Automatic classification of urban pavements using mobile LiDAR data and roughness descriptors

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ABSTRACT

Maintenance of urban road pavements is shown as critical in city management. Mobile Laser Scanning is well-established for achieving geo-reference point clouds and imagery depicting the reality in an accurate and productive manner and intense efforts have been made to implement automatic methods for extracting geometric and semantic useful information. This work shows a method based on evaluating roughness descriptors from mobile LiDAR data to automatically segment and classifies asphalt and stone pavements. The method includes segmentation of 1 m slices from the road, extraction of profiles, evaluation of roughness parameters, and K-means clustering. Among the evaluated roughness descriptors, only arithmetic average of absolute values (between 2.5 x [10.sup.3] m to 4 x [10.sup.3] m for stone and [10.sup.3] to 2 x [10.sup.3] m for asphalt) and root mean squared (between 3 x [10.sup.3] m to 5 x [10.sup.3] m for stone and [10.sup.3] m to 2 x [10.sup.3] m for asphalt) show robust classification. The methodology is tested in three real case studies.

Keywords:

Mobile LiDAR

Urban roadway

Point cloud

Urban management

Pavements

1. Introduction

Maintenance of urban road pavements is shown as critical in urban management [1-3]. In this context, an extensively work has been done for the development of pavement management and maintenance systems [4] in which the inventory of pavement materials is one of the main operations.

The use of imaging and scanning techniques for inspecting constructive materials of pavement roads has emerged as an attractive and viable option over the current manual procedures [5], Traditionally imaging based techniques allow the inspection and classification of pavements. Gavilan et al. [6] develop a road distress detection system based on a vehicle equipped with line scan cameras and laser illumination. Automatic classification between up to 10 different types of pavement is done using support vector machine-based methodology. Chambon and Moliard [7] address the problem of crack detection, in French national roads by automatic analysis of optical images. They use a multi-scale extraction and Markovian segmentation. Zhou et al. [8] use an automated inspection system that consists of image acquisition and distress image processing. Nejad and Zakeri [9] use multi-resolution analysis such as wavelet decompositions for pavement analysis and distresses classification.

Laser scanners are well-established in the remote sensing community for acquiring geometry and imagery depicting the reality in an accurate manner. In comparison with traditional Terrestrial Laser Scanners (TLS), Mobile Laser Scanners (MLS) combines LiDAR sensors and cameras with position and navigation systems allowing the collection of high-quality geo-reference point clouds in a productive manner. Benefits from the use of mobile LiDAR over aerial and conventional ground survey instruments include cost savings (they gathers all required data point measurements in one strip), time savings (up to 1 MHz of data acquisition compared to one point every few minutes with traditional survey technologies such as traditional Total Stations), high resolution (the system provides a more complete dataset of the object with accurate point measurements enabling the localization of features that may be inaccessible with other methods), and safety (data are collected remotely, removing the need for traffic diversion required by traditional surveying techniques) [10], Some applications of MLS are corridor project works, including roadway and rail transportation, pipelines and electric transmission lines, construction management, airport design and layout plans, harbor and shoreline mapping, 3D asset inventory mapping, and digital terrain models [11-14],

Although a few years ago LiDAR data were not usual, at present it is becoming more common the fact that municipalities own mobile LiDAR databases from their streets. The main problem with these databases comes from the high volume of information and its complex processing and management. For example, a Spanish city as Avila, with 58,000 residents has approximately 250 km of streets. At a scanning speed of 30 km/h a total of 30 x [10.sup.9] points are obtained (1 MHz pulse repetition rate). Therefore, the main technological challenge to optimize the use of LiDAR data is focused in providing an efficient and robust data processing, since the end user typically does not require a 3D point cloud. In contrast to point clouds, simplified geometrical models with associated semantic information can be easily managed in CAD or GIS software.

In the recent years, intense efforts have been made to implement automatic methods for extracting geometric and semantic useful information of construction materials from LiDAR data. Major literature is about detecting geometrical defects such as cracks or determining geometrical properties of construction materials with the aim of classifying them. Guan et al. [15] propose a method for the automatically detection of pavement cracks using Mobile Laser Scanning Data. They propose an algorithm to separate road points and interpolate them into georeferenced feature images using an inverse distance weighted algorithm. Finally, they search for cracks using an iterative tensor voting algorithm. Anochie-Boateng et al. [16] explore the use of laser scanner to determine flakiness index of aggregates and ballast materials used in the construction of road, airfield, and railway track infrastructures, while their fundamental shape properties such as form, angularity, and surface texture are not quantified because of their irregular and non-ideal shapes.

