

AUTOMATIC CLASSIFICATION AND 3D MODELING OF LIDAR DATA

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ABSTRACT:

Light Detection And Ranging (LIDAR) data has been recognized as a valuable data source for mapping and 3D modelling of the Earth surface. Classification of LIDAR data for the purpose of extracting ground, vegetation, and buildings is a preliminary step to build 3D models. This paper presents a classification approach of single return LIDAR data that uses area growing technique to extract patches based on neighbourhood height similarity. The extracted patches are classified according to its area into buildings, vegetation, and ground. The classification technique exhibits fast results as it avoids the iterations needed by many classification techniques while maintaining high accuracy level. The presented technique enables simple tuning of parameters because it is directly related to the data specifications. The boundaries of the extracted buildings are then traversed to detect the significant points that help to build the 3D model. The heights of the significant points are computed using the neighbour ground points. Detailed results are presented to show the effectiveness of the proposed approach.

1. INTRODUCTION

The last decade witnessed an explosive demand for accurate Digital Terrain Models (DTMs) due to its important role in different applications such as urban planning, civil engineering projects, and environment protection. Despite the sophisticated approaches of signal processing and feature extraction and matching, automatic DTM generation using optical images exhibits problems such as occlusions, shadows, and steep slopes; these problems can be obviously reduced using LIDAR technology that offers reliable height data regardless of objects textures and illumination conditions. The effectiveness of LIDAR is very noticeable due to its level of accuracy and its highly automated data acquisition workflow. The classification of LIDAR data into terrain/non-terrain points is a primary step to generate the DTM; additional classification can be performed to classify the non-terrain points into different classes such as buildings and vegetation. The automation of this task is highly needed as the manual processing is costly and time consuming. Depending on the targeted application, these classes can be needed to aid in various purposes such as visualization, mapping, and building 3D models. Different approaches have been proposed for this classification task using single/multiple return LIDAR data. Many iterative schemes have been introduced to filter the non-terrain points out using different approaches such as fitting an interpolating surface using iterative least squares (Kraus et al., 1998), using interpolating method iteratively on the levels of a data pyramid (Rottensteiner et al., 2002), iterative densification of a triangular irregular network (TIN) (Axelsson, 2000), successive spline interpolation using gradient and surface orientation analysis (Brovelli et al., 2002). Several clustering strategies have been proposed to cluster the LIDAR points using different clustering algorithms such as k-means (Miliareisis et al., 2007; Chehata et al., 2008), and fuzzy c-means (Zulong et al., 2009). Geometric descriptors such as curvature, static moments, and data anisotropy have been used by (Roggero, 2002) for clustering LIDAR data. Filin,

2002, used connectivity and principal component analysis to cluster LIDAR data in surface categories. Parrish, 2008, and Wang et al., 2006, have utilized wavelet analysis to detect vertical objects and classify buildings from LIDAR data points. Song et al., 2002, assessed the possibility of using LIDAR intensity data for land-cover classification.

The proposed approach, presented in this paper, uses a single return LIDAR data to classify LIDAR data into ground, buildings, and vegetation, and to build a simple 3D model for the extracted buildings. First, the raw LIDAR data is gridded to facilitate the further processing, and then a patch extraction algorithm is conducted over the entire data set based on the neighbourhood similarity along with efficient labelling mechanism to minimize the computation cost. The same traverse of data during patch extraction is exploited to calculate the area of each patch to be used in the classification step. Based on neighbourhood similarity used in extraction of patches, the points of each extracted patch tend to belong to the same object. A minimum area threshold is used to classify vegetation patches; the rest of patches are classified as buildings except for large patch which is classified as ground. For building a simple 3D model of the extracted buildings, the corners of the buildings with the height at each corner is required. The first step for the proposed corner detection is to encode the boundaries of the patches. As the patches are already extracted, edges can be traced along the boundaries of the patches classified as buildings. An edge encoding is conducted on the boundaries of each patch to form the boundary point's sequence. Then this sequence of points is traversed to detect the significant curvatures as corners. The absolute height provided by LIDAR raw data at the detected corners is compared to the nearest ground point to find the building height at this corner. The corners detected and their heights are used to build a simple 3D model of the buildings without texture or roof modelling. Unlike the heuristic clustering algorithms, the proposed approach has the potential of controlled tuning of parameters to suit the data set specifications. The proposed approach avoids

the computational cost introduced by the transformation based methods and the iterative methods that needs many traversals of the LIDAR data. Through all the steps of the presented approach, only simple mathematical/logical operations are performed and the number of computations is at most in the same order of the data itself.

