Proceedings of the 33rd European Safety and Reliability Conference (ESREL 2023)
Edited by Mário P. Brito, Terje Aven, Piero Baraldi, Marko Čepin and Enrico Zio

doi: 10.3850/978-981-18-8071-1_P379-cd

Condition monitoring of railway overhead catenary through point cloud processing

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Railway overhead catenary (ROC) is a linear asset and spread over large area. Different regions of the linear asset are exposed to different climate conditions such as temperature, wind, and ice accretion and operating conditions. If these conditions disrupt the functionality, then it leads to failure resulting in line closure. Being ROC is a linear asset, condition monitoring (CM) is difficult due to large distances, climate conditions, costly due to requirement of special equipment at the location and effects the scheduled traffic by occupying the tracks. Hence, there is a need for technologies to monitor the condition of ROC through a cloud-based approach which has faster response time. Light Detection and Ranging (LiDAR) can be used for CM of ROC. It collects spatial data in the form of 3D point cloud in various domains such as construction, mining and railways. LiDAR devices will be mounted on locomotives on a regular traffic. The point cloud data is processed to extract the railway assets such as tracks, masts, catenary etc. and surrounding vegetation. Further, processing of point cloud data can be used to extract exact location and position of the assets. One of the failure modes for ROC, if the distance between the two wires is less than the specifications, then it leads to failure. This paper develops a cloud-based approach to measure the distance between specific wires, through processing of point cloud data. This approach forms the foundation for data augmentation and development of hybrid digital twins (DT) of railway overhead catenary.

Keywords: Railway overhead catenary, LiDAR, point cloud, digital twin.

1. Introduction

Asset management of railway system is essential for robust, resilient, and reliable operations. Railway Overhead Catenary (ROC) powers the electric locomotives. Use of electric power is the main reason behind low greenhouse emission of railways among all the modes of transportation at 0.4% (Statista 2021).

In case of ROC, prominent failure mode is due to interaction of wires with high potential difference such as tension wire (ground potential) and reinforcement conductor (15KV). Such failures can result in delayed traffic, loss of property and reputation for the infrastructure owner and in extreme cases lead to accidents. Since, the power lines are linear assets, there are several challenges in inspection of such distributed assets. The existing condition monitoring methods usually carried by maintenance personnel through visual examination which are time consuming, expensive and introduce uncertainty due to human errors. In addition, it is dependent upon heavy equipment and presence of personnel on location which needs longer processing time. Additionally, such methods can also cause delay in the scheduled traffic since the equipment occupies the tracks. Hence, the existing condition monitoring methods are inefficient and ineffective. 2D imaging-based methods are unsuitable because of the loss of depth information which is critical for inter wire distance measurement. Other condition monitoring methods rely on using on-board sensors. Overall, these factors result in lowering

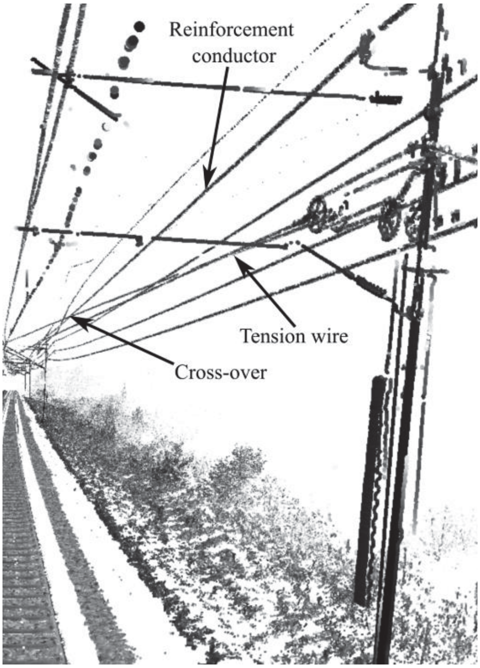

Figure 1. Railway overhead catenary point cloud

the frequency of inspections. Hence, it is necessary to utilise technologies that enable the faster response time (through cloud-based approaches).

