3D point cloud data enabled facility management: A critical review

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Abstract: Although the value of 3D point cloud data (PCD) has been increasingly recognized by the architectural, engineering, construction and facility operations (AECO) sectors, there is much less actual application of PCD in facility management (FM) than other stages. In order to facilitate the exploration of using PCD for FM, this study aims to summarize existing research effort and identify the gaps based on a systematic review of previous studies touching upon the PCD-enabled FM. This review was guided by a conceptual model that consists of four key components associated with PCD application process, including target objects, PCD sensing, model output and applications. 47 papers published in 21 academic journals were collected for the analysis. It was found that Light Detection and Ranging (LiDAR), photogrammetry, and Synthetic Aperture Radar (SAR) were the three mostly used technologies for collecting the PCD. The raw signals, such as fragments of point cloud and photos, collected by these technologies need to be pre-processed for generating the PCD, and segmentation and meshing are two general aspects of PCD post-processing to create models. It was also found that most studies focused on geometric properties, data processing, feature extraction, object recognition, and model generation, seldom would they dig deeper for decision-making support of FM applications. Based on the results, three major gaps of PCD-enabled FM were concluded, including (1) overlooking the valuable non-geometric properties (e.g. specifications of materials, relations between objects); (2) less focusing on providing decision support functions; and (3) hovering at data level rather than information level. Eleven possible research directions including semantics enrichment, real-time model generation, longitudinal analysis, and smart living applications of PCD-enabled FM were thus suggested for future research.

Keywords: Point cloud data; facility management; decision support; as-built modeling; semantics.

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1 Introduction

Nowadays, with the increasing affordability of obtaining accurate 3D point clouds data (PCD) by Synthetic Aperture Radar (SAR), Light Detection and Ranging (LiDAR) and photogrammetry, PCD has been widely used as digitalized representations of buildings[1] and infrastructure. Many studies in computer vision, remote sensing, and AEC have adopted PCD for 3D building and city model generation and 3D Global Positioning System (GPS) navigation. Typical applications of PCD in the construction industry include object recognition[2], building information modeling (BIM)[3], progress tracking[4], safety assessment[5], quality control and management[6], site activity monitoring[7], and energy performance modeling[8], most of which are at the construction stage[9].

In contrast, research on the use of PCD in facility management (FM) is not as intensive as that in other project phases. FM is a profession that encompasses multiple disciplines to ensure functionality of the built environment by integrating people, place, process, and technology[10]. FM covers a wide range of operation and maintenance services and is directly connected with the success of the facilities and their relevant business[11]. All these services required the accurate, real-time information, which can be retrieved from PCD. However, current applications of PCD in FM is rather limited. In order to allow future exploration on PCD-enabled FM to proceed on a more solid foundation, it is necessary to summarize the existing efforts and identify the gaps.

The aim of this paper, therefore, is to revisit the PCD-enabled FM. In this paper, the PCD-enabled FM is conceptualized into a closed loop of processes, i.e., (1) object property measurement, (2) PCD sensing and processing, (3) model supported decision-making, and (4) applications in object-based FM. Each process is extensively reviewed based on the existing literature. As a result, the limitations of current PCD-enabled FM studies are concluded and future research directions are recommended.

The remainder of the following parts is: A summary of the research method is presented in Section 2. Section 3 shows the analytical results of the systematic review. Section 4 discusses the limitations of current research and suggests future research directions. Finally, the conclusion is given in Section 5.

2 Research method

To investigate the PCD-enabled FM, a preliminary search in Elsevier *Scopus* Database was conducted on March 13, 2018. Scopus is one of the biggest databases of research publications with access to more than 12000 journals[12]. The search conditions were setup as *(TITLE-ABS-KEY ("point cloud") AND TITLE-ABS-KEY (facility OR operation)) AND (LIMIT-TO (DOCTYPE, "ar")) AND (LIMIT-TO (SRCTYPE, "j"))*, Which means the searched results must contain “point cloud” and at least one of “facility” and “operation” in the title, abstract or keywords of journal articles. There were only 25 results returned. Based on their titles and abstracts, only 5 were identified as relevant to civil engineering and construction domains. Using a snow-ball search, i.e., checking their reference and the authors’ other publications not in the prior searched results manually, another 42 articles were found based on the first-identified 5 papers. All the 47 articles are screened by the authors to ensure that they are closely related to PCD-enabled FM. A list of the journals of the selected articles is shown in Table 1.

