TwinGen: Advanced technologies to automatically generate digital twins for operation and maintenance of existing bridges

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ABSTRACT: The high effort of operating and maintaining existing infrastructure facilities resulted in a large stock of structurally deficient bridges in most industrialized countries. Today, the condition assessment of bridges is conducted mostly manually. To relieve effort and costs, the digitization and automation of conventional manual, labour-intensive methods is necessary. We interpret the ambiguously used term "digital twin" (DT) in this study as a semantic-geometric model of an existing asset (here, a bridge) that contains all information required for assessing its current condition. This paper proposes an approach to automatically generate the DT of existing bridges from point cloud data (PCD) and images captured from the structure. The PCD of the bridge is semantically segmented by means of ML techniques, and a digital model is created using parametric modeling. Subsequently, detected damages and data from existing bridge maintenance systems are linked to the model to create a full DT. This paper reports the main results of the TwinGen research project: The digital twinning process of bridges can be automated to a large extent, in order to efficiently support the maintenance process of bridges.

1 INTRODUCTION

In the transportation infrastructure of industrialized countries, there is a large stock of aging bridges that requires maintenance. The recent ASCE's report card (ASCE 2021) shows that the number of deficient bridges is increasing as the deterioration rate exceeds the rate of repair, rehabilitation, and replacement. Following the structural provisions (AASHTO 2020), the condition of existing bridges needs to be assessed at regular intervals over the service life of the structure. This condition assessment process generally results in a rating system that provides a basis for decision-making on the possible rehabilitation of the structure. Despite the feasibility of the existing techniques for assessing bridges, they are loosely and only partially supported by digital methods.

In the architecture, engineering, construction and operation (AECO) industry, building information modeling (BIM) has revealed tremendous applications by representing the digital description of the structure throughout its life cycle. As one of the most promising recent developments, BIM is able to significantly improve the design and construction phase of projects. To do so, a building information model contains the geometry and corresponding semantic data to support the design and construction activities (Eastman et al. 2011). In recent years, there have been concerted efforts to optimize and create BIM for the as-designed and as-performed phases of the structures (Zhu et al. 2010). However, the lack of comprehensive and descriptive methods in the as-is phase is still tangible (Technion 2015, Sacks et al. 2016, Sacks et al. 2018).

The "Digital Twin (DT)" concept, originating from the manufacturing industry (Negri et al. 2017), is concerned with a virtual model representing the digital counterpart of an existing object or a system. In the domain of digital construction, a DT can be defined as a geometric-semantic model that provides a coherent replica of the existing structure in its as-performed or as-is phases. This descriptive model reflects the interaction of humans with the structure and is updated at specific intervals (Pan et al. 2019). For bridges,

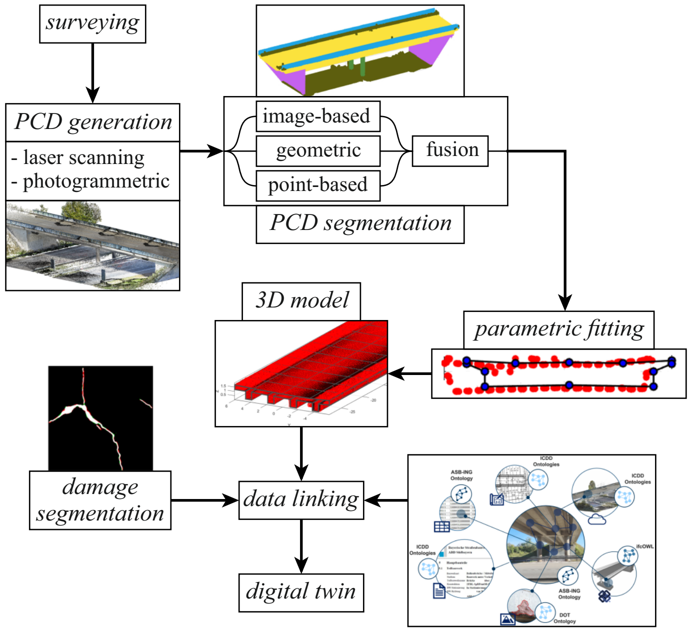

Figure 1: Workflow developed the TwinGen project to create digital twins.

