From point cloud to IFC: A masonry arch bridge case study

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Abstract. For the last several years, laser scanning has become one of the reference technologies when talking about the monitoring of assets. Nowadays, the trend is to use these data for creating semantically rich three-dimensional (3D) models, broadly known as digital twins. The bottleneck appears when processing the large amount of data acquired with the laser scanner. This paper tackles the creation of IFC data models using classified point cloud data. The point labelling methodology is based on one in the state-of-the-art, whose results have been improved. Then, each group of points is converted to a triangulated mesh, and the resultant geometrical objects are placed in an IFC-based model in a low and high level of detail. Moreover, the resultant IFC model allows the enrichment of the captured geometry with additional information.

1. Introduction

The modern society is increasingly dependent on digital representations of the environment. Since the majority of the assets are already built, there are usually no digital as-built representations of them available. Assets are likely to change during their life cycle due to deterioration caused by impacts or sudden events. Therefore, digital representations should represent assets during their entire lifecycle, from design to their end-of-life, so that periodic maintenance and analysis can be performed in order to evaluate their behaviour.

The digital replica of the real-world data is known as digital twin (El Saddik, 2018). This “twin” should contain not only 3D geometrical data, but also semantically rich information representing the characteristics associated with the asset (materials, safety, occupancy, relations between components, etc.). A digital twin (DT) of the infrastructure will ensure its normal functionality and operation, being able to detect changes in its condition due to the constant update of its information. This will decrease the disruption of service, the risk to which the end-users are subjected to, and costs savings for the infrastructures owners as a consequence of the previous (Lu and Brilakis, 2019a). It is important to highlight that the characteristics of DTs will depend a lot on their purpose, so a DT can have different levels of detail (LoD): from non-geometrical representation, to two dimensional (2D) geometry, or 3D data models (i.e. plans, B-reps, point clouds). In some cases, the geometry of the DT will not be required, being uniquely dependent on the semantic information. This calls for linked data approaches so that the needed information is easily available, accessible, and properly organised. One example of linking information could be the use of ontologies, useful for data hierarchies (Beetz, 2018).

Although the creation of DT during the design phase of an infrastructure is broadly extended, it is not the case during the rest of its life cycle. This is motivated by the resource consumption of this task in comparison with doing it the traditional way. This is where LiDAR technology comes into place. Point clouds provide geometrical information about the environment where the survey was performed, but it is not enough. This information needs to be processed and interpreted so that it can be used in a BIM (Building Information Modelling) model or as a DT. The paper aims to demonstrate a full toolchain from the capturing process to the validation of the IFC (industry foundation classes) data format. The proposed workflow shows the capability of IFC to store not only design data but also the results of processed point clouds. The definition of end-user requirements (EURs) for digital twins is not a defined task for this paper. Lu and Brilakis (2019b) prepared the fundamental information that a DT should contain in the form of six EURs. The present work has been developed in order to fulfil these requirements.

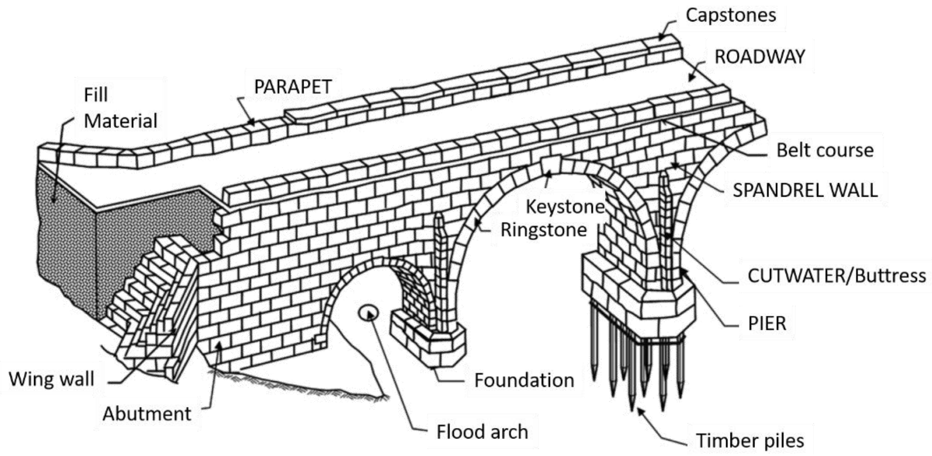

Figure 1: Main components of a masonry arch bridge (Ural *et al.*, 2008)

