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Automated Detection of Vegetation Close to Catenary Wires using LiDAR Data

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Abstract

The vegetation near railway catenary wires can have various impacts on both the safety and efficiency of the railway system. If vegetation is too close to the catenary wires, it increases the risk of fire, especially during dry periods. Excessive vegetation near catenary wires can lead to electrical interference. This can disrupt the proper functioning of the railway electrical system, affecting trains' power supply quality. LiDAR plays a crucial role in the detection and analysis of vegetation. This work leverages LiDAR to identify geographical areas where vegetation is close to the catenaries and thus may pose a risk of damaging them. This information will facilitate organizing maintenance and preventing incidents related to vegetation.
The process involves the following steps: Determine, within the point cloud, the wire points corresponding to the contact wire and the vegetation points using a classification algorithm. For each vegetation point, compute a deviation corresponding to the shortest distance between the vegetation point and the nearest wire point. Estimate the number of vegetation points associated with deviations lower than a specified threshold distance in order to evaluate the maintenance need at each longitudinal section of the railway track.

Keywords: LiDAR, Cloud Point, Random Forest, vegetation management, maintenance automation, Railway Maintenance

1 Introduction

SNCF Réseau is responsible for managing the national rail network and is therefore responsible for infrastructure development and a total of 95 000 hectares of railway rights-of-way to maintain. As a result, it is important to know the status of track areas and prepare the appropriate resources for maintenance operations. Vegetation control is a part of these operations and is SNCF Réseau's main track maintenance expense. The control of vegetation represents the second-largest expense for SNCF Réseau (€120 million per year) because the vegetation resource regularly affects the availability of the railway system and traffic safety (fires, tree falls…) [1].

The vegetation near railway catenary wires can have various impacts on both the safety and efficiency of the railway system. It is mandatory to monitor and maintain the railway to avoid incidents caused by the presence of vegetation in railway rights-of-way.

A catenary is an assembly of bronze, steel or aluminium cables and of conductor cables in pure or alloyed copper designed to supply power to electric trains via a pantograph. Falling trees (whether caused by bad weather or not) can cause catenary to break. Branches caught in the wires can also cause a catenary pull-out as the train's pantograph passes overhead. When the copper wires of the cable break, the electric current no longer flows over the entire perimeter affected by the damaged catenary. Another consequence of the presence of vegetation near the catenary is the risk of catenary ignition. If branches are in the immediate neighborhood of electrical wires, this can lead to faults in the traction current supply. The risk of catenary ignition varies according to the type of power supply on the line. In both cases, train traffic is affected until field operatives can intervene.

The traditional field-based inspection is labor-intensive and costly. In areas with a lot of trees, which is the case around the railway rights-of-way, the canopy interferes with visual recognition. That’s why power lines are not always visible from aerial images in such conditions. The identification of power lines with Airborne Laser Scanning (ALS) over the past decades has already been documented [2]. The main disadvantage of these methods is the impossibility of covering a large area and the difficulty to deal with the surrounding high vegetation. Liang Cheng and al [3] studied on their side the use of vehicle-borne LiDAR data for the extraction of urban power lines by filtering the voxels and clustering. The interesting methodology cannot be applied to railway infrastructure because of the lack of roads along the railroad’s tracks.

The aim of this study is to go further and to use the possibilities offered by train-borne LiDAR data to automatically classify the electric wires and the vegetation and in a second step to calculate the density of vegetation around the catenary for a 100m section of electrified track. Each section of track will then be assigned to a risk level. The use of train-borne LiDAR data has the advantage of covering a large proportion of the French rail network several times a year.

This method is based on the computation of geometrical descriptors [4] on each point of the points cloud. A random forest [5] classification is then used to segment the vegetation and the wires. According to Wang and al [6] who compared different classifiers to detect power lines, Random Forest is highly suitable. The classification is then refined with different filters prior to the computation of the distance between the vegetation and the wire. This paper aims to describe the methods used to provide informations to support the maintainer's decision making in order to prioritize his operations thanks to the LiDAR data.

2 Methods

2.1 Train-borne LiDAR Data

SNCF Réseau conducts LiDAR (Light Detection and Ranging) surveys of its national infrastructure using three specialized surveillance trains known as ESVs ("Engin de Surveillance de la Voie"). Each ESV is outfitted with three LiDAR scanners (refer to Figure 1a), capturing data that is then amalgamated into individual point clouds representing the entire railway scene as the trains traverse France (see Figure 1b). LiDAR technology employs laser light for highly precise distance measurements. Currently, SNCF railroad network LiDAR acquisitions are refreshed approximately every 8 weeks, covering about 180,000 km annually (see Figure 2). The LiDAR scans obtained with the existing systems exhibit an absolute precision of 5 cm on average, attributed to fluctuations in the GPS system equipped on each ESV, and a relative precision of 6 mm. Although this precision level may not be ideal for tasks such as pinpointing small objects on the railway, it is considered sufficient for the intended goal of assessing vegetation density close to catenary wires along hundreds of kilometres of tracks.

