BIM Integration for Automated Identification of Relevant Geo-Context Information via Point Cloud Segmentation

Judith Krischler, Mohamed Said Helmy Alabassy, Christian Koch
Bauhaus University Weimar, Germany
judith.krischler@uni-weimar.de

Abstract. This research presents an economical approach for Railway projects in their early stages of planning that utilizes freely available geodata to generate further geo-context information that enriches the semantical and geometrical aspects of Building Information Modelling (BIM). Based on publicly available data from the Official Property Cadastre and Topographic Cartographic Information Systems, orthophotos, LiDAR scans, and land use properties a dataset is generated and semi-automatically annotated. Two Deep Neural Network (DNN) models (i.e., PointNet++ and 2DPASS) have been trained and tested to segment point cloud data (PCD) from LiDAR scans. The best performing model is adopted for deployment in the conducted case study as a proof of concept for the suggested methodology. From the segmented PCD, meshes are being created and eventually converted to the open format Industry Foundation Classes (IFC).

1. Introduction

Digitising the existing rail network is a costly and time-consuming undertaking, especially in Germany, where there are more than 33,000 kilometres of railway (Deutsche Bahn AG, 2021). Particularly, in the case of early project states of large construction projects, the planning basis in the form of status-quo data (i.e., plans, drawings, surveying data) is often incomplete, not digitized or not available at all, let alone ready for an integrated way of working based on building information modelling (BIM). The process from project initiation to completion can often take decades and the acquisition of surveying data of the location is urgently needed to avoid biased decision-making and incorrect planning. Especially at a very early point in time of the project, there is often no or little budget, but a high demand for decisions (e.g., on demand, possible projects variants, extent, etc.).

A patchy data basis can be improved using commercial aerial LiDAR scanning services. However, surveying services are often very expensive and therefore not always available and/or are regarded as obstacles. Hence, to follow a cost-effective approach, such as using free of charge geographic and location information from online web mapping platforms, and Geographic Information Systems (GIS), would be beneficial. The open geodata, which are published by official surveying authorities and are available for free, could be an economical solution for processing and creating status-quo building information models by using them for the creation of as-is-models.

The techniques of intelligent object recognition in Point Cloud Data (PCD) have already been established in systems for self-driving navigation and aerial scans' segmentation, which could be repurposed for the segmentation of synthetic point clouds generated from available geodata. This would help identify classes of interest in areas where labels are not available or difficult to gather and help derive further insights and semantic information by identifying interdependencies and relations between classes and requirements set by public authorities and project planners. The differing types of data models and formats used to process such information raise the need of using data formats that are widely and freely available, information-lossless convertible and compatible with the software resources of the stakeholder. This phase always requires extensive data exchange between various stakeholders, which emphasizes the importance of using big open BIM to facilitate interoperability and reduce the incompatibility of different data formats individually used by the parties involved.

The reconstruction of the status-quo as sufficiently accurate BIM-ready as-is railway models using freely available PCD (Scan2BIM) could improve decision-making in early planning phases immensely. A hybrid approach that incorporates not only PCD but also geospatial data could help to overcome many obstacles regarding an insufficient data basis.

1.1. Point Cloud Segmentation

Over the past decade, 3D capturing devices, such as LiDAR scanners, Microsoft Kinect, Google Project Tango, and Apple's iPhone LiDAR integration have been regularly improved in terms of performance, output quality and price affordability. Thus, making point cloud acquisition more widespread and leading to increased need for fast and reliable ways to classify each point in the point cloud automatically for a wide range of applications. The earliest works for semantic segmentation, like feature extraction, attribute clustering, region growing, and model fitting relied heavily on predefined specific semantic features and assumptions of spatial relations and geometric constraints in the point clouds that were too rigid and constrictive for generalised classification and segmentation tasks (Zhang *et al.*, 2021). Hence, the early adoption of semantic segmentation via Machine Learning methods began in mid-2000s with (Lalonde *et al.*, 2005) leading the way to further significant improvements with the adoption of classification methods like Random Forests, Markov Networks, Bayesian Discriminant rule and Support Vector Machine (SVM) (Chehata *et al.*, 2009).

The focus has shifted a decade later towards deep learning methods for their superior outcomes, with the publication of the Multi-view Convolutional Neural Network (MVCNN) (Su *et al.*, 2015) and VoxNet (Maturana and Scherer 2015). The former utilised max-pooling of multiple views' features, which kept only the maximum valued elements of each view per se, yet caused loss of information for smaller features. Huang and You (2016) used the latter VoxNet architecture to label large scale LiDAR PCD for urban scenes including 7 main categories like buildings, trees, poles, cars, plane, wires and a miscellaneous class.