The bridge under study is to be divided into six different elements: spandrel walls, vaults, piers, cutwaters, roadway and parapet (Figure 1). The present article is divided as follows: Section 2 summarizes the state of the art in relation with the field of research; Section 3 introduces IFC as one of the most frequently used data structures for BIM processes; Section 4 describes the methodology developed from the point cloud classification to the IFC instance model creation; the results are presented in Section 5; and, finally, a summary of the conclusions extracted from this work is exposed (Section 6).

2. Literature Review

Point clouds acquisition can be performed using aerial laser scanning (ALS), mobile laser scanning (MLS), or terrestrial laser scanning (TLS) systems. Depending on the use of the point clouds in a later step, a different system is to be used. In this relation, Soilán *et al.* (2019) presented a review with the most relevant laser scanning technologies available in the market and their applications regarding transport infrastructures. Since the present work is focused on masonry arch bridges, the better approach is to use TLS systems to perform the survey. They usually work mounted on a stand or tripod and obtain high-resolution scans in a short period of time (in a range of minutes) (Olsen *et al.*, 2010).

In order to create a 3D data model of an asset using a point cloud, a first classification of points is needed so that the elements forming the asset are grouped. Over the years and thanks to the evolution of technology, numerous works concerning the automatic or semi-automatic classification of point clouds started to arise. When specifically talking about arch bridges, Walsh *et al.* (2013) started classifying points into different structural elements using laboratory specimens and testing real bridges. Later on, Riveiro, DeJong and Conde (2016) developed a methodology for automatically segment their structural elements. Concerning the inspection of masonry arch bridges, Sánchez-Rodríguez *et al.* (2018) showed an automatic processing method for laser scanning data in order to detect faults in their piers. The current trend for point cloud classification is to use algorithms that automatically predict the class of a point based on learning algorithms. Barrile, Candela and Fotia (2019) worked with an aerial survey of a concrete viaduct in order to apply photogrammetric reconstruction to classify the structural elements of the asset. They applied image analysis techniques and used the Mask-RCNN (Region-Based Convolutional Neural Network) (He *et al.*, 2017) to perform this classification.

After processing the point cloud data, the next step would be to create a 3D data model of the structure using that information. In this paper, the standard IFC is to be used. There are already some works developed in this respect. Ma *et al.* (2018) manually prepared the 3D model using Revit, tracing the points in the cloud. Later, a pipeline for going from point clouds to IFC models was presented in (Zhao and Vela, 2019). They detect and classify objects using a machine learning approach and then, each individual element is parametrized to create the IFC objects. Lu and Brilakis (2019a) created a method for creating DTs of reinforced concrete bridges from already labelled point clusters. Those clusters are sliced and projected to the XY-plane in order to fit a 2D ConcaveHull α-shape. The obtained contour is then transformed to 2D Cartesian points (*IfcCartesianPoint*) to create the IFC instances.

Another approach for the point cloud-to-IFC conversion is to make use of the (3D) laser scanning data reconstructing the geometric surfaces needed to produce a mesh. Numerous methods have been proposed to tackle this problem. Most commonly, the variational methods (Zhao *et al.*, 2000), tensor voting (Medioni, Lee and Tang, 2000), implicit surface (Hoppe *et al.*, 1994), and Delaunay triangulations (Cohen-Steiner and Da, 2004). Delaunay triangulations are greedy algorithms that reconstruct the surface as a result of the union of sequentially selected triangles. Such algorithms start with a seed triangle, and then the triangulated surface incrementally grows by using the previously selected triangles to select a new triangle for advancing the front. The idea presented in this paper is that IFC provides geometric representations within its geometry resources to store meshes like the created ones.