these intervals can be longer as the physical features of the assets change gradually (Mafipour et al. 2021). The DT of an existing bridge is formed by a semantically rich 3D model linked with information from the inspection and condition assessment of the bridge. This 3D model contains the geometric features as well as semantics that correspond to the collected information from the construction site. This information can include cracks, possible areas of defect, and their location on the body of the structure. This descriptive data as well as construction documents such as drawings and specifications can be interrelated with their digital counterpart in the DT. Compared with a conventional bridge management system, a DT is highly flexible, up-to-date, accessible, and information is made accessible for interpretation and analysis by domain experts. The DT encompasses current descriptive details of the existing structure and provides a basis for the involving team members to collaborate efficiently and make decisions more accurately.

Considering the application phase of a DT, it is generally created based on the data demonstrating the current status of the structure. Laser scanning and photogrammetry are two common methods that are utilized for capturing the existing assets. The resulting point cloud data (PCD) from these techniques shows the geometrical and topological conditions of the structure. The PCD can be used for model reconstruction and spatially localizing crack regions (Valença et al. 2017). Images, on the other hand, can depict the defect areas on the body of the structure and be used as a data source for the detection of the various forms of deterioration. In comparison with a visual inspection, these techniques can capture the existing asset in a lower time with higher measurement accuracy. Also, the labouring costs decrease as they need a lower number of people for data collection (Zhu et al. 2010). In addition to this data, information from existing conventional management systems, 2D-drawings and previous damage reports can be taken into account. Despite the potential applications of DTs in the operation and maintenance phase of bridges, they are not available yet for many existing bridges. Also, the manual process of digital twinning is error-prone, labor-intensive, and time-consuming. To benefit from the advantages of DTs, the creation process of these models need to be automated or at least semi-automated.

This paper aims to propose an end-to-end approach to automate the Digital Twinning process of existing bridges as developed in the TwinGen research project (1). PCD and images captured from existing bridges are utilized as the main sources of data. As the first step, the PCD is semantically segmented to provide the point cloud of each bridge element separately. For this purpose, three different methods including image-based, geometric, and heuristic point cloud segmentation are proposed. Next, the segmented elements from the point cloud are used for creating a digital model by using parametric modeling techniques. A prototypical parametric profile of the bride elements is created and instantiated with random values in reasonable ranges inspired by bridge engineering knowledge. These profiles are then optimized by a metaheuristic algorithm to be fitted into the PCD. In the next part of the process, captured images from the body of bridges are used and a deep learning model is trained to detect four common types of damage in bridges. Finally, the technical information of the structure including documents of the planning and building phase as well as the semi-structured inspection data from the last decades are linked to the model.

2 POINT CLOUD SEGMENTATION

The proposed Scan-to-Twin process of bridges can be divided into two separate steps of semantic segmentation and parametric modeling. Semantic segmentation is the process of assigning points in PCD to different predefined object classes. Semantic segmentation of a bridge PCD results in point clusters that represent the bridge elements (e.g., wing wall, piers, etc.). In recent years, there have been efforts for automating the segmentation process of bridges. The proposed methods can be divided into image-based, point-based, and heuristic segmentation. Lu et al. (2019) employed a heuristic top-down approach to detect the bridge elements in the point cloud of concrete bridges. Hu et al. (2021) elaborated a hybrid image-based-geometric point cloud segmentation method to extract features from images and train a multilayer perceptron (MLP). Qin et al. (2021) applied a density-based heuristic algorithm to detect elements in the point cloud of bridges. As a geometric approach, Lee et al. (2021) added contextual features of points to improve the accuracy of PointNet (Qi et al. 2017) and deep graph-convolutional neural network (DGCNN). Yan & Hajjar (2021) introduced a heuristic algorithm based on the existing connection rules in the the point cloud of steel bridges for semantic segmentation. Xia et al. (2022) defined a local descriptor to calculate the local features of points for semantic segmentation of bridges through a geometric method.

