FILTERING OF AIRBORNE LIDAR POINT CLOUD USING GRAPHICAL MODEL

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ABSTRACT: The development of robust and accurate filtering approach for automated extraction of digital terrain model from airborne LiDAR data continues to be a challenge. The problem is due to the nature of LiDAR point cloud, the complexity of scene components, and the intrinsic structure of terrain itself. This paper proposes a novel approach for filtering LiDAR data based on graphical model for energy minimization, which exploits spatial structure among raw point cloud for progressive segmentation. The energy model encodes both point-wise closeness and pair-wise smoothness as soft constraints to achieve high segmentation accuracy and help to alleviate the ambiguities on segment boundary. The needs for predefined hard constraints, which are not always attainable by users, are avoided. The formulation of point cloud filtering with energy minimization is firstly introduced, after which the optimization using graph cuts is presented. The definition of energy functions and the construction of graph model are proposed, taking into account the spatial coherence of neighboring terrain structure. The proposed approach has been tested in a number of datasets. The experimental results are reported and discussed. These results demonstrate the efficiency and the potential of the proposed approach for improved filtering of LiDAR point clouds.

1. INTRODUCTION

Digital Terrain Model (DTM) characterizes the geometry of the bare earth surface in terms of terrain shape and pattern. This digital model also provides virtual environment for a variety of applications. For instance, the DTM is one of the critical input data sets for predicting flooding in urban areas as it influences the flood direction, flood extends and flow velocity to simulate flood physics (Abdullah et al., 2009). In addition, DTM has been extensively utilized as contextual information for subsequent processing such as object classification (Xu et al., 2014) and 3D urban reconstruction (Alharthy and Bethel, 2002).

Airborne Light Detection and Ranging (LiDAR), also referred to as airborne laser scanning (ALS), is a widely used technology for the acquisition of fast and reliable elevation data. The LiDAR data directly delivers a set of geo-referenced point cloud over large areas with high accuracy and high resolution (Baltsavias, 1999), thus opens up an new geospatial applications ranging from building reconstruction (Oude Elberink and Vosselman, 2009) and forestry canopy mapping (Lee and Lucas, 2007) to heritage applications (Alshawabkeh, 2005). A comprehensive introduction of LiDAR technique and applications can be found in Vosselman and Maas (2010).

The raw LiDAR point cloud represents all visible landscape surfaces, also known as Digital Surface Model (DSM). Relevant measurements of the bare-earth surface have to be separated from the raw point cloud to obtain DTM. This can be time-consuming. Usually, over 60-80% of post-processing time is consumed on manual classification and quality control (Flood, 2001). Consequently, automated extraction of DTM from LiDAR data has generated much research interest over decades and intensive efforts have been conducted. The challenge of automated LiDAR data filtering to classify the laser returns from terrain and non-terrain surface is partially due to the complexity of the terrain, for instance, the co-existence of flat terrain and large size flat-topped buildings in urban areas (Meng et al., 2010), complex intrinsic structure of terrain with sharp discontinuity, such as dikes or cliffs (Sithole and Vosselman, 2003). Moreover, the unavoidable noises and irregular distribution of point cloud further complicates filtering. A comprehensive study and comparison can be found in Sithole and Vosselman (2004). Usually, methods fall into the four categories. LiDAR point cloud can be classified using the local slope information (Vosselman, 2000), or with region-based methods similar to those in classification of remote sensing imagery (Wack and Wimmer, 2002). These approaches treat each LiDAR point individually. In contrast, points can be grouped into segments according to some homogeneity criterion, and subsequently, the LiDAR point clouds can be classified with the segments (Tóvári and Pfeifer, 2005). LiDAR data can be also treated with surface-based filtering (Axelsson, 2000), where a set of ground points are identified to form the initial ground surface, and the DTM is then progressively generated by determining the rest ground points using a certain criteria. Recent attempts also include employment of hierarchical model to eliminate the effect of large buildings (Chen et al., 2013). In addition, efforts are made to determine parameters adaptively (Kim and Shan, 2011; Mongus and Žalik, 2012). Existing methods have their own strengths and weaknesses, and show varying degree of success on the test datasets with different landscape and environment types. Nevertheless, it is still a challenge for an approach to efficiently cope with a dataset over complex environment with mixed landscape and terrain types.