This paper examines whether and to what extent bridges can be better described using the latest schema extension proposal IFC4x2. Thus, a framework was developed which converts the captured geometries into an IFC4x2 based instance model. During the processing, two LoDs were considered to make the resulting model lightweight and easy to consume in various use case scenarios. Moreover, the models are enriched with semantic information that was extracted during the segmentation and processing of the point cloud.

3. Data Formats for Digital Twins

The way in which information is stored, exchanged, and shared between different parties in a project needs to be standardized. The use of data models ensures it's the success of data exchange processes, with information encoded using a specific data model. For the use of BIM models or DTs, they have to meet specific geometric and semantic requirements, which have been defined exemplarily by the BIM4INFRA2020 project (BIM4INFRA2020, 2018). Data models can provide geometric and semantic information or only geometric content. DXF and OBJ can be considered as the most representative ones when talking about geometric data models (Autodesk, 2017; Wavefront, 2019). Since in this work semantic information is also used, IFC2x3, IFC4, IFC4x1, IFC4x2 and CityGML should be the ones coming into place (buildingSMART International Alliance for Interoperability, 2007; buildingSMART International, 2018). In this work, IFC 4x2 is the data model to be used since it covers requirements for detailed geometric representations paired with specific product classifications for each component. This will avoid the need for re-implement a way of combining geometry with semantics in a formal way.

The IFC data model was initially designed to transfer digital models of buildings. Since the interest in BIM technology is constantly increasing during the last years, the international non-profit organization buildingSMART International (bSI) decided to extend the IFC data model for civil infrastructure assets. The first initiatives in this regard were the IfcAlignment project (buildingSMART International, 2018) and the IFC Overall Architecture report (Borrmann *et al.*, 2017). Upon these projects, the IfcBridge extension project has added new classes and types to enable a more detailed description of bridge structures. The final deliverables include a comprehensive requirements analysis as well as a schema extension proposal (Borrmann *et al.*, 2019). Besides IfcBridge, several other projects like IfcRoad, IfcPortsAndWaterways, and IfcTunnel are conducted inside the Infra room, which is a subsection of bSI. Additionally, the IfcRail project (located inside the RailwayRoom) proposed a schema extension for railbounded traffic. It is ongoing work to harmonize all proposals among the individual projects to deliver a harmonized infra extension in the end. This deliverable will most likely build the base for the next major release IFC5.

Even though the toolchain discussed in this paper was not in the primary scope of the IfcBridge extension project, data exchange scenarios of processed point cloud information can be realized using IFC classes.

4. Methodology

The methodology presented in this paper is in charge of creating IFC instance models in order to store bridge models created out of a laser scan. It is divided into three parts: (i) point cloud classification; (ii) point cloud-to-mesh conversion; and (iii) generation of the IFC model.

4.1 Point Cloud Classification

The point cloud classification methodology follows the steps previously stated in Riveiro, DeJong and Conde (2016), where a methodology for the segmentation of masonry arch bridges from TLS datasets was presented. In the present work, this method has been modified in order to improve the performance of the algorithms, as presented in Figure 2.

The method starts with a masonry arch bridge point cloud, already aligned and prepared for its processing. This point cloud $B = (x, y, z, I)$, is formed by the 3D spatial coordinates (x, y, z), and the reflected laser pulse intensity, I. In this case, only the geometrical information is to be used. The point cloud is oriented to the y coordinate axis, resulting $B_r = (x, y, z)$ applying principal component analysis (PCA), and taking the first component as basis to perform the rotation (Gressin *et al.*, 2013). Next step is to distinguish between points forming vertical and non-vertical elements. This is done calculating the elevation angle histogram of the points cloud, in which two main peaks are present. The points are thus classified in two classes: vertical elements $V = (x, y, z) \in B_r$ and non-vertical elements $N = (x, y, z) \in B_r$.

