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# ANNOTATION RULES AND CLASSES FOR SEMANTIC SEGMENTATION OF POINT CLOUDS FOR DIGITALIZATION OF EXISTING BRIDGE STRUCTURES

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## Abstract

Germany's large stock of existing bridge infrastructure must be digitalized as BIM due to political requirements. Therefore, point cloud data can be used, and available open-source datasets and different approaches on semantic segmentation are being researched. To bridge the gap between theoretical research on point cloud data and manual inspection, a list of object-oriented classes for semantic segmentation is proposed. These classes are put into context with entities of the IFC schema and the German ASB-Ing. An application example with the proposed classes is shown using a manually segmented point cloud and an approach with the RANSAC Shape Detection algorithm.

## Introduction

The German infrastructure network includes a large number of bridges. In 2021 the federal highway network contained about 40.000 bridges (BAST, 2021). Around 86% of these bridges are reinforced or prestressed concrete bridges, and almost 64% of the bridge constructions have a length between 2 m – 30 m (BAST, 2021). These statistics show that the majority of bridges are shorter concrete bridges and not large span constructions with special designs. During bridge inspections in Germany, every bridge receives a condition grade to rate the structural integrity. The range of this condition grade varies between 1,0 (best) and 4,0 (worst) with steps of 0,1. In 2021, the main amount of federal highway bridges received condition grades between 2,0 to 2,4 (47,4%). Around 5% of the bridges were graded between 3,0 to 4,0 (BAST, 2021). While the majority of highway bridge structures was built between 1965 to 1985, the condition grades for many bridges will become worse in the future (BAST, 2021). Due to the deterioration of the bridge grades more manual inspections and maintenance becomes necessary. With the Federal Trunk Roads BIM Masterplan (BMDV, 2021), the Federal Ministry for Digital and Transport (BMDV) of Germany presents the regulatory framework for the nationwide application of the building information modeling (BIM) methodology for public highway infrastructure projects. The plan prescribes that the BIM methodology must be applied in planning new infrastructure projects and in every other use case, such as operation and maintenance (BMDV, 2021). In this paper, the abbreviation BIM stands for the digital representation of the model itself, not the methodology. Otherwise, it is specified in the text. While the BIM methodology is currently still being tested in infrastructure and civil engineering in execution (Schneider & Tschickardt, 2021) and maintenance phases, the extension of the industry foundation classes (IFC) format for infrastructure and bridges is currently under further development (buildingSMART, 2022a). Still, it is politically enforced that the large stock of bridges in German infrastructure must be digitalized and transferred into a BIM. Manual remodeling of single bridges is already a labor-intensive task (Bednorz et al., 2020), and it is not feasible for the number of professionals in Germany. In summary, it is necessary to at least support or fully automate the digitalization and BIM generation of the existing bridge stock using digital methods. One approach for generating initial digital representations of the bridge constructions is point cloud data (PCD), which can be gathered from methods such as laser scanning or photogrammetry. PCD represents scanned objects as points in a 3D-coordinate system with X, Y, and Z coordinates and often with RGB-color information. As a first step towards a BIM representation of a scanned bridge, semantic segmentation of the point cloud data is necessary. Semantic segmentation involves finding context within the various points of the PCD. In this case, different construction parts of the bridges must be detected. Additionally, the BIM could be enriched with further information such as material properties or damages (Kaufmann, Glock & Tschickardt, 2022). There are already different approaches for the semantic segmentation of PCD. Two main approaches can be differentiated: (i) heuristic and (ii) machine learning methods. In the following section, related research on this topic is addressed. Crucial for any approach on automated or semi-automated semantic segmentation is the amount and quality of existing PCD. This data is necessary for testing and validation of the segmentation results and is also required for training in machine learning. Furthermore, the classes, that represent the different bridge parts in the semantic segmentation are highly important. Only a segmentation process with appropriate classes can add value for practical application in the construction business. For this reason, the following paper highlights related work on existing bridge datasets of PCD and different approaches on (semi-)automatic semantic segmentation. Additionally, relevant objects for segmentation classes are proposed and discussed in the context of the current manual procedure of bridge inspection and digitalization.

