

MODEL-BASED VEHICLE DETECTION FROM LIDAR DATA

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ABSTRACT:

Airborne laser scanning has established itself as a dominant technology providing high quality surface data for a variety of applications. LiDAR has substantially widened the use of mapping, for instance, in the late nineties, telecommunication industry required large volumes of high-density DSM data. In addition, research has recently shown promising results in extracting features such as man-made objects, for example buildings, from the point cloud. More recently, research started to explore the feasibility of using Lidar data for transportation applications, including infrastructure, emergency and environmental mapping along corridors. Initial investigation on assessing the performance of extracting vehicles from LIDAR data and then categorizing them has proved that valuable traffic flow information can be obtained. The vehicle classification was mainly based on simple four-parameter description of the vertical profile of the vehicles. This paper is a continuation of that research effort by introducing an improved model of the vehicle profile description. A model library is formed based on the ground-based laser scanning data and an analytical approximation of the vehicle profile will replace the previous four-parameter description. The anticipated benefits are twofold: 1) a better extraction and a more robust coarse classification of the vehicles are expected, and 2) it is very likely that subclasses of vehicles can be introduced such as small cars, full-size cars, light trucks, SUVs and so on. This paper describes a newly developed model of vehicle profile description, the classification method, implementation, and algorithmic aspects. Extensive tests have been carried out to validate the method and assess its performance.

1. INTRODUCTION

Due to decreasing sensor prices and improved navigational accuracy, laser scanning technology (also known as LiDAR) has become a dominant technology in topographic mapping. LiDAR rapidly produces high density, accurate spatial data with minimal need for post processing (Flood 1999). Due to its data acquisition characteristics, LiDAR is mainly used for digital surface/elevation model (DSM/DEM) generation, but its application rapidly widens for instance in urban planning, agriculture or transportation.

Transportation as a major momentum of modern economy creates even more complex tasks for engineers. Its environmental impact, accidents, and wasted time spent in congestion mean serious economical damage for motorized countries (Zhao 1997). Old city structures do not allow major changes in the road network; the problem should be solved in the area of operation and controlling. Nowadays, intelligent transportation systems (ITS) continuously gain ground in transportation management. ITS, as a sophisticated information system, however, requires accurate, high-density spatial data, which demand cannot be satisfied with conventional data acquisition technologies.

Remote sensing, including LiDAR can contribute to this task. The research presented in this paper has been conducted as part of the NCRST-F (National Consortium for Remote Sensing in Transportation - Flows) project. We will discuss some aspects of the potential use of laser scanning technology in transportation, especially, focusing on different methods of vehicle classification.

2. FIRST APPROACH: PCA

In our initial approach we derived basic geometric features of the vehicles, such as length, width and height values. First, the vehicles have to be segmented from the data set, which can be accomplished applying well known techniques, such as thresholding, or edge detection. However, it's not a straightforward task, since various effects may corrupt the resulted vehicle point cloud in the LiDAR data set.

In order to reduce the dimensionality of the feature space, principal component transformation had been carried out. The input matrix contained the above mentioned parameters of all the involved vehicles. For the training, we used a data set acquired in Ohio, and for the tests, LiDAR data sets obtained from Michigan and Ontario. Further details of the Principal Component Analysis can be found in Toth et al. 2003a. As a result, the desired vehicle categories (e.g., passenger car, multi-purpose vehicles, and trucks) can be nicely separated and easily distinguished (Lovas 2004a). Figure 1 shows the vehicle categories in the 2D classification space.

The result of this clustering served as a basis for automated pattern recognition methods. All three developed techniques (rule-based method, minimum distance method (Duda et al. 2001), and neural network-based classifier, (Rojas 1993) are able to categorize the vehicles (72 training vehicles + 30 test vehicles) with accuracy better than 80 % (Toth et al. 2003b).