Table 1. Source of the selected articles

Journal Title	No.	Journal Title	No.
Automation in Construction	14	Structural Survey	1
Journal of Computing in Civil Engineering	8	Structural Control and Health Monitoring	1
Sensors	3	Surveying and Built Environment	1
Advanced Engineering Informatics	2	Journal of Surveying Engineering	1
Computers, Environment and Urban Systems	2	Remote Sensing	1
Construction and Building Materials	2	Simulation Modelling Practice and Theory	1
Computer-Aided Civil and Infrastructure Engineering	2	Digital Applications in Archaeology and Cultural Heritage	1
Mediterranean Archaeology and Archaeometry	1	IEEE Journal on Selected Topics in Signal Processing	1
International Journal of Automation and Computing	1	Electronic Journal of Information Technology in Construction	1
Open Construction and Building Technology Journal	1	ISPRS Journal of Photogrammetry and Remote Sensing	1
Journal of Civil Engineering and Management	1		

As shown in Table 1, the 47 articles were collected from 21 journals, among which 14 journals published only one relevant paper. *Automation in Construction* and *Journal of Computing in Civil Engineering* are the top two journals publishing PCD-enabled FM research. Figure 1 shows the yearly distribution of the selected articles. As shown in Figure 1, the combination of FM and PCD started around 2006 as far as we concerned and it is still in an early stage. However, the publication number remained at a very low level until 2013 and achieved a peak in 2014. The overall number was steady and relevant research continued to be active after 2014. What lies behind this development trend is the fact that the affordable price and the popularization of remote sensing equipment in the 2010s made it possible to widely apply this technology. Another possible reason was the fever of digitalizing everything from the 2010s. Even though, the publication number of PCD-enabled FM was much less than that of PCD-enabled construction applications [9].

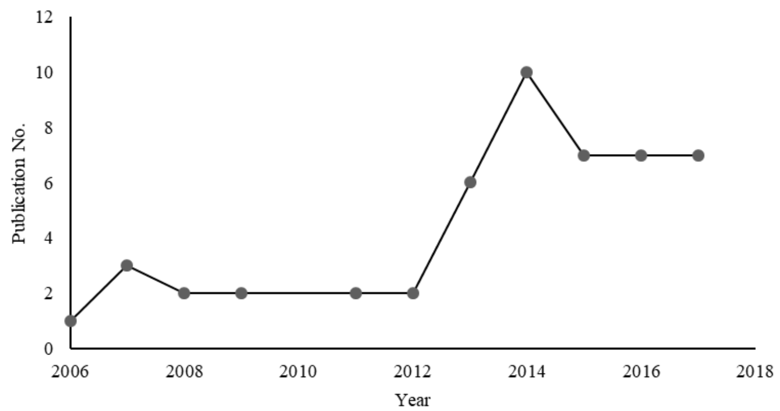

Figure 1. Yearly distribution of selected articles

A conceptual model is proposed to guide the analysis of the collected articles (Figure 2). The four blocks in different color in Figure 2 signify the four important nodes of the information flow while the arrows speak for the processes of data/information handling. The dashed arrows represent the links between the physical and cyber systems. The ‘Object’ block includes the target human beings and facilities. The properties of an object comprise its geometrical and non-geometric features. PCD sensing is the process of data acquiring with equipment such as laser scanners or digital cameras. Processing the obtained PCD to recognize objects and generate 3D models is the field where the majority research concentrates. This step is crucial because it transforms massive and noisy signal data to valuable information. With data processing, the isolated PCD sets will be ready to fabricate a semantically rich model for decision support. Moreover, PCD and the generated model have the potential to monitor target facilities and protect human beings. This model and its elements, procedures and approaches as well as the logic behind the closed loop are further elaborated in the next section.

