FEATURE RECOGNITION FROM MOBILE LASER SCANNING DATA FOR ROAD SAFETY INSPECTION

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ABSTRACT: The latest mobile mapping systems provide an efficient technique for acquiring very dense point clouds along road corridors, so that automated procedures for recognizing and extracting structures can be developed. This paper presents a framework for structure recognition from mobile laser scanned point clouds. It starts with an initial rough classification into three larger categories: ground surface, objects on ground, and objects off ground. Based on a collection of characteristics of point cloud segments like size, shape, orientation and topological relationships, the objects on ground are assigned to more detailed classes such as traffic signs, trees, building walls and barriers. Two mobile laser scanning data sets acquired by different systems are tested with the recognition methods. Performance analyses of the test results are provided to demonstrate the applicability and limits of the methods.

1. INTRODUCTION

In 2007 42,448 persons were killed in traffic related accidents on European roads (European Commission, 2009). To improve safety on European roads, a road infrastructure directive is to be implemented by the end of 2010 (Mc Elhinney et al., 2010). One of the four regulatory actions is on the inspection of safety of existing roads (Francesconi, 2007). An important input component to the risk assessment is a complete description of the road surface geometry, including the road shoulder, and all objects on, above or near that surface, like road sides, road markings, street lights, traffic lights, traffic signs, crash barriers, buildings and vegetation. The objective of the research presented here is the automated extraction of all objects above the terrain from point clouds acquired with a mobile laser scanner.

The objective of this paper is the development of a recognition concept for objects in road corridors that could be used in a mobile mapping system, and the analysis of its performance on different test sites acquired by different MLS systems. Related work on MLS and feature extraction for road inventory purposes is discussed in Section 2. Our method presented in Section 3 is aiming to classify and recognize selected objects, which have major importance in road safety and risk assessment. It starts with an initial rough classification into three categories: ground surface, objects on ground, and objects off ground. Based on a collection of point cloud segment characteristics such as size, shape, orientation and topological relationships, the objects on ground are assigned to more detailed classes such as traffic poles, trees, building walls and barriers. The conducted tests are described and analyzed in Section 4. Conclusions and recommendations are presented in Section 5.

2. LITERATURE REVIEW

Currently, operational road safety inspections are carried out either by time-consuming site inspections or semi-automatically by visually analysing imagery and video data. Mobile mapping systems with camera systems combined with GPS/IMU have been developed since the early 1990's. A good overview is presented in (Ellum and El-Sheimy, 2002). Significant progress has been reported on automatic identification of road lanes and traffic signs (Huang et al., 2004; Timofte et al., 2009; Escalera et al., 2010. Road lane and traffic sign recognition are very important for vehicle guidance. For road safety inspections the acquisition of the geometry of all objects on and around the road is required. Image based acquisition typically requires good lighting conditions (e.g. day time and weather). It cannot robustly provide precise object geometry information under poor conditions. Recently, advances in laser scanning technology led to the integration of laser scanners on mobile mapping platforms (Barber et al., 2008). Mobile laser scanning (MLS) also referred as Mobile LiDAR has proven to be very efficient in acquiring very dense point clouds (over 800 points per square meter) along road corridors. Integrated in a mobile mapping system, the data acquired by laser scanners can be used to robustly capture the geometry of the road environment and be the basis for the recognition of a wide range of objects. A detailed classification of objects, in particular traffic signs and road lanes will, however, remain largely based on optical imagery.

3. METHODS

Our feature recognition method attempts to recognize the objects which have significant influences on the road safety inspection from the MLS point clouds. In this research, the objects within a scanning scene (i.e. the road area in MLS) are described as features using a number of distinguishing attributes and organised hierarchically. The main steps are:

1. The segmented laser points are roughly classified into ground, on-ground and off-ground.
2. The on-ground segments are further examined using a knowledge based method to recognize the interested features for road inventory such as poles and crash barriers.

3.1 Rough classification

In the case of MLS, the ground points represent probably always the largest data volume, while our features of interest are usually placed on the ground. The purpose of the rough classification is to divide the MLS data to three groups: ground, on-ground and off-ground points.

3.1.1. Knowledge based feature recognition

Our feature recognition method is developed from the knowledge based feature recognition theory for building facade reconstruction as described in Pu and Vosselman (2009a, 2009b).

