ON THE SEGMENTATION OF HETEROGENEOUS LASER SCANNING DATA

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ABSTRACT

The segmentation of Laser scanning data into planar features is a crucial first step in the post processing of Laser data. Classically, a planar segmentation procedure is performed over a single scan, or a group of homogeneous and co-registered scans. In this work, we address cases where the datasets used vary significantly in terms of local point density, relative point accuracy, and the collection method (i.e., ground versus airborne). First, an initial segmentation procedure is performed over individual strips to collect vital pieces of information about the scan nature such as local point densities, approximate surface roughness and surface normal of segmented regions. Once the aforementioned information is collected, and the registration of overlapping scans is verified, the combined segmentation stage may begin. In the combined case, a recursive weighted least squares and a region-growing-based algorithm is adopted. Weighting of individual points is estimated using the information collected in the initial segmentation step. Using the proposed combined segmentation is beneficial for multiple reasons: (1) missing or incomplete features in one or more scans are likely to be complete in the combined dataset, (2) the overall increased point density is very beneficial for detecting finer planar patches, and the weighted least squares will ensure that the integrity of the combined dataset is maintained, and (3) the results of the combined segmentation is useful to verify the correctness of the registration procedure. In this paper, we present a case study of two sets of airborne scans and one set of six tripod mounted laser scans. Results demonstrate improved extraction of planar features from the combined dataset as appose to segmenting individual strips.

KEYWORDS: LiDAR, Laser scanning, Heterogeneous data, Segmentation

INTRODUCTION

Laser scanning, whether airborne or terrestrial is being used nowadays for wide spectrum of applications. In addition, many advances have been introduced to the laser scanning technology in the last decade; thus resulting into increased performance in terms of the point density, measurement range, and expected point accuracy. On the other hand, users are encountering scenarios where they need to integrate various laser datasets in order to avoid data gaps. For example, missing building roofs in the terrestrial scans, or missing structure facades in the airborne strips.

Two alternatives could be thought of for addressing the aforementioned problem. The first one is to ignore the knowledge of overlap between the laser scans and thus process them independently. And the second alternative is to merge them into one dataset and perform the segmentation as if the dataset comprise a single scan. In the former case, it is obvious that one is not exploiting the full potential of the dataset, that is since there will be higher chance of discontinuities and shadows within a single strip. In the latter case, merging the datasets without attention to the variations in point density could result into artifacts as the point density will vary significantly in the overlap areas.

Segmentation of LiDAR data is useful for multiple applications: (1) in terrain extraction (Tovari & Pfeifer, 2005), where a segmentation algorithm is used to perform a ground vs. non-ground separation (2) in building detection (Kim et al., 2007), where mostly planar patches that are found above ground level are extracted, and finally (3) in data filtering (Sithole & Vosselman, 2005) where non-planar points are identified as outliers.

To the best of the authors’ knowledge, there is no literature that addresses the segmentation of heterogeneous Laser data. However, any of the currently existing segmentation may be extended to accommodate heterogeneous datasets. Please refer to Vosselman & Maas, 2010 and Shan & Toth, 2008 for variants of segmentation algorithms.
In this paper, we present our strategy of expanding our region growing based segmentation algorithm to take into account scans with varying characteristics.

**METHODOLOGY**

It is crucial to realize that depending on the data collection mechanism and post processing, estimates of the laser points’ accuracy might be reported differently. Three main scenarios are possible here: (1) the data accuracy is reported for each point within a scan. (2) The average point accuracy is estimated and one value is reported for the entire scan and or sensor. And finally, (3) no point accuracy is provided due to various reasons such as inaccessibility to metadata.

Apparently, each of the aforementioned cases must be treated differently. Our goal is to establish a work flow that results in a standardized process to segment any of (or a combination of) the cases mentioned previously. To begin with, let's first discuss the case of performing the classical segmentation over a single strip with the assumption of uniform point accuracy over the entire point cloud.

The following flowchart demonstrates the process established to perform segmentation for an individual strip. This segmentation procedure is straight forward, it mainly focuses on the extraction of planar surfaces; these planar surfaces could be associated with building’s rooftops, facades, road surfaces, or even terrain over a short range. An adequate percentage of the LiDAR points are randomly selected and flagged as seed points. Then, for each seed point, the nearest neighbors are retrieved from a previously built kd-tree. A plane fit procedure is attempted over these neighboring points. If the a posteriori variance factor of the plane fit was found to be too large, then this seed point is discarded and another seed point is investigated. Once a seed point region with reasonable plane fit variance factor is found, the region growing process begins.

![Figure 1. Segmentation algorithm workflow.](image-url)

In the region growing step, the aforementioned neighbors are now used as seeds, and new neighbors are searched for. Instead of re-estimating the plane parameters after the addition of new points, we update them. The impact of adding one observation (point) on the plane parameters could be estimated using the Recursive Least Squares (RLS) adjustment procedure (Sayed, 2003). This recursive process continues across all neighboring points, and then across all seed points until no point is left unexamined.

