Business Paper

Automated Inventory of Railway Infrastructure Using Artificial Intelligence

Julia Richter[1], Mario Neumann[1], Jannes Mennenga[1], Mark Spitzner[1], Ulrike Aesche[1], Peter Hintze[1], Philipp Britten[1], Christian Foltin[1], Eric Krumbiegel[1], Stefan Schulz[1], Luka Daniel Sondersorg[1]

[1] SIGNON Deutschland GmbH, Ein Unternehmen der Deutschen Bahn AG

1 Introduction

The efficient collection and analysis of railway infrastructure data is a prerequisite for establishing digital planning foundations, the automation of railway operations, and the maintenance of infrastructure. Key to this endeavor is the automated acquisition of accurate data. Using the detected positions and geometries of recorded objects, existing databases can be continuously kept up to date. The data obtained can be used, among other things, to support automating workflows from surveying to the approval of construction into operation and digital documentation. For example, in the planning of reconstruction or new construction projects, the initial state of the infrastructure must be recorded to ensure a correct digital planning basis. Additionally, during construction projects and their inspections, automated checks can already be conducted before formal approval to ensure that newly installed infrastructure elements have been correctly installed according to the plans.

Usually, infrastructure data is collected through on-site inspections, manual measurements, or manual data analysis of recorded infrastructure data from measurements campaigns. These methods may entail track closures and enormous time investments required by specialists to walk the tracks or review all data materials. The required effort grows with the size of the rail network to be recorded potentially exceeding the available resources.

By conducting measurements with cameras and LIDAR scanners to produce geo-referenced point clouds as a three-dimensional representation of the infrastructure, on-site track inspections can be avoided or at least significantly reduced. However, finding and measuring relevant areas and objects often still requires a manual, laborious, and error-prone review of the recordings. When comparing installed objects with the inventory data, the positioning of objects in the point clouds is still carried out manually by specialists. This manual object identification step is very time-consuming, especially identifying smaller objects such as axle counters within a reasonable amount of time and effort (see Fig. 1) is virtually impossible.

[1] Corresponding author: Dr. Julia Richter, Julia.Jl.Richter@deutschebahn.com



Fig. 1 Deep neural networks accelerate the detection of objects in 3D point clouds. Example of a point cloud: catenary pole (dark blue), pre-signal sign (light blue), axle counter (red).

Against this background, SIGNON Deutschland GmbH (Signon) is working on innovative solutions in the innovation project “Signon InfraAI - Technical Equipment” (InfraAI – TE) for the automated, AI-supported acquisition of railway infrastructure in point clouds, which are collected directly from measurements using multi-sensor platforms. The use of such AI enables comprehensive and reliable recording of infrastructure data and is an important building block for efficient digital data management of railway infrastructure. The following chapter presents the software solution developed in this project.

2 Process Chain

The developed AI analysis is embedded in a process chain ranging from measurement campaigns, through post-processing of raw data, up to application (see Fig. 2).

