Ontology-Driven Analytics for Indoor Point Clouds

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ONTOLOGY-DRIVEN ANALYTICS FOR INDOOR POINT CLOUDS

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Abstract. Automated processing, semantic enrichment and visual analytics methods for point clouds are often use-case specific for a given domain (e.g, for Facility Management (FM) applications). Currently, this means that applicable processing techniques, semantics and visual analytics methods need to be selected, generated or implemented by human domain experts, which is an error-prone, subjective and non-interoperable process. An ontology-driven analytics approach can be used to solve this problem by creating and maintaining a Knowledge Base, and utilizing an ontology for automatically suggesting optimal selection of processing and analytics techniques for point clouds. We present an approach of an ontology-driven analytics concept and system design, which supports smart representation, exploration, and processing of indoor point clouds. We present and provide an overview of high-level concept and architecture for such a system, along with related key technologies and approaches based on previously published case studies. We also describe key requirements for system components, and discuss the feasibility of their implementation within a Service-Oriented Architecture (SOA).

Keywords. Knowledge Base; Point Clouds; Semantic Enrichment; Service-Oriented Architecture; Ontology.

1. INTRODUCTION

An ontology can be used to define the relationships between entities, methods, data, semantics, and processes for a given domain. An ontology can also be used to set up and maintain a Knowledge Base, and for performing related inferencing operations. A Knowledge Base contains all of the semantics, rules and facts used to infer a decision based on provided ontology (usually with ontological metadata). As such, a Knowledge Base employs a given ontology to structure its data. When the ontology is updated by various process results and inputs (e.g., domain expertise, computed semantics, etc.), so is the Knowledge Base with new rules, facts and associated semantics. Thus an interdependent relationship exists between the two concepts, as they are both used to contribute to the definition, creation and updating of knowledge within a given domain. Indoor point clouds, once

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processed and analyzed, have the potential to provide insights into the structure, state, and dynamics of buildings and other constructions, and, by that, to support decision making, e.g., in Facility Management (FM).

1.1. PROBLEM STATEMENT

However, since point clouds are ambiguous by nature, they impose constraints for being applied due to phenomena such as visual clutter and self shadowing. Even more crucial is the lack of any semantics or even ontology within their context (e.g., ontology of a typical office building). An ontology-driven approach would enable automated selection of optimal processing and analysis techniques of point clouds for indoor environment representations, and also enhance decision making through insightful analytics within the subdomain of Operations and Maintenance (O&M) in FM (e.g., for space and inventory management as well as for the optimization of room utilization, occupant comfort, emergency routes, etc). Even when point clouds are semantically enriched, they seldom contribute to the ontology of a building and are only used for single-use decision making cases. Therefore, an ontology needs to be formed that relates to the digital representation and associated O&M processes for the operation of a building. There is a paucity for an ontology-driven analytics,where users can simply query such a system in order for it to generate, associate and present useful semantics for FM decision making tasks (using point clouds as the main representation of the physical environment). In turn, the knowledge of such a "smart" system would be expended when performing any subsequent tasks.

1.2. RESEARCH CONTRIBUTIONS

We present and discuss conceptual system and process designs for each of the key components for an ontology-driven analytics system. We propose an ontology-driven approach that can adapt specific algorithms for segmentation and classification of point cloud clusters, perform such processing operations, and make use of visualization methods to present the resulting semantics to FM stakeholders.

2. FOUNDATIONS AND RELATED WORK

Point clouds can be used to visually inspect and assess the current state of the built environment, can help to track construction-related or refurbishment-related changes over time, and can be used as base-data for the generation of as-is and as-built Building Information Models (BIM) (Qu and Sun 2015). A point-cloud based representation of indoor environments within the context of interactive 3D visualization enables enhanced stakeholder engagement and communication (Xu et al. 2018). Since point clouds do not contain any other information besides spatial distribution in 3D space and possibly color and/or intensity values, they need to be enriched with semantics to effectively support the various FM-related tasks. This process can be error-prone and time-consuming when performed manually (e.g., introducing errors in decisions due to incorrect observations). Generation and injection of semantics into point clouds is based on associating each segmented point cluster with either metric (Armeni et al. 2017), domain expertise (Sacks et al. 2018), or probabilistic deep-learning-based processes and their outputs (Che et al. 2019).

