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Railway reconstruction from 3D point cloud using Deep Learning and Parametric Modeling

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Abstract

Railway infrastructure is crucial for transporting goods and passengers, making its maintenance and reconstruction vital for safety and reliability. Traditional methods reliant on manual surveys are time-consuming and prone to inaccuracies. Although 3D point cloud data provides detailed representations of railway environments, its unstructured nature complicates processing and modeling. This paper presents a methodology that combines deep learning with parametric modeling to reconstruct railway environments from 3D point cloud data, focusing on key components such as rails, catenary wires and poles. The results are represented in a standardized CityJSON format, in compliance with the Transportation module of CityGML 3.0, and textured to create photo-realistic 3D railway models. The proposed approach uses the KPConv (Kernel Point Convolution) architecture for semantic segmentation to classify railway components. The model is trained on Rail3D dataset and achieved a mean Intersection-over-Union (mIoU) of 84%. Instance segmentation of catenary poles is performed using Label Connected Components (LCC) algorithm, followed by a second-level classification through template matching using Fast Global Registration (FGR) and Iterative Closest Point (ICP). Rail reconstruction combines Region Growing and H-DBSCAN algorithms for clustering, vectorization for linear geometry extraction, and extension to ensure continuity despite gaps or noise in the data. Catenary poles are reconstructed using parametric models, taking as input a scale factor and a rotation matrix calculated from the extracted height and azimuth. Wires are added accordingly to connect the reconstructed poles. The methodology was validated on Belgian railway data, producing accurate, interoperable and photo-realistic 3D models suitable for digital twin integration, infrastructure monitoring and urban simulations.

1. Introduction

Railway infrastructure plays a crucial role in modern transportation, facilitating the efficient movement of goods and passengers. It offers significant economic, environmental and logistical benefits. To ensure optimal performance, railway networks require consistent maintenance and periodic reconstruction. Traditionally, these tasks have relied usually on manual surveys and physical inspections. While effective to some degree, such approaches are labor-intensive, time-consuming and prone to human error, often limiting the precision and comprehensiveness of data collection.

The arrival of advanced sensing technologies, particularly Light Detection and Ranging (LiDAR), has revolutionized the way railway modeling and analysis are performed. LiDAR technology employs laser-based scanning to generate highly accurate spatial data, capturing details of railway infrastructure in the form of high-resolution 3D point clouds. These point clouds offer a detailed view of the railway environments, including tracks, overhead lines, catenary poles, bridges and nearby vegetation. As a result, LiDAR provides engineers and decision-makers with a powerful tool to monitor infrastructure conditions, plan upgrades and enhance safety protocols.

Despite its potential, the unstructured and complex nature of point cloud data presents significant challenges for processing and modeling, particularly in railway environments characterized by a diverse array of components and structures. Unlike traditional data formats, point clouds consist of millions—or even billions—of discrete points that lack inherent connectivity or predefined organizational structures. This makes it difficult to extract meaningful information, identify features and integrate the data into existing railway management systems. Moreover, variations in environmental conditions, such as occlusions caused by vegetation or weather, can further complicate the interpretation of LiDAR data. Addressing these challenges requires the development of robust algorithms and workflows capable of efficiently processing and analysing large-scale point cloud datasets while maintaining accuracy and reliability.

As the demand for smarter and more resilient railway systems grows, leveraging LiDAR technology to create photo-realistic 3D railway environments presents an opportunity to enhance infrastructure management. By transforming how railways are modeled, monitored and maintained, LiDAR can help meet the challenges of modern transportation systems, providing accurate 3D point clouds to generate railway digital twins.

This study proposes an integrated methodology combining deep learning and parametric modeling to address the challenges of railway reconstruction using 3D LiDAR point clouds. Semantic segmentation with KPConv classifies key components, while advanced instance segmentation techniques, such as Label Connected Components and H-DBSCAN, refine the identification of individual objects. The final step involves parametric reconstruction of the segmented components and exporting the models in the CityJSON format, ensuring interoperability with urban digital twins.

