remote sensing

Review

3D Point Cloud for Cultural Heritage: A Scientometric Survey

Su Yang [1], Shishuo Xu [2,*] and Wei Huang [3,4,5]

[1] College of Geosciences and Surveying Engineering, China University of Mining and Technology, Beijing 100083, China
[2] School of Geomatics and Urban Spatial Informatics, Beijing University of Civil Engineering and Architecture, Beijing 100044, China
[3] College of Surveying and Geo-informatics, Tongji University, Shanghai 200092, China
[4] Urban Mobility Institute, Tongji University, Shanghai 200092, China
[5] Department of Civil Engineering, Toronto Metropolitan University, Toronto, ON M5B 2K3, Canada
* Correspondence: xushishuo@bucea.edu.cn

Abstract: Three-dimensional point cloud has been widely used in the cultural heritage field in the last two decades, gaining attention from both academic and industry communities. A large number of scientific papers have been published concerning this topic, which covers a wide range of journals, countries, and disciplines. There has been no comprehensive and systematic survey of recent literature performed in a scientometric way based on the complex network analysis methods. In this work, we extracted the terms (i.e., noun phrases included in the title, abstract and keywords), the documents, the countries that the research institutions are located in, and the categories that the literature belongs to from the Web of Science database to compose a term co-occurrence network, document co-citation network, collaborative country network and category co-occurrence network using CiteSpace software. Through visualizing and analyzing those networks, we identified the research hotspots, landmark literature, national collaboration, interdisciplinary patterns as well as the emerging trends through assessing the central nodes and the nodes with strong citation bursts. This work not only provides a structured view on state-of-art literature, but also reveals the future trends of employing 3D point cloud data for cultural heritage, aiding researchers carry out further research in this area.

Keywords: point cloud; cultural heritage; CiteSpace; scientometric; visual analysis

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1. Introduction

Three-dimensional (3D) point cloud data refers to a set of points defined by the X, Y, and Z in the geo-coordinate system [1], which can be obtained from various sources such as laser scans, images, and videos based on specific equipment and technologies [2–4]. Three-dimensional point cloud data is capable of representing the external surfaces of objects with geometric details and texture, which can be imported and processed by computers, providing effective support for digital storage as well as further analysis. Cultural heritage, such as historical buildings, archaeological sites, and stone carvings, etc., are objects with complex geometries and the historical memory of mankind. It is critical to reconstruct, protect and restore cultural heritage in digital forms and sustain them in the long run, and this is where 3D point cloud data proves to be a reliable data source [5–7]. Applying 3D point cloud data in the cultural heritage field has gained more and more attention in academic and industry communities since 2000 [8–10]. In recent years, it has become a multidisciplinary field that interacts with a number of disciplinaries, covering art, archaeology, computer science, environmental science, applied physics, and chemistry analysis [11–14]. As such, it is necessary to provide insightful information for those interested in investigating how this field has evolved over the past two decades.

Some scholars have conducted literature reviews and surveys on specific topics through organizing the related work of 3D point cloud in the cultural heritage field in a methodology-based way. For example, Cheng et al. (2018) [15] presented a comprehensive review of LiDAR data registration in photogrammetry and remote sensing. It reveals that multi-angle and multi-scale data obtained from various types of LiDAR hardware plays an essential role in diverse applications serving cultural heritage protection. Tobiasz et al. (2019) [16] surveyed the state-of-the-art documentation, management, and sustainability techniques in cultural heritage. Moyano et al. (2021) [17] reviewed the historical building information modeling (HBIM) process to extract geometries of cultural heritage from the point cloud to create digital twins, particularly for the archaeological and architectural heritage. Santos et al. (2022) [18] summarized existing work on historical timber structures using HBIM, focusing on various geometric surveying and 3D modeling methods and nongeometric information used for conservation, testing, and monitoring. However, those reviews and surveys do not conduct a comprehensive, systematic, or quantitative analysis to reveal the research topics, research trends and patterns, and future research directions in the domain of utilizing 3D point cloud for cultural heritage.

Scientometrics is defined as the "quantitative study of science, communication in science and science policy" [19], which is regarded as the science of science by some scholars. Fortunato et al. (2018) [20] explained "science of science" as using large-scale data on the production of science to search for universal and domain-specific patterns. The scientometric analysis used for literature review is a branch of informatics that quantitatively analyzes and maps patterns in scientific literature in order to understand the research themes, emerging trends, and the knowledge structure of a research. Zhao et al. (2017) [21] conducted a scientometric review of building information modeling (BIM) research between 2005–2016, providing researchers and practitioners with an in-depth understanding of the status and trend of BIM research worldwide. Martinez et al. (2019) [22] conducted a scientometric review of the articles published between 1999 and 2019 concerning the computer vision techniques applied for construction to provide support for future research efforts. Rashidi et al. (2020) [23] quantitatively analyzed the research patterns in the modern bridge monitoring field, consisting of dominated sub-fields, co-occurrence of keywords, network of researchers and their institutions within the last decade. Balz (2021) [24] presented in-depth scientometric analysis of the full texts of all papers published in MDPI's Remote Sensing between 2009 and 2021, revealing distinctive styles and writing patterns, trends in publications, readability of abstracts and papers, and institutional co-authorship worldwide.

As such, we explore the literature concerning 3D point cloud used in the cultural heritage field from the Web of Science (WoS) database, which returns a large number of publications in English including title, author, abstract, keyword, journal, and citation information. The non-English publications not included in the bibliographical database are out of scope for our scientometric exploration, which may introduce a bias among the academic range of publishes we are surveying. The publications in other languages and databases can be further added for a larger-scale analysis. The co-occurrence and co-citation relationship exist between different publications. Such information lays a solid information for composing multi-type networks of various entities, such as keyword co-occurrence and document co-citation, which are sufficient to represent the intellectual landscape of a scientific field [25]. Those networks can be visualized by knowledge mapping, which is an emerging approach and the knowledge structure for literature analysis. It is helpful for researchers and engineers, as well as business investigators, to uncover and understand the hot topics, multidisciplinary interaction patterns, developing trends, academic cooperation between scholars and countries, etc., providing a holistic and comprehensive portrait for a research domain. In this study, we use CiteSpace [26], a scientometric analysis and visualization software, to make a co-citation and co-occurrence analysis of those studies related to 3D point cloud data in the field of cultural heritage.

The main objectives of this study focus on making a term (i.e., key noun phrases) co-occurrence network analysis to acquire hot topics, making a document co-citation network analysis to identify key literature, making a collaborative country network analysis to reflect national cooperation, and making a category co-occurrence network analysis to explore the interdisciplinary intersection in the domain of 3D point cloud data for cultural heritage.

There is no scientometric network-based review of recent studies on 3D point cloud data for cultural heritage to investigate the hot topics and general development trends of this domain through collecting and analyzing the qualified journal publications from WoS. Our work fills this gap and contributes to the identification of emerging hotspots, research structure and research evolution of this domain through constructing the scientometric networks based on those WoS publications and discovering the clusters and bursting entities from scientometric networks. The scientometric analysis results not only provide scholars (architects, archaeologists, art historians, geographers, etc.) with a structured view on state-of-art literature, but also aids them to capture the research hotspots, landmark literature, as well as the changes of research themes over time in an efficient way. Such information is critical for scholars, especially for those beginners who are new to this domain.

The rest of this paper is organized as follows. Section 2 introduces the background knowledge concerning the technological and application aspects of 3D point cloud data in the cultural heritage field. Section 3 presents the methodological framework for reviewing the relevant studies and provides an overview of CiteSpace software as an analysis and visualization tool. Section 4 analyzes and discusses the results. Finally, the main conclusions are drawn in Section 5.

2. Background

2.1. Data Acquisition and Fusion

Three-dimensional point cloud data is an important data source for the 3D virtual reconstruction of cultural heritage, which mainly includes 3D spatial geometry information, color information and sensor reflection intensity information [27,28]. Such data can be collected using 3D laser scanning technology and photogrammetry technology, equipped with UAV (Unmanned Aerial Vehicle), mobile vehicle, ground, and other platforms, providing various approaches for obtaining point clouds of cultural heritage [29–33]. Recently, ultra-light UAV systems [34], a handheld mobile 3D laser mapping system [35], low-cost spherical cameras [36], and smart mobile phone LiDAR sensors [37,38] have been widely used for 3D surveying in the cultural heritage domain. The emergence of these lightweight devices makes 3D data collection of cultural heritage more popular and available to more non-professional users. It also reflects how the application of point cloud data in the field of cultural heritage has gained more and more attention in a wide range of fields and among non-professionals.

The 3D point cloud data acquired by laser scanning mainly includes registration, noise filtering, hole filling, surface reconstruction and texturing [39]. Shao et al. (2019) combined Terrestrial Laser Scanning (TLS) in millimeter-scale resolution and a structured light scanner in sub-millimeter resolution techniques to acquire detailed point cloud and register them in the spatial reference to build 3D models of large artefacts. Ghorbani et al. (2022) [40] introduced 3D key point detection for the registration of point cloud data. Since there usually exists noise in the raw data, several noise filtering algorithms [41,42] have been applied to eliminate noise points and outliers. Hole filling aims to fill the missing regions caused by occlusions in the reconstructed 3D models. Yong et al. (2022) [43] proposed a multi-scale upsampling GAN-based framework to build complete 3D cultural heritage models with grained details. Regarding the 3D point cloud data acquired by photogrammetry technology, other steps are required for data preprocessing. Shao et al. (2016) [44] designed the Multi-View Stereo (MVS) algorithm to weaken the influence of occlusion and noise on matching results. The whole image dataset is processed with color enhancement, image denoising, color-to-gray conversion and image content enrichment to improve the performance of orientation automation and dense 3D point cloud reconstruction [45].