Therefore, the published DL networks fall mainly into four categories, i.e., projection- and discretisation-based for the earlier works, point-based methods more recently, and hybrid methods that fit no single label precisely. These early approaches rose up to address the need of fitting nonstructured, unordered and irregular PCD inputs into encoders, where the projection-based architectures, like SnapNet (Boulch *et al.*, 2018; Yang *et al.*, 2021), addressed it by using an image segmentation backbone on multiple image views of a point cloud to generate depth maps, then back-projecting the predictions into 3D space. Alternatively, 3D-CNN relied on bird's eye view projections to learn to fill occlusions (Yang *et al.*, 2021). The latter discretisation method (Maturana & Scherer, 2015; Yan *et al.*, 2018), relied generally on combining features between regions or points for estimating closeness or similarity between points or voxels and merging them when a threshold for surface property and/or spatial criteria are met, which may cause problems related to information loss and higher computational complexity.

The point-based methods rely on Pointwise Multi-Layer Perceptron, like the PointNet++ architecture (Qi *et al.*, 2017) or its modified versions, as well as the Kernel Point Convolution method (KPConv) (Thomas *et al.*, 2019). Those methods proved highly capable of semantically segmenting point clouds for LiDAR scans of railway tunnels for 4 classes (i.e., ground, lining, wiring and rails), albeit with the latter model architecture garnering better evaluation metrics values across all classes (Soilán *et al.*, 2020).

1.2. Scan2BIM in Railway Infrastructure

The Scan2BIM approach for the as-is reconstruction of rail infrastructure has been the subject of many recent publications. In most cases, the focus of the investigations is the extraction of the horizontal alignment and/or the vertical gradient from PCD (Yang & Fang, 2014; Cheng *et al.*, 2019; Soilán *et al.*, 2021; Cserép *et al.*, 2022). The design of the alignment is subject to a strict set of geometric rules in planning, which can be utilized in the detection of the alignment. However, rail infrastructure consists not only of tracks, but also of track-related equipment, such as overhead contact lines or electrical power supply systems and their attachment to masts (Grandio *et al.*, 2022). Since these components are geometrically aligned with the track, the course of the track can be used for identification (Ariyachandra & Brilakis, 2020; Cserép *et al.*, 2022). (Chen *et al.*, 2020) used PCD to derive, among others, the railroad tunnel cross-sections.

What the aforementioned publications have in common is the highly detailed point cloud data they are using. Often ground-based Mobile Mapping systems were used, resulting in high point densities and accuracies in millimetre range. The object detection furthermore was only relying on the PCD itself, sometimes including also geometric planning rules. Additional geodata was not considered. Many relevant objects could be identified and reconstructed, such as poles, cables, signals, the tracks, traffic lights, etc. In some cases, IFC models of the reconstructed objects were generated and therefore made the results possibly available for further usage in planning (Ariyachandra & Brilakis, 2020; Soilán *et al.*, 2021).

1.3. Research Questions

This publication focuses on the question on how to combine open geodata from GIS and PCD to enhance recognition of railway objects within point clouds. Subsequently, by semantic segmentation of PCD, railway object may be reconstructed as 3D meshes and then transformed into the open IFC, which can provide an as-is model for a BIM-based planning workflow. This paper focuses therefore on the semantic segmentation of PCD and the transfer from reconstructed 3D meshes to the open format IFC. We hypothesize that the inclusion of GIS data can help to overcome obstacles related to insufficient data basis. For this purpose, we relied only on freely available data, using only open-source tools and converted our results into the open BIM data format IFC.

2. Methodology

Figure 1 demonstrates a general overview of the devised workflow. The input data for the training, testing and validation of the semantic segmentation DL model is freely downloaded from open geoportal sources. Those LiDAR scans generally lack meaningful classification of points except for ground. The point clouds would be automatically pre-processed for inclusion of textures from orthographic photos, cleaning of noise, use of publicly available labelling data to create the annotation masks of said point clouds and augmentation.

Amongst the labels of interest for the research are nature protected areas, construction sites, railways, roads, vegetation, water areas and water ways, pedestrian roads (e.g., hiking and cycling routes), etc. The PointNet++ Deep Learning architecture (Qi *et al.*, 2017) would be utilised to train a model capable of segmenting the aforementioned classes of interest on similar unseen (for the trained model) LiDAR scans via inference. The segmented point clouds are then used to generate more meaningful digital surface models to be exported into IFC. The integration of the 3D buildings of development level 2 (LoD2) into the model and the enrichment with further semantics derived from the identified classes is thus facilitated. This would enhance the storage, processing and retrieval of data between all parties involved in the planning phase without technical limitations or restrictions.

