Automation in Construction 107 (2019) 102947

Contents lists available at ScienceDirect

Automation in Construction

journal homepage: www.elsevier.com/locate/autcon

Review

A scientometric analysis and critical review of computer vision applications for construction

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ARTICLE INFO

Keywords:
Computer vision
Construction
Critical review
Scientometric analysis
Off-site construction

ABSTRACT

Practical interest in 'computer vision' has risen remarkably over the last 20 years, transforming the current state of construction-related research and attracting the worldwide attention of scholars and practitioners. This study conducts a scientometric review of the global research published between 1999 and 2019 on computer vision applications for construction, through co-author, co-citation, keyword and clustering analysis. A total of 1158 journals and conference proceedings from Scopus database were analyzed. Trends within the field are identified, as are the dominant sub-fields and their interconnections, as well as citation patterns, key publications, key research institutions, key researchers, and key journals, along with the extent to which these interact with each other in research networks. The provided results were analyzed to identify the deficiencies in current research and propose future trends. Among these is a bias in the research literature towards traditional on-site construction and a concerning gap of off-site construction research, as well as a lack of inter-relationships and collaboration between researched areas, the researchers themselves, and/or the research institutions. In the near future, computer vision will play a key role in the future development of smart construction and improvement of quality in construction projects. This study hopes to bring awareness to the industry, the journal editors, and the researchers of the need for a deeper exchange of ideas in any future research efforts.

1. Introduction

Image processing and computer vision have been used in numerous different scientific fields to provide information or data as a substitute for human eyes. Due to the decreasing cost of visual sensors and the availability of robust visual systems, the integration of computer vision in industrial environments has grown exponentially in the last decades in a broad range of sectors, such as retail, security, automotive, healthcare, and agriculture. In the construction industry, computer vision has drawn attention because it can be used for the automation of critical tasks that require continuous object recognition, identification, and monitoring, or motion, behavior, location estimation, and so forth. The rich dataset of information that can be obtained from a construction-related scene by taking images or videos that facilitate the understanding of complex construction tasks rapidly, accurately, and comprehensively [1]. However, the dramatic increase in the amount of literature published regarding the development of computer vision-based systems for civil construction operations has not had the desired impact on the construction industry. Despite their importance, current practices are still time-consuming, costly, and error-prone [2].

In the last decades, computer vision research has been diverse as more emerging technologies have been integrated into construction-related projects. Literature review is regarded as an expedient approach to gain an in-depth understanding of a research area. Existing review publications target relevant topics of computer vision applications in civil construction. For example, computer vision technologies have been applied to monitor for unsafe conditions and actions with the aim of mitigating potential hazards in construction projects in a timely manner. Although its application is still premature, it demonstrates that major research contributions and challenges for technical and practical automatic vision-based safety and health monitoring are needed [3]. Also, image processing techniques are the key factor in the research and development of the most recent building information model (BIM)-based technologies applied in construction. *As-built* modeling has proven to be a challenge that involves both disciplines, computer vision and civil engineering, and an important effort is being made to consolidate and integrate existing techniques, along with developing new methods, to automatically generate a working BIM [4]. The increasing demand on intelligent technologies requires pragmatic and cost-effective methods that not all the proposed methods provide for the

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https://doi.org/10.1016/j.autcon.2019.102947
Received 14 May 2019; Received in revised form 23 July 2019; Accepted 29 August 2019

construction industry [5]. In fact, *as-built* BIM automatically generates digital representations for existing assets from very different visual techniques and devices, such as camera systems [6], laser scanners [7] mounted on mobile robots [8] or flying unmanned aerial vehicles (UAV) [9]. These systems generate 3D point clouds that provide detailed information to reconstruct the BIM model of an existing element. BIM information is also collected using the same methods for project control purposes, targeting the inspection and quality control of building elements [10]. Whereas existing review publications showcase detailed analyses on certain areas of research, the application of computer vision methods has been diverse and with varying degrees of complexity, thus a research effort is needed to provide a full scope of the use and impact of computer vision in construction-related fields.

Scientometrics is defined as the "quantitative study of science, communication in science and science policy" [11], and includes the measurement of research impact, investigates the impact of institutions and journals in a certain field of research, and provides deeper understanding of scientific citations [12]. Scientometrics has been used for the analysis of the latest research in other construction-related research fields, such as construction engineering and management (CEM) [13], or BIM [14]. The study presented in this paper attempts to conduct a scientometric review of the scientific literature relating to computer vision in construction-related activities and to gain an overall description of the developments in this research field over the past two decades (1999–2019). The findings can provide researchers with a better understanding of the current state of visual applications and research in civil construction and identify the main topics in the literature.

2. Research methodology

To achieve the research objectives of this paper, academic publications within the field were identified. The list of publications was obtained using Scopus database. Given the difficulty of searching each related article, a delimitation of the research boundary is frequently necessary [15]. The main points of each publication will be determined by its research title, objectives, methodology, and major contributions. The methodology for this current study will be explained below and an overview can be found in Fig. 1.

2.1. Bibliometric analysis

Data acquisition of existing literature is crucial in this research since it determines the scientific articles from which any conclusions will be drawn. For this reason, the database selection and searching strategy are carefully selected. For this study, Scopus database was selected as the literature database due to the wide range of coverage in the domain of construction-related research compared with other databases such as Web of Science, Google Scholar, and PubMed, among others [16]. Scopus database is a better choice for inter-disciplinary research topics, such as the one reviewed in this paper, than the previously mentioned databases [17], and also has a wider range of journal publications [18].

The existing literature related to computer vision applications in the construction sector in this database was then retrieved by using keywords, i.e. "computer vision*" and "construction*" (note that the wildcard character * is used to capture variations of one keyword, such as "vision system", "visual system", and "vision-based system"). According to the objective of this review, the selected keywords were: ("Computer vision*" OR "Machine vision*" OR "Vision systems*") AND ("Construction*"). The keyword search in Scopus was set as title/abstract/keywords in order to retrieve all the publications containing the selected keywords in their title, abstract, or selected keywords section. The search period was set to include the last 20 years, from January 1999 to February 2019, which is suitable considering the development history of computer vision within construction-related research. A screening process was conducted successively for the purpose of refining the results to the relevant engineering scope. For example, research papers within the subject area of medicine or agriculture that may mention "construction" in another sense of the word were excluded in this step. Only papers in peer-reviewed English journals or conference proceedings were considered for the review process and book reviews or editorials were also excluded so that all the retrieved papers could be screened using an identical construct in terms of research aims and methods. A further refining process was conducted by checking the source title and abstract in order to exclude papers from

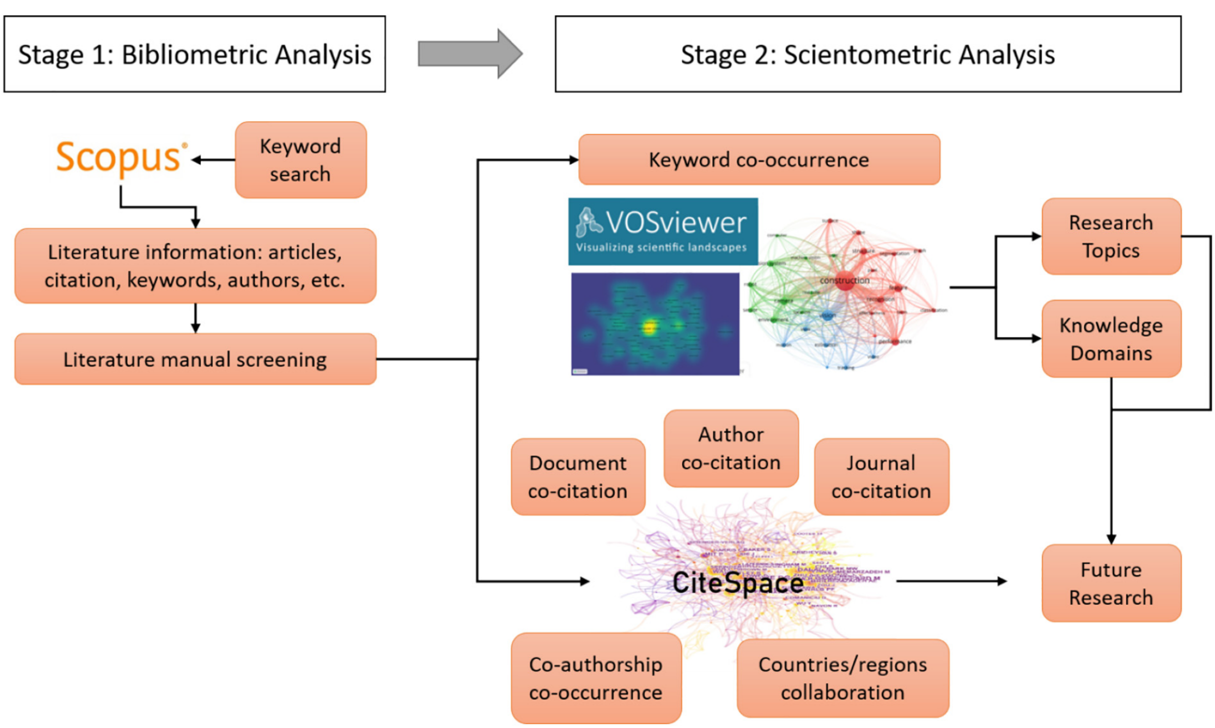

Fig. 1. Overview of the proposed research methodology.

irrelevant journals or conference proceedings. Those remaining after the screening process were fed into the bibliometric analysis. The initial search yielded over 3000 documents, while the results after the manual screening filtered down the number of documents to 1158, namely 325 journal papers and 833 papers published in conference proceedings. The large number of irrelevant papers that needed to be filtered out can be explained by the colloquial use of the word “construction” in other contexts and research fields.