In most cases, the single data acquisition method is challenging to obtain complete point cloud data of the target scene within limited observation conditions and viewing angles [46]. For instance, TLS usually obtains information on building facades, whereas

UAV photogrammetry can provide the information for building roofs. Many scholars have been attempting to completely represent geometric shapes of cultural heritage through multi-source point cloud fusion through leveraging the advantages of multiple sensors and data acquisition platforms. For instance, Achille et al. (2015) [47] integrated multi-source point cloud data including TLS point cloud and photogrammetric data that were collected by a UAV system. This solved the problem of data incompleteness in the vertical direction caused by the restricted flying area of the UAV. Galeazzi (2016) [48] used 3D laser scanning and photogrammetry techniques to produce archaeological records of the microscopic strata of caves under extreme environment and light conditions. Rodriguez-Gonzalvez et al. (2017) [49] synchronized LiDAR sensors with the inertial and global navigation systems that are installed on mobile platforms to generate point clouds with absolute geographic coordinates. It significantly improved the data acquisition efficiency of large cultural heritage sites and reduced the problems caused by multi-site cloud splicing. Erenoglu et al. (2017) [50] incorporated multiple sensors on the UAV to obtain visible, thermal and infrared radiation in the electromagnetic spectrum. In addition to generating high-precision geometric models. The classification results of the spectral analysis could reveal the characteristics of materials. Puente et al. (2018) [51] reconstructed high-resolution 3D digital models of archaeological sites using ground-penetrating radar and terrestrial light detection and ranging (T-LiDAR) techniques.

All in all, data fusion has proven to be a powerful method for documenting and preserving cultural heritage sites, historical buildings, archaeological records, and monuments. However, multi-platform and multi-sensor coupling observations lead to different point cloud densities and spatial scales, and the overlap between data brings difficulties to point cloud data registration [52], which are potentially to be addressed in the future. In addition, the results of point cloud data acquisition (e.g., accuracy, resolution, and chromatic quality) need a comprehensive consideration of the ease of use, time consumption, economy, instrumental and operator [53].

2.2. Data Processing and Application

Due to the large-scale and unorganized (without neighborhood information) characteristics of 3D point cloud data, it is still challenging to directly apply point cloud data to the cultural heritage field [54]. Therefore, certain data processing algorithms are required for orthophoto image production, damaged area investigation, HBIM and geographic information (GIS) system, virtual restoration, etc.

2.2.1. Orthophoto Image Production

With the aim of life-cycle conservation of cultural heritage, documentation is required for the digital archiving of cultural heritage [55,56]. Orthophoto images are attractive for archaeological and architectural documents since they guarantee both geometric precision and visual quality. As cultural heritage is not always perpendicular or parallel to the ground, the critical factor in the process of orthophoto image production is the selection of an appropriate projection plane. In this case, plane detection algorithms of point cloud data are often used to generate accurate projection planes to produce orthophoto images automatically. For example, Markiewicz et al. (2015) [57] used RANdom SAmple Consensus (RANSAC), Hough transform and a region growing algorithm to extract the projection planes from the TLS point cloud of historical buildings, respectively. The digital image is then matched with the projection plane to generate an orthophoto image.

2.2.2. Damage Detection

Three-dimensional point cloud data can be used to identify and evaluate façade surface features (e.g., edges and cracks) from cultural heritage [58,59]. For instance, the point cloud data obtained by TLS is able to detect cracks and defects that are caused by weather, age, infiltration, and solar radiation at the millimeter level [60]. Galantucci et al. (2018) [61] identified and quantified the surface damage of cultural relics caused by cracks or material loss through the line and surface extraction algorithm that was embedded in the close-range photogrammetry-based 3D model. Wood et al. (2021) [62] employed geometric surface descriptors including covariance, normal vector and curvature as damage-sensitive features, based upon which, an ordering points to identify clustering structures (OPTICS) algorithm was used to detect the lesion area of surface damage, defects and cracks in the mural. Alkadri et al. (2022) [63] introduced and analyzed local features of geometric information and radiation information of point cloud data to identify cracks and surface material characteristics of cultural relics.

2.2.3. HBIM

HBIM, as a reverse modeling technique for 3D point cloud data post-processing, allows the management of the geometric structure of buildings, the creation of complete engineering drawings of historical buildings and cultural heritage sites, and the information exchange (e.g., construction method and material composition) among cultural heritage conservation experts [64,65]. Intelligently recording, interpreting and managing complex and culturally significant heritage buildings make building protection, as well as project design and management, more systematic and efficient [66]. The approach of capturing accurate building geometries from 3D laser scanning to build a BIM or HBIM model is called Scan to BIM [67]. Rocha et al. (2020) [68] established the HBIM of using 3D laser scanning and photogrammetric techniques. Park et al. (2021) [69] constructed a BIM model based on 3D point cloud data to detect changes in historical buildings. Ursini et al. (2022) [70] used scan-to-BIM to generate a structural finite element model of built heritage for dynamic simulation. Pepe et al. (2020) [71] proposed a novel workflow named Scan to BIM to FEA(finite element analysis) to make the 3D model suitable for structural analysis and the parameterization of rheological and geometric information of every single element of the structure. Moyano et al. (2020) [72] applied BIM in archaeology, i.e., A-BIM, to create parameterized objects with complex archaeological shapes from 3D point cloud data.

Despite the above-mentioned research on semi-automatic or automatic BIM reconstruction from point cloud, there exists certain space for improving the accuracy, applicability, and automation of existing techniques [73–76]. HBIM can be improved through extracting geometric primitives for knowledge management and by establishing their connection to manage heterogeneous knowledge. Yang et al. (2021) [77] combined the geometric elements of HBIM with semantic ontologies and obtained an integrated model with object-oriented knowledge. Identifying basic geometric elements or objects from point cloud data and connecting them with semantic information mainly relies on feature extraction and semantic segmentation algorithms [78–80]. Deep learning techniques for 3D point cloud semantic segmentation can help identify historic building elements at a finer level involving more details, improving the performance of the HBIM building process from point cloud data [81,82]. In addition to geometric information, realistic textures are also a challenge for HBIM, as the standard textures and materials provided in the HBIM library are not sufficient for the reliable representation of cultural heritage [83].

2.2.4. Integration with 3D GIS

Point cloud data acts as one of the data sources for processing the geospatial information of a wide range of cultural heritage items (such as historical sites) in geographic information systems (GIS) and for recording 3D information [84]. HBIM focuses on the geometric structure and attribute information of cultural heritage, while GIS enables the integration of 3D model and geospatial information, supporting spatial analysis and heritage conservation [85,86], as well as risk and vulnerability analyses [87,88] at a large scale. Tobiasz et al. (2019) [16] presented GIS for management, storage, and maintenance of cultural heritage documentation. Costantino et al. (2020) [89] developed a Web-GIS based database for integrating different types of information layers (e.g., regional maps, orthophotos, regional territorial landscape plans) according to a landscape approach. Pepe et al. (2021) [90] built a 3D GIS model using point cloud data to connect different databases and provided a multidisciplinary approach. Sanchez-Sanchez et al. (2022) [91] constructed a 3D model of ancient archaeological sites and heritage buildings based on photogrammetry technology. The obtained model allowed geometric quantification of seismic deformation (e.g., displacement, amplitude, and direction) in a GIS-based 3D environment to quantify oriented damage of seismic origin.

2.2.5. Virtual Restoration

Principles of Seville defines virtual restoration as "using a virtual model to reorder available material remains in order to visually recreate something that existed in the past" (http://sevilleprinciples.com/, accessed on 21 October 2020). Virtual restoration in the cultural heritage applies digital technology for restoration, which aims to infer the historical geometric forms of cultural heritage under a certain assumption. This is not in conflict with physical restoration since virtual restoration has no effect on the physical cultural heritages [92]. In contrast, virtual restoration can assist physical restoration to rebuild the damaged heritage, restore visual assets and reconstruct artifacts. Chen et al. (2016) [93] determined the geometric shape of cultural relics based on the mechanical analysis of the precise 3D models of the existing cultural relics and recovered the details of each component. Setty and Mudenagudi (2018) [94] used region of interest (ROI)-based and patch-based methods to restore naturally damaged models which were partly broken or incomplete in artifacts at cultural heritage sites. Baik (2021) [95] provided an interactive and virtual 3D model for cultural relics and conducted information interaction with users based on the built BIM models, collecting historical photographs, documents about materials and past restoration projects. Hou et al. (2018) [96] analyzed the spatial distribution and relationship of the complex geometric structures of grottoes statues using 3D point cloud data, assisting the physical restoration project. Yang et al.(2020) [97] performed virtual stitching of cultural relic fragments based on contour feature extraction and an iterative nearest point algorithm. In the absence of sufficient historical data, the results of virtual restoration may not be verified. However, through feature extraction, feature matching and feature description, it can provide effective references for physical restoration from the geometric perspective.

2.3. Summary

The development of 3D point cloud data in the cultural heritage field is very dependent on the data-information-knowledge model [98]. Firstly, 3D point cloud data obtained by 3D laser scanning and photogrammetry provides a high-precision 3D digital model for cultural heritage documentation. Since a single data acquisition platform usually cannot meet the comprehensive analysis requirements of cultural heritage, many scholars have achieved such goals (e.g., recording the indoor-outdoor, ground-façade-roof, and sight occlusion areas of cultural heritage) based on multi-source point cloud fusion technology. The geometrical information in the point cloud can be extracted by point, line and surface feature extraction and segmentation. Subsequently, the point cloud semantic segmentation methods are employed to associate the geometric information with the semantic information. This information can be further used for 3D GIS integration or HBIM building, aiding cultural heritage management, spatial analysis, and structure analysis. Learning-based methods (machine learning and deep learning) provided the possibility of associating more semantic information with cultural heritage through automatically semantic segmentation and classification models [99]. However, these methods highly rely on a public benchmark dataset, which are currently lacking.