The following section illustrates the steps of the proposed approach. Then, experimental results for LIDAR raw data are presented. Finally, the conclusions are provided.

2. METHODOLOGY

2.1 Patches Extraction

The preliminary step of the proposed approach is to divide the LIDAR data into patches depending on the height similarity. LIDAR data has to be gridded first by interpolating the randomly distributed points into matrix form. The matrix is then scanned using 2x2 window to check the height similarity between each pixel and its top and left neighbours. If the height difference is within a specified threshold the checked pixel is given the same label given to the similar height pixel, otherwise a new label is given to this pixel. If the two neighbours found to be similar but have different labels, both of them are given the smaller label. And this substitution is considered afterwards. A second scan is performed to ensure proper substitution of the labels and also for counting each patch pixels to serve as an area measure. The height difference threshold is estimated based on the data specifications. Figure 1 depicts the patch extraction process. Figure 2 presents the extracted patches with random color given for each label. This extraction step needs only two visits for each data pixel.

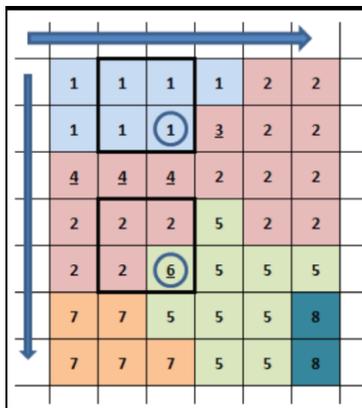


Figure 1. Patch extraction process.

2.2 Classification

Three different categories of patches can be easily observed in Figure 2. The first category is the group of tiny patches. The second one is the largest patch. The remaining patches form the third category. LIDAR data that corresponds to vegetation exhibits a high variation, and therefore the corresponding patches are very small as it fails to satisfy the height similarity condition across large areas, while the ground tends to have a large corresponding patch because it exhibits the most gradual height difference across the entire data set. These observations are used to build a straightforward classification approach that avoids any iterative processing required by many clustering algorithms. The classification is performed based on the area of

the patches. The patches under a specified area threshold are classified as vegetation, the largest patch is classified as ground, and the remaining patches are classified as buildings. The area threshold is estimated based on the data set specifications. Figure 3 depicts the classification result for the same area presented in Figure 2 where red color patches indicates building class, green color patches indicates vegetation class, and white color patches indicates the ground class.

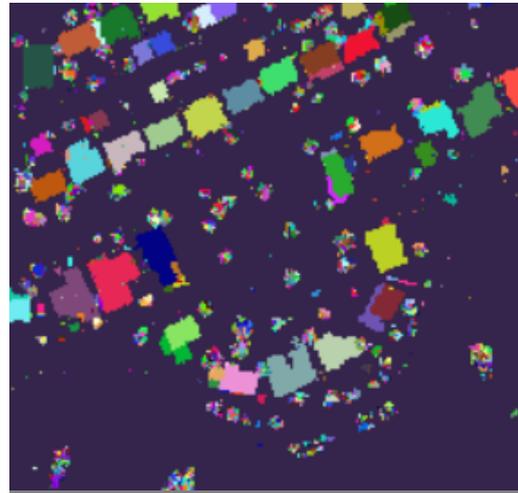


Figure 2. Extracted patches with random color given for each label.