The structure of this paper is as follows: Section 2 reviews related work, Section 3 describes the methodology, Section 4 presents the experiments and results, Section 5 concludes the paper and outlines future work.

2. Related Work

Point cloud data has been increasingly used for railway infrastructure analysis, encompassing various tasks such as segmentation, modeling and digital twin development. Soilán et al. (2021) introduced a methodology for delineating railway lanes and generating alignment models, demonstrating the potential of automated workflows. However, object-level modeling in complex railway environments, such as junctions or stations, remains a challenge. Preprocessing steps, including noise filtering, segmentation, and normalization, are fundamental for effective analysis. Díaz Benito (2012) emphasized the importance of preprocessing, showing that sectional division and outlier removal are critical for reconstructing accurate rail geometries from point clouds. Similarly, Neubert et al. (2008) used RANSAC to detect rail tracks, but their work focused on detection without addressing detailed reconstruction.

Advances in deep learning have revolutionized semantic segmentation of 3D point clouds. Techniques such as Kernel Point Convolution (KPConv), introduced by Thomas et al. (2019), have shown remarkable success in classifying complex railway components like rails, poles, and catenary wires. Despite these advancements, segmentation methods are often limited to isolating individual components and lack integration into structured parametric models. Riveiro et al. (2018) demonstrated the feasibility of parametric modeling for linear objects, yet significant challenges persist when applying these methods to more intricate railway setups.

Digital twins represent the next frontier in railway modeling, offering dynamic and interactive systems for monitoring and managing infrastructure. Dekker et al. (2023) highlighted the increasing interest in digital twin technologies for railway applications but noted the scarcity of standardized datasets, which limits reproducibility and comparability in research. Despite these challenges, studies like that of Díaz Benito (2012) have demonstrated the feasibility of achieving sub-centimeter accuracy in rail reconstruction, paving the way for robust digital twin applications.

3. Methodology

Our methodology combines deep learning with parametric modeling to reconstruct railway environments from 3D point cloud data. The goal is to model key railway components—rails, catenary wires and poles—and represent them in a standardized CityJSON format.

The process involves several key steps: First, semantic segmentation is applied to the railway point cloud using a trained KPConv model (Thomas et al., 2019) on Rail3D dataset (Kharroubi et al., 2024) to classify points into categories such as ground, rails, poles, and wires. Next, instance segmentation of catenary poles is performed using the Label Connected Components (LCC) algorithm in CloudCompare (CloudCompare, 2024), which isolates individual poles. The segmented poles are further classified through template matching, and global registration is achieved with the Fast Global Registration (FGR) and Iterative Closest Point (ICP) algorithms. Rail points are clustered using the Region Growing algorithm (Rusu & Cousins, 2011) and H-DBSCAN (McInnes et al., 2017) to ensure complete segmentation. The rail segments are vectorized and connected, with buffering and centerline extraction ensuring accurate reconstruction, while missing sections are filled as necessary. Finally, a parametric reconstruction method is used to model the extracted components, including rails, catenary poles, and wires, which are then exported into CityJSON format for integration into a digital model.

3.1 Data description

The study focuses on creating accurate and photo-realistic 3D railway models using LiDAR data. For this purpose, we are using Rail3D dataset (Kharroubi et al., 2024) to train our semantic segmentation models. The Rail3D dataset is the first multi-context point cloud dataset designed for railway scene understanding. It includes three separate datasets from Hungary, France and Belgium, that were collected using different LiDAR sensors, ensuring a range of point densities and varying acquisition conditions. This diversity is important for building models that are accurate and adaptable across different railway environments.

