Historic-Building Information Modeling and Artificial Intelligence

Subjects: Engineering, Civil

Contributor: Valeria Croce, Gabriella Caroti, Andrea Piemonte, Livio De Luca, Philippe Véron

Heritage- or Historic-Building Information Modeling (H-BIM) reconstruction from laser scanning or photogrammetric surveys is a manual, time-consuming, overly subjective process, but the emergence of AI techniques, applied to the realm of existing architectural heritage, is offering new ways to interpret, process and elaborate raw digital surveying data, as point clouds. The proposed methodological approach for higher-level automation in Scan-to-BIM reconstruction is threaded as follows: (i) semantic segmentation via Random Forest and import of annotated data in 3D modeling environment, broken down class by class; (ii) reconstruction of *template* geometries of classes of architectural elements; (iii) propagation of *template* reconstructed geometries to all elements belonging to a typological class. Visual Programming Languages (VPLs) and reference to architectural treatises are leveraged for the Scan-to-BIM reconstruction.

Keywords: machine learning ; Historic-Building Information Modeling (H-BIM) ; Building Information Modeling ; artificial intelligence

1. Introduction

In recent years, the Building Information Modeling (BIM) methodology was transferred from the realm of new construction to that of the built heritage. Since the early studies by Murphy and Dore [1][2], the scientific literature on Heritage or Historic-BIM (H-BIM) has expanded [3][4][5][6][7][8], aiming to illustrate how geometrical data can be linked to: architectural grammar and styles [9][10][11], material characterization [12], degradation patterns [13], façade interventions and historical layers [14][15], structural damage and FEM analysis [16][17][18], data collection and simulation of environmental parameters [19], archival photographs [20] and text documents [21][22].

Hichri et al. [8] and Macher et al. [23] emphasized that H-BIM techniques require the transition from the existing condition of the object to the modeling environment. The shift from the *as-built* condition (registration of a building after construction) to the *as-is* representation (registration of its current condition) implies reference to surveying data, as point clouds acquired via laser scanning or photogrammetry [24] and reverse engineering techniques. On the one hand, the elaboration of 3D surveying for the construction of BIM models, known as Scan-to-BIM [21], is seen as a manual, time-consuming and subjective process [3][5]; on the other hand, the emergence of Artificial Intelligence (AI) techniques in the architectural heritage domain [25][26][27] is reshaping the approach of heritage experts towards the interpretation, recognition and classification of building components on raw surveying information.

2. Historic-Building Information Modeling and Artificial Intelligence

2.1. State-of-the-Art Scan-to-BIM Reconstruction Processes

Scan-to-BIM processes [7][21][28] focus on translating existing survey data, as point clouds, into BIM. They involve three main steps: (i) data acquisition by laser scanning or photogrammetry; (ii) processing of survey data; and (iii) 3D modelling (**Figure 1**). In the processing phase (ii), it is essential to semantically describe the objects that make up a building over unstructured point clouds [28]. This interpretative issue is a major bottleneck in current research, as the main limits of the Scan-to-BIM processing workflow are identified as:

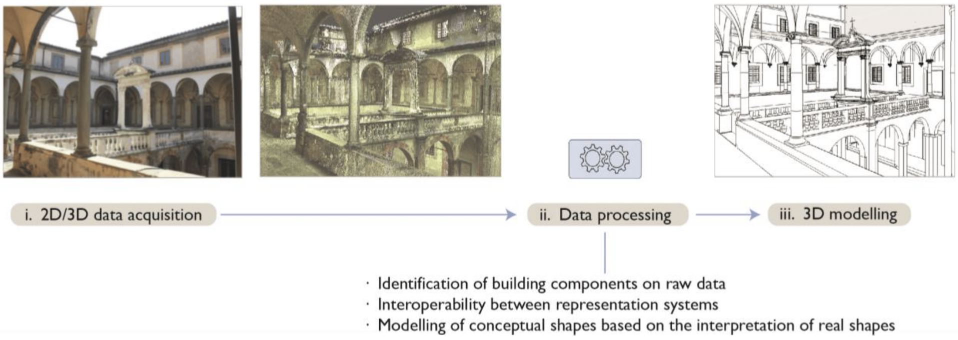

Figure 1. Steps of the Scan-to-BIM workflow using example from Grand-Ducal cloister, Pisa Charterhouse.

