

Application of Railway Topology for the Automated Generation of Geometric Digital Twins of Railway Masts

M.R.M.F. Ariyachandra & Ioannis Brilakis

University of Cambridge, Cambridge, United Kingdom

ABSTRACT: The digitisation of existing railway geometry from point clouds, referred to as “twinning” is a labourious task; currently outweighing the perceived benefits of the resulting model. State-of-the-art methods have provided promising results, yet they cannot offer large-scale rail class segmentation requires over kilometres without forfeiting precision and labour cost. The authors exploit the potential benefits of railway topology to automate the twinning process. The preliminary step is automatically segmenting mast point clusters as their positions are critical for the subsequent railway assets’ class segmentation. The proposed method first removes vegetation and noise; then segments masts using the RANSAC algorithm relative to the track centerline, and delivers final models in IFC format. The authors validated the method on 18 km railway point cloud and yielded an overall segmentation accuracy of 90.1% F1 score. The proposed method lays foundations to efficiently generate geometry-only digital twins of railway assets with no prior information.

1 INTRODUCTION

This paper discusses an automated twinning process to generate geometric digital twins of railway masts from airborne light detection and ranging (LiDAR) point cloud data. The authors define railways masts as trackside poles, either made of highly weathered metal or wood; which hold the overhead cables in place. Other pole-like objects class consists of tree trunks/branches, signal, traffic sign and light (road) poles, and columns on rail infrastructure. The authors define class segmentation as the partitioning of the railway point cloud to clusters such as rails, sleepers, masts, etc. The challenge that the research addresses is how to efficiently generate the geometric models [referred to in this study as a geometric digital twin (gDT)] of railway masts such that the perceived benefits of the gDT outweigh the investment made to create it. This is a significant challenge because of the potential value of gDTs, that is expected to bring in the construction, operation and maintenance of railways.

The UK has the fastest-growing railway network in Europe, with an increase in passenger numbers of 40% expected by 2040 (Office of Rail and Road, 2020). In light of this increased demand, £48 billion funding has been recently approved for Network Rail including 16% for maintenance and 34.6% for renewals of existing railways (Department of Transport, 2017). These operations often require efficient and effective record-keeping that currently prevails as major bottlenecks. Railway survey com-

panies have already explored the potential benefits of laser scanned data to support these operations. Yet, the resulting laser survey data are often unstructured, and do not contain any meaningful information of the documented rail assets. The digitisation of rail infrastructure mapping from point clouds; generally referred to as “twinning” process is therefore introduced to utilise the need for high-level digital representation in a structured format. However, this process remains a daunting task, which takes years rather than months before data collected reaches the database in a useable format (HM Government, 2020). The authors argue that this establishes the need to create and maintain up-to-date digital twins (DT)s of rail infrastructure assets using quicker and more efficient approaches. An up-to-date gDT employs advanced data tools to provide back-and-forth connection between the twin and its physical asset while describing its geometry in real-time.

Leading software vendors like Autodesk, Bentley, Trimble, AVEVA and ClearEdge3D produce advanced semi-automated commercial solutions for DT generation. Yet, these software are tailored for generic or pre-defined geometries, and far from being fully automatic (Wang, Cho and Kim, 2015; Agapaki and Brilakis, 2018). The authors’ previous work (Ariyachandra and Brilakis, 2019) reviewed the existing problems of twinning arbitrary geometries of rail infrastructure in detail by investigating the entire workflow of gDT generation of rail assets

from point cloud data. The analysis summarised that the twinning of non-standardised geometries of rail assets require extensive manual costs to model sub-point clusters. This demands 95% of the total modelling time on customising shapes and fitting them to the sub-point-clusters which generally lengths over kilometres. There is no single software that can offer a one-stop DT generation solution. Modellers have to shuttle intermediate results in different formats back and forth between different software packages during the modelling process, giving rise to the possibility of information loss. This explains why very few assets today have a usable DT. Hence, the authors contend that there is a pressing need to create less labour-intensive railway modelling techniques that can automate the twinning process with overall reduced costs and timescales.