Now let’s consider the heterogeneous case, basically, the same method mentioned above for a single scan is adopted except for few changes. Multiple data structures (kd-trees) are constructed for each available laser scan. Next, while the first scan is being segmented, one also searches across all the other strips for points belonging to the.
plane under examination. If a point or group of points in the neighbouring scans were found to belong to the current plane while considering the respective accuracy of that point, we calculate their impact on plane parameters. To accommodate the variations in point accuracy, we incorporate the points’ accuracies in our RLS solution. And to take into account variation in the point density, a different range parameter for searching the neighbours is used for each scan.

By performing this procedure, we are able to successfully exploit the full potential of the dataset while maintaining the scans unaltered. It is worth mentioning also that the cost of constructing and searching through a group of smaller kd-trees is faster than performing the same operations on one kd-tree of the same number of points.

**DATA USED**

Our heterogeneous segmentation algorithm was tested using a dataset of significantly varying characteristics. A set of six tripod mounted laser scans were collected over a complex structure at the University of Calgary, the Rozsa center building (Figure 2a), which has a set of aluminum-zinc gable rooftops. This type of surfaces could be very challenging for most segmentation algorithms due to the surface patterns. The terrestrial laser scans have been collected at a very high point density (8000 – 12000 pts/m²). However, for this experiment, the point density has been reduced to an average of 200 pts/m² to increase the processing speed. In addition, a set of three airborne laser scans with varying characteristics are available for this experiment. One should notice that the ratio in point density between the airborne and terrestrial data remains significantly high (~1: 100). The following table summarizes the average point density and accuracy for this dataset. Notice the shadowing effect in Figure 2b resulting from tree crowns occluding parts of the Rozsa center rooftop.

<table>
<thead>
<tr>
<th>Scan Name</th>
<th>Average point density ( (\text{pts/m}^2) )</th>
<th>Average 3d point accuracy ( (\text{mm}) )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Station 1</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Station 2</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Station 3</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Station 4</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Station 5</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Station 6</td>
<td>200</td>
<td>&lt;0.02</td>
</tr>
<tr>
<td>Airborne 1</td>
<td>2.5</td>
<td>0.06-0.09</td>
</tr>
<tr>
<td>Airborne 2</td>
<td>2.5</td>
<td>0.06-0.09</td>
</tr>
<tr>
<td>Airborne 3</td>
<td>1.5</td>
<td>0.03-0.04</td>
</tr>
</tbody>
</table>

The registration of all these scans into a common reference frame was performed using a further developed version of the Iterative Closest Project Point (ICPP) described in Al-Durgham et al., 2011. Discussion on how the heterogeneous ICPP works is the subject of a future publication.

![Figure 2](image-url)

**Figure 2.** (a) A photo of the Rozsa Centre taken at the data acquisition time from one of the terrestrial laser stations. (b) The resulting laser scan captured from that angle.
In the following set of snapshots shown below, we present the six terrestrial and three airborne laser scans used for examining our algorithm. Note that this partial coverage of the structure’s facades is very common in terrestrial scans. Also, note the significant difference in the point density among terrestrial and airborne scans.

Figure 3. Snapshots (a) to (i) showing the 3d point cloud of laser scans used.

RESULTS AND DISCUSSIONS

In this section, we examine the outcome of our heterogeneous segmentation procedure relative to single scan segmentation. The most obvious observation is demonstrated in Figure 4. In part (a) of Figure 4 the segmentation of a single scan (Station 6) is performed. Note how due to the nature of occlusions caused by trees and the region growing algorithm, the rooftop has been segmented into three separate features.
In the second part of Figure 4, we demonstrate the result of performing the segmentation over two scans, namely, Station 6 and Airborne. It should be noted that even if one attempts to merge the two scans and perform a single classical classification, it would still result into three segments, unless the change in point density has been carefully tracked. That is due to the high ratio between the two scans densities, the region growing algorithm is unable to properly search for neighbouring points.

In the following graph, we show the outcome of performing the segmentation over all the nine scans available. Using our heterogeneous segmentation, we were able to extract all the facades and rooftops of the structure in question. The shadowing effect has been minimized, and the output segments are complete and dense.

CONCLUDING REMARKS

In this paper, the authors present their heterogeneous LiDAR data segmentation algorithm. It has been shown that challenges caused by variations in the average point density and point accuracy have been overcome. It has also been demonstrated that the integration of multiple data sources is crucial for the complete coverage of the objects of interest.
Future research will focus on the optimization of this heterogeneous segmentation algorithm. In addition, more testing over wider spectrum of datasets is to take place. Furthermore, it is possible to accurately integrate LiDAR point clouds with other datasets originating from different sources such as point sets extracted from photographs using the semi global matching technique.

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