- Difficulties in modeling complex or irregular elements and representing architectural details of existing buildings [1][29][30], and the need to intervene with classification, hierarchical organization and simplification assumptions [14][23];
- Measurement uncertainties [23], as surveying data may contain occlusions [31];
- Compared to BIM for new constructions, there is an absence of pre-defined, extensive libraries of parametric objects [3] and lack of existing standards for H-BIM artefacts [1][28][30];
- High conversion effort [1], since most BIM software for new buildings offer tools for the construction of regular and standardized objects while the free-form geometry modeling functions that are available are limited [15][29][32][33].

For the above limits, Scan-to-BIM techniques are never unambiguous. However, they can be distinguished based on the degree of human involvement in the data processing stage, classified as manual or semi-automated.

2.1.1. Manual Scan-to-BIM Methods

Most common approaches to the Scan-to-BIM are manual, as they require visual recognition and subsequent manual tracing of building components starting from a point cloud (**Figure 2**). Extensive literature reviews provided by Logothetis et al. [6], Volk et al. [7], Tang et al. [34] and more recently by López et al. [3] and Pocobelli et al. [4], demonstrate that manual methods [1][35], although widely consolidated, result in time-consuming, laborious processes. Indeed, operators are asked to manually identify, isolate and reconstruct each class of building elements [7][23]. This entails a considerable amount of time and resources, besides implying the risk of making too subjective choices [36].

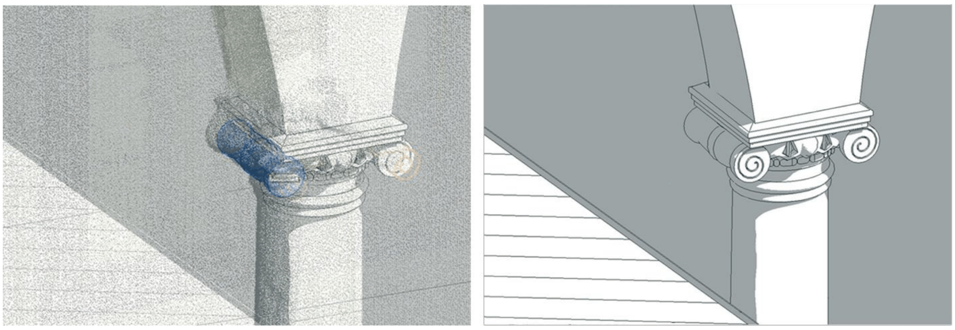

Figure 2. Instantiation of a capital by direct reconstruction over the raw point cloud using example from Grand-Ducal cloister, Pisa Charterhouse.

2.1.2. Semi-Automated Scan-to-BIM Methods

Fundamental issues in the definition of semi-automated methods are the recognition and labelling of data points on raw point clouds with a named object or object class (e.g., windows, columns, walls, roofs, etc.) [34][35][36][37][38]. Existing methods can be distinguished according to the solution identified over time for this issue:

Primitive fitting methods. They fit simple geometries, such as planes, cylinders and spheres [39], to sets of points in the scene via robust estimation of the primitive parameters. The Random Sample and Consensus [40] and the Hough Transform [41] are common algorithms of this type, used in commercial solutions for the semi-automatic recognition of walls, slabs and pipes, proposed by software houses [3][42][43][44] including: EdgeWise Building by ClearEdge3D (clearedge3d.com) as a complement for Autodesk Revit; Scan-to-BIM Revit plug-in by IMAGINiT Technologies (imaginit.com); and Buildings Pointfuse from Arithmetica (pointfuse.com). Primitive fitting methods mostly apply to indoor environments [31][37][38][42] for the detection of planar elements, as floors and walls [23][37][45]. Shape extraction and BIM conversion are limited to simple geometries with standardized dimensions; application to complex existing architectural structures, varying in forms and types, is hardly possible unless the model is oversimplified [23][42].