The Belgian railway point clouds, provided by INFRABEL, were collected using LiDAR technology as part of their ongoing efforts to monitor the railway network. The Z+F 9012 LiDAR sensor was mounted on the front of a train (EM202 vehicle), capturing point cloud data while the train travels along the tracks. Point clouds are collected for every railway line in Belgium at least twice a year, which is valuable for 3D change detection studies planned for future research. Along with LiDAR, four cameras (two at the front and two at the back) record color images, but for this study, only the LiDAR point clouds with intensity, and no color, were used. The data is stored in LAS format, with coordinates in Belgian Lambert 72 (EPSG:31370). Three areas in Belgium were chosen for the dataset: Brussels, midway between Brussels and Ghent and south of Ghent.

The dataset has a length of 2 kilometers and consists of 39 million points distributed over 9 classes as illustrated in Figure 1: ground, vegetation, rail, poles, wires, signalling, fence, installation and building.

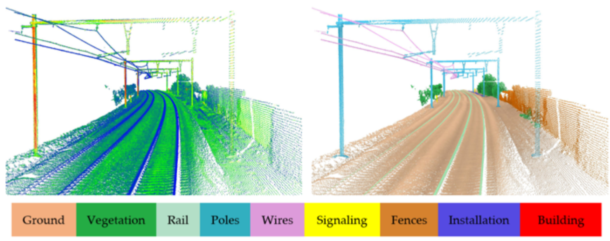

Figure 1. Point cloud from the INFRABEL dataset, displayed in intensity (left) and corresponding labels (right). (Kharroubi et al., 2024)

3.2 Semantic segmentation

The Rail3D dataset is used to train 3D semantic segmentation models. Kharroubi et al. (2024) evaluated the performance of different state-of-the-art architectures including KPConv (Kernel Point Convolution). KPConv, introduced by Thomas et al. (2019), is a convolutional neural network architecture specifically designed for point cloud processing. It operates by defining convolution kernels directly in the 3D space, making it highly effective for learning geometric features in unstructured data. This enables KPConv to achieve superior performance in

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tasks such as segmentation and classification on irregular 3D datasets like Rail3D.

Therefore, a KPConv model for semantic segmentation is trained on the Belgian point cloud of Rail3D dataset and used to classify our raw LiDAR point cloud data into the above identified classes as shown in Figure 2.

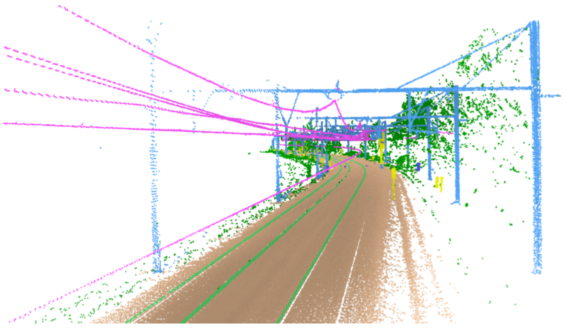

Figure 2. The results of semantic segmentation of the 3D point cloud using KPConv.

3.3 Instance clustering

To perform instance clustering of catenary poles, we use an unsupervised machine learning algorithm called Label Connected Components (LCC), available within the CloudCompare software (CloudCompare, 2024). LCC works by identifying connected points within the dataset that belong to the same object. By doing this, it effectively isolates individual poles as separate instances. This approach allows us to segment the poles from the surrounding data without requiring prior labeling or manual intervention. The result is a clear separation of each pole as its own distinct object as illustrated in Figure 3.

Points of separated rails were clustered using Region Growing algorithm (Rusu & Cousins, 2011). A second clustering level was added using H-DBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise) to ensure correct and complete segmentation of rails (McInnes et al., 2017).

Figure 3. Label Connected Components results on catenary poles.

3.4 Registration

After instance clustering, a second classification via template matching is applied by matching the segmented pole point cloud with a pre-defined catenary pole template database (Figure 4). Global registration is conducted using the Fast Global Registration (FGR) algorithm for coarse alignment, followed by refinement with the Iterative Closest Point (ICP) algorithm.

For each pole, we calculate the Root Mean Squared Error (RMSE) of the registration to decide the best fit. As shown in Figure 5, the corresponding pole template presents the lowest error, thus, the best match for the extracted instance.

