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A Semi-Automatic Approach for Roof-Top Extraction and Classification from Airborne LiDAR

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ABSTRACT

Airborne LiDAR provides us point cloud of the topographic features of an area. Point cloud classification is important to recognize which points corresponds to which target. Researches has been carried out for the extraction of building, trees, electric lines. But only few researches have been carried out for classification of different types of roof like flat, inclined and dome shaped. This research is aimed to achieve a semi-automatic approach to classify buildings and further classify the roof top type into flat, or inclined. Four subsets were taken from the LiDAR dataset, depending on the roof type. Initially, all the ground points are removed and non-ground points are segmented out. Later, the roof points of the buildings are classified on the basis of inclination into flat, inclined or dome type roof. A tool was generated in the Arc scene software using model builder. In which the subsets were used as the input and the different types of roof were classified. The accuracy assessment was done to calculate how accurately the classified points obtained belongs to the flat, inclined or dome roof tops. For all the four subsets, the overall accuracy for the flat, inclined and dome type roof obtained were 78.26%, 89.62% and 72.94%. This semi-automatic approach for the roof top classification is limited to categorize into flat, inclined or dome roof top only. Further, this research can be extended for the automatic classification of roof types and increase the accuracy.

Keywords: Airborne LiDAR, Roof Top Extraction, Roof Top Classification, Accuracy Assessment.

1. INTRODUCTION

LiDAR (Light Detection and Ranging) is a very advancing field of remote sensing. Its ability to provide dense point cloud with greater geometry accuracy helps us in many application. In this research airborne LiDAR dataset is used for building roof type extraction and classification. Many researches have been carried out for extracting building footprint but few approaches have been made to classify the roof types of the building like flat, incline or dome shaped roof structure. A similar type of research is done to classify roof types as either pitched or flat, by integrating already available vector-based data with the LiDAR elevation data [1]. A research was done to generate models of 3D buildings from liDAR point cloud automatically using a skew error distribution function [2]. Points corresponding to the terrain can be filtered out using height variation from the actual LiDAR dataset. Morphological filters were used to separate ground and non-ground points. Ground and building detection were done using differential morphological profiles on points residual [3]. A work has been done for the reconstruction and segmentation of polyhedral building roofs from aerial LiDAR data. In which surface normal were generated for each point to classify it into planar and nonplanar ones, further, clustering planar points with fuzzy k-means algorithm and segmenting coplanar and parallel segments depending on connectivity and distances [4]. Building measurements are done with the help of region growing algorithm based on plane fitting technique[5]. Further the edge points are used to extract the building footprint [6]. Precise building boundary extraction is achieved by integrating high resolution imagery and liDAR data. Precise boundary position was obtained from the imagery. Accurate boundary lines were segmented with the help algorithm developed on the basis of Kmeans clustering and lidar point density analysis [7]. With the help of 2D and 3D contextual information of the scene a stochastic image interpretation model is developed. Markov Random Field (MRF) model is used to provide hierarchy of the dependency using contour based grouping [8]. An analytical comparison of RANSAC algorithm and Hough-transform automatic detection of roof planes is done in which RANSAC algorithm was more efficient [9]. Automatic building extraction from high resolution space image is done by removing non-building portions by image classification.

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Further trees were separated by using Normalized Difference Vegetation Index (NDVI) [10]. Boundary of the largest part describes the building footprint considering area, height and number of stories attribute. spectral data is used to remove vegetation and possibly to classify the roof type material of the buildings [11]. An approach is made to extract building roof by integrating LiDAR and multispectral orthoimagery. In which the non-ground points are segmented using image line guide segmentation to extract the roof planes [12]. Depending upon the cluster of points, the points may correspond to the building or a tree. But to filter out tree points the coplanarity of points and their locality is considered [13]. In this research, a tool is developed for classifying roof tops and further specifying the type of the roof based on the inclination angle. The height and the slope parameters are considered to classify non-ground points and further to classify their roof type. The overall accuracy obtained in this research is sufficient to determine which type of roof it is.