## Related work

### Data sets for semantic segmentation in bridge construction

The biggest open-source and structured data set of PCD with reinforced concrete bridges is proposed by (Lu, Brilakis & Middelton, 2019). In this dataset, ten reinforced concrete highway bridges are provided. The PCD was scanned using the Terrestrial Laser Scanner FARO Focus 3D X330. All bridges are located in United Kingdom, around Cambridgeshire. The dataset has non-data ratios (on-site traffic noise, trees, large ground surfaces and ramp) between 11,1 % and 55,1 %. Version 2 of the dataset contains 10 to 82 million points per bridge point cloud, captured from 14 to 25 scanning points. Version 1 of the dataset consists of the same PCD but with a lower point density, respectively lower file sizes (Lu, Brilakis & Middelton, 2019). Furthermore, various PCDs of different single bridges can be found. One concrete bridge from Westlandseweg in Delft, NL, was scanned during a Master´s program at TU Delft. The mixed-vehicle and tram bridge is available as a 2,1 GB large .e57-file, with 118 million points. The PCD was scanned with a Leica ScanStation P40, from nine different scanning points, registered, and downsampled to a sampling step of 5 mm with the Leica Cyclone software (Truong, Lindenbergh et al., 2021). Another PCD was scanned by TU Delft on Schipluiden, Zuid-Holland, NL. It contains a steel truss bridge that was previously used for trams and is now used for light traffic, like pedestrians, bicycles, and motorbikes. The data is provided as a 0,46 GB large .e57-file, consisting of 40 million points. The settings for data capturing were the same as the bridge from Westlandseweg: a Leica ScanStation P40 and down sampled to a sampling step of 5 mm with the Leica Cyclone software. Fourteen different scanning points were needed (Truong, Papalexiou et al., 2021). (Turkan & Xu, 2022) generated a PCD of a concrete bridge in Corvallis, Oregon, USA using a combination of photogrammetry and laser scanning with UAS images. Therefore, a DJI Mavic 2 Drone and a combination of a Leica GS14 GNSS, a Leica CS15 and a Leica Nova MS50 MultiStation was used. Besides the bridge PCD with approximately nine million points in .las format, 1247 high-resolution images in .dng format and the coordinates (WCS) of 12 ground control points and 15 visual targets attached to the bridge surface in .txt format are provided. Three PCDs of a three-span bridge are provided by (Abraham, 2016). The so-called Wolf Creek Bridge dataset contains just the roadway and rails without any load-bearing structures of the actual bridge. The PCDs consist of approximately 21 – 23 million points and can be downloaded in .laz format. No further information about the capturing methods etc. is available. PCD of a steel truss bridge contains the Inglewood bridge data set with 14 registered 3D scans of a single bridge. It is provided by (Hvidberg, Dawson & Robinson, 2019) in .las format. The 14 available single scans sum up to an approximately 8 GB PCD file with round 340 million points, resulting in a high point density. For scanning a Z+F 5010X laser scanner and for processing the Z+F Laser Control (v.8.9.0) software was used.

*Table 1: Overview of existing bridge point cloud datasets*

| Name | Generation method | File type | Number of points |
|---|---|---|---|
| Cambridgeshire | Laser scanning | .bin | 10-82 Mio. per bridge (V2) |
| Westlandseweg | Laser scanning | .e57 | 118 Mio. |
| Schipluiden | Laser scanning | .e57 | 40 Mio. |
| Corvallis | Photogrammetry Laser scanning | .las .dng .txt | 9 Mio. |
| Wolf Creek | n.a. | .laz | 21-23 Mio. per point cloud |
| Inglewood | Laser scanning | .las | 340 Mio. |