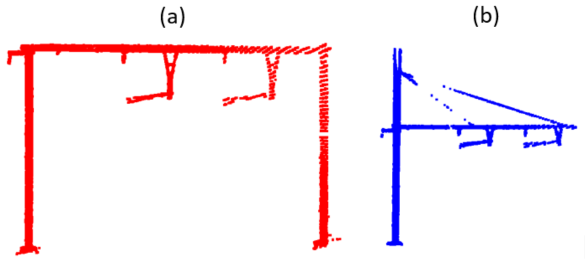

Figure 4. Pre-defined catenary pole template database: (a) Double pole (b) Single pole.

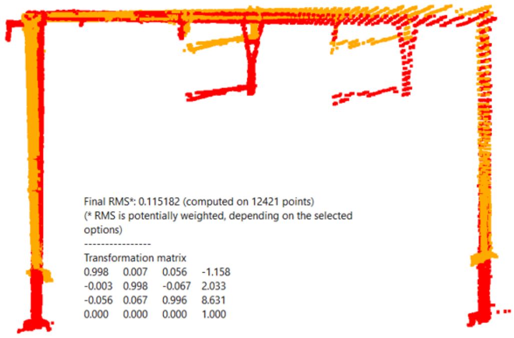

Figure 5. FGR/ICP registration with double pole template.

3.5 3D modeling

As shown in Figure 6, for rail reconstruction, the process begins with a vectorization step, where the point cloud of each rail segment is converted into linear geometry. This step is followed by an extension operation to connect the linear segments into continuous lines. To ensure precise and complete connections between these lines, a buffering technique is applied. The rails are then extracted as the centerlines of the resulting polygons. Any missing sections are identified by counting the number of detected rails and recreating the gaps, accordingly, ensuring a complete rail structure.

Once the rails are vectorized, a parametric reconstruction method is used to model the extracted lines The tracks are generated from the vectorized rails using buffering and extrusion operations to produce the rail geometry. Sleepers are added to the model with a specified separating distance to replicate the physical layout of the tracks.

Catenary poles are extracted as points, each with a height parameter derived from the original point cloud data. This height is used as a scale factor in the parametric design of the poles. The orientation of each pole is determined by calculating the azimuth of a line perpendicular to the rails that intersects the pole's position. This calculated azimuth is used to attribute a rotation matrix to the parametric 3D models, ensuring their correct alignment with the track geometry.

For single-pole configurations, poles are placed on one side of the track, while for double-pole setups, they are placed on both sides. A cantilever structure is added to each pole to act as a support for the catenary wires. These wires are reconstructed based on the geometry of the poles, incorporating their height, cantilever positions, and the number of rails covered by the pole.

Figure 6. Rails before and after linearization: Before (Top) and After (Bottom)

Between each pair of catenary poles, two types of wires are reconstructed. Linear wires represent straight connections, while curved wires are modeled as arcs to account for the natural sag of catenary systems. This reconstruction process ensures that the geometry of the wires aligns with the parametric design of the poles and the underlying rail tracks. The combined model of rails, sleepers, poles, and wires forms a comprehensive representation of the rail system.

3.6 Models' integration

The final step involves exporting the reconstructed models into the CityJSON (Ledoux et al., 2019) format, a JSON encoding for CityGML 3.0 (Kutzner et al., 2020). Both formats are Open Geospatial Consortium (OGC) standards, and they define a conceptual model and exchange format for the representation, storage and exchange of virtual 3D city models.

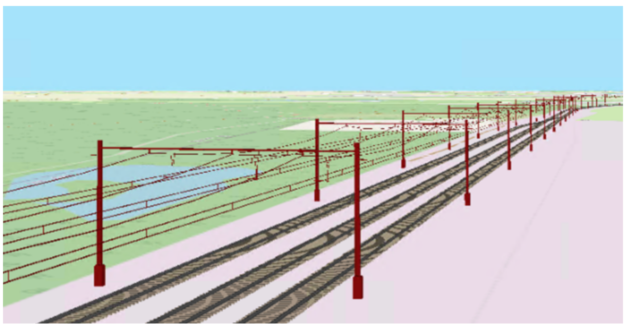

Figure 7. Results of the CityJSON railway model.