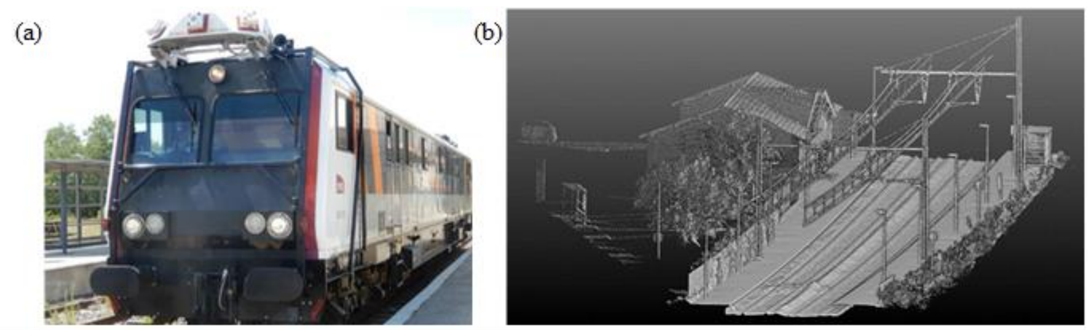

Figure 1 : (a) Surveillance machine (ESV); (b) LiDAR points cloud of a railway

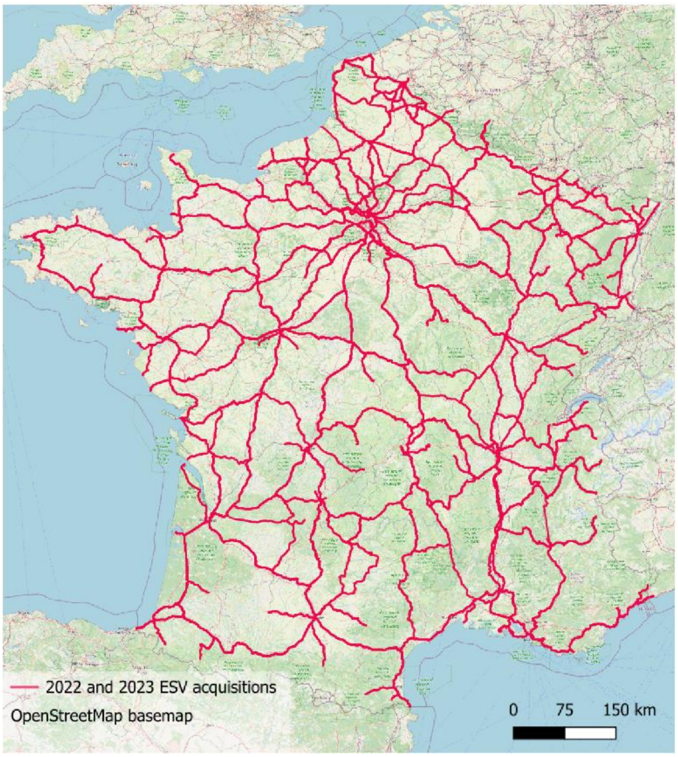

Figure 2 : Each year, 180000km of train-borne LiDAR acquisitions are available on the French rail tracks

2.2 Data pre-processing

Subsampling

To reduce the processing time, the points cloud is subsampled to 1pt/cm3. Therefore, the result of the process will be an estimation of the cubic volume of vegetation in cm3 in each class of distance from the wire.

Digital Terrain Model generation

The methodology behind the generation of the DTM (Digital Terrain Model involves manipulations of the LiDAR points cloud but falls beyond the scope of the study and is therefore omitted in this paper. The DTM will be used to filter different kind of objects according to their elevation.

Geometrical descriptors computation

The geometrical descriptors are geometrical characteristics of each point based on itsneighborhood These descriptors allow the random forests algorithm to establish classification rules according to the spatial context of the points. To efficiently extract the neighborhoods, a KD-Tree is employed.In this study, 6 local descriptors have been computed: linearity, planarity, sphericity, verticality, omni variance, curvature. These descriptors are computed for each point of the points cloud on their 10,20 and 40 nearest neighbors.

2.3 Points classification with Random Forest

Once the descriptors are computed, the points are classified, with a Random Forest, as one the 3 following classes : Vegetation, Wire, and Other. . The model has been trained once with samples distributed as follows: 38% for "vegetation" class, 20% for "wire" class and 42% for "other" class. To improve the result of this classification, some further steps are taken.