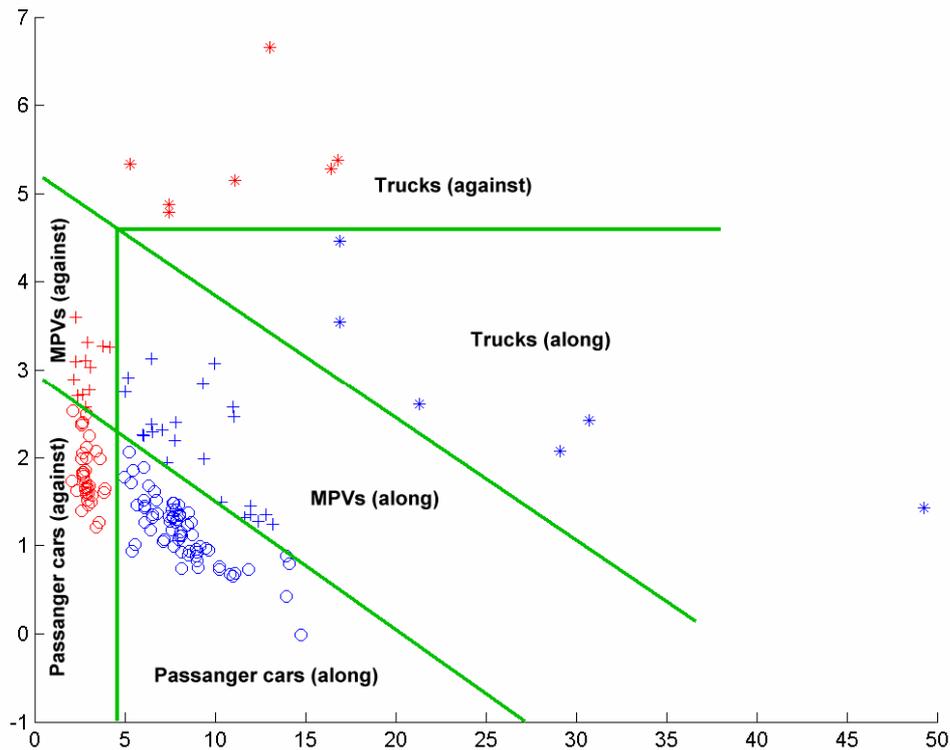


Figure 1. Applying rule-based classifier based on PCA.

2.1 PCA REFINEMENT: INTENSITY VALUES

Applying more features could improve the performance of PCA-based classification. Since our latest dataset also contains intensity values, our next idea was to use them as additional parameters. Comparing the dataset with spatial coordinates and the one with X, Y and intensity values, it can be clearly seen how the vehicles differ from the road surface (Figure 2).

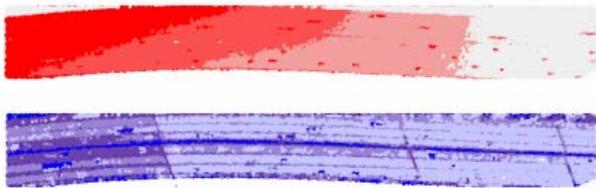


Figure 2. Elevation (red) and intensity (blue) road map

Supposedly, different vehicle categories produce different reflection intensity. For example, an MPV or light truck has very steep rear window (if any), hence the rear sections of the car theoretically reflect more points, or points with higher intensity values, so does a lorry or an eighteen-wheeler.

We stored the intensity values associated with the segmented vehicles in a database management system. The input matrix previously contained the following parameters: length, width and four mean height values (h1-h4) along the vehicle. In the next approach, the input matrix is extended with four further columns corresponding to the four mean intensity values (int1-int4), see Table 1.

length	width	h1	h2	h3	h4	int1	int2	int3	int4
7,37	1,2	0,9	1,1	1,2	1,1	87,5	69,4	27,0	17,8
5,72	1,2	0,7	1,0	1,2	1,2	33,2	30,6	39,4	45,5
8,18	1,7	0,9	1,3	1,2	1,0	55,1	38,1	81,1	75,0

Table 1. The structure of the input matrix

As opposed to the striking positive results of the PCA method which is based on geometric parameters, the enhanced algorithm did not result in good distinguished categories; the deviation between the intensity values turned out to be too high..

3. MODEL-BASED CLASSIFICATION

Our next approach is also based on geometric parameters of vehicles, this method uses height values and the length/width of the vehicle, and its objective is deriving the shape, i.e., the profile of the vehicle.

The dataset used as training data for the PCA was acquired over Route 35 (Dayton, OH). In order to investigate the effect of the point density, we used a dataset obtained in Toronto (in 2004) for our shape and profile investigations (Table 2). The dataset collected in Ohio has relatively modest point density, but, still we could apply it for classification purposes. However, the data from Toronto had a higher point density that we were able to use for developing a refined technique.

