Creating digital twins of existing bridges through AI-based methods

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Abstract

Bridges require regular inspection and maintenance during their service life, which is costly and time-consuming. Digital twins (DT), which incorporate a geometric-semantic model of an existing bridge, can support the operation and maintenance process. The process of creating such DT models can be based on Point cloud data (PCD), created via photogrammetry or laser scanning. However, the semantic segmentation of PCD and parametric modeling is a challenging process, which is nonetheless necessary to support DT modeling. This paper aims to propose a segmentation method that is the basis for a parametric modeling approach to enable the semi-automatic geometric modeling of bridges from PCD. To this end, metaheuristic algorithms, fuzzy C-mean clustering, and signal processing algorithms are used. The results of this paper show that the scan to BIM process of bridges can be automated to a large extent and provide a model that meets the industry's demand.

Keywords: bridge; digital twin; building information modeling; semantic segmentation; parametric modeling; artificial intelligence; metaheuristic algorithms; fuzzy C-mean clustering

1 Introduction

In building information modeling (BIM), a digital twin (DT) can be defined as the high-level digital replica of an existing asset. This model coherently contains the geometric and semantic information of buildings, infrastructures, and built environments and is updated regularly [1, 2]. It also visualizes all the gathered information from the construction site and provides an appropriate basis for inspection, condition assessment, and rehabilitation.

Bridges, as critical structures, require regular inspection during their service life. In current practice, these inspections are conducted through direct observation at the location of existing bridges. However, this process has disadvantages: 1) some elements of bridges are not easily accessible or even observable, 2) the results of inspection might be subjective, 3) data management after detecting the possible defects is not simple, and 4) localizing any defects or potential problem areas is not possible. To support direct inspection, capturing methods such as laser scanning and photogrammetry can be employed. Compared with a visual inspection, these methods are faster and have higher measurement accuracy [3]. The resulting point cloud data (PCD) of these scanning methods can be used for creating the digital twin models of bridges [4-8]. The DT of a bridge visualizes the existing structure's current status and provides a basis for monitoring and further analyzing elements based on their current conditions. Despite the advantages of digital twins and recent scanning methods, digital twinning based on PCD is not easy. To create the DT of a bridge, the PCD of the corresponding bridge needs to be semantically segmented, and the instance model is instantiated based on a parametric model. Both of these steps are costly, labor-intensive, and error-prone.

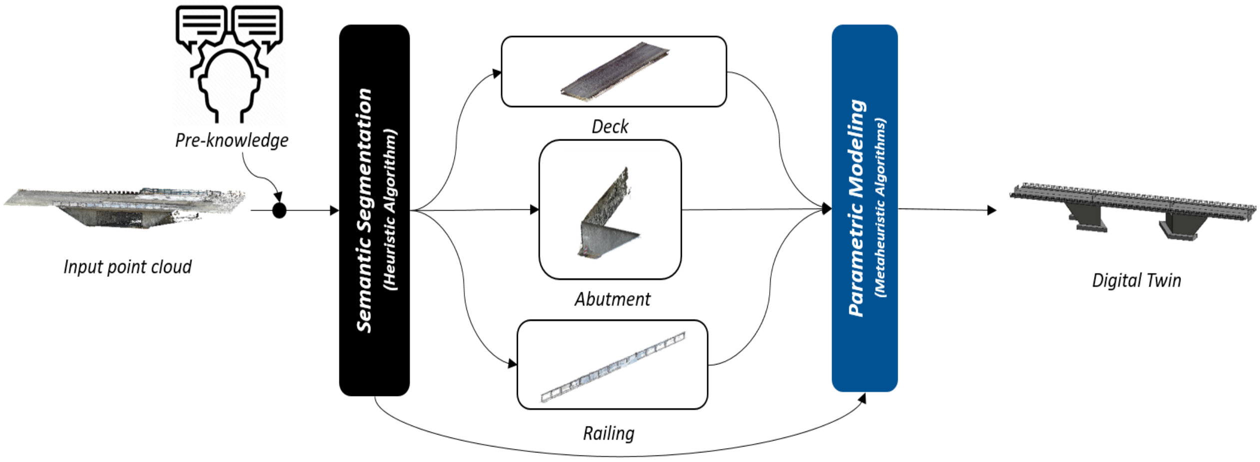


Figure 1 Proposed processing workflow

Hence, authorities do not usually invest in the high costs of digital twining and still prefer the conventional methods to manage bridges.

