A LiDAR based obstacle detection framework for railway

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Abstract. Obstacle detection on the railway, a crucial operational safety concern, is a complex task that encompasses a multitude of challenges. While Machine Learning (ML) algorithms are commonly employed in analogous applications such as autonomous car driving [1] [2], the railway field faces a significant barrier due to the scarcity of available data (particularly images), rendering conventional ML approaches impractical.

In response to this challenge, this study proposes and evaluates a framework which uses LiDAR (Light Detection and Ranging) data for obstacle detection on the railways. The framework aims to address the limitations posed by image data scarcity while enhancing operational safety in railway environments.

The developed methodology combines the use of a long-range LiDAR capable of detecting obstacles at distances of up to 500 meters, with the train's GPS (Global Positioning System) coordinates to accurately determine its position relative to detected obstacles. The LiDAR data is processed using a data fusion approach, where pre-existing knowledge regarding the track topography is combined with a clustering algorithm, specifically DBSCAN (Density-based spatial clustering of applications with noise), to identify and classify potential obstacles at a pre-defined distance.

Tests of the proposed framework were conducted within the confines of a moving locomotive, specifically the CP 2600-2620 series, along a designated section of the Contumil-Leixões line. These tests served to validate the effectiveness and feasibility of the approach under real-world operating conditions.

Overall, the utilization of LiDAR data coupled with advanced algorithms presents a promising avenue for enhancing obstacle detection capabilities in railway operations. By overcoming the challenges associated with data scarcity, this framework holds the potential to significantly improve operational safety and efficiency within railway networks. Further research and testing are warranted to validate the framework's performance across diverse railway environments and operating conditions.

1 Introduction

The railway is still a dominant mean of transportation around the world, with an estimated, of at least, 1 300 000 km worldwide [3], 211 430 km in Europe alone. With such a vast expanse of railway lines, one of the biggest safety concerns is railway intrusion (when a potentially harmful object is within the region of interest, or ROI, of the railway line). The timely detection of these objects, obstacles, on the railway line can prevent serious accidents with potential loss of people and property, an area that has been studied over the last few decades [4] [5].

Over the years, several methods have been used to detect intrusions in the railway, such as infrared, vibrations, laser, radar, video, to name a few [6], [7], [8], [9]. Each of these technologies has inherent limitations that can compromise their effectiveness in ensuring the safety and reliability of railway systems.

Camera-based systems rely on visual data to detect obstacles, but they are heavily dependent on lighting conditions. In low-light environments, such as during night-time or in tunnels, cameras may struggle to accurately identify obstacles. Additionally, cameras are susceptible to environmental factors such as rain, fog, dirt, or glare from the sun, which can obscure the field of view and lead to missed detections.

Radar technology offers better performance in adverse weather conditions and can detect objects at longer ranges than cameras. However, radar generally lacks the high spatial resolution needed to distinguish between small or closely spaced objects. This limitation can result in less precise obstacle detection, particularly in complex environments with multiple potential hazards.

Ultrasonic sensors are typically used for short-range detection and are valued for their simplicity and cost-effectiveness. However, they are prone to inaccuracies due to noise and can be less reliable in varying environmental conditions. The limited range and resolution of ultrasonic sensors make them insufficient for comprehensive obstacle detection on railways, where early and accurate detection over longer distances is critical.

LiDAR (Light Detection And Ranging) is one of the technologies that are widely used in autonomous vehicles for detecting obstacles, usually in conjunction with other technologies, such as cameras (sensor fusion) [10] [9].

LiDAR is an optical remote sensing technology that uses light, in the form of a pulsed laser, to measure distances. The laser is sent from a source (transmitter) and is reflected by

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objects present within the laser's range. The reflected light is detected by the system's receiver and the time it takes for the reflected light to return to it (time of flight - TOF) is used to develop a distance map of the objects. LiDAR has some advantages over cameras [11] [12]:

- Allows to create a 3D map of the surrounding environment;
- It is not affected by night and low light conditions;
- Measures distances to objects with great precision.