In this paper, the authors address a core step of creating gDTs of rail infrastructure, i.e. the generation of gDTs of railway masts. The reliable mast class segmentation is extremely useful for the other rail assets' class segmentation. It is the only vertical element which is in regular spatial offset on the trackbed. Hence, the segmentation of masts would provide the relative positional layout for the rest of the rail assets. Yet, automatic gDT generation of masts is often challenged by the presence of vegetation often surrounding them, the extremely thin shape of the sought object and the similar shape of tree trunks/branches. The following section analyses the state-of-the-art research methods proposed to streamline the mast and other pole-like objects twinning processes.

2 BACKGROUND

The geometrical shape of the mast and other pole-like objects in railway point clouds such as light poles, signal poles and traffic sign poles are quite similar. Hence, this section analyses both masts and other pole-like object class segmentation methods.

There is only one method exists Pastucha (2016) for segmenting points belonging to the masts using three-dimensional (3D) data. The method first segmented rail catenary system objects into different classes and then localised the mast positions relative to previously segmented rail catenary objects classes. However, this method used geometrical distances from the trajectory of the scanner to set the thresholds and required manual user inputs to specify the geometric properties of the objects. Moreover, they manually removed the initial vegetation and noise. This makes the method impractical to use, as the automation achieved is small compared to the manual work needed.

Methods exist that can automatically remove the vegetation and noise of the point cloud. For example, a two-dimensional (2D) horizontal slicing based method could remove tree crowns and upper/lower

structures (i.e. signal boards, traffic lights) attached to vertical pole-like objects (Luo and Wang, 2008; Pu *et al.*, 2011; Huang and You, 2015). Pu *et al.* (2011) used a percentile-based method to detect poles as pillars. Their results were a good start, reaching 63% precision and 60% recall. Yet, this method required the main pole to be an isolated pole-shaped object, without any structural attachments. In railroads, masts are always connected to cables and cantilevers. Hence, rather than being an isolated pole-shaped object, a mast is always a part of a structure. On railway point clouds, trees are often closely located. Consequently, tree crowns often overlap and can occlude masts. This is why their method classified tree trunks as pole-like objects and did not remove them. Fukano and Masuda (2015) used patterns of the scan lines of Mobile Laser Scanning (MLS) data as a basis to segment walls, roads and poles separately. However, if the poles were closely located, the scan lines belong to the same class of objects represented one pole or combined multiple poles. Hence, the precision was reduced to 76% making the results ambiguous.

Existing semi-automated approaches can remove the vegetation and other noise up to a certain extent. Yet, these methods did not provide a clear and concise approach to distinguish trees from other pole-like objects and still depended on the scanner profile information. In addition, the presence of vegetation, ground and facades that connect every object in a point cluster imposed a huge computational load on these methods (Fukano and Masuda, 2015; Huang and You, 2015; Yadav *et al.*, 2015). These limitations highlighted the need for automated filtering and segmentation of data at the initial stages of the process.

The issue has been addressed by methods that segment the dataset at the earlier stages of the process (Lehtomäki *et al.*, 2010; El-halawany and Lichti, 2013). El-halawany and Lichti (2013) used a segmentation method that employed 2D density-based calculations for the removal of the ground plane. Next, they applied vertical region growing to extract upright objects and then merged segments that belonged to the same object. The major problem left unresolved was that their ground removal method was sensitive to point densities and to the trajectory line of the scanner. This method did not perform well when segmenting poles surrounded by trees; distinguishing pedestrians from poles; segmenting incomplete poles and poles close to building facades.

Li *et al.* (2018) addressed these limitations using a three-step procedure to automatically decompose road furniture (including poles) into different components based on their spatial relations. This included ground plane removal relative to the scanner profile, and finally a slicing-based method, a random sample consensus (RANSAC) line fitting method

and a 2D density-based method to extract vertical objects. However, the method required high-quality point clouds (35 points/m² to 350 points/m²). Therefore, the performance of the algorithm was not promising for poor quality datasets. Likewise, this method recognised small booths supported by pillars as pole-like road furniture in both test sites. The segmentation algorithm was not enough to discriminate the difference. The slicing-based segmentation steps segmented trees as poles when the trees are connected to the pole-like road furniture. The method did not categorize trees and road poles in separate groups.