2 Related research

As there is a large stock of existing bridges in industrialized countries, the DT creation process needs to be (at least partially) automated to avoid overly high effort and costs. Therefore, semantic segmentation and parametric modeling should be automated as essential steps in digital twinning. Recently, there have been some research efforts in this regard.

Lu et al. [9] used a top-down approach for detecting elements in the point cloud of RC bridges and represented the geometry of the bridge by the alpha-concave hull. Lee et al. [10] decomposed the point cloud of a bridge deck and extracted the value of parameters by detecting planar faces and measuring the distance between these planes. Hu et al. [11] employed a multi-view convolutional neural network (CNN) and a modified version of PointNet to extract features from different views of a bridge element and its corresponding point cloud for semantic segmentation. Qin et al. [12] also considered a top-down approach for detecting elements in bridges based on the density of points and parametrically modeled cylindrical and cuboid shapes. Lee et al. [13] employed PointNet and deep graph convolutional neural network (DGCNN) to extract features of points in the point cloud of bridges and used hierarchical KNN for semantic segmentation. Yan and Hajjar [14] applied heuristic algorithms to segment elements in the point cloud of steel bridges based on the connection rules of elements in these bridges. Girardet and Boton [15] proposed a BIM approach to foster the parametric modeling of bridges by visual programming in commercial software. Mafipour et al. [16] employed a model-based approach to fit the typical 2D profile of bridge elements by metaheuristic algorithms and estimate the value of parameters.

This paper aims to contribute a novel approach to automating the digital twinning process of bridges by AI methods, including metaheuristic algorithms, density clustering, region growing, signal matching, and fuzzy clustering. We investigate bridges in one of Germany's most common categories of highway bridges. Methodologies for semantic segmentation and parametric modeling are developed. In the first part of the paper, the PCD of an existing bridge is semantically segmented into different elements by proposing a heuristic algorithm. In the next section, the values of specific parameters are extracted by a metaheuristic algorithm from the segmented PCD. To this end, the parametric profile of the element is created, and all the human-definable constraints are applied. This profile is then instantiated as a dummy model with a random value of dimensions. Next, based on the PCD, the parameter values are adjusted to fit this parametric model into the PCD. These elements can finally be assembled to create the geometric model required for the digital twinning of the bridge. The proposed overall processing workflow is depicted in Figure 1.

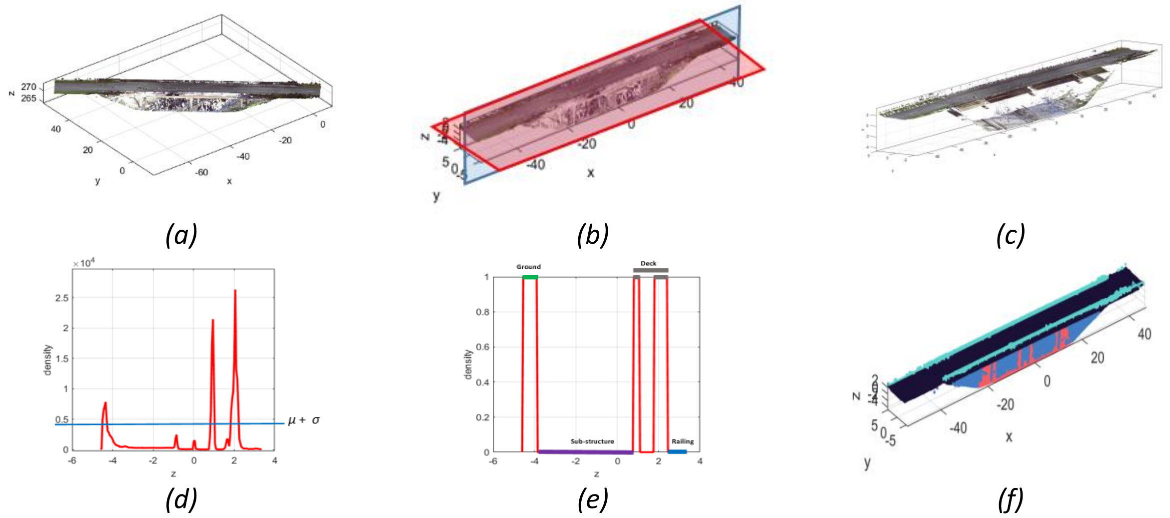


Figure 2 top-down segmentation: (a) input PCD; (b) alignment of the bridge; (c) points with normal in the z-direction; (d) signal of density; (e) detected clusters; (f) resulting segments