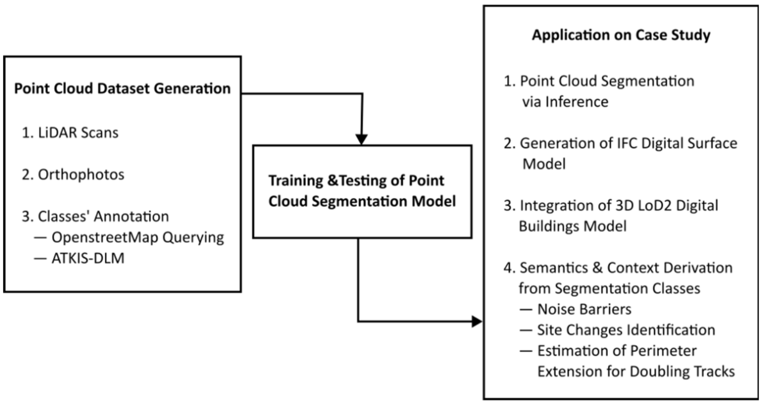

Figure 1: General workflow of integrating geodata derived contexts into BIM and potential use cases.

3. Implementation

The data sources used originate from the German official registers for topographical and cadastral data (ATKIS/ALKIS) and Thuringian State Office for Land Management and Geoinformation via the Geoportal of the State of Thuringia (Thüringer Landesamt für Bodenmanagement und Geoinformation, 2023). The position reference system is ETRS89, UTM zone 32N (respectively 33N for Saxony) and the German height reference system DHHN2016. The following table shows the used data.

Table 1: Freely available input data used within the implementation and case-study.

Data	Format	Description
Digital Surface Model (DSM)	*.laz	3D PCD, uncoloured
Digital Elevation Model (DEM)	*.laz	3D PCD, uncoloured
Digital Orthographic Photos (DOP)	*.tiff	2D images, coloured
Cadastral Maps (ALKIS)	*.shp	2D vector data
Topographical Maps (ATKIS)	*.shp	2D vector data
Buildings, LoD 2 (CityGML1)	*.gml	3D city model data

The following Figure 2 shows the applied implementation process which is coarsely separated into three steps.

Firstly, the input data is prepared using the GeoPandas library for Python. This includes the import of the Digital Surface Model, the DOP and the ATKIS/ALKIS data. From ATKIS/ALKIS the class layers are generated and in a next step, the PCD is segmented according to the class layers. From the DOP, the colours are assigned to the initial PCD. The results of the first step are two point cloud sets, one serving as a mask and the second serving as the colour-enriched data set that the mask will be applied to.

Secondly, the LiDAR scans, coloured orthophotos, and mask information derived from the ALKIS/ATKIS vector data form the dataset compiled for training the DNN model. Initially, a colour is deduced for each point as the LiDAR scans do not contain colour values for points, by sampling the RGB channels of the relevant orthophoto for the matching grid cell using a predefined pipeline script from PDAL (Howard Butler *et al.*, 2023). Next, the .laz files are split into the 3 main classes identified, i.e., ‘unclassified’, ‘ground’ and a reserved overground class ‘20’ comprising all other classes combined. The annotation masks of the subclasses for buildings, water areas and vegetation classes are annotated automatically based on the label masks from ALKIS/ATKIS using spatial predicate queries. Only the classes for traffic (i.e., roads and railway) had to be annotated semi-automatically relying on the polylines available from ALKIS as a guiding alignment. Figure 3 showcases a grid cell sample of the utilised geodata.