	Flight 1	Flight 2
Flying Height (AGL):	470 m	660 m
Average Ground Speed:	56.6 m/sec	58.5 m/sec
Heading:	290 degrees	250 degrees
Scan Frequency:	50 Hz	46 Hz
Field of View (Half Angle):	6 degrees	20 degrees
Laser Repetition Rate:	10 kHz	70 kHz
Point density	1.5 points/m ²	2.4 points/m ²
Area	Route 35, OH	Toronto, Canada

Table 2. Flight parameters

Practically, in the Ohio dataset, 20-30 points were collected from a passenger car (and 40-60 points from a truck) traveling along the direction of flight. In the opposite direction, the value of collected points/vehicle is under 10, based on which we were not able to reliably determine the vehicle profile. However, from at least 20 points, reasonable vehicle profiles could be calculated

Due to multipath reflection or processing errors, the coordinates of some points are wrong, but our main problem is caused by out-of-shape points. For classification, we need points describing the profile of the vehicle; therefore, airborne LiDAR seems to be an appropriate technology for this purpose, since points are reflected from the top of the vehicle. However, the flight line does not always coincide with the road (or centerline of the road) and from the side of the scan swath points tend to reflect also from the side of vehicles; these points have smaller height values than the profile points.

Points reflected from the side of vehicles, or from roadside objects, as well as multipath reflection can corrupt the results. In order to eliminate this effect, the sides of vehicles have been cropped; only points in the middle strip were used for creating the profile (Lovas 2004b).

Shape Detection

First, the vehicles are divided into equal parts along their profiles (not laser profile, which is across!), each containing at least two points. In every section, the mean height value of the points, i.e., the points of the profile are calculated. Our experiments show that the minimum resolution should be at least 8 sections along the profile; this makes also visual recognition possible. In case of a passenger car, the engine hood and the trunk lid are clearly shown, so is the MPV's bulky figure (presumably an SUV or van), and the shape of the eighteen-wheeler is even better outlined on the picture below (Figure 3).

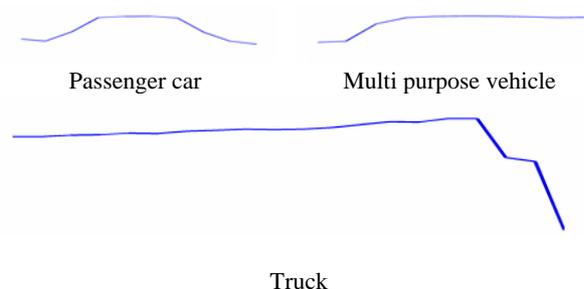


Figure 3. Typical vehicle shapes

The partition of each vehicle depends on the number of reflected points and the point distribution. All the

vehicles used in this shape-definition were previously classified with PCA-based clustering and controlled by visual recognition based on color-coded 3D models.

In order to compare the shapes, we have to normalize for length. The deviation in actual vehicle length is only one factor (more than 90% of vehicles are between 4 and 5 meters); the other contributor is elongation which is proportional to speed.

The previously categorized vehicles tend to have similar profiles (Figure 8). Creating a buffer zone (envelope curve) based on profile points with extreme values shows the key to the profile based vehicle detection. These buffer zones have to be created for each predefined category; every new vehicle profile is evaluated whether it fits or not in the particular buffer zone. The upper and lower boundaries are marked in red, the sample shape in green, respectively.

4. GROUND-BASED LIDAR DATA

In general, ground-based laser scanning technology has similar advantages as airborne LiDAR. It rapidly produces high density, accurate spatial data. On the ground, the sensor coordinates can be obtained by accurate positioning methods, such as DGPS or conventional geodetic measurements. Recently LiDAR sensors are frequently complemented with digital camera systems, and besides the 3D coordinates and the laser intensity values, the "color" of each point, can be attached (Figure 4).

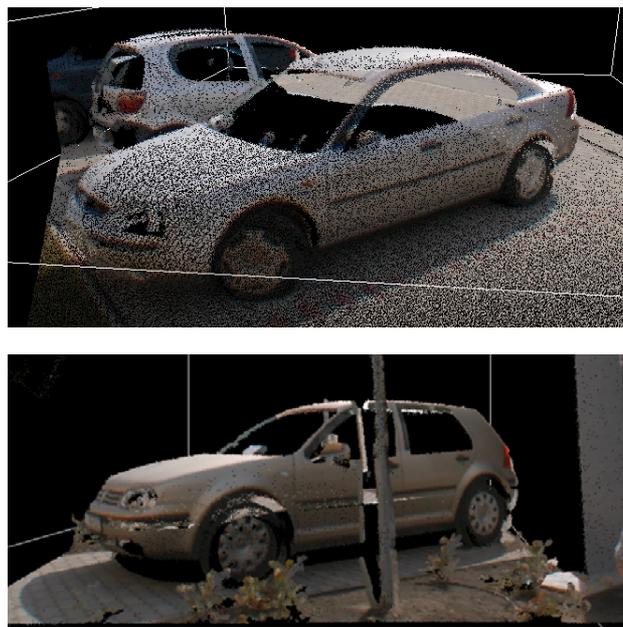


Figure 4. Test cars (laser points fused with camera image)