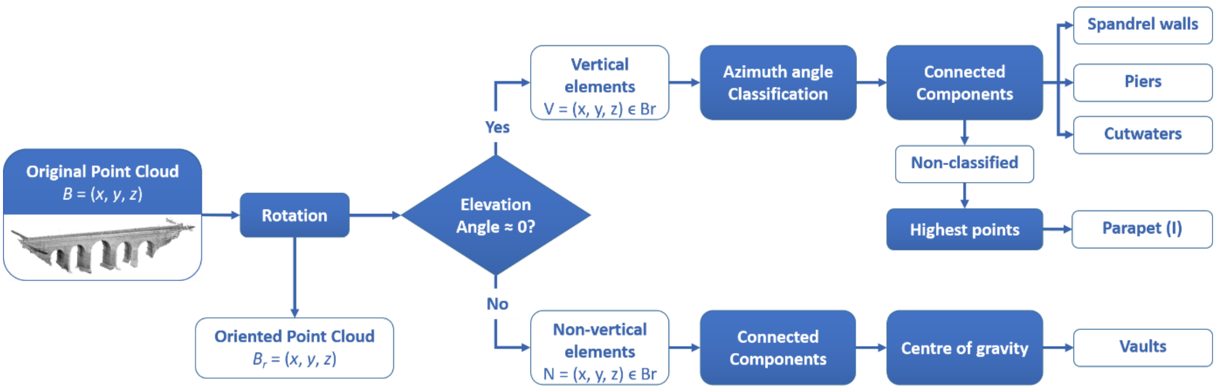

Figure 2: Proposed classification workflow

Working with the point cloud containing vertical bridge elements, *V*, a first classification based on the azimuth angle of each point is performed. As before, this angle was computed in a neighbourhood of 0.25 m. Then, a *k-means* clustering (Lloyd, 1982) is applied to the data, dividing the point cloud into four main classes: possible spandrel walls, possible piers, possible cutwaters, and non-classified points. Each of these new sections is specifically analysed so that the wrongly classified points are reclassified. A connected components detection algorithm is applied for this matter. Points belonging to the parapet of the bridge are present in both the vertical and non-vertical elements point cloud. In both classes, the parapet is detected as the highest points in the cloud.

Lastly, from the point cloud of non-vertical elements, points forming vaults are detected applying a connected components detection algorithm, and each individual one is isolated thanks to their center of gravity.

4.2 Point cloud-to-Mesh Conversion

Once the point cloud is segmented, multiple steps are performed to reconstruct the final mesh (as illustrated in Figure 3). First, each segment is preprocessed by omitting noise. Here the points are sorted in an increasing order of the average squared distance to their nearest neighbors, and the points with the largest value are deleted. The reconstructed mesh could be used for multiple different purposes, including performing simulations and renovation. Thereby, in some cases, a highly detailed or a coarse representation could fit more to the intended purpose.

Based on the purpose, a level of detail (Trimble, 2013) is selected. Accordingly, capturing reality (LoD 500), focuses first on reconstructing the outer surface of the geometric features by approximating its shape. Once the surface is reconstructed, an additional step is required to fill any remaining gaps / holes. These holes could result due to scanning or processing issues, which are hard to completely avoid, like because of defects in the scanning process or inaccuracies in the segmentation or noise omitting algorithms. On the other hand, selecting a low LoD requires much less processing as only rough placeholders that represent the overall dimensions are required. In this regard, based on the convex hull (Barber, Dobkin and Huhdanpaa, 1996) of each segment, a triangulated mesh, which does not suffer from any holes, is generated.