Light Detection and Ranging (LiDAR) can be one of the sensors to monitor ROC. It is a sensor which creates a 3D representation of the surroundings by scanning a LASER beam, the scanning is performed by two mirrors to provide horizontal and vertical scan. The resulting data is called point cloud and provides the positional coordinates and intensity value for each scanned point. The position value is generally represented as x, y, z components and may have latitude, longitude and altitude values derived from GPS. LiDAR device can have integrated camera which provides color information for each of the points.

Since the LASER beam may penetrate through low density regions points collected near each other may have large depth variation. Due to these reasons, in the point cloud data the order of stored points does not indicate vicinity in real world unlike as in 2D images.

In order to localize and translate the points when LiDAR is mounted on a moving train, Simultaneous Localization And Mapping (SLAM) algorithms are integrated within the device (Durrant-Whyte and Bailey 2006). This method allows efficiency in scanning for coverage of large areas.

The point cloud data generated from LiDAR scanning is inherently discrete in nature. Algorithms designed for point cloud processing should mitigate the effects of varying resolution.

For monitoring the position of catenary wires, the LiDAR is mounted in front of a train and resulting point cloud can be seen in Fig 1. Researchers have developed algorithms to extract assets from power line point cloud by developing various methods such as shape based segmentation, altitude based segmentation, and feature based segmentation (McLaughlin 2006; Shen et al. 2018; Kim and Sohn 2010). Similarly in case of ROC researchers have developed methods for extraction of various assets from the point cloud (Arastounia 2017). Chen et al have proposed two stage classification method based on semantic features extracted from point cloud (Chen et al. 2021). Semantic features generated from Eigenvalues of point clouds is a suitable technique to bring structure and further classify the points (Chehata, Guo, and Mallet 2009). These semantic features generated from point cloud data can be used for classification through various machine learning algorithms (Weinmann et al. 2015). However, measurement of minimum distance between two hanging wires has not been addressed in literature.

In addition, there is lack of automated approaches that will have significant benefits on CM and maintenance of linear assets. The purpose of this paper is to enhance the operational reliability of ROC. The objective of this paper is to develop a cloud-based approach for detecting a failure mode of minimum distance between tension wire and reinforcement wire. This can be expressed by converting point cloud wire data to mathematical form and extracting minimum inter-wire distance to detect failure condition. For the implementation of cloud-based approach, it will be efficient to represent the ROC in a digitised format. Representation of ROC in mathematical form will allow automated analytics to extract the condition of this asset. Additionally, this automated process will enable for development of models which will become a part of ROC DT. This work is the extension of our research towards development of digital twins of ROC (Voorwald 2022; Patwardhan 2022).

2. Methodology and Results

The end-to-end process flow of point cloud data can be described from data acquisition to its use for information representation or visualisation as shown in Fig 2. This process flow is being implemented in a developed cloud-based architecture (Patwardhan 2022). Pre-processing, processing, and post-processing stages are the focus of this paper.

2.1. *Point Cloud Pre-processing*

The pre-processing stage for point cloud data involves removing of points and regions which are not required for the failure mode of ROC such as noise points and the ground surface. Suspended dust particles and fog results in noise in the point cloud. When the LiDAR is mounted on the locomotive two meters from the ground, more than 60% of the scan data is generated from the ground surface and is discarded at this stage. However, the level of ground plane is retained since the height of the contact wire from the ground level is a known as a standard value see Fig 3 (a). Decimation of point cloud is also performed to reduce the number of points to