2.1 *Image-based Point Cloud Semantic Segmentation*

The workflow for image-based point cloud segmentation consists of four stages: neural network training, semantic image segmentation, 3D projection and post-processing. For semantic image segmentation Mask R-CNN, a high-quality network capable of predicting object classes and segmentation masks, has been chosen. However, training data sets for bridge components do currently not exist, therefore a Mask R-CNN pre-trained on the Microsoft COCO data set (Lin et al. 2014) has been used as a foundation. To adapt the network for the underlying problem, transfer learning is used to have the network predict the three bridge components deck, abutment and railing. For this process, a small data set consisting of roughly 600 hand-annotated images is used for training, with typical data augmentation operations aiding in making the resulting classifier more robust.

For transferring the image masks to the 3D point cloud, the intrinsic and extrinsic parameters describing camera position and projection parameters are required and must be collected during surveys alongside image and point cloud data. Using these parameters, the 2D classification masks and 3D point cloud data can be projected into a common coordinate system such that points overlapping with the masks can be labelled accordingly (result shown in Figure 2). Furthermore, this step also allows for the generation of a depth map for each camera which is key for skipping points occluded or non-visible points during the labelling process. Problems arising from conflicting labels are resolved through use of majority voting and result in a robust semantic segmentation where bridge deck, abutment and railing are labelled accordingly, while background objects are being ignored.

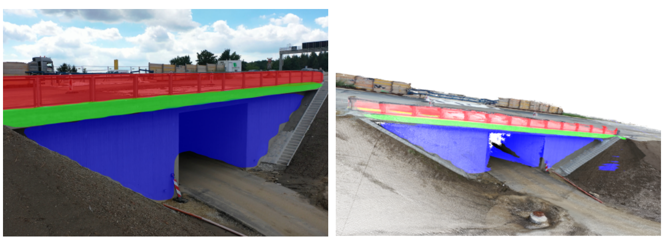

Figure 2: Results of image-based point cloud segmentation: segmented image (left), point cloud with projected labels (right).

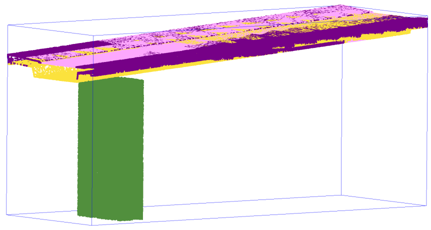

Figure 3: Results of point-based point cloud segmentation: Pier (green), grider (yellow), cap (purple) and deck (pink) are distinguished.

2.2 *Point-based Point Cloud Semantic Segmentation*

Alternatively and complementary to image-based classification, machine learning algorithms can be used to segment the PCD through point-level processing. To do so, the following approach, consisting of three different parts, is proposed: 1) Preprocessing of the point cloud data, 2) Classification of points, and 3) Consolidation of predictions.

A bridge is a linear structure, meaning that the main expansion of the construction is horizontal in most cases. In addition, most of the components are oriented along the alignment of the transferred traffic route. Building on this observation, the first preprocessing step is to align the point cloud so that the long axis of the bridge is parallel to the spatial x-axis. To achieve this, principal component analysis (PCA) is applied. PCA finds the vector with the largest variance across the points, which corresponds to the x-axis of the structure. Assuming that the z-axis of the point cloud already matches the z-axis of the bridge, the point cloud is then rotated around the z-axis so that the variance vector and the spatial x-axis lie on top of each other. For point clouds of compact bridges that are not longer than wide, the minimum axis-oriented bounding box is used for orientation. Next, the point cloud is normalized to a unit cube. At the same time, the point cloud is shifted so that the lowest point on the far left lies at the origin of the three-dimensional space.

The goal of the next step is to employ a PCD neural network to classify the points into the classes girder, bridge cap, deck and pier. In our study, we use of PointNet (Qi et al. 2017) – a well-known point-cloud classifier. To employ the neural network for point classification, it must be trained once in advance. As the number of available labelled data sets from real-world bridges is insufficient for training, we create synthetic point clouds and use them as training data. They are generated by simulating virtual laser scans (Winiwarter et al. 2022) on various parametrically created 3D bridge models. Since PointNet requires a fixed input vector size, a grid of voxels is placed in 3D space. Within each voxel, a fixed number of points is randomly sampled.