2.2. Scientometric analysis

The definition of scientometrics is first proposed by Mulchenko [19] as “a quantitative study of the research on the development of science”. It can be considered as a technique that measures research impact and citation processes and maps the current knowledge and its evolution in a domain based on large academic datasets. Due to the wide spectrum of research topics related to computer vision in construction, there is little prospect of characterizing the overall field through systematic literature analysis. Although manual review provides insightful overview of the research field, it remains prone to bias and is limited in terms of subjective interpretation [20]. Therefore, the current study proposes a holistic analysis of computer vision within construction-related activities using the scientometric technique, a research method to ease visualization and mapping of knowledge domains [21]. This methodology applies bibliometric techniques to published literature and is used to map the structure and evolution of numerous subjects based on large-scale scholarly data sets [22]. Through network modeling and visualization, scientometric research aims to analyze the intellectual landscape of a knowledge domain and to perceive questions that researchers may attempt to answer, as well as methods that authors have developed to achieve their goals [23]. Visualizing the entire field of computer vision in construction will enable readers to gain a global perspective of research patterns and trends in the field.

Keywords and abstracts are considered clear and concise descriptions of the research contents, which require these keywords as units of analysis to identify prominent groupings that affect the structure of the researched field. In this study, the literature of computer vision for construction was analyzed in terms of keywords and abstract terms to retain the opinions of the authors as much as possible. The following methodologies were applied to reveal research patterns: Keyword co-occurrence analysis and keyword clustering, co-author analysis and burst detection, country co-occurrence and co-citation analysis, and abstract term cluster analysis. Firstly, the keyword and author co-occurrence analysis makes an aggregate representation of the research field and the network indicators provide evidence for the posterior clustering analysis. Secondly, the burst detection sheds further insight on the relative changes of significance over time to identify trends and changes in computer vision for construction, in contrast to the previous analysis that simply provides a static description of the field as a whole. Finally, abstract term clustering indicates the research patterns within the field in detail, as well as various specific research themes associated to lay out the research conceptual framework. These techniques have been recommended in previous studies of similar nature [24,25].

3. Results

3.1. Data acquisition

The keyword search strategies mentioned in Section 2.1 were employed to identify relevant academic articles in journals and conference proceedings, which have been summarized in Table 1. The majority of academic publications on computer vision applications for construction are found in journals related to both fields, including *Automation in Construction*, *Advanced Engineering Informatics*, *Journal of Computing in Civil Engineering*, *International Journal of Computer Vision*, *Computer Vision and Image Understanding* and *Machine Vision and Applications*. Among these journals, *Automation in Construction* is the journal that includes the most publications on this topic. Similarly, conference proceedings that make considerable contributions to the field are *Proceedings of the IEEE Computer Science Conference on Computer Vision and Pattern Recognition,* and *Proceedings of the IEEE International Conference on Computer Vision*. Notably, most of the selected journals and conference proceedings contained one or two publications related to the researched field: 37.22% of the journal articles and 79.84% of the conference proceedings were published in such conditions.

Fig. 2 shows how the number of publications, in either journals or conference proceedings, on the research topic under review varies each year. Publications on computer vision applications in construction show an overall upward trend since 2003–2004, showing two main bursts of publications in 2007–2008 (+87% number of publications) and 2015 (+47% number of publications), that curiously match with the initial development of BIM [7] and big data techniques in construction [26], respectively. Note that the study considers, for the year 2019, publications in the first 2 months of the year, hence the lower number of publications in that year. If a linear regression is performed, 2019 keeps the upward trend and estimates over 100 publications on the reviewed topic.

3.2. Keyword co-occurrence analysis

Keywords represent the core content of the published documents and showcase the range of areas researched within the boundaries of any domain [27]. To construct and map the knowledge domain between construction and computer vision, keyword co-occurrence in the research area was obtained using VOSviewer. The visualization of the keyword's network was chosen to demonstrate the results of the bibliometric analysis of the literature. The output of the VOSviewer software is a distance-based map in which the distance represents the strength of the relation between two knowledge domains [28]. A bigger distance generally indicates a weaker relationship between the two items. The item label size is directly proportional to the number of publications in which the keyword was found and different colors represent different knowledge domains clustered by the clustering technique of VOSviewer [29]. The minimum number of occurrences was set to 5 so that 44 of the 510 keywords meet the threshold. This threshold selection was based on multiple experiments with other parameters to generate the optimal clusters. Fig. 3 Shows the network of co-occurring keywords with 44 nodes, 145 links, and a total link strength of 263. Table 2 Summarizes the keyword occurrences and each individual node strength.

As shown in Table 2, the occurrence shows the number of times each keyword was retrieved in the existing literature from the author keywords. For example, other than the main keyword “Computer Vision”, “Image Processing” is the keyword that appears most frequently among all the keywords, which means that it has been widely researched in this field. The average year published shows the average time period in which a given keyword is used by researchers in their publications. For example, studies involving mobile robots or robotics received more attention during the period 2009–2010, while studies involving construction workers or construction safety were published with greatest frequency in 2016 and 2018, respectively, indicating the latest applications of computer vision in construction research. The links are the number of linkages between a given node and others, while the total link strength reflects the total strength linked to a specific item [30]. For instance, the total link strength of Image Processing is 39, which is in the high level of all the keywords and indicates the strong inter-relatedness between Computer Vision and Image Processing.

Keyword co-occurrence networks are static representations of the researched field that do not consider changes over time. However, VOSviewer provides a time zone perspective so that each node is represented by the average year in which the keyword was used in

Table 1
List of most widely read academic journals and conference proceedings from January 1999 to February 2019 that published research related to computer vision applications for construction.

Journal title	Number of relevant articles	% Total publications
Automation in Construction	45	13.85%
Advanced Engineering Informatics	18	5.54%
Journal of Computing in Civil Engineering	16	4.92%
International Journal of Computer Vision	15	4.62%
Computer Vision and Image Understanding	13	4.00%
Machine Vision and Applications	11	3.39%
Advances in Intelligent Systems and Computing	9	2.78%
Pattern Recognition and Image Analysis	9	2.78%
Advanced Materials Research	7	2.15%
Image and Vision Computing	7	2.15%
Pattern Recognition	7	2.15%
Industrial Robot	6	1.85%
Applied Mechanics and Materials	6	1.85%
IEEE Transactions on Image Processing	5	1.54%
IET Computer Vision	4	1.23%
Journal of Intelligent and Robotic Systems Theory and Applications	4	1.23%
Procedia Computer Science	4	1.23%
Journal of Visual Communication and Image Representation	3	0.92%
Pattern Recognition Letters	3	0.92%
IEICE Transactions on Information and Systems	3	0.92%
Procedia Engineering	3	0.92%
IEEE Transactions on Cybernetics	3	0.92%
IEEE Transactions on Robotics	3	0.92%
Autonomous Robots	3	0.92%

Conference title	Number of relevant articles	% Total publications
Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition	54	6.48%
Proceedings of the IEEE Conference on Computer Vision	45	5.40%
ACM International Conference Proceeding Series	15	1.80%
IEEE International Conference on Intelligent Robots and Systems	14	1.68%
Proceedings IEEE International Conference on Robotics And Automation	13	1.56%
Proceedings International Conference on Pattern Recognition	5	0.60%
Congress on Computing in Civil Engineering Proceedings	4	0.48%
Proceedings of the International Joint Conference on Neural Networks	3	0.36%
Proceedings of the IEEE International Conference on Systems Man and Cybernetics	3	0.36%
International Conference on Signal Processing Proceedings ICSP	3	0.36%
Canadian Conference on Electrical and Computer Engineering	3	0.36%
IEEE International Conference on Image Processing	3	0.36%
Proceedings of The World Congress on Intelligent Control and Automation WCICA	3	0.36%

literature. As shown in Fig. 4, the evolution of computer vision application in the construction sector continued in the past decade. Notably, the first applications (2006–2008) were related to "robotics" and "virtual reality", tending to focus on well-known techniques that required minimal integration within the construction field, and thus were easier to implement. Unsurprisingly, general keywords such as "computer vision", "machine vision", "construction", "image processing" and "object recognition" are represented in the middle spectrum (around 2010). This result could be due to an emphasis on such topics around that period of time (2009–2011) or that the topic was evenly researched during the whole period of time researched (1999–2019). This last option is considered as the most plausible explanation. The latest research topics relate to "construction safety" and "construction worker", potentially indicating a shift in the focus of research in this field. Whereas earlier contributions considered the construction sector as a plausible target area of application for certain computer vision applications, later publications target more specific problems in the construction industry, while the computer vision methods and technologies used are relegated to second place. An exception would be the keywords related to novel techniques such as "machine learning" or "deep learning".

3.3. Co-author co-occurrence analysis

The information with respect to the article authors is available from the bibliographic records, and, thus, identification of the leading researchers in the field, as well as the collaborations between researchers, can be mapped. Then, a co-authorship network can be generated. According to the number of publications, the top 10 most productive authors were identified first. As shown in Table 3, I. Brilakis (University of Cambridge), M. Golparvar-Fard (University of Illinois), and Z. Zhu (Concordia University) occupied the top three positions.

Co-authorship networks can be generated in CiteSpace, as it can visualize and analyze scientific knowledge to capture the notion of a logically and cohesively organized body of knowledge [31]. Such an approach has been recognized as an advantageous scientometric method to discover the hidden implications of a vast amount of information. CiteSpace is strong in mapping knowledge domains through

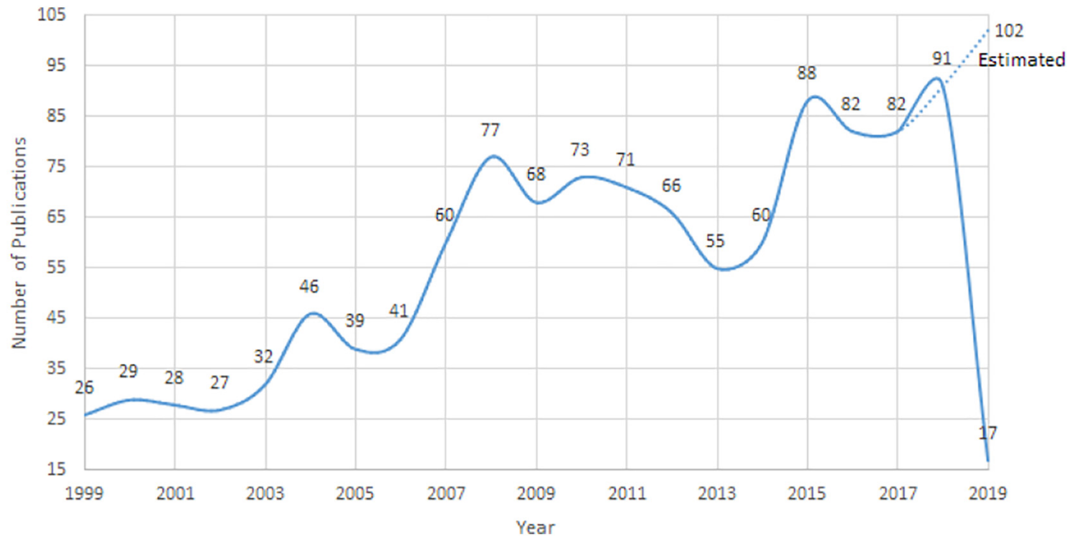

Fig. 2. Historical trend of published studies in computer vision for construction (period 1999–2019).

systematically creating various accessible graphs [31]. Therefore, it was used to generate and analyze the co-author networks, country co-occurrence, and co-citations networks, as well as generate the abstract clustering. In CiteSpace, the burst detection is based on the algorithm developed by Kleinberg [32].