The framework proposed in this paper combines LiDAR's high-resolution 3D mapping capabilities with GPS's precise geolocation data. This approach addresses many of the limitations of existing technologies by providing accurate 3D information with high resolution and precise positioning information. LiDAR enhances detection in diverse environmental conditions, while GPS ensures precise localization of obstacles relative to the train's position.

In this paper we will describe the proposed framework for obstacle detection in the railway as well as the tests performed during the development of the framework.

2 Method

Although Machine Learning algorithms are currently widely used to detect obstacles, the lack of data as well as the difficulty in carrying out acquisitions with LiDAR in the railway environment, made this solution unfeasible.

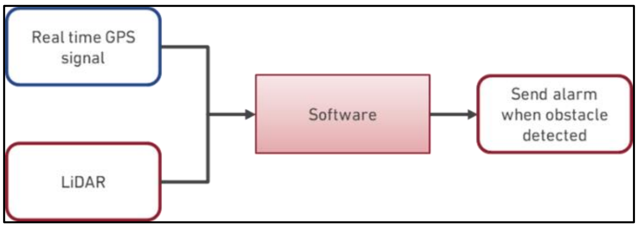

Fig. 1. Proposed Solution Overview.

The conceived solution, presented in Fig. 1, is based on GPS (Global Positioning System) coordinates and the train path. The GPS coordinates are used to determine the train's position and calculate, at a predefined distance, if there are obstacles on the track.

Obstacles were identified resorting to the use of the DBSCAN (Density-Based Spatial Clustering of Applications with Noise) clustering algorithm (Fig. 2). DBSCAN is a non-parametric density-based clustering algorithm proposed in 1996 by Martin Ester, Hans-Peter Kriegel, Jörg Sander, and Xiaowei Xu [13]. It is based on the idea that clusters are formed by dense regions of points, separated by less dense regions. In the presented solution, two DBSCAN parameters are used: the eps (the maximum distance between two points for them to be considered part of the same neighborhood) and the minimum samples (the minimum number of points required to form a dense region). Both parameters can be configured in order to be adjustable to different search distances. The regions identified by the DBSCAN algorithm will be considered obstacles if they have more than a configurable number of points within the same neighborhood. It is one of the clustering algorithms frequently used in Data Mining and Machine Learning [14, 15].

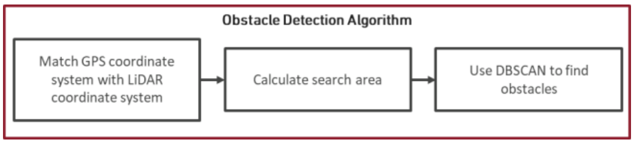

Fig. 2. Proposed Solution Overview.

As mentioned before, the devised solution relies on the GPS coordinate system and the fact that the travelled train path is always the same. Before the processing of the LiDAR data occurs, it is necessary to prepare a train path file. This file contains the GPS coordinates and altitude for the whole train path, with intervals of a configurable distance (for example, 5m distance between each GPS coordinate) and always in the middle of the railway. This path file is used to identify the location of the area where obstacles will be searched for, which is dependent on the current train location.

During the processing, for each LiDAR data acquisition the GPS train coordinates are also acquired. These coordinates are then searched for in the train path file, and the closest coordinates from the file are used as the train position. Using this position, the obstacle search area can be determined. The central point of the obstacle search area, the goal point, is determined by getting the point in the path (in the path file) in front of the train at a configurable distance (for example 100 m). The GPS goal point is converted into the LiDAR field of view coordinate system and obstacles are searched inside a predefined area around that point. The search area size, around the goal point, is defined in a configuration file (for example 4m in directions around the goal point, height, width, depth).

The decision to define a search area is related to the necessity of minimizing the processing time, considering the size of the point cloud acquired by LiDAR and the response time that is needed when obstacles are detected on the train track. Only obstacles that are directly on the path travelled by the train and within the field of view of the LiDAR will be searched for (Fig. 3 and Fig. 4). This method allows for an efficient search of obstacles even if the railway track follows a curved path.