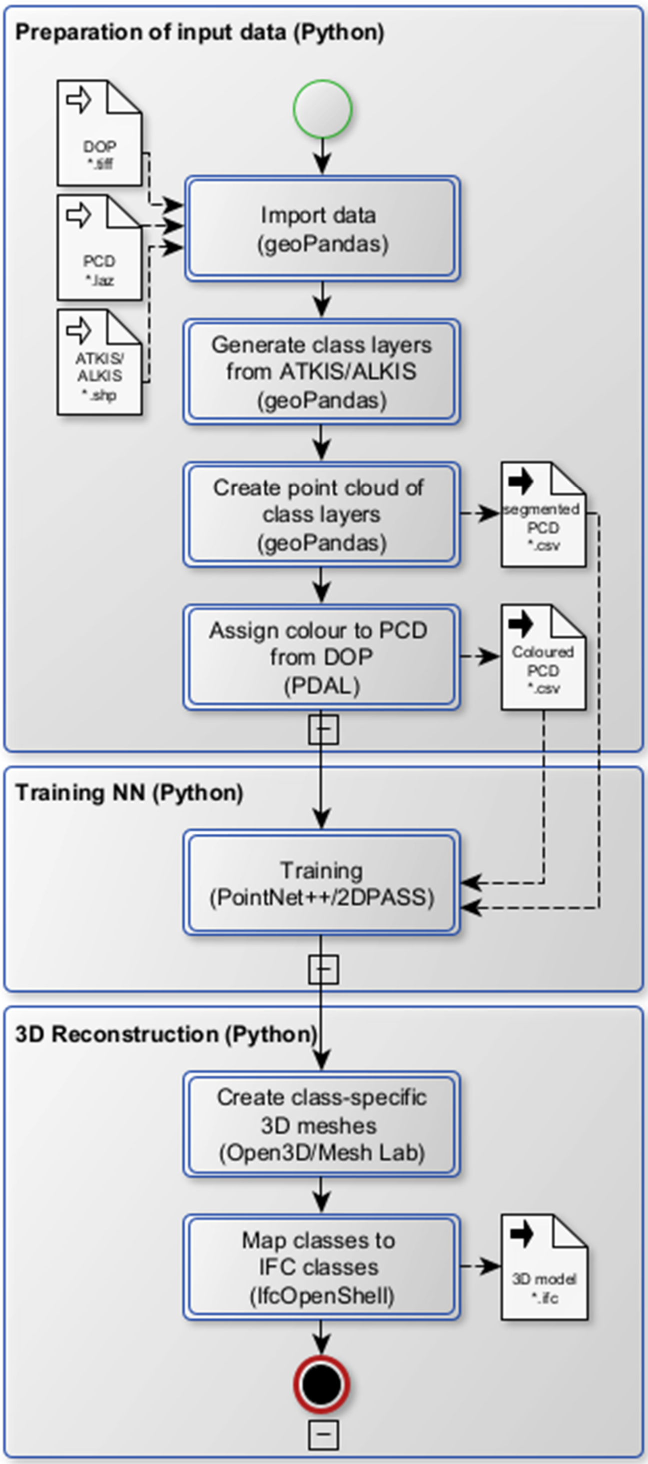

Figure 2: Implementation workflow for 3D reconstruction of relevant geo-context objects.

Both resulting PCD sets are used to train the neural network architecture using Python as the programming language. Both PointNet++ and 2DPASS architectures were used for training, where the former relies on colourised PCDs and annotations as input, and the latter on PCDs, orthophotos and annotation masks respectively (Qi *et al.*, 2017; Yan *et al.*, 2022). The latter model was decided on for the semantic segmentation of the classes buildings, water areas, roads, railway and vegetation. The dataset contains 549 grid cells in total from the Free States of Thuringia and Saxony for the cities of Erfurt, Jena, Weimar, Leipzig and Dresden respectively. Every PCD tile consisted of between 10 and 20 million points in an area of 1 km², meaning a point density of around 10.000 to 20.000 points per m². Not only points from the Geoportal of Thuringia were considered, but also from the Geoportal of Saxony (Landesamt für Geobasisinformation Sachsen, 2023). The model was trained for 200 epochs on GPU (Nvidia RTX 5000 Graphics Card).