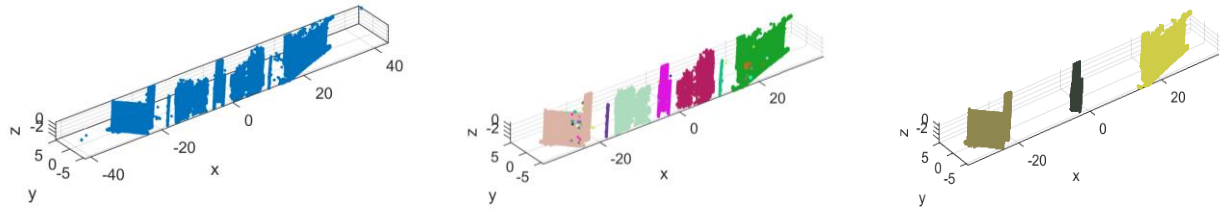
3 Semantic Segmentation

Semantic segmentation is the process of labeling point cloud data at a point level. Bridge1 from the Cambridge data set [9] is used in this paper. Different elements can be found in bridges, including railings, decks, abutments, and piers. To create the parametric model of the elements from PCD, the corresponding point cloud of these elements should be segmented. The semantic segmentation method proposed in this section is based on the assumption that 1) the bridge has a straight and flat deck and 2) only the point cloud of the actual bridge is considered for semantic segmentation. Therefore, the points over the railing and the sides of the bridge are removed. However, noises between the piers and points of the ground can be kept in the space of the problem.

3.1 Orientation of the bridge

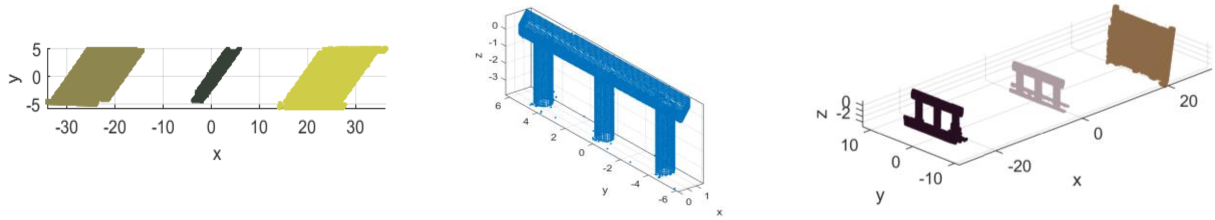
The input point cloud might be noisy and have any rotation or translation, see Figure 2(a). As a preprocessing step, the point cloud is denoised. For this purpose, a clustering algorithm is proposed, which can also denoise points. This algorithm is based on the connectivity of points and region growing (RG) algorithms. It starts from a random point and checks the distance of the point to its nearest neighbors. kd-tree and KNN algorithms are used for finding the nearest neighbors. If the distance of the point to its neighbor is lower than a threshold (radius), that neighbor is added to the cluster, and the region grows. This algorithm can result in many clusters that represent points with connectivity. Selecting the cluster with the highest number of points (density) leads to the denoised point cloud of the bridge.

The bridge is also required to be translated to the origin. Additionally, the longitudinal axis of the bridge is aligned with the x-axis, while the deck is placed at the top region (Figure 2(b)). To this end, a conventional method is principal component analysis (PCA) [9]. However, PCA is dependent on the variance of points and fails in cases that the variance in all directions is close. As an alternative, an optimization problem is defined, and all the conditions mentioned above are defined as penalty functions. This optimization minimizes the volume of the point cloud's axis-aligned bounding box (AABB). An AABB has its minimal volume only if the point cloud within the AABB is aligned with coordinate axes [16]. Thus, the rotation angles for which the AABB is minimized can form the rotation matrix necessary for axis alignment. Also, the length of the AABB in the x-direction should have the highest value, and the top region of the box (if the AABB is divided into four regions) should have the highest density (Figure 2(b)).