Cabo et al. (2014) and Rodríguez-Cuenca et al. (2015) applied 3D voxelization to isolate poles from other noise data. They analysed the horizontal sections of the voxelized point clouds using 2D plane projection analysis. Yet, the method did not perform well when the poles were affected (a) by severe occlusions from large objects such as vehicles or large bins, parapets of bridges; (b) by the existence of other features such as pedestrians nearby; (c) when the poles were surrounded by bushes, or (d) when poles were too close to guardrails or walls. Li et al. (2019) investigated the continuity of surface roughness as a basis to differentiate poles from trees considering the various attachments of man-made poles (i.e. lamps, traffic lights, signboards etc.). The method was unable to detect poles with linear attachments (i.e. cables in masts). Also, trees that were occluded by another tree located in front of them were wrongly detected as poles.

2.1 Knowledge gaps, objectives, and research questions

The review provided in the previous section demonstrated that the existing pole segmentation methods have been tailored for MLS data (Zhu and Hyyppä, 2014; Arastounia, 2015; Fukano and Masuda, 2015; Pastucha, 2016; Li, Elberink and Vosselman, 2018), therefore, they cannot be directly applied to Airborne Laser Scanning (ALS) data. The ALS data is unorganised, meaning it does not contain any profile information; and has arbitrary position and orientation. In addition, these methods were not robust to occlusions and sparseness (Pu et al., 2011; Elhalawany and Lichti, 2013; Li, Elberink and Vosselman, 2018). Railway point clouds are noisy and imperfect, suffering from both occlusions and sparseness. Masts are thin and hence often don't have many points representing them. Hence, the mast class segmentation is a very hard problem also due to the presence of vegetation and tree trunks, shaped like poles. These factors render existing methods ineffective.

Despite the growing state-of-the-art, a fully automated railway mast twinning process is still in its infancy. This requires the development of a fully au-

tomated method to generate gDTs of masts from railway ALS data, as, in this case, no method in the literature meets all user requirements. To tackle this challenge, the authors propose an automated twinning method for masts in existing railways, aiming to meet the following objectives:

- *Objective 1:* Automatically remove the vegetation surrounding railways. This will be done by answering the following research question; *RQ1:* How to automatically remove vegetation and other noise data without using any additional prior information such as neighbourhood structures, scanning geometry and intensity of input data?
- *Objective 2:* Automatically segment masts in the form of point clusters by differentiating masts from other pole-like objects. This will be done by answering the following research question: *RQ2:* How to automatically detect and separate masts from pole-like objects in imperfect railway point clouds where occlusions and varying point density exist?

3 PROPOSED SOLUTION

3.1 Scope

The proposed method twins only the typical double-track railways because they make up 70% of the existing and under-construction railway network in the UK and Europe (Eurostat, 2019). The proposed method exploits the railway topology knowledge as guidance to directly extract point clusters corresponding to masts. Railways are not perfectly straight or flat and they usually contain varying horizontal and vertical elevations with curves and slopes. Nevertheless, railways are a linear asset type; their geometric relations remain roughly unchanged often over very long distances. Close inspection of railway point cloud validates this effect, with repeating railway topological features such as: (1) the geometric relationships among railway masts, catenary and contact cables, and rails remain fairly unchanged along the railway corridor (Network Rail, 2018); (2) the connections between railway masts and cables are placed in regular intervals (60 m intervals on average); (3) the main axis of the railway masts (Z-axis) is roughly perpendicular to the rail track direction (X-axis) [error tolerance is 11° (Network Rail, 2018)]; and (4) railway masts are always positioned as pairs throughout the rail track. The study employs these four geometric features as railway topological relationships and uses as assumptions when developing the proposed method. The workflow of the proposed method is illustrated in Figure 1.