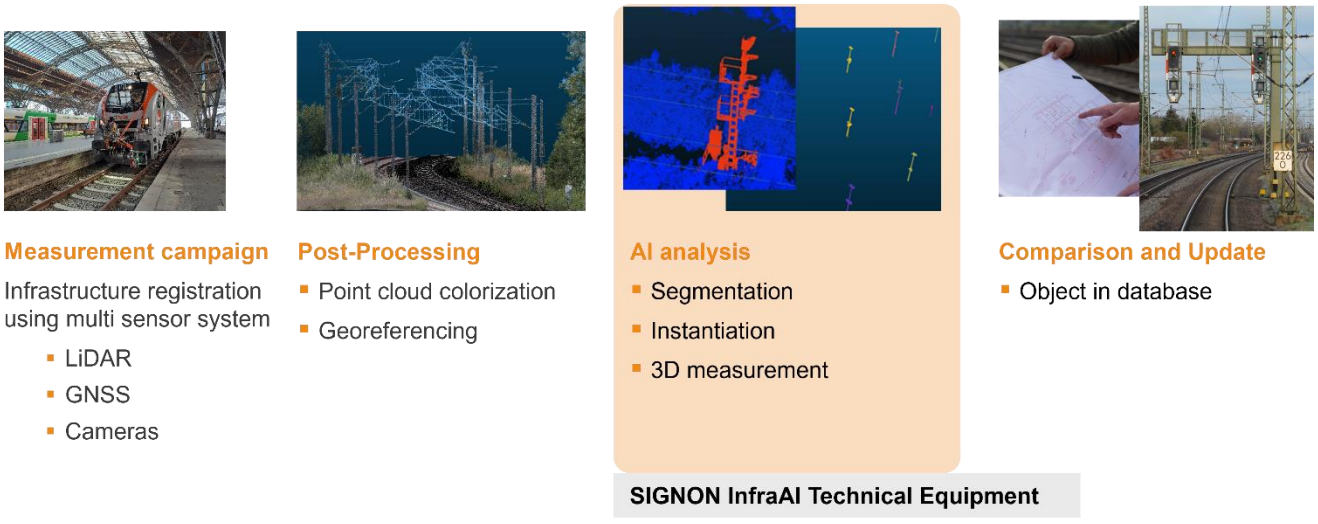


Fig. 2 Placing the innovation project in the process chain

2.1 Data Collection

Point cloud data is collected using measurement trains, which have sufficiently high travel speeds and can be integrated into regular railway operations. Among others, GNSS data, 360° panoramic images, and point clouds are recorded and referenced to the DB_REF2016 reference system. For the innovation project, data from measurements of the Gäubahn [1] were used.

2.2 Post-Processing of Raw Data

In a post-processing step, the monochrome LiDAR raw data is colorized using the recorded panoramic images, and the trajectory of the multi-sensor system is determined using GNSS correction services. This data forms the basis for the subsequent AI analysis.

2.3 AI Analysis

Following measurement and post-processing, the machine learning component of the system is applied to automatically detect objects of interest. This is done using a deep neural network for semantic segmentation, hereafter called the segmentation network, which directly processes point clouds and assigns points to predefined object classes (segmentation). The points belonging to an object class are grouped into object instances (instantiation), so individual objects in the point cloud can be identified and measured. These detected individual objects can then be compared to the infrastructure information stored in databases.

In the InfraAI – TE innovation project, the feasibility of the automatic detection and measurement of a selection of object classes from the field of train control and safety technology (LST) as well as catenary poles in point clouds was demonstrated. The segmentation network was trained with the following seven object classes: axle counters (AC), catenary poles (CAT), track magnets (MAG), balises (BAL), pre-signal signs (Ne3), blocking signals (SP), and speed limit signs (Lf7).

The trained object classes were selected to expose the development to challenging conditions and test the performance by setting high requirements with respect to variations in object size and visibility. The object types vary greatly in their frequency, size, and number of points, and some are hardly distinguishable from their surroundings by color. These aspects complicate detection and, in manual evaluation, lead to high effort, so even this early stage of automation offers suitable advantages.

2.3.1 Segmentation

The segmentation network was trained using a dataset prepared by specialists (see Fig. 3). For this, point clouds were annotated by marking all points belonging to each object class in the recorded point clouds. These annotated point clouds form the input data for training the segmentation network, which thus learns the identifying features of the objects. The system can then independently find objects of the trained categories in unseen point clouds not used in training. Points not assigned to any class are considered background—including classes not yet known to the model.