2.4 Wire points refinement

A filter based on the elevation of the points from the class "wire" is applied to keep only the points located at least 2.5m above the ground. The purpose of this step is to keep only the wires corresponding to catenary wires.

Afterwards, RANSAC (RANdom SAmple Consens) is used to extract candidate power lines. Up to 20 lines , of width 3cm, are extracted from the points classifed as wires and lines made of less than 500 points are considered wrongly classified. Parameters were set empirically to meet the constraints of LiDAR data in railway environments.

Lastly, a clustering by DBSCAN and a PCA(Principal Component Analysis) computation for each cluster are used to filter out any linear cluster oriented in a wrongful direction (see Figure 3).

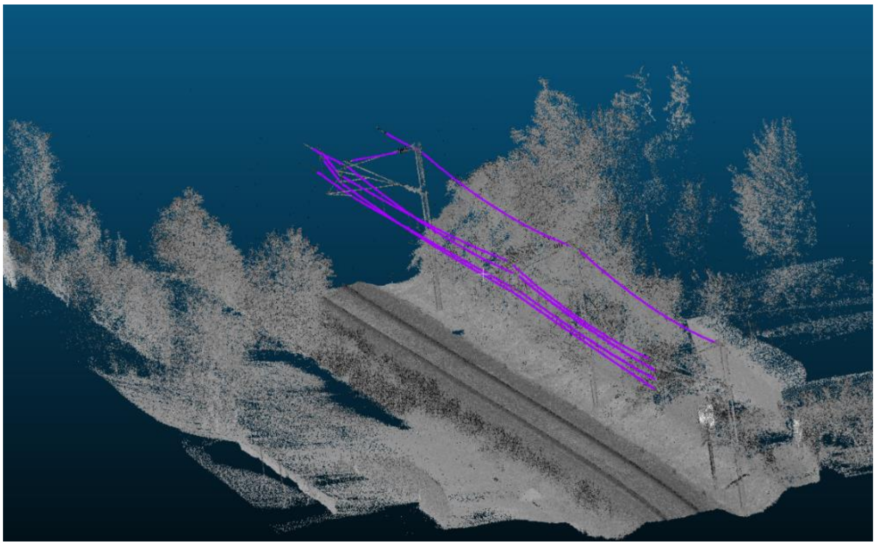

Figure 3: Points classified as wire after refinement

2.5 Vegetation points refinement

As vegetation is the main element to be measured in this study, it is necessary to ensure that no false positives from this class inflate the results. The learning model used to differentiate vegetation from catenary wires and the rest is indeed susceptible to misclassification of objects such as portions of catenary poles, insulators at wire level, and other structures supporting signage that have not been included in the model training set. As a result, these objects appear as groupings of "floating" points in the vegetation detection. To filter out these elements, a method is used which assumes that the real vegetation (the "true positives") is correctly detected globally and forms continuous groupings of points which either start from the ground or extend to the lateral edges of the polygon being processed. To extract this information, DBSCAN clustering is performed to isolate each group of vegetation points and filter out any groups that are not attached to the ground or to the end of the polygon.

As catenary wires are detected by extracting linear elements using a 2D RANSAC method, we make sure to filter out catenary wire points incorrectly detected as vegetation by using the various straight lines extracted in RANSAC. Any vegetation points that lie exactly in line with the straight lines corresponding to catenary wires are removed from the study. In this way, the false positives found directly at the wires, and which indicated an important presence of vegetation near the wires, are correctly filtered out (see Figure 4).

