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Segmentation and classification of road markings using MLS data

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ABSTRACT

Traffic signs are one of the most important safety elements in a road network. Particularly, road markings provide information about the limits and direction of each road lane, or warn the drivers about potential danger. The optimal condition of road markings contributes to a better road safety. Mobile Laser Scanning technology can be used for infrastructure inspection and specifically for traffic sign detection and inventory. This paper presents a methodology for the detection and semantic characterization of the most common road markings, namely pedestrian crossings and arrows. The 3D point cloud data acquired by a LYNX Mobile Mapper system is filtered in order to isolate reflective points in the road, and each single element is hierarchically classified using Neural Networks. State of the art results are obtained for the extraction and classification of the markings, with F-scores of 94% and 96% respectively. Finally, data from classified markings are exported to a GIS layer and maintenance criteria based on the aforementioned data are proposed.

1. Introduction

While driving a vehicle, a human driver perceives numerous visual information that indicates potential dangers, speed limits, or road layout among others. Even though road markings may not be the most important type of traffic sign, they are crucial for pedestrian safety in populated environments. An optimal positioning and condition of pedestrian crossings will definitely help to reduce and prevent run-over accidents.

The automatic detection of road markings has been used for autonomous vehicle guidance (Vacek et al., 2007; Hoffmann et al., 2007) or for Lane Departure Warning (LDW) systems, which are a common active safety feature in commercial cars (Kibbel et al., 2005) that prevent involuntary lane departure (Rimini-Doering et al., 2005). Furthermore, this automation may assist the maintenance and inventory tasks reducing both the cost of the process and the subjectivity of the results, as these activities are normally carried out by inspectors. The inspectors are who subjectively report the maintenance needs of a surveyed road based on a technical specification. For Spanish roads, road marking specifications are defined by Ministerio de Fomento (1987).

There are several studies in the literature that deal with road marking detection. Typically, computer vision techniques have been applied to line tracking (McCall and Trivedi, 2006) and road object classification (Danescu and Nedevschi, 2010) using RGB images and video. Road marking detection in images is a challenging task, as there are a number of factors that determine the robustness of an algorithm, namely weather conditions, pavement material and color, shadowing and lighting changes, etc. Therefore, there is a need to study the robustness of different data sources for this task.

Nowadays, one of the most popular sources of data for infrastructure surveying is laser scanning. These instruments are able to collect geometric and radiometric properties of their surroundings in a cost-efficient, reliable manner. When mounted on a Mobile Mapping System (MMS), laser scanners collect dense, accurate 3D point clouds driving at standard speeds (Puente et al., 2013; Ussyshkin, 2009).

Although it is still an active research topic, promising results have been achieved using Mobile Laser Scanning (MLS) technology, transforming unorganized 3D data into a meaningful set of segments. Yang and Dong (2013) segment point cloud scenes using Support Vector Machines (SVM) for classifying each point as linear, planar or spherical, based on features extracted from a Principal Component Analysis (PCA) of the optimal neighborhood of each point. Points within the same class are subsequently merged and refined into significant segments. Vo et al. (2015) developed an octree-based region growing which segments a point cloud in a coarse-to-fine process. First, it groups together points on a vox-

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elized space that have similar normal vectors and residual values, and then performs a refinement that studies the unallocated points and the boundaries of the previously computed segments. Different classification techniques are used for giving a semantic meaning to each point cloud partition. Serna and Marcotegui (2014) computed geometric, contextual and color features of segmented objects and classified them in 20 classes (cars, bollards, fences, etc.) using hierarchically trained SVM. Although SVM are extensively used for remote sensing applications (Mountrakis et al., 2011), other authors use heuristics for classifying point cloud segments. In (Yang et al., 2015) seven urban objects are classified from the saliency and the geometry of each segment, and in (Pu et al., 2011) pole objects and five classes of shapes are distinguished by computing their Minimum Bounding Rectangle (MBR), Minimum Bounding Circle (MBC) and convex hull, and studying their geometrical relationships. The segmentation-classification approach is employed for road marking extraction as well. The only relevant segment in this case is the road, therefore ground segmentation is the usual first step. Douillard et al. (2011) computed height and vertical variance of each voxel in a 3D grid, and segmented the ground based on local differences between adjacent voxels. Serna and Marcotegui (2013) use the λ-flat zones labeling algorithm to segment the ground and defines it as the largest flat zone in a range image that contains height information of the point cloud. Guan et al. (2014) detect curbs in consecutive profiles of a point cloud and delineate the limits of the road using the curbs as road limits. Although it performs robustly in roads with curbs, the performance of this segmentation algorithm in roads without curbs remains unclear. In Guan et al. (2014) road markings are extracted from geo-referenced intensity images using Inverse Distance Weighted (IDW) interpolation and a point density dependent thresholding. As road markings are reflective surfaces, the intensity feature is commonly used for creating raster images where road markings can be extracted. For instance, Kumar et al. (2014) applied a range dependent thresholding process and morphological operations over an intensity image, and Chen et al. (2009) used Hough Transform Clustering for detecting lane markings. Recently, Yu et al. (2015) extracted road markings directly from the 3D point cloud via multisegment thresholding and Otsu binarization, classified them in four classes using Deep Boltzmann Machines (DBM) and, in a second level of hierarchy, in seven classes of road markings comprising arrows, pedestrian crossings or stop lines.