In terms of extracting semantic information of construction materials from LiDAR data, Gonzalez-Jorge et al. [17] present a method to automatize the detection of road overpasses and mortar efflorescence using mobile LiDAR data. It uses the incidence angle obtained from the LiDAR sensors to separate overpasses from pavement data. An algorithm to classify efflorescence [18] considering its reflectivity lower than the surroundings is developed. Riveiro et al. [19] show an algorithm for the automatic detection of zebra crossings from mobile LiDAR data. The algorithm begins with a curvature analysis for each laser cycle to segment the pavement. Then, the point cloud from the pavement is rasterized and converted to an intensity image. Hough Transform is used to detect lines and positioning of each crossing. The method shows a completeness of 83%.

Despite the progress shown in the algorithmic developed for the automatic management of mobile LiDAR datasets, there are still some areas of improvement. One of them lies in the use of mobile LiDAR data for the automatic classification of the roadway type. For example, in historic cities, it is common the existence of road sections in which both asphalt and stone are alternatively used. It is important that this information is reflected in the information management systems as maintenance needs are different.

In the present work, different road roughness descriptors are presented to automatically determine the roadway type using geometric data from mobile LiDAR system and without other complementary information from LiDAR intensity of RGB imaging. The manuscript is structured as follows. Section 2 shows the materials and methods, Section 3 the results and discussion, and Section 4 the conclusions.

2. Materials and methods

2.1. Area of study

The area of study is focused in three roads in the city of Ourense (NW Spain). These roads show a change between asphalt and stone pavement, which is very common in this city forcing to customize the maintenance for each type of pavement. Fig. 1 shows one of the case studies consisted of Parada Justel Steet (stonepaved road) and O Progreso Street (asphalt-paved road).

22. Data acquisition and processing

The mobile LiDAR system used for surveying the roads used as case studies in this work is the Optech Lynx Mobile Mapper (Fig. 2) [10]. The acquisition system consists on an accurate positioning and navigation system, two LiDAR sensors, and four digital cameras. As this work is focused on the use of geometric data from the mobile LiDAR, digital imaging is not acquired. Pavement roughness, a geometrical parameter, will be used as descriptor for the classification. The positioning and navigation system is manufactured by Applanix (model POS LV 520). All the systems (navigation, LiDAR sensors, and cameras) are boresighted and time stamped to provide accurate point clouds. The LiDAR sensors show a measurement range up to 200 m with 4 returns for each laser pulse. The accuracy of range measurements is 8 mm. The absolute accuracy of the point clouds is around 5 cm. This value includes the errors of the Applanix navigation system, the LiDAR sensors, and the boresighting between the systems. The laser measurement rate for these surveys is programmed to 1 MHz, which provides the maximum resolution in the point clouds. This value can decrease up to 75 kHz if project requirements are lower. The scan frequency is programmable between 80 and 200 Hz. Here, the maximum value of 200 Hz was selected to increase the resolution of the point cloud. The scanner field of view is 360[degrees]. The Optech system requires a power of 12 VDC and 30 A. Operating temperature ranges between -10[degrees]C and 40[degrees]C [20].

The processing of the Lynx data to obtain a point cloud is done after the survey. The POSPac MMS software is used to process the positioning and navigation data to create an accurate trajectory. This software uses data from a base station located in Ourense city and provided by the National Geographic Institute (1GN) to correct the positioning data from the global navigation satellite systems (GNSS) and obtain accurate positioning. In addition, the data are combined with those provided from the inertial measurement system (INS) using Kalman filtering to calculate the best estimated trajectory (SBET).

Finally, DASHMap software combines the SBET with the LiDAR data to provide the 3D geo-referenced point cloud. The visualization of the point cloud is performed using Cloud Compare software (Fig. 1C). In addition, the area of study was delimitated to 100 m in each case (50 m asphalt and 50 m paving stone road).

2.3. Algorithm description

Fig. 3 shows the workflow of the algorithm. All the implementation is performed in MatLAB software. The main steps are next described.

23.1. Segmentation of road slices

The first step of the proposed methodology consists on segmenting the point cloud in order to select regions belonging to road pavements. The mobile LiDAR system provides a 3D point cloud dataset from the area around the vehicle (Fig. 3a). This point cloud is made of 2D profiles that correspond with each rotation of the LiDAR mirror. A scan frequency of 200 Hz involves the generation of 200 profiles per second. Taking into account the average speed of the vehicle (50 km/h), it provides a profile approximately each 7 cm. Each coordinate from the profile has an associated angle related with the position of the scanner mirror. As the distance between the scanner mirror and the road is approximately constant (around 2.5 m), the determination of the angles to provide 1 m width profile is a simple trigonometric operation. In this case, it results in angles between 354.35[degrees] and 5.65[degrees]. The angular origin of the system is positioned on the centre of the road. Fig. 3b shows one of the slices obtained and a zoom to understand the composition of each slice by a number of profiles (Fig. 3c).