Figure 2. The conceptual model beneath PCD-enabled FM research

3 PCD-enabled FM research

As shown in Figure 2, the information in PCD-enabled FM research flows from the object to PCD, then to a PCD generated model and finally from a model supported application to the object, which forms a closed loop. The basis of this cycle is the data collected from objects, the target of FM. However, data not transformed to information is just a pile of loose sand, only when converted to information which can support decision-making, does the PCD data become the solid foundation of FM applications. The information is valuable only when it consists of one or more well-formed data that are meaningful[13] by providing the details of ‘who’, ‘what’, ‘where’, and ‘when’ (4Ws), i.e., tell end-users what is happening to who at which place at an exact time. The 4Ws, the essence of information, are directly concerned with the decision-making. In this section, the properties of objects that can be recorded by PCD, the PCD sensing and processing approaches, the output of the PCD and how to use them in FM applications will be thoroughly concluded, and the research gaps will be revealed.

3.1 Object properties

Objects are the cells of facilities which facilitate the function of a convenience or service. Facilities have an all-encompassing scope, ranging from physical ones, such as transport facilities, medical facilities and telecommunication facilities, to spiritual ones like cultural facilities and correctional facilities. Therefore, there are myriads of objects in these facilities, varying from as big as walls, roofs, highways to as small as bulbs, bolts and sockets. When researchers talk about facility management, they typically refer to the physical facilities, for instance, transportation infrastructure, buildings of residence, commerce, administration and medical care. These built facilities are all designed, constructed, utilized, operated and maintained by human beings and serve for better living of human beings. Generally, the properties of these objects can be divided into geometry and non-geometry category.

Geometry concerns about the shape, size, dimensions, symmetry, position, color, texture and their topology[14]. In AECO sector, the shapes of columns, beams, plates, walls, and windows are usually basic cylinders or polyhedrons like cubes or prisms with polygons, especially quadrilaterals. But there are also more and more special-shaped structures, e.g., the roofs of Sydney Opera House and China's National Centre for the Performing Arts (the Egg Building). Table 2 illustrates some examples of different types of objects in AECO sector, it can be noticed that the shape of the same type object can be completely changed. However, the current database of PCD objects, the most representative online open source platform Point Cloud Library (PCL) for instance, are usually too generalized to optimize all parts[15]. Consequently, there are presently three types of geometry-related methods of point clouds modelling, i.e., model-driven, data-driven and hybrid-driven[16]. The top-down model-driven methods search best match between PCD and existing object models from a model library with quicker speed. In contrast, the bottom-up data-driven processes identify geometric primitives and their topology to extract object models from PCD. While hybrid-driven methods combine model-driven and data-driven methods, which forestall the limitations of both methods, to convert the object modeling to graph matching with basic topology graph elements in a model library [14].

Table 2. Examples of common and special objects in AECO sector

Scores of researchers have been contributing to the geometry modelling of PCD with building objects. Holz et al. [17] proposed a modular registration framework for aligning 3D PCD with objects in PCL, they also overviewed registration algorithms, usage examples and application tips for 3D PCD model-driven registration. Furthermore, Balali et al. [18] conducted a 3D traffic sign detection and classification method based on the geometrical features, i.e., the shape together with color. More precisely, cylinder was used to automatically detect pipes, conduits, and some ducts from 3D PCD in real-life buildings with very high accuracy [19]. Polygonal models from unstructured PCD were automatically created by extracting a group of RANSAC (Random sample consensus)-based locally fitted planar primitives, their boundary polygons, and local adjacency relations[20]. On the other hand, symmetry is another significant property which can be adopted for regular or repeated geometric 3D structure discovery [21]. However, recent symmetry detection and symmetry-aware geometry processing studies are mostly conducted in computer graphics, while AECO sector hasn't gone deep into this level yet to our best knowledge. Besides, Gao et al. [22] pointed out that there can be discrepancy of shape, dimension and composition between as-designed BIM and PCD. Therefore, the classification and extraction of different geometry property need to be further explored, together with the combination and interoperability of different open source databases.

Non-geometry properties, including the specifications of materials, family types, functions, assembly order [14], and relations between objects, are of significant importance by adding rich information to the properties. These properties embedded in BIM make BIM essentially different from and more advanced than CAD. They provide more compact, high-level description of objects in a facility instead of purely raw PCD [23], enabling robots, computers to reason about objects and interact with its environment in a goal-directed way [24]. Chen et al.,[25] concluded the geometry and non-geometry information requirements of construction and FM stages, as displayed in Table 3. It can be easily noticed that both the types and requirements of non-geometric information are greater than that of geometric information. However, limited research explored the non-geometric properties in depth.