2. STUDY AREA AND DATASET

LiDAR data under consideration: Niagara Region, Ontario, Canada. Coordinate System: UTM, Zone: 17N. Extent of the Study Area: -78.9164W to -78.9047W 43.0944N to 43.1029N.

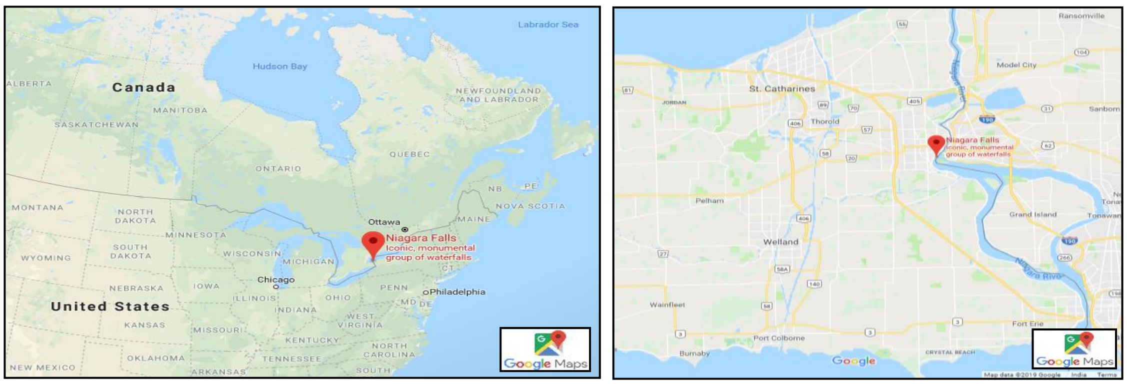


Figure 1: Study Area

3. METHODOLOGY

A semi-automatic approach for classification of rooftop is aimed to achieve in this research. The primary idea is to remove the outlier points on the basis of slope tolerance and height criteria and segment out the required data. A tool is built in the model-builder (ArcScene). The LiDAR dataset is converted into .txt format which is taken as the input for the tool developed. Triangulated Irregular Network (TIN) is generated to classify ground and non-ground points. The height criteria is used to filter out ground points and the slope criteria is to classify the roof types. From the overall Lidar dataset, 4 subsets were generated depending upon the roof type and its complications. The model developed is used to classify different rooftypes on the 4 subsets. Accuracy assessment of classified rooftops is done on the basis of the number of actual points present on the roof and the number of points classified according to the roof type, carried out in Cloud Compare software.