Mesh-reconstruction methods. For each architectural component or group thereof, a mesh is reconstructed via triangulation techniques, starting from the distribution of points in the original point cloud. References [15][17][29][31][46][47][48] converted 3D textured meshes derived from surveying into BIM objects; however, the mesh manipulation and geometric modification are limited as the mesh models cannot be edited and controlled by parametric BIM modeling [29].

Reconstruction by shape grammar and object libraries. Such approaches rely on the construction of suitable 3D libraries of architectural elements (families) to handle the complexity of materials and components that characterizes historic architecture [10][49][50][51]. In detail, De Luca et al. [52] studied the formalization of architectural knowledge based on the analysis of architectural treatises, to generate template shape libraries of classical architecture. Murphy et al. [53] modelled interactive parametric objects based on manuscripts ranging from Vitruvius to Palladio to the architectural pattern books of the 18th century. Since relying on the formalization of architectural languages as derived from treatises of historical architecture, such methods are valid regardless of the modeling type or representation chosen [52].

Reconstruction by generative modelling. In this case, the reconstruction is again guided by the formalization of architectural knowledge, and VPLs are considered to manipulate each geometry by interactively programming, via a graphical coding language made up of nodes and wires, the set of modeling procedures, primitive adjustments and duplication operations performed in 3D space [33][52][54]. Grasshopper, a visual programming interface for Rhino3D, and Dynamo, a plug-in for Autodesk Revit, are commonly used for these tasks in the case of new constructions. By contrast, VPLs are rarely exploited for existing monuments and sites. The 3D content could be created, based on surveying data [17][47][54][55][56], by a series of graphic generation instructions, repeated rules and algorithms [57]. The release of Rhino.Inside.Revit (rhino3d.com/it/features/rhino-inside-revit, accessed on 18 December 2022), allowing Grasshopper to run inside BIM software as Autodesk Revit, goes in the direction of novel VPL-to-BIM connection tools.

2.2. State-of-the-Art AI-Based Semantic Segmentation

In the digital heritage field, ML and Deep Learning (DL) techniques emerge to help digital data interpretation, semantic structuring and enrichment of a studied object [25] e.g., to assist the identification of architectural components [58], the re-assembly of dismantled parts [59], the recognition of hidden or damaged wall regions [60], and the mapping of spatial and temporal distributions of historical phenomena [61].

In the architectural heritage domain, AI techniques have proven to be crucial in streamlining the so-called semantic segmentation process, understood as the reasoned subdivision of a building into its architectural components (e.g., roof, wall, window, molding, etc.), starting from surveying data. With respect to other common computer vision tasks exploiting AI, such as object recognition, instance localization and segmentation, the semantic segmentation process classifies pixels or points as belonging to a certain label and performs this operation for multiple objects of the 2D image or of the 3D unstructured scene (**Figure 3**). The term *semantic*, indeed, underlines that the breakdown is done by referring to prior knowledge on the studied 2D/3D architectural scenes.

