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Safety assessment on pedestrian crossing environments using MLS data

Mario Soilán[a,*], Belén Riveiro[a], Ana Sánchez-Rodríguez[b], Pedro Arias[b]

[a] Department of Materials Engineering, Applied Mechanics and Construction, School of Industrial Engineering, University of Vigo, 36310, Spain
[b] Department of Natural Resources and Environmental Engineering, School of Mining Engineering, University of Vigo, 36310, Vigo, Spain

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ABSTRACT

In the framework of infrastructure analysis and maintenance in an urban environment, it is important to address the safety of every road user. This paper presents a methodology for the evaluation of several safety indicators on pedestrian crossing environments using geometric and radiometric information extracted from 3D point clouds collected by a Mobile Mapping System (MMS). The methodology is divided in four main modules which analyze the accessibility of the crossing area, the presence of traffic lights and traffic signs, and the visibility between a driver and a pedestrian on the proximities of a pedestrian crossing. The outputs of the analysis are exported to a Geographic Information System (GIS) where they are visualized and can be further processed in the context of city management. The methodology has been tested on approximately 30 pedestrian crossings in cluttered urban environments of two different cities. Results show that MMS are a valid mean to assess the safety of a specific urban environment, regarding its geometric conditions. Remarkable results are presented on traffic light classification, with a global F-score close to 95%.

1. Introduction

The assessment and improvement of traffic safety is essential for the development of contemporary and humanized cities. According to the European Road Safety Observatory (ERSO), more than 5000 pedestrians were killed in road accidents in the EU in 2014, being that a 21% of all road fatalities (ERSO, 2016). The most common cause of road fatality involving pedestrians are run overs in urban areas. In 2013, run overs were the cause of 50% of the fatal accidents in urban areas in Spain (AXA, 2014). Moreover, more than 3500 people were injured on run over accidents, being contusions and bone fractures the most common consequences. However, run overs are easy to prevent to a certain extent (Fundación Mutua Madrileña, 2013). Most of the run over accidents happen in pedestrian crossing areas, being the driver the main responsible of the accident. There exists an extensive literature regarding characteristics and behavioral analysis of run over accidents as well as measures to take in order to prevent these accidents (Hamed, 2001; Jiménez-Mejías et al., 2016; Retting et al., 2003; US Department of Transportation, 2001; Várhelyi, 1998). In order to assess the safety of the road environment, different models have been developed: Lassarre et al. (2007) measure the accident risk based on the exposure of a pedestrian at a certain location on an urban area; Kelly et al. (2007) assess the walkability of pedestrian environments by identifying and weighting parameters such as the quality of the pavement, the traffic volume or the street lightning. Basile et al. (2010) develop a safety index for the assessment of the safety on pedestrian crossing environments which is based on four main criteria: Spatial and temporal design, day-time visibility, night-time visibility and accessibility.

All the mentioned safety assessments are conducted manually, based on on-site inspections and surveys. Nowadays, LiDAR based mobile mapping technology is able to collect 3D data in a reliable, accurate manner (Puente et al. 2013a,b) and allows for the automatic or semi-automatic collection of geometric and semantic parameters in road environments, hence avoiding the manual collection of a large proportion of the required assessment data. The literature regarding the acquisition of data that may be used for safety assessments is vast. Works as (Miyazaki et al., 2014; Zhou and Vosselman, 2012) are focused on the detection of curbs in 3D data acquired with laser scanner. Serna and Marcotegui (2013) propose an accessibility analysis once the curbs are detected, establishing itineraries for people in wheelchairs according to the obstacles found in the road. In addition to being detected, several urban objects with an impact on road safety assessment can be semantically classified in order to get a better understanding of a 3D scene. For example, in Refs. Serna and Marcotegui (2014) and Yang et al. (2015) objects such as buildings, vehicles, trees or poles are classified from cluttered urban 3D scenes. Recently, Yang et al. (2017) proposed a semantic labelling framework of 3D point clouds based on appending several features on different scales of previously segmented objects. Combining point-based features such as Fast Point Feature Histogram (FPFH), segment-based features (principal directions, sizes

* Corresponding author.
E-mail address: msoilan@uvigo.es (M. Soilán).