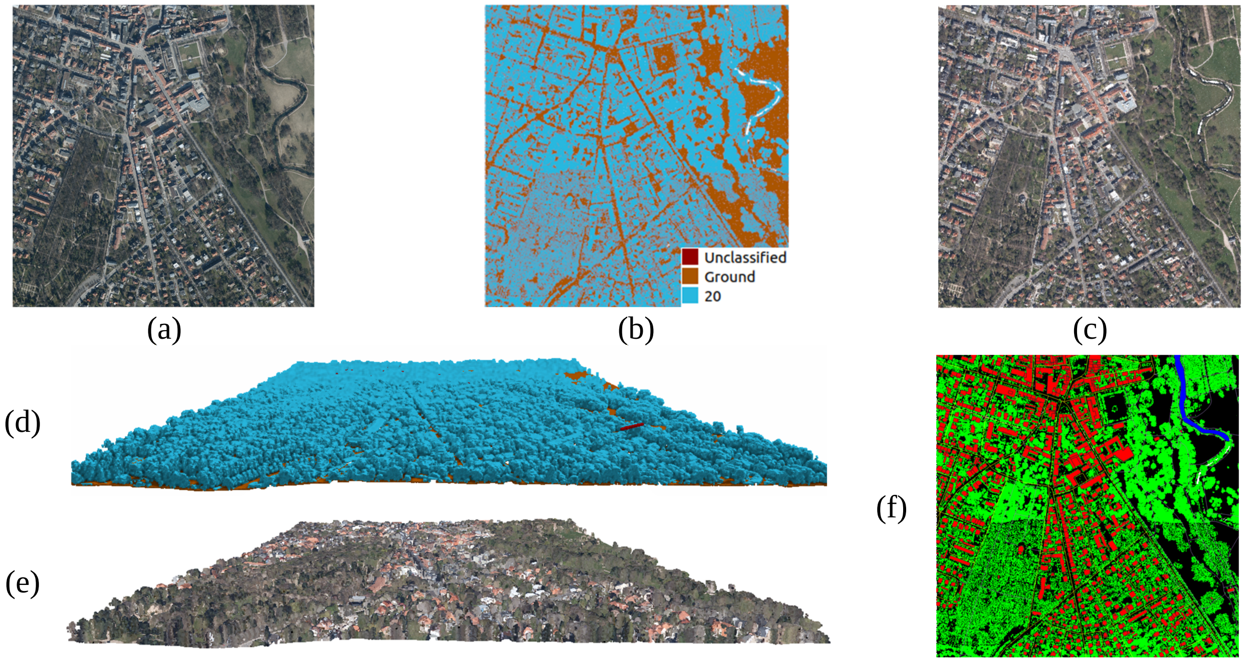

Figure 3: Pre-processing Steps on a grid cell sample. (a) Exemplary orthophoto of the cell, (b) Original LiDAR scan of the relevant cell comprising the 3 main LAS classes, (c) Colourised LiDAR scan via sampling colours from the orthophoto, (d) Bird's eye view of the LiDAR scan, (e) Bird's eye view of the colourised LiDAR scan, (f) ALKIS mask.

Thirdly, from the classified point cloud, 3D meshes can be reconstructed using Python Open3D and the MeshLab libraries. Finally, the segmented PCD inferred from the trained model can be mapped to selected IFC classes (see Table 3) and exported as a 3D model into IFC4x3 using IfcOpenShell. The respective IFC classes have been chosen manually. In case of the extracted railway body, IfcAlignment first seems like an appropriate match, but due to its nature of a calculated curve by using starting point, direction angle and length, the railway body has been exported as IfcElementProxy. This was considered more appropriate because not only the alignment was extracted from the PCD, but the whole railway body including railroad ballast, sleepers, rails, catenary, etc.

4. Case Study and Results

To test the aforementioned methodology, a case study is carried out. To that end, a PCD grid cell of the city of Dresden was used (Landesamt für Geobasisinformation Sachsen, 2023), including the famous Dresden Frauenkirche and the main train station. The chosen area is around 1 km² and includes around 32.300.000 points, equalling around 32 points per m². For railway planning this is a particularly interesting area due to dense urban development and limited moving space.

Depending on the source of the .laz files, they include already a basic classification. Usually, the classified .laz data is not available for free and only three default classes exist within the files: Not classified, Unclassified and Ground. Even if there are more classes available, the target classes for extraction within this case study are always a mix of several provided .laz classes and have to be extracted separately.

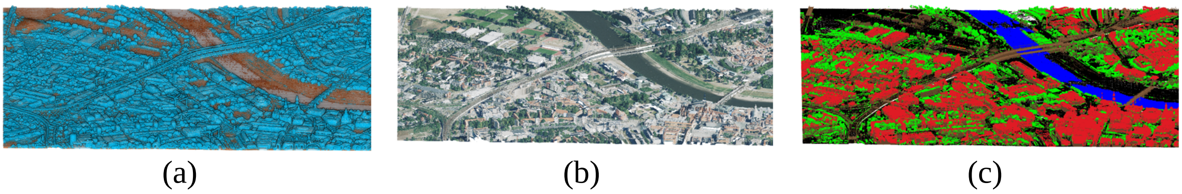

Figure 4: Pre-processing of PCD for case study. (a) Original LiDAR scan, (b) The colourised PCD for the LiDAR grid cell based DOP colour sampling, (c) Inferred segmentation from the trained 2DPASS model.

The PCD tile, the referencing DOP were pre-processed and fed into the trained 2DPASS model as described in chapter 3. The reconstructed model was then converted into IFC. For the conversion to IFC4x3, the relevant segmentation classes were derived and mapped to its identified most suitable IFC entity as detailed in Tables 2 and 3 respectively.

Table 2: Values and meanings of default LAS classes in LiDAR scans of dataset used.