A particular challenge is dynamically assigning semantics or adapting processing algorithms for generalized use-cases when using point clouds. The process of semantic enrichment of point clouds is in most current situations unidirectional (e.g., point clouds are semantically enriched at a single time for a single purpose, with the semantics remaining valid only for the current version of the point cloud). Therefore, in order to be able to dynamically generate and query semantics for point clouds, a feedback system using a Knowledge Base for semantics generation and updating is required. Cursi et al. (2017) describe the development of a prototypical BIM Semantic Bridge system, that can map Industry Foundation Classes (IFC) semantics to an ontology representation using OWL (Web Ontology Language). They state that the main advantage developing a knowledge base using an ontology-drive approach is that is allows experts from different AEC domains to access and exchange knowledge during the design phase of a building (as BIM by default focuses on geometric representation of a building or structure).

Poux et al. (2017) advocate the use of a multi-level semantics framework, in which the first level of semantics represents the point cloud data structure, the second represents the connection elements between the point cloud data structure and the spatial context, while the third level connects specific ontologies with the point cloud that is used by domain experts for performing various semantic queries. All three semantic levels are connected within a feedback loop to a Knowledge Base. The Knowledge Base is updated through inputs from analytic results, devices and domain expertise. Ponciano et al. (2019) describe a fully semantically guided approach for the detection of objects in indoor point clouds. They propose the use of a constantly updated knowledge base that, in turn, is used to select and adapt the most appropriate processing algorithm based on the observed ontologies. Sadeghineko et al. (2018) describe the generation of semantically rich BIM models from point cloud data, where each segmented region of a point cloud is given a unique annotation using the Resource Description Framework (RDF) schema specification, thus enabling relationships between BIM elements to be captured and queried.

The use of visualization for enhancing stakeholder decision making can be accomplished using various annotation methods, and plays an important role for focusing the viewers attention to the semantics of a 3D point cloud scene. Florio et al. (2019) describe different visualization techniques for exploring BIM models using semantically-driven representation configurations. Savva et al. (2017) describe a context-driven annotation approach for 3D indoor scenes, which automatically suggests and presents possible object semantics to the user while they are exploring the scene. A similar approach is described by Zhang et al. (2016), using statistical inference based on user-guided image annotations of indoor environments and their potential spatial arrangements. Another important point is that approaches for semantic enrichment, ontology generation and visual analytics can be implemented using an Service-Oriented Architecture (SOA), which can help for e.g., decoupling of hardware and software requirements between the user and the processing system (Döllner et al. 2012).

3. CONCEPTUAL SYSTEM DESIGN

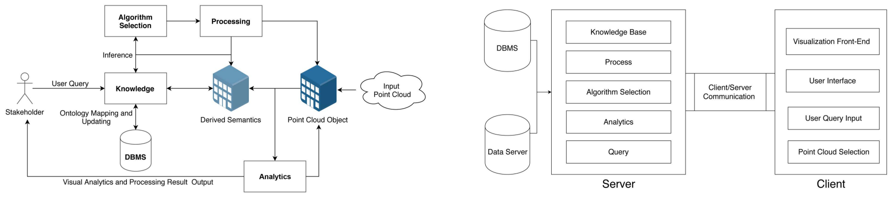

Figure 1. A high-level overview of the main architecture and components of the ontology-driven analytics system for indoor point clouds. The stakeholders interact with the point cloud and are provided with analysis outputs. User tasks such as spatial or inventory queries are inferred from the Knowledge Base component, which is derived and updated using the ontology-driven approach. Conceptual design of an SOA that satisfies the integration requirements of the conceptual system components is shown on the right diagram. The server is responsible for the processing, inference, DBMS operations, and ontology updating tasks, while the client enables the users to select the initial point cloud they want to perform semantic queries on, to visualize the result of the query, as well as to use and update the ontology. .