Table 1 shows an overview of available bridge PCDs obtained from different sources. The homogeneity of the point clouds varies, so the number of points does not necessarily guarantee high point densities. None of the datasets have annotated PCDs or BIMs available as a ground truth, thus requiring manual work for automatic semantic segmentation and BIM generation. For future generation of bridge PCDs, it is essential to have a sufficient point density to detect smaller bridge parts, such as bearings, rails, or joints for automatic semantic segmentation or further research on PCDs. However, many existing bridge PCDs are not open source due to bridges being classified as critical infrastructure, making it challenging to share them for research purposes. A practical legal way to share these datasets for research purposes has yet to be found. In case of an economical perspective special capturing methods could be evaluated, like path planning for data acquisition (Tschickardt, Kaufmann & Glock, 2022). This approach could focus different capturing densities, depending on the size of the specific objects to be scanned.

### Heuristic methods

In (Lu, Brilakis & Middelton, 2019) heuristic methods for semantic segmentation of bridges in PCD are proposed. Therefore, a top-down approach and recursive slicing algorithms are combined. In the first step, a principle component analysis is used to align the bridge PCD in a global XYZ-coordinate system. There the x-axis follows the direction of the superstructure, the z-axis is defined perpendicular to the ground and the y-axis is perpendicular to both. After this alignment, the PCD is sliced in 0,5 m thick point clouds along the x-axis. Then a feature detector is used, where every point cloud slice is bounded by a 3D axis-aligned-bounding-box (AABB). In the midplane of these AABBs, a 2D skeleton of the slice is used for a height comparison. While the height of the pier area is much higher than the deck area, each slice is classified into two classes: pier assembly and deck assembly regions. Continuing this logic, the two classified regions are focused on themselves to separate further classes for semantic segmentation of the bridge PCD. (Lu, Brilakis & Middelton, 2019) distinguishes four semantic classes: piers, pier caps, slabs and girders. With the proposed methods (Lu, Brilakis & Middelton, 2019) achieved high detection rates for semantic segmentation for straight bridges with flat decks. As stated in the publication, this approach is not suitable for non-even bridges, like diaphragm bridges, bridges with complex geometries or small spacings between girders. Steel bridges, like truss bridges are not suitable as well. (Qin et al., 2021) proposed a methodology for semantic segmentation by using average point cloud densities to divide the PCD in different bridge parts. The methodology is developed with a clean, synthetic point cloud without noise points, so no preprocessing is needed. For semantic segmentation, the PCD is divided into intervals along the z-axis. Then, the point densities are determined for each interval by using the kd-tree algorithm. Every horizontal plane in the PCD leads to a peak in the interval density. Each density peak is interpreted as the top or bottom surface of a bridge part, and all points in between are assigned to the corresponding class. In addition, (Qin et al., 2021) proposed a method for handling uneven planes by projecting the point cloud onto the xy-coordinate plane and using point density segmentation.