The co-authorship network is shown in Fig. 5, where each node represents an author and the links between the authors represent collaboration established through co-authorship in publications. The network pruning was used to remove excessive links through Pathfinder, which is recommended in previous studies [33]. Finally, there were 153 nodes and 203 links in the generated network. The node size represents the number of publications and the link thickness represents the level of cooperation between authors. Table 4 summarizes the overall characteristics of the presented network. In particular,

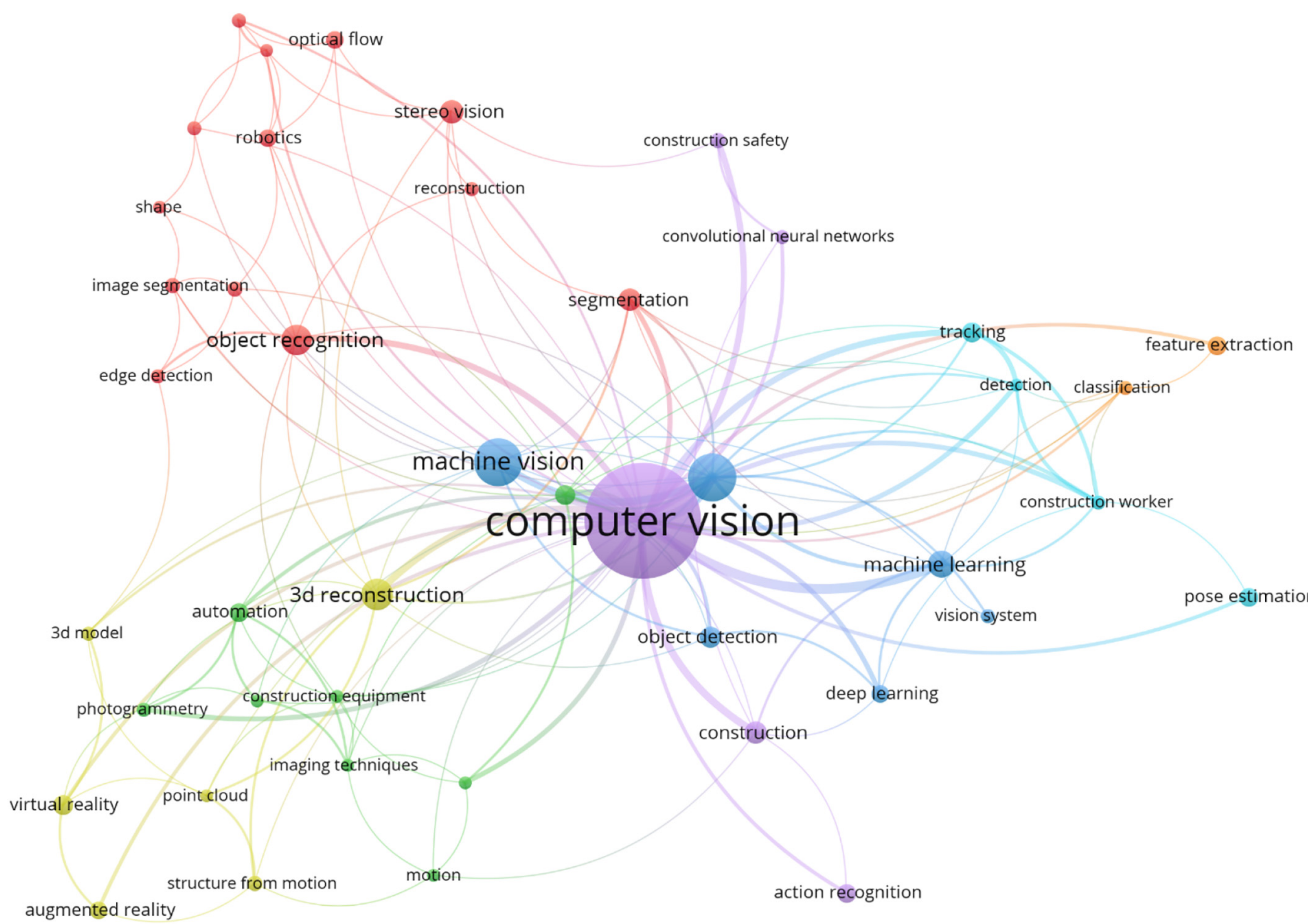

Fig. 3. Network of co-occurring keywords related to computer vision application in construction (1999–2019).

Table 2
List of selected keywords and relevant network data.

Keyword	Occurrences	Average year published	Links	Total link strength
Computer vision	237	2013	37	125
Image processing	36	2011	17	39
Machine learning	15	2016	10	22
3D Reconstruction	20	2013	11	21
Construction worker	6	2016	9	19
Machine vision	36	2011	10	18
Detection	5	2013	8	17
Pattern recognition	10	2010	11	17
Tracking	10	2012	6	17
Construction	12	2013	7	14
Object recognition	19	2013	8	14
Segmentation	12	2012	8	13
Automation	9	2014	7	12
Deep learning	8	2018	5	10
Virtual reality	10	2009	5	10
Imaging techniques	5	2013	7	9
Monitoring	5	2013	5	9
Object detection	11	2014	5	9
Photogrammetry	6	2012	5	9
Classification	6	2013	7	8
Construction safety	7	2018	3	8
Point cloud	5	2016	6	8
3D Model	6	2013	5	7
Construction Equipment	5	2015	7	7
Information Technology	5	2013	5	7
Mobile robots	6	2010	5	7
Navigation	5	2009	5	7
Stereo vision	13	2013	7	7
Structure from motion	7	2013	5	7
Augmented reality	8	2012	3	6
Convolutional neural networks	6	2018	3	6
Robotics	8	2009	6	6
Edge detection	6	2011	4	5
Image segmentation	7	2008	5	5
Motion	5	2011	5	5
Neural networks	5	2007	5	5
Robot vision	7	2011	5	5
Action recognition	9	2014	2	4
Feature extraction	9	2012	2	4
Optical flow	8	2012	4	4
Pose estimation	9	2014	2	4
Shape	5	2010	3	4
Reconstruction	6	2011	3	3
Vision system	6	2008	2	3

modularity Q and mean silhouette scores are two significant metrics, yielded by CiteSpace, that determine the structural properties of the network. Notably, a modularity Q of 0.9278 is high ($Q > 0.3$), which indicates that the network is reasonably divided into loosely coupled clusters [34], and a mean silhouette score of 0.5625 suggests that the provided clustering for the network is quite heterogeneous [35].

In terms of collaboration, there are some small circuits in Fig. 5, indicating that the researchers in these circuits have established strong collaboration, such as the circuit of I. Brilakis, M. Golparvar-Fard and M. Park, or the slightly larger one led by H. Li and H. Luo. However, none of the circuits represented groups responsible for > 4% of the research in the field. In general, this research field could benefit from more international research collaboration. Centrality is defined as the ratio of the shortest path between two nodes, in this case authors, to the sum of all such shortest paths [36]. In this research field, the highest centrality node is H. Li (centrality = 0.02). Such a low value justifies the need for further collaboration between researchers in this field. However heterogeneous this field may be, several key contributors can be identified by burst detection. Author bursts represent notable increases in citations over a short period of time. Three bursts are identified within the network: I. Brilakis (burst strength: 3.87–2011), M. Golparvar-Fard (burst strength: 3.40–2013) and S. Zafeiriou (burst strength: 3.37–2014). These authors attracted an extraordinary degree of attention in the corresponding years. It is also worth mentioning that no bursts have been identified in the last 5 years, which is consistent with the fact that the field has been getting world-wide attention in recent years. Thus, a single author may find it difficult to receive high citations over a short period of time.

3.4. Network of countries/regions and institutions

Similarly, a network was produced based on the contributions of countries/regions to explore the distribution of research publications on computer vision applications in civil construction. This network includes 48 nodes and 55 links. As shown in Fig. 6, the USA (335 articles), China (154 articles), United Kingdom (87 articles), Japan (76 articles), France (65 articles), Canada (58 articles), Germany (56 articles), and Australia (42 articles) have made major contributions to the publications in this field of research. It is implied that the larger the number of publications, the more advanced the research is in the country/region. In contrast to the co-author network presented previously, the countries/regions network is quite homogenous and efficient. Nodes with high centrality were identified and highlighted with darker outer rings (purple) in Fig. 6. Countries or regions such as Hong Kong (centrality = 0.80), United Kingdom (centrality = 0.70), Canada (centrality = 0.60), United States of America (centrality = 0.51), Netherlands (centrality = 0.46), France (centrality = 0.33) or Switzerland (centrality = 0.19) have occupied key positions in the network and connected research activities between different countries/regions. Furthermore, citation bursts representing notable increases in citations over a short period of time were found in some countries/regions. Citation bursts are summarized in Fig. 7.

The contributions of institutions were also identified. Computer vision research for applications in the construction sector has been quite active at institutions such as the University of Michigan (22 publications), Carnegie Mellon University (20 publications), and Georgia Institute of Technology (19 publications). However, similarly to co-authorship, no relevant institutions can be considered as main centers of research around the world as they represent a very low percentage of the world-wide research (around 1%).