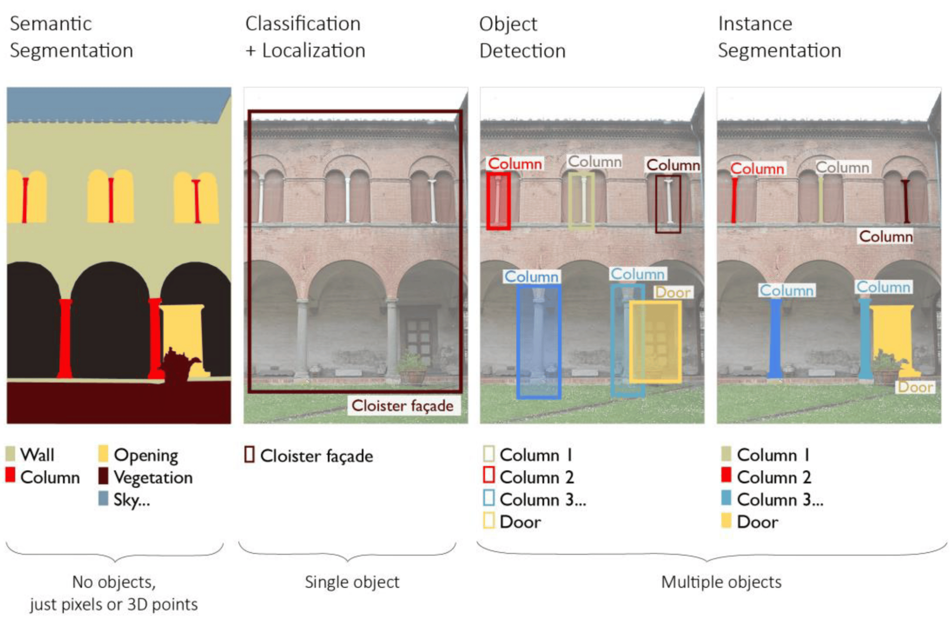

Figure 3. Semantic segmentation compared to other computer vision tasks using example from Cloister of the National Museum of San Matteo, Pisa.

Though earlier experiments of digital heritage classification were geared towards the semantic segmentation of images [60][62][63], research is now moving in the direction of segmenting textured polygonal meshes [27] and/or 3D point clouds [64]. In the architectural domain, the classification is either focused on automatically recognizing, via ML algorithms and through a suitable amount of training data, on the one hand, the presence of alterations on historical buildings [65] or the mapping of materials (*texture-based* approaches) [27][66][67], and, on the other hand, the distinction into architectural components based on prior historical knowledge (*geometry-based* approaches) [26][68][69][70].

Depending on the type of approach chosen, the classification can act on either two kinds of properties of the raw data: (a) geometric features, such as height, planarity, linearity, sphericity, etc. [71], that are better suited for the recognition of architectural components based on respective shapes of elements, or (b) colorimetric attributes, such as RGB, HSL or HSV color spaces [65], that are widely used for the identification of decay patterns (as biological patina or colonization, chromatic alterations, spots, etc.) or of materials.

Geometry-based classification techniques, formerly exploited for classifying urban scenes [17][71][72], are now applied to the scale of the individual building, for the segmentation of walls, moldings, vaults, columns, roofs, etc. [69]. Grilli et al. [69] investigated the effectiveness of covariance features [71] in training a Random Forest (RF) classifier [73] for architectural heritage, even demonstrating the existence of a correlation between such features and many main dimensions of architectural elements.