Table 3. Geometric and non-geometric information requirements of construction and FM stages [25]

Stage	Geometric	Non-geometric
Construction	Site information (coordinate's data and layout); Building spaces (floor, zones, rooms, openings); Utility lines; Dimension of building components.	Construction materials (status, quality, category, manufacturer); Precast elements (quality, category, manufacturer); Equipment attributes (ID, type, status); Financial data; Location of labor, materials, and machine; Project performance data; Construction schedule; Construction activity status; Site environment.
Facility Management	Building services (location, relationship); Building spaces (floor, zones, rooms, openings); Utility lines; Specification of exterior enclosure products; Furnishing.	Building services (identification number, manufacturer); Status of mechanical, electrical, and plumbing equipment; Maintenance record; Indoor environment; Attributes of replaced components; Maintenance status; Maintenance schedule; Operation records.

Both geometric and non-geometric information can be generalized to semantic information, which are increasingly used throughout a building's life cycle, from design, through construction, and into the FM phase[26]. To name a few, a predefined semantic net encompassing general architectural knowledge about indoor environments was used for in-door semantic scene interpretation from the scanned PCD [27]. Koppula et al. [28] proposed a graphical semantic labeling model to capture a variety of properties and contextual relationships (local graphic appearance and shape cues, object co-occurrence and geometric relationships included) in 3D indoor scenes of homes and offices. Though growing attention has been paid to the semantics of objects and models of facilities, most of the transformations from raw 3D PCD into semantic information were conducted manually through labor-demanding, time-consuming, and error-prone processes [23]. In addition, few studies provided rich enough semantics model to enable decision-making and applications of smart FM till now.

3.2 PCD sensing and processing

3D PCD is obtained by visible access to scanned surface of physical objects using SAR, LiDAR technology or photogrammetry. Figure 3 illustrates the sensing methods of PCD. SAR employs radar operating at the microwave region of the electromagnetic spectrum to acquire point clouds or images. Since radar has the ability to penetrate the cloud, it can be used on a spacecraft or aircraft for high resolution of earth observation and surveying. Different from radar used in SAR, LiDAR is a widespread technology used for 3D scanning of various objects with pulsed laser light at ultraviolet, visible, or near infrared regions. There are generally three types of LiDAR, i.e., Airborne Laser Scanning (ALS), Mobile Laser Scanning (MLS), and Terrestrial Laser Scanning (TLS). A laser scanning system typically consists of a LiDAR unit, a scanner, a GPS receiver and an Inertial Measurement Unit (IMU). ALS is an active remote sensing system with a LiDAR instrument mounted on an airplane platform, while the LiDAR of MLS or TLS is mounted on a moving platform (e.g., vehicle or mobile phone) or a tripod respectively. Photogrammetry is also commonly employed for 3D mapping and object reconstruction in AECO sector by extracting PCD from massive 2D photos taken by digital cameras equipped within a spacecraft (spaceborne), a plan or drone (airborne), or mounted on a vehicle or built in a mobile phone (mobile). Either adopting a single digital camera to acquire 2D calibrated images or a Multi-view Stereo (MVS) camera to take 3D stereo pictures is common and workable. Stereo-photogrammetry, a special case of photogrammetry which focuses on 3D coordination of objects is emerging as a robust technique in 3D reconstruction and dynamic characteristics detecting. Jalayer et al.[29] evaluated different technologies including field inventory, photo/video log, integrated GPS/GIS (Geographic Information System) mapping systems, aerial/satellite photography, TLS, MLS, ALS for collecting roadside features data. Discussions of each types of PCD sensing equipment and their instructions is not within the scope of this paper.