In this paper, a novel approach for filtering LiDAR data is proposed through energy minimization using graphical model, which encodes both point-wise closeness and pair-wise smoothness as soft constraints to achieve high segmentation accuracy and help to alleviate the ambiguity on segment boundaries. The spatial structure is adopted to provide contextual information as the terrain usually exhibits strong spatial coherence and the neighboring points support each other to maintain terrain continuity. The filtering works in a progressive manner to gradually refine ground surface, which exploits the current result for the optimization in the successive process. These are presented in the next Section. Afterwards, the experimental results of the proposed approach over a test site in Melbourne, Australia, are reported. Discussions then follow and the paper ends with a conclusion.

2. METHODOLOGY

Filtering LiDAR point cloud for the separation of terrain and non-terrain points is naturally analogue to binary labeling, where the data points are partitioned into two disjoint sets. Such labeling can be achieved through energy minimization by graph cut (Boykov and Jolly, 2001). Graph has proven to be an effective optimization tool which can enforce piecewise smoothness while preserving relevant sharp discontinuities. In particular, iterative graph cut allows automatic refinement of soft constraints with newly labeled points, resulting in more robust point cloud segmentation. The general scheme of the proposed iterative graph-cut based approach for segmentation of LiDAR point clouds is presented in Figure 1.

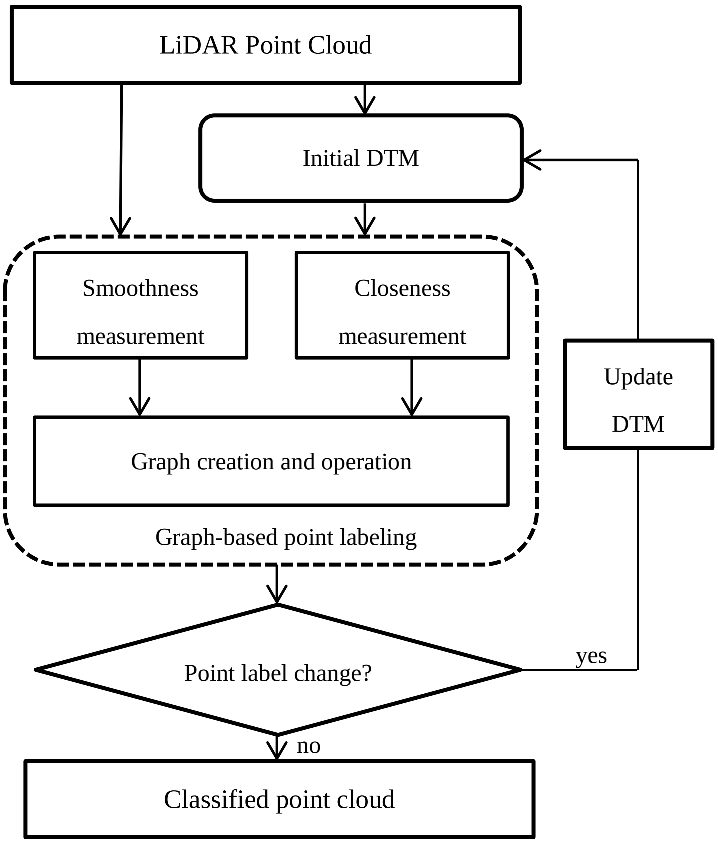

Figure 1**.** General scheme of LiDAR point cloud segmentation with iterative graph cuts.