(a) *(b)* *(c)*

Figure 3 bottom-up segmentation (RG): (a) sub-structure; (b) resulting segments of RG; (c) remained clusters after removing noises based on the AABB of clusters



(a) *(b)* *(c)*

Figure 4 alignment of piers: (a) remaining clusters; (b) target cluster; (c) piers after rotation

$$To\ minimize: V(\alpha,\beta,\gamma) = l \times w \times h$$

$$subjected\ to: \begin{cases} -\pi/2 \leq \alpha,\beta,\gamma \leq \pi/2 \\ density_{top} > density_{bottom}, \\ density_{left\ side}, \\ density_{right\ side} \\ l > w, h \end{cases}$$

where *l*, *w*, and *h* are the length, width, and height of the AABB.

Since the rotation angles cannot be seen in the objective function, derivative-based algorithms cannot solve this problem. Hence, particle swarm optimization (PSO) [17] is used as it is a metaheuristic and derivative-free algorithm.

3.2 Railing

In the point cloud of bridges, density at the location of the super-structure is higher. This density is due to the deck's surfaces whose normals are in the z-direction. The normal of points can be calculated to detect these points, and the points whose z-components are higher are clustered (Figure 2(c)). Next, the density of points from the bottom to the top of the bridge is calculated, resulting in a density signal (Figure 2(d)). The sharp peaks of this signal show the locations where the density is higher, i.e., the ground and the deck. To detect these peaks, a threshold should be set. Considering the mirror of the signal around the horizontal axis, the distribution can be assumed normal. Therefore, the threshold is set to mean plus one standard deviation ($\mu + \sigma$).To detect the ends of any peak, the intersection points of the signal with the threshold line are computed and extended to the basis of the signal. Also, to avoid tiny and sequential peaks, the peaks whose ends are close to each other are merged. The points over the road surface (last cluster) are selected to segment the railing. The points belonging to the ground can also be detected based on the endpoint of the first cluster (Figure 2(e)).

3.3 Deck

After extracting the points of railing and ground, the points of the deck, abutments, and piers remain. Among these elements, the deck is the only horizontal element along the x-axis. Therefore, projection of all the points on the *yz*-plane results in a higher local density for the deck points. This local density can be calculated by considering a circle around every point after projection and counting the number of points within the circle. The local density of points is then used in a Fuzzy C-means (FCM) clustering algorithm with two clusters. Finally, the cluster with a higher z component is considered the deck points. Figure 2(f) shows the resulting segments of the railing, deck, sub-structure, and ground.

