

# AN IMPROVED PROGRESSIVE MORPHOLOGICAL FILTERING ALGORITHM BASED ON SPATIALLY-DISTRIBUTED SLOPE VALUE OVER TROPICAL VEGETATED REGIONS

## Article history

Received  
6 June 2015  
Received in revised form  
27 August 2015  
Accepted  
20 October 2015

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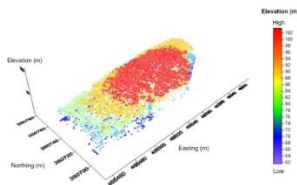
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## Graphical abstract



## Abstract

This paper presents a thorough investigation on integrating slope map on the existing progressive morphological filtering algorithm for ground point's extraction. The existing filtering algorithm employs constant slope value for the entire area. The slope map is either generated from field collected elevation data or ground point obtained from initial filtering of airborne LiDAR 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 results show that both data used for slope map generation have decreasing pattern of DTM error with increasing in filtering iteration. The spatially-distributed slope map has significantly improved the quality of the DTM compared to the results of filtering based on a constant slope value.

Keywords: Airborne LiDAR; slope map; progressive morphological filter; digital terrain model

## Abstrak

Kertas kerja ini membentangkan siasatan menyeluruh kepada penggunaan peta cerun dalam algoritma penapisan progresif morfologi yang sedia ada untuk pengekstrakan titik permukaan tanah. Algoritma penapisan yang sedia ada menggunakan nilai kecerunan malar untuk keseluruhan kawasan. Peta cerun dihasilkan samaada dari data ketinggian yang dikumpul di lapangan atau titik permukaan tanah yang diperolehi daripada penapisan awal data LiDAR udara. Proses penapisan telah dilakukan dengan teknok lelaran dan akan berhenti selepas keputusan penurasan tidak menunjukkan sebarang peningkatan dan kesilapan DTM lebih besar daripada lelaran sebelumnya. Keputusan menunjukkan bahawa kedua-dua data yang digunakan untuk penghasilan peta cerun mempunyai corak ralat DTM yang berkurangan dengan peningkatan dalam lelaran penurasan. Peta cerun dengan ketara meningkatkan kualiti DTM berbanding keputusan penurasan berbanding dengan kaedah penurasan menggunakan nilai cerun malar.

Kata kunci: LiDAR platform udara; peta cerun; penurasan progressive morfologi; model permukaan bumi digital

## 1.0 INTRODUCTION

Tropical forests can be considered as the most structurally complex forest compare to other types of forest and it also are experiencing rapid change due to climate factors and anthropogenic [1]. This complexity is caused by the distribution of woody stems and the arrangements of tree elements such as leaves, branches, trunks etc. Researches on the structures of tropical forest have been done using a variety of approaches such as remote sensing applications. Nowadays, remote sensing is widely used in determining the forest parameters for various applications where LiDAR technology is one of the most commonly approach in deriving all the important forest parameters. LiDAR is an active remote sensing technique that 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 [2]. In addition, LiDAR is emerging as a technology of choice due to high accuracy of the products [3] and low cost per unit area over large areas which is lower than other methods such as aerial photogrammetry. Besides that, the ability of LiDAR signal to penetrate the vegetation canopy [4] make this technique much better than other techniques.

However, it has been reported that the LiDAR technology is capable of delivering the digital information with certain accuracy where the error of LiDAR data and products (e.g. DTM, DSM, CHM) might be come from various sources of errors such as LiDAR system measurements, horizontal displacement, interpolation error, and surveyor error [5]. The error also introduced in data handling and processing stage where caused by interpolation and filtering errors [6]. The difficulties for major filtering algorithms including dense vegetation on slopes area, high surface roughness, low vegetation, etc. [7]. Area with rough terrain, dense forest with low vegetation areas is often ignored by major filtering algorithms [8]. These condition are predominantly observed in tropical forest regions [9].