The raw LiDAR point clouds undergo a process to detect the lowest point in a certain neighborhood. This will determine a set of sparsely distributed ground points over the scene, which produces a preliminary rough terrain surface. This process will also allow for detection of blunders and removal of outliers. The outliers are usually the occurrence of multi-path effect which generates extreme low height values (Sithole and Vosselman, 2004). In particular, negative outliers with extreme low height value to ground surface interfere with the assumption that lowest points in relative large area must belong to ground surface and should be removed. This is done with a method proposed in Silvan-Cardenas and Wang (2006). A graph is then constructed with the LiDAR points as nodes, and the links of the graph are determined by the point property in relation to the preliminary terrain surface and the spatial structure among points. The terrain and non-terrain points are then differentiated in an energy minimization procedure achieved by iterative graph cut. In each iteration, the newly identified ground points are added to the previous terrain surface, gradually densifying the terrain model. In turn, the improved terrain model enables refinement of the weights of the links in the graph, facilitating efficient identification of the rest ground points in the successive iteration. This process repeats until all ground points are identified and selected, therefore progressively completing the terrain model. In the following, the energy minimization and graph models are firstly presented. Afterwards, the definition of energy function and construction for LiDAR point cloud are discussed in detail.

2.1 Energy Minimization and Graph Cut

Let P denotes a set of LiDAR points. Each point $p \in P$ will be assigned a unique label in the label set L {"terrain point", "non-terrain point"}. The goal of segmentation is to find a labeling f that assigns each point $p \in P$ a label $f_p \in L$, where f is both piecewise smooth and consistent with the observed LiDAR data.

This labeling problem can be formulated in terms of energy minimization (Boykov and Jolly, 2001). The general form of energy function is defined as

$$E(f) = E_{smooth}(f) + \lambda \cdot E_{data}(f) \quad (1)$$

E_{smooth} measures the extent to which f is not piecewise smooth, while E_{data} measures the disagreement between f and the observed data. The form of E_{data} is typically

$$E_{data}(f) = \sum_{p \in P} d(f_p) \quad (2)$$

where $d(f_p)$ measures how inconsistence label f_p fits the point p in the observed data.

Considering the pairwise interaction of data points, the E_{smooth} can be defined as

$$E_{smooth}(f) = \sum_{\{p,q\} \in \mathcal{N}} B_{\{p,q\}} \cdot \delta(f_p, f_q) \quad (3)$$

where $B_{\{p,q\}}$ is interpreted as a pair-wise interaction function. The indicator function $\delta(\cdot)$ is 1 if $f_p \neq f_q$ and 0 otherwise to only measure the discontinuity along segment boundaries.

Energy minimization has been used in computer vision and photogrammetry to infer information from observation data. For instance, Yang and Förstner (2011) formulated image interpretation as a labeling problem, where labeling likelihood is calculated by a randomized decision forest and piecewise smoothness is taken as a prior, which is encoded by spatial coherence based on conditional random fields. Shapovalov et al. (2010) and Lafarge and Mallet (2012) also utilized piecewise smooth priors for scene interpretation within point clouds. Kolmogorov and Zabih (2002) imposed spatial smoothness in a global cost function over a stereo pair of images to determine disparity. Instead of using a smooth prior, Zhou and Neumann (2010) combined quadratic error from boundary and surface terms to achieve both 2D boundary geometry and 3D surface geometry. Energy minimization is also explored to extract building footprints from airborne LiDAR data (He et al., 2013).

The major challenge with energy minimization lies in the enormous computational costs and problem of local minima. Graph cuts have proven to be a useful multidimensional optimization tool which can enforce piecewise smoothness while preserving relevant sharp discontinuities. It has been proven to be able to locate global minima for a certain class of two-label energy function (Kolmogorov and Zabih, 2004). A graph cut is a set of edges such that the linked nodes are in disjoint sets while each node has to connect with only one terminal node which corresponds to its label. The minimum cut problem is to find a cut that has the minimum cost among all cuts. This is equivalent to identify the lowest cost for a discrete labeling f that gives the optimum segmentation with energy minimization (Kolmogorov and Zabih, 2004).

2.2 Definition of Energy Function and Construction of Graph

Successful point cloud segmentation depends on both the formulated energy function and the optimization graph cut method. Energy function defines the required segmentation and graph should be constructed to sufficiently represent an unstructured point clouds. The graph cut algorithm minimizes the energy function in the weighted graph, resulting in an optimized segmentation of point cloud.