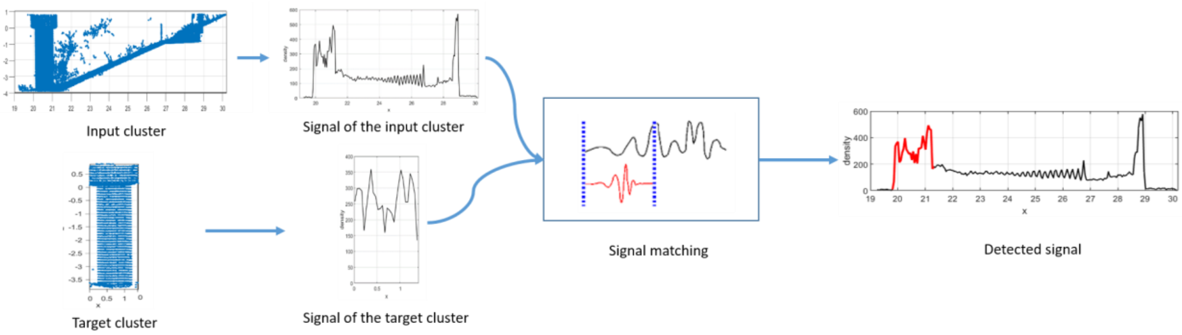


Figure 5 detecting piers in larger clusters

3.4 Piers and abutment

Piers and abutments are elements that are not connected in most cases. Also, piers and abutments connect the bottom of the bridge deck to the ground. Based on these observations, the proposed algorithm in section 3.1 is used for clustering the sub-structure points. As mentioned, this algorithm results in many clusters in which the connectivity of points in a pre-defined radius is ensured (Figure 3(b)). To detect the cluster of abutments and piers out of all the clusters, the height of the AABB of each cluster is compared with the height of the sub-structure, and the clusters with a close height to the sub-structure are kept only (Figure 3(c)). The connectivity algorithm and the height of AABB guarantee that the points are close to each other and connect the deck to the ground. This step can result in the cluster of piers and abutments. The two remaining clusters with the highest and lowest value of x for their center are considered abutments and other clusters as piers. However, in some bridges, a part of lateral piers and abutments are covered by terrain. Also, piers are not perpendicular to the alignment of the deck. To segment these piers, the remaining clusters are projected on the *xy*-plane, as shown in Figure 4(a). Next, the cluster with minimal AABB is selected from the middle clusters, i.e., the cleanest pier (Figure 4(b)). By applying PCA to this cluster, all the piers can be rotated and placed perpendicular to the deck (Figure 4(c)). Note that these piers are transformed again to their initial location after labeling the points. To detect the piers in the larger clusters, the density signal of the target cluster is obtained. Then, this signal is matched with the signal of other clusters by moving and calculating the absolute distance of the signals. As a result, the remaining piers in other clusters can be recognized from the ground, as shown in Figure 5. Besides, the retaining wall of the abutment can be detected in the lateral clusters by passing the filters through the signal.

3.5 Pier cap and column

Columns are vertical elements, while the cap is an almost horizontal element. In some bridges, the side faces of the cap incline; thus, passing horizontal planes might not always work. As an alternative, all the points of the pier are projected on the *xy*-plane, and the 2D density of points in a circle is calculated. This feature illustrates the density difference between column and cap. The other feature is the z-coordinate of points. The cap is located at a higher level in comparison with columns. Finally, the z-component of normal vectors is lower at the location of columns. Combining these features (2D density and z-coordinate of points, z-component of normal) leads to a feature vector. Based on this feature and using a Fuzzy C-means (FCM) clustering algorithm (for two clusters), the points of pier cap and column can be segmented automatically (Figure 6).

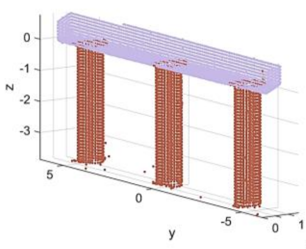


Figure 6 resulting segments from FCM

4 Parametric modeling

A parametric model is a model which is capable of being dynamically updated as soon as the parameter values (dimensions) are modified. As a result, this model should have an exact number of parameters and include all the required constraints for an accurate adjustment. To this end, the initial profile of the element is created based on the type of the existing element into the PCD, and all the constraints are applied. Next, this profile is instantiated with random values in reasonable ranges determined by bridge engineering knowledge. Finally, the distance of the existing points to the edges and vertices of the profile is minimized. This optimization process results in a profile fitted into the point cloud, representing the actual value of parameters. Further explanation can be found in our previous work [16]. To extract the value of parameters from the bridge's deck, a profile as shown in Figure 7 is considered. All the parameters of the profile are encoded in PSO.

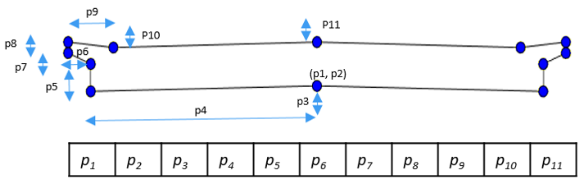
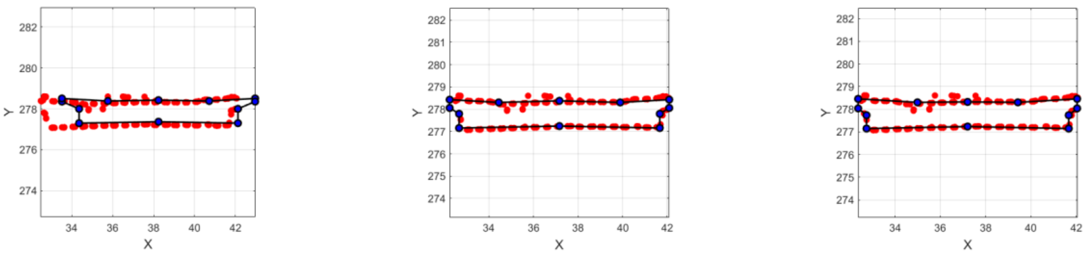


Figure 7 profile of the deck and encoded parameters in PSO

The profile is then optimized to be fitted into the existing points, see Figure 8. Note that the profile is only fitted into the points of the deck, which have been semantically segmented in section 3.3. Thus, semantic segmentation is necessary for parametric modeling.