**Machine learning methods**

Besides heuristic methods, approaches using machine learning have gained larger popularity. Due to the increasing computing capacities of related hardware, machine learning has become more and more capable of handling complicated tasks. Machine learning can be divided into three different approaches: (i) unsupervised learning, (ii) supervised learning, and (iii) reinforcement learning. Most proposed methods of machine learning for semantic segmentation of PCD focus on supervised learning, respectively deep learning. Therefore, a pre-segmented dataset of annotated PCD is used to train a neural network. Additional unannotated data is needed for validation purposes. After the training of the neural network is finished, a test data set with both annotated and raw PCD is used to measure the capability of the trained neural network. In (Mafipour, Vilgertshofer & Borrmann, 2022b) the so called RandLA-Net is used. The trained features contain normal vectors, 2D point density, 3D point density, XYZ-coordinates, and RGB-features of the PCD, after (Pan, Mafipour & Mehranfar, 2022) showed better results in the performance of the neural network, compared to training on just XYZ-coordinates and RGB-features. For training, validation and testing the above-mentioned Cambridgeshire dataset of (Lu, Brilakis & Middelton, 2019) was used. The neural network was trained on four classes, named deck, railing, pier and background. During preprocessing the data was sub-sampled in 5 cm uniform grid voxels. After further data augmentation, including random rotation of the PCD around the z-axis and a class weighting on the number of points to equalize the impact on the loss function. The RandLA-Net was built with four layers, a ratio of 1/4, 8 neurons, a batch size of 3, a learning rate of 0,01 and was trained for 512 epochs. As a result, a mean Intersection over Units (mIoU) of 88,45% and a mean accuracy (mAcc) of 95,62% was reached. Due to the lack of qualified and similar PCD, (Mafipour et al., 2022) proposed a method to enrich datasets of real with synthetic PCD. Therefore, a workflow was developed to generate synthetic PCD. First 3D models of bridges were designed with a BIM-authoring system, containing of Autodesk Revit® and SOFiSTiK Bridge Modeler, based on structural drawings of real bridges. By varying dimensions and number of spans different shapes are varied. A similar method for the generation of synthetic data is proposed by (Hoop, Tschickardt & Schmitt, 2022). Additionally, trees and dense vegetation are modelled in the approach by (Mafipour et al., 2022). The transition from the 3D geometrical model to the PCD was realized with a virtual laser scanner, named Helios++ (Esmoris et al., 2022). Therefore, a frequency of 120 Hz, a pulse frequency of 5000 Hz, a 180° scanning angle and 10 head rotations per sec/deg were set. Occlusion and RGB information based on interpolation of real PCD were simulated additionally. Finally, the enriched dataset with real and synthetic PCD reached an improvement of + 5,5 % on mIoU and + 3,1 % on mAcc. (Xia, Yang & Chen, 2022) combined a machine learning approach with a local descriptor. Therefore, the dataset of (Lu, Brilakis & Middelton, 2019) was used as well. First, disturbances and noise were removed, using Density-Based Spatial Clustering of Applications with Noise (DBSCAN). For the proposed method no preprocessing like voxelization or subsampling of the PCD is needed. The workflow is divided into three steps. First, a multi-scale descriptor for describing the geometric features of bridges is designed. Second, a pipeline for pointwise classification of the PCD is developed, using the deep learning neural network PointNet. In the last step, the results are refined. (Xia, Yang & Chen, 2022) distinguishes five classes, named background, slab, girder, pier cap and pier. The results of the proposed method state an improvement of the mIoU from 45,92% to 94,62% by combining PointNet with a local descriptor, compared to PointNet without a local descriptor. Furthermore, (Xia, Yang & Chen, 2022) lists the results where the proposed workflow can contribute to recent research question and the specific limitations of the methodology. A comparison of different deep learning algorithms for semantic segmentation of bridge PCD was published in (Kim & Kim, 2020). The neural network architectures that were used were PointNet, PointConvolutionalNeuralNetwork (PointCNN) and DynamicGraphConvolutionalNeuralNetwork (DGCNN). A non-public dataset of 27 scans on three bridges, scanned with a Trimble TX8, was used. Six classes were focused on for the semantic segmentation, namely abutment, girder, slab, background, pier and surface. During the proposed methodology the PCD was partitioned in samesized blocks, free from data loss and overlapping, first. After the training was finished, the overall accuracy (OA) and the mIoU were determined for comparison. After a cross-validation, a hyperparameter tuning was made. Overall, the DGCNN performed best with a mIoU of 86,85%, followed by PointNet (84,29%) and PointCNN (76,78%). Concluding for all of the above-mentioned approaches on semantic segmentation of bridge PCD, a large amount of real-world point clouds is needed for either training, testing and validation. The majority of the related work is based on PCD of ten bridges, provided by (Lu, Brilakis & Middelton, 2019) and shows a significant lack of data for scientific research.