Fig. 1 illustrates the overall high-level design for the ontology-driven analytics system. The proposed system design is made up of six key components: (1) the Knowledge Base component, (2) DBMS (Database Management System) component, (3) Algorithm Library, (4) Analytics, the (5) the Processing component and (6) the Query component. The six components work together in order to update ontologies, generate semantics and parameter values for selected processing algorithms. It is assumed that a core ontology is defined, which is then subsequently updated through the introduction of new semantics, expert knowledge and existing digital documentation. Initially, the Processing component would be used to filter the input point cloud (e.g., generate normal vectors, remove duplicate points, or sub-sample). The user can enter a new analysis task - a semantic query, that would be interpreted by the Query component. The Query component uses this query (translated into a machine-readable format), to infer a decision using the ontology represented by Knowledge Base component. In turn, the Knowledge Base component then utilizes the existing semantics objects accessed by the DBMS component to form a decision. In this case the selected decision is based on matching the algorithm for the required task from the Algorithm Library component.

The selected algorithm would then be sent back to Processing component, which would apply it along with specific parameters to the point cloud. The result of the processing would be semantics that can be injected into the point cloud for further semantic enrichment. These associated semantics would then be sent to the DBMS component in the form of standardised semantics description object, where they would be once again utilized by the Knowledge Base component next time a new task is initiated by the user. In such a scenario the Knowledge Base acts as an inferencing component of the system. In an example scenario, a user wants to take an inventory of all types of specific chairs in a given office room (Fig. 2). The point cloud is first processed by the Processing component (e.g., for normals compuation, planar surface segmentation, etc). Next, the user's semantic query for selecting all chairs will be sent to the Knowledge Base component that will compare all existing semantics obtained from semantics objects in the DBMS component, in order to select a specific algorithm for detecting the objects via the Algorithm Library component. For example, it is known that chairs are often found in rooms with desks, and that each office has at least one computer desk, which in turn has specific dimensions for the room object that is evaluated from segmented planar clusters obtained from the initial processing of the point cloud. It would also be known that the point cloud has RGB values, and that it was captured using commodity mobile hardware (so it is a coarse representation of the real-world with a lot of noise). Based on this ontology, the Knowledge Base component could formulate an algorithm suggestion and request the Algorithm Library component for a multiview classification algorithm with specifically tuned parameters (based on the derived semantic relations). Once the selected classification algorithm detects and classifies the chairs, the associated resulting semantics that are injected and presented to the user via the Analytics component would also be sent to the DBMS component. This would make the whole ontology-driven system "smarter", as new semantics are introduced with each new user query, and new relations are used to update the ontology that is inferred by the Knowledge Base component for future use.

Visualization of the semantically-enriched clusters of a point cloud scene is vital for highlighting their location in 3D space, and bringing them to the attention of the user for further inspection and assessment. Often, indoor point clouds may contain visual clutter that requires the user to manually navigate and select regions-of-interest for inspection, semantic enrichment and further annotation. In order to draw the users attention to areas of interest in a point cloud that may contain a lot of visual clutter, we can consider the use of visualization idioms (Haber and McNabb, 1990) for highlighting and possibly abstracting, through visualization, the spatial areas of interest in the point cloud. The Analytics component fulfils the role of generating the visual representation of the 3D point cloud, specific point cloud clusters and their associated semantics. We propose the use of specific visualization styles for representing the semantics that were injected into specific point clusters as a result of the ontology-driven scene analysis. These could, e.g., include cluster color coding, floating boxes, abstracted geometry, and manipulation of opacity values (Fig. 3). We also propose the concept of a "smart scene annotation" sub-system as part of the Analytics component, using a probability-based recommendation approach (Fig. 4). Such a component would take into account the currently visible point clusters and would automatically provide suggestions to the user of the object that is currently in view, based on the probabilities derived from the associated semantics of that point cluster (essentially a semi-automated semantics-annotation process).