Recently, researches have focused on the effective fusion of point cloud data and knowledge, so that point cloud data can be directly used in knowledge mining and decision-making [100]. For instance, Poux et al. (2016, 2017) [101,102] proposed a smart point cloud structure for cultural heritage. Yang et al. (2021) [103] proposed a smart point cloud modeling process for complex geometric cultural relics. Ponciano et al. (2021) [104] stated three knowledge-based 3D digitization processes of cultural heritage, including a recommendation process of cultural data acquisition, object recognition process to structure the raw data, and an enrichment process based on Linked Open Data to document cultural objects. In a word, the development of 3D point cloud application in the field of cultural heritage shows the trend of data-information-knowledge, involving data collection, information extraction, and knowledge fusion. However, the topics and hotspots of each aspect vary over time and location. It is necessary to learn a wide range of research topics from the massive published high-level literature based on scientometrics analysis in order to find the most important and key terms, clarify its past and present development process, and identify the most active research frontiers and development trends.

3. Methodology

This section presents our data collection strategy, visualizes new trends, analyzes general development, and identifies roles with significant influence in employing 3D point cloud data for cultural heritage. Figure 1 demonstrates the overall framework for the scientometric analysis of the literature in this domain, which mainly includes data collection, term co-occurrence analysis, document co-citation analysis, national collaboration analysis and category co-occurrence analysis.

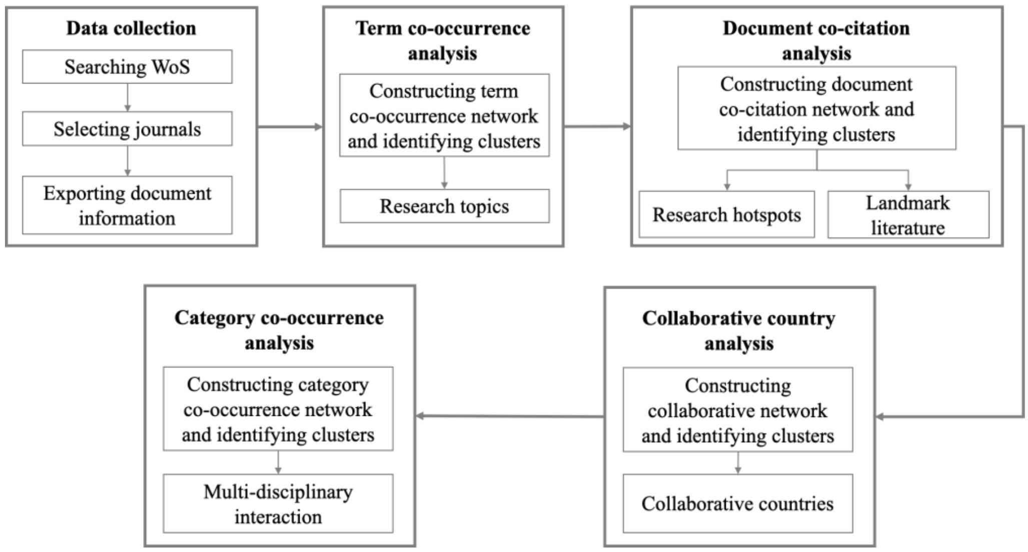


Figure 1. The overall framework of the scientometric survey in the domain of 3D point cloud data for cultural heritage.

First, we collected qualified literature from the WoS using appropriate queries, e.g., topics and journals. The obtained literature was then processed by a series of analysis and visualization using CiteSpace software. We conducted term (i.e., noun phrases included in the title, abstract, keywords and keywords plus) co-occurrence analysis through a knowledge network to identify the main clusters, representing a wide range of research topics in the domain of 3D point cloud for cultural heritage.

Landmark articles were identified through the document co-citation network, and the research basis and research hotspots that scholars are interested in were determined according to the clustering results. Moreover, the collaborative country network and category co-occurrence network were established to indicate the national collaboration and multidisciplinary intersection, respectively. More details regarding each are elaborated in the following sections.

3.1. Data Collection

In this work, we selected the high-quality papers that were published in journals rather than those published in conference proceedings as our research data. This is because the content of conference papers is limited to the themes of the conferences, which usually leads to a surge of papers in certain research directions in a short period of time. Such bursts in a short time undermines the balance of the survey data. As such, we only selected journal papers to review the research dynamics regarding 3D point cloud data used in the cultural heritage field.

The paper data were retrieved from three databases on the Thomson Reuters Web of Science (WoS) on 15 August 2022, including Science Citation Index Expanded (SCI-Expanded), Social Sciences Citation Index (SSCI), Arts & Humanities Citation Index (A&HCI). A set of topics combined with "AND" and "OR" logic was selected for querying the literature to be reviewed. Specifically, the keywords and their logic used in this work are ((point cloud*)) AND ((heritage*) OR (relic*) OR (historic building*) OR (ancient*) OR (architectural*) OR (archaeological*)), where "AND" means the topics occur at the same time in a paper, "OR" means at least one of those topics occur, and "*" represents any characters. For instance, the papers including "point cloud" and "heritage" and the papers including "point cloud" and "historic buildings" can be returned by the above-mentioned query. As a result, a total of 349 qualified journal papers (article, early access, and review article) included in the WoS were obtained, covering a wide range of journals with the scope of cultural heritage as well as remote sensing and surveying and mapping. Among the search results, journals with more than or equal to three related articles were selected. Table 1 lists the selected journals and the number of related papers included by each journal, which can be used as an indicator illustrating the closeness of the journal scope to 3D point cloud for cultural heritage. For example, the journals named "*Remote Sensing*", "*ISPRS International Journal of Geo-Information*" and "*Journal of Cultural Heritage*" include more related papers, revealing researchers in the surveyed field have more intention to publish their work in those journals.

Table 1. Selected journals and the number of relevant papers.

Journals	Papers
Remote Sensing	62
ISPRS International Journal of Geo Information	37
Journal of Cultural Heritage	31
Sensors	27
Applied Sciences Basel	17
ISPRS Journal of Photogrammetry and Remote Sensing	16
International Journal of Architectural Heritage	16
Automation in Construction	16
Sustainability	11
ACM Journal on Computing and Cultural Heritage	10
Journal of Archaeological Science Reports	9
Photogrammetrie Fernerkundung Geoinformation	7
Mediterranean Archaeology Archaeometry	7
Photogrammetric Record	6
Measurement	6
IEEE Access	6
Computers Graphics UK	6
Journal of Archaeological Science	5
Drones	5
Advanced Engineering Informatics	5
Symmetry Basel	4
Journal of Construction Engineering And Management	4
Journal of Building Engineering	4
International Journal of Remote Sensing	4
Heritage Science	4
Forests	4
Buildings	4
Archaeological Prospection	4
Survey Review	3
Remote Sensing of Environment	3
Journal of Computing in Civil Engineering	3
International Journal of Computer Vision	3

Besides that, we also counted the number of papers published yearly to investigate general research development. As shown in Figure 2, the first journal paper related to 3D point cloud and cultural heritage was published in 2006 [63]. Since then, the yearly number of published papers follows an increasing trend, especially after the year of 2016. There is a decrease from 2021 to 2022 since only journal papers published before September 2022 were counted in this survey. The ever-increasing pattern indicates that researchers have shown more and more interest in exploring the capability of leveraging 3D point cloud for cultural heritage and this research direction has gained more and more attention during the past two decades.

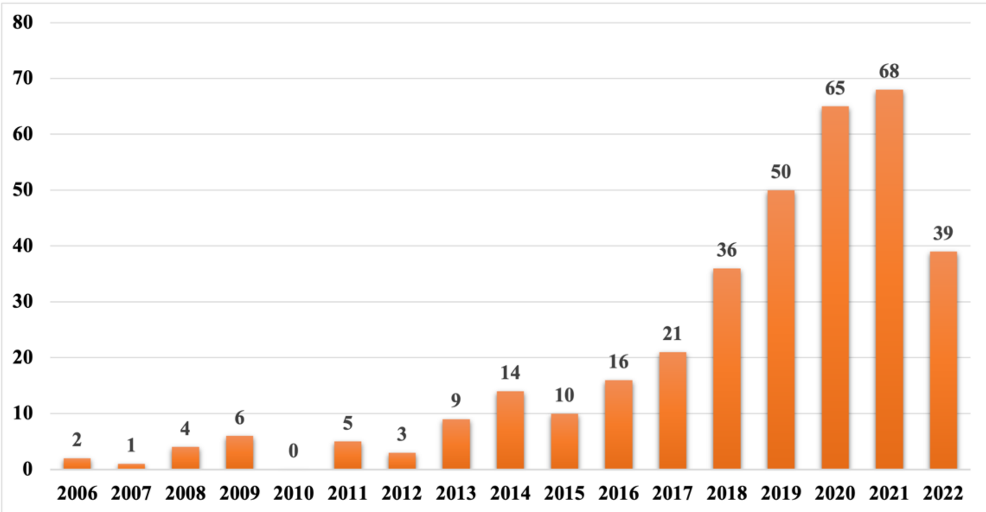
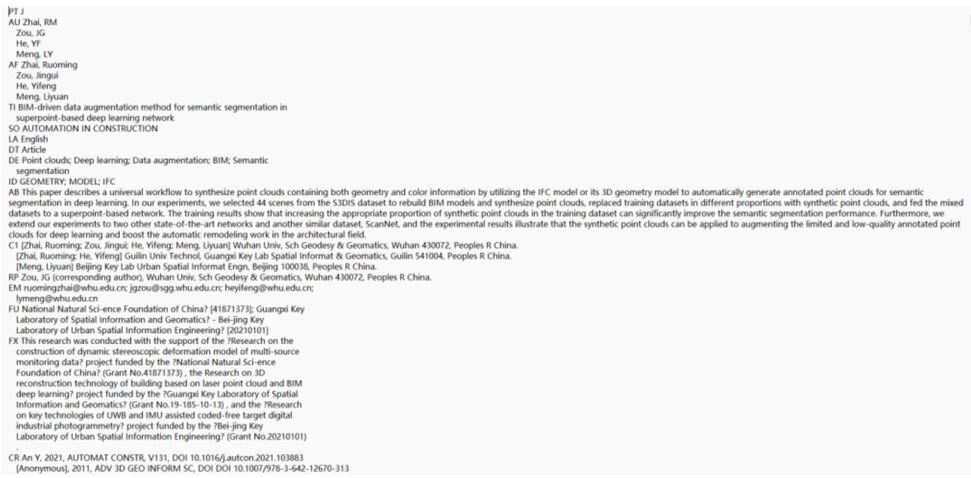


Figure 2. The chronological distribution of the number of articles published from 2006–2022.

