RECONSTRUCTION OF LASERSCANNED VEHICLES

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Commission I, Working Group 2

KEY WORDS: Laser scanning, Object reconstruction, Modeling, Classification, Data compression

ABSTRACT:

The application field of laserscanning (LiDAR) has undergone significant extension in the last years. As advancing airborne LiDAR technology continues to provide denser point clouds, its applicability broadens into important sectors, such as emergency mapping or transportation applications. This paper is a continuation of a research reported last year, focusing on modeling moving objects (vehicles) extracted from laserscanner data.
Previously, we presented methods for extracting, modeling, and classifying laserscanned vehicles. Now we put emphasis on the refined modeling of the extracted vehicles. In our approach we approximate the shape of the vehicles with cubes as pre-defined geometric primitives. The more precise the shape approximation is, the more accurate the volume of the object can be determined.
Several tests with LiDAR data sets of different characteristics (frequency, point density) have been carried out. In this paper a modeling technique is described considering different point densities.
The derived shapes and volumes of the vehicles are the bases of several transportation applications. Regarding the load of the road pavement, the higher volume indicates higher weight. Considering the environmental issues, the size of a vehicle is in strong correlation with its emission. The previously developed profile-based classification can be further enhanced with the refined shapes resulted from the current modeling technique.

1. INTRODUCTION

As the state-of-the-art airborne LiDAR systems provides even denser and more accurate spatial data sets, new fields, such as transportation applications open to this capable mapping technology. Not only the most obvious road network detection but even traffic flow data estimation, vehicle classification seem achievable goals using data acquired by LiDAR sensors.
Our previous works focused on vehicle classification; details about the PCA-based approach can be found in (Toth et al. 2003a nad 2003b), about the model-based solution in (Lovas et al. 2004a and 2004b). Our results proved that vehicles extracted from airborne laserscanned data sets with moderate point density (1.5 points/m^2) can be classified into coarse categories, such as passenger cars, multi-purpose vehicles and trucks. The model-based approach enables to distinguish even finer subclasses; e.g. differentiate the hatchbacks from the sedans in the passenger car category. In the model-based phase the results have been validated applying terrestrial laserscanned sample vehicles.
In this paper we show a refined modeling procedure with voxel-based vehicle reconstruction, which provides promising intermediate results in the field of classification. Moreover, applying sophisticated compressing techniques, the data management (from storage to representation) can be executed in an efficient way.

2. VEHICLE RECONSTRUCTION

2.1 Data Preparation

By using LiDAR data in transportation applications, the initial step is always extracting vehicles from the data set. For road detection these features are simply erased, but obviously can be also used for further investigations in traffic flow data estimation. Because of the modest point density of our test data sets (1.5-2.4 points/m^2), the shape of the extracted objects (vehicles) are fuzzy, as are the derived covering curves. As it shown in Figure 1, we have chosen an eighteen-wheeler truck for the better visualization.

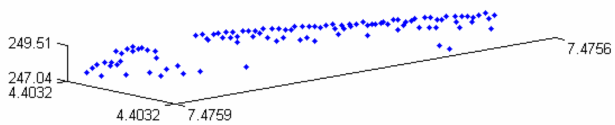

Figure 1. Vehicle (truck) from LiDAR dataset

Although for the performed tests the vehicles were cut manually, we have developed effective segmentation algorithms for extracting objects from LiDAR data sets; further details can be found in (Rakusz et al., 2004).

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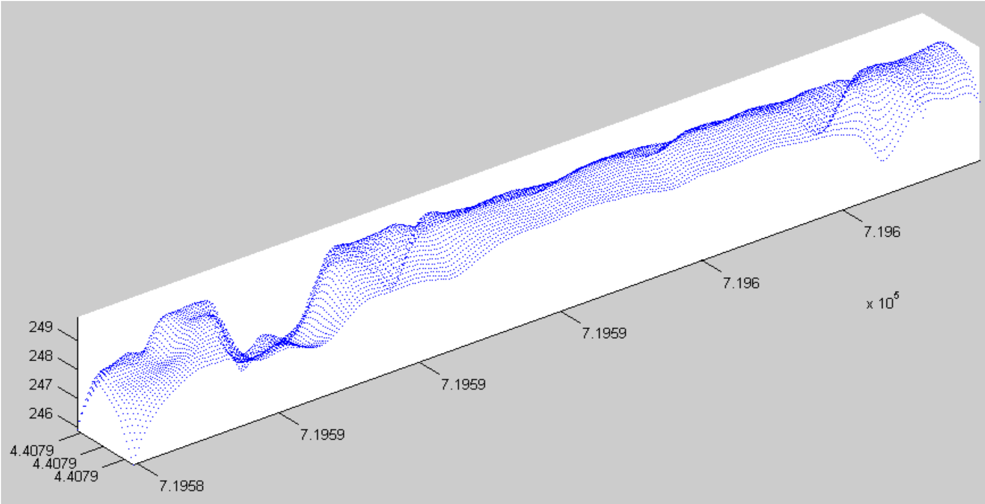