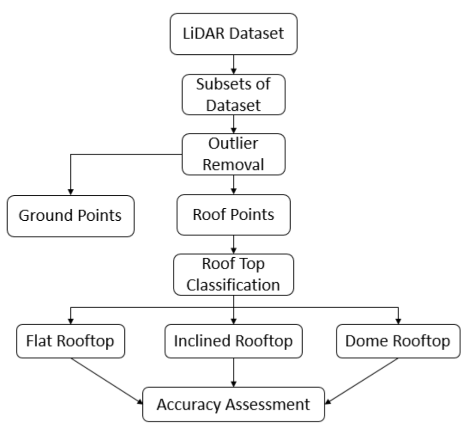
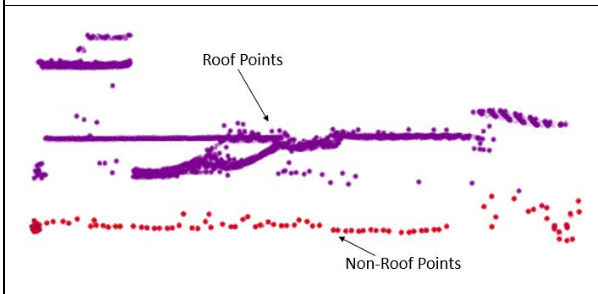
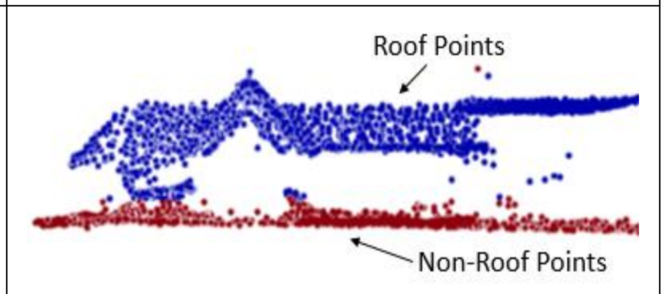
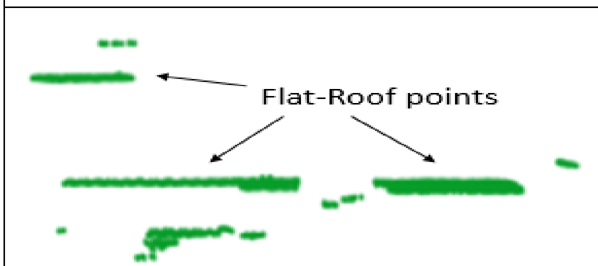
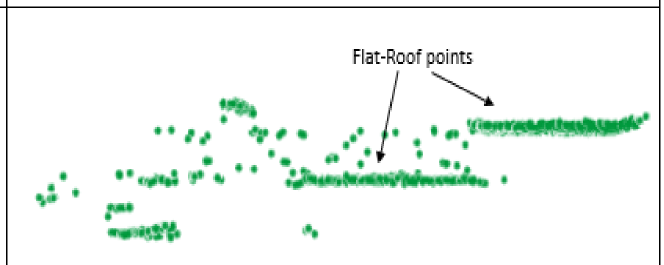
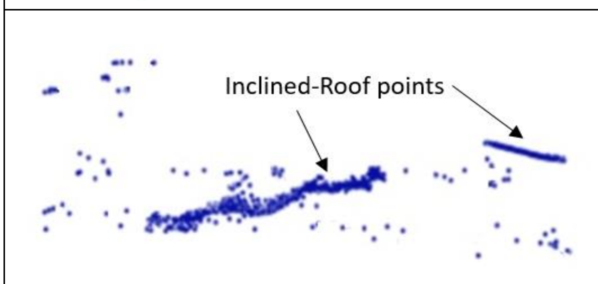
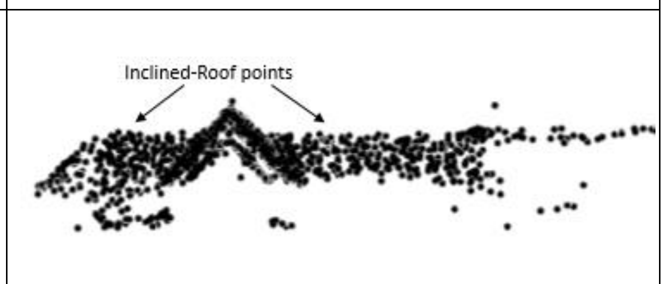
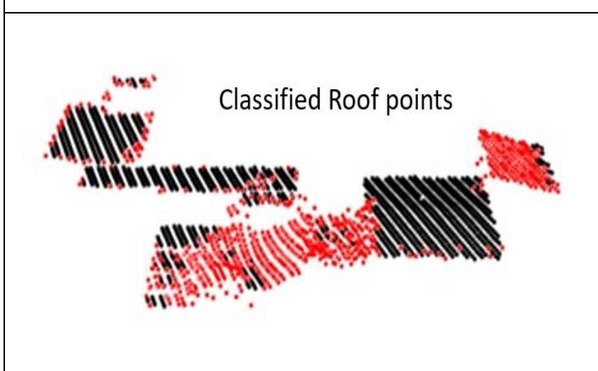
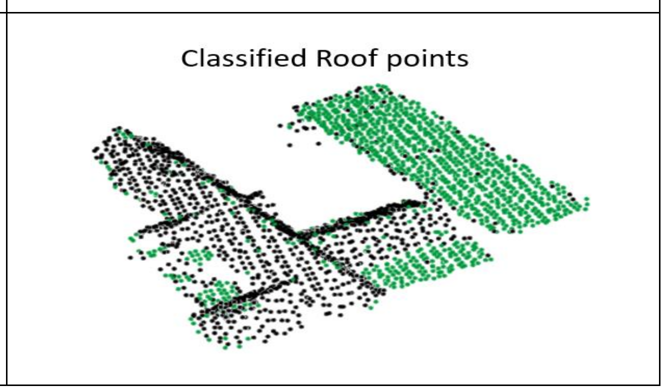