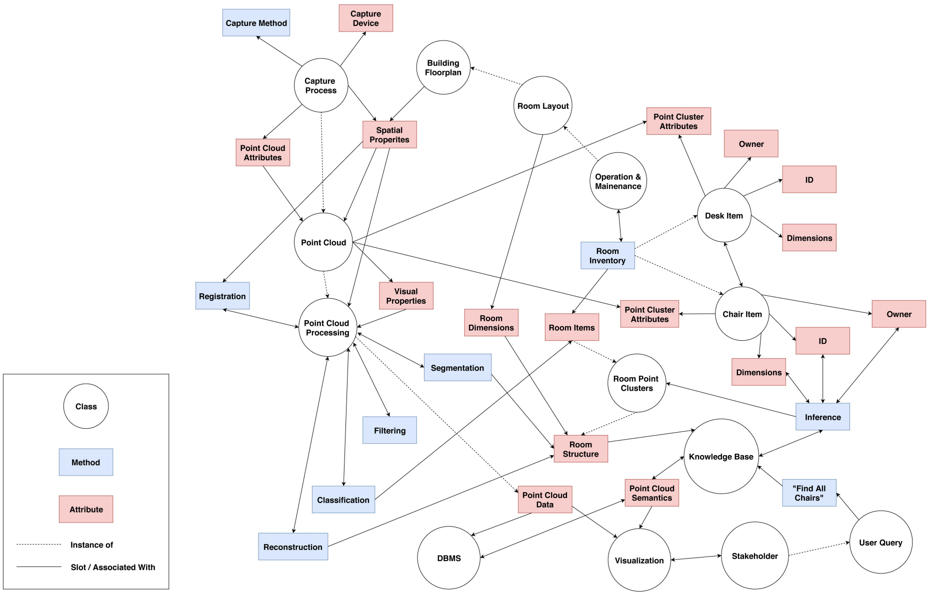

Figure 2. A core ontology example for using a point cloud representation for an O&M task.

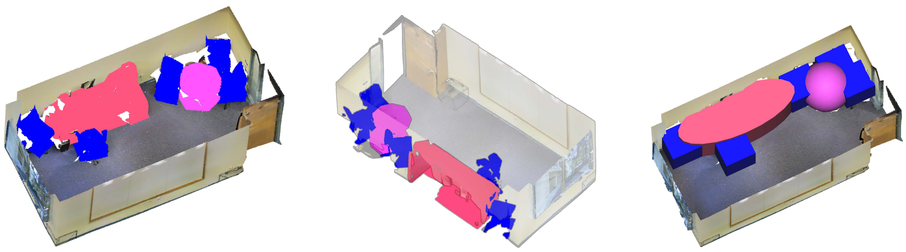

Figure 3. Examples of different visualization idioms used to highlight semantics in a typically cluttered point cloud of an office (from the Stanford dataset by Armeni et al. 2016). The examples feature simple color coding of different object-type point clusters (left), opacity-based visualization in order to avoid visual occlusion (center), and use of abstracted 3D geometry in place of the point clusters in order to simplify the visualization and draw more visual attention from the viewer (right).