3.2 Step 1: Automated refinement to remove noise

The method initially uses principal component analysis (PCA) to find the principal axis of the point

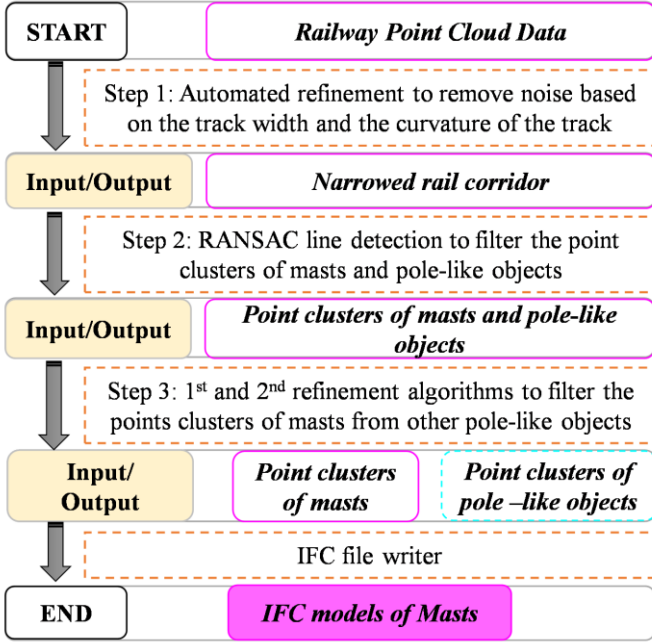


Figure 1: Workflow of the proposed method

cloud and to align the railway point cloud such that the horizontal alignment of the rail track is positioned roughly parallel to the global X-axis.

This would enable one to easily exploit features of the point cloud using various feature extraction algorithms because all features to be extracted in further steps lie in a global coordinate system. The Z-axis of the data is now parallel to the global Z-axis, yet due to the horizontally curved alignments and vertical elevations of the rail track, X and Y axes of the track are continuously varying throughout the track. While PCA selects the most populated data axis parallel to the global X-axis, the track direction of the point cloud is not always parallel to the global X-axis. Thus, the centreline of the track does not reflect the true centreline of the rail track as it is occluded by many points specially belong to vegetation, surrounded its environment. This restricts the usage of the centreline of the dataset to set a distance threshold to remove the noise. To address this challenge, the authors used an automated segmentation technique to align X and Y axes of datasets parallel to the global reference system. The following paragraph discusses each step in detail.

The proposed segmentation method first automatically crops the roughly aligned point cloud into near-straight pieces of rail track. Next, the method aligns these resulting pieces by computing PCA for each of these pieces and creates an axis-aligned bounding box around each in its principal direction. The result of this step gives a set of sub-bounding boxes (*SBB*), in each the track direction is now parallel to the global X-axis and Y and Z axes of each *SBB* are now parallel to global Y and Z axes. Prior to this step, the method required an optimum *SBB* count, which: (a) provides near-straight pieces of the rail track; (b) removes the maximum number of vegetation and noise points, and (c) prevents the cropping of masts. The authors gauged the remaining

number of masts as a percentage of the original number of masts with many *SBB* counts to decide the optimum *SBB* count for each dataset. This finally gives 24, 30 and 17 as the optimum *SBB* for Dataset A, B and C respectively. In this paper, the authors haven't illustrated the graphs representing calculations for these parameters due to limited space.

Following this step, the method gauges the minimum; the maximum; and the centre point ($q_{centreSBB}$) of each *SBB*. Note that $q_{centreSBB}$ is now aligned on the principal axes of the *SBB* and the width of the rail track (W_i) is now aligned to Y-axis. Using $q_{centreSBB}$, the method determines a threshold distance (d_{SBB}) which is based on the W_i . W_i is used to set d_{SBB} , where d_{SBB} equals to $W_i/2$. The proposed method then uses d_{SBB} to remove the vegetation and other noise from the rail corridor data. The method computes d_{SBB} from $q_{centreSBB}$ on both sides along the Y direction (Figure 2) and removes the rest of the points of each *SBB*.