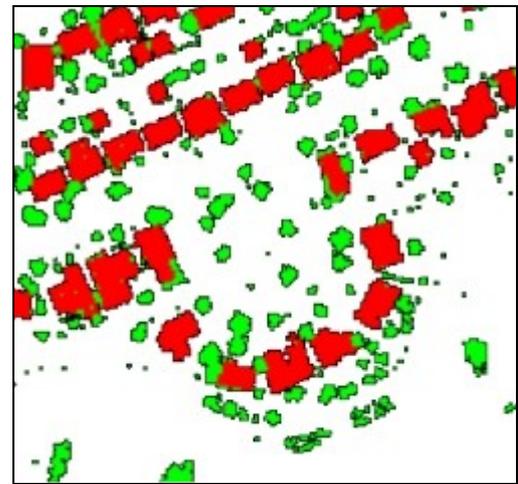


Figure 3. Classification results of the area in Figure 2. buildings (red), vegetation (green), ground (white).

2.3 3D Modelling

For a fast visualization of the extracted buildings, the extracted buildings are processed to get a suitable form for 3D rendering. The boundary of each building patch is extracted using chain coding. These boundaries have to be reduced to a set of lines to be suitable for rendering. Each boundary is approximated as a set of lines connecting the significant points of boundary. To detect these significant points, the percentage of the neighbour points belonging to the patch is used as a measure of boundary curvature at this point. The points that exceed a specified threshold are chosen to be significant points. Figure 4 shows the significant point extraction process. The neighbourhood of each

significant point is searched for the nearest ground point to help compute the building height at this significant point. Each building patch is represented as a polygon associated with height information at each polygon vertex. This representation is then rendered as triangle surfaces using COLLADA modelling language for visualization.

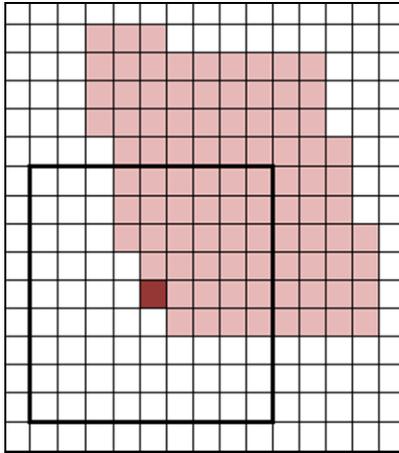


Figure 4. Significant point extraction process.

3. RESULTS

The proposed approach has been evaluated using a LIDAR data set for an area in Calgary city (only one return signal). The dimensions of the bounding rectangle of the data set area are 2416.93 m, and 1125.40 m and the LIDAR covered area is about 1.9 km² with point's count of 1,834,455. The LIDAR point's density is about 1 point/m². With this density, the threshold for height similarity has been chosen to be 1 m, and the area threshold used for classification has been selected to be 50. The curvature threshold has been chosen to be 0.43 based on visual trials.

Figure 5.a depicts the height profile of a sample area of the test data, the brighter points represents higher elevation points. Figure 5.b shows an aerial image of the same area presented in Figure 5.a. Figure 5.c shows the classification results over the previous aerial image. The ground class is the visible region of the aerial image. Figure 5.d illustrates the buildings boundary and its significant points. Another sample area with its results is shown in Figures 6.a-6.d.

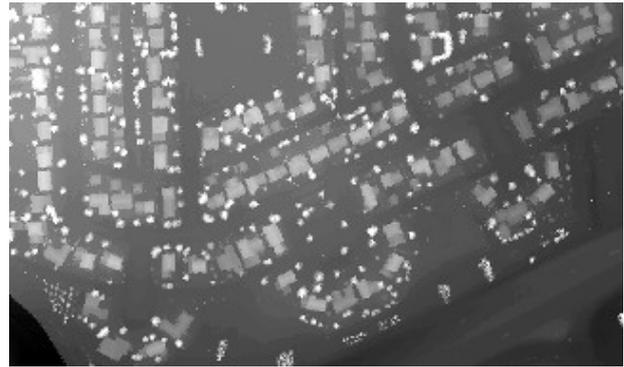


Figure 5.a. Height profile of area (I).