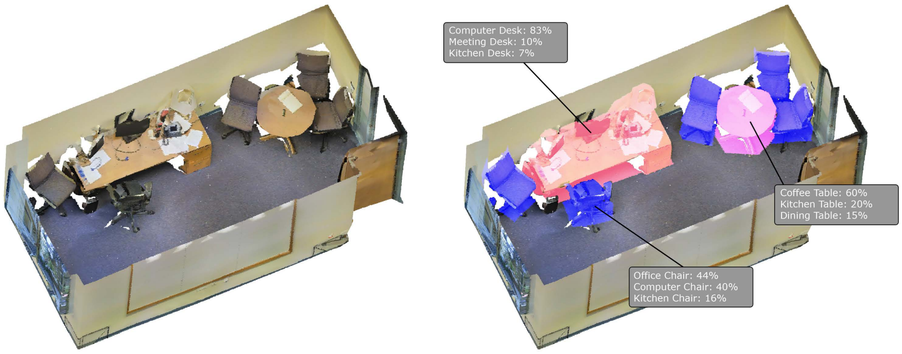

Figure 4. Example of the proposed smart scene annotation, based on the derived probabilities introduced with the classification of point clusters as specific furniture objects. The user is presented with the top three possible semantics for each of the point clusters that are highlighted as "office furniture" objects. The user would, in turn, be able to select the correct semantic for each cluster, and this selection would then be sent to the Knowledge Base component in order to update relations, semantics and processes between the related room and building. Furthermore, a user could manually add semantics that is not already offered and, by that, could extend or refine the underlying ontology itself.

In the context of visualisation and analytics systems, the use of a SOA can help to decouple the often complex image generation process (e.g., on a dedicated high-performance rendering server) from the display of and interaction with those images on clients of various classes (i.e., running various hardware configurations, such as smartphones and tablets), which may be of an older generation, and may not have the hardware and software capabilities to process and render data in real-time and in high quality. Other services could implement and advertise other complex computation tasks including, e.g., deep-learning-based classification of point clouds. The proposed Algorithm Library and Processing components will contain all of the related algorithms used for processing, reconstructing, classifying and evaluating point clouds. Additionally, the design of the Knowledge Base and DBMS components as separate services allows for running the generation and association of semantics as well as ontology management, on dedicated workstation computers with high-performance computing and storage capabilities, whilst rather lightweight clients can access this functionality through the service interfaces.

4. DISCUSSION

In terms of feasibility of implementing the conceptual ontology-driven analytics system, four specific system design requirements and tasks need to be considered. Firstly, a key requirement for the proposed system is an existing and suitable ontology for buildings and indoor spaces. This ontology could then be interpreted and used as the default ontology by the Knowledge Base component when formulating the Algorithm Library component selection response based on the user's initial semantic query. For actual implementations of an ontology, it can be defined essentially as a schema (e.g., RDF). Attempts at defining a formal ontology for buildings and using it to derive semantic relationship for FM-related applications, in most cases those based on BIM requirements, have been discussed by Iskidag et al. (2013), Emgård and Zlatanova (2007) and Nagel et al. (2009). Valid topologies can be derived form BIM-based representations of indoor spaces (e.g., office building related), though this is dependent on using and parsing IFC, CityGML or other related BIM and GIS files. In most cases relationships between specific entities, e.g., in the IFC file representation, can be used to generate connectivity graphs between spaces in a building representation. However, the building and indoor space ontologies are often derived for a single use-case, and therefore difficult to generalize. There is specific paucity for forming any sort of ontologies based on point clouds, which has no standardized semantic file format that is comparable to that of IFC or CityGML (unless an extension is used to embedded point clouds into those file formats, though important semantics and reconstructed geometry are generally not preserved).

Secondly, the task to evaluate and select a suitable DBMS that can handle the parsing, updating and querying of semantic objects would need to be undertaken. Such a database system could be a relational or non-relations DBMS oriented towards semantics and spatial queries. Borrmann (2010) propose an octree-based spatial query database system for retrieval of VRML digital building and city models, implemented and tested using extended versions of relational and object-oriented SQL for custom spatial queries. Ma and Sacks (2016) describe a NoSQL cloud-based database for storage, sharing and retrieval of BIM models (in addition to allowing further semantic enrichment by supporting custom IFC-complaint mapping and representation using the Binary JavaScript Object Notation (BSON) format). Solihin et al. (2017) define and test a BIM-based rule language and describe a system for transforming BIM-data into SQL-based representation for allowing simplified access to FM-related data for stakeholders. The authors note that while relational (also known as SQL-based) DBMSs can be easily extended without rewriting interfaces from scratch, there are still issues concerning the speed of access to data from user queries, as well as enriching such data with custom information due to having to parse and convert IFC-related schematics.