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and dimensionality of each segmented object), object-based features (viewpoint feature histogram) and contextual features, a classification model was developed to distinguish objects such as traffic signs, guardrails or power lines among others. Research is also focused on the classification of road network assets, such as vertical signage (Riveiro et al., 2015; Wen et al., 2015) and road markings (Cheng et al., 2017; Guan et al., 2014), with promising results for both elements. Yu et al. (2016) are able to detect and classify traffic signage with state of the art accuracies using bag-of-visual-phrases representations for the detection task and a deep Boltzmann machine feature encoder for the classification task, where features are directly extracted from 2D images where the detected 3D traffic signs have been previously projected. Similarly (Yu et al., 2015a) propose a method for the extraction and classification of road markings consisting of a segmentation process which relies on an intensity-based multisegment thresholding, and a classification based on heuristic decisions for large-size markings and a deep learning model that takes binary representations of the road markings as feature.

Regarding visibility analysis, there exist research that study the effects of different hazards that may deteriorate the visibility conditions (Abdel-Aty et al., 2011; Mueller and Trick, 2012), but there is little research analyzing visibility parameters from dense 3D point clouds. A relevant work is the one presented by Alsadik et al. (2014) where they address three different problems related with visibility: Camera network design, guidance with synthetic images and gap detection in a point cloud; based on surface triangulation and voxel-based approaches.

In this work, a methodology that assists the safety assessment on pedestrian crossing environments taking advantage of mobile mapping technology is proposed. The motivation for this work is to close the gap that exists between the manual safety assessment analyses that are carried out to this day and the capabilities of mobile mapping technology to offer an accurate description of road environments in an automated way. The contributions of this work are therefore (1) The definition of a workflow that extracts geometric and semantic information from a 3D point cloud which can be utilized to define the safety of a pedestrian crossing environment; and (2) The organized visualization, as a safety map, of all the data on a Geographic Information System (GIS).

2. Methodology

The proposed methodology is organized in four modules, each of them aiming to collect geometric and semantic information on the environment of a pedestrian crossing: (1) Accessibility analysis, (2) Traffic lights classification, (3) Traffic signs classification, and (4) Visibility analysis. Data defining pedestrian crossings are considered as an input for this work as obtained from (Soilán et al., 2017). The methodology workflow is shown in Fig. 1.

2.1. Point cloud preprocessing

Let $\{\boldsymbol{P},\ \boldsymbol{t},\ \mathcal{M}\}$ be the inputs for this work, where $\boldsymbol{P} = \{\boldsymbol{x},\ \boldsymbol{y},\ \boldsymbol{z},\ \boldsymbol{I},\ \boldsymbol{t_s}\}$ is a point cloud containing the $(x,\ y,\ z)$ coordinates together with intensity and time stamp for each 3D point, $\boldsymbol{t} = \{\boldsymbol{x_t},\ \boldsymbol{y_t},\ \boldsymbol{z_t},\ \boldsymbol{t_{st}}\}$ represents the trajectory of the vehicle as collected by its navigation system, and $\mathcal{M} = \{M_1,\ ...,M_i,\ ...,M_n\},\ i = 1...n\,|\,M_i \subset \boldsymbol{P}$ contains the set of pedestrian crossing objects that have been detected within $\boldsymbol{P}$ applying (Soilán et al., 2017) methodology, which consists of a number of processing steps that, given a point cloud $\boldsymbol{P}$, selects 3D points belonging to road markings by taking advantage of the reflective properties of the paint material, and subsequently classifies them (distinguishing several types of arrows and pedestrian crossings), finally allowing to extract each pedestrian crossing as a subset of $\boldsymbol{P}$.

First, the input point cloud $\boldsymbol{P}$ is preprocessed. This work intends to study the environment of the pedestrian crossings in the point cloud, therefore a large proportion of the 3D points will not provide relevant information and can be removed from further processing steps. For that purpose, a transformation matrix $\boldsymbol{T}$ is obtained for each pedestrian crossing in $\mathcal{M}$ such that

$$\boldsymbol{T} = \begin{matrix} \boldsymbol{R}_{3x3} & \boldsymbol{t}_{3x1} \\ 0_{1x3} & 1 \end{matrix} \quad (1)$$

where $\boldsymbol{R}_{3x3}$ represents a rotation around z-axis of an angle α_z formed between the y-axis and the longitudinal direction of the road marking, and $\boldsymbol{t}_{3x1}$ represents a translation equal to the centroid of the pedestrian crossing coordinates.