**Standards for bridge inspection**

Maintenance management of bridges in Germany is predominantly based on preventive maintenance. This means that instead of merely reacting to damage and repairing it, the condition of traffic facilities is to be maintained at a constant level of quality by means of targeted, efficient strategies, considering the available maintenance budget. The conceptual system of maintenance of traffic facilities distinguishes between operational maintenance, for control and maintenance of the facility parts and structural maintenance which covers maintenance, repair and renewal (BMVI, 2021). This results in various fields of activity and a broad spectrum of participants involved the implementation of strategic maintenance management. One of these fields of activity is condition recording and assessment, which includes the regular inspection and monitoring of the condition of the system, the road surface and the engineering structures (BAST, 2017). The (DIN 1076, 1999) and the guideline for the uniform acquisition, assessment, recording, and evaluation of results of structural tests according to DIN 1076 (RI-EBW-PRÜF) (BMVI, 2017) form the essential basis for the uniform recording and evaluation of engineering structures in Germany. A further step towards standardization is achieved through the defined information content provided by the Instruction Road Information Bank for Engineering Structures, Subsystem Structure Data (ASB-ING) (BAST, 2013). In general, the ASB-ING lists and describes different structural parts of the bridge that must be focused on during inspections in detail. It specifically defines general information for determining the length, height, or width, as well as describing different cross-sections for the main structure and various support and bearing types. Additionally, for example different cross-sections for the main structure or various support and bearing types are described. For clarity and assignability every listed detail is assigned to a continuous number with fifteen digits that can be referred to. Due to the necessity of the digital representation of the existing bridge structures in the Federal Trunk Roads BIM Masterplan (BMDV, 2021) the open-source data schema IFC becomes even more important. Throughout 2018 and 2019, buildingSMART started the extension of the IFC with a variety of infrastructure domains, including bridge structures. This extension approach was initiated while the alignment work and harmonization of the IFC 4 release took place. Thereby bridge specific part types (IfcBridgePart) like abutment, deck, foundation or pier, to name a few, were added in the IfcProductExtension. For less bridge-specific parts already existing entities from the shared element data schema, like IfcBeam, IfcBearing or IfcWall can be used for BIM generation (buildingSMART, 2019).

**Research gap**

Based on this literature research, various research gaps can be identified In the case of real-life data acquisition of bridge PCD, requirement definitions must be examined. Therefore, specific targets must be defined for what the data is going to be used for and what specific requirements are necessary for this data. Examples could include the point density, level of surface completeness (LOC), lists of building parts that must be scanned, etc. In particular, the LOC could be further determined in the context of semantic segmentation. Furthermore, a methodology for data capture for semantic segmentation of PCD can be developed. Both the scientific approach for data capture (e.g., high point density, everything has to be scanned in detail) and an economic approach (e.g., high-speed scanning, just points of interest with needed densities) could be discussed as well. In the field of semantic segmentation of bridge PCD, various approaches have already been evaluated and can be expanded in the future. Promising approaches can be enhanced to become more reliable and accurate for different types of bridge constructions. Additionally, fundamental research in e.g., augmented vision is under constant development and could open further approaches in the future. For semi-manual segmentation of PCD rather simple algorithms, like the random sample consensus (RANSAC) (Schnabel, Wahl & Klein, 2007) can be applied and refined. Many parameter studies are yet to be made. To fill the gap between the theoretical issue of semantic point cloud segmentation and the current manual bridge inspection the definition of semantic classes and rules for annotation have to be discussed.