The main difference lies in the point density; ground laser sensors usually mounted on tripods, the objects to be mapped are not moving during measurements, and hence there is enough time to scan through the area with the desired point density. Of course, the application area of airborne LiDAR significantly differs from that of ground sensors, similarly to the relation between airborne and close-range photogrammetry.

In our first approach, we derived the "mean-shape" from the training data set and then generated a buffer-zone for the classifier. In order to improve the resolution of the profile, we performed a ground-based laser scanning campaign in a packed

parking lot. The goal was to get information about as many vehicle categories, as possible.

Categorizing Issues

The ground based laser scanning measurement was performed in Hungary, where the traffic patterns are basically representative for Europe, while in our research we used airborne data sets acquired in the USA and Canada, where characteristics of the traffic are noticeably different. From the nineties, there are much more MPVs (especially light trucks) sold in the US as passenger cars. In Europe, there are much less MPVs running on the roads, and most of them are minivans, not SUVs and light trucks, while in the passenger car category, the proportion of hatchback cars is definitely higher, whereas the proportion of the sedans is much higher in the US. Therefore, we focused on vehicles that can be representative in both regions.

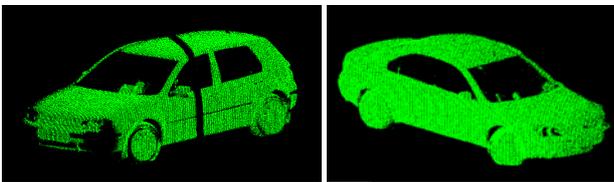


Figure 5. The point clouds of the test vehicles

For our model-based investigations, we used the data set acquired about a Ford Mondeo with a conventional sedan profile, and about a VW Golf, which is a hatchback; two very popular cars with very typical shapes (Figure 5).

PCA Test

First, these two typical vehicles were classified using PCA; the cars have been categorized correctly. In the PCA, where 6 parameters were involved (length, width, heights), these cars are on the border of two groups (passenger cars traveling along and against flight direction): the cars from the airborne mapping are either elongated or shortened, that is why the moving directions can also be distinguished in the 6 parameter case.

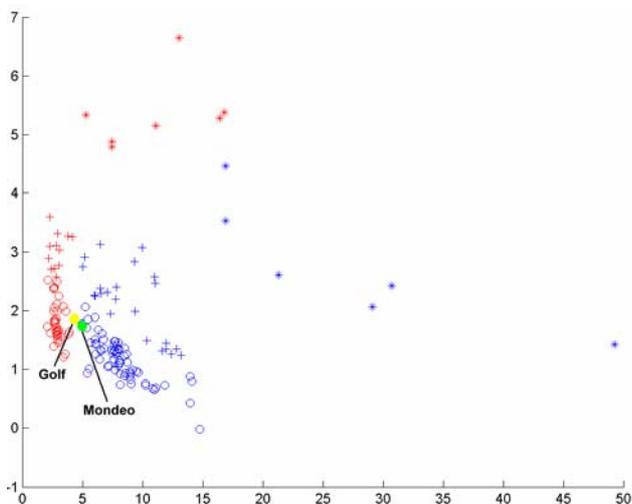


Figure 6. The new cars in the PCA-based clustering

In our ground based laser measurements the cars parked in a parking lot, therefore, their length values in the dataset fall between the shortened and elongated length values of the airborne dataset (Figure 6).

Profile Determination

In order to derive the shape of vehicles, the sides have been cropped, since the points reflected from the side of the vehicle are not included in the profile determination. Just for the sake of comparison, in the airborne campaign, typically 20-30 points are reflected from an elongated car, in the ground based dataset these test vehicles have about 200-300 000 points, despite the side-looking sensor position (the back of the car is shadowed).