Despite the general statistical information described above, the detailed information of each qualified paper can be found in the bibliography document, including title, authors, institution, fundings, abstract, keywords, references, etc. A capture of such information is shown in Figure 3.



PT J
AU Zhai, RM
Zou, JG
He, YF
Meng, LY
AF Zhai, Ruoming
Zou, Jingui
He, Yifeng
Meng, Liyuan
TI BIM-driven data augmentation method for semantic segmentation in superpoint-based deep learning network
SO AUTOMATION IN CONSTRUCTION
LA English
DT Article
DE Point clouds; Deep learning; Data augmentation; BIM; Semantic segmentation
ID GEOMETRY; MODEL; IFC
AB This paper describes a universal workflow to synthesize point clouds containing both geometry and color information by utilizing the IFC model or its 3D geometry model to automatically generate annotated point clouds for semantic segmentation in deep learning. In our experiments, we selected 44 scenes from the S3DIS dataset to rebuild BIM models and synthesize point clouds, replaced training datasets in different proportions with synthetic point clouds, and fed the mixed datasets to a superpoint-based network. The training results show that increasing the appropriate proportion of synthetic point clouds in the training dataset can significantly improve the semantic segmentation performance. Furthermore, we extend our experiments to two other state-of-the-art networks and another similar dataset, ScanNet, and the experimental results illustrate that the synthetic point clouds can be applied to augmenting the limited and low-quality annotated point clouds for deep learning and boost the automatic remodeling work in the architectural field.
C1 [Zhai, Ruoming; Zou, Jingui; He, Yifeng; Meng, Liyuan] Wuhan Univ, Sch Geodesy & Geomatics, Wuhan 430072, Peoples R China.
[Zhai, Ruoming; He, Yifeng] Guilin Univ Technol, Guangxi Key Lab Spatial Informat & Geomatics, Guilin 541004, Peoples R China.
[Meng, Liyuan] Beijing Key Lab Urban Spatial Informat Engn, Beijing 100038, Peoples R China.
RP Zou, JG (corresponding author), Wuhan Univ, Sch Geodesy & Geomatics, Wuhan 430072, Peoples R China.
EM ruomingzhai@whu.edu.cn; jgzou@sgg.whu.edu.cn; heyifeng@whu.edu.cn; lymeng@whu.edu.cn
FU National Natural Sci-ence Foundation of China? [41871373]; Guangxi Key Laboratory of Spatial Information and Geomatics? - Bei-jing Key Laboratory of Urban Spatial Information Engineering? [20210101]
FX This research was conducted with the support of the ?Research on the construction of dynamic stereoscopic deformation model of multi-source monitoring data? project funded by the ?National Natural Sci-ence Foundation of China? (Grant No.41871373) , the Research on 3D reconstruction technology of building based on laser point cloud and BIM deep learning? project funded by the ?Guangxi Key Laboratory of Spatial Information and Geomatics? (Grant No.19-185-10-13) , and the ?Research on key technologies of UWB and IMU assisted coded-free target digital industrial photogrammetry? project funded by the ?Bei-jing Key Laboratory of Urban Spatial Information Engineering? (Grant No.20210101)
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CR An Y, 2021, AUTOMAT CONSTR, V131, DOI 10.1016/j.autcon.2021.103883
[Anonymous], 2011, ADV 3D GEO INFORM SC, DOI DOI 10.1007/978-3-642-12670-313

Figure 3. A bibliography document showing the detailed information of a qualified paper exported from WoS.

3.2. Analysis Tools—CiteSpace Software

CiteSpace [105–108], a citation and co-occurrence network analysis and visualization software based on scientometrics, was used to analyze and visualize the knowledge embedded in the scientific literature that were collected in Section 3.1. The analysis results presented by CiteSpace can reveal the research network structure and research regularity, as well as the spatial distribution related research. It identifies landmarks, hot spots, emerging trends, and key points based on the literature collected from various knowledge bases.

In this work, we conducted four types of network analysis, including term co-occurrence network analysis, document co-citation network analysis, collaborative country network analysis, and category co-occurrence network analysis. The nodes and links are the basic elements of the networks returned by CiteSpace. The types of nodes include noun terms (e.g., keywords, abstracts, and titles), authors, countries, categories, etc. The size of the nodes reflects the frequency of relevant data occurrence. The links are the relationships between nodes, e.g., co-citation relationship and co-occurrence relationship. The thickness of the links indicates the strength of the relationship between the nodes.

Specifically, the term co-occurrence network analysis was conducted to identify the main research topics in the field of 3D point cloud for cultural heritage. A knowledge map showing the term co-occurrence can reflect hot topics [109]. The term is defined as noun phrases extracted from the title, abstract, keywords, and keywords plus, providing information about the main content of an article. The part-of-speech (i.e., POS) tagging technology, a widely-used natural language processing (NLP) tool, was used to realize the above-mentioned term extraction [110]. Since the research topics are usually composed of a set of noun phrases that highlight the main idea of the research, we selected the top K terms to reflect hot research topics. The nodes are the terms, and the links are drawn by investigating the co-occurrence relationship between terms. This paper reflects a research topic through the top ten noun phrases that are most relevant to the topic. With regard to a research domain, the term co-occurrence network analysis can reflect the temporal distribution and strength change of research topics. The document co-citation network analysis illustrates that if there exists a co-citation relationship between two documents (i.e., articles), it indicates that those two documents are associated and there is a link connecting them. In this case, a node in the network represents a document. The milestone documents are judged by the importance of nodes in the network. The structure and characteristics of the document co-citation network is able to show the research focus, research interest, research intention as well as research trends in the reviewed field [111]. The collaboration country network analysis identifies the association between research communities that may locate in different countries, depicting the research cooperation at the national level. The size of nodes (i.e., countries) and the thickness of links (i.e., the times that different countries cooperate) help to identify the contributions of different countries to the research domain [112]. As each article is assigned with one or more subject categories (e.g., cultural heritage, geography, and remote sensing), the category co-occurrence network analysis aims at finding out the key disciplines as well as the interaction between different disciplines. Furthermore, the clustering analysis was conducted based on the four types of networks, from which the hot research topics, the key articles, the popular research location and closely-related research subjects can be identified over time.

In order to quantificationally explain the network analysis results, a number of parameters were selected [107,108,110,113]. The degree of modularity reflects the structure's clarity at the decomposed cluster level, which is usually measured by Q value. If the Q value is more than 0.3, it means that the modularization of the network is significant. As the Q value increases, the clustering performance of the network improves. The silhouette score of a cluster (i.e., S) measures the homogeneity of its members. If the S value is over 0.7, it means that the clustering results are reasonable. As S moves closer to 1, the homogeneity of the network increases. A network with a high modularity degree and high average silhouette score is desirable. With regard to investigate the centrality of nodes, two types of measures were used, including betweenness centrality and degree centrality. The betweenness centrality is generally derived as a measure of centrality, which refers to the times that a node as an intermediary bridges another two nodes on the shortest path [108,114]. The degree centrality of a node refers to the number of links it connects [115,116]. The higher the degree centrality, the more central the node. The bursts value measures the rate of changes over time [117]. The higher the bursts value is, the more potentially an abrupt change occurs. A node with strong bursts usually indicates an exciting work that has attracted significant attention during a short period.

4. Results and Discussion

4.1. Term Co-Occurrence Network Analysis

Since researchers often express in different ways, the words used in different forms are likely to represent the same meaning, e.g., synonyms, singular, plural, abbreviations, etc. In this work, we configured CiteSpace software in order to keep the semantic consistency of certain terms. For instance, in terms of synonyms, we converted "3-d model" and "three-dimensional model" to "3d model". The "historical building" was unified as "historic building". The plural, such as "3d point clouds ", "3d documentations", "buildings", "3d scanners", "devices", etc., were all replaced with their singular form. With regard to abbreviations, "tls" and "terrestrial laser" were replaced with "terrestrial laser scanning", "uav" was replaced with "unmanned aerial vehicle", "bim" was replaced with "building information modeling", "hbim" was replaced with "historic building information modeling", etc. There also exists certain differences between American English and British English, resulting in spelling problems. In this case, we used American English for consistency, e.g., replacing "modelling" with "modeling".

The literature was analyzed using CiteSpace software by setting the time slice as two years, e.g., ranging from 2008 to 2009. The nodes (i.e., terms) of each time slice were derived from the noun phrase of the top N cited articles, where N is equal to 100, that has been widely used for such analysis. As a result, a total of 3380 nodes and 60,850 links were included in the term co-occurrence network, which are visualized in Figure 4. A link between two nodes represents the term co-occurrence relationship. The link color corresponds to the color of the time slice when the link was first established between a pair of terms.