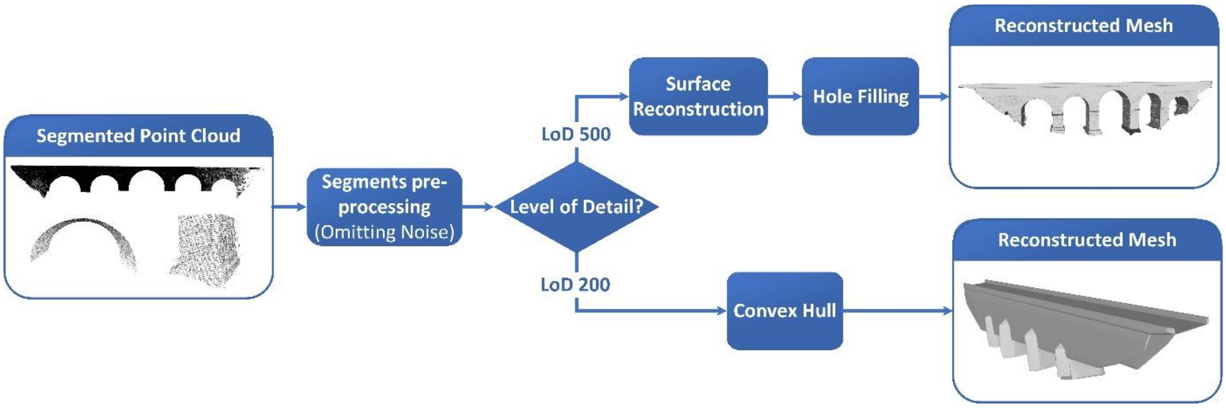

Figure 3: Proposed framework for transforming point cloud segments to 3D mesh. The framework provides two approaches, one for reconstructing surfaces with high details, and another for generating a coarse representation of each segment

4.3 Generation of the IFC Model

The IFC data model provides huge flexibility to model use-case specific requirements. An example of this is the flexibility to assign the best-fitting geometry representation for a given source geometry. Product representations can be modeled by using explicit or implicit (i.e. procedural) geometries. Besides, a huge advantage of IFC compared to other data models is the opportunity to represent several levels of details using the same data standard. This makes the results easier to consume in a variety of existing tools since IFC is widely adopted in the AEC (Architecture, Engineering, and Construction) market. The generation of the IFC instance model containing the captured bridge is done by a console app written on top of the IFC framework XBIM (Lockley, 2007). It creates a basic spatial structure typically used for bridges which splits the construction into logical parts (e.g., superstructure, substructure, foundation). Several products are assigned to these logical containers afterwards. A simple JSON-based dictionary enables the engineer to assign the segmented geometries to a suitable *IfcProduct* class.

The computed meshes are stored as instances of the class *IfcTriangulatedFaceSet* and linked to instances that are derived from *IfcProduct*.

5. Results

5.1 Case Study

The bridge selected to validate the presented process is a masonry arch bridge. It is the roman bridge of Segura, located on the border of Portugal and Spain and crossing the river Erjas. The bridge is used to communicate the provinces of Castelo Branco (Portugal) and Cáceres (Spain) by a national road (Durán, 1996). This bridge has been selected since it has already been studied in previous works (Arias *et al.*, 2010; Riveiro, DeJong and Conde, 2016).

Data Acquisition. Each survey has to be planned according to the needs given by the structure to be scanned and its environment. In this case, the survey is done in an outdoors environment, and so the meteorological conditions have also to be considered. The point cloud acquisition was performed using the TLS Riegl LMS-Z390i (*RIEGL*, 2020). The operations of recording point clouds with this RIEGL scanner were controlled with Riscan PRO Software (Riegl©). In order to perform the survey leaving as less non-scanned bridge parts as possible, the scans were taken from seven different positions from which a different point cloud was obtained. These were aligned thanks to the use of reflective targets placed over several planes in the surroundings of the structure. For the case of this paper, the point cloud was reused from a previous survey, which is described more in detail in (Arias *et al.*, 2010). The obtained point cloud is formed by 1,259,148 points.

Ground Truth Preparation. The ground truth used to compare the point cloud classification has been obtained using the software *CloudCompare* (v2.10.2) (*CloudComapre*, 2020), in order to manually segment the point cloud into seven different classes of points: roadway, parapet, spandrel walls, vaults, piers, cutwaters, and non-classified points.