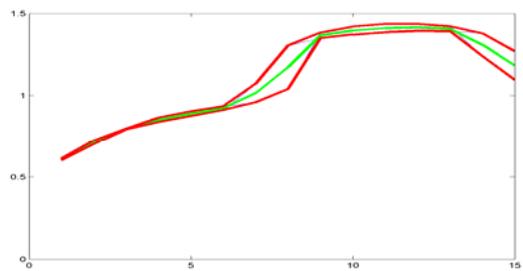


Figure 7. Shapes of the ground-laser measured vehicles

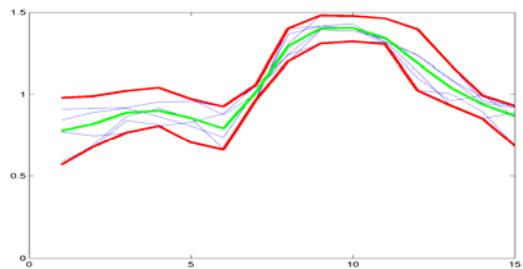


Figure 8. Shapes of the airborne campaign

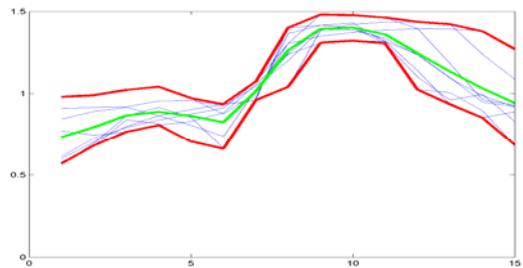


Figure 9. The combined shape curves and envelopes

As it can be seen in the Figures 7 to 9, the shapes of the cars measured with the ground sensor are fit in the previously defined buffer zone. The only difference is the back part of the vehicles, where the hatchbacks are remarkable higher than the sedans. The classification cannot be exclusively based on the length, since it depends on the speed of the vehicle; therefore, the shapes in the figures are normalized in length.

Using the ground models, sample shapes can be derived for the subclasses, e.g. hatchbacks, sedans and caravans in the passenger car category and minivans, light trucks and SUVs in the MPV category.

5. CONCLUSIONS

The vehicle classification and recognition methods described in this paper show reasonable performance in categorizing vehicles, which proves the capability of LiDAR in supporting traffic flow applications. This paper focused on classification using ground-based laser scanning datasets that could lead to a refined classification in the future. In addition, we developed technics to decrease the impact of corrupting points (reflected from the side of the vehicle, multipath reflection, other objects on the road etc.), since the vehicle points can be filtered either by cropping the outliers or filtering the shapes and adjusting the resolution along the profile.

As opposed to airborne measurements, the ground-based laser scanning campaign was performed in Hungary, where the traffic pattern is significantly different from that in the US. Therefore, we have chosen widely used vehicle models as test vehicles, which can be representative even in the US. In the ground laser dataset the point density was exceptionally high, especially compared with the airborne set; in the profile determination process the overwhelming number of points ensured a very good resolution. The resulted shapes are nicely fit within the previously derived buffer zone (with sample shape); the only visible difference is caused by the higher back parts of European cars.

The shape-based method can be directly used as a classifier, or can be used to enhance the previously used PCA based classification. Applying ground based laser scanned data, a detailed shape library can be established, which can be used to distinguish between sub-classes within the categories.

The potential of using intensity values in the classification procedure has also been investigated. Although, the intensity maps seem to be applicable for segmentation, the point density of our dataset (2.4 points/m²) might not be sufficient for that purpose.

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References

Duda, R. O., Hart, P. E., Stork, D. G. (2001): Pattern Classification, Wiley, New York

Lovas, T. (2004a): Comparison of Vehicle Recognition Methods Using LiDAR Data, II. PhD Civilexpo Conference, Jan 29-30, in press, Budapest

Lovas T. , Barsi A., Toth C., (2004b): Detecting Moving Targets in Laser Scanning, Proc. ASPRS Annual Conference, Proc. ASPRS Annual Conference, Denver, CO, May 23-28, CD ROM.

Rojas, R. (1993): Theorie der neuronalen Netze – Eine systematische Einführung, Springer Verlag, Berlin

Toth C., Grejner-Brzezinska D., Lovas T. (2003a): Traffic Flow Estimates from LiDAR Data, Proc. ASPRS Annual Conference, May 5-9, pp. 203-212, CD ROM.

Toth C., Barsi A., Lovas T. (2003b): Vehicle Recognition from LiDAR Data, International Archives of Photogrammetry and Remote Sensing, Vol. XXXIV, Part 3/W13, pp. 162-166, CD ROM.

Zhao, Y. (1997): Vehicle Location and Navigation Systems, Artech House, Inc., Boston

Flood, M. (1999): www.airbornelasermapping.com