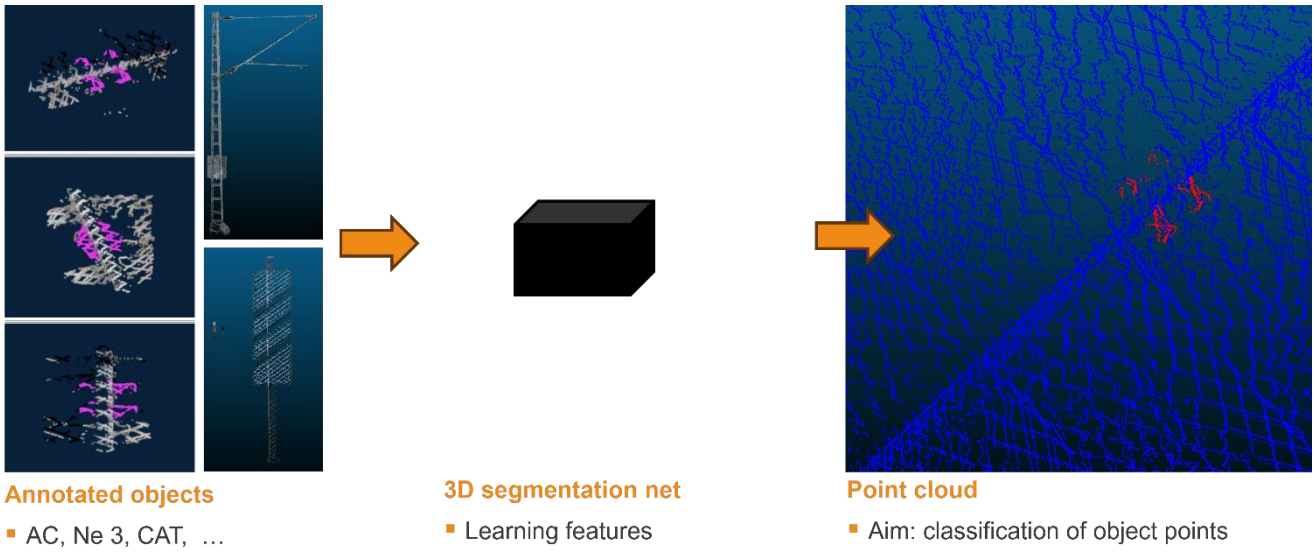


Fig. 3 Training of a segmentation network using annotated objects (labels)

A transformer-based architecture for point cloud segmentation was used for the segmentation network. This type of neural network specializes in the semantic (class-wise) segmentation of 3D point clouds.

To enable higher resolution and resource-efficient training and inference, irrelevant areas of the point cloud located too far from the track axis were cropped (see Fig. 4) before being fed into the network.