Figure 2: Methodology

4. RESULTS AND DISCUSSIONS

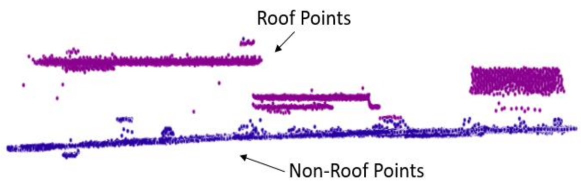
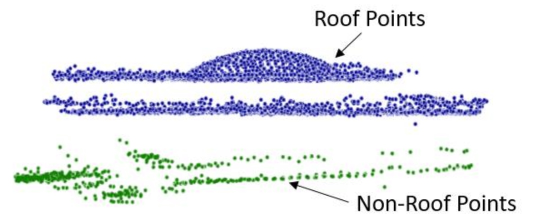
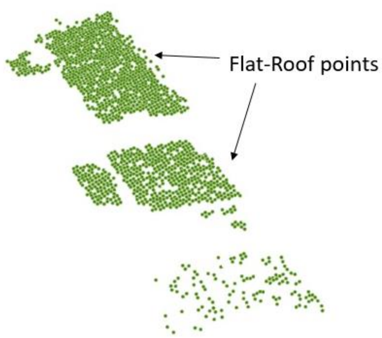
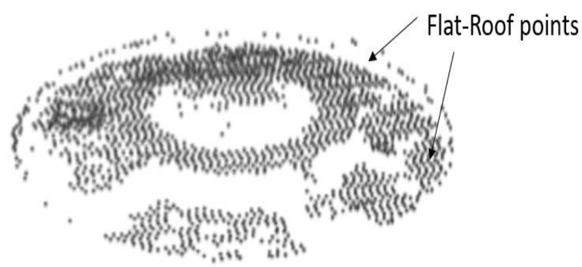
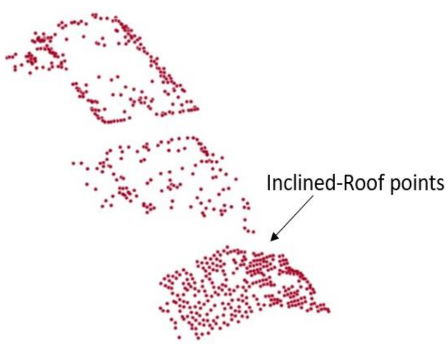
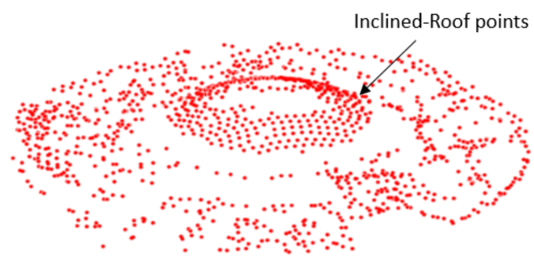
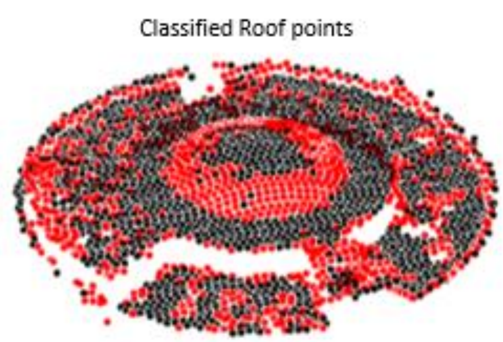
By varying the height and slope parameters the datasets were classified and the roof top classification was done. The results are tabulated and shown in the table 1 and table 2. Fourth dataset was choosen in such a way that it had dome shaped roof.

