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Planning for Terrestrial Laser Scanning in Construction: A Review

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Abstract

Terrestrial Laser Scanning (TLS) is an efficient and reliable method for collecting point clouds which have a range of applications in the Architecture, Engineering and Construction (AEC) domain. To ensure that the acquired point clouds are suitable to any given application, data collection must guarantee that all scanning targets are acquired with the specified data quality, and within time limits. Efficiency of data collection is important to reduce jobsite activity disruptions. Effective and efficient laser scanning data collection can be achieved through a prior planning optimisation process, which can be called Planning for Scanning (P4S). In the construction domain, the P4S problem has attracted increasing interest from the research community and a number of approaches have been proposed.

This manuscript presents a systematic review of prior P4S works in the AEC domain and presents a categorisation of point cloud data quality criteria. The review starts with the identification and grouping in three categories of the point cloud data quality criteria that are commonly considered as constraints to the P4S problem. The three categories of data quality criteria include 1) completeness, 2) accuracy and spatial resolution, and 3) 'registrability'. The prior P4S works are then reviewed in a structured way by contrasting them in the way they formulate the P4S optimisation problem: the type of inputs they assume (model and possible scanning locations), the constraints they consider, and the algorithm they utilise to solve the optimisation problem. This work makes two contributions: (1) it identifies gaps in knowledge that require further research such as the need to establish a fully automated scan plan which provides the optimum coverage in construction domain specifically for indoor construction; and (2) it provides a framework — principally a set of criteria — for others to compare new P4S methods against the existing state of the art in the field. This will not only be valuable for young researchers who want to start research in solving the P4S problem, but also for the ones already working in the domain to rethink the problem from different perspectives.

Keywords: Laser Scanning, Network design, Planning for Scanning, Data Quality, Level of Accuracy (LOA), Level of Detail (LOD), Level of Completeness (LOC), Computer-Aided Design (CAD), Building Information Modelling (BIM), Point Cloud, Optimisation

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1. Introduction

1.1. Reality Capture in Construction

Different reality capture technologies have been proposed for application in the construction domain, especially with the upsurge in the application of Building Information Modelling (BIM) in recent years. These applications vary from monitoring and managing construction projects to preparing as-built/as-is documentations, and more. Akinci et al. [1] are among the pioneers who suggested application of sensor systems in construction projects for active quality control and defect detection. They linked inefficiency of quality controls on construction sites to late detection of construction defects, and discussed the importance of efficient inspection of construction sites. They also proposed three-dimensional (3D) laser scanning as an essential data collection technology to perform active project control through frequent, complete, and accurate dimensional and visual assessment of as-built conditions at construction sites [1].

3D laser scanner is one of the technologies used to create detailed and accurate indoor and outdoor building models. Terrestrial Laser Scanning (TLS) is a ground-based 3D reality capture technology that produces dense 3D point clouds of its surrounding by utilising time-of-flight or phase-based distance measurement principles. Point clouds come with additional data like colour or intensity information per point or support images, which helps the user to better visualise the raw point cloud. TLS' single-point accuracy is at the mm level and below, and the technology can measure millions of points in a matter of minutes. This makes TLS suitable for a wide range of applications in the Architectural Engineering Construction and Facilities Management (AEC/FM) sector, such as creating as-built/as-is documentation, monitoring construction activities, dimensional quality control, asset monitoring, reverse engineering, cultural heritage recording, and urban planning [1, 2, 3, 4, 5, 6, 7, 8, 9]. Although mobile laser scanning (MLS) is also now relatively common for outdoor point cloud acquisition for construction purposes, there are still some challenges (e.g. GPS limitations) that make it less practical for indoor applications [5]. Application of Simultaneous Location and Mapping (SLAM) is investigated as a substitute to GNSS (Global Navigation Satellite System) for indoor MLS, but the result remains inadequate for obtaining high scanning accuracy [10]. While these technologies and their performances are improving rapidly, this review only focuses on ground-based TLS.

Photogrammetry is an alternative approach to the production of 3D point clouds for some similar applications [11, 12, 13, 14, 15]. It has advantages over TLS in terms of portability and price; but it also presents a number of limitations in terms of accuracy, data completeness, scaling, robustness to various material textures, etc.