References

1. Dore, C.; Murphy, M. Semi-automatic techniques for as-built BIM façade modeling of historic buildings. In Proceedings of the 2013 Digital Heritage International Congress (DigitalHeritage), IEEE, Marseille, France, 28 October 2013–1 November 2013; pp. 473–480.
2. Murphy, M.; McGovern, E.; Pavia, S. Historic building information modelling (HBIM). Struct. Surv. 2009, 27, 311–327.
3. López, F.; Lerones, P.; Llamas, J.; Gómez-García-Bermejo, J.; Zalama, E. A Review of Heritage Building Information Modeling (H-BIM). MTI 2018, 2, 21.
4. Pocobelli, D.P.; Boehm, J.; Bryan, P.; Still, J.; Grau-Bové, J. BIM for heritage science: A review. Herit. Sci. 2018, 6, 30.
5. Pătrăucean, V.; Armeni, I.; Nahangi, M.; Yeung, J.; Brilakis, I.; Haas, C. State of research in automatic as-built modelling. Adv. Eng. Inform. 2015, 29, 162–171.
6. Logothetis, S.; Delinasiou, A.; Stylianidis, E. Building Information Modelling for Cultural Heritage: A review. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2015, II-5/W3, 177–183.
7. Volk, R.; Stengel, J.; Schultmann, F. Building Information Modeling (BIM) for existing buildings—Literature review and future needs. Autom. Constr. 2014, 38, 109–127.
8. Hichri, N.; Stefani, C.; De Luca, L.; Veron, P.; Hamon, G. From point cloud to BIM: A survey of existing approaches. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2013, XL-5/W2, 343–348.
9. Miceli, A.; Morandotti, M.; Parrinello, S. 3D survey and semantic analysis for the documentation of built heritage. The case study of Palazzo Centrale of Pavia University. VITRUVIO Int. J. Archit. Technol. Sustain. 2020, 5, 65.
10. Oreni, D.; Brumana, R.; Georgopoulos, A.; Cuca, B. HBIM for conservation and built heritage: Towards a library of vaults and wooden bean floors. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2013, II-5/W1, 215–221.
11. Arayici, Y. Towards building information modelling for existing structures. Struct. Surv. 2008, 26, 210–222.
12. Fai, S.; Sydor, M. Building Information Modelling and the documentation of architectural heritage: Between the 'typical' and the 'specific'. In Proceedings of the 2013 Digital Heritage International Congress (DigitalHeritage), Marseille, France, 28 October 2013–1 November 2013; Volume 1, pp. 731–734.
13. Bacci, G.; Bertolini, F.; Bevilacqua, M.G.; Caroti, G.; Martínez-Espejo Zaragoza, I.; Martino, M.; Piemonte, A. HBIM methodologies for the architectural restoration. The case of the ex-church of San Quirico all'Olivo in Lucca, Tuscany. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2019, XLII-2/W11, 121–126.
14. Angulo-Fornos, R.; Castellano-Román, M. HBIM as Support of Preventive Conservation Actions in Heritage Architecture. Experience of the Renaissance Quadrant Façade of the Cathedral of Seville. Appl. Sci. 2020, 10, 2428.

15. Barazzetti, L.; Banfi, F.; Brumana, R.; Gusmeroli, G.; Previtali, M.; Schiantarelli, G. Cloud-to-BIM-to-FEM: Structural simulation with accurate historic BIM from laser scans. Simul. Model. Pract. Theory 2015, 57, 71–87.

16. Croce, P.; Landi, F.; Puccini, B.; Martino, M.; Maneo, A. Parametric HBIM procedure for the structural evaluation of Heritage masonry buildings. Buildings 2022, 12, 194.

17. Pepe, M.; Costantino, D.; Restuccia Garofalo, A. An efficient pipeline to obtain 3D model for HBIM and structural analysis purposes from 3D point clouds. Appl. Sci. 2020, 10, 1235.

18. Brumana, R.; Oreni, D.; Cuca, B.; Binda, L.; Condoleo, P.; Triggiani, M. Strategy for integrated surveying techniques finalized to interpretive models in a Byzantine Church, Mesopotam, Albania. Int. J. Archit. Herit. 2014, 8, 886–924.

19. Pocobelli, D.P.; Boehm, J.; Bryan, P.; Still, J.; Grau-Bové, J. Building Information Modeling for monitoring and simulation data in heritage buildings. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018, 42, 909–916.

20. Martinez Espejo Zaragoza, I.; Caroti, G.; Piemonte, A. The use of image and laser scanner survey archives for cultural heritage 3D modelling and change analysis. ACTA IMEKO 2021, 10, 114.