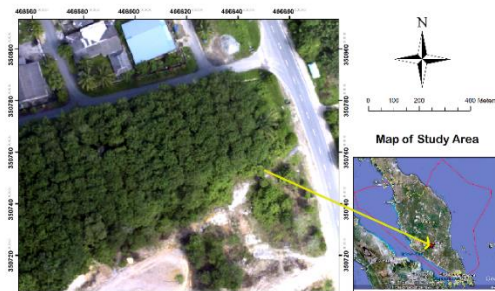
Progressive morphological filtering method is one of the widely used techniques in extraction of airborne LiDAR ground points. This algorithm have the ability to eliminate building and vegetation by increasing window size gradually [10] and this filter works well in an urban setting with a gentle slope and a mixture of vegetation and buildings [11]. However, this filtering algorithm does not perform well at the topographic high area because it often removes ground points incorrectly due to constant threshold slope value used which resulting to cut-off errors [11]. Besides that, omission error is obvious because of the actual slope value is greater than inserted slope value [12]. Therefore, this paper presents a modified method of Progressive Morphological LiDAR data filtering

algorithm in order to reduce an error of LiDAR-derived DTM over tropical forest area by including spatially distributed slope value into the algorithm.

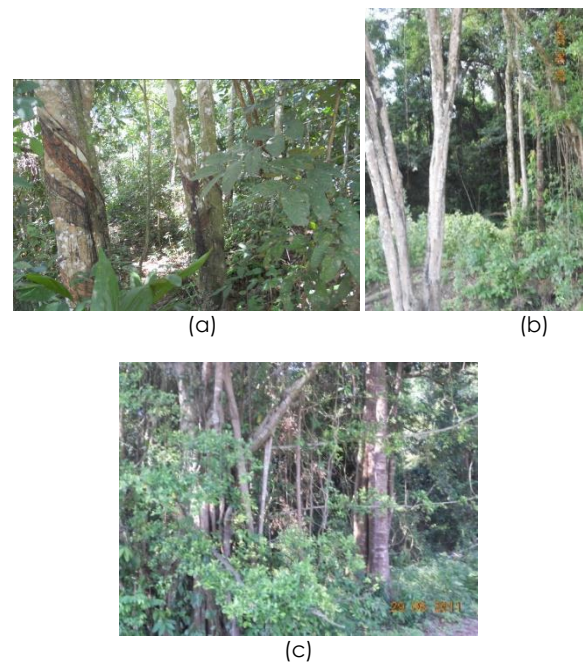
## 2.0 MATERIAL AND METHODS

### 2.1 Description of the Data and Study Area

The study area is located in the south-west of Bentong District, State of Pahang, Malaysia (see Figure 1). This area mostly covered by rubber trees with moderately dense understorey vegetation and mixed forest (Figure 2a, 2b, and 2c). The total study area is about 400 m<sup>2</sup> and it is characterized by irregular topography with slope gradient range between 0° and 20°.



**Figure 1** Study area in Bentong District, State of Pahang, Malaysia



**Figure 2** Examples of photograph taken for study site covered by rubber trees (a and b) with understorey vegetation (c)

The LiDAR data were (Figure 3) collected on January 2009 using an REIGL laser scanner mounted on a British Nomad aircraft. The data were delivered in the classified LAS format of three-dimensional point cloud. The average LiDAR data sampling density across the area is about 2.2 points per meter m<sup>2</sup>. The total area covered by the LiDAR campaign is approximately 1.4 ha.