Figure 3. Point cloud sensing methods

Closely following the sensing step is the PCD processing, which transforms raw PCD to well-formed objects or models. A general workflow of PCD processing is shown in Figure 4. A pre-processing procedure including filtering, registration, shearing and re-sampling is the prior step, among which densification might be needed before re-sampling if the density of point clouds is too sparse. Noise is inevitable due to the surrounding environment, scene complexity, weather conditions and equipment status, therefore noise filtering or reduction is fundamental to generate ideal datasets for further processing. Another most-studied pre-processing step known as registration (or point matching) is essential to align the local coordinate frame of different point clouds datasets in a global coordinate system[30]. Iterative closest point (ICP) is a frequently adopted algorithm in registration to minimize the difference between two sets of PCD [17]. There are other registration algorithms, for example, robust point matching (RPM), thin plate spline robust point matching (TPS-RPM), kernel correlation (KC), Gaussian mixture models (GMM), coherent point drift (CPD), and sorting the correspondence space (SCS). This paper won't go in-depth with the introduction of these algorithms and their comparison. There are a lot research dealing with the semi-automated registration[31] or automated registration[32][33]. Shearing is to clip redundant parts of the registered PCD of targeted facilities. If some PCD parts of the targeted facility are obviously intensive or scattered than other parts after the former pre-processing procedures, a data re-sampling will be needed to ensure the equal density distribution of the whole PCD.

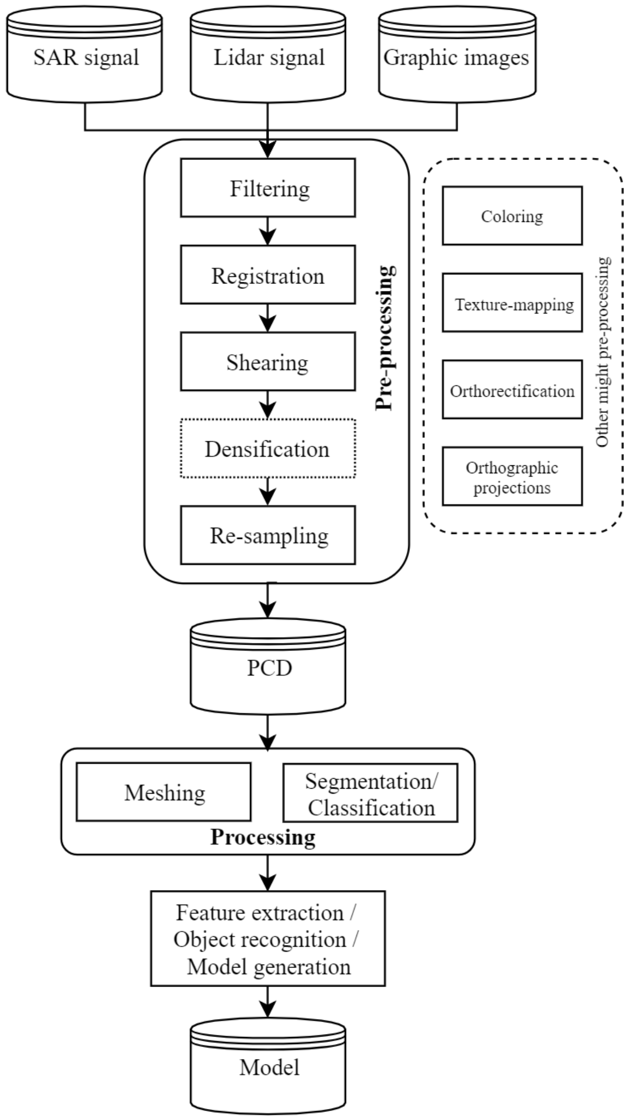

Figure 4. General PCD processing workflow

After pre-processing, comprehensive PCD will be well-prepared for main processing which generally includes meshing and segmentation/classification. Depending on different requirements or situations of PCD usage, order of the two steps are not fixed. Meshing of point clouds is to represent a geometric object with a set of simple polyhedral meshes from PCD. Meshing comprises a set of processing steps, including mesh representation, mesh compression, rendering, progressive transmission, editing operations, smoothing, parameterization, and shape reconstruction[34]. Mesh simplification, removing elements whilst preserving mesh fidelity, is the basis of constructing Level of Detail (LoD) mesh representations and was the most discussed in meshing[35]. Majority of meshing simplifications are triangular dominated[36], with an increase in quadrilateral dominated[37] with the growth of data complexity. After mesh representation, shape/object reconstruction will be conducted for segmentation or model generation, after other might procedures such as smoothing, lighting, rendering, etc. depending on the requirements of models.