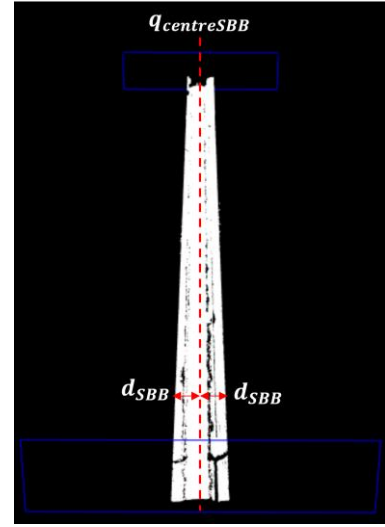


Figure 2: Resulting *SBB* after vegetation removal

3.3 Step 2: Mast and other pole-like objects class segmentation

Masts are now parallel to the global Z-axis, which is in-line with observation 3 mentioned earlier. Hence, the proposed method then segments masts as lines parallel to the global Z-axis using the RANSAC line detection algorithm since it is only long vertical element remains after pre-processing and removal of vegetation. The proposed method allows for a deviation of 11° because the masts aren't always perfectly parallel with the global Z-axis according to the railway design standards (Network Rail, 2018). Prior to the RANSAC algorithm, the method uses two-pre-processing steps as given below to reduce the computational load.

(a) Remove the ground plane to eliminate all ground points - This ensures that all points around masts are removed prior to further calculations and significantly reduces the points for faster computational performance.

(b) Divide the remaining dataset into sub-boxes - This further increases the speed of RANSAC due to the small number of points considered each time.

The method then uses RANSAC for each *SBB*. The authors gauged the performance of the mast class segmentation using performance metrics precision (*Pr*), recall (*R*) and F1 score (*F1*) as expressed below (Table 1).

- True Positive (*TP*): Masts were correctly detected as masts;
- False Negative (*FN*): Masts were not detected as masts and;
- False Positive (*FP*): Other pole-like objects were detected as masts.

Table 1: Performance matrices for RANSAC line detection

Dataset	# of masts	TP	FP	FN	Pr	R	F1
A	212	134	24	78	84.8%	63.2%	72.4%
B	172	88	50	84	63.8%	51.2%	56.8%
C	188	69	76	119	47.6%	36.7%	41.4%
Avg.		291	150	281	66.3%	50.9%	57.6%

The segmented vertical lines at this stage represent both masts and other remaining pole-like objects in railway point clouds. As a result, the segmentation accuracy was fairly satisfactory (57.6% F1 score). This required additional research to differentiate masts from other pole-like objects.

3.4 Step 3: Differentiate masts from other pole-like objects

The authors incorporated two refinement algorithms to differentiate masts from other pole-like objects based on the assumptions mentioned in section 3.1. At this stage, the surrounding of a mast has few or no points as all the ground points have been already removed at step 2, while other pole-like objects such as trees, bridge piers or walls usually contain few points that often belong to tree leaves, bridge columns and/or tree trunks. The authors used this observation to create 1st refinement algorithm which consists of three steps to filter masts from other pole-like objects.

The 1st step is creating an inner box (*IB*) around the segmented lines, such that the point cluster of the segmented line (a mast or other pole-like objects) is tightly fit into the *IB*. The *IB* only contains points belongs to a mast or other pole-like object. The 2nd step is creating an outer box (*OB*) around the inner box such that this *OB* should only contain one mast and should not overlap with the other mast of the same pair. This box might contain any other points surrounded the pole usually caused by tree leaves, bushes, walls etc. The authors expect two different outcomes for masts and other pole-like objects as given below (Figure 3).