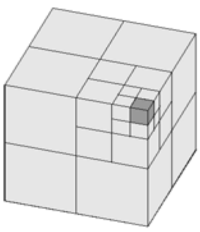
Figure 2. Interpolated vehicle points (0.1 m grid size)

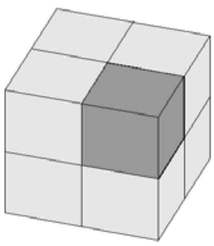
2.2 Interpolation

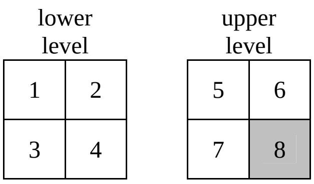
Our primary goal is to represent the laserscanned vehicles with geometric primitives (with cubes). This approach needs to be based on regularly interpolated grid structure. The gap between the grid points are to be depend on the overall point density, and on the demanded surface smoothness. The test vehicle is extracted from a 1.5 points/m^2 point cloud; about 60 points reflected back from the elongated (from 20 m actual length to 29 m in data set) truck. We interpolated the elevation data to 0.1 m spaced grid applying linear interpolation (Figure 2.).

2.3 Oct-tree decomposition

Since the key idea of our approach is to build up the extracted objects with easily definable objects, we have chosen the simplest solution, and used voxels as basic elements in the reconstruction. Voxel cubes can be divided into further cubes; so can a “super-voxel” be built up by aggregating unit voxels. (Figure 3)


a) Oct-tree for hierarchical voxel decomposition


b) The first subdivision of the "Big cube"



c) Numbering of the oct-tree elements

Figure 3. The oct-tree structure

Representing objects with the biggest possible voxels (i.e. the homogenous volumes are filled with appropriately sized cubes) has the advantage of an efficient data compression. As the quad-tree at the pixels divides one rectangle to four elements; the oct-tree at the voxels results in 8 sub-voxels. Figure 4 shows the graph representation of the oct-tree decomposition.

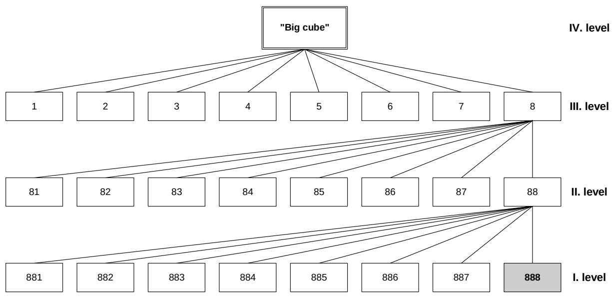


Figure 4. Oct-tree representation as graph structure

This data structure results in an efficient data storage capacity. The voxels are structured in voxel pyramid with sparse logical 3D arrays as elements. In the sparse array only the non-zero elements (voxels belonging to object; i.e. vehicle) are stored, which elements are logical “true”. This binary array ensures the efficient storage solution, and fast computing process. The decision process is described in the following equations:

If the following condition is fullfilled for a voxel with its initial coordinates of i ,j ,k at level q:

$$\mathop{\wedge}_{i}^{i+1} \mathop{\wedge}_{i}^{j+1} \mathop{\wedge}_{i}^{k+1} v_q\left(i, j, k\right) = 1 \tag{1}$$

then

$$v_{q+1}(i, j, k) = 1 \tag{2}$$

and

$$v_q(i, j, k) = 0 \tag{3}$$

where

$\wedge$ is the logical AND operator for vector input.