3.5. Author co-citation network

Author co-citation analysis can identify the relationship among authors, whose publications are cited in the same publications and analyze the evolution of the research community for the studied field. Fig. 8 presents the author co-citation network, containing 317 nodes and 657 links. The node size reflects the number of co-citations of each researcher, and the links between authors represent indirect collaborations established by co-citation frequency. Thus, the most highly cited authors were identified, including D. Lowe (frequency = 89, Canada), J. Yang (frequency = 58, China), N. Dalal (frequency = 52, USA), M. Golparvar-Fard (frequency = 51, USA), H. Bay (frequency = 49, Switzerland), I. Brilakis (frequency = 48, United Kingdom), K. Mikolajczyk (frequency = 46, United Kingdom), *P. viola* (frequency = 42, USA), and J. Gong (frequency = 42, USA). The diversity in the location of these most cited authors demonstrate that this field of research had been widely performed around the world.

Furthermore, several authors had citation bursts with rapid increases in citation frequency over short periods of time. The top identified bursts in the network are included in Fig. 9. Their articles, while not necessarily directly linked to the research field, tended to affect in great measure the direction of computer vision in construction research and were worth following.

3.6. Journal co-citation network

As shown in Table 1, the top source journals and conference

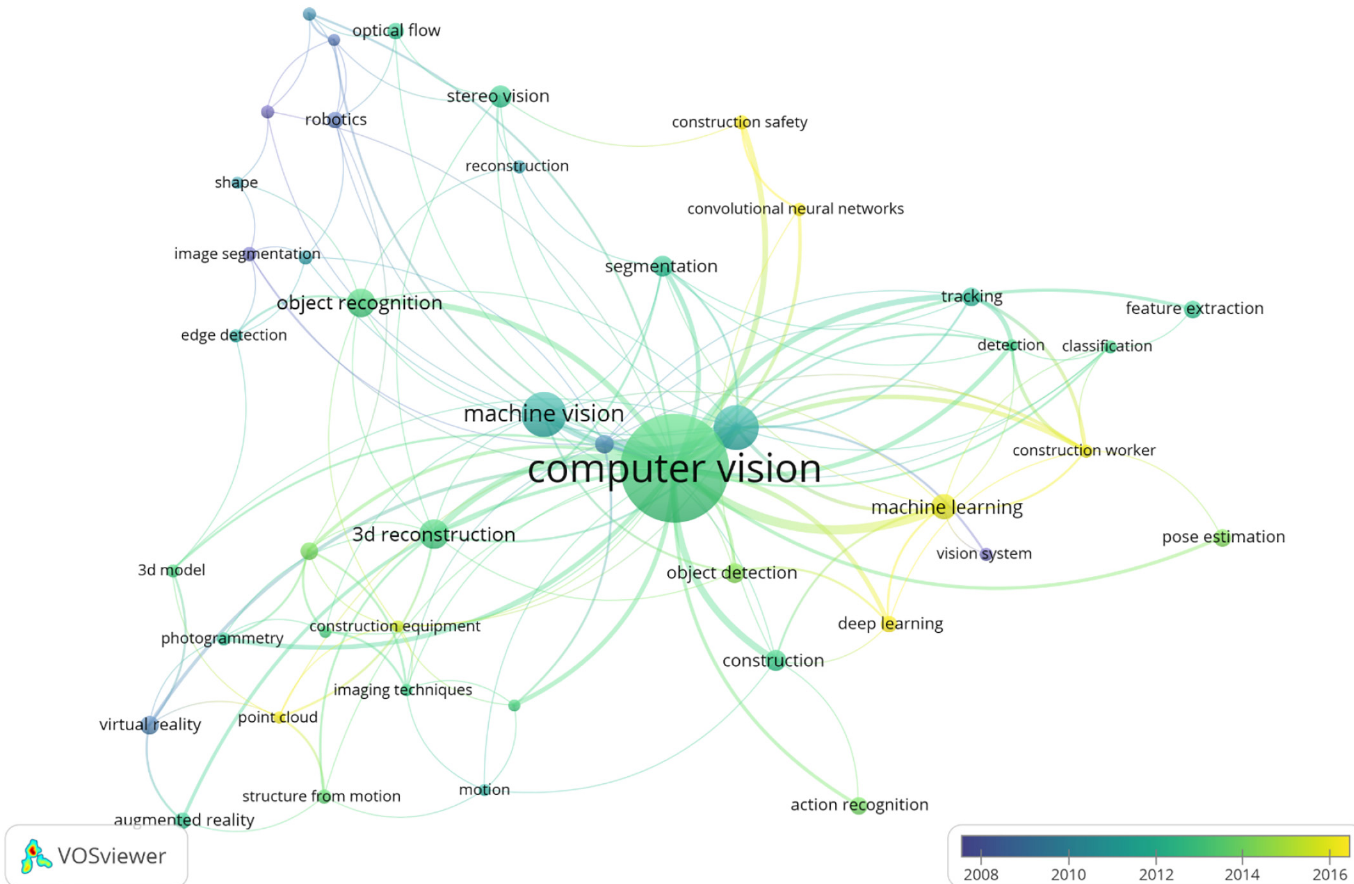

Fig. 4. Network of co-occurring keywords timeline related to computer vision application in construction.

Table 3
List of the top 10 most productive authors in the 1999–2019 time period.

Author	Institution	Country	Count	Percentage
I. Brilakis	University of Cambridge	UK	13	1.12%
M. Golparvar-Fard	University of Illinois	USA	9	0.78%
Z. Zhu	Concordia University	Canada	9	0.78%
M. Park	Myongji University	South Korea	8	0.70%
S. Zafeiriou	Imperial College London	UK	8	0.70%
H. Kim	Yonsei University	South Korea	7	0.60%
H. Li	Hong Kong Polytechnic University	Hong Kong	7	0.60%
H. Luo	Huazhong University of Science and Technology	China	7	0.60%
B. Y. McCabe	University of Toronto	Canada	7	0.60%
K. K. Han	North Carolina State University	USA	6	0.52%

proceedings for computer vision in construction were identified, according to the statistics from Scopus database. The references cited in those publications were analyzed and then a journal co-citation network with 337 nodes and 1195 links was generated to identify the most cited journals, as indicated in Fig. 10. The node size denotes the co-citation frequency of each source journal. With respect to co-citation frequency, the top most influential journals were *International Journal of Computer Vision* (frequency = 287), *IEEE Transactions on Pattern Analysis and Machine Intelligence* (frequency = 235), *Pattern Recognition* (frequency = 160), *Automation in Construction* (frequency = 100), *Journal of Computing in Civil Engineering* (frequency = 85), *Image and Vision Computing* (frequency = 68), *Computer Vision and Image Understanding* (frequency = 65), and *Advanced Engineering Informatics* (frequency = 59). It is worth noting that these journals were also among the top source journals in which publications related to computer vision for construction were published. Thus, the journals with more contributions to this research field also attracted more citations. However, it is worth noting that this effect is multiplied in journals which focus on the civil engineering field, as a lesser amount of source publications generated more citations than regular computer vision journals.

3.7. Document co-citation network and clustering

Document co-citation analysis enables underlying intellectual structures of a research field and demonstrates the quantity and authority of references cited by publications. In this section, a network of document co-citation is generated to represent the relationship between citations at an individual level. According to Fig. 11, the top 25 cited documents in the field are summarized in Table 5. It is important to note the low centrality of the most cited documents. Note that centrality is defined as the ratio of the shortest path between two nodes, in this case publications, to the sum of all such shortest paths. A node is considered central to a mapped network when its centrality value is above 0.3 [36]. Meaning that even the most cited documents cannot be considered as central for the co-citation network.

A network of document co-citations and co-citation clusters, which contains 315 nodes and 661 links, is presented in Fig. 11. Each node represents a publication and its label shows the first author's name and the publication year. Each link represents the co-citation relationship between the corresponding publications. The co-citation frequency between documents is represented by the node size. As seen previously, centrality is represented by a darker outer ring (purple) and the selected documents with high centrality are shown in Fig. 11. They can be seen

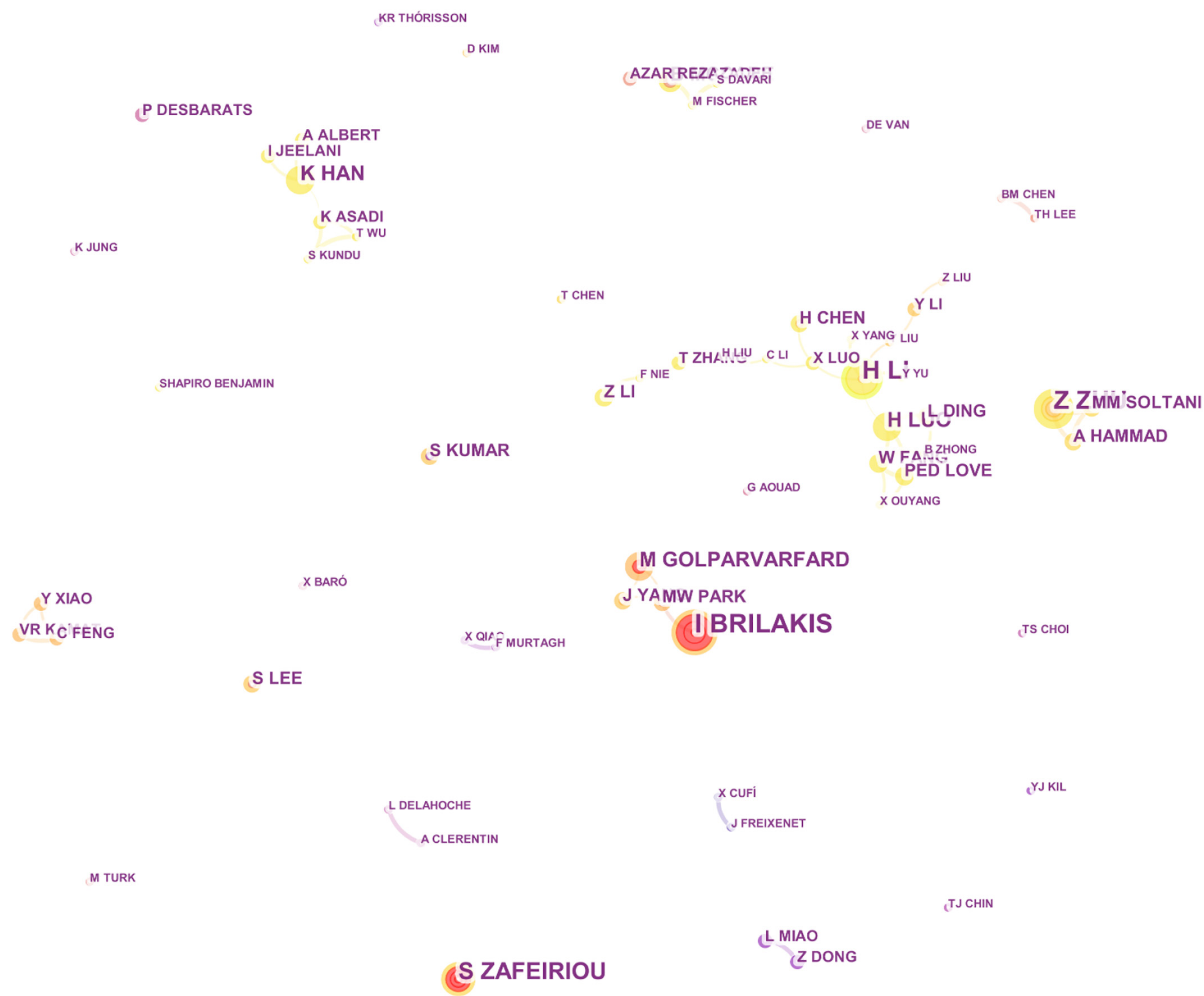

Fig. 5. Network of co-authorship for publications related to computer vision application in construction.