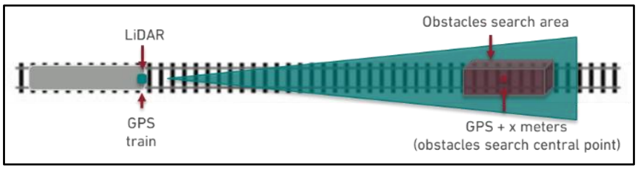

Fig. 3. Obstacle search inside LiDAR FOV.

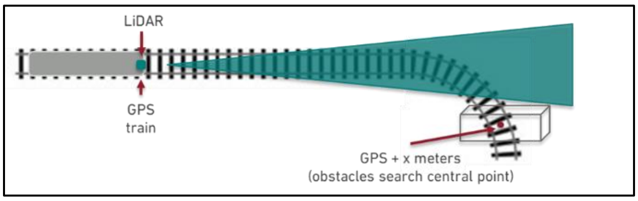

Fig. 4. Obstacle search outside LiDAR FOV.

3 Tests and Results

The tests and results presented in this paper were conducted using the LiDAR Livox Tele-15 [16], a long-distance detection LiDAR with a 500m range, and a GPS module from the u-blox, the ZED-F9P-02B [17], which provides multi-band GNSS to high-volume industrial applications.

In order to better understand the advantages and limitations of the LiDAR and how to integrate it into an obstacle detection system, initial acquisitions were performed. The first set of acquisitions was a controlled experience, at several distances, to collect information of what a person looks like in a point cloud. That information is then used to define, in the DBSCAN algorithm, what should constitute an obstacle, for a certain distance. This was a static acquisition, meaning, both the LiDAR and the person were stationary. Acquisitions were performed, with the person, at: 50m, 100m, 150m, and 200m (Fig. 5).

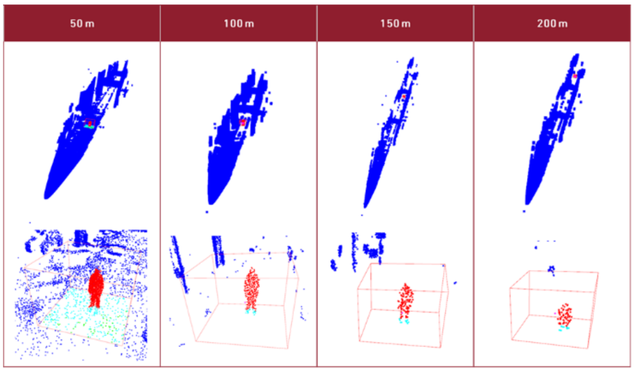

Fig. 5. Proposed solution – initial static tests.

The next step was the execution of static tests in a railway environment (Fig. 6). Tests with a person inside the rail track, near, and outside were performed and the obstacle successfully detected.

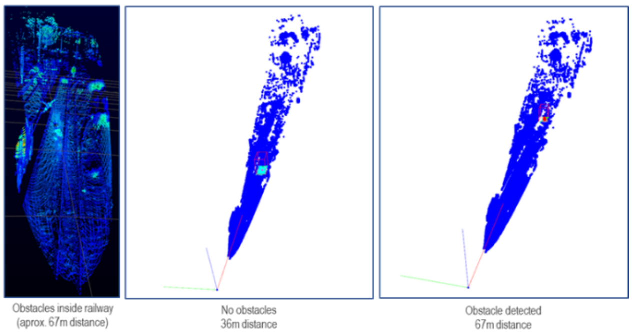

Fig. 6. Proposed solution – static tests in a railway environment.

The next step was the execution of tests in a moving environment, in this case inside a car (Fig. 7).

Fig. 7. Proposed solution – moving tests in a car.

The average speed of the car was 10-20 km/h. The obstacles were search at a distance of 100m in front of the car. In this scenario, the detection of obstacles was also successful, a person crossed the road during the test and was detected as an obstacle (Fig. 8).