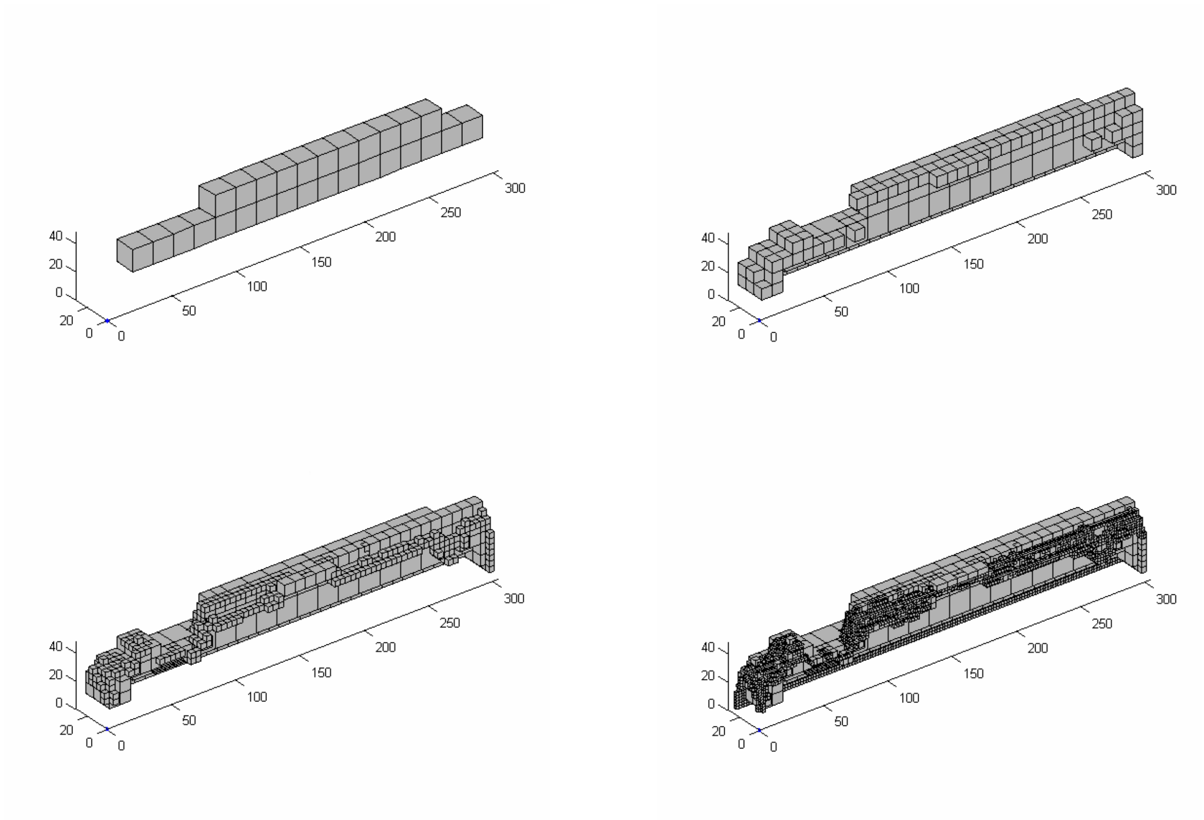


Figure 4. Iterative refinement in truck visualization (modelling) using the voxel pyramid structure

2.4 Voxel-based modeling

The effective oct-tree partition enables approximating the volume of the objects. First, the maximal voxel size is to be defined, then the number of the sub-structures (or the minimum voxel-size). In case of the eighteen-wheeler shown above, the maximum voxel size is 16×16×16 units (1 unit = grid size; now: 0.1m) and has 5 sub-layers (minimum voxel size: 1×1×1) (Figure 4.). The size of the truck in the data set is 30 m (l) × 2.5 m (w) × 4.6 m (h), thus the voxel composiotion for the minimum closing box is 300 × 25 × 46 voxels. Table 1 shows the progressivity of the oct-tree levels for 6 layers.

Level	Unit size in voxels	No. of elements
I	1×1×1	1 (8^0)
II	2×2×2	8 (8^1)
III	4×4×4	64 (8^2)
IV	8×8×8	512 (8^3)
V	16×16×16	4096 (8^4)

Table 1. Progressivity of the oct-tree levels

300 729 voxels are needed to fill the complete volume of the vehicle, based on the interpolated covering surface. Applying the oct-tree divided layers, 22 892 voxels represent the whole volume, which means 7.61%! Regarding the processing speed, the complete modelling process takes less than a minute in an ordinary office PC (Table 2).

Layer	No. of voxels	Compression rate* [%]	Processing time [s]
1	300 729	100.00	3.67
2	53 300	17.72	10.69
3	26 056	8.66	11.72
4	23 088	7.68	11.86
5	22 892	7.61	12.01

Table 2. Compression rates and processing times

3. CONCLUSIONS

The discussed modelling method can be used for several transportation purposes. For sophisticated traffic flow analysis, transportation management needs additional information about the vehicles travelling on the roads. One important issue is the vehicle classification; LiDAR provides high accuracy elevation data, which – as our previous research works proved – enables coarse vehicle categorization even with modest point density.

As a continuation, instead of modelling vehicles with discrete points or the envelope curve (what we did in our previous research), the voxel-based object reconstruction provides an effective solution for modelling the complete volume of an object. Therefore the size of every vehicle sections (depending on the desired resolution) can be computed. Based on these sections the vehicle types can be distinguished; our prior studies showed that among others, the major difference for example between a passenger car and an MPV can be found in the shape/size of the back of the vehicle.

* with the meaning of: no. of hierarchical voxels compared to the whole voxel amount

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