The predicted point labels as shown in Figure 3 are projected onto the points that were not sampled by the algorithm. This is done by searching for the nearest

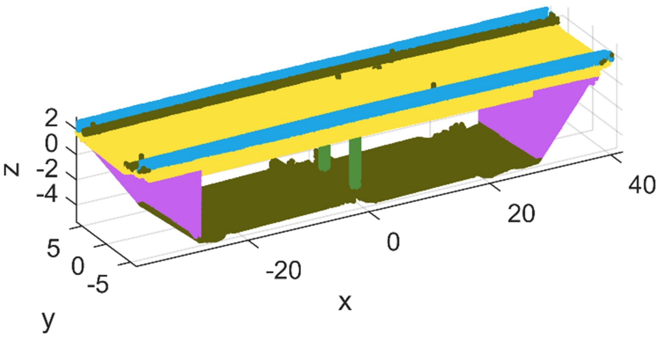

Figure 4: Results of heuristic point cloud segmentation: Railing (blue); Deck (yellow); Abutment (purple); pier (green); Noise (dark green)

labeled point using K-nearest neighbors (KNN) in the point cloud and transferring the class labels.

When training is finished using the synthetic point clouds, the resulting trained network can be employed on any number of real-world bridges.

2.3 *Heuristic Point Cloud Semantic Segmentation*

Alternatively, heuristic approaches can be applied for PCD segmentation. Most of the existing elements in bridges are either horizontal or vertical. Vertical elements such as piers and abutments have the role of transferring live and dead loads of the structure to the ground. These elements are generally placed with some space along the length of the structure. Based on these observations, a heuristic algorithm is proposed following two assumptions: 1) the deck of the bridge is almost horizontal and 2) no point exists over the railings and sides of the bridge.

In the first step, the bridge is aligned with the x-axis and histogram of density along the z-axis is calculated. Due to the existence of road surface and ground two sharp peaks in the signal of flat bridges is observed. The points over the last peak and under the first peak are considered as railing and ground, respectively. Next, the railing points are refined by calculating the density of points along the y-axis and extracting the first and last sharp peaks as railing instances. To detect the points of the deck, all the remaining points (sub-structure) are projected onto the *yz* plane. Next, the local density of points in a circle with a predefined radius is calculated. Due to the horizontal alignment of the deck and the impact of overlaying points after projection, the density of the deck points is higher. This feature can thus be used to segment the points of the deck. To this end, a fuzzy c-means (FCM) algorithm is employed with two clusters.

After clustering, the cluster with higher mean along the *z-axis* is considered as the points of the deck. To detect piers and abutments from the remaining points, a region growing algorithms based on the connectivity of points is proposed. In this algorithm the nearest neighbors of each point is calculated by a kd-tree and KNN. Next, the relative distance of each point to its neighbors is computed. Any neighboring point that is located in a predefined radius with respect to the query point is added to the same cluster. Applying this algorithm to the remaining points (sub-structure) results in clusters in which points satisfy the conditions of connectivity. To detect the clusters of interest, i.e. abutments and piers, out of all the clusters, the AABB of each cluster is calculated and its height is compared to the height of the sub-structure. The clusters with a close height to the sub-structure are finally extracted as piers and abutments. From these clusters, the first and last clusters along the x-axis are considered as abutments and other remaining clusters as piers. Throughout this segmentation process, every cluster that does not meet the predefined conditions is identified as noise. Figure 4 shows the visual results of applying the heuristic algorithm to the PCD of a multi-span bridge. For this sample, a radius of 15 cm for calculating the local density and 75 neighbors for KNN were considered.

2.4 *Comparison of segmentation methods*

Image-based, point-based, and heuristic methods can be used for semantic segmentation of bridges. Each of these methods, however, comes with its own advantages and disadvantages.