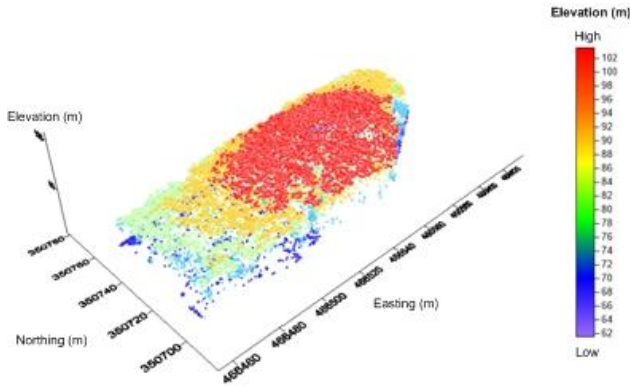


Figure 3 Airborne LiDAR data over study area

In this study the ground elevation data (Figure 4) is used to validate the elevation value obtained from LiDAR derived DTM.

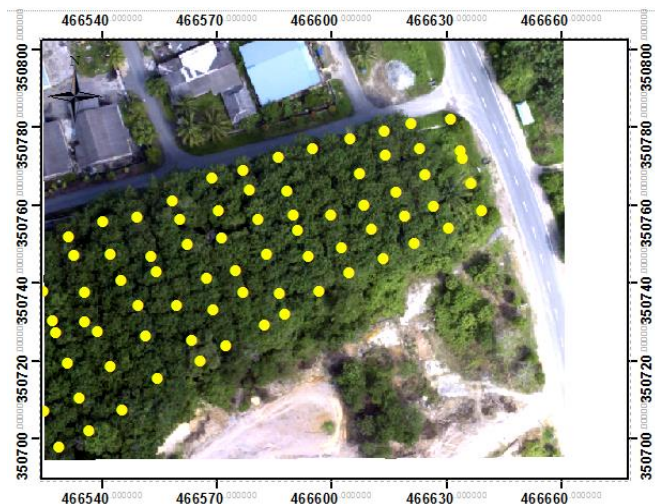


Figure 4 Ground elevation data (yellow points) observed over study area

The ground elevation measurements were carried out using a Nikon Total Station with an optical levelling technique. In total, there is about 126 surveyed ground reference points (GRP) were collected in year 2012. The measurement points were distributed at a distance between 10 and 15 meter from each other.

## 2.2 Progressive Morphological Airborne LiDAR Filtering Based On Spatially Distributed Slope Value

In order to fulfill the filtering algorithm objectives, the development process is divided into two main parts. First part is concerned with generating the slope map and another part concerned on employing the spatially distributed slope value for point clouds filtering process. This development consider the effect of slope towards the performance of the algorithm due to the significant effect of terrain slope on the accuracy of LiDAR derived DTM [13]. Thus, slope parameter which is used as a constant value in existing algorithm been replaced with spatially distributed slope value. The general flow process of this development can be seen in Figure 5.

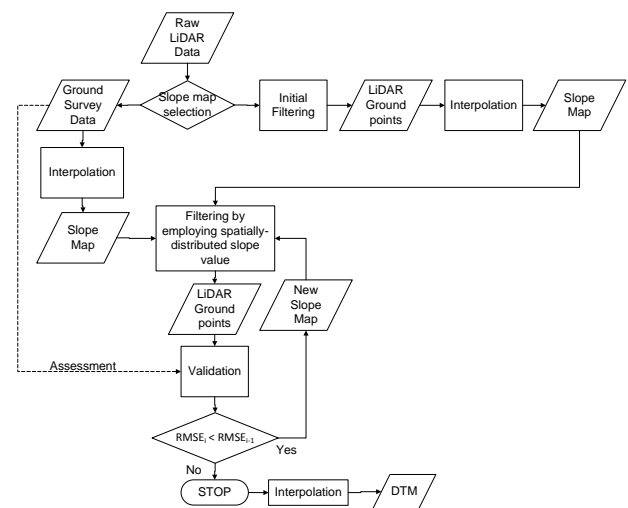
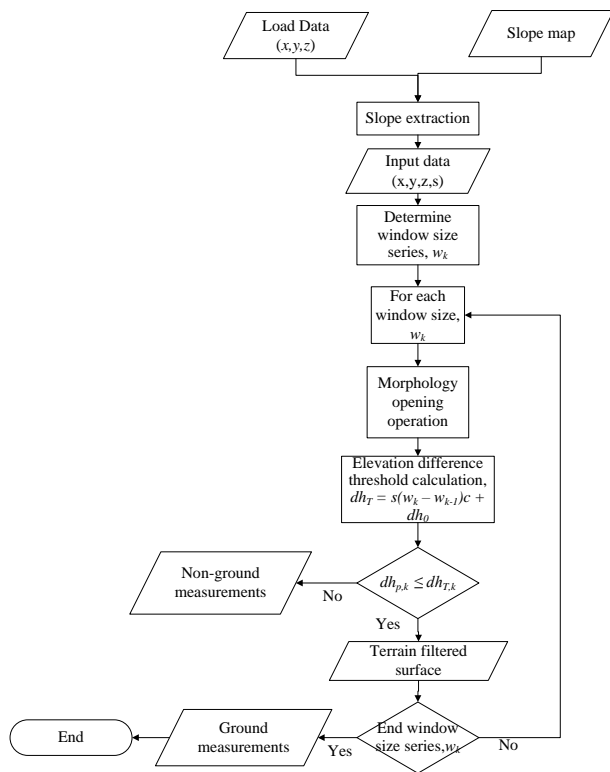