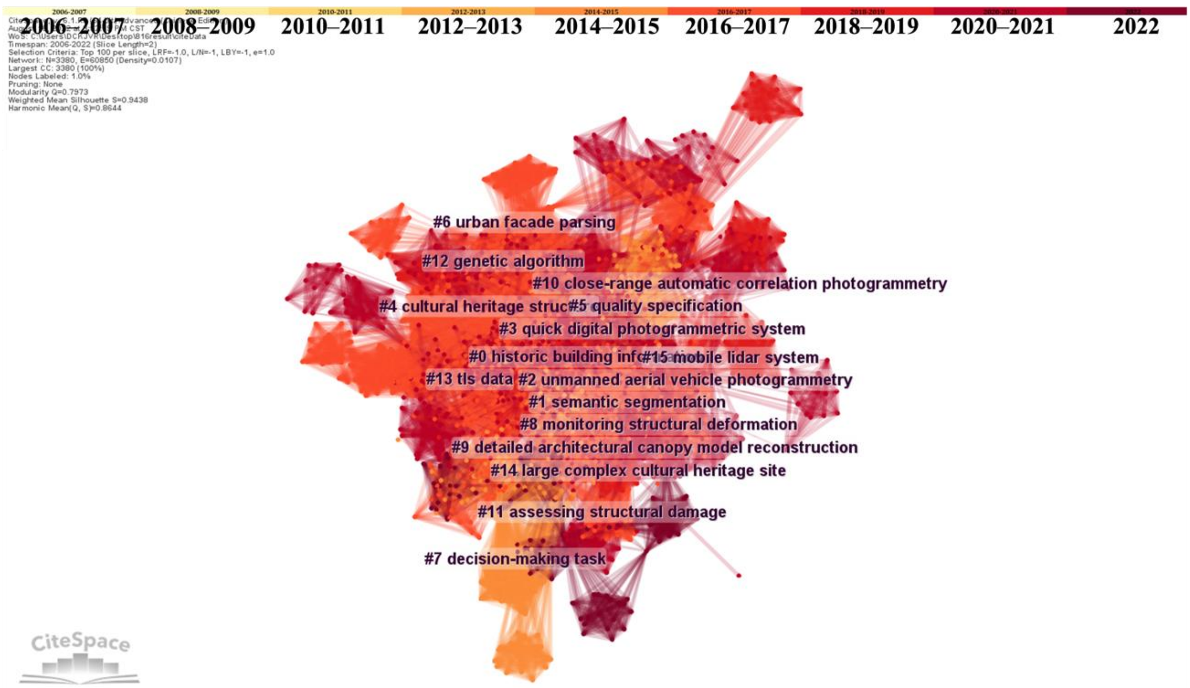

Figure 4. The term co-occurrence network and cluster analysis results.

Based on the composed term co-occurrence network, we further conducted a clustering analysis to better explore the research patterns and extract the hot research terms. The Modularity indicated by Q is equal to 0.7973 that is over 0.3, and the Weighted Mean Silhouette indicated by S is equal to 0.9438 that is over 0.7, which both fall into the reasonable range by referring to the explanation of those parameters in Section 2.2. This illustrates the efficiency of our clustering analysis results. As shown in Table 2, the cluster labels, average research year, cluster size, and silhouette score are summarized for the top 16 clusters. The label of each cluster was automatically extracted from the terms that were included in this cluster using the log-likelihood ratio (LLR) algorithm provided by CiteSpace [110]. The average year was computed by averaging the publishing years of all articles in this cluster. The cluster size indicates the number of articles included in this cluster. The Silhouette scores are all over 0.7 and close to 1, meaning high homogeneity of the network. In other words, the terms grouped in the same cluster are highly similar.

Table 2. A summary of the top 16 clusters in the term co-occurrence network.

ClusterID	Size	Silhouette	Label (LLR)	Average Year
0	208	0.848	historic building information	2018
1	189	0.808	semantic segmentation	2017
2	184	0.896	unmanned aerial vehicle photogrammetry	2014
3	165	0.911	quick digital photogrammetric system	2016
4	143	0.944	cultural heritage structure	2016
5	140	0.939	quality specification	2018
6	138	0.969	urban facade parsing	2016
7	118	0.947	decision-making task	2012
8	116	0.946	monitoring structural deformation	2018
9	109	0.965	detailed architectural canopy model reconstruction	2018
10	108	0.951	close-range automatic correlation photogrammetry	2013
11	105	0.956	assessing structural damage	2016
12	97	0.961	genetic algorithm	2015
13	95	0.95	tls data	2017
14	94	0.933	large complex cultural heritage site	2016
15	91	0.963	mobile LiDAR system	2018

Each cluster consists of a list of terms and they own different degree centrality. The degree centrality measures the number of connections this term has, which can reflect the importance of this term in the network. In other words, those terms with higher degree centrality are more frequently used in the surveyed domain. The higher the degree centrality of the term is, the more focus and attention it gains in the research field. As such, those terms with high degree centrality, together with the cluster label, can be used to infer the research topics of each cluster. In this work, we selected the top ten terms by ranking their degree centrality to represent the research topics. The research topics of the top 16 clusters are summarized in Figure 5, including the representative terms and their degree centrality.

As shown in Figure 5, the topic number aligns with the cluster number. Topic #0 was retrieved from the largest and latest Cluster #0, which includes 208 articles. The cluster was labeled as "historic building information". The average research year is 2018. The representative terms in this cluster include "terrestrial laser scanning", "bim platform", "hbim", "architectural structure", and "parametric object", revealing that 3D point cloud data is the main data source in the BIM and HBIM, which are both used for parametric modeling of architectural cultural heritage to express the architectural structure. The top-term analysis results align with the background ground knowledge presented in Section 2.2.3, e.g., HBIM is a typical application of 3D point cloud data in the cultural heritage field, indicating that the scientometric analysis holds the potential to efficiently mine the hot research topics in the reviewed field.

Topic #1 refers to the second largest Cluster #1 and was labeled as "semantic segmentation". The topic includes terms such as "architectural element", "deep learning" and "convolutional neural network". It reflects the most advanced technology level of point cloud semantic segmentation that is mainly applied to the geometric structure segmentation of historical buildings.