Heuristic methods, in contrast to the two other methods, are unsupervised and do not need an annotated dataset for training. Nevertheless, their success is diminished if the underlying assumptions are not fulfilled, as most heuristic algorithms are tailor-made to deal with specific scenarios, expect certain geometrical properties and are not designed to deal with background objects. This implies that these rules exploited by the heuristics could also be used to validate existing PCD segments.

Image-based segmentation is based on deep learning on the image dataset of bridges. In this method, the predicted labels of images are transferred to the points of the corresponding PCD. Due to the availability of images, providing large dataset is more straight forward than laser scanning PCD. However, it requires the corresponding images and camera parameters as well. Furthermore, a post-processing step is necessary to project the image labels to the respective PCD. While it is quite efficient at dealing with background objects, borders of the detected regions may overlap, leading to slight fuzzyness, especially for far-away objects. This makes a robust, but slightly coarse segmentation method.

Point-based segmentation is also a deep learning method that directly uses the PCD dataset of bridges and predicts points label. This method has high accuracy, is consistent and memory efficient. It is also highly flexible and generic as it learns the pattern of points in PCD. However, it requires a large dataset of annotated point clouds for training, which is laborious to obtain. In addition, the available deep learn-

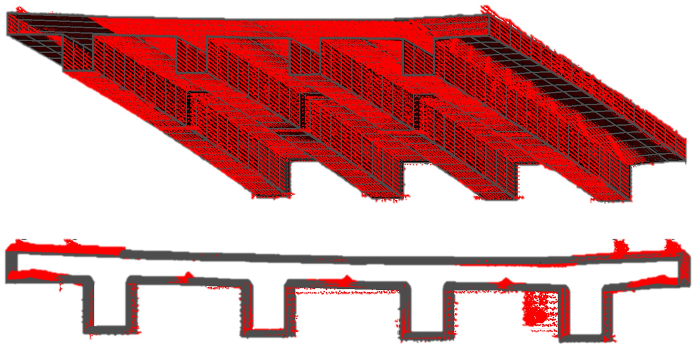

Figure 5: Results of parametric modeling for a four-girder deck.

ing models are usually limited when processing large point clouds. However, unlike the image-based approach, it requires pre-processing and expects the PCD to contain the bridge without background objects.

3 MODEL FITTING

The semantically segmented point cloud produced by the aforementioned methods is not yet sufficient for a digital twin. Instead a high-quality model is required providing solid volume geometry and consistent spatial relationships. To achieve this, we developed the approach of fitting predefined parametric prototype models into parts of the segmented point cloud.

Parametric modeling is the process of creating a model with the capability of changing shape when dimensional parameters are updated. A parametric model contains a finite number of parameters with constraints that preserves the desired shape of the object while being updated. Recently, there have been efforts to automate the modeling process of bridges (Qin et al. 2021, Lee et al. 2020, Lu et al. 2019). The proposed methods, however, have been mostly limited to primitive shapes. Bridges generally consist of complicated elements such as deck and abutments that cannot be simply defined by 3D primitive shapes.

To address this issue, a *model-based* approach is proposed which is also capable of parametric modeling bridge elements. As the first step, the prototype of the element of interest is created. Each profile is defined by a set of parameters that determine the location of vertices on a 2-D plane. To meet the requirements of a parametric model, geometric constraints such as orthogonality, symmetry, and parallelism are applied to the profile. As a result, a parametric profile is obtained with a finite number of parameters which is completely dependent on the input values. This profile is to be capable of updating its shape when the input values change. As the next step, the value of parameters in the dummy profile is adjusted so that the profile can be fitted into the cloud. To this end, the minimum distance of edges and vertices of the profile to the PCD is minimized. Since these profiles are not in the form of primitive shapes, their parameters cannot be directly seen in the cost function of the problem. As a result, gradient-based algorithms that require the partial derivatives of the objective function cannot simply solve the problem.

