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Automated detection and decomposition of railway tunnels from Mobile Laser Scanning Datasets

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ABSTRACT

Since the mid-19th century, the railway network has occupied a crucial place at the heart of the world's transport systems. Its infrastructure is often situated in harsh environments where an extreme event, or even daily use, could lead to a catastrophic accident. This is one of the main reasons why inspecting these constructions is so important. Despite the advances in this field, the human component continues to be part of the final inspection process. In order to improve on this, this paper shows the use of laser scanning as a leading technology in automating the inspection of railway infrastructures. The proposed methodologies provide the essential processed and classified data needed for the structural health monitoring of the various assets related to railways. It is divided into three main parts, which pre-process the point cloud, divide the cloud into ground and non-ground points, and detect the elements present in each of these clouds. The methods are validated in three case studies, each containing different railway tunnels. The results demonstrate that laser scanning technology, together with customized processing tools, can provide data for further structural operations with no requirement for either training in geomatics or high-performance computers for the data processing. Significant results are obtained for the developed classification methods: the classification of the tunnel elements returns a global F-Score of between 71 and 99% in a point-by-point comparison. With regard to the labelled rails classification, a global F-Score of 100% is achieved for the analyzed datasets, and between 56 and 73% for the point-by-point classification.

1. Introduction

Modern society is increasingly dependent on transportation networks in its daily activities, railway being one of the main means of transportation for both passengers and goods all over the world. In many cities, there are metropolitan transport systems based on railway infrastructures, which are among the most vulnerable in terms of maintenance expenditure. These types of buildings suffer degradation over the years due to their ongoing use and depending on their environment. This affects their structure and general maintenance, which may result in service and safety problems. Moreover, this type of infrastructure must be prepared for the occurrence of an extreme event. To guarantee the quality, continuity and safety of their services, it is necessary to perform regular inspections of the electrical power, railway tracks, and structural and signaling infrastructures. Over the years, their inspection has been based on visual methods as the most extensive practice. With the development of technology, railway inspections have also evolved. Thanks to the use of special inspection units based on non-destructive techniques such as Eddy current systems or ultrasonic methods in rail inspection, a specialized technician can visually detect any possible existing damage [1]. This type of method has several disadvantages: it provides local information; it is performed slowly and usually implies high costs; the information obtained is limited to a specific exposure time; visual inspection introduces a subjective and unreliable human element; and, in some cases, it is necessary to interrupt railway services in order to carry out inspection tasks. In the future, it is expected that the strategies developed for inspecting this type of infrastructure will fit the concept of predictive maintenance. Along with the technological advances that are taking place over time, continuous control of the key elements of these infrastructures' networks is becoming more and more in demand, determining zones of potential incidents and programing maintenance activities according to them. With this type of maintenance, the service life of the assets could be extended, costs could be reduced, the structures' recovery guarantees could be increased, future conditions could be adapted to, etc.

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In this sense, spatial information science could provide a framework for reconsidering the management of data collected during inspections of large infrastructures. In accordance with this, there is the idea of using laser scanning technology in this field, starting as a tool for the geometric characterization of the elements in the study's environment. Initial data are obtained through LiDAR sensors, which are able to collect large amounts of data in short periods of time. Additionally, they can access places that cannot be reached using other systems without needing to make contact with the structure in order to obtain data from it [2]. Thus, laser scanners provide a very primitive 3D model, where all the information is georeferenced so that the elements are not only detected and parameterized, they can also be documented in the context of a spatial database. Despite the amount of data that can be collected this way, there is little information that can actually be exploited. This means that the inspection process is still not efficient enough and the data processing implies a major challenge. The huge volume and complexity of these data, together with the difficulty of collecting, managing and processing them, is what defines point clouds' data as *Big Data*. Depending on the location where the data are captured and the users' needs, point clouds should be divided into different parts or objects automatically. For example, in an urban environment, this means distinguishing buildings from sidewalks, cars, benches, trees and every possible object in the street [3,4]. The actual commercial software for point cloud management is not completely automated, which means that some segmentation and classification tasks must be done semiautomatically or manually by an expert in this field. This makes analyzing the extracted data tedious and is the main reason that has encouraged researchers in the geomatic domain to develop new techniques and models for completely automating data processing tasks, taking into account the particular needs of different types of users. In this way, LiDAR technology is put to full use, thus becoming a basic tool for infrastructure assessment and asset management.