The network of data acquisition for any reality capture device (TLS, photogrametry, etc.) can be optimally arranged to best capture the scanning targets given constraints (requirements) in quality, time, cost, etc. This is generally called network design and in the case of scanning, we refer to it as Planning for Scanning (P4S). In Geodesy, geodetic network design combines general concepts of mathematical optimisation to the design concept. The design of geodetic networks is dated back to 1974 [16]. The network design problem in photogrammetry is also relatively well-addressed in the literature [17, 18]. This review paper focuses on 3D point clouds acquired by terrestrial laser scanners only, and investigates the works that have been published on P4S to date. Although the main focus has been given to TLS alone, the findings and the framework will benefit other types of point cloud generating devices, as the problem statement is broad and can be adjusted to different hardware associated limits. The comparison approach presented for TLS would also be useful in any other novel application of scanners (e.g aerial scan or scanner on robots, mobile laser scanning (MLS)), however the corresponding criteria for evaluation and the device limitations need to be identified for any device first.

1.2. *Planning for Scanning (P4S)*

Some domain experts formalised the P4S problem as the problem of finding the minimum number of predefined view points that give a full coverage of the scanning targets while satisfying the data quality requirements. This problem is similar to Art Gallery problem for monitoring with minimum cameras [19, 20], and the Next Best View (NBV) problem for robotic navigation in unknown environments [21, 22].

The algorithms to solve Art Gallery and robotic navigation problems focus on the line-of-sight factor that influences the coverage of the collected 3D point clouds, with limited consideration for other factors [22]. In contrast, in the context of P4S, other parameters that affect data quality must be taken into account in addition to visibility, such as single point incident angle and range [23, 24]. Interestingly, only González-Baños and Latombe [25] applied these constraints as well as visibility in their randomized Art-Gallery approach to find the best locations for (robot- mounted) sensor placement.

Current practice of laser scanning data acquisition relies on human intuition for planning the scanning locations and acquisition parameter settings at each selected location. Yet, construction sites are complex and constantly changing environments, which makes it impossible, even for experienced surveyors, to guarantee that the acquired point clouds fully cover all scanning targets with the specified levels of quality [5, 26, 27, 28]. The complexity is further increased by the fact that scanners present varying technical performances, and all scanning targets (e.g. objects) across a site may have differing data quality requirements.

Naturally, the risk of incomplete and insufficiently accurate data can be reduced by increasing the amount of scanning done on site (i.e. increasing the number of scanning locations, and/or changing the scanner settings); But increasing the number of scans and/or scanner settings can introduce redundancies in the data and result in inefficiencies. Point cloud data are notoriously large and redundancies make data storage and management a challenge. Moreover, collecting more data always needs more time and labour, and thus can be costly [27, 28] and result in further site disruptions. There is, therefore, a need to optimise scanning operations to achieve the required data completeness and quality while minimising site interferences and data quantity. Figure 1 graphically represents the P4S optimisation elements.

P4S is commonly done manually, before site visit using 2D sketches of the environment or 2D CAD models when available. On-site visual investigation can be used to complement this process. However, it has been shown

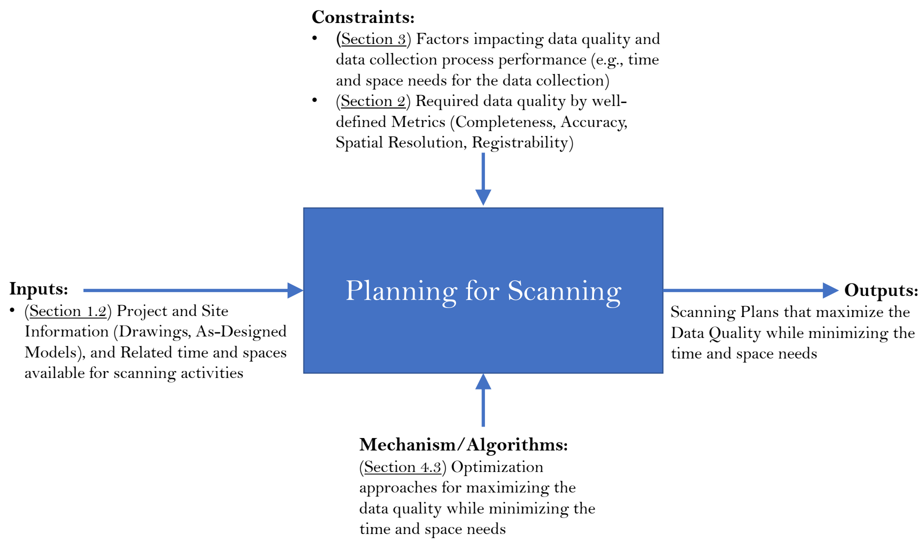


Figure 1: P4S Optimisation Elements.

that such manual approaches based on intuition and experience often lead to sub-optimal plans. For example, Zhang et al. [27] asked two experienced surveyors to generate plans to scan target points on the facades of a building with specified point accuracy and detail. The results showed that (1) the plans were only able to capture 60% to 75% of all target points with the specified quality, and (2) the additional scans subsequently required to capture all remaining target points with the specified quality increased the overall scanning time by 60 to 80%. Such findings motivate the development of (semi-)automated P4S approaches, and recent years have indeed seen a growing number of research publications in this area. These can be categorised as:

- *model -based* approaches where existing information about the environment to be scanned is provided, e.g. 2D (CAD) floor plans [29, 30, 31, 32]. These approaches are typically employed for offline P4S; or
- *non-model -based* approaches, generally used for online planning. These approaches are commonly considered within the robotics field of Simultaneous Localisation And Mapping (SLAM). In that context, the terms *view planning* or *next best view (NBV)* are commonly employed [22, 33, 34, 35, 36, 37, 38, 39].