Figure 5.b. Aerial image of area (I).



Figure 5.c. Classification results over aerial image of area (I). (red for buildings, green for vegetation, and the rest is ground)



Figure 5.d. Building boundaries and its significant points (red color) of area (I).

| | | Classification Results | | |
|----------------|------------|------------------------|------------|--------|
| | | buildings | vegetation | ground |
| Reference Data | buildings | 68848 | 890 | 2066 |
| | vegetation | 54 | 10980 | 107 |
| | ground | 394 | 477 | 245128 |

Table 1. Confusion matrix of the proposed approach.

Table 1 shows the confusion matrix of the proposed approach computed using a manually classified area of the data set. As a measure of the overall accuracy, the kappa index of agreement for this matrix is computed and found to be 0.96 which indicates very good performance.

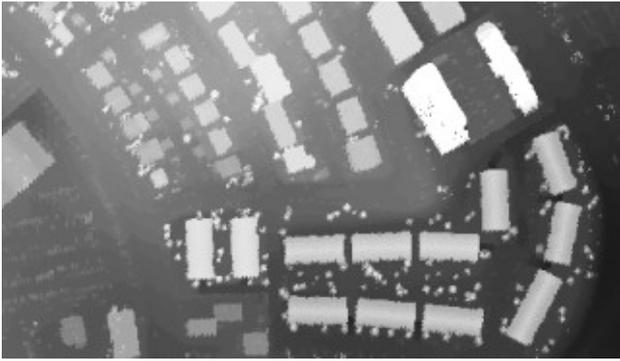


Figure 6.a. Height profile of area (II).



Figure 6.b. Aerial image of area (II).



Figure 6.c. Classification results over aerial image of area (II). (red for buildings, green for vegetation, and the rest is ground)

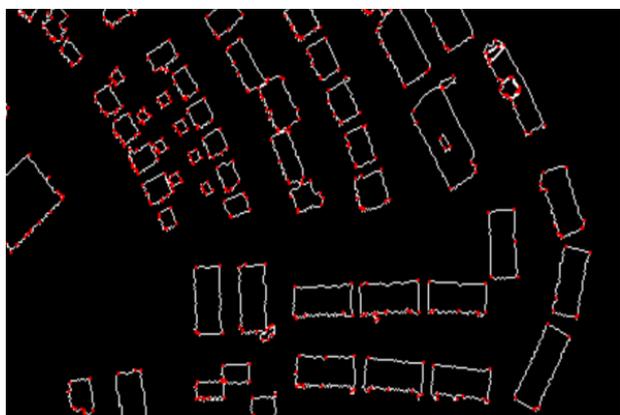


Figure 6.d. Building boundaries and its significant points (red color) of area (II).

95.9% of the reference building area has been correctly classified, while 98.5% of the reference vegetation area has been correctly classified. 3.8% of the area classified as vegetation belongs to ground class, this percentage of misclassification is mainly due moving objects on the roads such as cars, and can be corrected using the neighbourhood of these areas. 7.2% of the area classified as vegetation belongs to building class; this error is mainly caused by the small architectural details that fails to form a large patch, and by the overlap between buildings and trees, and again the first reason can be avoided if the neighbourhood of these areas are considered.

The results of the proposed approach are interpretable and directly linked to the deployed parameters, and therefore there is a high potential to tune these parameters and enhance the performance accordingly.



Figure 7. 3D model of the entire data set rendered over Google Earth scene of test area using COLLADA language.

4. CONCLUSIONS

A fast approach for classification of LIDAR data has been proposed and evaluated using test data. The high accuracy level achieved signifies the value of the single return LIDAR data as a convenient source for classification. It also denotes the validity of the assumptions used in the proposed approach. In contrast to the heuristic clustering algorithms, the presented classification approach is not based on iterative processing and it requires accessing the data points twice only. The interpretability of the obtained results and its direct link to the used parameters enables discovery of improvement opportunities and parameter tuning in a controlled fashion. A fast 3D rendering technique is presented for the visualization purposes.

5. ACKNOWLEDGMENTS

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