Figure 5 General flow chart of employing spatially distributed slope value into Progressive Morphological technique

According to Figure 5, the filtering process started by loading the airborne LiDAR data in ASCII format which contains with x,y coordinates and elevation then followed by generating the slope map either from two different sources of data; (i) raw LiDAR data, or (ii) ground survey data. In case there is no ground survey data collected, the raw airborne LiDAR data need to be filtered to produce LiDAR ground points and DTM. The slope map is generated from the DTM data. Otherwise, ground survey data are preferred because of slope map generated from ground survey data will produce more accurate results than generated from ground points of LiDAR data. However, ground survey data is quite difficult to be acquired especially in tropical forest area due to the environment factors such as undulating terrain and bulk density of vegetation canopy coupled with high cost and time. Therefore, slope map derived from ground points of LiDAR data is sufficient in enhancing the performance of progressive morphological filtering algorithm. Next, the raw LiDAR data has been processed using an improved method by including the spatially

distributed slope value as one of the parameter in extracting the LiDAR ground points. The filtering process is performed as an iterative module and each iteration need to be feed with the spatially distributed slope value generated from LiDAR ground points of the previous iteration. The process will continue until we reach at the lowest error of LiDAR-derived DTM. The error of LiDAR derived DTM is calculated by using Root Mean Square Error (RMSE) which compared the elevation value of the DTM with the ground survey data. Figure 6 shows the flowchart or procedure in employing spatially distributed slope value into progressive morphological technique.



**Figure 6** Procedure in employing spatially distributed slope value into Progressive Morphological technique

Based on Figure 6, the filtering process starts by loading airborne LiDAR point clouds data and generating the slope map. This procedure continues with the inserting slope value into raw airborne LiDAR point clouds which finally gives each point cloud with  $x$ ,  $y$ ,  $z$  coordinates and slope value. Next, the process continue with the creation of minimum surface grid and followed by determination of window size series ( $w_k$ ) which is important in order to gradually increase the window size for removing object points and preserving ground points. Then, morphology opening operation is applied to the grid surface for all window size series. An elevation difference threshold ( $dh_T$ ) in equation (1) used as a method of avoiding from

removing ground points and preserving object points mistakenly.

$$dh_T = s(w_k - w_{k-1})c + dh_0 \quad (1)$$

where;

$dh_T$  = elevation difference threshold;

$s$  = slope;

$w_k$  = window size;

$c$  = cell size and;

$dh_0$  = initial elevation difference threshold.