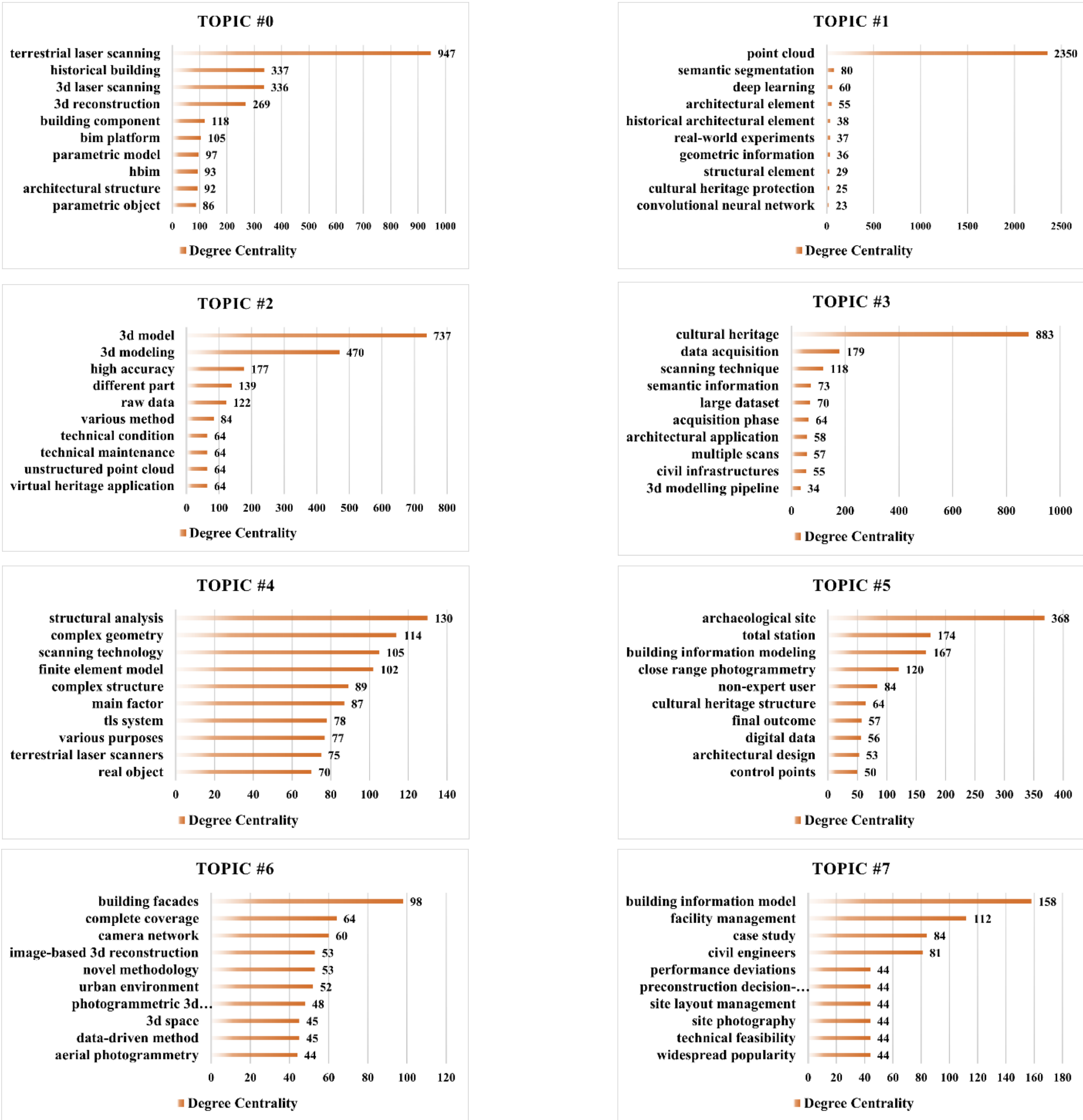

Figure 5. *Cont.*

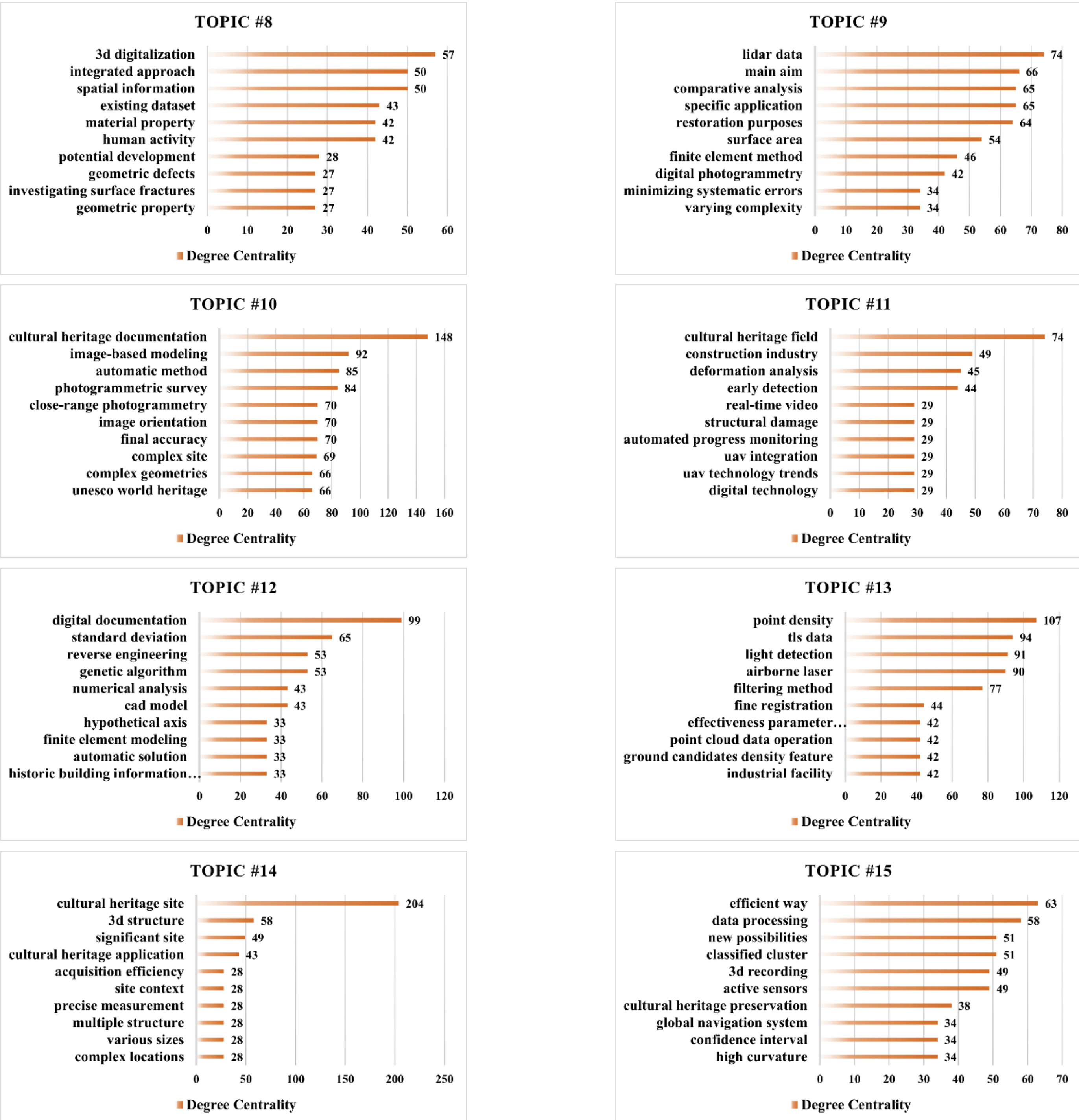

Figure 5. The representative terms of the top 16 clusters.

Topic #2 labeled as "unmanned aerial vehicle photogrammetry", Topic #3 labeled as "quick digital photogrammetric system", Topic #10 labeled as "close-range automatic correlation photogrammetry", Topic #13 labeled as "tls data" and Topic #15 labeled as "mobile lidar system" are all related to the technical approaches of 3D point cloud data acquisition. The average research years of the above topics is relatively early because point cloud data acquisition is the primary task in the research field. Different topics reflect the distinctive technical characteristics of point cloud data acquisition methods in cultural heritage. For example, the term "global navigation system" is included in the topic "mobile lidar system", indicating that the mobile lidar data acquisition equipment needs to be equipped with a navigation system.

Topic # 5 labeled as "quality specification" is related to the quality assessment of 3D point cloud data. Topic #4 was labeled as "cultural heritage structure", where the term "finite element model" indicates an important method used for the structural analysis of architecture heritage. Topic #6 labeled as "urban facade parsing", Topic #7 labeled as "decision-making task", Topic #8 labeled as "monitoring structural deformation" and Topic #11 labeled as "assessing structural damage" all focused on the practical applications of point cloud data for cultural heritage protection.

4.2. Document Co-Citation Network Analysis

The document co-citation network analysis was performed for the identification of key articles in the domain of 3D point cloud for cultural heritage during the timespan ranging from 2006 to 2022. Similar to Section 4.1, the node selection was based on the Top 100 articles in each time slice covering two years. Each time slice was rendered with a unique color. The link color corresponds to the specific time slice. As shown in Figure 6, the merged document co-citation network contains 412 nodes and 4199 links. The nodes represent the cited references among the collected articles. The links connecting nodes represent the document co-citation relationship. The concentric tree rings represent the temporal pattern of the publications in the corresponding years. The pink circle around the nodes represents a betweenness centrality score more than 0.1. The Red circles around the nodes indicate the number of times an article has been cited in a short period of time, representing strong citation burst patterns. The purple circles indicate those articles that hold strong centrality, which means that this paper is a hub between two research directions in the surveyed domain. Larger node sizes suggest that the publication had been cited more frequently and implies that the paper is an important one within the knowledge domain. In other words, those articles with a large nodal size and purple rings are critical and worth reading for researchers who intend to grasp the main idea of this domain efficiently. The indexes of clustering effects are illustrated by a Modularity Q equal to 0.5191 > 0.3 and a Weighted Mean Silhouette S equal to 0.8139 > 0.7, indicating that the composed network is supportive for exploring document co-citation patterns.

We further investigated the details of those articles surrounded by purple circles and red circles, which are with high betweenness centrality and strong citation bursts, respectively. The article details are summarized in Table 3, including the authors, titles, journal names and publication year. These articles can be regarded as the landmark articles in the domain of leveraging 3D point cloud for cultural heritage. The most central article was proposed by Grilli et al. (2017) [118], who concluded that 3D point cloud semantic segmentation technology could improve the knowledge expression ability of cloud data and could be applied for BIM. Dore et al. (2015) [119] proposed HBIM technology for the structural simulation analysis of historical buildings. Both of these two articles were published in the *Int Arch Photogramm*, which indicates that this journal plays a central role among all journals that are relevant to 3D point cloud for cultural heritage on the other side. Furthermore, those landmark articles extracted by the scientometric analysis tool exactly reflect the research trends that was discussed in Section 2.3.

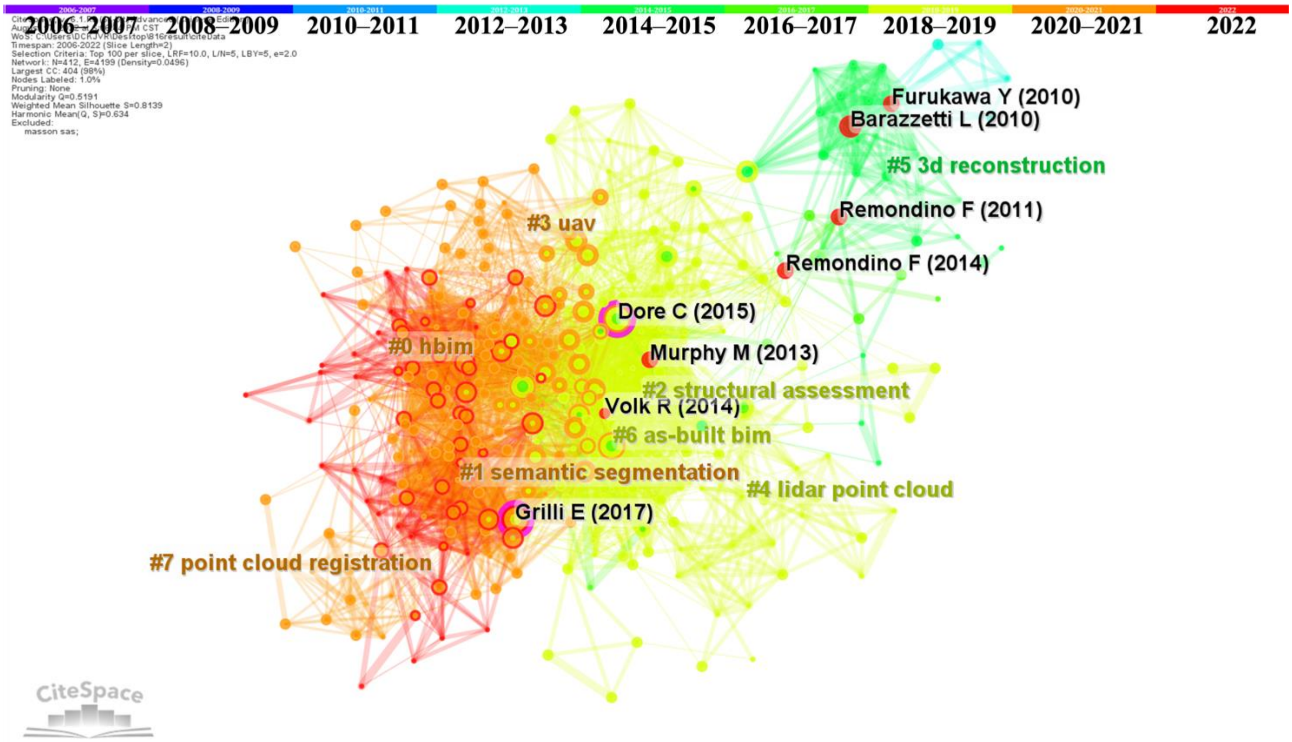

Figure 6. The visualization of the document co-citation network for the years 2006–2022 [118–125].