Using the matrix $\boldsymbol{T}$, the input 3D data get centered on a pedestrian crossing, and orientated towards its principal direction (Eq. 2).

$$\boldsymbol{P_{Th}} = \ \boldsymbol{T}\cdot\boldsymbol{P}_h \quad (2)$$

where $\boldsymbol{P_{Th}}$ contains the homogeneous coordinates of the transformed point cloud and $\boldsymbol{P_h}$ the original homogeneous coordinates. Let $\boldsymbol{P_T}$ be the transformed point cloud removing the homogeneous notation.

The second preprocessing step consists of the definition of the pedestrian crossing environment. Using the transformed point cloud $\boldsymbol{P_T}$, it is straightforward to select those points that define the surroundings of the crossing area. Indices $\boldsymbol{i}_s$ of points whose y coordinate is between $(l/2 - 5)m$ and $(l/2 + 5)m$, where l is the length of the pedestrian crossing along y axis, are selected. Let $S(\boldsymbol{P},\ \boldsymbol{i})$ be a function that selects a subset of points with indices $\boldsymbol{i}$ within a point cloud $\boldsymbol{P}$. The environment of the pedestrian crossing is defined as $\boldsymbol{P}_s = \ S(\boldsymbol{P_T},\ \boldsymbol{i_s})$

Finally, ground and non-ground points are segmented on point cloud $\boldsymbol{P}_s$. For this purpose, a voxel-based segmentation inspired on (Douillard et al., 2011) algorithm for dense data is applied. The point cloud is voxelized, that is, a cubic cell grid is defined. Then, for every voxel, vertical mean and variance are computed and subsequently a region growing algorithm groups neighboring voxels whose mean and variance differences are less than two respective thresholds, d_μ and d_σ. In order to speed up this process, voxels that contain points from the pedestrian crossing are selected as seeds for the region growing algorithm, and the ground segment is defined with the grouped voxels once the growing process finishes. The algorithm returns the indices of the points in $\boldsymbol{P_T}$ and $\boldsymbol{P}$ (both point clouds share the same indices) that belong to the ground and non-ground segments, $\boldsymbol{i}_g,\ \boldsymbol{i}_{ng}$, defining ground and non-ground point clouds as $\boldsymbol{P}_g = S(\boldsymbol{P}_s,\ \boldsymbol{i}_g)$ and $\boldsymbol{P}_{ng} = S(\boldsymbol{P}_s,\ \boldsymbol{i}_{ng})$ respectively.

2.2. Accessibility analysis

The Spanish Ministry of Public Works and Transport has defined the maximum transversal and longitudinal slope on accessible pedestrian routes as 2% and 8% respectively. Furthermore, the maximum slope on accessible ramps has been set as 12% (Ministerio de Fomento, 2010). These specifications ensure an accessible and safe route for disabled people, and therefore they are essential for the quality of the crossing environment. In this section, accessibility at the entrances of a pedestrian crossing is studied. First, it is necessary to detect non-accessible areas on the ground segment. Normally, urban areas intended for circulation of vehicles and pedestrians are separated by curbs, small steps forming an edge between the road and the sidewalk. An accessible pedestrian route cannot include curbs, therefore the presence or absence of this obstacle has to be detected in the crossing area.

Given the geometric information in the 3D point cloud $\boldsymbol{P}_s$, curbs are detected following a modification of Wang et al. (2015) road boundary detection algorithm, consisting on a saliency analysis which separates the input point cloud in two segments, one of them containing points that belong to horizontal surfaces, and other with the remaining points (including façades, walls or curbs). Salient points are grouped via Euclidean clustering (Yu et al., 2015b) and filtered based on their elevation, horizontal length and distance to the trajectory (Wang et al., 2015), obtaining a set of point indices $\boldsymbol{i}_c$ that represent potential curbs. Finally, false detections are avoided intersecting indices $\boldsymbol{i}_c$ and $\boldsymbol{i}_g$, such