Particle swarm optimization (PSO) is a metaheuristic and derivative-free algorithm (Kennedy and Eberhart 1995). In PSO, a swarm of particles is randomly generated and distributed in the n dimensional space of the problem. These particles are then updated based on their best local and global locations. For cloud fitting, every particle is a parametric profile and a swarm is a set of parametric profiles. To instantiate the profiles, the value of parameters are randomly distributed in the ranges inspired by bridge engineering knowledge. Next, these values are adjusted by PSO to minimize the distance of profile to the PCD. Finally, the best solution, i.e. the profile with the minimum distance to the points, is reported as the fitted model. The parameters after cloud fitting represent an approximation of the values corresponding to the parameters of the cloud. Figure 5 shows the results of cloud fitting to the point cloud of a deck with four girders. To fit this model, a dummy parametric profile compatible with the point cloud is created. For a more precise estimation of parameters' values, the PCD of the deck is sliced along its length. Next, the parametric profile is fitted into every slice of the cloud by PSO. Finally, the average value of parameters after removing outliers is used to create the 3D model of the deck.

4 DAMAGE SEGMENTATION

Machine learning-based semantic segmentation can streamline the inspection process and provide detailed information and consistency in the damage evaluation. Many approaches were suggested for the segmentation of concrete cracks as in (Chen and Lin 2021, Çelik and König 2022). Some few publications deal with a wider range of damage types. In (Li et al. 2019), a fully convolutional network (FCN) is trained on 2750 images of size 504 × 376 pixels to segment cracks, spalling, efflorescence, and holes. The FCN yielded 84.53 % mean intersection over union (mIoU). In (Kim and Cho 2020), Mask R-CNN is trained on a data set of 765 images with sizes ranging from 600 × 600 to 2000 × 2000. The data set encompasses cracks, spalling, efflorescence, and reinforcement exposure. Mask R-CNN achieved 87.24 % precision and 87.58 % recall. Yet, in another publication (Miao et al. 2021), a U-Net-like network is proposed for the segmentation of cracks, spalling, concrete crushing, reinforcement exposure, buckling and fracture. The corresponding data sets consist of 2782 images of size 300 × 300 for crack and 3530 images of size 300 × 300 for other damage types. A mIoU of 70.11 % and 71.12 % was achieved, respectively.

In the framework of this project, we conducted a study on the recognition of damage to bridges. Firstly, a concrete damage data set of 2642 images with image size 1024 × 1024 was created. The damage images are from multiple concrete structures such as

Table 1: Prediction results by FPN (first columns) and DeepLabv3+ (second columns) for four damage classes.

Class	Precision		Recall		IoU	
SPAL	79.83	72.72	88.80	87.45	72.50	65.85
CR	68.32	66.85	78.51	75.16	57.56	54.75
COR	81.08	72.35	80.71	78.57	67.92	60.43
HON	81.43	75.88	81.30	74.33	68.58	60.13
Mean	77.67	71.95	82.32	78.88	66.64	60.29

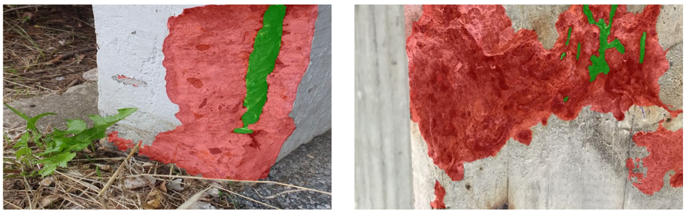

Figure 6: Segmentation results by FPN: a common damage structure (left) and a complex damage structure (right).

parking ramps, walls, bridges, and pedestrian paths. The labels of the data set include the damage classes spalling (SPAL), crack (CR), corroded steel (COR), and honeycomb (HON). The data set labels do not reflect the exact granularity of the damage labels according to the German DIN standard 1076 for bridge inspection. The labelling according to the DIN standard requires expert knowledge, which is not affordable, as the labelling of images is time- and labour-intensive. An alternative solution was the initial labelling of damage images by undergraduate students. The labels were chosen such that students could differentiate the corresponding damage visually.