21. Brumana, R.; Oreni, D.; Barazzetti, L.; Cuca, B.; Previtali, M.; Banfi, F. Survey and Scan to BIM Model for the Knowledge of Built Heritage and the Management of Conservation Activities. In Digital Transformation of the Design, Construction and Management Processes of the Built Environment; Daniotti, B., Gianinetto, M., Della Torre, S., Eds.; Springer International Publishing: Cham, Switzerland, 2020; pp. 391–400. ISBN 978-3-030-33570-0.

22. Bruno, S.; Musicco, A.; Fatiguso, F.; Dell'Osso, G.R. The Role of 4D Historic Building Information Modelling and Management in the Analysis of Constructive Evolution and Decay Condition within the Refurbishment Process. Int. J. Archit. Herit. 2019, 15, 1250–1266.

23. Macher, H.; Landes, T.; Grussenmeyer, P. From Point Clouds to Building Information Models: 3D Semi-Automatic Reconstruction of Indoors of Existing Buildings. Appl. Sci. 2017, 7, 1030.

24. Bevilacqua, M.G.; Caroti, G.; Piemonte, A.; Terranova, A.A. Digital Technology and Mechatronic Systems for the Architectural 3D Metric Survey. In Mechatronics for Cultural Heritage and Civil Engineering; Intelligent Systems, Control and Automation: Science and Engineering; Ottaviano, E., Pelliccio, A., Gattulli, V., Eds.; Springer International Publishing: Cham, Switzerland, 2018; Volume 92, pp. 161–180. ISBN 978-3-319-68645-5.

25. Fiorucci, M.; Khoroshiltseva, M.; Pontil, M.; Traviglia, A.; Del Bue, A.; James, S. Machine Learning for Cultural Heritage: A Survey. Pattern Recognit. Lett. 2020, 133, 102–108.

26. Matrone, F.; Grilli, E.; Martini, M.; Paolanti, M.; Pierdicca, R.; Remondino, F. Comparing Machine and Deep Learning Methods for Large 3D Heritage Semantic Segmentation. IJGI 2020, 9, 535.

27. Grilli, E.; Remondino, F. Classification of 3D Digital Heritage. Remote Sens. 2019, 11, 847.

28. Rocha, G.; Mateus, L.; Fernández, J.; Ferreira, V. A Scan-to-BIM Methodology Applied to Heritage Buildings. Heritage 2020, 3, 47–67.

29. Yang, X.; Koehl, M.; Grussenmeyer, P. Mesh-To-BIM: From segmented mesh elements to BIM model with limited parameters. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018, 42, 1213–1218.

30. Bruno, S.; De Fino, M.; Fatiguso, F. Historic Building Information Modelling: Performance assessment for diagnosis-aided information modelling and management. Autom. Constr. 2018, 86, 256–276.

31. Previtali, M.; Barazzetti, L.; Brumana, R.; Scaioni, M. Towards automatic indoor reconstruction of cluttered building rooms from point clouds. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2014, 2, 281–288.

32. Bruno, N.; Roncella, R. HBIM for Conservation: A New Proposal for Information Modeling. Remote Sens. 2019, 11, 1751.

33. Tommasi, C.; Achille, C. Interoperability matter: Levels of data sharing, starting from a 3D information modeling. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, XLII-2/W3, 623–630.

34. Tang, P.; Huber, D.; Akinci, B.; Lipman, R.; Lytle, A. Automatic reconstruction of as-built building information models from laser-scanned point clouds: A review of related techniques. Autom. Constr. 2010, 19, 829–843.

35. Dore, C.; Murphy, M. Current state of the art Historic Building Information Modeling. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2017, 42, 185–192.

36. Xiong, X.; Adan, A.; Akinci, B.; Huber, D. Automatic creation of semantically rich 3D building models from laser scanner data. Autom. Constr. 2013, 31, 325–337.

37. Jung, J.; Hong, S.; Jeong, S.; Kim, S.; Cho, H.; Hong, S.; Heo, J. Productive modeling for development of as-built BIM of existing indoor structures. Autom. Constr. 2014, 42, 68–77.