Segmentation is to divide or disintegrate the given PCD set into non-overlap objects or regions with homogenous spatial and spectral characteristics for feature extraction, object recognition or model generation[38]. Traditional segmentation is data-driven using images with region growing approach or range data with edge-based technique. Model-driven segmentation methods will be used when the mathematical expression of the objects to be extracted is known, for which Hough Transform (HT) and RANSAC approaches are frequently adopted[39]. For most of the time, segmentation was done manually or semi-automatically, which is slow, painstaking, skill-specialized, and prone to errors. For example, Yang and Dong had to manually select training and validation targets, manually count number of objects in a shape-based segmentation method for MLS point clouds; Rau and Chen[40] proposed a semi-automated segmentation of building rooftops from photogrammetric 3D lines (either complete or incomplete). Challenges including density, surface roughness, curvature, clutter, occlusion, messing/erroneous data, abstraction and scale lead to the complexity and difficulty of automated segmentation[41]. However, researchers never stop exploring automated segmentation methods, to name a few, Khaloo and Lattanzi[42] proposed a region growing algorithm to automatically segment large scale PCD of surfaces with planar and non-planar; Díaz-Vilariño et al.[43] presented a model-driven approach to automatically segment columns of as-built buildings based on HT.

The sensing and processing procedures are so complex that not all aspects can be concluded and discussed due to the limitation of words. However, the key point is choosing sensing methods and equipment, as well as processing procedures and algorithms according to the requirements of the applications. Researchers should bear in mind that how to make the most of data sensed and convert them into valuable information in this whole process is always the first priority. In FM, the accuracy and richness of data and information deserve most attention, which does not necessary mean that the process methods can be neglected. Considering the complexity and huge amount of objects in FM, automated processing approaches are in urgent demand. Coming research has a duty to promote semantic enrichment during PCD sensing and processing to foster smart applications of buildings, infrastructure and cities.

3.3 PCD output and decision support

Based on the 3D PCD sensing and processing procedures, final feature extraction, object recognition or model generation will be conducted for applications. Features, higher level entities that model the correspondence between information and activities[44], can be divided into spatial-based features and shape-related features according to Gao et al.[22], as illustrated in Table 4. In practice, Priestnall et al.[45] extracted surface roughness from a digital surface model produced by LiDAR using both topographic and spectral characteristics; Yoon et al.[46] detected concrete tunnel installations and physically damaged parts of the liner using the geometric and radiometric features from 3D PCD for automated tunnel routine inspections and maintenance; Yang et al.[47], proposed a framework to identify contextual features like relative positions, relative directions, and spatial patterns for road facilities using MLS data.

Table 4. Classification of features and object recognition approach, summarized from [22] and [48]

Features	Examples	Object recognition approach
Spatial-based features	Relative location, distance, angle, relationships (i.e., orthogonal, parallel, adjacent, coplanar), surface roughness, connectivity	2D overlap area matching; Spatial relationship-based graph matching
Shape-related features	Shape, shape distribution, size, similarity, surface area, surface normal, orientation, volume, dimension, linearity, planarity, scattering, omnivariance, anisotropy, eigenentropy, eigenvalues and change of curvature	Distribution-based 3D shape matching; Distribution-based 2D shape matching

Object recognition is the next step of feature extraction. The objects can be outdoor objects such as pedestrians[49], railways[50], poles[51], traffic signs[52], and trees[53] and indoor objects like walls[54], floors, ceilings, windows, doorways, and steel structures[55] etc. Different features of point clouds help to recognize objects; thus object recognition approaches can also be divided into two categories according to two different types of features, i.e., spatial-based object recognition methods and shape-based object recognition methods. Among the four object recognition approaches displayed in Table 4, spatial relationship based approach achieved the best precision and recall of spatial relationship, but it takes the longest time, while 2D overlap area mapping is on the contrary[22]. Recently, Sharif et al.[2] adapted and examined an automatic model-based 3D objects finding from 3D construction PCD robustly and quickly.