In reality features appear in a wide amount of types. Despite their varieties in function, shape, colour and material, humans seem to have no difficulty understanding most features within their field of vision, and can even speculate about the areas which are not directly visible. In MLS, plenty information about roads and their surroundings are recorded in laser points and images. The knowledge base of the recognition agent can be derived from human experiences or statistical learning from training data. Selection of an appropriate reason engine is strongly related with the sensor data's quality and the complexity of the target feature type.

3.1.2 Characterisation of features

Fig. 1 gives a generic category of the features from MLS. Most of these features, such as poles, barriers and vegetation, are important for road inventory purpose. Each feature is described with a number of distinguishing attributes and its relations with other features. Strong clues can be derived by comparing the sensor data with the feature's descriptions to suggest the most likely feature type.

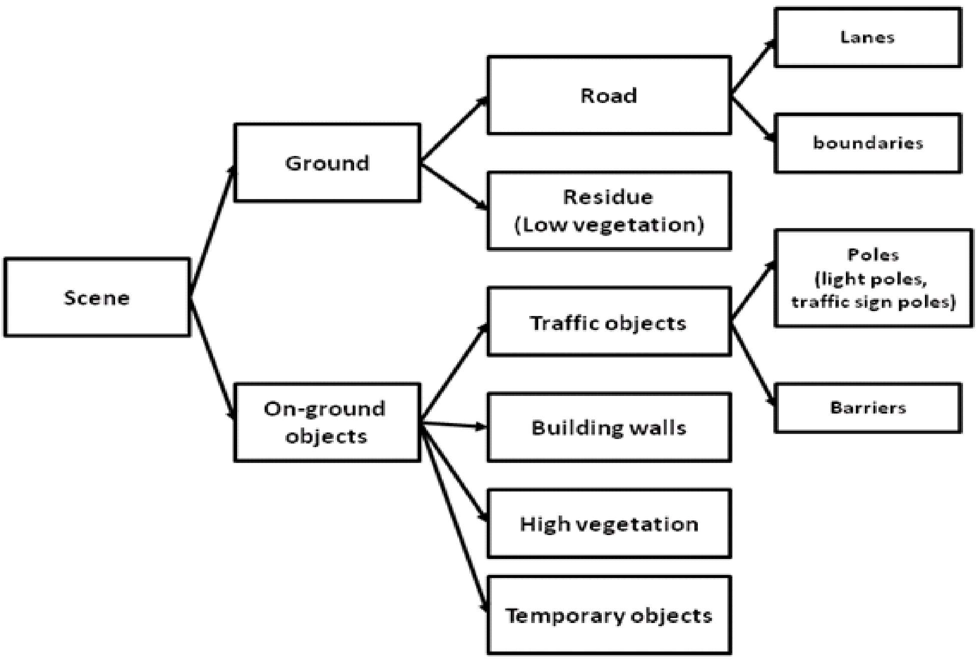


Fig. 1. A generic category of the interested features for MLS data

The considered geometric attributes include:

- Size. The term size can refer to a feature's length, width, height, area, or volume, which is probably the most distinguishing attribute..
- Position. Some features can be expected at certain relative positions inside a scene. The positions of smaller structures (such as traffic signs) are relatively more random, but at least they always appear at the higher locations to achieve good visibility.
- Orientation. Feature's orientations are also often predictable.
- Shape. Man-made objects often have regular and common shapes.
- Colour. Colour is probably the most important information for humans to perceive the world. The colour pattern of objects can be used to identify a large number of features.
- Material. Most traffic signs and road marks are painted with special acrylic paint with high reflectivity to increase their visibility. The reflectance of laser points with such objects provides an important clue for distinguishing traffic signs and road marks.

Besides a feature's own geometric attributes, some topological relations between features can also be predicted. These spatial relations include:

- Intersect. Intersection is a basic spatial relation indicating the neighbouring relation of two features. All on-ground objects intersect ground.
- Angle. Angles between man-made objects are often parallel or perpendicular.
- Based on the above attributes and relations, all the feature types in Fig.1 can be defined and organized.