Among the six articles with strong citation bursts, Furukawa et al. (2009) [120] and Barazzetti et al. (2010) [121] proposed different image-based 3D reconstruction methods, which were cited 3757 and 233 times, respectively, and extracted from Google Scholar on 16 August 2022. Remondino et al. (2011) [122] surveyed the 3D scanning and photogrammetry techniques that contributed significantly to the digital 3D documentation, mapping, conservation, and representation of landscapes and heritages. Remondino et al. (2014) [123] also presented a critical review and analysis of the dense image-matching algorithms, available as open-source and commercial software, for the generation of dense point clouds. Image matching is one of the key steps for 3D modeling and mapping. As such, the above four papers can be regarded as the knowledge base of image-based and LiDAR sensor-based 3D reconstruction of cultural relics. In addition, Murphy et al. (2013) [124] and Volk et al. (2014) [125] reviewed HBIM and BIM technology for cultural heritage protection.

The clustering analysis of the document co-citation network was also conducted to investigate the large and active areas of the domain. Combined with the clustering analysis and the cluster labels shown in Figure 6, the knowledge structure of point cloud data in the field of cultural heritage is constantly formed. Image-based and 3D laser scanning are the main techniques for 3D reconstruction, which are indicated by three clusters including Cluster #3 uav and Cluster #4 lidar point cloud and Cluster #5 3D reconstruction. As indicated by Cluster #6 as-built bim and Cluster #0 hbim, the point cloud semantic segmentation technology has been used to enhance the knowledge expression ability of point cloud data and assist in the automatic construction of BIM and HBIM. Besides, the structural assessment of cultural heritage represented by Cluster #2 relies on the parametric model constructed by BIM and HBIM technology.

Table 3. Landmark articles in the document co-citation network analysis.

Author	Year	Journal Abbr.	Title
		Articles with high betweenness centrality score	
Grilli et al. [118]	2017	*Int Arch Photogramm*	A review of point clouds segmentation and classification algorithms
Dore et al. [119]	2015	*Int Arch Photogramm*	Structural simulations and conservation analysis Historic Building Information Model (HBIM)
		Articles with strong citation burst	
Furukawa et al. [120]	2010	*IEEE T Pattern Anal*	Accurate, sense, and robust Multiview stereopsis
Remondino et al. [123]	2014	*Photogramm Rec*	State of the art in high density image matching
Barazzetti et al. [121]	2010	*Photogramm Rec*	Orientation and 3D modelling from markerless terrestrial images: combining accuracy with automation
Volk et al. [125]	2014	*Automat Constr*	Building Information Modeling (BIM) for existing buildings—Literature review and future needs
Remondino et al. [122]	2011	*Remote Sens-Basel*	Heritage recording and 3D modeling with photogrammetry and 3D scanning
Murphy et al. [124]	2013	*ISPRS J Photogramm*	Historic Building Information Modelling—Adding intelligence to laser and image based surveys of European classical architecture

4.3. Collaborative Country Network Analysis

This section aims at analyzing and visualizing the national research collaboration network that is made by research institutions worldwide. In the collaborative country network, the country information was extracted from the authors' affiliation. A country acts as a node, and the collaboration between countries compose the links. As shown in Figure 7, a total of 31 nodes and 57 links were included in this network. The concentric tree rings reveal the temporal patterns of the articles published by this country. The color of each concentric circle indicates the year of the publications, while the pink circle around the nodes represents how the betweenness centrality score is over 0.1. The thickness of the pink circles reflects the importance of this country in the research domain. The color of the links aligns with the colors of the corresponding year when the national research cooperation first appeared. The thicker the link, the stronger the national collaboration. The red circles around the nodes indicate the citation bursts of the node. The Modularity Q is equal to 0.4172 that is over 0.3 and the Weighted Mean Silhouette S is equal to 0.8026 that is over 0.7, both of which indicates this collaborative country network is meaningful.

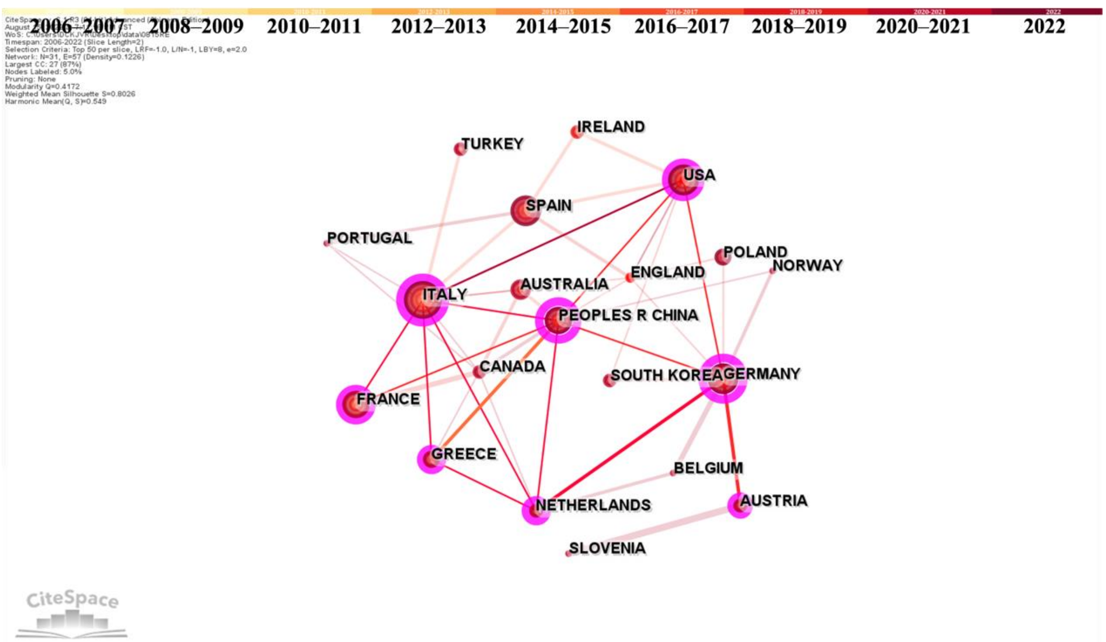

Figure 7. The visualization of the collaborative country network.

As shown in Figure 7, Italy is the landmark node with the largest radius, indicating that the key article in the domain of 3D point cloud for cultural heritage comes from Italy. As evidence, the first author of this key article titled "From point cloud data to building information modelling: an automatic parametric workflow for heritage" is a researcher from the Department of Architecture, Built Environment, and Construction Engineering, Politecnico di Milano, Milan, Italy. In addition, USA, China, Germany, Netherlands, France, and Greece also own thick pink circles, indicating that they are central countries and make critical contributions to this research domain.

The top five central countries ranked by the betweenness centrality are shown in Table 4. The number of world heritage sites of each country is also listed for correlation analysis. Among all of the countries, Italy has the highest degree centrality of 12 and a betweenness centrality of 0.40. This aligns with the fact that Italy plays a landmark role in the reviewed files, and it owns the largest circle with the most connections with other countries as is shown in Figure 7. In contrast, Germany has a degree centrality of 10 but has the highest betweenness centrality of 0.46. It reveals that Germany can be regarded as the most important intermediary bridging other countries via the shortest path. Furthermore, it presents a positive correlation between the centrality scores and the number of cultural heritage sites located in each country. The countries with more international cooperation also tend to have more cultural heritage sites. For example, Italy owns 58 world cultural heritage sites, ranking first with regard to the number of world cultural heritage sites. Similarly, China owns 56 world cultural heritage sites and Germany owns 51 world heritage sites, ranking second and third regarding the number of world cultural heritage sites all over the world, respectively, both of which have higher centrality scores.

Table 4. The top five countries ranked by betweenness centrality.

Country	Betweenness Centrality	Degree Centrality	Number of World Heritage Sites
Germany	0.46	10	51
Peoples R China	0.41	11	56
Italy	0.40	12	58
Netherlands	0.23	7	12
Greece	0.18	6	18

We further performed a burst analysis to explore the development trends of deploying 3D point cloud for cultural heritage from 2006 to 2022 in terms of each country. The top four countries with the strongest citation burst are illustrated in Figure 8. The USA has the strongest citation burst of 4.13 in five years ranging from 2014 to 2019, while the citation burst occurring in Germany lasts the longest period but with the weakest pattern among those four countries. Italy showed a burst around 2010. The publications originating from Italy drew burst attention concerning the point cloud data used in the cultural heritage field around 2010. England owns the newest citation burst from 2018 to 2021. It shows that England has received a lot of attention from other researchers in recent studies. Such changes may be affected by policy guidance.

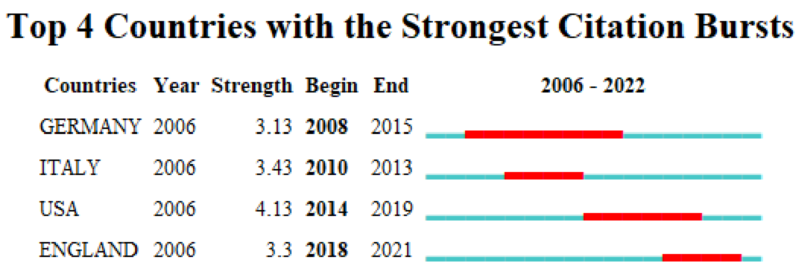

Figure 8. Citation burst history of countries in the timespan ranging from 2006 to 2022. Germany has the longest citation burst, whereas USA has the strongest citation burst.