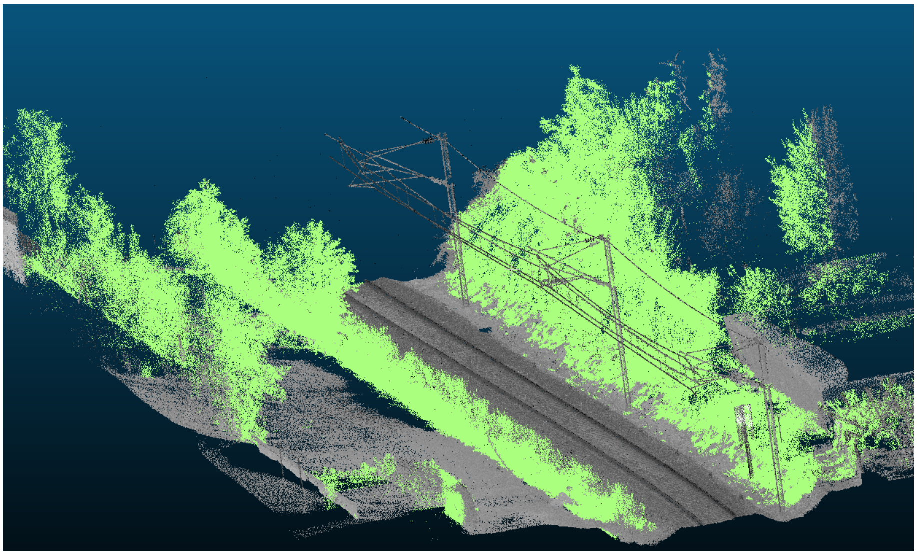

Figure 4: Points classified as vegetation after refinement

2.6 Distance computation

A KDTree algorithm is used on each point classified as "vegetation" to identify the nearest point classified as “wire”. The distance between the pair of points is then calculated thanks to the x,y,z coordinates. In that way, for each “vegetation” point a distance to the nearest “wire” point is assigned. The results are then aggregated to provide a vegetation density in each class of distance (0-1m, 1-2m, 2-3m, 3-4m) for each longitudinal 100 meters long section of tracks (see Figure 5 and Table 1).

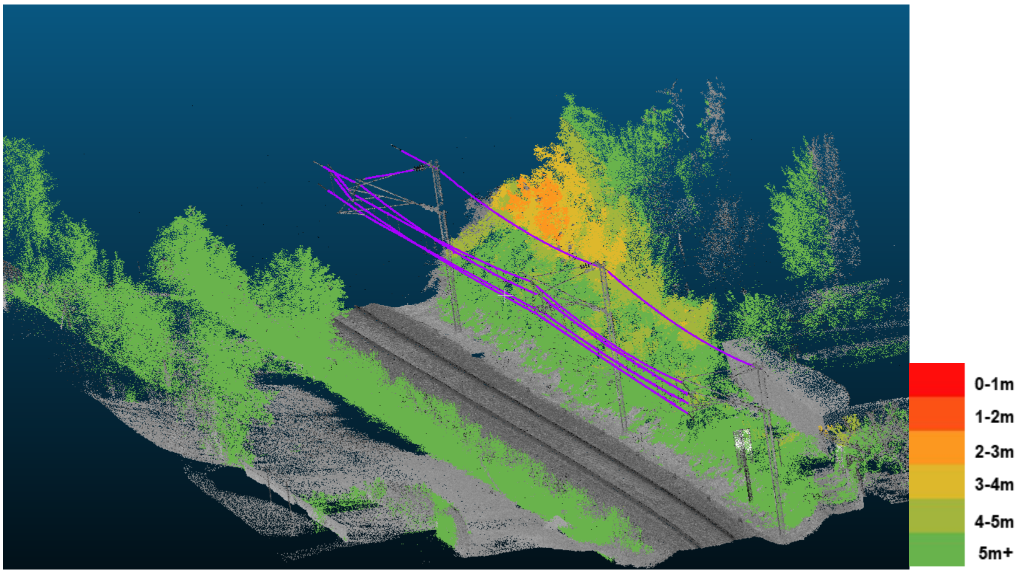

Figure 5 : Points cloud in which the vegetation points were colored by their distance from the catenary wire

Distance from the catenary wire	0-1m	1-2m	2-3m	3-4m	4-5m	> 5m
Vegetation volume (cm^3)	0	0	8229	35573	107167	1340080

Table 1: Vegetation density in each class for a 100m long section

3 Results and discussion

The results are analyzed by comparing the density computed by LiDAR data and a visual approach of pictures taken from the train cab at in the same period of the year. The results have been analyzed on three different electrified train lines described in Table 2.

Train line	Length of the section	Acquisition date
655000 : Bordeaux-Irun	221 km	09/2020 and 05/2022
852000 : Dole-Belfort	140 km	09/2022
897000/900000/90300 : La Tour du Pin - Annemasse	150 km	06/2023

Table 2: Section of railway line analysed

This recursive validation approach with the maintainer made it possible to refine the filters applied on the classified points cloud. For example, the number of points detected as vegetation within 1m around the wire has decreased between the two analyses on the train line 655000 without any vegetation work. This reduced the number of false positives by 40%.

The longitudinal sections are then affected to a risk level according to the vegetation density. A section with high density of vegetation at a distance under one meter will be classified as riskier than a section without any vegetation points in a three meters radius. The risk level of each longitudinal section is provided in the SNCF Réseau's GIS (Geographical Information System) application dedicated to vegetation control. Maintainers can prioritize their work thanks to this information.

4 Conclusions

The first results are very promising they allow the maintainer to identify the risky sections of tracks where some interventions must be made. One limitation lies in the setting of parameters, especially in the RANSAC used to filter wire points. The classification can still be improved with more fitting samples and some other methods like neuronal networks could be tested to have a better classification of the point clouds.

Another interesting study could be the analysis of two successive LiDAR acquisitions classifications on the same area without any vegetation work to identify the speed of growth of the vegetation.

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