Each point in the LiDAR point cloud is considered as a node in the graph. The graph also contains two terminal nodes *S* and *T*, representing labels {terrain} and {non-terrain}, respectively. The edges between the nodes are defined such that each node is connected to its 3-D voronoi neighbors with an edge. All points are also connected to the terminal nodes representing labels. When mapping E_{data} to graphical model, an equivalent graph with the edge weight of {p, *T*} as the inconsistence with terrain labelling and similarly the edge weight of {p, S} as the inconsistence with non-terrain labelling is established such that any cut on the graph will result in a corresponding labelling (Vu, 2008). These weights correspond to the data term of the energy function and will be summed at each candidate labelling configuration. The weight is referred to as closeness and is evaluated in relation to the height residual (Δz) between that point and terrain surface. For a ground point p, Δz is close to zero, resulting in a small weight linking p to *T* while the weight edge of {p, S} is large. Such definition encourages points close to terrain tend to be labelled as terrain points. The closeness is defined as

$$d(l_p) = \begin{cases} exp\left(-\frac{\Delta z}{\sigma_1}\right) & \text{when point links with \{terrain \}} \\ 1 - exp\left(-\frac{\Delta z}{\sigma_1}\right) & \text{when point links with \{nonterrain \}} \end{cases} \quad (4)$$

As indicated in Equation (4), the weights of a point links with *S* and *T* complement each other. A smaller value of $d(l_p)$ indicates a higher consistence between the point and the terrain. Therefore, the definition of data energy favours terrain points in the LiDAR point cloud and penalizes the points above the ground, therefore, enforcing the desired solution to conform to the terrain.

The edges that connect points with each other correspond to n-links in the graph. These edges are also assigned weights representing the smoothness term of the energy function. This weight corresponds to the E_{smooth} in the energy function. The choice of E_{smooth} is an also critical issue. An appropriate E_{smooth} will enforce spatial coherence and encourage LiDAR points with smooth neighbours to be assigned with the same label and preserves discontinuity around sharp height changes.

Triangulated irregular network (TIN) neighbor system is constructed on the raw point cloud to ensure the connectivity. The Euclidean distance between a pair of points is adopted to measure the smoothness and the $B_{\{p,q\}}$ is determined as

$$B_{\{p,q\}} = exp(-\frac{D_{pq}}{\sigma_2}) \quad (5)$$

where

$$D_{pq} = sqrt((x_i - x_j)^2 + (y_i - y_j)^2 + (z_i - z_j)^2) \quad (6)$$

σ_2 is selected the same as the average point spacing of the LiDAR datasetQ $\cdot$ $\mathrm{w_i(n)}$. As observed in Equation (5), closely located points generate larger smoothness value while the smoothness value is small for distant points. This allows for detection of abrupt changes and therefore facilitating extraction of boundaries. It can be seen the larger the point distance, the lower the smoothness value. The large distance usually accompanies with abrupt height changes, at the places between ground and tree or between ground and buildings.

Combining E_{data} and E_{smooth} in energy function, the differentiation of terrain and non-terrain points in LiDAR point clouds is achieved through energy minimization by graph cuts.

3. EXPERIMENTAL RESULTS

The proposed approach has been tested and evaluated in a number of datasets with varying terrain complexity and land covers. The performance with data collected in a typical suburban in Australia is reported in this paper. The test site lies in Eltham about 25 kilometres northeast of the Melbourne CBD. The site of Eltham is hilly with rolling terrain and steep slopes. The site covers diverse objects including a big shopping mall, residential houses, rivers, bridges and vegetation. The LiDAR data was acquired by an Optech Gemini scanner in October, 2008, which is early spring with leafs on the trees. The average point spacing is 0.75. The aerial imagery and hillshaded TINs of the DSM are shown in Figures 2(a) and (b).