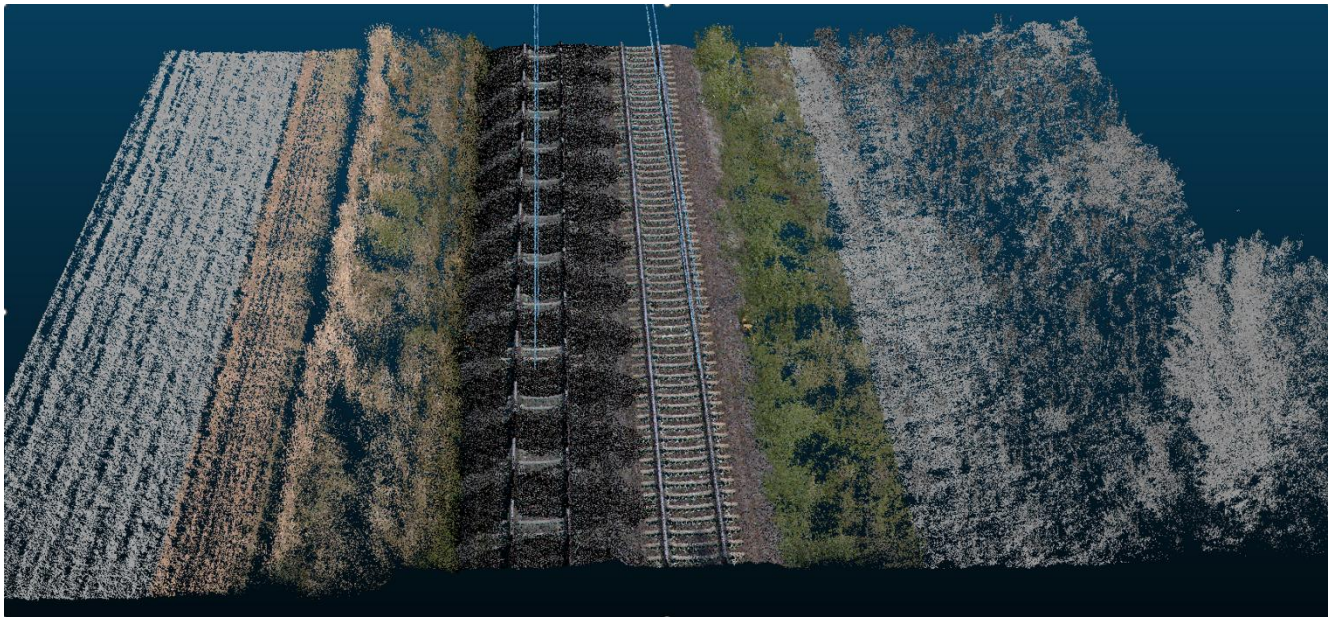


Fig. 4 Cropping irrelevant areas (marked in grey here) enables higher resolution and saves resources.

2.3.2 Instantiation

After segmentation, points belonging to an object class are grouped into existing instances. For this, the clustering algorithm DBSCAN (Ester et al. 1996, p. 226). is used, which, for example, extracts the points belonging to a particular catenary pole from all catenary pole points and assigns them an instance identification number. As a result, each point of the input point clouds receives an object or background class and an instance ID.

2.3.3 3D Measurement

After instantiation, individual objects can then be measured in three dimensions. In digital inventory data collections, objects are usually represented as 3D coordinates with corresponding attributes. Depending on the project, various coordinates can be calculated based on the required measurement point definitions, for example the object's center at the plane formed by the tops of the rails. The calculated object points are output in GeoPackage format [3], which can be imported using tools such as QGIS [4] for further processing and comparison with inventory databases.

2.4 Comparison with Inventory Data/Plans

Both the generated object points and the point clouds assigned with object classes and instance IDs can be further processed using GIS tools and used for comparison with inventory data (see Fig. 5). With the help of AI, objects are automatically highlighted in color, and their identified positions are displayed, which significantly speeds up comparison. Currently, the comparison of the highlighted and imported object positions is still carried out manually. In the future, this process can be automized by software as well to further accelerate the process.

Using the automated detection and measurement of objects in 3D point clouds, specialists can thus verify, correct and update inventory data faster than using previous manual methods.