Any elevation difference of LiDAR points ( $dhp$ ) lower than elevation difference threshold ( $dh_T$ ) considered as ground measurements and vice versa. However, an existing progressive morphological algorithm use constant slope,  $s$  value in determining the  $dh_T$  value which become a challenging for steep area. Thus, the spatially-distributed slope values are applied in order to increase the effectiveness of  $dh_T$  value. The process is repeated for all the window size series. The implementation of the algorithm in this study is further explained as follows:

#### Input:

- A set of points representing LiDAR measurements. Each point has three components ( $x$ ,  $y$ , and  $z$ ) to represent horizontal coordinates and elevation of a LiDAR measurement
- Slope map,  $s$
- Cell size,  $c$
- Initial elevation difference threshold,  $dh_0$
- Maximum elevation difference,  $dh_{max}$
- Window base,  $b$
- Power increment,  $k$

#### Implementation:

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  $w_k$  using (4) or (5), where  $w_k \leq$  maximum window size.
5.  $dh_T = dh_0$
6. for each window size  $w_k$
7.  $P_i = A[i;]$  ( $A[i;]$  represents a row of points at row  $i$  in  $A$  and  $P_i$  is a 1-D array)
8.  $Z \leftarrow P_i$  (Assign elevation values from  $P$  to a 1-D elevation array  $Z$ )
9.  $Z_f = \text{erosion}(Z; w_k)$
10.  $Z_f = \text{dilation}(Z_f; w_k)$
11.  $P_i \leftarrow Z_f$  (Replace  $z$  values of  $P_i$  with the values from  $Z_f$ )
12.  $A[i;] = P_i$  (Put the filtered row of points  $P_i$  back to row  $i$  of array  $A$ )
13.  $dh_T = s(w_k - w_{k-1})c + dh_0$  [ $s$  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

At the end of the filtering implementation, a set of ground points of LiDAR data is produced and the data need to be interpolated for DTM generation and assessment purpose. The process is repeated using newly slope map generated from the previous LiDAR ground points until the lowest error obtained.

### 2.3 Generation of Digital Terrain Model (DTM)

In the phase of DTM generation, the LiDAR ground points obtained from the phase of filtering are interpolated with a 1.0 m spatial resolution using Kriging interpolation method. Kriging is an advanced geostatistical procedure that generates an estimated surface from a scattered set of points with z-values.<sup>18</sup> <sup>19</sup> It is based on the regionalized variable theory that assumes that the spatial variation in the phenomenon represented by the z-values is statistically homogeneous throughout the surface.

### 2.4 Accuracy Assessment of LiDAR-derived DTM

For the assessment purpose, the DTM generated from LiDAR ground points is assessed by using Root Mean Square Error (RMSE), Mean Absolute Error (MAE) and Bias calculation as shown in Equation (2) to Equation (4). The use of ground survey data are the most common method for estimating the accuracy of LiDAR data. In this study, the quality of DTM is expressed in terms of vertical accuracy which is how close the LiDAR technique to the reference value established from in-situ ground survey technique.

$$RMSE = \sqrt{\frac{\sum_{i=1}^n (Z_{DTM_i} - Z_{GCP_i})^2}{n}} \quad (2)$$

$$MAE = \frac{\sum_{i=1}^n |Z_{DTM_i} - Z_{GCP_i}|}{n} \quad (3)$$

$$Bias = \frac{\sum_{i=1}^n (Z_{GCP_i} - Z_{DTM_i})}{n} \quad (4)$$

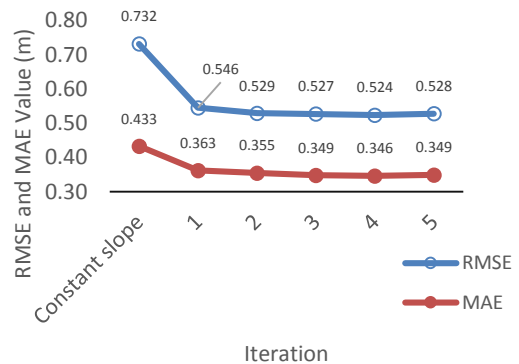
where  $n$  is the number of samples,  $Z_{DTM}$  is the terrain elevation obtained from the LiDAR-derived DTM,  $Z_{GCP}$  is ground measured elevation.