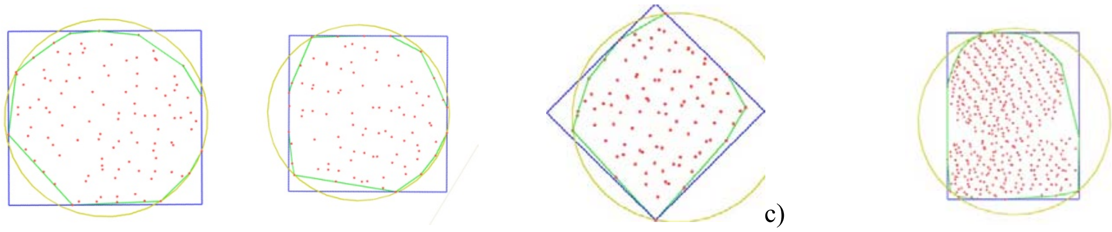
3.2 Shape recognition in MLS data

Before the actual feature recognition starts, the feature types of interest should be defined according to the knowledge based method as presented in the previous subsection. The geometric attributes of a segment and the topological relations between segments are important information for feature recognition. Pu and Vosselman (2009a) present the details how to derive size, position, orientation, and topology information from laser segments. The following subsection contributes a new algorithm which recognizes the shapes of laser point segments.

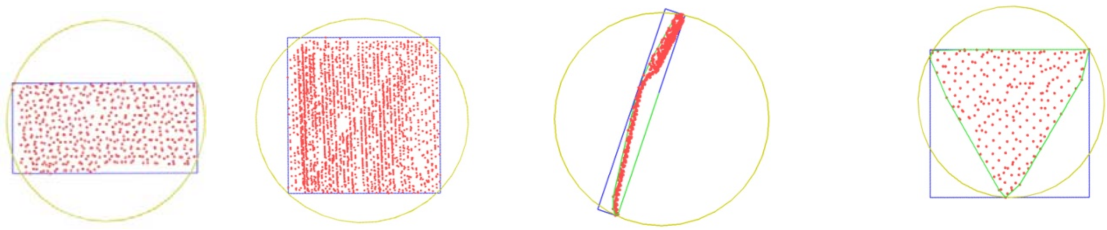
Five classes of shapes are considered in this research: rectangle, circle, triangle, volume and others. In Europe, the rectangular signs usually provide traffic information such as directions, distances and area names; the triangular signs give warnings; the circular signs are generally prohibitive signs. The main steps of the shape recognition algorithm are given as follows:

a) Geometric fitting. A laser segment is fitted with its convex hull, Minimum Bounding Rectangle (MBR), and Minimum Bounding Circle (MBC, see Fig. 2). The MBR refers to the oriented minimum bounding rectangle which guarantees the smallest area of the rectangle. The MBC is approximated by the gravity centre of the laser points and the longest distance between the laser points and the gravity centre.
b) Recognizing rectangle or circle. The areas of the convex hull, MBR and MBC are calculated. The matching rates of a laser segment to rectangle shape or circle shape are indicated by the ratio between the convex hull's area to MBR's area and MBC's area.
c) Recognizing triangle. The Hu moments based shape matching method is applied. See Hu (1962) for a detailed description of this method. If the matching rate to MBR and MBC are both lower than the matching threshold, the part will be matched with a triangle grey image using the Hu moments based method to check whether it is actually a triangle.

Fig. 2 illustrates the shape recognition of eight laser segments. The matching threshold is set to 80%. The matching rates of the convex hull with MBR, MBC and triangle are listed in Table 1.



a) forbidden sign b) forbidden sign c) priority sign d) forbidden sign with instruction sign



e) direction sign f) information sign g) light head h) warning sign

Fig. 2. Recognizing shapes by comparing fitted geometries (red: laser points; green: convex hull; blue: MBR; yellow: MBC)

	a	B	C	D	E	f	g	H
Rectangle	79%	**82%**	**89%**	76%	**92%**	**96%**	22%	57%
Circle	**84%**	81%	59%	54%	49%	67%	5%	48%
Triangle				25%			2%	**93%**

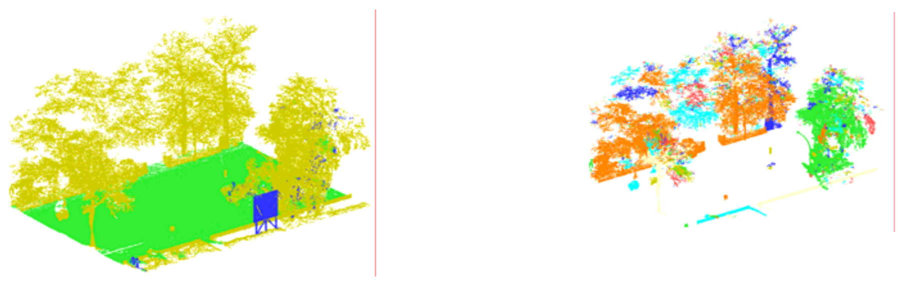
Table 1. Matching rates of the laser segments in Fig. 3

It can be seen from Table 1 that the shapes of most parts can be correctly recognized. The matching rate can be up to more than 90 percent (part e and f) when the part is completely scanned and the point density is sufficient. The recognition of irregular shapes (such as part d and g) is also possible since their matching rates with any of the three shapes are rather low. The matching rates of MBR and MBC become similar for circular parts when the points are not so dense. Part b is even recognized as a rectangle although it is actually a circular forbidden sign. At this moment we do not yet have an efficient solution for recognizing hybrid shape such as part d .