Two state-of-the-art segmentation networks were trained on the data set. These are Feature Pyramid Network (Lin et al. 2017) and DeepLabv3+ (Chen et al. 2018) with ImageNet-pre-trained EfficientNet-B0 (Tan and Le 2019) weights in the encoder of each segmentation network. The initial learning rate of the networks was set to 10^{-4} with a reduction schedule and an early stopping schedule for learning stagnation. The batch size was 4, and the epoch size was 200 epochs. The dice loss was used as a loss function, and the Adam algorithm was used for optimization. The data set was split into a training set ($80\,\%$) and a validation set ($20\,\%$). To augment the training set, we applied rotation with $90°$, $180°$, and $270°$ on each image.

The model results were evaluated with precision, recall, and IoU for each damage class and the mean values over all damage classes. In Table 1, it can be seen that FPN gives constantly better results than DeepLabv3+. Both models provide the highest results for spalling and the lowest results for crack. Generally, honeycombs are slightly better segmented than corroded steel. Based on the results on test images, the following explanations regarding the results in Table 1 can be made: a) Spalling can be segmented best as it is of a relatively large area with a simpler form than crack and corrosion (see the left image in Figure 6). b) Cracks are segmented with the lowest results, as cracks are more intricately formed and take the smallest area (data imbalance). c) Corroded steel objects can be small and have intricate forms that can be challenging to recognize, especially if the corrosion discolours the concrete (see the right image in Figure 6). d) The differentiation between honeycomb and spalling is challenging, as both can merge seamlessly. Well-labelled, more complex data and optimized data pre-processing can improve the results. Further steps will be the size measurement of damage instances and the refinement of the labelling. The latter includes the class refinement (e.g. not only corrosion but corroded exposed reinforcement bar) and the damage degree assessment according to DIN 1076.

5 DATA LINKING AND MODELLING

In order to create common information spaces for legacy information as well as novel reality capturing and interpretation data presented in earlier sections, a comprehensive information model was devised. This model incorporates available and relevant data necessary to represent the existing bridge and its current state accurately and can be considered as a DT.

To achieve object-level linking between the heterogeneous data obtained from the presented methods, Linked Data approaches are used. They enable to link elements of the geometry model to the corresponding sections from the point cloud, and damage information to defined segments of damage pictures.

As the DT represents the entire life span of the bridge, the existing data set from the asset documentation and inspection must be considered in addition to the newly acquired data. The existing data contain technical information about the asset, planning and building phase documents, and semi-structured inspection data from the last decades. Thus, it complements the newly captured data with essential information.

To capture the wide range of heterogeneous, cross-media information ranging from inspection data to construction documents in interoperability formats, a structured vocabulary is required. Several ontologies have been proposed in the past that can be used to represent the 3D model and the segmented damage pictures, including ifcOWL (Beetz et al. 2009) and the Damage Topology Ontology (DOT) (Hamdan et al. 2019). However, as we want to include legacy bridge and inspection documentation into the model, we decided to convert the existing national data model for bridge documentation into an ontology.

In Germany, the authoritative data model for infrastructure asset documentation is the *Anweisung Straßeninformationsbank, Teilsystem Bauwerksdaten (ASB-ING) [engl.:Instruction for the Road Information Database, Subsystem structural data]* (Bundesministerium für Verkehr, Bau und Stadtentwicklung, Abteilung Straßenbau. 2013). It is an extensive domain model with 120 classes, 80 datatype definitions, and 500 properties, capturing information pertaining to structure and inspection, including condition assessments, damages, and maintenance measures. The data model is implemented in the national German database application for bridge (inspection) documentation *Staßeninformationsbank – Bauwerke (SIB-Bauwerke) [engl.: Roaddatabase – Structures]* (WPM-Ingenieure GmbH).

Using the existing ASB-ING domain model, we derived the ASB-ING Ontology (Göbels and Beetz 2021) that contains all the original model's classes, properties, relations, and constraints and represents them using RDF(S) and OWL vocabularies. Based on this ontology, we implemented an automatic conversion process of the inspection datasets stored in *SIB-Bauwerke* into the Linked Data format (a Resource Description Format (RDF) graph) (Göbels 2021).