Table 4
Overall characteristics of the co-authorship network.

Network	Nodes	Links	Density	Modularity Q	Mean silhouette score
Co-authorship	153	203	0.0175	0.9278	0.5625

as the major intellectual turning points for the researched field, and almost all of them were included in the top 25 most cited publications, as shown in Table 5.

A total of 11 co-citation clusters were identified based on the abstract of each of the documents cited in each cluster. Note that all the presented clusters are loosely coupled but their boundaries are clearly defined. In Table 6, alternative labels are shown, such as the log-likelihood ratio (LLR) algorithm that selects cluster labeling based on keywords and provides uniqueness and a decent coverage [31].

Given the data in Fig. 11 and Table 6, in the first decade of the period studied in this review, the research was focused on developing computer vision algorithms that could be easily applied to construction tasks. As the reviewed research field was starting to grow at the time, most of the initial cited documents were related to previous computer vision algorithms or the image processing techniques used. As such, cluster #4 (mean publication year = 2006) and cluster #2 (mean publication year = 2007) contain publications that are grouped by the use of either images or collections of images and videos, respectively, to implement existing or novel computer vision algorithms in construction activities. The construction activities may vary from earth moving operations monitoring to equipment tracking and optimal utilization. Such variation in the research topics makes their analysis more complicated. The publication in 2011 by Gong et al. [41] on object recognition and contextual decision making introduced the possibility of productivity analysis from vision-based data in construction, thus opening the link between previous computer vision work and the complexity of construction operations and management. Since then, most researchers have focused on the integration of computer vision within on-going construction operations (cluster #3, mean publication year = 2011), in tracking resources (cluster #1, mean publication year = 2012 and cluster #16, mean publication year = 2010), and ensuring safety within construction sites (cluster #0, mean publication year = 2012 and cluster #7, mean publication year = 2014). More recent work includes inspection and as-is modeling of construction products (cluster #11, mean publication year = 2015) and the assessment of possible defects (cluster #12, mean publication year = 2013).

Note that different clusters that are located far away from each

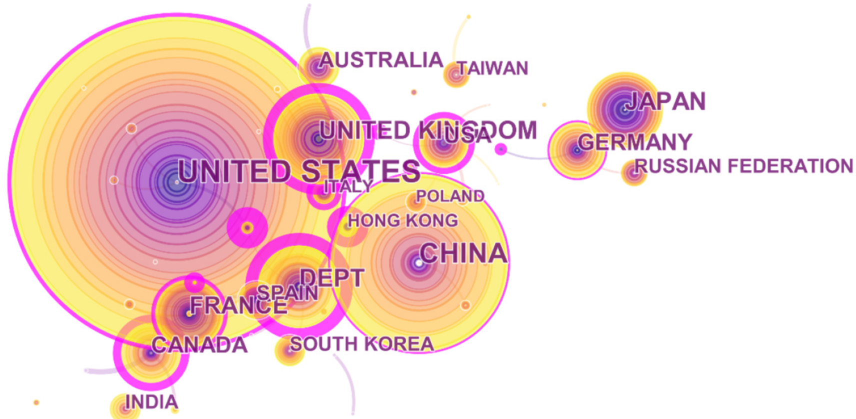

Fig. 6. Network of countries/regions.

other in the network (see Fig. 11) present similar cluster labels. For example, cluster #0, cluster #6, and cluster #7 contain publications that target the safety of operators, either by monitoring unsafe operations and personnel or by identifying on-site operators not wearing personal protective equipment (PPE). Encountering similar research topics with limited common co-citations shows that solutions targeting the same problem are provided within the same research field using completely dissimilar sources of information. Interestingly, different researchers using different literature are proposing solutions to similar problems.

4. Current research

Based on the data presented in Table 6, this section will provide insight by reviewing the most representative and recent works grouped by the previously mentioned clusters. The analyzed research topics are ordered based on the overall research interest and number of publications found in literature, starting from the most relevant topic.

4.1. Construction safety and personnel monitoring

For construction safety and workers' health, continuous monitoring of unsafe conditions is essential in order to eliminate potential hazards in a timely manner. Computer vision has been applied in this case as a robust and automated means of field observation. Information and images extracted from site videos are regarded as effective solutions complementary to manual observatory practices to mitigate safety risks [3]. Safety at the construction site has been the main target of many researchers in the past decades and is the most researched and prolific area (publication wise) in the computer vision field for construction. Three clusters were mapped in Table 6 around this research area: cluster #0, cluster #6, and cluster #7. Cluster #0 is the biggest cluster in the map (see Fig. 11) with 232 publications, while cluster #6 and cluster #7 are smaller, but no less significant, with 34 and 33 publications, respectively. Looking at Fig. 11, the three aforementioned clusters are closely located; however, the links between clusters are not numerous. Namely, 5 publications from cluster #6 and 3 publications from cluster #7 are cited by several publications in cluster #0. Given the size of the clusters, the number of co-citations between clusters is considered low.

First, the most representative work in cluster #0, published by Brilakis et al., suggests using vision systems to automatically track construction resources, such as equipment, materials, and personnel [38]. The suggested vision-based framework served as the foundation for enhancing safety on site and monitoring health in real-time. At the time of writing, this framework is still cited in the most recent construction safety publications. For example, a real-time warning system was proposed to prevent collisions between heavy equipment and people working on construction sites [63]. To address safety with respect to scaffold work platforms, verification of regulation compliance was accomplished automatically using 3D point cloud data [64]. To improve current capabilities to monitor dynamic workspaces and ensure worker safety, recent AI-based detection and tracking algorithms were proposed [65].

Countries	Year	Strength	Begin	End
JAPAN	1999	13.7744	**1999**	2005
RUSSIAN FEDERATION	1999	4.1397	**2005**	2011
FRANCE	1999	4.8305	**2005**	2010
SPAIN	1999	5.3227	**2005**	2009
AUSTRALIA	1999	3.2994	**2006**	2007
TAIWAN	1999	6.3887	**2009**	2013
SINGAPORE	1999	3.7778	**2010**	2014
BRAZIL	1999	3.3709	**2011**	2014
POLAND	1999	6.368	**2012**	2014
AUSTRIA	1999	3.1578	**2012**	2015
COLOMBIA	1999	3.5558	**2013**	2015

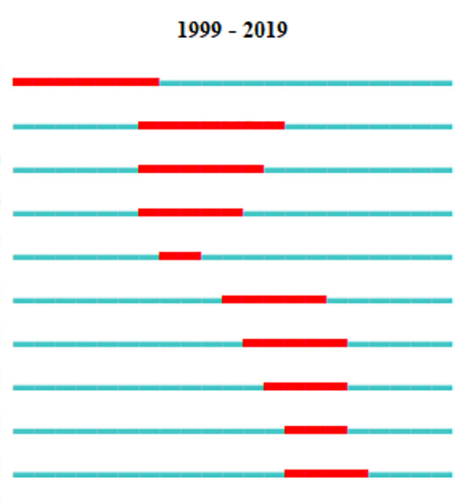

Fig. 7. List of the relevant countries with citation bursts in the 1999–2019 time period.