The raw data contains 2,577,387 points, of which 1,375 are detected as outliers. Figure 2(c) shows the distribution of the 420 initially detected terrain points. A visual inspection is carried on the detected points to ensure their validity. The filtering process runs in four iterations. In the first iteration, 1,059,346 terrain points are detected as shown in red in Figure 2(d). These represent the majority of the ground returns in the LiDAR point cloud. Nevertheless, an additional 342,455 terrain points are detected in the successive refinement process, as shown in blue in Figure 2(d). This constitutes around 25% of terrain points, highlighting the necessity of the iterative filtering. The final result is presented in Figure 2(e). Obviously, the iterative graph cut process results in more terrain points, particularly in steep areas, providing detailed DTM shown in Figure 2(f).

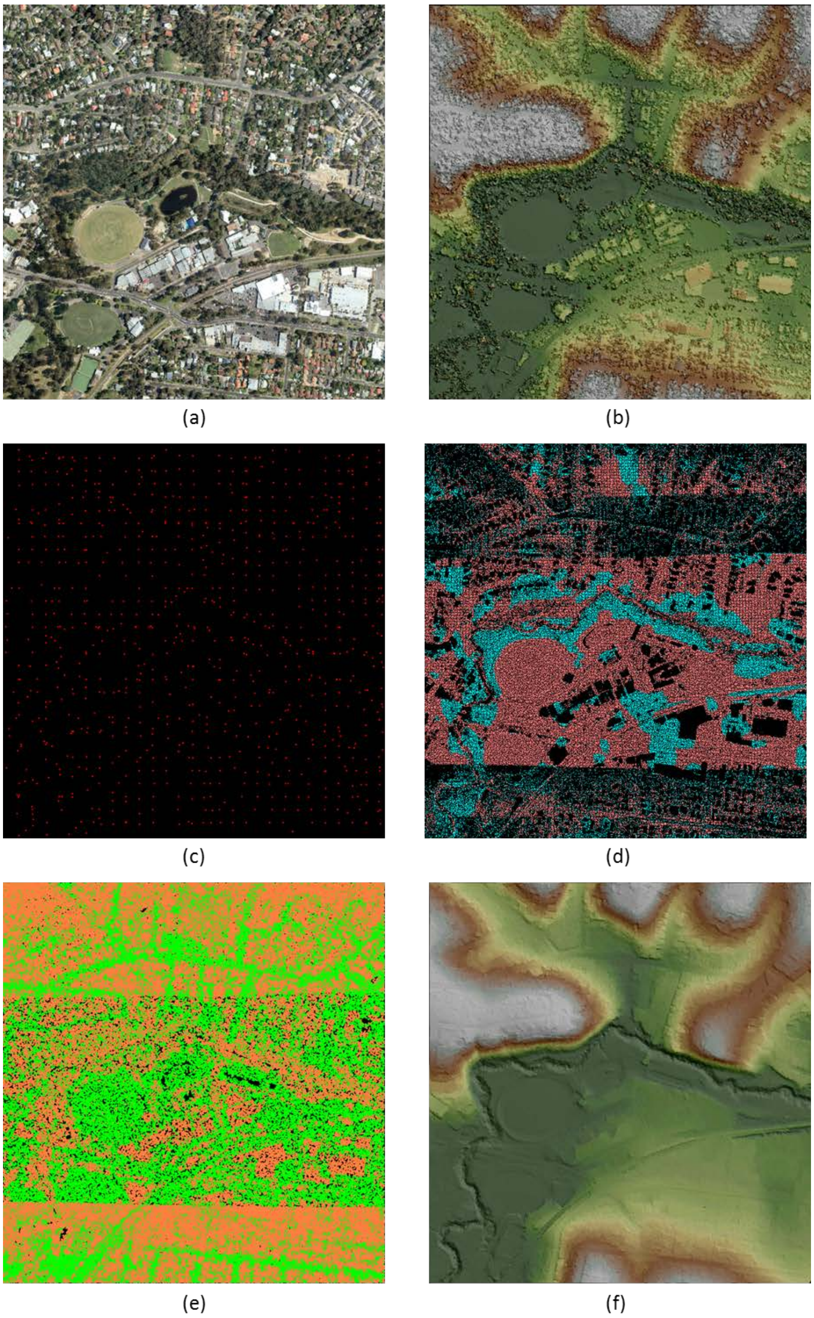

Figure 2. Filtering result. (a) aerial image, (b) shade TIN of DSM, (c) initial ground points, (d) iterative segmentation (red: ground points. blue: non-ground points), (e) classification result (green: ground points. red: non-ground points), (f) shade TIN of DTM.