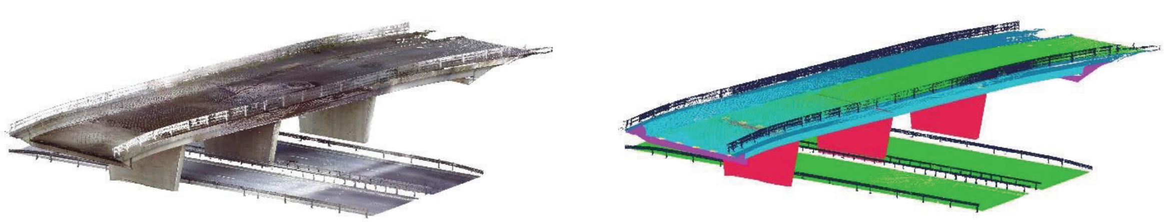

*Figure 1: Example of the raw RGB point cloud data (left) and the colorized, manual semantic segmented point cloud data (right) of bridge 2 (Lu, Brilakis & Middelton, 2019)*

## Object-oriented bridge inspection

### Class definition of important bridge components for semantic segmentation

As stated above various approaches for a necessary semantic segmentation of point clouds of existing bridge structures already exist and work within limitations. Limitations are e.g., a specific type of bridges, simple geometries or few segmentation classes of broad bridge parts. For practical use cases, the quality and details of the digital bridge representation are very important. The mentioned classes cannot fulfill the requirements needed for the manual and laborious task of the current procedure of bridge BIM generation with bridge components and a sufficient level of detail (LOD). To fill the gap between scientific research on semantic segmentation of PCD with generic classes and practical applications for an automated digitalization of existing bridge structures, the specific segmented classes are highly important. Therefore, this paper proposes a list and specific annotation rules for the semantic segmentation of bridge PCD. The proposed classes are linked to specific representations in the current IFC schema and the equivalent numbers in the German ASB-Ing.

### Annotation classes and rules

The following stated classes in Table 2 represent the first excerpt of possible practical relevant classes and can be extended anytime. The proposed classes focus on reinforced concrete bridges and the most common components in this type of bridges. In accordance with the proposed classes and annotation rules, this list can be extended further for special bridge types. The specific labels name the different classes of the bridge parts for the semantic segmentation of PCD. Additionally, a short description is given for each label to ensure clarity during the segmentation process. These descriptions must be precise enough so that every point in the sparse 3D data can be assigned to a specific class. To simplify the segmentation process with better visualization, each label is connected to an individual, unique color. The coloring of the points during the semantic segmentation process serves for the simplification of the manual process with visual feedback. For training, testing or validation of automated semantic segmentation approaches the connection of the specific points with the corresponding label is important. The unique colors are listed in the 6-digit Hex Color Code. For every label, possible representations in the IFC schema are listed. Therefore, the currently under development version IFC4.3.1.x dev with the newest documentation is used (buildingSMART, 2022b). The entities from the IfcProductExtension of the core data schemas for bridge-specific parts, including precise enumerations of different types, and general entities from the shared element data schema are used. Furthermore, the segmentation classes are linked to relevant bridge parts of the manual bridge inspection using the fifteen-digit-long numbers of the ASB-Ing.

### Application example

To show the application of the listed classes on real bridge PCD, bridge 2 of the above-mentioned Cambridgeshire (Lu, Brilakis & Middelton, 2019) dataset was randomly chosen. The manual semantic segmentation and coloring of the points was carried out with the open-source software CloudCompare (cloudcompare.org). Figure 1 shows the raw RGB data of bridge 2 from the Cambridgeshire dataset on the left-hand side. For visualization noise points from scanning and background points of no interest were removed. Only the relevant points for the listed structural classes were obtained. The bridge PCD was cut into various smaller point clouds, containing the specific bridge parts to be labeled, by using the implemented segmentation tool. Afterwards, the sliced sub-point clouds of the bridge parts were colorized with the listed Hex Color Code. The result can be seen in Figure 1 on the right-hand side. To highlight the result of the different approaches with more detailed segmentation classes, Figure 2 shows a cross-section of the application example bridge 2. In this detail, the bridge caps on both sides of the roadway can be seen in a slightly darker blue (207EA0). Bridge caps belong to important bridge components in terms of inspection and maintenance. Therefore, they should play an important role in semantic segmentation and automated bridge reconstruction in BIM.