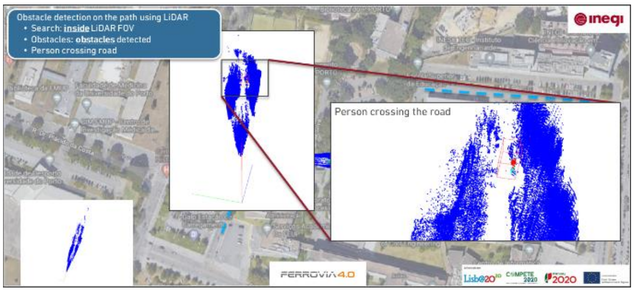

Fig. 8. Proposed solution – moving tests in a car (map from: www.google.com/maps).

The final tests of the proposed solution were conducted within the confines of a moving locomotive, specifically the CP 2600-2620 series, along a designated section of the Contumil-Leixões line. These tests served to validate the effectiveness and feasibility of the approach under real-world operating conditions.

The LiDAR and GPS were placed inside the train locomotive. For that purpose, a physical support was design and constructed, using aluminium 3.3315 (EN-AW 5005), as shown in Fig. 9.

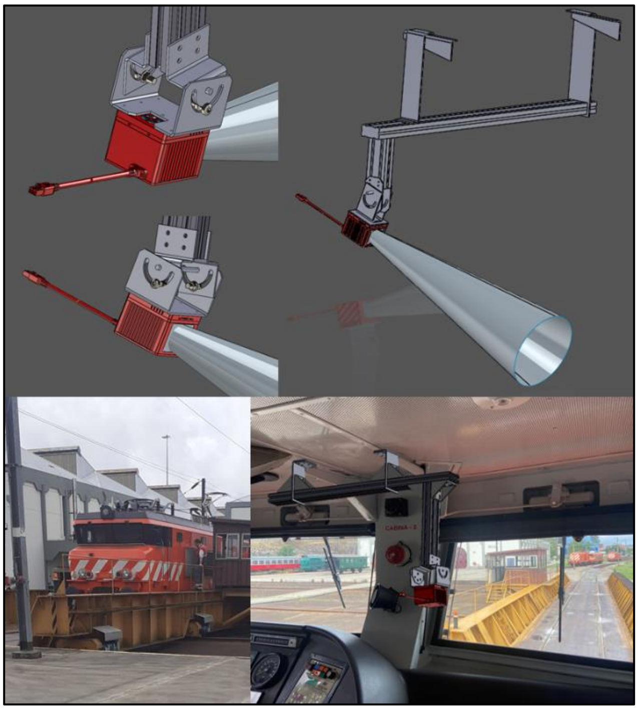

Fig. 9. LiDAR Physical Support.

As previously stated, the validation in relevant environment was conducted in the Contumil-Leixões line, Porto, Portugal (Fig. 10).

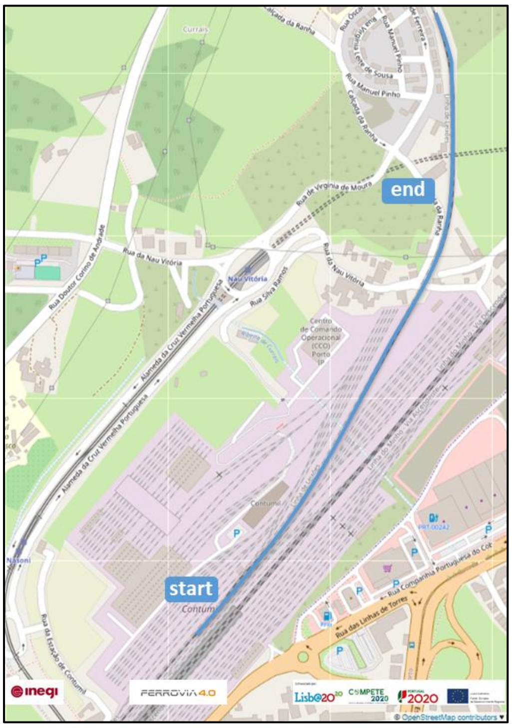

Fig. 10. Line track for validation in relevant environment (map from: www.openstreetmap.org).