The advantage of the iterative process is also illustrated in Figure 3. The initial terrain points from local minima estimation, shown in red in the left figure, are sparse in order to avoid the inclusion of large buildings. In the first iteration, most of terrain points received closeness penalty from the initial DTM. As a result, these points are classified as non-terrain, as shown in the profile on the right side. With the iterative refinement, points on slopes are progressively classified as terrain points due to the refinement of the closeness penalty from the more detailed DTM.

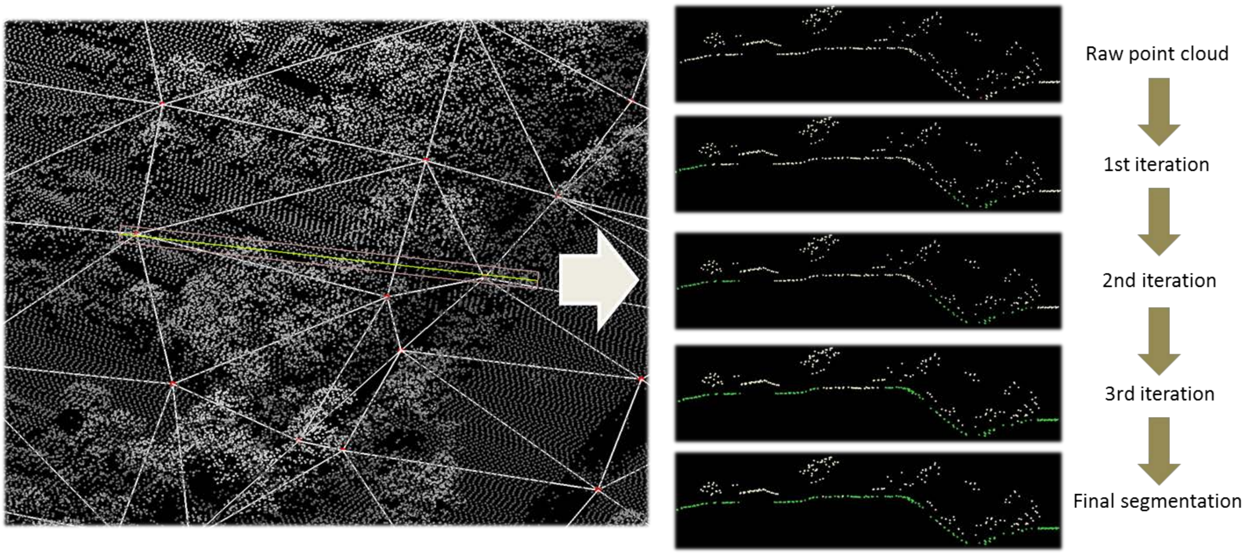

Figure 3. Illustration of the advantage of iterative filtering .

4. CONCLUSIONS

This paper has presented a new approach to filtering of airborne LiDAR point cloud for DTM generation. The new approach formulates the filtering process in energy minimization, which is optimized via graph cut. The definition of the energy functions takes into account the spatial coherence of terrain structure which allows for modeling the continuity of the terrain as well as the discontinuity with abrupt height change. The graph cut for optimization is performed iteratively. This allows for gradually refinement of the graph and dynamically updates of the energy models, thus progressively refining the terrain surface model and facilitating the separation of terrain and non-terrain points.

The experiment results demonstrate the efficiency of the proposed approach. Even in the complex landscape, the terrain points are picked with the terrain break lines preserved well in visual inspection. The experiment also indicates the importance of the iterative approach. The dynamic adjustment of models and parameters avoid errors when hard thresholds are applied, thus improving the robustness of the process and the quality of the results.

The results are inspected visually. An assessment with precise reference data will be implemented. Current efforts are also made to adapt and improve the developed approach to further differentiate points of various objects. This will allows for object classification from LiDAR point cloud for a wide range of applications.

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