5.2 Point Cloud Classification

The classification of points in masonry arch bridges point clouds has been proven as valid in a previous work by Riveiro, DeJong and Conde (2016). That methodology has been modified for this work in order to improve its performance. The dataset described in Section 5.1 is used to prove the validity of the classification methods proposed. This point cloud is segmented in seven categories depending on their geometrical characteristics, as exposed in Section 4.1. An overview of the results is presented in Figure 4. Figure 4(a) and (c) show the original point cloud (upstream and downstream, respectively), while in Figure 4(b) and (d), points are depicted with different colours depending on their specific group.

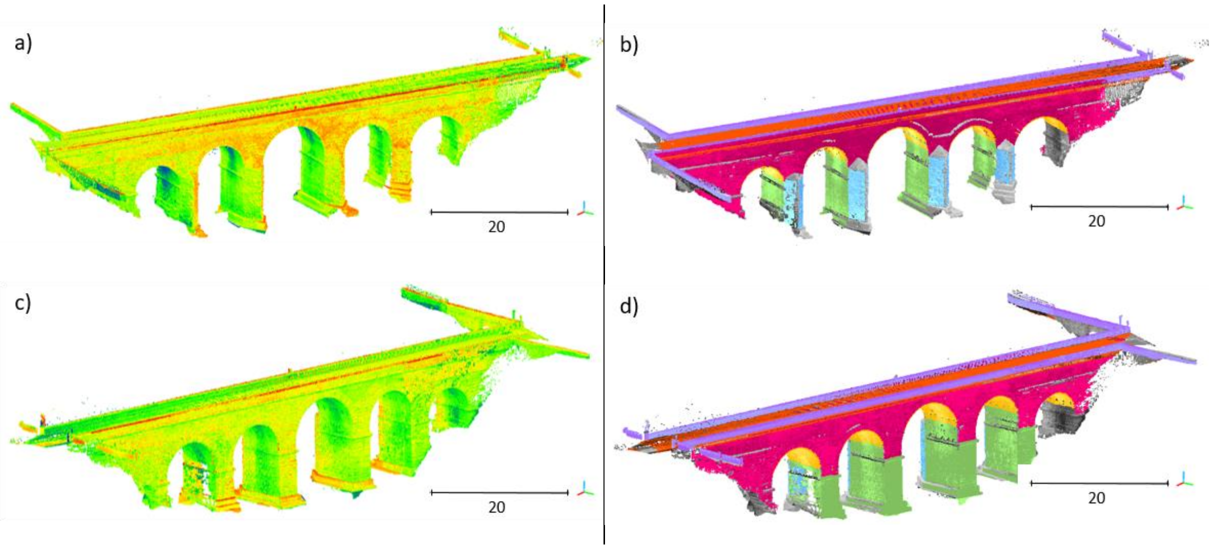

Figure 4: Original point cloud upstream (a) and downstream (c) compared with the classification results: roadway (orange), parapet (lilac), spandrel walls (magenta), vaults (yellow), piers (green) and cutwaters (blue)

The results obtained with this new methodology are compared quantitatively with the previously labelled ground truth. The same is done with the ones obtained by Riveiro, DeJong and Conde, (2016). The parameters chosen to summarise the performance of each method are the precision, recall, and F-Score metrics. The methodology developed for this work shows better results than the previous one presented in (Riveiro, DeJong and Conde, 2016).