(a) *(b)* *(c)*

Figure 8 model fitting process: (a) iteration = 1; (b) iteration = 20; (c) iteration = 100

5 Results

The density filters were passed in intervals of 5 cm, and the sequential peaks with a distance lower than 75 cm were merged. The radius of growing in the RG algorithm was considered 0.5 m. Figure 9 shows the results of semantic segmentation for this bridge. As can be seen, most of the points have been labeled correctly. Comparing the labels with the ground truth of the bridge showed that the proposed method can achieve an accuracy of around 96%.

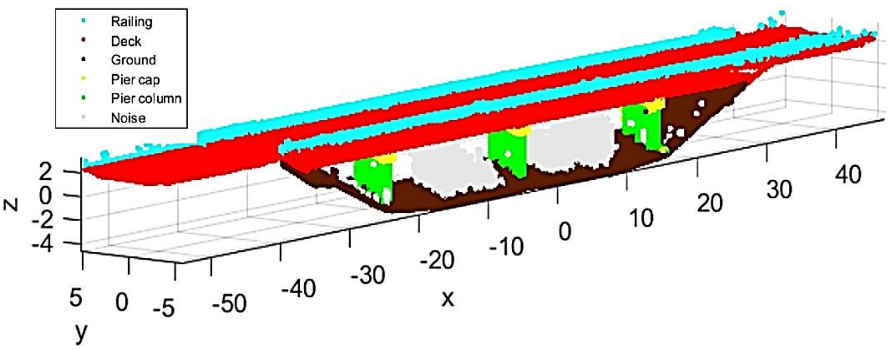
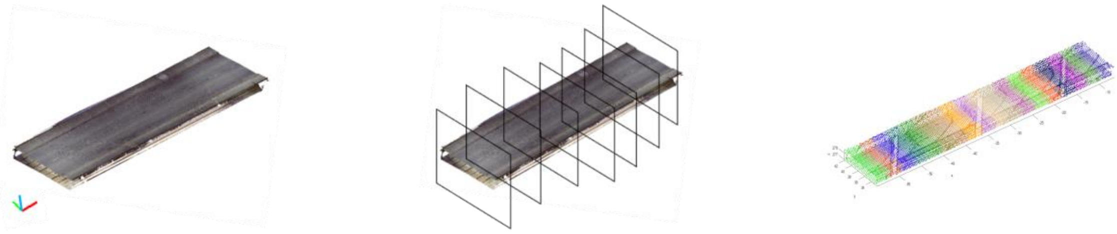


Figure 9 Resulting point cloud after semantic segmentation



(a) *(b)* *(b)*

Figure 10 segmenting the deck into intervals: (a) input deck; (b) passing planes; (c) segmented points

For parametric modeling of the deck, the points were segmented into intervals of 3 m, as shown in Figure 10. For every segment, the corresponding model of the deck was fitted. For this purpose, PSO with 35 particles and 100 iterations was applied. c1, c2 coefficients were also set 2, and a damping factor of 0.99 was considered. Next, all the sequential vertices resulting from the PSO were connected. Since these lines might not be smoothed, a polynomial was fitted to the vertices, and the model's vertices were modified. Figure 11 shows the fitted model into the point cloud. As can be seen, the model is symmetric and represents a highly parameterized model with an exact number of parameters that were close to a manually modeled deck. The convergence (loss) diagram of PSO showed an error of around 5 cm for each segment. This shows that the proposed methodology can extract the value of parameters with an error of approx. 1.67 cm/m.