Our approach consists of modeling most of the railway objects are reconstructed following the "Transportation" module. The tracks are modeled as objects of the "Railway" class, with rails as "TrafficArea" and sleepers as "AuxiliaryTrafficArea". Meanwhile, the catenary wires and poles are considered instances of the "CityFurniture" class and modeled accordingly.

4. Experiments and Results

Our methodology was tested on railway point cloud data between Andenne and Huy, Belgium, and showed promising results. The fine-tuned KPConv model achieved a mean Intersection-over-Union (mIoU) of 84% in semantic segmentation, demonstrating its performance in classifying railway LiDAR data even when RGB values are missing. Table 1 shows the overall accuracy (OA), mIoU and IoU of the relevant classes.

OA	mIoU	Ground	Rail	Poles	Wires
0.99	0.84	0.99	0.95	0.97	0.99

Table 1. Quantitative experimental results of KPConv inference.

The instance segmentation of catenary poles using LCC was successful, and the poles classification based on the pre-defined template database and FGR/ICP registration produced minimal matching errors. The RMSE of the registration varies between 10 to 30 centimeters depending on the data completeness and the existence of occlusions or not. The rail vectorization step resulted in a continuous and accurate rail model which confirms that our approach connects line segments representing the rail even in cases where parts are missing or misaligned due to noise or gaps in the point cloud data.

Key components of the railway environment were successfully reconstructed in 3D, leveraging semantic and instance segmentation to guide parametric modeling. Figure 8 shows the results of 3D reconstruction of a continuous track model, including rails and sleepers. As shown in Figure 9, catenary poles were modeled using extracted height and orientation parameters, ensuring alignment with the track geometry, while cantilever structures were added to support the catenary system. Finally, wires were reconstructed as linear or curved elements to reflect their natural sag and connectivity between poles. The results are illustrated in Figure 10. Together, these elements form a comprehensive 3D representation of the railway infrastructure.

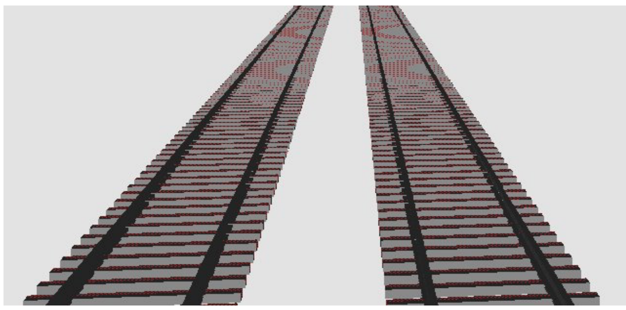

Figure 8. 3D models of tracks showing rails and sleepers.

Additionally, using 3D city model standards, CityGML3.0 and its CityJSON encodings, ensures that the models are compatible with urban modeling frameworks, which facilitates their integration into urban digital twins. Finally, to enhance realism, textures were applied to the 3D models, resulting in a photo-realistic visualization of the railway environment, as shown in Figure 11.

Figure 9. 3D railway model with reconstructed poles.

Figure 10. 3D railway model with all the reconstructed objects.

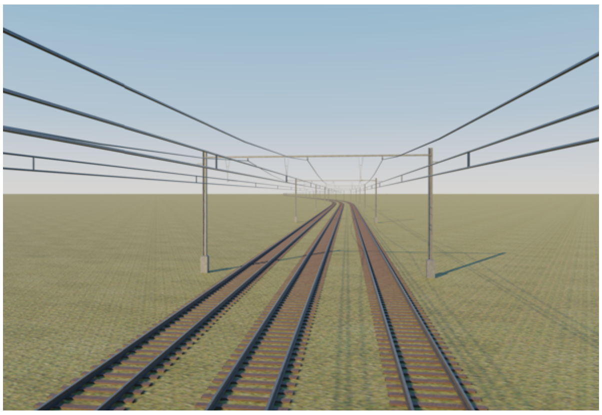

Figure 11. 3D photo-realistic model of railways.