Class Value	Meaning	Class Value	Meaning
0	Created, Never Classified	10	Rail
1	Unclassified	11	Road Surface
2	Ground	12	Reserved
3	Low Vegetation	13	Wire Guard (Shield)
4	Medium Vegetation	14	Wire Conductor (Phase)
5	High Vegetation	15	Transmission Tower
6	Building	16	Wire Structure Connector (Insulator)
7	Low Point (Noise)	17	Bridge Deck
8	Reserved	18	High Noise
9	Water	>18	User Defined

Table 3: Freely available input data used within the implementation and their suggested relevant shape representation and entity in IFC.

Main/Sub Segmentation Class	Class Value	IFC Shape	IFC Entity
Ground Terrain	2	TriangulatedFaceSet	IfcSite
Overground	20	-	IfcProxy
Vegetation	3,4,5, 20	Brep	IfcProxy
Buildings	0,1,6, 20	TriangulatedFaceSet	IfcBuilding
Water	2,9	TriangulatedFaceSet	IfcProxy
Roads	2,11	TriangulatedFaceSet	IfcPavement
Railway Body	2,10	TriangulatedFaceSet	IfcProxy
Miscellaneous	0,1,2	TriangulatedFaceSet	IfcProxy
Unclassified	0,1	Brep	IfcProxy

Figure 5: Outcomes of the case study. (a) Segmented ‘Building’ class, (b) Segmented ‘Vegetation’ class, (c) Segmented ‘Railway’ class, (d) Connected component labelled instances for the class ‘Building’, (e) Connected component labelled instances for the class ‘Vegetation’, (f) Connected component labelled instances for the class ‘Railway’

The resulting segmentation was visually checked. The visual inspection did not reveal obvious divergences. Figure 5 showcases the resulting semantic segmentation of the PCD and the integration of the meshed classes into IFC, whereas the resulting IFC file ultimately consists of nine classes, allowing a semantic differentiation within the BIM model. To not only rely on the IfcType, the class names from the segmentation process were additionally included as an attribute of IfcLabel. Following Figure 5 shows the most relevant extracted classes (buildings in red, vegetation in green, railway body in brown) as segmented PCD (via inference) and the post-processed segmented PCD as instances. To split instances for meshing, connected component labelling was used.

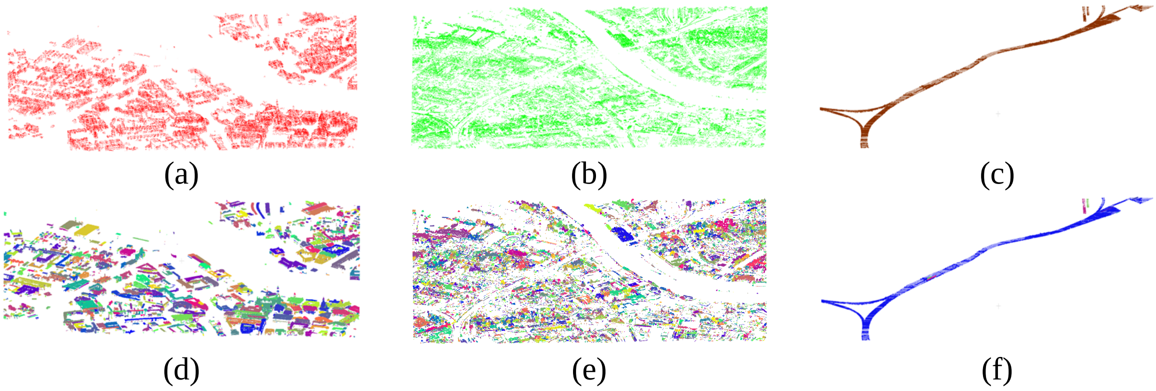

Figure 5: Outcomes of the case study. (a) Segmented ‘Building’ class, (b) Segmented ‘Vegetation’ class, (c) Segmented ‘Railway’ class, (d) Connected component labelled instances for the class ‘Building’, (e) Connected component labelled instances for the class ‘Vegetation’, (f) Connected component labelled instances for the class ‘Railway’

5. Discussion

This paper shows a completely open-source, semi-automated process to speedily create ready-to-use data of surroundings with a focus on railway projects. It presents a methodology for 3D reconstruction of as-is data considering publicly available PCD and GIS data. The used GIS data helps to semantically segment the PCD, especially when the available data is not very detailed and taken only from aerial scans. The conducted case study was successfully carried out, resulting in an IFC model of the segmented classes from the PCD of the city of Dresden, as can be seen on Figure 6.