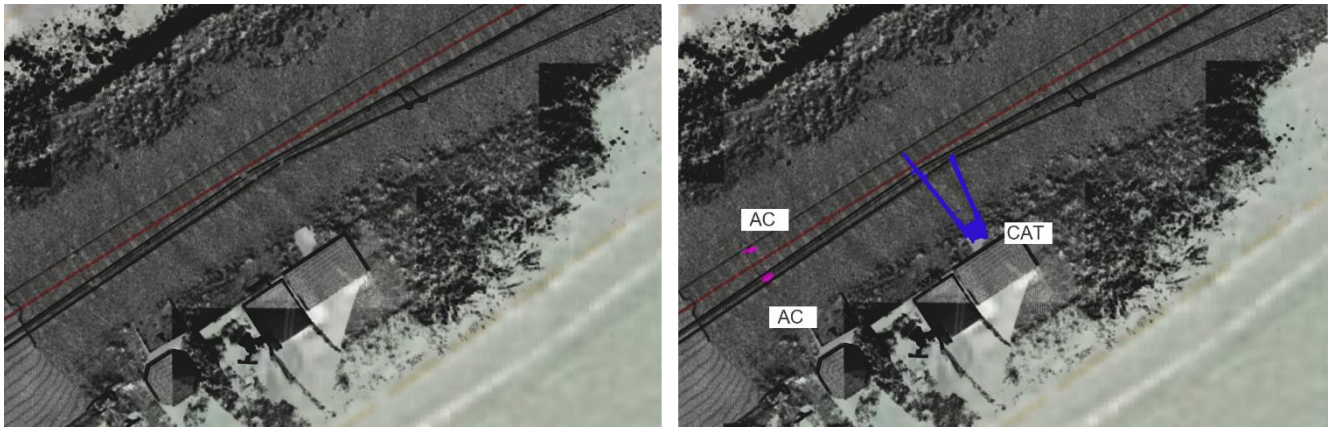


Fig. 5 Left: Error-prone, time-consuming, and manual object detection in QGIS within a point cloud without AI support. Right: Efficient AI-based object detection through color highlighting and import of detected object points.

3 Results

Tests conducted within the project have demonstrated that the software developed can automatically detect and measure the selected infrastructure objects within previously unseen point clouds. For correctly detected object instances, the achieved positional accuracy has a median Euclidean distance of less than 2.5 cm between the center point of the segmented object points and the center point of the labeled reference points (see Tab. 1).

Tab. 2 Positioning accuracies for correctly detected instances

Object	Median Euclidean distance between label and prediction center points in cm
AC	1.64
Ne3	0.28
CAT	2.16
MAG	1.70
BAL	1.12
SP-dwarf	0.93
Lf7	0.50

Fig. 6 shows a selection of point clouds in which objects were correctly detected. Nevertheless, occasional misclassifications occur, such as axle counters being erroneously detected as part of the rail, or other signs not yet known to the deep neural network being classified as pre-signal or speed limit signs.