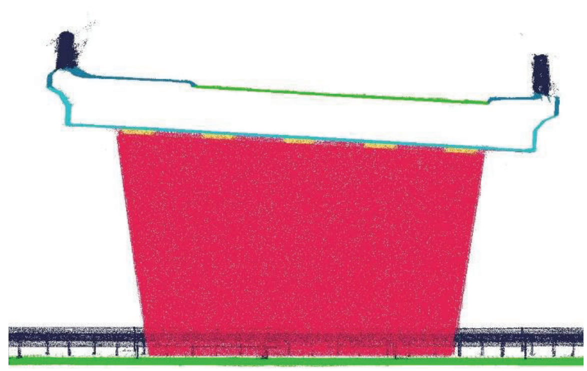

*Figure 2: Cross-section of the semantic segmented point cloud of bridge 2*

Furthermore, the bearings (F2DE61) of the superstructure can be identified on top of the pier (E12752) in Figure 2. By recognizing structurally important parts as the bearing the reconstructed BIM reaches a higher level of detail and usability for practical bridge inspections. Besides the manual annotation of bridge 2 the approach with the also in CloudCompare (cloudcompare.org) implemented RANAC (Schnabel, Wahl & Klein, 2007) Shape Detection plugin was tested. The main idea of the RANSAC algorithm is the detection of simple primitives, as planes, spheres, cylinders, cones or toruses in sparse point cloud data. Within the range of different parameters possible primitives are fit in. In the implemented dialogue the minimum number of support points per primitive has to be set. In case of the shown example this number was randomly set to 10.000 points. As primitive to be detected,

*Table 2: Classes/ Labels of important bridge components for semantic segmentation of bridge point cloud data*

| Class/Label | Description/Rule | Color-Hex | Possible IFC representation | ASB-ING-Nr. |
|---|---|---|---|---|
| roadway | asphalted top layer of superstructure | 29C70D | IfcBuildingElementProxy | 130023193000000 |
| concrete_deck/ concrete_slab | slab-like superstructure made out of concrete with width/height > 5 | 2AC3D1 | IfcSlab IfcBridgePart[TypeEnum(Deck)] | 130011111100000 |
| concrete_beam | mostly rectangular beams made out of concrete, incl. Piercaps | 20CAAA | IfcBeam | 130011121200000 |
| steel_beam | mostly with specific steel shapes, like I-frame or C-frame etc. | 53E7E3 | IfcBuildingElementProxy | 130011131420000 |
| box_girder | box girders made out of concrete, just girders without horizontal slab on top | 2E88F6 | IfcBeam | 130011141000000 |
| tendon | steelcable to prestress a structure | ED23ED | IfcTendon | 130021110000000 |
| foundation | foundation of the bridge/ piers etc. | AE11ED | IfcFooting IfcBridgePart[TypeEnum(Foundation)] | 130021200000000 |
| piers | vertical, load bearing elements, like piers/columns | E12752 | IfcColumn IfcBridgePart[TypeEnum(Pier)] | 130011920000000 |
| bearing | bearing between superstructure and load bearing elements, like wingwalls/abutment or piers | F2DE61 | IfcBearing | 130021500000000 |
| rail | rails around the bridge for security of bridge | 26284C | If Railing | 130022100000000 |
| joint | bridge expansion joint; gap between roadway and street to secure temperature deformation between the bridge and connecting street | F8F80C | IfcDiscreteAccessory | 130021600000000 |
| caps | not driveable edge of the superstructure where the rails are mounted on and to secure the superstructure before outer impact | 207EA0 | IfcBeam IfcBeam[TypeEnum(Edge beam)] | 130021800000000 |
| abutment | concrete walls that secures the transition between bridge and connecting street, incl. Ground incl. Transition of forces to the ground from bearings/superstructure | C42BDD | IfcWall IfcBridgePart[TypeEnum(Abutment)] | 130011910000000 |
| stairs | stairs e.g. along the abutment | 04FA3F | IfcStairs | 130016300000000 |