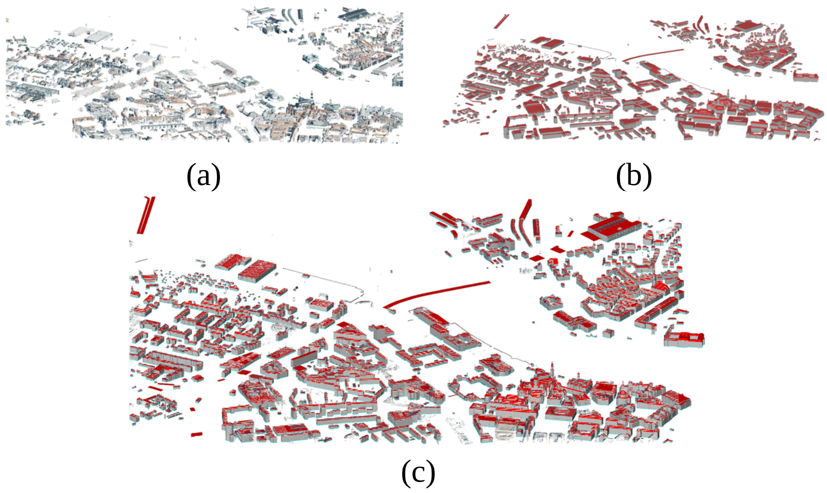

Figure 6: Resulting meshes and IFC files. (a) Colourised building instances based on colour sampling, (b) Converted CityGML LoD2 model into IFC4x3, (c) Overlay of the meshed instances from Subfigures 5(a) and 5(b) respectively for visual comparison.

Previous research usually considers highly detailed PCD, specifically surveyed for a purpose and using ground-based Mobile Mapping Systems. GIS data was not considered within the reviewed literature. Our findings contribute to the approach of not relying on a well-situated data base but to combine the best available data in order to reach results that are sufficient for the project phase and the use case.

There are several limitations to be stated: Firstly, the mapping between the IFC schema and the segmented classes is only superficially considered, leading in a relatively coarse use of IFC classes. The difficulty with the IfcAlignment class is that it consists of both the 2D alignment and the 3D gradient, making the reconstruction from scratch more challenging than other classes. The reconstruction of the IFC alignment in particular and the proper mapping of the railway equipment will be the subject of further case studies (Wijnholts *et al.*, 2016). Secondly, the results were visually checked and compared with the ground truth data (in this case for example using CityGML data from the case study area for the comparison of the building class). The visual inspection did not reveal obvious divergences, nonetheless future work will quantify the exact accuracy of the semantic segmentation. It appeared that the buildings at the borders of the PCD tiles were incomplete due to being cut into 1km² tiles. The provided CityGML data from Landesamt für Geobasisinformation Sachsen did not take into account the cropping of bordering building instances at the edges of the grid cell. Therefore, all buildings that were only slightly overlapping the borderline have been included. The PCD on the other hand includes only points within the grid cell. It was not quantified, if the number of buildings is significant, yet the treatment of incomplete features will be object to further research.

We investigated how PCD and GIS data can be combined for the creation of low-threshold, BIM-ready as-is models. For this, only freely available data and software were used. Future application could cover many different use cases relevant for infrastructure planning and to enhance decision-making with poor data conditions. Furthermore, the integration and BIM and GIS data has high relevance when considering spatial effects like noise, floods, impacts on humans, flora and fauna, and so on. If applied systematically, this approach can help reduce cost and effort digitizing infrastructure stock with open data to make better decisions from an early stage on. It contributes to solving the common problem of insufficient data and is a flexible approach towards taking the best out of a heterogeneous data basis.

References

Ariyachandra, M.R.M.F. & Brilakis, I. (2020) Detection of Railway Masts in Airborne LiDAR Data. *Journal of Construction Engineering and Management*, 146(9). Available from: https://doi.org/10.1061/(ASCE)CO.1943-7862.0001894.

Boulch, A., Guerry, J., Le Saux, B. & Audebert, N. (2018) SnapNet: 3D point cloud semantic labeling with 2D deep segmentation networks. *Computers & Graphics*, 71, 189–198. Available from: https://doi.org/10.1016/j.cag.2017.11.010.

Chen, C., Zhang, T., Kan, Y., LI, S. & Jin, G. (2020) A rail extraction algorithm based on the generalized neighborhood height difference from mobile laser scanning data. In: Kimata, M. (Ed.) *SPIE Future Sensing Technologies*, p. 18.

Cheng, Y.-J., Qiu, W.-G. & Duan, D.-Y. (2019) Automatic creation of as-is building information model from single-track railway tunnel point clouds. *Automation in Construction*, 106, 102911. Available from: https://doi.org/10.1016/j.autcon.2019.102911.

Cserép, M., Demján, A., Mayer, F., Tábori, B. & Hudoba, P. (2022) Effective Railroad Fragmentation and Infrastructure Recognition Based on Dense Lidar Point Clouds. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 103–109. Available from: https://doi.org/10.5194/isprs-annals-V-2-2022-103-2022.