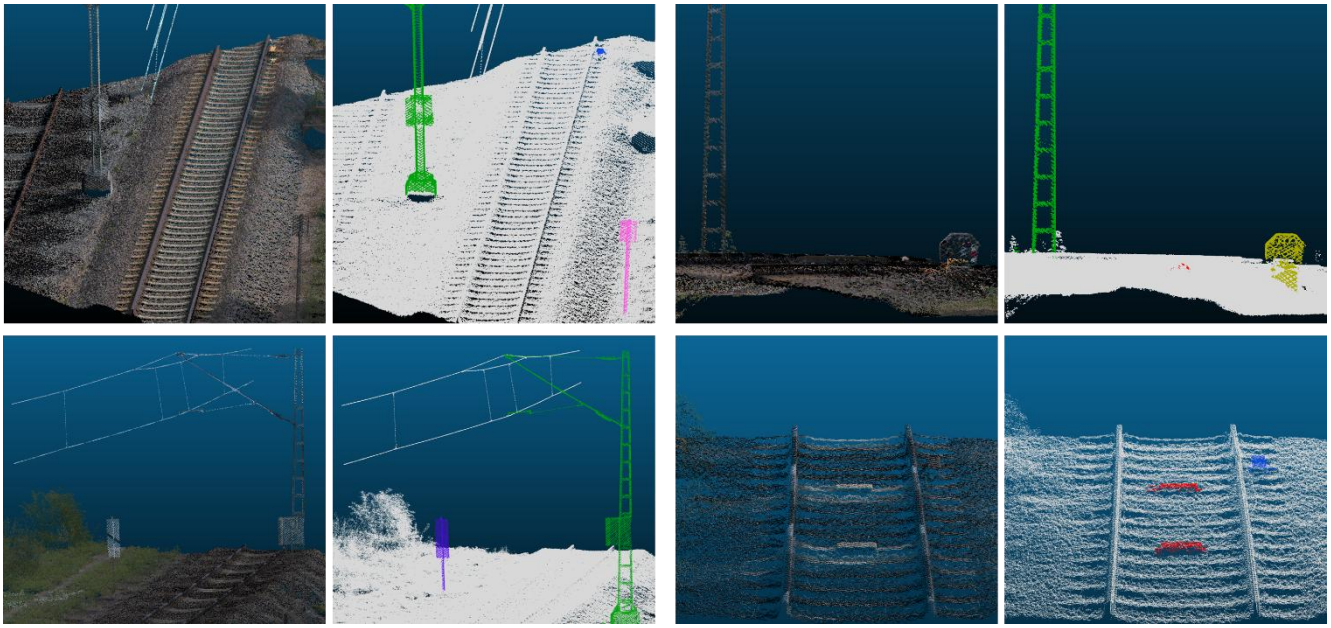


Fig. 6 Exemplary segmentation results. Top left: CAT (green), MAG (blue), Lf7 (pink). Top right: CAT (green), SP (yellow), AC (red). Bottom left: Ne3 (purple), CAT (green). Bottom right: BAL (red), MAG (blue).

4 Conclusions and Future Work

The innovation project has demonstrated the feasibility of automated detection using segmentation networks in point clouds for a selection of LST objects and catenary poles. With the developed software, objects can be automatically detected in point clouds to compare their positions and geometry with digital inventory plans. For very frequently occurring objects, and for objects that are hard to identify

in point clouds, acquisition and reconciliation can thus be accelerated. But also, for rare objects the advantage of automated methods is substantial, since their manual detection typically demands considerable effort and time to scan through extensive point cloud data. As a result, the costs and time required for evaluating such survey data can be significantly reduced in the future.

Ongoing and planned developments focus on the application to real-world projects, to collect experience in production settings, to obtain more user feedback, and to adapt the solution to specific requirements of different stakeholders. Additionally, new object classes as well as finer-grained measurements will be added depending on the application needs for data fidelity. For example, individual parts of the catenary system (see Fig. 7) could be added to integrate with SIGNON's OLAcad software tool [5]. Further efforts will target enhanced detection accuracy, improved computational efficiency, and the integration of plausibility checks. Looking ahead, combining train-borne measurements with other data sources such as video or aerial imagery could further enhance the application scope and quality.

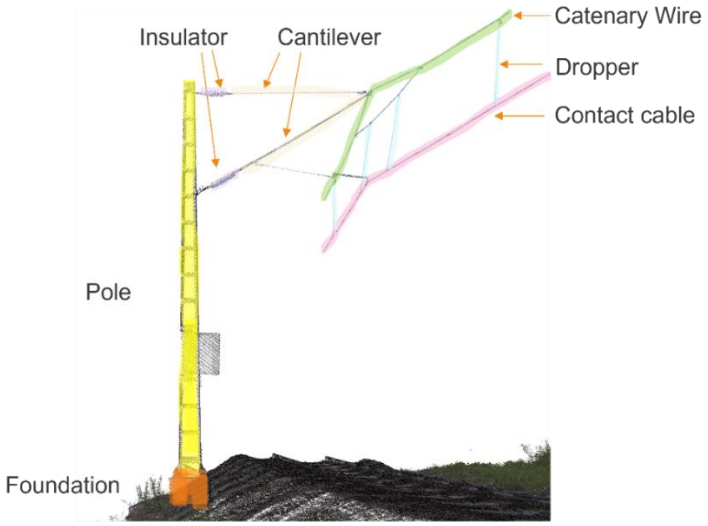


Fig. 7 Finer-grained measurements, for example of individual parts of the catenary system.

The automatic detection of railway infrastructure assets enables rapid verification and correction of existing data, resulting in substantial reductions in both cost and time for infrastructure documentation and processes involved in construction projects. The productive deployment of our system can support more efficient and reliable digital management of railway infrastructure in the future.

5 References

[1] https://www.gaeubahn.de/ (Accessed: 20 March 2026)

[2] Ester, Martin; Kriegel, Hans-Peter; Sander, Jörg; Xu, Xiaowei: A density-based algorithm for discovering clusters in large spatial databases with noise. In *kdd* (1996, August), Vol. 96, No. 34, pp. 226-231

[3] https://qgis.org/ (Accessed: 20 March 2026)

[4] https://qgis.org/ (Accessed: 20 March 2026)

[5] SIGNON OLAcad - Planning of overhead contact line systems - Olacad (Accessed: 20 March 2026)