RMSE obtain which indicates as most accurate results.

3. Result and Discussion

This section is going to discuss the performance of revised PM filtering algorithm. Various number of ways to quantify errors in LiDAR data and DTM using empirical procedures. One of the standard methods is to specify the height errors in the vertical plane. This involves comparing the height or elevation of LiDAR-derived DTM against the height or elevation at a reference point. However, this approach was a challenging technique due to the lack of ground reference data. Hence, this study also utilizes qualitative assessment to support quantitative assessment procedure. Table 3 depicts the assessment of revised PM algorithm.

Table 3 Assessment of LiDAR derived DTM for different iteration of filtering by employing spatially distributed slope map using revised PM filtering algorithm

Iteration	RMSE (m)	MAE (m)	MBE (m)	Type I (%)	Type II (%)	Total Error (%)
1	±0.546	0.374	-0.363	29.17	0.05	3.19
2	±0.529	0.366	-0.355	29.51	0.06	3.25
3	±0.527	0.367	-0.349	29.55	0.05	3.25
4	±0.524	0.365	-0.346	29.51	0.06	3.25
5	±0.528	0.367	-0.349	29.51	0.06	3.25
6	±0.560	0.389	-0.345	29.51	0.06	3.25
7	±0.589	0.407	-0.347	29.55	0.06	3.25

**The green row considered as the best result*

Referring to Table 3, the experimental results show the significant results from this implementation. The root mean square error (RMSE) values ranges from ±0.524 m to ±0.589 m. This value is relatively high which caused by the tropical vegetation characteristics. The RMSE value for the first iteration is ±0.546 m and decreased to ±0.529 m and ±0.527 m for second and third iteration, respectively. The fourth iteration recorded the lowest RMSE value of ±0.524 m and increased to ±0.528 m, ±0.560 m, and ±0.589 m for the rest of iterations. When compared with mean absolute error (MAE), there are high deviations from RMSE value indicating that RMSE is affected by extreme value. High deviation was mainly contributed from high canopy density. High canopy density tends to create large error of filtering results due to small number of point clouds able to penetrate high dense canopy surface. Figure 4 illustrates the sample of residual distribution of LiDAR-derived DTM for the first iteration at different canopy classes.

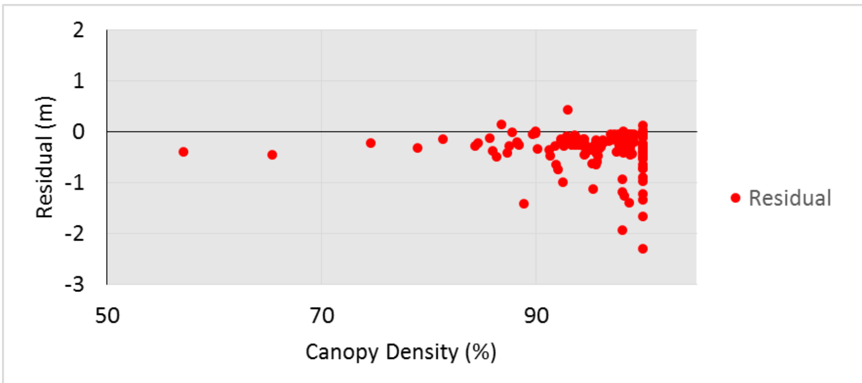

Figure 4 Residual distribution of LiDAR derived DTM based on canopy classes

According to Figure 4, many extreme values were concentrated at canopy class three (90% - 100%). In order to avoid the effect of this phenomenon, MAE serve as a better indicator in explaining the results. The lowest MAE value observed at the fourth iteration with 0.365 m. On the other hand, the largest MAE value (0.407 m) has been recorded at seventh iteration. The negative Mean Bias Error (MBE) value for this dataset reveals that underestimated of DTM produced at the end of result for all iterations.

The ranges of Type error for Type I (29.17 percent to 29.55 percent), Type II error (0.05 percent to 0.06 percent) and Total error (3.19 percent to 3.25 percent) show no significant changes of the results throughout iterations. For qualitatively visual assessment, the DTMs produced from the first iteration to the fifth iteration considered as perfectly represents the real landscape with very small bumps and pits whereas an increasing the number of bumps exists for the DTM generated under the sixth and the seventh iteration.

For the purpose of comparing the performance of revised PM algorithm with the other prominent filtering algorithms (i.e. existing PM, ETEW, and ATIN), five type of assessments have been assessed in measuring the performance of filtering methods (i.e. RMSE, Type I, Type II and Total Error, and visual assessment). Table 4 shows the comparison between revised PM algorithm and other prominent algorithms.

According to the Table 4, the results obtained using revised PM algorithm were compared with those obtained using prominent filtering algorithms (i.e. existing PM, ETEW, ATIN). The lowest RMSE value recorded from the revised PM algorithm was ±0.524m. Compared with the RMSE values of other filtering algorithms, revised PM algorithm generated promising and competitive results. Approximately 9 cm error was reduced. The quantitative assessment shows a quite similar trend. The computed errors (over all the datasets) ranged from 27 percent to 32 percent, 0 percent to 0.13 percent, and 2 percent to 10 percent for Type I, Type II, and Total errors, respectively. Most of the filters focus on minimizing

Table 4 Comparison of RMSE, Type I, Type II, Total errors and qualitative assessments of revised PM and selected algorithms

Assessment methods	Existing PM	ETEW	ATIN	Revised PM
RMSE (m)	±0.608	±0.614	±0.66	±0.524
Type I Error (%)	31.22	27.00	23.56	29.17
Type II Error (%)	0.03	0.13	0.07	0.05
Total Error (%)	3.49	2.94	9.35	3.19
Visual Assessment Good 1 2 3 4 5 Poor	2	1	1	1

Type II errors. In other words, filter parameters and procedure focusing on removing as many object points as possible. In term of qualitative assessment, all the filtering algorithms produce reasonable DTM quality. The best setting parameters should be used to produce a good result. In general, revised PM capable in filtering the LiDAR data over vegetated tropical region by applying spatially distributed slope value from LiDAR ground points.

4. Conclusion

Ground filtering is a fundamental issue in LiDAR processing which significantly affect the quality of DTM and other LiDAR-related deliverables. There are many studies that have been done in tackling this issue. However, this issue still not fully solved especially at a complex terrain area. This study demonstrated a procedure or improvement in filtering airborne LiDAR data using PM algorithm over tropical forest region. This improvement pertaining to include the spatially distributed slope value in PM algorithm. The algorithm was tested in specified area with tropical forest characteristics such as rugged and undulating terrain covered by vegetation, etc. The performance of revised PM filtering method was evaluated using quantitatively and qualitatively approaches. The results revealed that several significant advantages of revised PM method where the error of LiDAR-derived DTM getting lower compare to the other prominent algorithms.

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