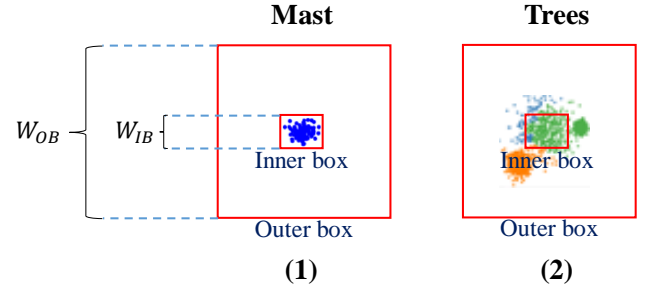


Figure 3: Ideal point distribution around masts (1) and other pole-like objects (2)

(1) Since the ground plane is already removed, the area around the mast is sparse in terms of points. Almost no point should be detected in their immediate surroundings. This is the ideal point distribution around a mast. Therefore, the ratio of *IB* point count over the *OB* point count should ideally be 1. But even after removal of the ground plane, there might be points around a mast caused by other catenary system assets. This reduces the ratio to 0.9 or below.

(2) There are other pole-like objects located within the inner and outer boxes. Hence, even after the removal of the ground plane, there should be more points around other pole-like objects caused by other tree trunks and leaves. Therefore, the ratio of inner box point count over the outer box point count should be lower than outcome 1.

The outer box width (W_{OB}) value should not exceed the span between two masts of the same pair. In line with the railway design standards (Network Rail, 2018), the authors hypothesized $W_{OB} = 9.0$ m and inner box width (W_{IB}) = 1.5 m. The authors confirmed these values using a point-based calculation method for different W_{OB} and W_{IB} values.

The 3rd step of the refinement algorithm is defining the threshold (R_D) which satisfies $0 < R_D < 1$, to filter masts from tree trunks. The authors obtained the optimum R_D by computing F1 scores for different R_D values. According to the results obtained, the optimum R_D is 0.2 for all the datasets. Due to the limited space in this paper, the authors haven't included the graphs representing calculations for R_D , W_{OB} and W_{IB} . Using R_D , the method filters masts from other pole-like objects in Dataset A. However, for Dataset B and C, this algorithm did not perform well when filtering masts from other pole-like objects (Table 2). When tree trunks, walls and rail bridges satisfy R_D this method recognises other pole-like objects as masts.

To remedy the resulting outcome, the authors used a 2nd refinement algorithm. This algorithm takes railway geometric observations into account and limits the region of search to a certain radius from the first pair of masts. Hence, the 2nd refinement algorithm starts from the left side of the track and repeats over the spans between masts on the right side of the track as explained below (Figure 4).

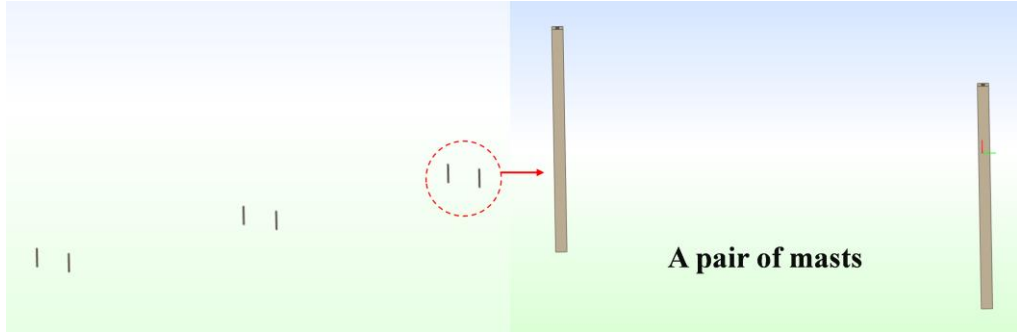


Figure 5: A close up of the resulting IFC models of masts (viewed on Solibri Model Viewer)

od uses the shape definition of an I section and the resulting parameters of the 2nd refinement algorithm to define a mast (Figure 5).