5. Conclusions

This study demonstrates an integrated methodology for reconstructing railway environments from 3D point cloud data using a combination of deep learning and parametric modeling techniques. Key railway components, including rails, catenary poles, and wires, were successfully segmented, classified, and reconstructed in 3D with high accuracy. Semantic segmentation using KPConv achieved a robust performance, while instance clustering and registration methods ensured precise classification and alignment of catenary poles. The vectorization and parametric modeling techniques effectively handled gaps and noise in the point cloud, resulting in a continuous and accurate rail representation.

The final models were exported in the CityJSON format, in alignment with CityGML 3.0 "Transportation" module. This ensures compatibility with urban modeling frameworks and supports integration into digital twins. By incorporating CityJSON, the methodology benefits from simplified data handling, interoperability and broader adoption in web-based applications.

The results illustrate the feasibility of creating detailed and interoperable railway models, which can be used in future applications, such as infrastructure monitoring, change detection, and urban simulations. This approach establishes a foundation for further research into scalable and automated modeling techniques, including more assets like signals and other infrastructures.

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References

CloudCompare, 2024: CloudCompare (version 2.14) [GPL software].

Dekker, B., Ton, B., Meijer, J., et al., 2023: Point cloud analysis of railway infrastructure: A systematic literature review. *IEEE*.

Díaz Benito, D., 2012: Automatic 3D modeling of train rails in a LiDAR point cloud. Master's thesis, University of Twente.

Kharroubi, A., Ballouch, Z., Hajji, R., Yarroudh, A., Billen, R., 2024: Multi-context point cloud dataset and machine learning for railway semantic segmentation. *Infrastructures*, 9(4), 71. doi.org/10.3390/infrastructures9040071.

Kutzner, T., Chaturvedi, K., Kolbe, T.H., 2020: CityGML 3.0: New functions open up new applications. *PFG – Journal of Photogrammetry, Remote Sensing and Geoinformation Science*, 88(1), 43–61. doi.org/10.1007/s41064-020-00095-z.

Ledoux, H., Arroyo Ohori, K., Kumar, K., Dukai, B., Labetski, A., Vitalis, S., 2019: CityJSON: A compact and easy-to-use encoding of the CityGML data model. *Open Geospatial Data, Software and Standards*, 4(1), 4. doi.org/10.1186/s40965-019-0064-0.

McInnes, L., Healy, J., Astels, S., 2017: hdbscan: Hierarchical density based clustering. *The Journal of Open Source Software*, 2(11). doi.org/10.21105/joss.00205.

Neubert, M., Beger, B., Gedrange, C., Hecht, R., 2008: Detecting railway tracks in LiDAR data using RANSAC and profile classification. *International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences*.

Riveiro, B., Conde, B., Caamaño, J., 2018: Parametric modeling of railway infrastructure using geometric primitives and 3D laser scanning. *Transportation Research Record*, 2672(3), 109–118.

Rusu, R.B., Cousins, S., 2011: 3D is here: Point Cloud Library (PCL). In *Proceedings - IEEE International Conference on Robotics and Automation*. doi.org/10.1109/ICRA.2011.5980567.

Soilán, M., Nóvoa, A., Sánchez-Rodríguez, A., Justo, A., Riveiro, B., 2021: Fully automated methodology for the delineation of railway lanes and the generation of IFC alignment models using 3D point cloud data. *Automation in Construction*, 126, 103684. doi.org/10.1016/j.autcon.2021.103684.

Thomas, H., Qi, C.R., Deschaud, J.E., Marcotegui, B., Goulette, F., Guibas, L., 2019: KPConv: Flexible and deformable convolution for point clouds. In *Proceedings of the IEEE International Conference on Computer Vision*, 6410–6419. doi.org/10.1109/ICCV.2019.0065.