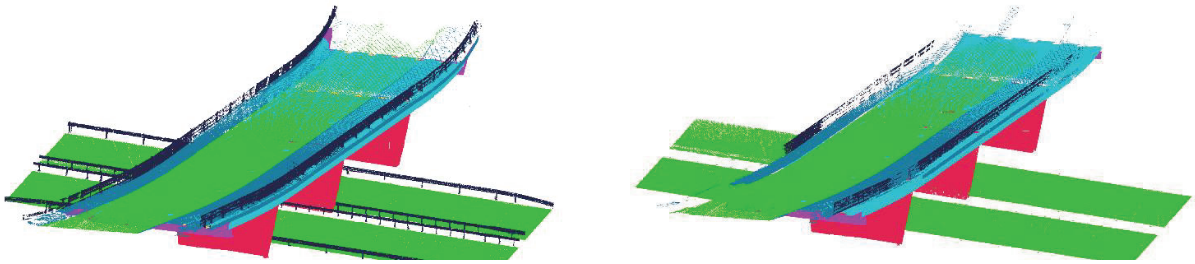

*Figure 3: Example of the manual annotated point cloud data (left) and approach with the RANSAC Shape Detection plugin (right) of bridge 2 (Lu, Brilakis & Middelton, 2019)*

just planes were chosen, due to the fact, that the main parts of the bridge consist of planar areas. Furthermore, advanced parameters must be set. The maximum distance of points to the primitive (e = 0,333) and the sampling resolution (b = 0,666), that basically sets the maximum distance of one point to the next point to be still counted within the primitive. Moreover, the maximum normal deviation angle (a = 10°) in degree, that compares the direction of the point normals to each other and finally the overlooking probability (0,01), that secures that no better primitive for the considered candidate is overlooked. For a first segmentation try the default values for the advanced parameters were used. The comparison of the manual segmentation and the results of the RANSAC Shape Detection plugin are shown in Figure 3. Due to a minimum number of points a primitive has to include, the resulting, segmented point clouds contain less points than the ground truth. In the shown example 18,7 % of points of the ground truth do not fit into a primitive with the chosen parameters and get lost. Figure 3 shows good results for planar areas as the roadways, piers or slabs. Smaller, non-planar parts, as rails or bearings loose points as well or get lost in total. By refining the inputs with a parameter study the results of the RANSAC Shape Detection plugin could be improved. This can add value to the laborious and time-consuming work of manual point cloud annotation.

## Conclusion and Outlook

The proposed paper provides an overview of the related work in the field of semantic segmentation of bridge PCD for (semi-)automatic reconstruction and digitalization of existing bridge infrastructure. Therefore, highly crucial, open-source available datasets of PCD were researched and listed. Furthermore, different scientific approaches using heuristic and machine learning methods are focused on, and the specific considered classes are highlighted. To link the theoretical, digital field of semantic segmentation of PCD with usability in practice, the standard manual approach of German bridge inspection is analyzed. Finally, a proposal for important bridge parts as classes for the semantic segmentation of bridge PCD is developed. These specific bridge parts are linked to possible representations in the IFC schema and the German ASB-Ing for manual bridge inspection. Additionally, descriptions and rules for the different classes are given. As an application example, the point cloud of bridge 2 from the Cambridgeshire dataset is used to show a possible semantic segmentation with the more detailed and proposed classes. Therefore, the point cloud was both fully manually segmented, and the RANSAC Shape Detection algorithm was used for segmentation. The RANSAC Shape Detection provides good results for the segmentation of bridge parts, with a loss of 18.7% of points from the ground truth. Additionally, some labeling work needs to be done after segmentation. By using the listed classes for semantic segmentation of bridge PCD, a common ground for the annotation of future datasets is proposed. By focusing on the same classes, different approaches can be more easily and thoroughly compared with each other. Furthermore, the results will gain higher relevance and value for practical use. In future research, the various methods listed can be evaluated using the proposed detailed classes to compare their accuracies.

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