Thirdly, the specific algorithms to be included in the Algorithm Library and used by the Processing components need to be selected and evaluated. While there is a wealth of algorithms available for specific processing tasks of point clouds, certain algorithms are, e.g., better suited towards outdoor point clouds. We have found that certain classification and clustering algorithms provide promising results for classifying indoor point clouds (Stojanovic et al. 2019a).

Fourthly, it is important to define if a specific system is developed only for observation-based analysis and decision making, or if the results from semantic enrichment will be used to infer specific condition-based rules within e.g., Building Management System (BMS), Computer Aided Facilities Management (CAFM), Integrated Workplace Management System (IWMS) or Environmental

Management Systems (EMS). In such a case it would be necessary to introduce more safeguards, and perhaps restrict the system to non-critical O&M monitoring and forecasting tasks.

5. CONCLUSIONS

Based on the provided literature review and discussion of related and influential work, it can be concluded that there is currently no straightforward implementable software solution for ontology-driven analysis of indoor point clouds. While there are promising research results and prototypical implementations showing how ontologies can be formed and integrated with point clouds in principle, using semantics derived through various classification and processing algorithms, the design and end-to-end implementation of a use-case oriented expert system as described in this work is still an open issue. This is especially the case when using domain expertise from FM stakeholders as most current ontology-driven software prototypes for BIM and FM applications are not user-centered (e.g., no focus on user interfaces, qualitative analysis of user input and feedback, etc) The feasibility of implementing an ontology-driven approach is also supported by the authors previously published research for semantic enrichment and visualization (Stojanovic et al. 2019b). Additionally, previous work by the authors has also demonstrated the feasibility of integrating various processing and representation components for visualization of spatio-temporal data as well as point cloud data (Stojanovic et al. 2019c). Based on this and the resulting prototypical implementations and testing of core components, we conclude that a user-oriented, analytics-focused and ontology-driven system can be designed, implemented, and deployed, provided that a suitable ontology of buildings and indoor spaces can be established. After the service-based implementation and successful testing of these key components, we are currently working towards developing a working prototype of the full concept proposed in this paper.

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References

Armeni, I., Sax, S., Zamir, A.R. and Savarese, S.: 2017, Joint 2d-3d-semantic data for indoor scene understanding, *arXiv preprint arXiv:1702.01105*.

Armeni, I., Sener, O., Zamir, A.R., Jiang, H., Brilakis, I., Fischer, M. and Savarese, S.: 2016, 3d semantic parsing of large-scale indoor spaces, *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition*, 1534-1543.

Borrmann, A.: 2010, From GIS to BIM and back again–A Spatial Query Language for 3D building models and 3D city models, *5th international 3D geoinfo conference, BerlinV*.

Che, E., Jung, J. and Olsen, M.J.: 2019, Object recognition, segmentation, and classification of mobile laser scanning point clouds: A state of the art review, *Sensors*, **19**(4), 810.

Cursi, S., Simeone, D. and Coraglia, U.M.: 2017, An ontology-based platform for BIM semantic enrichment, *Kepczynska-Walczak, Anetta (2019) Building Information Modelling Implementation in Progress, Proceedings of the 35th eCAADe Conference*, 649-656.

Döllner, J., Hagedorn, B. and Klimke, J.: 2012, Server-based rendering of large 3D scenes for mobile devices using G-buffer cube maps, *Proceedings of the 17th International Conference on 3D Web Technology*, 97-100.

Emgard, K. and Zlatanova, S.: 2007, Design of an integrated 3D information model, *Urban and regional data management: UDMS annual*, 143-156.