Although the automated segmentation and classification of data are shown as being one of the main challenges for LiDAR technology, there are already a lot of authors who are focusing on trying to find solutions for this challenge in many fields. One important application of this technology is structural health monitoring (SHM), where lots of tools are commonly used to determine and track structural integrity, assessing the nature of damage in civil infrastructure. In Sánchez-Rodríguez et al. [5], a methodology for damage detection in piers of large bridge point clouds is developed. It is based on heuristic methods, searching for geometric anomalies that could help with detecting potential faults. This paper and the segmentation methods proposed by Riveiro, B. et al. [6] are being used as the basis for developing the present work. Another important application for inspecting civil infrastructure is the use of mobile laser scanners (MLS) as a tool for roadway management and inventory. In this sense, Serna and Marcotegui created an inventory of 3D urban objects based on machine learning algorithms (SVMs, *Support Vector Machines*) working with both geometrical and contextual features [4]. Luo, H. et al. developed a similar work on labelling a road location from colorized MLS data, also working with machine learning tools [7]. Continuing with roadway point clouds, Holgado-Barco, A. et al. developed a method for the inventory of road cross-sections based on the geometrical characteristics of points, as well as their parameter of intensity for road mark classification [8]. Similarly, Soilán, M. et al. also worked with MLS data, creating an algorithm for the geometrical and image-based semantic inventory of vertical signage using machine learning approaches [9]. Complementing this work, Soilán, M. et al. developed a segmentation and classification method for road markings. To this end, they used neural networks by implementing a two-layer feedforward network [10]. It is also important to highlight the use of ALS (Aerial Laser Scanner) data for the inventory of point clouds. He, Y. et al. analyzed this type of data for the inventory of highways, processing this information with ArcGIS software [11]. When talking about railway infrastructure, it is important to highlight some works such as the one shown by Zhu & Hyyppa, where a methodology for object recognition in railway environments was developed, working with image processing techniques [12]. In this field, a study by Arastounia also showed the development of new automatic methods for railway infrastructure key component recognition. This was done using data extracted from MLS point clouds, and by applying peak detection algorithms and geometric/shape-based methods to classify points according to their spatial distribution [13]. With regard to tunnel inspections, the use of LiDAR technology as an information source was also studied. Yoon, J.S. et al. proposed a method for extracting installations in tunnels based on intensity histograms and distance comparisons. Moreover, they detected possible damage in the lining surface by searching for physical variations in the point cloud [14].

This paper aims to develop algorithms to automatically classify elements of railway tunnel point clouds. This classification is an essential stage prior to the structural evaluation of any critical infrastructure when the aim is to use LiDAR data. A proper segmentation and classification of a tunnel's structural elements is key for inspectors to be able to easily handle and identify damage or structural anomalies, either manually or when subjected to customized algorithms for damage detection and parametrization. The counterpoint of this research with respect to the previously mentioned segmentation or classification works from point clouds is the increased robustness of the developed methodology, which is valid for any tunnel typology. This strategy is based on combining heuristic and machine learning tools to process and automatically classify point clouds. The validation is performed using three datasets, each with different geometries. Finally, this paper is divided into the following three sections: Section 2 includes the methodology, which is in charge of the pre-processing and segmentation of the point clouds; Section 3 presents the results obtained for the datasets on disposal; and finally, the conclusions are in Section 4, together with some future lines of work.

2. Methodology

A methodology for the automated processing of point cloud data is developed. This methodology is designed to optimize the density of registered point clouds; namely, the clouds are filtered from pseudo-random noise data and optimized in order to make them more manageable. Subsequently, the resulting point cloud is segmented into different point clouds that correspond with the data from tunnel components. That is to say, the cloud is partitioned in such a way that the ground points are distinguished from those forming the lining of the tunnel and some other objects in the cloud. Finally, every element in the cloud is classified.

2.1. Initial data

Laser scanner technology is of major significance with regard to structural inspection. The scanning data are extracted with a mobile laser scanner (MLS), which is based on LiDAR technology, to make a 3D reconstruction of its environment. In MLSs, the instruments' positions do not change, rather, the vehicle follows a specific trajectory during the scanning process. This allows a large infrastructure to be scanned in a short period of time. Once the data are extracted, they are organized in a matrix of rows and columns, representing the point cloud. Each row in the matrix represents one point, and each column represents the attributes extracted with the laser scanner. The process presented in this paper uses the spatial coordinates (x, y, z), the number of returns (r) and the time stamp (t_s). The trajectory followed by the inspection vehicle is also used as input data. It is also represented as a row-column matrix. Subsequently, a summary of the methods developed for the automatic classification of railway tunnels' point clouds is shown.

2.2. Point cloud pre-processing

LiDAR point clouds usually comprise a large amount of data, where