38. Zhang, X. Curvature estimation of 3D point cloud surfaces through the fitting of normal section curvatures. Proc. Asiagraph 2008, 8, 23–26.

39. Schnabel, R.; Wahl, R.; Klein, R. Efficient RANSAC for Point-Cloud Shape Detection. Comput. Graph. Forum 2007, 26, 214–226.

40. Fischler, M.A.; Bolles, R.C. Random sample consensus: A paradigm for model fitting with applications to image analysis and automated cartography. Commun. ACM 1981, 24, 381–395.

41. Hough, P.V.C. Method and Means for Recognizing Complex. Patterns. Patent 3,069,654, 18 December 1962.

42. Thomson, C.; Boehm, J. Automatic Geometry Generation from Point Clouds for BIM. Remote Sens. 2015, 7, 11753–11775.

43. Bosché, F.; Ahmed, M.; Turkan, Y.; Haas, C.T.; Haas, R. 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. Autom. Constr. 2015, 49, 201–213.

44. Wang, Z.; Shi, W.; Akoglu, K.; Kotoula, E.; Yang, Y.; Rushmeier, H. CHER-Ob: A Tool for Shared Analysis and Video Dissemination. J. Comput. Cult. Herit. 2018, 11, 1–22.

45. Hong, S.; Jung, J.; Kim, S.; Cho, H.; Lee, J.; Heo, J. Semi-automated approach to indoor mapping for 3D as-built building information modeling. Comput. Environ. Urban Syst. 2015, 51, 34–46.

46. Santagati, C.; Lo Turco, M.; Garozzo, R. Reverse information modeling for historic artefacts: Towards the definition of a level of accuracy for ruined heritage. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018, 42, 1007–1014.

47. Yang, X.; Lu, Y.-C.; Murtiyoso, A.; Koehl, M.; Grussenmeyer, P. HBIM Modeling from the Surface Mesh and Its Extended Capability of Knowledge Representation. IJGI 2019, 8, 301.

48. Rodríguez-Moreno, C.; Reinoso-Gordo, J.F.; Rivas-López, E.; Gómez-Blanco, A.; Ariza-López, F.J.; Ariza-López, I. From point cloud to BIM: An integrated workflow for documentation, research and modelling of architectural heritage. Surv. Rev. 2018, 50, 212–231.

49. Quattrini, R.; Battini, C.; Mammoli, R. HBIM TO VR. Semantic awareness and data enrichment interoperability for parametric libraries of historical architecture. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018, 42, 937–943.

50. Baik, A. From point cloud to Jeddah Heritage BIM Nasif Historical House—Case study. Digit. Appl. Archaeol. Cult. Herit. 2017, 4, 1–18.

51. Fai, S.; Rafeiro, J. Establishing an appropriate Level of Detail (LoD) for a Building Information Model (BIM)—West Block, Parliament Hill, Ottawa, Canada. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2014, 2, 123–130.

52. De Luca, L.; Véron, P.; Florenzano, M. A generic formalism for the semantic modeling and representation of architectural elements. Vis. Comput. 2007, 23, 181–205.

53. Murphy, M.; McGovern, E.; Pavia, S. Historic Building Information Modelling—Adding intelligence to laser and image based surveys of European classical architecture. ISPRS J. Photogramm. Remote Sens. 2013, 14, 89–102.

54. Tommasi, C.; Achille, C.; Fassi, F. From point cloud to BIM: A modelling challenge in the Cultural Heritage field. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2016, 41, 429–436.

55. Andriasyan, M.; Moyano, J.; Nieto-Julián, J.E.; Antón, D. From Point Cloud Data to Building Information Modelling: An Automatic Parametric Workflow for Heritage. Remote Sens. 2020, 12, 1094.

56. Capone, M.; Lanzara, E. Scan-to-BIM vs. 3D ideal modela HBIM: Parametric tools to study domes geometry. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2019, 42, 219–226.