The graph of each inspection data set contains general asset information, building element objects, and recordings of all damages, measures, and condition assessments since the bridge's construction. Compared to the original data structure of *SIB-Bauwerke*, the key advantage of the graph representation is the object-oriented structure, which allows appropriate, precise linking to other resources. Concurrently, it is still backward compatible with the mandatory ASB-ING data model.

Nevertheless, the converted graph only reflects the same depth of knowledge as the original data. There are no links between damages and the affected elements, and it is challenging to track damage and element conditions properly. To improve the information quality, the advantage of Linked Data becomes essential. By querying and inferring the graph's data, missing links are generated, and by integrating external ontologies, proper data traceability and damage documentation are implemented.

We link the inspection data graph with the results of the point cloud segmentation, model fitting and damage segmentation, as well as, with the existing 2D plans and damage pictures 7. To include these resources into the Linked Data model, we use the ifcOWL Ontology to represent the geometry model and the vocabularies of the ISO-standard *Information container for linked document delivery (ICDD)* (ISO 2020) to reference the documents. The segmented damage pictures can be added to the Linked Data model by employing the DOT Ontology.

To automate the process of linking, we use a mapping between IFC (Bridge) and the ASB-ING Ontology. Combined with location specifications of elements and damages in each bridge data set, links between the geometry model elements and the inspection data objects are implemented.

The linking of these two resources already creates significant benefits. The legacy tabular inspection data are enriched with spatial representations, which improves the inspection process, as the location of damages can be easily retrieved. On the other hand, the geometry model is enhanced with material and type specifications from the bridges' documentation data.

In ongoing work, a prototypical application that displays and processes the geometry model together with the linked semantic information and documents is developed. It will enable the execution of space-, time-, and object-based queries and analyses.

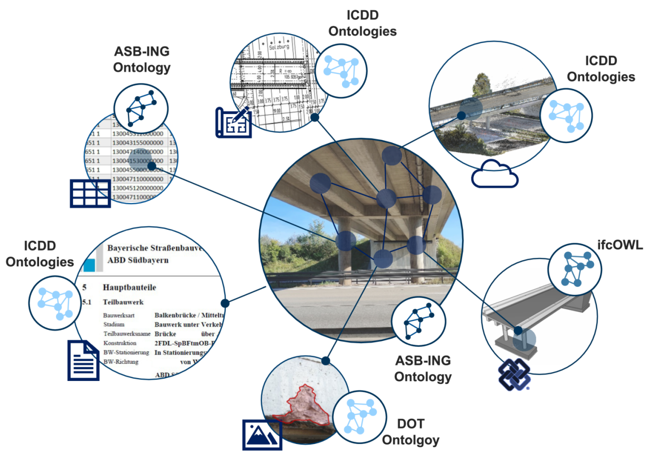

Figure 7: Linked Data model of heterogeneous data sources.

6 CONCLUSION AND OUTLOOK

Bridges are critical structures and require regular maintenance during their service life to allow secure and long-term use. The conventional methods for data collection, condition assessment, and management of existing bridges are loosely and only partially supported by digital techniques and require a high manual effort. As a result, the number of deficient bridges that need essential attention increases. To relieve the costs associated with bridge maintenance and operation, a digital twin (DT) of existing bridges can be created. DTs are highly flexible and interpretable and can provide all the information required to evaluate the existing bridges.

This paper proposes algorithms and techniques to facilitate the digital twinning process of bridges. Point cloud data (PCD), images, and existing bridge documentation as the main data sources showing the current conditions of existing bridges have been used. The PCD is processed by image-based, geometric, and heuristic semantic segmentation to obtain the point cloud of each element in bridges. These clouds are then fitted by particle swarm optimization (PCD) to create the 3D model required for DTs. Captured images from the body of the structure are also processed by deep learning models to detect and recognize the type of damage. Finally, the 3D model and the captured damage pictures are linked to the existing inspection and construction data to provide a DT model that is interpretable in regard to geometric and semantic information. The paper results show that the digital twinning process of existing bridges can be automated to a large extent. These models can efficiently support the maintenance process of the bridge and reduce costs. However, the proposed algorithms still need to be tested on more samples of bridges to provide a robust tool for the automatic creation of DTs for various bridge types.

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