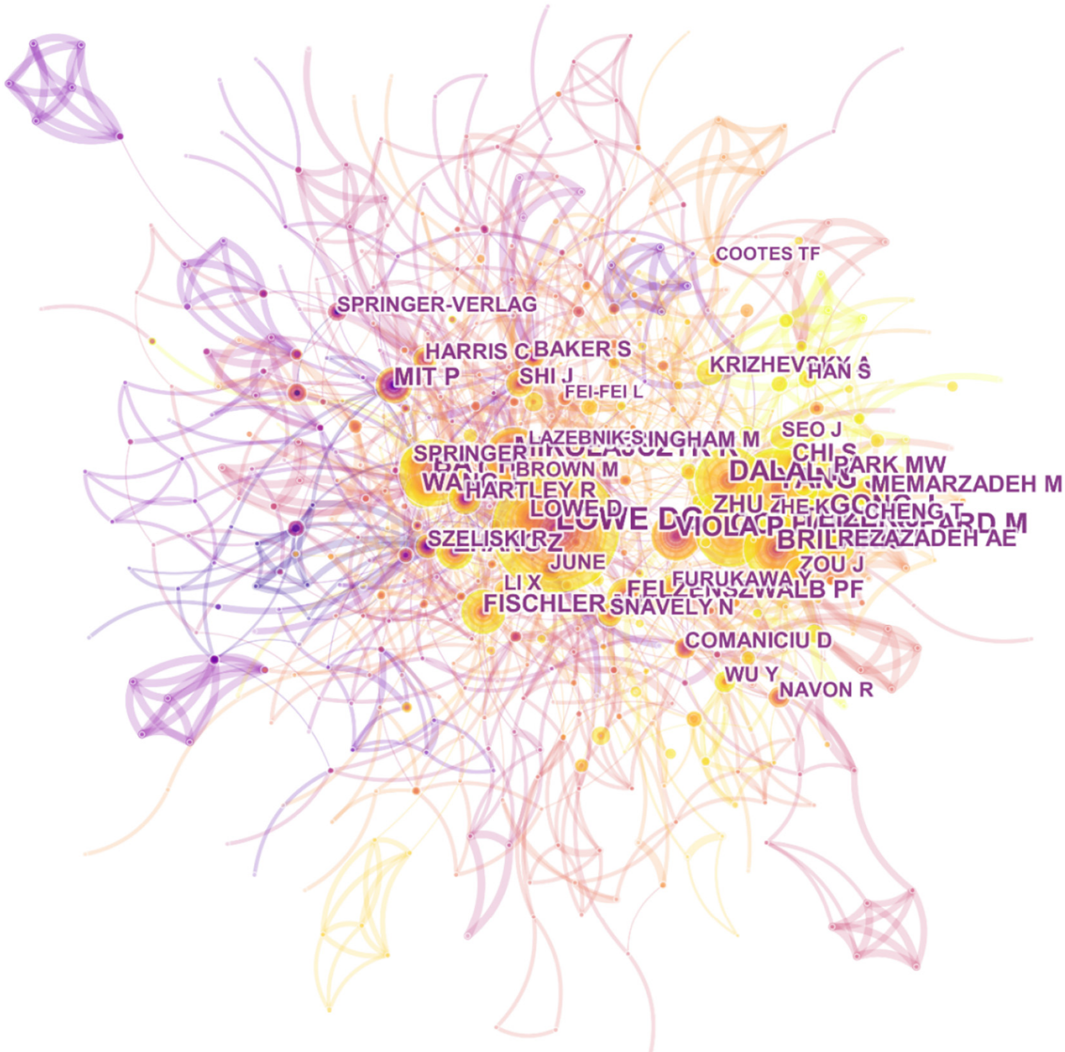

Fig. 8. Network of author co-citations for publications related to computer vision application in construction.

Then, for cluster #6, its most representative work, published by Ding et al., proposes applying computer vision and pattern recognition approaches to recognize unsafe behaviors on construction sites. By focusing on spatial and temporal information, the detection and recognition of workers' actions were possible through the use of deep learning methods. The proposed method of combining convolutional neural networks (CNN) with long-short term memory architectures (LSTM) enabled very detailed motion recognition in unsafe operations such as ladder climbing [60]. In general, cluster #6 contains publications related to the use of new artificial intelligence algorithms in this research field. For example, the use of CNN improved the approaches to assess worker's labor and health [66,67]. By using more accurate detection and tracking algorithms, a more complex and individual risk assessment is targeted [68].

Finally, cluster #7's most representative work, published by Teizer and Vela, discusses the possibility and need for tracking a workforce on construction jobsites using video cameras [61]. To gather the information and then store the relevant knowledge for the purpose of recognizing unsafe behaviors and operations was a process first recognized from a management perspective by Rezguiet al. [69]. However, due to the enormous amount of data generated by onsite video cameras, ensuring workers' safety has become a knowledge modeling problem [70]. To store and analyze the data and provide meaningful changes to improve construction site safety is the current challenge.

4.2. Resource tracking and activity monitoring

Recordings of construction operations provide understandable data that can be used for benchmarking and analyzing resource performance. Such recordings support project managers in taking corrective actions on performance deviations and support decision making to improve operational efficiency [2]. Analysis of productivity in a construction site requires tracking of resources and monitoring activities. Four clusters were mapped in Table 6 around this research area: cluster #1, cluster #3, cluster #5, and cluster #16. Keeping track of the available resources on a construction site and linking that availability to the project schedule, site productivity, and construction activity monitoring is a tedious task for project managers that researchers are aiming to automatize. Cluster #1 is the second biggest cluster on the map, with 112 publications, and is only linked to cluster #0 and cluster #5. The relationship between the clusters has some significance, as safety, activity monitoring, and resource tracking have a meaningful correlation. Current research publications highlight this relationship: 12 publications from cluster #5 and 38 publications from cluster #0 are cited by multiple publications in cluster #1. Cluster #3 contains 47 publications and is interestingly quite isolated from its 'similar' clusters and is only linked by 4 publications to cluster #0. Cluster #5 contains 36 publications and is connected to clusters #0, #1, and #7. As mentioned previously, cluster #5 has a strong co-citation relationship with cluster #0 and cluster #1. However, the co-citation links between

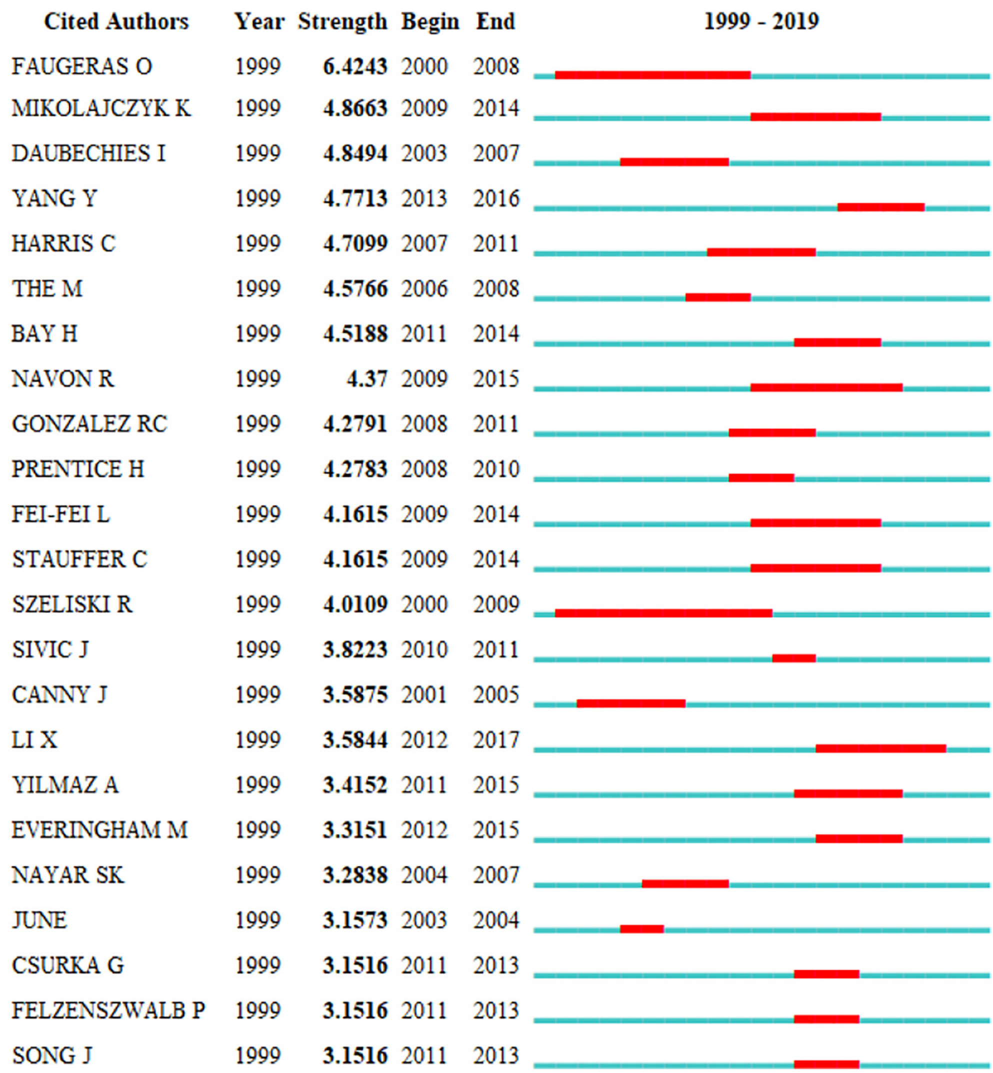

Fig. 9. List of the top authors with relevant co-citation bursts.

cluster #7 and cluster #5 are limited to 3 publications. Finally, cluster #16 contains 5 publications and, similarly to cluster #3, is only linked by 2 publications to cluster #0.

First, cluster #1 includes all the publications that pertain to research on visual resource tracking, i.e. equipment or workers, and their effect on productivity on the construction site. Cluster #1's most representative works were published by Memarzadeh et al. and Golparvar-Fard et al. The first publication proposes a vision-based algorithm to detect construction workers and equipment from site video streams. The suggested detector was based on histograms of oriented gradients and colors (HOG + C) and support vector machine (SVM) classifiers and could differentiate between resources performing construction activities or sitting idle [37]. The second work presents a computer vision-based algorithm to recognize earth-moving construction equipment actions. It showed successful results detecting, tracking, and identifying excavator and truck activities on the construction site, introducing the application of such techniques for construction activity analysis [40].

Then, cluster #3 groups the publications that aim at visual monitoring of on-going construction activities or construction progress. Its main representative work, published by Golparvar-Fard, employs observations of a concrete column and its periphery to recreate the as-built status of the project and assess discrepancies between the as-built and as-planned progress [49]. Such an approach would facilitate the decision making with respect to the necessary remedial actions and provide robust means for recognition of progress and productivity on the construction site.

Next, cluster #5's most representative publication, published by Han et al., employs the use of stereo cameras to improve the accuracy and efficiency of motion analysis by monitoring construction workers' behavior and measuring the impact on safety management [54].

Finally, cluster #16's most representative work, published by Silberman et al., proposes a segmentation algorithm to support the analysis of indoor complex scenes, such as indoor on-going construction scenarios [62]. By using cameras inside construction sites, real-time working conditions can be assessed and reconstructed in virtual 3D scenarios [71]. The capacity to observe and extract data from complex scenarios enabled researchers to track and monitor activities in late stages of construction projects [72].