57. Kelly, G. A survey of procedural techniques for city generation. ITB J. 2006, 14, 342–351.

58. Pierdicca, R.; Paolanti, M.; Matrone, F.; Martini, M.; Morbidoni, C.; Malinverni, E.S.; Frontoni, E.; Lingua, A.M. Point Cloud Semantic Segmentation Using a Deep Learning Framework for Cultural Heritage. Remote Sens. 2020, 12, 1005.

59. Paumard, M.-M.; Picard, D.; Tabia, H. Deepzzle: Solving Visual Jigsaw Puzzles with Deep Learning and Shortest Path Optimization. IEEE Trans. Image Process. 2020, 29, 3569–3581.

60. Ibrahim, Y.; Nagy, B.; Benedek, C. Deep Learning-Based Masonry Wall Image Analysis. Remote Sens. 2020, 12, 3918.

61. Varinlioglu, G.; Balaban, O. Artificial Intelligence in Architectural Heritage Research: Simulating Networks of Caravanserais through Machine Learning; The Routledge Companion to Artificial Intelligence in Architecture; Basu, P., Ed.; Routledge: Abingdon-on-Thames, UK, 2021; ISBN 978-0-367-42458-9.

62. Korc, F.; Forstner, W. eTRIMS Image Database for Interpreting Images of Man-Made Scenes. Comput. Sci. 2009, 12, 62918340.

63. Manfredi, M.; Grana, C.; Cucchiara, R. Automatic Single-Image People Segmentation and Removal for Cultural Heritage Imaging. In New Trends in Image Analysis and Processing—ICIAP 2013; Petrosino, A., Maddalena, L., Pala, P., Eds.; Springer: Berlin/Heidelberg, Germany, 2013; pp. 188–197.
64. Grilli, E.; Dininno, D.; Petrucci, G.; Remondino, F. From 2D to 3D supervised segmentation and classification for Cultural Heritage applications. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2018, 42, 399–406.
65. Musicco, A.; Galantucci, R.A.; Bruno, S.; Verdoscia, C.; Fatiguso, F. Automatic point cloud segmentation for the detection of alterations on historical buildings through an unsupervised and clustering-based Machine Learning approach. ISPRS Ann. Photogramm. Remote Sens. Spat. Inf. Sci. 2021, 2, 129–136.
66. Bassier, M.; Yousefzadeh, M.; Vergauwen, M. Comparison of 2D and 3D wall reconstruction algorithms from point cloud data for as-built BIM. ITcon 2020, 25, 173–192.
67. El Kadi, K.A. Automatic Extraction of Facade Details of Heritage Building Using Terrestrial Laser Scanning Data. J. Archit. Eng. Technol. 2014, 3, 2.
68. Morbidoni, C.; Pierdicca, R.; Paolanti, M.; Quattrini, R.; Mammoli, R. Learning from synthetic point cloud data for historical buildings semantic segmentation. J. Comput. Cult. Herit. 2020, 13, 1–16.
69. Grilli, E.; Farella, E.M.; Torresani, A.; Remondino, F. Geometric features analysis for the classification of Cultural Heritage point clouds. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2019, 42, 541–548.
70. Malinverni, E.S.; Mariano, F.; Di Stefano, F.; Petetta, L.; Onori, F. Modeling in HBIM to document materials decay by a thematic mapping to manage the Cultural Heritage: The case of Chiesa della Pietà in Fermo. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2019, 42, 777–784.
71. Weinmann, M. Reconstruction and Analysis of 3D Scenes; Springer International Publishing: Cham, Switzerland, 2016; ISBN 978-3-319-29244-1.
72. Özdemir, E.; Remondino, F.; Golkar, A. Aerial point cloud classification with deep learning and machine learning algorithms. Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. 2019, XLII-4/W18, 843–849.
73. Breiman, L. Ramdom forests. Mach. Learn. 2001, 45, 5–32.