2.3.2. Evaluation of roughness parameters

Roughness is a feature of surface texture that can be quantified by the deviations in the direction of the normal vector of the surface from its ideal form. Roughness is typically considered to be the high-frequency, short-wavelength component of a surface and its determination is crucial in different fields from mechanical engineering or tribology to topography [21].

[FIGURE 1 OMITTED]

[FIGURE 2 OMITTED]

There are many different roughness parameters in use [22], In this work, several parameters are tested (Fig. 3d) in order to determine which of them are reliable to be used for the automatic classification of road pavements from mobile LiDAR data. The mathematical formulation of the roughness descriptors taken into account is next described:

Arithmetic average of absolute values : Ra = 1/n [n.summation over (i=1)] [absolute value of [d.sub.i]] (1)

where [d.sub.i] is de distance between each point of the profile and a linear fit from the points, and n the number of points. Width of 1 m is selected to avoid important changes in the curvature of the profile and guarantee the quality of the results.

Root mean squared : [R.sub.q] = [square root of 1 [[summation].sup.n.sub.i=1][d.sup.2.sub.i]] (2)

Skewness : Rsk = 1/n[R.sup.3.sub.q] [n.summation over (i=1)] [d.sup.3.sub.i] (3)

Kurtosis : 1/n[R.sup.4.sub.q] [n.summation over (i=1)] [d.sup.4.sub.i] (4)

All the roughness parameters are smoothed using a moving average to increase the robustness of the clustering method (Fig. 4).

2.3.3. K-means clustering

Once roughness is evaluated for road slices, a K-means clustering algorithm is implemented for grouping those points with similar roughness values (Fig. 3e). K-means clustering is an unsupervised highly automated and fast computer procedure [231. This method automatically divides the range of the input data into clusters according to a statistical procedure, without any predefined knowledge [18], The K-means algorithm provides clustering of information according to their own data, based on analyses among their numerical values, and without a pre-existing classification.

The K-means method allows the user to define various parameters, including the desired number of cluster and the maximum number of the iterations allowed in the program. K-means method defines K centroids, one for each class and then associates each value of the dataset to the nearest centroid. Then, new centroids are recalculated and a new iteration begins. As this is an iterative process, the K centroids change their location until no further change is possible. This algorithm minimizes the following function.

I = [R.summation over (j=1)][n.summation over (i=1)] [[absolute value of [x.sup.j.sub.i] - [c.sub.j]].sup.2] (5)

where [[absolute value of [x.sup.j.sub.i] - [c.sub.j]].sup.2] is the chosen measurement of distance between a point [x.sup.j.sub.i] in the center class [C.sub.j], which is an indicator of the distances between n points and their respective centers of the classes.

[FIGURE 3 OMITTED]

[FIGURE 4 OMITTED]

[FIGURE 5 OMITTED]

The present work aims to distinguish between two types of common roadway in historic cities, asphalt and stone pavements, so two classes are sought. Fig. 3e shows an example of K-means clustering with two classes.

2.3.4. Classifying all the points that belong to the road

Once the one meter width profiles of the road are submitted to roughness estimation and clustering, they are classified as asphalt or paving stone assuming that asphalt pavement has lower roughness values than stone pavement.

Final step is to extend the classification up to the edge of the road (Fig. 3f). Parallel black lines indicate the limit of the 1 m width profiles. For this purpose, it is implemented the Principal Component Analysis (PCA) which is a mathematical procedure that reduces the dimensionality of a set of variables to a new set (principal components) that are linear combinations of the initial variables and are uncorrelated to each other [19,24,25], PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. The resulting vectors are uncorrelated orthogonal basis set. The principal components are orthogonal because they are the eigenvector of the covariance matrix, which is symmetric. The main components are obtained in decreasing order of importance and a number of them collect most of the information. The first eigenvector explains the main part of the total variance.

Each complete profile provided by the mobile LiDAR is represented in a 2D space and the PCA is performed using the altitude of each point and deflection angle. These two variables allow to easily detecting peaks denoting the transversal limits of the road when PCA analysis is performed into the local neighborhood (10 points). This information, combined with the roughness clustering, allows segmenting the road from the complete point cloud and differentiating between asphalt (red) and stone (green) areas. Non classified points appear in gray (i.e. trees, buildings) (Fig. 3f).

3. Results and discussion

Figs. 5-8 show the roughness parameters versus the profile number. The three case studies are inserted in each graph, numbered by #1, #2, and #3. Each case study contains stone and asphalt area. On the bottom of each figure the results from the K-means clustering are depicted. It shows "0" or "1" value depending the type of road ("0" asphalt and "1" stone).