Deutsche Bahn AG (2021) *Integrierter Bericht 2021*. Available from: https://ibir.deutschebahn.com/2021/fileadmin/pdf/DB_IB21_web_01.pdf.

Grandio, J., Riveiro, B., Soilán, M. & Arias, P. (2022) Point cloud semantic segmentation of complex railway environments using deep learning. *Automation in Construction*, 141, 104425. Available from: https://doi.org/10.1016/j.autcon.2022.104425.

Howard Butler, Andrew Bell, Michael P. Gerlek, chambbj, Pete Gadomski & Connor Manning et al. (2023) *PDAL/PDAL: 2.5.4: Point Data Abstraction Library*. Zenodo.

Huang, J. & You, S. (2016) Point cloud labeling using 3D Convolutional Neural Network. In: *2016 23rd International Conference on Pattern Recognition (ICPR)*. IEEE, pp. 2670–2675.

Lalonde, J., Unnikrishnan, R., Vandapel, N. & Hebert, M. (2005) Scale Selection for Classification of Point-Sampled 3-D Surfaces. In: *Fifth International Conference on 3-D Digital Imaging and Modeling (3DIM'05)*. IEEE, pp. 285–292.

Landesamt für Geobasisinformation Sachsen (2023) *Offene Geodaten*. Available from: https://www.geodaten.sachsen.de/.

Maturana, D. & Scherer, S. (2015) VoxNet: A 3D Convolutional Neural Network for real-time object recognition. In: *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 922–928.

Qi, C.R., Yi, L., Su, H. & Guibas, L.J. (2017) PointNet++: Deep Hierarchical Feature Learning on Point Sets in a Metric Space. In: *31st Conference on Neural Information Processing Systems (NIPS 2017), Long Beach, CA, USA*.

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*, 103684. Available from: https://doi.org/10.1016/j.autcon.2021.103684.

Soilán, M., Nóvoa, A., Sánchez-Rodríguez, A., Riveiro, B. & Arias, P. (2020) Semantic Segmentation of Point Clouds with PointNet and KPConv Architectures Applied to Railway Tunnels. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, 281–288. Available from: https://doi.org/10.5194/isprs-annals-V-2-2020-281-2020.

Su, H., Maji, S., Kalogerakis, E. & Learned-Miller, E. (2015) *Multi-view Convolutional Neural Networks for 3D Shape Recognition*. Available from: https://doi.org/10.48550/arXiv.1505.00880.

Thomas, H., Qi, C.R., Deschaud, J.-E., Marcotegui, B., Goulette, F. & Guibas, L.J. (2019) *KPConv: Flexible and Deformable Convolution for Point Clouds*. Available from: https://doi.org/10.48550/arXiv.1904.08889.

Thüringer Landesamt für Bodenmanagement und Geoinformation (2023) *Offene Geodaten*. Available from: https://www.geoportal-th.de/de-de/.

Wijnholts, L., Beetz, J. & Krijnen, T. (2016) *Automated Geometry Checking for Infrastructure Projects A research of implementing interoperable validation for IFC Alignment models in the Planning Phase of the System Engineering process based on open source*. Master Thesis.

Yan, X., Gao, J., Zheng, C., Zheng, C., Zhang, R. & Cui, S. et al. (2022) *2DPASS: 2D Priors Assisted Semantic Segmentation on LiDAR Point Clouds*. Available from: https://doi.org/10.48550/arXiv.2207.04397.

Yan, Y., Mao, Y. & Li, B. (2018) SECOND: Sparsely Embedded Convolutional Detection. *Sensors (Basel, Switzerland)*, 18(10). Available from: https://doi.org/10.3390/s18103337.

Yang, B. & Fang, L. (2014) Automated Extraction of 3-D Railway Tracks from Mobile Laser Scanning Point Clouds. *ISPRS International Journal of Geo-Information*, 7(12), 4750–4761. Available from: https://doi.org/10.1109/JSTARS.2014.2312378.

Yang, X., Zou, H., Kong, X., Huang, T., Liu, Y. & Li, W. et al. (2021) *Semantic Segmentation-assisted Scene Completion for LiDAR Point Clouds*. Available from: https://doi.org/10.48550/arXiv.2109.11453.

Zhang, R., Li, G., Wunderlich, T. & Wang, L. (2021) A survey on deep learning-based precise boundary recovery of semantic segmentation for images and point clouds. *International Journal of Applied Earth Observation and Geoinformation*, 102, 102411. Available from: https://doi.org/10.1016/j.jag.2021.102411.