Figure 2. Point cloud acquisition to visualisation

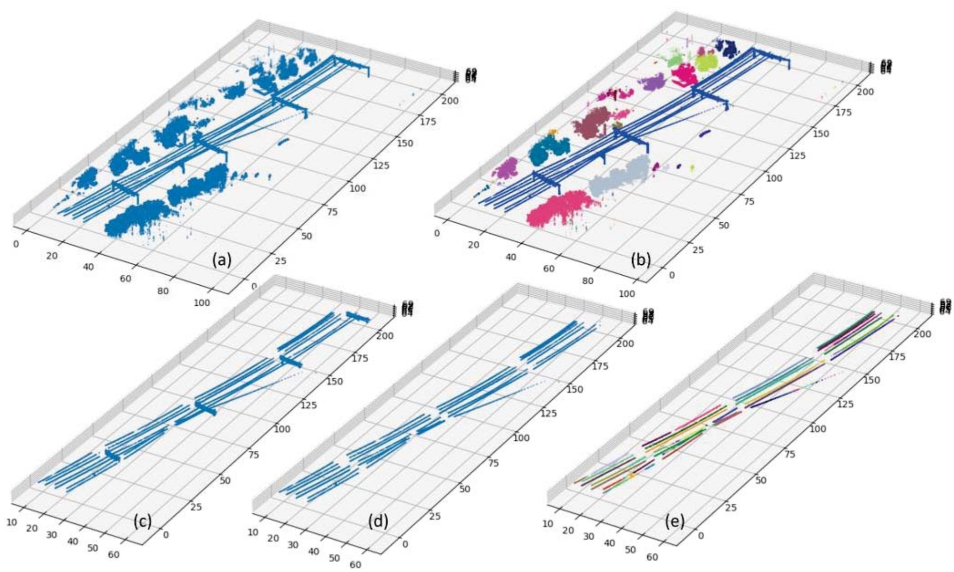

Figure 3. Extraction of individual wires

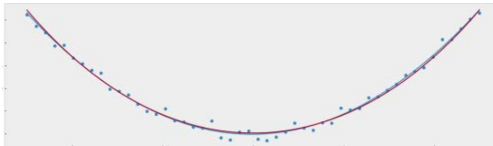

Figure 4. Point cloud to curve

reducing the computation time of point cloud processing.

2.2. *Point Cloud Processing*

This stage focuses of extraction of individual wires from the point cloud data. This is performed in various sub-stages such as cropping, clustering, and segmentation. Point cloud processing stages can be seen in Fig 2. Fig 3 (a) shows the point cloud without the ground plane but the catenary with the mast, portals, wires and surrounding vegetation is visible. Fig 3 (b) shows the result of DBSCAN clustering all the smaller clusters are removed to remove the vegetation from the point cloud. Vertical masts are detected and discarded while retaining their position in global coordinates (SWEREF 99) see Fig 3 (c). Points between the masts nearly perpendicular to the wire direction represent the portals, these points are extracted and discarded see Fig 3 (d). Finally, clustering is performed to extract individual wires see Fig 3 (e).

Since the focus is on detection of distance between the tension wire and reinforcement conductor, only specific regions where the tension wire is detected are retained. The tension wire is detected with the property that it is not parallel to the rest of the catenary wires. The reinforcement conductor is extracted through their relative position with respect to mast. Thus, individual wires are extracted as set of points.

2.3. *Post-processing*

The post processing stage focuses on extraction of information from the segmented point cloud data.

In mathematical terms catenary is defined as the shape formed by a weighted rope hung between two points. All wires except contact wire in ROC are freely hanging wires between two end points on the masts. Hence, they follow the catenary curve equation. The catenary equation in 2D space is as shown in Eq. (1), where a is the ratio of tension on the wire to its weight per unit length (Chatterjee and Nita 2010).

$$y = a\,cosh(x/a) \tag{1}$$

The tension wire and reinforcement conductor are fitted to equations numerically as shown in Fig 4. The extracted curve information is stored in a database with the following data values per curve a) date of scan b) two mast position c) curve parameters d) rotation and translation matrix and e) wire category. This step is critical since it transforms the wire information from discrete points to continuous mathematical form, hence, mitigating the limitations of discrete point cloud data. These stored variables allow reanimation of the catenary curves over a period of time. Since the data is stored in a database, any future information extraction requirements can be accomplished through targeted queries.