In this paper, a method for road marking extraction and classification from MLS data is proposed. Furthermore, with the aim at assessing and updating the state of the road markings in the context of a Smart City, the outputs of the proposed method are exported to a Geographic Information System (GIS) layer, and criteria for updating the road marking inventory is proposed, moving a step forward with respect to related work. The methodology is described in detail in Section 2. Section 3 presents the study case and the Mobile Mapping System characteristics. The performance of the method and its comparison with related work is summarized in Section 4, and finally the conclusions and future work are outlined in Section 5.

2. Methodology

An overview of the method is shown in Fig. 1. First, the pavement is segmented and an intensity filter is applied in order to extract reflective pavement points from the point cloud. Subsequently, a raster image is created and road markings are detected after several image processing steps. Two different sets of features are computed for each marking, which is classified in two levels of hierarchy, distinguishing pedestrian crossings and five classes of arrows. Finally, the data from each classified road marking is exported to a GIS layer, where maintenance assessment can be conducted.

2.1. Pavement segmentation

In Section 1 different road marking extraction approaches were remarked, all of them having in common a ground segmentation step. The road pavement is the only segment that contains relevant information. Furthermore, filtering out off-ground information reduces computational load and saves memory resources.

First, the raw 3D point cloud is preprocessed, filtering out points further than 10 m from the trajectory. That is, distant and noisy points are removed from the point cloud and only the data that are close to the trajectory are kept. This step reduces the size of the point cloud and it will likely remove data for adjacent streets, therefore the analysis will cover only the streets on which the MMS is moving along.

Let $\boldsymbol{P} = (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{I}, \boldsymbol{\alpha}, \boldsymbol{t_s})$ be the preprocessed point cloud, where $(\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z})$ are the 3D coordinates, $\boldsymbol{I}$ is the reflected laser pulse intensity, $\boldsymbol{\alpha}$ is the angle of the laser beam and $\boldsymbol{t_s}$ is the time stamp; and let $\boldsymbol{T} = (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z}, \boldsymbol{t_s})$ be the trajectory recorded by the navigation system of the vehicle.

First, the point cloud is partitioned in several sections $\boldsymbol{S}_i (i = 1 \ldots n)$. Defining $\boldsymbol{L_s}$ as the section length, a subset $\boldsymbol{N}_s = (\boldsymbol{x}, \boldsymbol{y}, \boldsymbol{z})$ with n coordinates of $\boldsymbol{T}$ is computed so that the distance between each $\boldsymbol{N}_s(i)$ and $\boldsymbol{N}_s(i+1)$ in the direction of the trajectory is approximately $\boldsymbol{L_s}$ (the exact distance will be determined by the spatial resolution of the trajectory). Then, the direction of the section is defined as $\boldsymbol{v} = \boldsymbol{N}_s(i+1) - \boldsymbol{N}_s(i)$, and $\boldsymbol{S}_i$ is extracted as a subset of points in $\boldsymbol{P}$ within the transversal sections defined by $\boldsymbol{N}_s(i)$ and $\boldsymbol{N}_s(i+1)$ along the vector $\boldsymbol{v}$ (Fig. 2a).

Secondly, a curb-based segmentation approach based on Wang et al. (2015) is proposed. This method constructs a saliency map on 3D point clouds by computing the dominant normal vector of the cloud via K-means clustering, and then projecting the distance between each normal vector and the dominant normal vector into a hyperbolic tangent function space, so the difference between a salient and a non-salient point is large enough to be easily classified. In order to efficiently apply the method, each section $\boldsymbol{S}_i \subset \boldsymbol{P}$ is voxelized, that is, a cubic grid with size g_s is defined and a voxel coordinate $(x^V, y^V, z^V)_i$ is assigned to each point $(x_i, y_i, z_i) \in \boldsymbol{S}_i$ following Eqs. (1)-(4).

$$x_i^V = \frac{x_i - \min(\boldsymbol{x})}{g_s} \tag{1}$$

$$y_i^V = \frac{y_i - \min(\boldsymbol{y})}{g_s} \tag{2}$$

$$z_i^V = \frac{z_i - \min(\boldsymbol{z})}{g_s} \tag{3}$$

$$id_i^V = x_i^V + N_x y_i^V + N_x N_y z_i^V \tag{4}$$

where indices id_i^V link each point in the cloud with its coordinate in the voxel grid space. Therefore, several features based on the points within each populated voxel can be computed. Specifically, the centroids of the points within each voxel define a point cloud where a 3D point represents a single voxel. Salient points (i.e. curbs, walls, poles, etc.) are found in this cloud following the method in Wang et al. (2015) (Fig. 2b).

Finally, the pavement is defined as a group of non-salient points delimited by salient points at both sides of the trajectory. Each section $\boldsymbol{S}_i$ is partitioned in a number of transversal profiles of length L_p, and the closest salient points with respect to the trajectory on its right and its left are selected. Outliers from each group of points