## 3.0 EVALUATION OF THE MODIFIED GROUND FILTERING ALGORITHMS

The main task for this phase is to make an assessment of the results for filtering process after incorporating the spatially distributed slope value into Progressive Morphological algorithm. The includes the assessment of number of iteration, consistency and RMSE value of improved Progressive Morphological technique in performing filtering process of airborne LiDAR data for selected areas which are characterized by tropical forest area. We will also compare the capability of slope map derived from initial filtering of LiDAR data and field collected elevation data. Table 1, Table 2, Figure 7 and Figure 8 show the results obtained from the improved method.

**Table 1** RMSE, MAE and Bias of LiDAR derived DTM for different iterations of filtering by employing slope map generated from LiDAR data

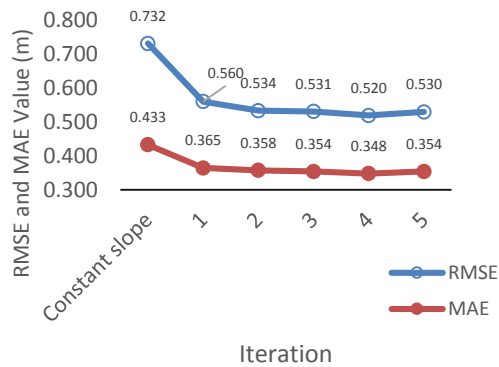
Iteration	RMSE (m)	MAE (m)	BIAS
Constant slope	0.732	0.433	0.002
1	0.546	0.363	0.0018
2	0.529	0.355	0.0018
3	0.527	0.349	0.0019
4	0.524	0.346	0.0019
5	0.528	0.349	0.0018



**Figure 7** Graph of RMSE and MAE for LiDAR derived DTM for different iterations of filtering process by employing slope map generated from airborne LiDAR data

**Table 2** RMSE, MAE and Bias of LiDAR derived DTM for different iterations of filtering by employing slope map generated from ground survey data

Iteration	RMSE (m)	MAE (m)	BIAS
Constant slope	0.732	0.433	0.002
1	0.560	0.365	0.002
2	0.534	0.358	0.0018
3	0.531	0.354	0.0018
4	0.520	0.348	0.0019
5	0.530	0.354	0.0018



**Figure 8** Graph of RMSE and MAE for LiDAR derived DTM for different iterations of filtering process by employing slope map generated from ground survey data

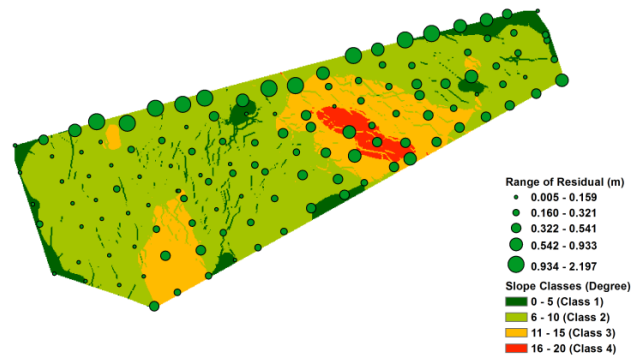
The experimental results show that the filtering technique proposed in this paper has significantly improved the filtering results compared to the constant slope value. Airborne LiDAR filtering based on the constant slope value marks 0.732m RMSE that is significantly high compared to the rest of the results based on spatially distributed slope map. Both sets of slope data have given consistent results with decreasing RMSE value by increasing the iteration. For the slope map derived from airborne LiDAR data, the elevation error ranges from 0.546 m to 0.524 m. This DTM error is relatively high due to typical tropical vegetation condition. The lowest error was observed at 4<sup>th</sup> iteration (0.524 m) and it was a slightly increase in 5<sup>th</sup> iteration (0.4 cm) at with 0.528 m RMSE.