Table 1: The roof points, non-roof points, flat roof points, inclined roof points and classified roof points corresponding to dataset 1 and dataset 2.

Dataset 1	**Dataset 2**
	
	
	
	

There were few misclassification of the points which were present on the edges of the roof and due to surface roughness change. The roof points classified depending on the roof type are shown with different colours for visualization purpose in table 1 and table 2 for all the 4 datasets.

Table 2: The roof points, non-roof points, flat roof points, inclined roof points and classified roof points corresponding to dataset 3 and dataset 4.

Dataset 3	**Dataset 4**
	
	
	
	

For dataset 4 which had dome type roof, the accuracy obtained was less but this accuracy is sufficient to identify which type of roof it is.

4.1 Accuracy Assessment:

The accuracy assessment was done to calculate the percentage of error obtained by this method of roof type. The percentage of accuracy is equivalent to the roof points classified by the tool developed to the actual points corresponding to the roof type multiplied by 100.

$$\text{Percentage of Accuracy} = \frac{\text{Classified points of the roof type}}{\text{Actual points of the roof type}} \times 100 \qquad \text{----------------------------(1)}$$

The classification accuracy obtained for different roof types corresponding to different subsets are showed in the table 3, table 4, table 5 and table 6.

Table 3: Accuracy for Dataset 1

Roof Types	No. of points in Classified Roof Top	No. of points in Original Dataset	Accuracy (%)
Slant Roof	201	215	**93.48**
Flat Roof	294	340	**86.47**

Table 4: Accuracy for Dataset 2

Roof Types	No. of points in Classified Roof Top	No. of points in Original Dataset	Accuracy (%)
Slant Roof	226	251	**93.44**
Flat Roof	770	824	**90.013**

Table 5: Accuracy for Dataset 3

Roof Types	No. of points in Classified Roof Top	No. of points in Original Dataset	Accuracy (%)
Slant Roof	422	515	**81.94**
Flat Roof	201	305	**75.59**

Table 6: Accuracy for Dataset 4

Roof Types	No. of points in Classified Roof Top	No. of points in Original Dataset	Accuracy (%)
Dome Roof	425	310	**72.94**
Flat Roof	282	172	**60.99**

The accuracy assessment is done with CloudCompare software. A small portion of the each dataset is clipped on different roof types and compare with the number of points classified in that portion of the dataset. With this methodology different roof types were classified on the basis of slope criteria. For dataset 4, the accuracy obtained for flat type roof is comparatively less with other datasets due to the change in the slope angle the points corresponding to the flat surface were misclassifying into dome.

5. CONCLUSION

Airborne LiDAR Point cloud classification has different needs of categorization like, buildings, forest cover, water bodies, agricultural land, and roads. Building footprint extraction helps to identify urban built-up space. Roof top extraction is very much important to measure the roof area exposed to the sky. This even contribute to install solar panels which can be used as a renewable source of energy. Percentage of energy generated from the solar panels depend upon the amount of solar energy received by the panels. The efficiency of the solar panels can be increased depending on the angle of the roof. Proper direction of the roof can be classified depending on the slope of the roof. Flat, inclined and dome roof classification helps us to decide the location of installation of the solar panels and further increasing the percentage of energy generation by solar panels. The energy generation depends mainly on the angle of incidence of sunlight. So, there is need for roof top classification. In this research the overall accuracy obtained were 78.26% for flat roof type, 89.62% for slant roof type and 72.94% for dome roof type. The accuracy is sufficiently enough to determine the type of roof structure.

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