4.4. Category Co-Occurrence Network Analysis

This section focuses on the analysis of the co-occurrence of categories to identify the main categories that the articles associate with as well as the interdisciplinary patterns among all categories. The category information was extracted from the field of "Categories/Classification" of WoS, indicating the research areas that this article belongs to. Figure 9 demonstrates the temporal visualization of those categories in the bibliographic literature that are related to 3D point cloud data for cultural heritage. The nodes refer to the subject categories. If two categories co-occur in one article, there is a link between them. We have selected the top 30 categories for each time slice in the timespan ranging from 2006–2022 to compose the category co-occurrence network. The merged network of subject categories consists of 24 categories and 70 links. The Modularity Q = 0.5461 > 0.3, Weighted Mean Silhouette S = 06745 > 0.7, indicating this network makes sense.

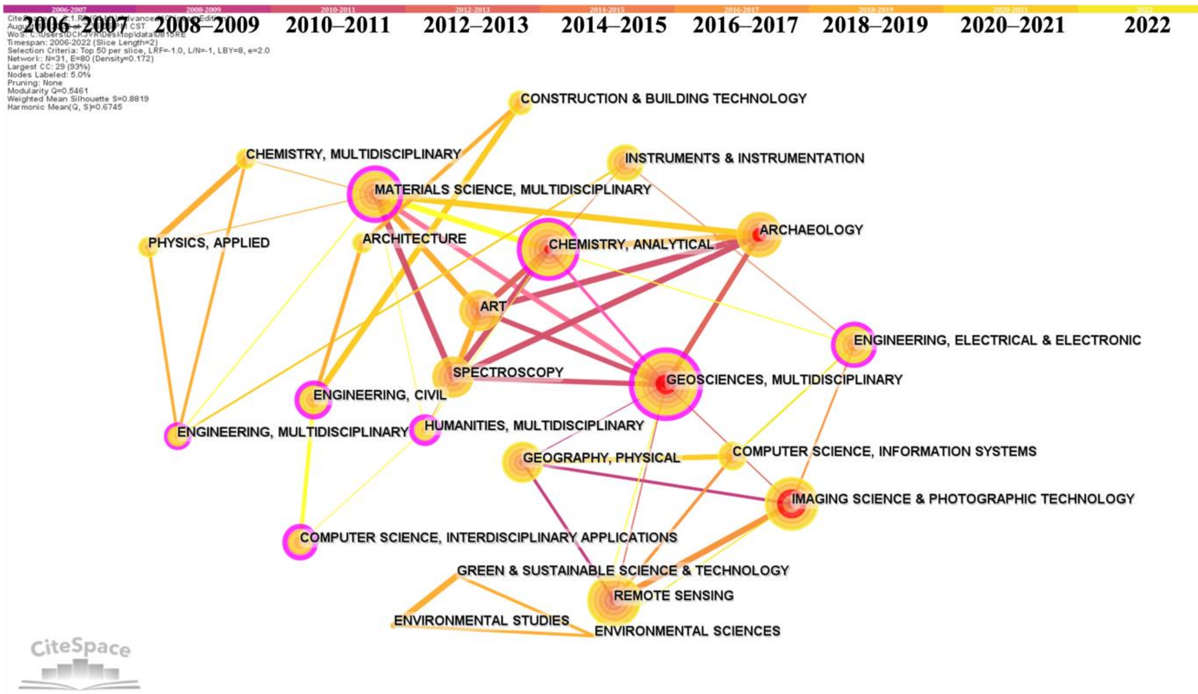

Figure 9. The visualization of the category co-occurrence network for the years 2006–2022.

In order to better interpret the results represented in Figure 6, we use the same color and symbols as were introduced in Section 4.3 for consistency. Correspondingly, the concentric tree rings reveal the temporal patterns of the articles published in this category, and the color of each concentric circle indicates the year of the publications. The pink circle around the nodes represents how the betweenness centrality score is over 0.1. The thicker the pink circle, the higher the betweenness centrality of this category. The color of the links aligns with the color of the corresponding year when the cross-disciplinary first appeared between the two categories. The thickness of the links reflects the strength of the category co-occurrence relationship. As the application of point cloud in the field of cultural heritage is a typical interdisciplinary research domain, a number of strong connections can be found between the categories. For instance, Geosciences is strongly correlated with archaeology, art, and spectroscopy. It is obvious that the category of "Geosciences Multidisciplinary" has the largest radius and is surrounded by a thick pink circle, indicating that it is the most highly cited category and a central category of the domain. This aligns with the fact that integrating point cloud data with 3D GIS is a typical application in the cultural heritage field that was introduced in Section 2.2.4. Aiming to investigate the centrality of each category and their contribution to facilitating the interdisciplinary research, we summarized the betweenness centrality scores of the top ten categories in Table 5. The quantitative scores prove that both "Geosciences Multidisciplinary" and "Humanities Multidisciplinary" are the most central categories in the domain of 3D point cloud data for cultural heritage, which holds the same centrality score of 0.53. A major difference exists in the publication year, illustrating that the former is the most central area researched in the last decade while the latter is the most central area researched in recent years. Following them closely are the categories of "Materials Science Multidisciplinary", "Computer Science Interdisciplinary Applications" and "Chemistry Analytical" with the centrality score of 0.44, 0.44 and 0.40, respectively.

Table 5. The top ten categories based on the betweenness centrality in literature for the years 2006–2022.

Category	Betweenness Centrality	Year
Geosciences Multidisciplinary	0.53	2006
Humanities Multidisciplinary	0.53	2018
Materials Science Multidisciplinary	0.44	2011
Computer Science Interdisciplinary Applications	0.44	2016
Chemistry Analytical	0.40	2009
Engineering Electrical Electronic	0.35	2014
Engineering Civil	0.35	2015
Environmental Sciences	0.24	2014
Engineering Multidisciplinary	0.15	2018
Imaging Science Photographic Technology	0.10	2008

Burstiness identifies the subject categories which are active in the relevant research area during a period. The higher the citation bursts of a disciplinary, the more connections it has with other disciplinaries. The history of the citation burst of the top five subject categories is demonstrated in Figure 10. The results reveal that "Archaeology" is the category with the strongest citation burst of 6.31 from 2010 to 2015. "Geosciences Multidisciplinary" is the earliest and the longest active category lasting for 9 years from 2006 to 2015. The most recent citation bursts occur in "Imaging Science Photographic Technology" from 2016–2017. This may be because more and more advanced image-based techniques (e.g., image-based dense point cloud matching algorithms) have been leveraged to improve the performance of employing 3D point cloud for cultural heritage in recent years. This aligns with the landmark article presented in Table 3, namely, Remondino et al. [123] (2014), which summarized the state of the art in high density image matching techniques and drew high attention in the field of 3D point cloud for cultural heritage.

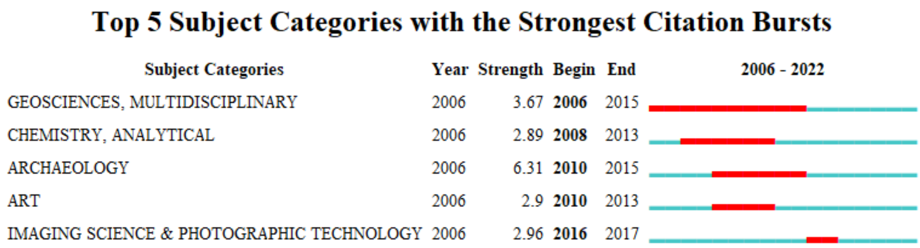

Figure 10. The top five subject categories with the strongest citation bursts.

5. Conclusions

In this work, CiteSpace software was used to conduct the scientometric analysis of the research concerning employing 3D point cloud for cultural heritage in order to investigate the research productivity as well as the emerging trends. The research, published as journal papers, were collected from the Web of Science database with a timespan ranging from 2006 to 2022. Based on the collected papers, a total of four networks have been generated and visualized for the scientometric analysis, including the term co-occurrence network analysis, document co-citation network analysis, collaborative country network analysis and category co-occurrence network analysis. A number of remarkable results have been obtained from those analyses. The main terms extracted through measuring their log-likelihood ratio and centrality can reflect multiple data acquisition methods (e.g., total station, terrestrial laser scanners and UAV integration), information extraction and fusion (e.g., building information modeling, historic building information modeling and semantic segmentation) as well as the popular applications (e.g., cultural heritage documentation, restoration purposes, deformation analysis, and structural damage), which compose the research hotpots in this field. Based on the document co-citation network analysis, the paper proposed by Barazzetti L et al. (2010) [121] has been the most cited work since 2010 and holds strong citation bursts, which can be regarded as landmark research in the surveyed domain. At the national level, it is interesting that countries such as Germany, China, and Italy, which own numerous world heritage sites, have also contributed more in the academic research of this domain. From the perspective of disciplines, the research of 3D point cloud for cultural heritage features has significant features of interdisciplinary, crossing "geoscience", "materials science", "chemistry", "environmental sciences" and "humanities". This, in turn, puts forward higher requirements for the research in this field, leading to greater challenges we are potentially facing in the future. It is an inevitable trend to strengthen the exchange and cooperation at the national level and the joint efforts of multiple disciplines. These findings provide valuable reference for those who are engaged in the field of 3D point cloud data for cultural heritage and helps them to have a comprehensive and systematic understanding of the research topics, hot issues and development trends.

Despite the achievements obtained in this work, there still exists space for improvement in the near future. As the articles surveyed in this work are only in English and collected from the Web of Science database, some relevant research may have been missed in this review. In the future, those articles either written in other languages (e.g., Chinese) or recorded in other databases (e.g., Scopus), can be included for further comparison analysis.

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