4.3. Surveying and as-is modeling

Building information models (BIM) are becoming the official standard in the architecture, engineering and construction (AEC) industry for storing and exchanging information about current assets. Throughout the construction process, the ability to use BIM to automatically generate asset's representations is expected to have a big impact on various construction stakeholders [4]. Visual systems, as a data acquisition platform, are becoming an important instrument for as-is modeling and surveying applications. The surveying of construction

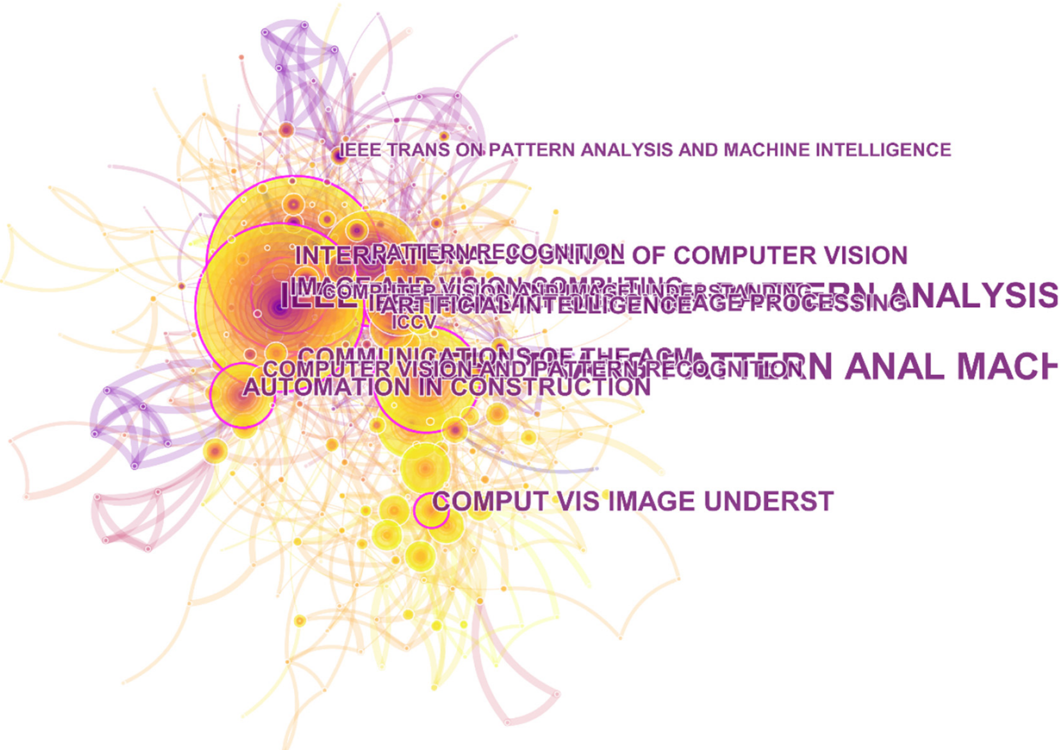

Fig. 10. Network of journal co-citations related to computer vision application in construction.

sites helps to visually monitor work-in-progress, which is particularly important in hard-to-reach areas. From static or mobile platforms, such as unmanned aerial vehicles (UAVs), visual systems play an important role in streamlining the collection, analysis, visualization, and communication of as-built infrastructure systems [9]. All the relevant publications in this research area were grouped into a single cluster: cluster #11. This cluster contains 27 publications and is only connected loosely to cluster #0 by 2 publications with common co-citations.

The most representative publication, published by Siebert et al., develops a novel platform for data acquisition of dense point clouds of large infrastructure projects using UAVs. The presented work detailed the process by which UAV systems are used as data acquisition systems and evaluated their performance against conventional surveying methods. The system was successfully tested in excavation and earth-moving construction sites [45]. More recently, aerial photogrammetry has been used in construction surveying for various tasks as the

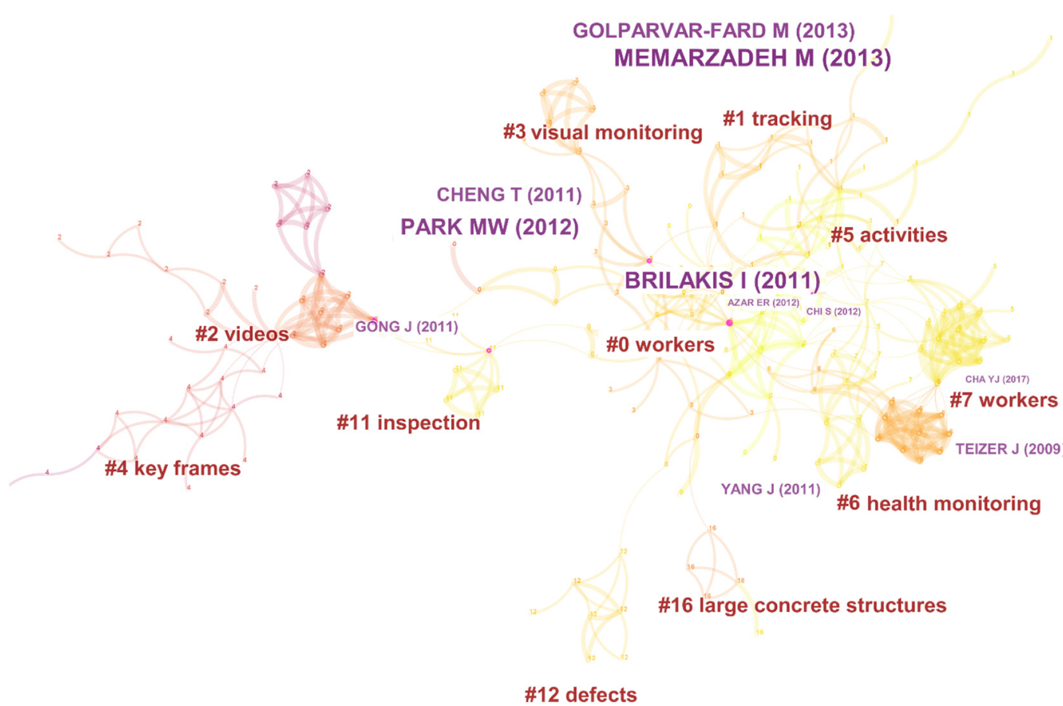

Fig. 11. Network of co-citations with abstract clustering.

Table 5
The top 25 most cited documents in the 1999–2019 time period.

No.	Article	Total citations	Centrality	No.	Article	Total citations	Centrality
1	Memarzadeh et al. [37]	64	0.03	14	Yang et al. [2]	7	0.02
2	Brilakis et al. [38]	58	0.05	15	Golparvar-Fard et al. [49]	6	0.05
3	Park et al. [39]	52	0.04	16	Gong et al. [50]	6	0.00
4	Seo et al. [3]	48	0.07	17	Yang et al. [51]	5	0.04
5	Golparvar-Fard et al. [40]	46	0.21	18	Chi et al. [52]	5	0.08
6	Gong et al. [41]	43	0.04	19	Felzenszwalb et al. [53]	5	0.00
7	Cao et al. [42]	41	0.04	20	Han et al. [54]	5	0.03
8	Dalal et al. [43]	37	0.09	21	Navon et al. [55]	5	0.04
9	Lowe [44]	31	0.04	22	Ray et al. [56]	5	0.03
10	Siebert [45]	24	0.17	23	Bay et al. [57]	4	0.03
11	Cheng et al. [46]	17	0.06	24	Brilakis et al. [58]	4	0.00
12	Fang et al. [47]	9	0.04	25	Dimitrov et al. [59]	4	0.10
13	Park et al. [48]	7	0.04				

platform has grown more popular. For example, a framework to automatically assess the structural condition and support the planned maintenance of bridges was proposed based on UAV data [73]. Additionally, a study by Kang et al. used surveying methods to identify construction materials on construction sites for on-going large-scale projects in order to monitor construction progress [74].

4.4. Inspection and condition monitoring

Computer vision techniques are advancing to support civil infrastructure inspection and monitoring. Manual inspection is currently the main means of assessing the condition of infrastructure, but manual inspection can be time-consuming, laborious, expensive and/or dangerous. Adopting vision-based frameworks is a natural step forward and will eventually replace manual visual inspections [75]. The condition assessment is performed by leveraging information obtained by inspection or monitoring processes. As such, applications vary from damage detection, i.e. concrete cracks [76], to structural change detection [77]. In general, vision-based inspection algorithms are researched to support real-time monitoring of critical systems in civil infrastructure systems. A total of 24 publications found in the literature delve into this research area and are grouped in cluster #12. This cluster is the most isolated one on the map is only connected by a single co-citation to cluster #0.

The most representative work in this area, published by Bay et al., presents a novel detector and descriptor based on speeded-up robust features (SURF). This detector and descriptor enables researchers to detect interest points on site images based on pre-defined parameters [57]. SURF has served as a base framework whereby researchers are evaluating the possible utilization of descriptors to recognize field objects in construction applications [78]. Given that the algorithms are less computationally demanding and that the detectors and descriptors are optimized, on-site operators can use mobile devices, such as smartphones, to update project information or interpret what is happening on the construction site [79]. However, civil infrastructure is usually composed of a mixed environment of small and large components, which renders the selection of distinctive features more difficult, and researchers end up selecting features on a case-by-case basis [80].

5. Discussion and future trends

5.1. Overview

This study uses scientometric analysis in order to review the existing literature dataset on computer vision applications for construction-related research. It extends earlier partial review work of the field by complementing existing subjective critical and integral studies with a strong quantitative approach delivered through science network mapping tools.

Studies were first published in the field in the late 1980s but it was only in the mid-late 1990s that double figures per year are seen. Indeed, almost two decades later, publication numbers keep rising, reaching 91 publications in 2018. This trend confirms the growing interest in research in the field of computer vision in construction. However, publications are highly dispersed between 64 different journals and conference proceedings. This is especially true for research studies presented at conferences, where only 20.16% of the total number of publications are found in the top conference proceedings (> 2 publications in the field) listed in Table 1. Although journal publications are equally dispersed, *Automation in Construction* seems to have published the highest number of research studies in the field (13.85% of the total journal publications). This suggests that researchers working on computer vision applications for the construction sector encounter issues when deciding where to publish their work; this is due especially to the lack of an international conference that gathers together authors around the topic.

This study considered the relationships between key individual researchers, research journals, and the countries of research origin by

Table 6
Co-citation clusters of vision-based research for construction 1999–2019.