Some research may also target at further 3D CAD or BIM model generation which has two categories of methods, i.e., data-driven and model-driven. The former is bottom-up aiming at organizing models from given geometrical and topological information; while the latter top-down requiring predefined typical sub-models matched with the raw data[56]. Data-driven methods can generate buildings with complex shapes but have no ability to handle strongly noisy data. On the contrary, model-driven algorithms are robust to erroneous data, however are not competent to describe buildings with miscellaneous shapes. Many researchers have been studying the automatical construction of 3D building models[57], historical architecture[58], indoor environment[59], pipelines[60], and industrial plants[61] from PCD, Hinks et al.[62] reported a flight planning optimization strategy using ALS to create urban infrastructure model. Früh and Zakhor[63] even proposed a drive-by-scanning methods of generating large-scale model of a city at ground-level.

However, with so much research focusing on algorithms and methods of processing PCD, extracting features, recognizing objects and generating models, few studies have tried to reach decision support of FM. Some special cases are: MLS data was adopted to analyze pedestrian crossing environments for safety management[49], extract vertical walls for solar potential assessment[54], and collision detection of 3D models[64]; TLS data was utilized to conduct concrete structures health assessment[65], monitor the structural health of a bridge[66], as well as automatic detect and analyze cracks in timber beams[67]; Gonzalez-Aguilera et al.[68] presented a method to analyze geometric information and urban density attributes automatically from ALS data; Ma et al.[69] proposed an approach to compile BIM and PCD to generate synthetic as-damaged models for post-earthquake operations. Actually, PCD supported models of built environment will ease communication between stakeholders about the maintenance, refurbishment and regeneration[70], which is of great potential value to support the decision of FM. Most current research just need to go a step further to exploit the information in their extracted features, recognized objects and generated models.

4 Discussion and conclusion

Based on the 47 selected articles which are closely related to PCD-enabled FM, this paper reviewed the geometric and non-geometric properties of objects, PCD sensing methods and processing workflow, and feature extraction, object recognition or model generation from processed PCD, as well as the gaps of decision support for FM applications. Among semantics information, geometric properties received more attention than non-geometric ones, though the latter add more value to information. To acquire data for information production, SAR, LiDAR, and photogrammetry are three main sensing methods of PCD. The raw signals need to be pre-processed through filtering, registration, shearing, resampling etc. for followed PCD processing, which mainly includes segmentation and meshing. After that, the processed PCD will be extracted and recognized for model creation. Generally, most research would stop after feature extraction, object recognition or model generation, with only a small number going further to support FM decision-making.

According to the analytical results, it is safe to conclude that there are three major gaps in the existing PCD-enabled FM research. First, few studies went deep to symmetry, not to mention semantics enrichment level. Second, little attention was paid to decision support and practical applications in FM. Third, previous studies often failed in converting data to information. Possible reasons for these three gaps could be: (1) FM research concerns more about strategy management than information management; (2) the improvement of hard aspects such as intelligence and automation of facilities and services draws more attention than soft parts such as documentation and information visualization; and (3) using PCD to facilitate FM requires multidisciplinary knowledge, which includes but not limited to FM, remote sensing, and computing. However, it is generally difficult for single researcher to obtain all the required knowledge.

To sum up, a lot of further research work is still needed in order to address the above-mentioned gaps in PCD-enabled FM research. Future research can be conducted in the following eleven directions: (1) enriching the semantics of 3D facility models generated from the PCD[71]; (2) utilizing geometric properties such as regularity[21], symmetry[14], and repetition for quick object recognition and model generation of typical facilities for further FM applications; (3) generating detailed models of complex facilities to supplement the scope of FM and study the uniqueness of their management; (4) generating more accurate and higher LoD models of exterior façades and interior environment for better visualization[72]; (5) improving the capacity and efficiency of PCD storage; (6) increasing algorithm scalability and computing performance for large-scale FM studies[67]; (7) developing unified framework, standards, libraries for sharing, updating and storing PCD of FM for wider range (city-level or even nation-level for example) of FM research; (8) modeling real-time status of facilities for monitoring and control, safety management, and emergency management[6]; (9) studying of real-life cases of PCD adoption in FM and its cost benefits; (10) analyzing longitudinal evolution of facilities to study the changes in facility properties and human behaviors; and (11) exploring potential applications including sustainable energy, intelligent services, smart living with the accurate facility models[73].

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