4 .TEST CASE

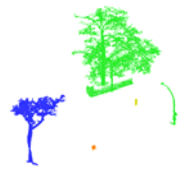
Test on one MLS data set is demonstrated in this section to evaluate the performance of the recognition method. The test site is located in Enschede, a city in the east part of the Netherlands. Mobile mapping data was acquired by TopScan GmbH in December 2008 using the Optech's Lynx Mobile Mapper system (Optech, 2010). The MLS of Enschede was carried out in 25 strips, and one of them is selected for the method evaluation. The tested data strip is about 1.4 km long, containing 20,424,631 laser points in total. The tested data strip is then partitioned along scanning trajectory into 28 road parts, with each road part 50 m long and 40 m wide.

a) Original MLS data (colored by elevation) b) Segmented data (colored by segments)



c) Distinguishing ground (green), on-ground (yellow) and off-ground (blue) points

d) Re-segmenting on-ground points by connected components (colored by components)



e) Recognizing poles by regular method (colored by components)

f) Recognizing poles by percentiles based method (colored by components)

Fig. 3. Recognizing structures from the Enschede data

The whole data strip was processed with an automated procedure which loops over the road parts (see Fig.3). A further classification is then applied to all objects with a detected pole. We have analysed the results of our extraction method followed by a visual performance analysis for completeness and correctness of the results. The performance analysis is based on the assumption that the human operator is able to correctly recognize every concerned feature.

From Table 2 we conclude that the class ‘other poles’ mainly contains lamp poles and poles with road signs (35 out of 46 belong to these two classes). The low detection rate of bare poles (5 out of 25 = 20%) is because 16 of them were classified as other poles. If the three pole classes (bare pole, traffic sign and other pole) are combined into one class the detection rate increases up to 87% (see Table 3). Improving the detection rate of poles and road signs can be done by correctly subdividing the features in class of other poles into bare poles and road signs. Integration with reflectance information and image information to better detect road signs is part of future research.

Enschede total		**Visual inspection**					False positives
		Bare poles	Trees	Traffic signs	Other poles	Total detected	
Algorithm	Bare poles	5	1	1	1	8	37.5
	Trees	1	33	4	1	39	15.4
	Traffic signs	0	2	45	0	47	4.3
	Other poles	16	2	19	9	46	80.4
	Missed	3	14	5	0	22	
	Total visual	25	52	74	11	162	
	Detection rate (%)	20	63.5	60.8	81.8		

Table 2. Confusion matrix of the feature recognition in Enschede data set

Enschede: bare poles, traffic signs and other poles combined		**Visual inspection**				False positives
		Poles	Trees	Others	Total detected	
hm	Poles	86	5	10	101	14.9
	Trees	5	33	1	39	15.4

	Missed	8	14		22	
	Total visual	99	52	11	162	
	Detection rate (%)	86.9	63.5			

Table 3. Confusion matrix of the feature recognition in Enschede data set after combining three pole classes (bare pole, traffic sign and other pole)

Table 3 also shows that out of total 162 objects the algorithm was not able to detect 22 objects, of which 14 are trees. Most of these objects are located near the outer boundary of the data sets, parallel to the driving direction. Direct reason for the majority of missing objects is that the segments on these objects were not considered to be on-ground features. Underlying reason is that those segments did not lie within the convex hull of on-ground segments. This indicates that improvements can be made in step 2 of our algorithm, the rough classification. Another reason why trees are not detected is that the trunk is not captured by the scanning system, so the object is not recognized as being a pole-like object.

5. CONCLUSIONS

In this paper we presented a feature recognition method which recognizes important features for road safety inspection from mobile laser point clouds with a largely automated process. After processing the MLS with the proposed method, important parameters (such as location, orientation, curvature, and distance) for safety analysis can be directly obtained from the intermediate results or easily extracted from the recognized feature segments. It is proven that feature configurations, scene complexity, and data quality are the vital factors to the recognition performance.

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