4 EXPERIMENTS AND EVALUATION

An approximately 18 km-long portion of the rail track located between 's-Hertogenbosch and Nijmegen in the Netherlands served as the input of the proposed method. The size of the file was over 100 gigabytes, hence, too large to process in terms of processor and memory capacity. The authors addressed this challenge by splitting the data file into three sub-point clouds, each roughly 6 km long; and termed as Dataset A, B, and C.

The validation consisted of two parts. The first part was to experimentally define the optimal values of the key parameters (SBB_i , R_D , R_T , E_T) used in the proposed method. The second part was to assess the proposed method using performance metrics; precision, recall and F1 score. The authors followed the entire workflow of the mast twinning process as explained in (Ariyachandra and Brilakis, 2019) to manually generate three ground truth (GT) datasets; each per one railway point cloud. The authors implemented the solution with the point cloud library (PCL) version 1.8.0 using C++ on Visual Studio 2017, in a laptop (Intel Core i7-8550U 1.8GHz CPU, 16 GB RAM, Samsung 256GB SSD).

Table 2: Performance matrices for three data sets

Sequence of steps	Dataset	Pr	R	F1
RANSAC	A	84.8%	63.2%	72.4%
	B	63.8%	51.2%	56.8%
	C	47.6%	36.7%	41.4%
	Average	66.3%	50.9%	57.6%
RANSAC with 1 st refinement	A	94.7%	75.9%	84.3%
	B	97.1%	57.6%	72.3%
	C	70.5%	55.9%	62.3%
	Average	87.4%	63.8%	73.8%
RANSAC with 2 nd refinement	A	96.5%	87.9%	92.0%
	B	97.4%	81.6%	88.8%
	C	87.6%	89.7%	88.6%
	Average	93.8%	86.6%	90.1%

Table 2 illustrates the results of the mast class segmentation. The authors used performance metrics as explained in section 3.3 to gauge the performance of the proposed method. The average segmentation accuracy for mast class was 90.1% F1 score (Table 2).

The removal of vegetation took 12.5 sec/km to deliver a narrowed aligned rail corridor of each dataset. The RANSAC line segmentation with 1st refinement algorithm needed 20 sec/km while 2nd refinement required 3.3 sec/km. Finally, the generation of IFC models took 2 sec/km. Hence, the processing time of the proposed method was on average 37.8 sec/km.

5 CONCLUSION

This paper presents a novel railway topological approach to develop a fully automated railway mast twinning process from airborne LIDAR data. Earlier in the paper, the authors explained why this was an unsolved problem by reviewing current industry applications and state-of-the-research methods that have been proposed to streamline the twinning process. The proposed method was tested on three railway point cloud datasets, lengths over 18 km. The validation outcome showed that the method is quite reliable. Given the high performance of the method on real railway point clouds containing occlusions and sparseness, the authors contend that the method is reliable, scalable, and is independent of scanning technology. The method outperforms state-of-the-art methods and manual operations given the high segmentation accuracy and low run-time performance. The contributions of this research are as follows:

The proposed method:

- (1) Can deal with complex, real railway topologies, such as varying rail track elevations and curved horizontal alignments of the rail track; meaning this method can segment masts despite the slope of the track.
- (2) Can handle challenging scenarios such as occlusions, extreme vegetation around the track, and local variable densities of points. Although some inputs are very noisy (i.e. dataset B and C) due to the extreme vegetation surrounded the track, the method still achieved quite good performance in these datasets.
- (3) Drastically reduces the computational cost by breaking down a lengthy railway point cloud into sub-bounding boxes. In this way, large-scale object detection can be significantly improved without sacrificing precision and manual cost.

However, the proposed method does not intend to be a cure-all. More railway data with different over-

head electrification structures and single and quadruple tracks should be included and investigated in future studies. In short, this proposed method indicated that it can significantly reduce the modelling cost and will accelerate the adoption of gDT for railway infrastructure mapping in existing railways. The future planned research will focus on overcoming of abovementioned limitations and addressing some of the assumptions; upgrading the algorithm to scale up to more complex railway configurations and detecting of more rail asset components.

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