Roughness values Ra (Fig. 5) range between 3 10'3m and 4 x [10.sup.3] m for stone #01 and #02, while range between 2.5 x [10.sup.-3] m and 3 x [10.sup.-3] m for stone #03. On the other hand, Ra values range between 0.8 x [10.sup.-3] m and 1.2 [10.sup.-3] m for asphalt #01, 1.5 [10.sup.-3] m and 1.7 x [10.sup.-3] m for asphalt #02, and [10.sup.-3] m and 1.5 x [10.sup.-3] m for asphalt #03. Roughness values Rq (Fig. 6) range between 4 x [10.sup.-3] m and 5 x [10.sup.-3] m for stone #01, 3.8 x [10.sup.-3] m and 5.2 x [10.sup.-3] m for stone #02, and 3 x [10.sup.-3] m and 3.5 x [10.sup.-3] m for stone #03. Rq values for asphalt range between [10.sup.-3] m and 1.4 x [10.sup.-3] m for #01, 1.8 x [10.sup.-3] m and 2.2 x [10.sup.-3] m for #02, and 1.3 x [10.sup.-3] m and 2.2 x [10.sup.-3] m.

[FIGURE 6 OMITTED]

[FIGURE 7 OMITTED]

Ra and Rq clearly show lower values for asphalt pavement in all case studies. In these cases, roughness from stone pavements approximately doubles the values obtained from asphalt pavements. Roughness variance is also lower for the asphalt pavement. These results are predictable since variability of stone surfaces is much larger contributing to a greater dispersion of the roughness values. In both cases the K-means clustering appears robust and it correctly allows the classification of the two types of road.

Fig. 7 shows the results for the skewness Rsk descriptor. Rsk range between -0.1 and 0.4 for stone #01, -0.3 and 0 for stone #02, and -0.1 and 0.1 for stone #03. On the other hand, Rsk range between -0.2 and 0.2 for asphalt #01, -0.6 and 0 for asphalt #02, and -0.3 and 0.3 for asphalt #03. Skewness is a measurement of the asymmetry of the variables. The data presented show no clear trend that sets the values of the different types of roads. This fact produces the failure of the clustering process. Fig. 8 exhibits the results for the kurtosis Rku descriptor. Rku range between 3 and 4 for stone #01, 3 and 3.5 for stone #02 and #03. Rku range between 2.5 and 3.5 for asphalt #01, 2 and 6 for asphalt #02, and 2.4 and 3.2 for asphalt #03. Kurtosis is a measure of the peakedness of the variables. It shows similar values in all cases and consequently, the K-means classifier fails.

Fig. 9 depicts the final results of the classified roads. Road points are classified using the methodology described in Section 2.3.4. Asphalt points are visualized in red while green is used to show stone points. Non-classifier points from the point cloud are gray colored. The roughness descriptor used for this final classification is Ra, although Rq could be also useful

[FIGURE 8 OMITTED]

4. Conclusions

A method to the automatic classification of asphalt and paver roads from mobile LiDAR data is developed. The method is tested in three different real case studies with road changes between asphalt and stone. It starts by the segmentation of 1 m width road slices using the known angles from the mobile LiDAR dataset. Once the slices are segmented, the roughness of each profile is analyzed. Roughness descriptors Ra, Rq, Rsk, and Rku are calculated and evaluated. Then, a K-means clustering algorithm is applied to each case to automatically group and classify points into the road types. Ra and Rq appear as reliable roughness descriptors that allow the correct classification of asphalt and stone pavements in the three cases under study. Roughness values range between Ra = 2.5 x [10.sup.-3] m to Ra = 4 x [10.sup.-3] m for stone and Ra = [10.sup.-3] to Ra = 2 x [10.sup.-3] m for asphalt, and between Rq = 3 x [10.sup.-3] m to Rq = 5 x [10.sup.-3] m for stone and Rq = [10.sup.-3] m to Rq = 2 x [10.sup.-3] m for asphalt. However, Rsk, and Rku do not show robust results and do not allow the automatic classification.

[FIGURE 9 OMITTED]

Once each 1 m profile is codified with the type of road (asphalt or stone), it is extended to the limits of the road using a method based in PCA. The method shows a correct differentiation between the road and the surroundings.

This research work shows promising to provide semantics to mobile LiDAR data for managing and improving urban maintenance. Future trends could be focused on the combination of roughness descriptors with other data, such as LiDAR intensity or RGB imaging, to differentiate between more types of roads and to detect defects on the pavements. The current procedure cannot classify different type of asphalts.

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HIGHLIGHTS

* Non-destructive techniques applied to inspection of urban scenes.

* Robust methodology for automatically segment asphalt and stone pavements.

* Point cloud processing for semantic characterization of urban road materials.

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