Cluster ID	Size	Abstract cluster label	Alternative labels	Mean publication year	Representative documents
#0	232	Workers	Construction workers/Unsafe operations	2012	Brilakis et al. [38]
#1	112	Tracking	Detection methods/Resource tracking	2012	Memarzadeh et al. [37], Golparvar-Fard et al. [40]
#2	77	Videos	Equipment Tracking/Earth Moving Operations	2007	Gong et al. [41], Gong et al. [50]
#3	47	Visual Monitoring	On-going Operation/Civil Infrastructure	2011	Golparvar-Fard et al. [49]
#4	42	Key Frames	Instance Detection/Training	2006	Lowe [44]
#5	36	Activities	Management/Construction Activities	2013	Han et al. [54]
#6	34	Health Monitoring	User Safety/Visual Monitoring	2016	Ding et al. [60]
#7	33	Workers	Machine Learning/Safety	2014	Teizer et al. [61]
#11	27	Inspection	As-is Condition/UAV	2015	Siebert et al. [45]
#12	24	Defects	Component Geometry/Testing	2013	Bay et al. [57]
#16	5	Large Concrete Structures	Assessment/Construction Equipment	2010	Silberman et al. [62]

means of co-citation network analysis. The results of the co-citation network mapping, performed in Section 3.4, Section 3.5, and Section 3.6, highlight the global and homogeneous interactions between researchers all around the world. First, the USA is shown to be the lead country in terms of research influence, along with, perhaps, China. In particular, the US maintains research links with all the countries represented in Fig. 6; however, those links seem to be weak with Germany, Japan, and the Russian Federation. Similarly, most of the co-citations between researchers are focused around important journal papers in the field of computer vision (Fig. 8 and Fig. 9) and then branch out from these initial contributions. This concurs with the observation, mentioned in Section 3.2 and Section 3.7, that initial contributions were focused on developing computer vision algorithms with possible applications in construction and, in the end, evolved over time into fully integrated solutions for the construction industry.

Finally, the story is more complex with regards to the publication outlets in which research is published on computer vision applications for construction. An obvious measure of a journal's worth as a source of knowledge is the number of studies in the field any particular journal publishes. In this respect, *Automation in Construction* has published the largest number of articles on the reviewed topic, 45 in total. However, other journals present a higher number of citations compared to *Automation in Construction*, such as *International Journal of Computer Vision*, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, and *Pattern Recognition*. This is explained by the importance that is given to the origins of the methods and algorithms used in the research publications. Focusing only on civil engineering related journals, *Automation in Construction* presents the higher number of citations, followed by the *Journal of Computing in Civil Engineering* and *Advance Engineering Informatics*. In a nutshell, *Automation in Construction* seems to be established as the main voice in the field.

The limitations in this body of knowledge become apparent, however, when analyzed for content. As presented in Section 3.2 and further analyzed in Section 4, publication keywords are representative of the core content of the publications in the field. In general, the keyword co-occurrence map (Fig. 3) shows weak links and detached keywords reflecting how scattered the knowledge is within the field. The most relevant applications of computer vision within construction activities, namely resource and safety monitoring, are on opposite sides of the network with minimal interconnections. Furthermore, the document co-citation mapping generated in Section 3.7 provides more insight and confirms the poor connection between some topics within the reviewed field, where, for example, a single publication is the only existing link between cluster #0 and cluster #12 (Fig. 11). This sharp compartmentalization, with little to no cross-fertilization between the researched areas, limits the impact that the previous research could have had in such an interdisciplinary field and its corresponding industry. While some sub-fields within this field of research can be identified, the impact and interference between sub-fields is almost negligible. Similarly, the co-authorship map in Section 3.3 explicitly shows that most of the researchers in the field work in isolation; though some small but relevant research circuits can be found led by I. Brilakis and H. Li. It is worth mentioning that researchers in collaborative circuits, as small as they are, populate the authorship of the most cited documents in the field (Table 5) and are authors of some important research documents associated with citation bursts, thus exhibiting once more the importance and relevance of collaboration in research.

5.2. Future trends

Although the knowledge seems to focus on all major themes in construction research, such as operational and management issues, safety and resource optimization, inspection and monitoring of construction sites, and resource and activity tracking, rising topics within the field and potential collaborations between research clusters can be identified. This section proposes to extend the current agenda in the research field of computer vision in construction to include the following topics.

5.2.1. Smart construction

In recent years, the terms Industry 4.0 or smart manufacturing have been introduced to describe the trend towards digitization, automation of processes, and increasing use of information and communications technology (ICT). In this context, the term Industry 4.0 comprises a variety of technologies to enable the development of a digital and automated environment, as well as the digitization of the value chain [81]. The expected outcome is to bring improvements in product quality and a decrease in time-to-market and costs by improving enterprise performance [82]. The impact of Industry 4.0 has already been analyzed from the supply chain management perspective [83] and its implications with respect to the digitization of the construction industry have been examined [84]. Researchers aiming to develop smart construction sites will require systems that delve with data related to workers (Section 4.1) and resources (Section 4.2) alike, as well as generated *as-is* models (Section 4.3). With real-time data provided by visual systems, a digital framework for a safe, efficient, and connected construction site can be developed.

In cyber-physical processes, computer vision plays a very significant role as a data generation and acquisition system, which is one of the key components in Industry 4.0. Targeting the integration of the current visual sensors, among others, into an internet of things (IoT) network and enabling a new level of connectivity between the construction site and other stakeholders should be a target for researchers in the near future. As a paradigm of smart construction sites, computer vision algorithms would provide real-time feedback to assess construction site status from all the perspectives mentioned in Section 4 in a general framework [85]. Recently, an initial framework to automate digital twinning, a digital replica of the real-world asset, was developed for reinforced concrete bridges from 3D labeled point clusters [86]. The proposed method showed better results than manual inspection of large structural components, but complex geometries are still a challenge. However, once these challenges are overcome, the entire digital twinning process can be streamlined, and the cost-benefit ratio of such techniques will be improved.

Furthermore, as computer vision systems are added to construction projects, the cost to store all the obtained data will become a challenge. Many industries, including the construction management sector, have developed ontology models to efficiently manage the knowledge acquired by their systems. With newer visual systems in place, current ontology models will need to be extended to include the knowledge obtained. A few publications in the use of computer vision for manufacturing of construction products have already been published, targeting the knowledge modeling of manufacturing and quality information [87,88].

In summary, computer vision has an important role to play in the future research of construction as the digital era pushes industries towards digitization and smart construction based on Industry 4.0 principles.

5.2.2. Quality inspection for construction products

Computer vision is a real-time quality control technique that has been widely adopted by several industries. The quality of construction components and the performance of the infrastructure have always been criticized, both in regards to life expectancy and maintenance requirements of the materials used. Although great efforts have been made in past decades to promote quality within the construction industry, some quality issues still remain. In residential housing, 68% of new homeowners claimed that rework was needed in their homes at handover according to a 2011 survey in New Zealand [89]. The amount of rework needed to rectify issues is a critical area for improvement.

Recent works can be found on the inspection of defects, quality control, and assurance of construction products, and product-centric computer vision algorithms in construction-related activities. For example, a vision system was developed recently to automatically perform quality inspection of slate slabs based on construction requirements [90]. Other developments include automatic quality inspection for masonry activities using photogrammetric point clouds [91], image processing to provide real-time quality inspection of external wall insulation [92], a vision-based real-time quality monitoring system for extruded products [93], and a visual framework for pre-inspection of steel frames [94]. However, given the enormous amount of different materials, shapes, and products, in general, used in construction projects, research on this area has barely started. As quality inspection and conformance assessment is a rule-based problem, analogies between frameworks could exist between safety regulations and quality specifications. Currently, automated check of compliance with safety regulations using computer vision is a widely studied field (see Section 4.1), and a similar approach could be used for quality inspection to deal with varying specifications and codes.

5.2.3. Off-site construction

Cluster labeling is able to highlight how current research is heavily biased towards the practicalities of computer vision applications in on-site construction. However, in the last decade, there has been steady and growing interest in the adoption and development of off-site construction (OSC) within the architecture, engineering and construction (AEC) industry. In fact, the research contributions associated with OSC have spiked in the last 5 years [7]. However, computer vision applications for OSC remain under-researched. A quick search for publications related to computer vision and OSC, following previous works to determine the keywords that define OSC correctly [95], yielded two results. Recent work was published to ascertain the quality of steel framing in an OSC environment [94,96]. Considering the expansion of OSC in the construction industry, researchers will need to address this gap to participate actively in the development and improvement of the field and, thus, benefit the modular and off-site construction knowledge domain.

6. Conclusions

Computer vision has started to transform certain key aspects of the construction industry and has attracted increasing attention from researchers and practitioners. A scientometric study was proposed to explore the status and global trends of computer vision research related to construction applications. Although a number of literature reviews have already been undertaken, this paper presents the first scientometric study of the field as a whole, in which 1158 journal articles and conference proceedings were examined using a ‘science mapping’ approach. The key scholars and institutions, the state of the research field, and relevant topics on computer vision research for construction were identified. Principally, the reviewed topic emphasizes traditional on-site construction issues that historically have been addressed by manual means, such as health and safety monitoring, resources and activity tracking, and surveying and inspection of construction sites. Moreover, the research work in this area is conducted largely in isolation; this is especially true when considered in terms of research themes and researchers. The message to be drawn out is that future work would do well to promote collaboration between researchers in order to enhance dialogue, debate, and cross-fermentation of ideas and initiatives. Certainly, the enhanced understanding that certain practices, mainly the use of computer vision for product-centric inspection and defect detection, are neglected in the research may cultivate industry support for deeper and more carefully focused research into the field, which in turn may aid research planning and funding efforts by policy makers and practitioners. Moreover, this study provides valuable information to off-site construction researchers about the current lack of initiative within the field with respect to research related to computer vision.

Despite the contributions offered in this study, the findings are to be considered in light of certain limitations. As discussed, the findings are circumscribed by the initial selection of keywords and thus limit the coverage of the current literature. In addition, given the objectives of the study, delving into the aspects of “why” and “how” research has been conducted so far remains beyond the scope of this paper. Therefore, while several problems within the research domain are identified, pursuing these problems to their source and providing solutions are study areas that may be addressed in future research. Additionally, conducting similar studies at future crucial junctures will continue to address the evolving nature of the researched field and help monitor its development.

Acknowledgements

This study was supported by Natural Sciences and Engineering Research Council of Canada. Grant ID not available.

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