Florio, A., Trapp, M. and D"ollner, J.: 2019, Semantic-driven Visualization Techniques for Interactive Exploration of 3D Indoor Models, *2019 23rd International Conference Information Visualisation (IV)*, 25-30.

Haber, R.B. and McNabb, D.A.: 1990, Visualization idioms: A conceptual model for scientific visualization systems, *Visualization in scientific computing*, **74**, 93.

Isikdag, U., Zlatanova, S. and Underwood, J.: 2013, A BIM-Oriented Model for supporting indoor navigation requirements, *Computers, Environment and Urban Systems*, **41**, 112-123.

Ma, L. and Sacks, R. 2016, A cloud-based BIM platform for information collaboration, *in* initials missing surname missing (ed.), *no title given*, ISARC.

Nagel, C., Stadler, A. and Kolbe, T.H.: 2009, Conceptual requirements for the automatic reconstruction of building information models from uninterpreted 3D models, *Proceedings of the Academic Track of the Geoweb 2009-3D Cityscapes Conference in Vancouver, Canada, 27-31 July 2009*.

Ponciano, J.J., Tr'emeau, A. and Boochs, F.: 2019, Automatic Detection of Objects in 3D Point Clouds Based on Exclusively Semantic Guided Processes, *ISPRS International Journal of Geo-Information*, **8**(10), 442.

Poux, F., Neuville, R., Hallot, P. and Billen, R.: 2017, Model for reasoning from semantically rich point cloud data, *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, **4**, 107-115.

Qu, T. and Sun, W.: 2015, Usage of 3D Point Cloud Data in BIM (Building Information Modelling): Current Applications and Challenges, *Journal of Civil Engineering and Architecture*, **9**(11), 1269-1278.

Sacks, R., Kedar, A., Borrmann, A., Ma, L., Brilakis, I., Hüthwohl, P., Daum, S., Kattel, U., Yosef, R., Liebich, T. and thers, initials missing: 2018, SeeBridge as next generation bridge inspection: overview, information delivery manual and model view definition, *Automation in Construction*, **90**, 134-145.

Sadeghineko, F., Kumar, B. and Chan, W.: 2018, A semantic web-based approach for generating parametric models using RDF, *Workshop of the European Group for Intelligent Computing in Engineering*, 361-377.

Savva, M., Chang, A.X. and Agrawala, M.: 2017, SceneSuggest: Context-driven 3D Scene Design, *arXiv preprint arXiv:1703.00061*.

Solihin, W., Eastman, C., Lee, Y.C. and Yang, D.H.: 2017, A simplified relational database schema for transformation of BIM data into a query-efficient and spatially enabled database, *Automation in Construction*, **84**, 367-383.

Stojanovic, V., Trapp, M., Döllner, J. and Richter, R.: 2019a, Classification of Indoor Point Clouds Using Multiviews, *The 24th International Conference on 3D Web Technology*, 1-9.

Stojanovic, V., Trapp, M., Hagedorn, B., Klimke, J., Richter, R. and Döllner, J.: 2019c, Sensor Data Visualization for Indoor Point Clouds, *Advances in Cartography and GIScience of the ICA*.

Stojanovic, V., Trapp, M., Richter, R., Hagedorn, B. and Döllner, J.: 2019b, Semantic Enrichment of Indoor Point Clouds-An Overview of Progress towards Digital Twinning, *Sousa, JP, Xavier, JP and Castro Henriques, G (eds.), Architecture in the Age of the 4th Industrial Revolution - Proceedings of the 37th eCAADe and 23rd SIGraDi Conference - Volume 2*.

XU, J., Chen, K., Xue, F. and Lu, W.: 2018, 3D point cloud data enabled facility management: A critical review, *The 23rd International Symposium on the Advancement of Construction Management and Real Estate*.

Zhang, S., Han, Z. and Zhang, H.: 2016, User guided 3D scene enrichment., *VRCAI*, 353-362.