Table 1: Performance metrics

Element	**Precision**	**Recall**	**F-Score**	**Precision**	**Recall**	**F-Score**
	Previous methodology			**New methodology**		
Spandrel walls	0.7694	0.1996	0.3170	0.8711	0.8956	0.8832
Vaults	0.9685	0.1147	0.2050	0.9452	0.7240	0.8199
Piers	0.7786	0.7563	0.7673	0.6794	0.9448	0.7904
Cutwaters	0.2016	0.1784	0.1893	0.9750	0.7444	0.8442
Roadway	0.8348	0.2975	0.4387	0.5427	0.9963	0.7026
Parapet	-	-	-	0.7512	0.6690	0.7078

5.3 Generation of the IFC Model

The model generation was performed by the developed methodology described in Section 4.2 and 4.3. The individual segments (vaults, piers, etc.) were preprocessed and reconstructed in both LoDs, 200 and 500. At the end, all segments are combined to represent the captured bridge as illustrated in Figure 5 and Figure 6. The resultant meshes were efficiently generated, producing models that are lightweight enough (in terms of the number of points per triangulated geometry) to be visualized in the common IFC viewers that support IFC4X2 (like *BIM vision* 2.23 or *FZK Viewer*).

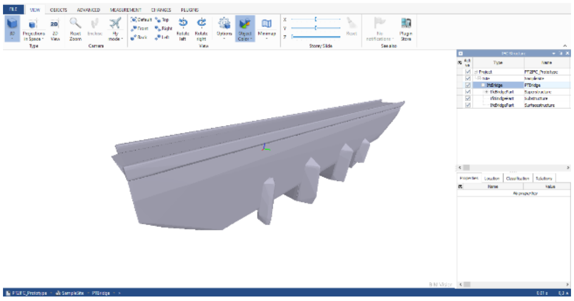

Figure 5: Resulting IFC Model in LoD 200

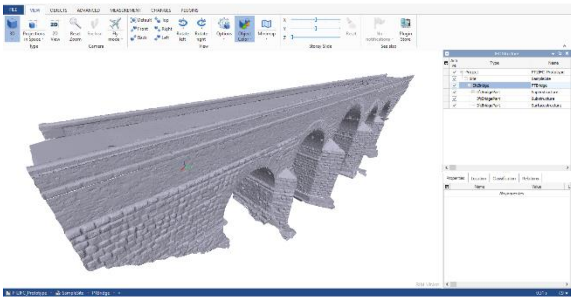

Figure 6: Resulting IFC Model in LoD 500

Additionally, the IFC models were semantically enriched by adding custom property sets to the *IfcProject* and *IfcSite* entities, incorporating the parameters used to capture the point cloud using the laser scanner as well as the parameters used to reconstruct the surfaces. This information enables the receiving engineer to roughly classify the quality of the given model. It is important to have such properties directly assigned to the model to enable a correct interpretation of the given geometry.

6. Conclusion

This paper presents an automatic methodology for transforming classified point clouds into IFC models for further applications. The presented methodology is divided into three main parts: (i) point cloud classification; (ii) point cloud-to-mesh conversion; (iii) mesh-to-IFC conversion. The methodology overcomes the gaps existing in the captured point cloud using advanced geometric reconstruction techniques and maps the segmented assets to the latest IFC schema. Furthermore, the IFC-based result is then ready to get further information attached to it, such as construction materials, structural health monitoring information, etc. This can be considered the first approach to transform masonry arch bridges' point clouds into Digital Twins.

The results presented show a good performance referring to point cloud classification, improving a previously published methodology. In addition, the models created using this information allow to present different level of detail, depending on the purpose of the DT. Finally, it is important to highlight that the end user's requirements are also fulfilled. This work proves that laser scanning systems can be considered as a tool for capturing the as-built environment and creating digital representations of it. Different aspects may be taken into consideration for future work regarding the transformation of point clouds into IFC. The results obtained in the classification of LiDAR data can always be improved. Nowadays, the use of deep learning algorithms is one of the latest trends developed, being in the state of the art for many applications. Progress is under way in the 3D data field, and it is foreseeable that the AI (artificial intelligence) is able of obtaining better results than heuristics for certain applications in the near future. Some works using specialized neural networks (kpconv, PointNet, PointNet++, splatnet, etc.) have already shown good results. Concerning the creation of IFC instance models, other techniques can be used to compare the results in the same datasets. Moreover, different bridge's typologies should be studied in order to prove a broader validity of the developed algorithms.

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