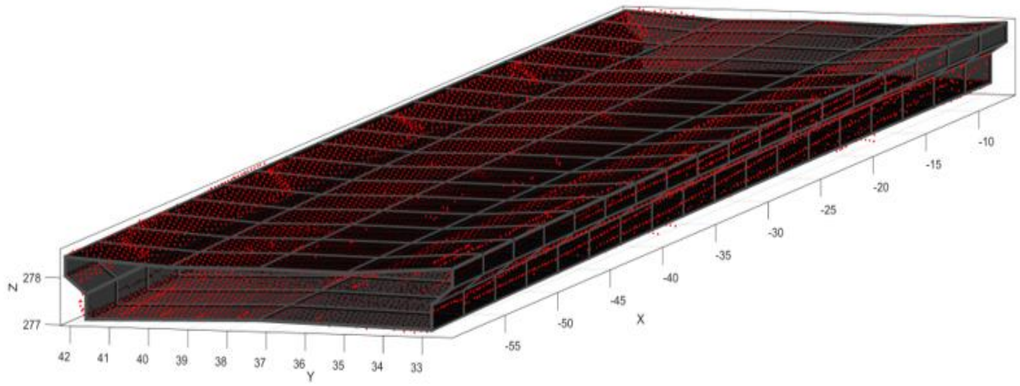


Figure 11 Fitted deck into the point cloud data

6 Conclusion

This paper presents a method for semantic segmentation and parametric modeling of bridges from point clouds. For semantic segmentation, metaheuristic algorithms, density clustering, region growing, signal matching, and fuzzy clustering are employed. For parametric modeling, the value of parameters is extracted by fitting the model of elements into the point cloud by metaheuristic algorithms. This paper shows that semantic segmentation and parametric modeling, two essential parts for digital twining, can be automated to a large extent. The main advantage of the presented method over existing ones is that a high-quality as-is BIM model is generated with a level of abstraction that fulfills the needs of bridge management systems. In this paper, the bridges with a straight deck have been investigated. However, the present methodology can be extended to a large variety of bridges with more complex geometries. Also, this methodology can cover a large category of bridges by highly parameterized models for rapid and automated digital twinning from PCD.

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References

[1] Lu, Q., et al., *Semi-automatic geometric digital twinning for existing buildings based on images and CAD drawings.* Automation in Construction, 2020. **115**: p. 103183.

[2] Pan, Y., et al., *Built Environment Digital Twinning*, in *Report of the International Workshop on Built Environment Digital Twinning presented by TUM Institute for Advanced Study and Siemens AG*. 2019: Technical University of Munich, Germany.

[3] Zhu, Z., S. German, and I. Brilakis, *Detection of large-scale concrete columns for automated bridge inspection.* Automation in construction, 2010. **19**(8): p. 1047-1055.

[4] Technion, *SeeBridge—Semantic enrichment engine for bridges*. 2015, Technion. p. 77.

[5] Bosché, F., et al., *The value of integrating Scan-to-BIM and Scan-vs-BIM techniques for construction monitoring using laser scanning and BIM: The case of cylindrical MEP components.* Automation in Construction, 2015. **49**: p. 201-213.

[6] Adán, A., et al., *Scan-to-BIM for 'secondary'building components.* Advanced Engineering Informatics, 2018. **37**: p. 119-138.

[7] Laing, R., et al., *Scan to BIM: the development of a clear workflow for the incorporation of point clouds within a BIM environment.* WIT Transactions on The Built Environment, 2015. **149**: p. 279-289.

[8] Rocha, G., et al., *A scan-to-BIM methodology applied to heritage buildings.* Heritage, 2020. **3**(1): p. 47-67.

[9] Lu, R., I. Brilakis, and C.R. Middleton, *Detection of structural components in point clouds of existing RC bridges.* Computer-Aided Civil and Infrastructure Engineering, 2019. **34**(3): p. 191-212.

[10] Lee, J.H., J.J. Park, and H. Yoon, *Automatic bridge design parameter extraction for scan-to-BIM.* Applied Sciences, 2020. **10**(20): p. 7346.

[11] Hu, F., et al., *Structure-aware 3D reconstruction for cable-stayed bridges: A learning-based method.* Computer-Aided Civil and Infrastructure Engineering, 2021. **36**(1): p. 89-108.

[12] Qin, G., et al., *Automated Reconstruction of Parametric BIM for Bridge Based on Terrestrial Laser Scanning Data.* Advances in Civil Engineering, 2021. **2021**.

[13] Lee, J.S., J. Park, and Y.-M. Ryu, *Semantic segmentation of bridge components based on hierarchical point cloud model.* Automation in Construction, 2021. **130**: p. 103847.

[14] Yan, Y. and J.F. Hajjar, *Automated extraction of structural elements in steel girder bridges from laser point clouds.* Automation in Construction, 2021. **125**: p. 103582.

[15] Girardet, A. and C. Boton, *A parametric BIM approach to foster bridge project design and analysis.* Automation in Construction, 2021. **126**: p. 103679.

[16] Mafipour, M.S., S. Vilgertshofer, and A. Borrmann. *Deriving Digital Twin Models of Existing Bridges from Point Cloud Data Using Parametric Models and Metaheuristic Algorithms*. in *Proc. of the EG-ICE Conference 2021*. 2021.

[17] Kennedy, J. and R. Eberhart. *Particle swarm optimization*. in *Proceedings of ICNN'95-international conference on neural networks*. 1995. IEEE.