During the test, the train reached a maximum speed of 80km/h. As in previous tests, the search for obstacles was executed at 100m distance from the LiDAR (in front of the locomotive). Fig. 11 and Fig. 12 illustrate results from the processing of the LiDAR acquisitions. Fig. 11 presents a search inside the LiDAR FOV (field of view). In this case no obstacles existed.

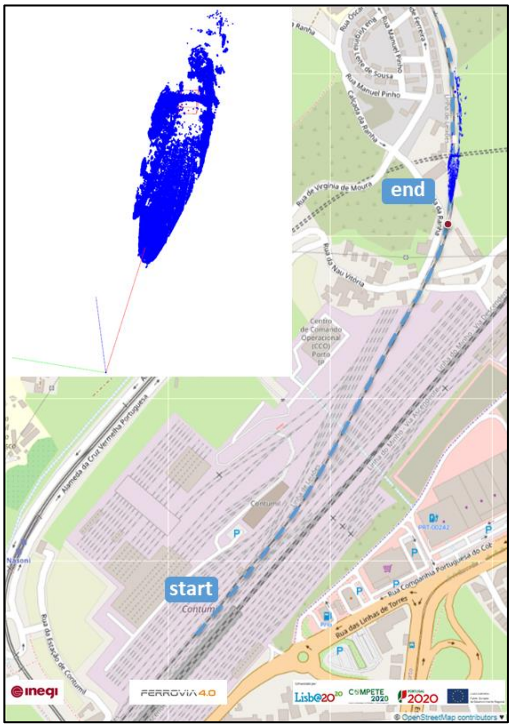

Fig. 11. Obstacle detection on the rail path using LiDAR - inside LiDAR FOV (map from: www.openstreetmap.org).

Fig. 12 represents the scenario were the search for obstacles is outside the LiDAR FOV. In this case, the search step is not executed, saving processing time, which is critical in a system like this one.

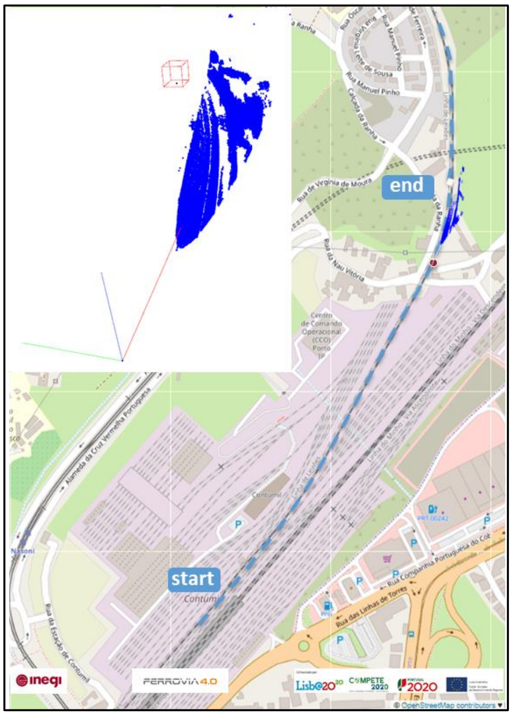

Fig. 12. Obstacle detection on the rail path using LiDAR - outside LiDAR FOV (map from: www.openstreetmap.org).

4 Conclusion

In this paper a framework for obstacle detection in the railway was described. The framework methodology combines the use of a long-range LiDAR capable of detecting obstacles at distances of up to 500 meters, with the train's coordinates to accurately determine its position relative to detected obstacles. The DBSCAN clustering algorithm was used to search for obstacles inside the determined area of interest. Several tests were conducted, including tests within the confines of a moving locomotive, along a designated section of the Contumil-Leixões line. These tests served to validate the effectiveness and feasibility of the approach under real-world operating conditions.

Overall, the utilization of LiDAR data coupled with advanced clustering algorithms presents a promising avenue for enhancing obstacle detection capabilities in railway operations. Further research and testing are warranted to validate the framework's performance across diverse railway environments and operating conditions

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