The minimum permissible distance between the tension wire and the reinforcement conductor is about 20 cm. A failure is considered when these two wires are closer to each other than the permissible value. Hence an approach to measure the minimum distance between the two wires is required. Since, the wire information is stored in continuous mathematical form, mathematical analysis can be applied to the generated wire equations.

$$C_1 = T * R * a_1\,cosh\left(\frac{t1}{a_1}\right) \tag{2}$$

$$C_2 = T * R * \ a_2\,cosh\left(\frac{t2}{a_2}\right) \tag{3}$$

$$d_{12} = \ \|C_1 - \ C_2\| \tag{4}$$

$$d_{min} = \min(d_{12}) \tag{5}$$

Where C_1 and C_2 are the equations generated for the two wires, *T* and *R* respectively are the translation and rotation operations performed based on the stored parameters for each wire. The distance between the curves is represented by d_{12} and its graphical representation can be seen in Fig 5 as a set of convex curves. The minimum distance d_{min} is extracted as the minimum value of d_{12}, Fig 5 shows a graphical representation of d_{12} and the lowest point of intersection of the set of curves formed in represents d_{min}.

The final result d_{min} provides the coordinates on the curves and which allows

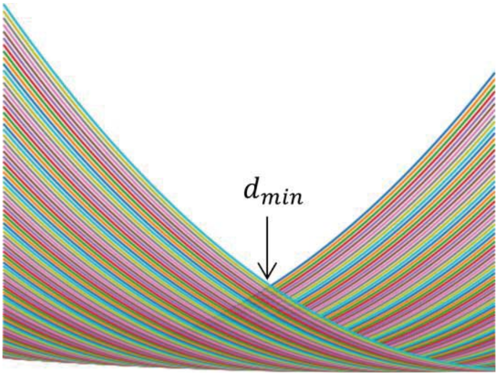

Figure 5. Curves representing the distance set

distance measurement at the closest point of the two curves representing the wires. Computed minimum distance is represented by line of red colour in Fig 6.

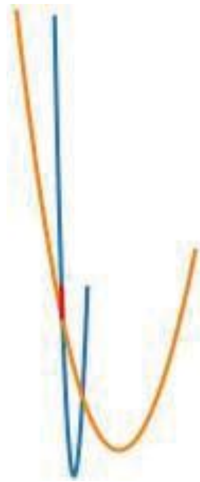

Figure 6. Detected position of minimum distance

3. Analysis and Discussion

The presented approach can extract the minimum distance between the two wires represented as catenary curves in 3D space. However, one condition, not encountered in the current dataset is possibility of vanishing gradient in the generated distance function. This condition may occur if the two wires are at a constant shortest distance over some distance.

Implementation of point cloud data processing pipeline will automate the inspection process hence reducing the time and cost requirements as well as reducing the dependency on specialized equipment and presence of personnel on site. It will be a highly beneficial approach towards CM for linear assets.

As discussed in the paper representation of extracted information as numerical values (mast positions) and mathematical equations (catenary wires), and stored in a database allows to a) store the digitalized catenary in significantly less space b) supports better condition monitoring c) perform computation d) perform comparison over a period of time e) perform data augmentation f) generate visualization for virtual reality environments g) provide on ground asset information through augmented reality devices and, h) supports development of simulation models useful for developing digital twins.

4. Conclusion

This article presents continuation of our previous work towards development of digital twins of ROC by using point cloud data.

In this paper, we have presented a method to extract ROC wires and inter-wire distance from point cloud data and represented it mathematically. This mathematical representation enables for the detection of possible failure mode. This conversion also reduces the amount of information required to digitize ROC information. This approach can be extended to various other linear or non-linear assets for improved CM and asset management.

The resulting data driven model of ROC representing wires in mathematical form will be used for data augmentation and become a part of a ROC DT. The envisioned DT will be used for predictive maintenance based on climate conditions.

Acknowledgement

The authors would like to thank the Swedish Innovation Agency Vinnova, JVTC (Luleå Railway Research Center), Trafikverket, for their financial support to carry out this work within the framework of AIFR Project (https://www.ltu.se/research/subjects/Drift-och-underhall/Forskningsprojekt/AI-Factory?l=en). The opinions and findings expressed in the paper

are those of the authors and do not reflect the views of the organizations mentioned above.

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