The MAE values show some gaps with the RMSE, which reflects several extreme residuals between DTM and field collected data. In this case, to avoid the effect of this residual, the error in DTM can be explained by the MAE values. The lowest MAE value is at the 4<sup>th</sup> iteration with 0.346m. On the other hand, the largest MAE value (0.433m) has been obtained for ground filtering with constant slope value. In general based on the bias calculation each iteration and filtering process has produced a DTM with very low underestimation with values approach to zero.

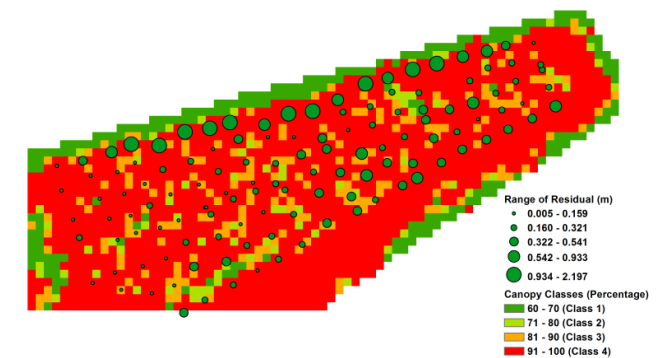
Similar situation observed for slope map derived from the ground survey data. Based on the results as shown in Table 2 (also in Figure 8), the RMSE value of LiDAR-

derived DTM were decreased across all the iterations where the lowest error recorded at 4<sup>th</sup> iteration (0.520 m) and slightly increased with 1 cm at 5<sup>th</sup> iteration (0.530 m). The MAE value for each DTM produced by the filtering process marks some gaps with the calculated RMSE. As stated earlier in previous results this might due to the several extreme residual values between DTM and reference data. The lowest MAE value observed at the 4<sup>th</sup> iteration with 0.438m and the largest MAE (0.433) marked by the filtering process with constant slope value. The filtering process has been successfully produced DTMs with very small underestimation of elevation values.

The results produced by the slope map derived from ground elevation data are comparable to the LiDAR-derived slope map. This clearly shows that the slope map is unnecessarily derived from intensive ground data collection, in which comparable results are attainable by carefully filtering the airborne LiDAR data in the first iteration. However more accurate slope map as derived from ground elevation data is still necessary to be used together with ground data generated from airborne LiDAR data for better slope map production. The results show that more accurate slope map generated using field collected data gives slightly better results compared to slope value obtained from airborne LiDAR. In general large elevation residuals between DTM and field collected data has been found at steep area and area covered by dense vegetation (Figure 9 and Figure 10).



**Figure 9** Example of elevation residuals distribution (obtained from 4<sup>th</sup> iteration of filtering) between DTM and reference data with different slope classes of the study area



**Figure 10** Example of elevation residuals distribution (obtained from 4<sup>th</sup> iteration of filtering) between DTM and reference data with different vegetation canopy cover classes of the study area

## 4.0 CONCLUSION

Ground filtering is one of the important issues in LiDAR related researches. There have been tremendous amount of researches tried to tackle this issue [14]. However, this issue has not been fully solved especially at complex terrain area of tropical vegetated environment. This study demonstrates a novel framework to improve the filtering process airborne LiDAR data by upgrading the existing Progressive Morphological algorithm over tropical forest region.

The improvement pertains on the inclusion of the spatially distributed slope value instead of constant slope value in existing algorithm. The improved filtering procedure has been tested in specified study area with tropical vegetated terrain characteristics i.e. rugged and undulating terrain covered by dense vegetation. The results show significant improvement on DTM accuracy and slope map generated using airborne LiDAR data is enough to produce comparable results as the map obtained from more accurate field data. This is very useful for inaccessible area where acquisition of field data is very limited.

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