Within the construction context, the focus has been primarily on developing offline model-based solutions. This is motivated by the wide use of CAD, or even the ease of rapidly creating 2D floor plan sketches of sites to be scanned. However, the recent decade has seen Building Information Modelling (BIM) becoming increasingly employed in the AEC/FM sector to integrate design, construction and management processes of building projects [40]. Some governments, such as the UK government, are even mandating BIM on public projects [41]. BIM processes are typically based upon the production of (semantically-rich) 3D models, and has been shown that the integration of TLS and BIM can hugely improve the delivery of as-built documentation, construction quality control, progress control, etc. [42, 1]. These applications can be categorised as 'Scan-to-BIM' (generating a 3D BIM model from a reality point cloud) [43, 44, 42, 45] or 'Scan-vs-BIM' (comparing a reality point cloud with a 3D BIM model) [6, 46, 47]. For example, Turkan et al. [3] suggested a 4D progress tracking system by combining point cloud -based 3D object recognition with schedule information. Note that they also highlighted the need for an effective P4S, because the results of their case study showed that incomplete scan data has a negative impact on the proposed 4D progress tracking system.

The advent of 3D modelling and BIM indicates that the availability of such digital models can help generate 2D (CAD) floor plans that could be used to support P4S. More interestingly, such digital models could replace 2D (CAD) plans, so that complete 3D geometric and semantic information contained in those models could be leveraged to achieve more efficient and effective P4S.

In fact, a number of works have already been conducted to solve the P4S problem given 3D models of the target scene [27, 48, 49, 50, 51].

Given the progress made in the last decade in the area of P4S, this paper aims to conduct a systematic review of prior P4S works in the construction domain with the aim to synthesis the progress made to date and identify areas requiring further research. Section 2 first reviews the criteria that are commonly considered to assess point cloud data quality, and that should thus be taken into account by P4S algorithms. It is proposed to group the criteria in three categories reflecting their general importance in the P4S problem. Section 3 subsequently explores the various parameters impacting those criteria, such as time and space constraints, and various data collection parameters (e.g., incidental angle, range). Section 4 reviews prior P4S works in construction, analysing them in the light of their capacity to account for the identified data quality performance criteria. Section 5 complements this analysis with a short discussion of P4S works in the manufacturing sector. Section 6 summarises the review with a discussion of the main challenges and gaps to be addressed moving forward.

This work makes two contributions: (1) it identifies knowledge gaps that needs further research, such as the lack of systematic investigation into geodetic network setup in the construction domain, and the lack of comprehensive characterisation of scan planning algorithms to reveal trade-offs among data quality, time, and space constraints; and (2) it provides a criteria-based comparison framework for others to compare new P4S methods against the existing state of the art in the field, giving them an overview of what needs to be sought in order to optimise P4S process.

2. Point Cloud Data Quality Criteria

Point clouds are increasingly acquired to generate semantically-rich 3D model of sites (i.e. BIM models) or to compare the as-is state they capture against some prior "as-design" state represented by a 3D (BIM) model or even prior point clouds. In all cases, the quality of the obtained data is important; hence the need to define point cloud data quality criteria. This paper proposes to group data quality metrics into *primary*, *secondary* and *tertiary* categories based on the priority of certain metrics in field applications. Normally, surveyors first emphasise the need for *coverage* or *completeness* of scanning targets in the field, and then consider the *accuracy* and *spatial resolution* of data points covering those targets. Adequate *overlapping* between adjacent scans must also be achieved to enable reliable alignment of all scans into a global coordinate system. We refer to this *tertiary* criterion as *'registrability'*. The following sub-sections will present firstly the *primary* category related to the completeness of 3D data collected (Section 2.1), then the *secondary* category about the accuracy and spatial resolution of the collected data (Section 2.2), and finally the *tertiary* category related to registrability of multiple scans collected (Section 2.3).

2.1. Primary Criteria - Completeness

The most critical, and therefore *primary* point cloud data quality criterion is arguably that all scanning targets are captured in the final point cloud. In other words, each scanning target should be scanned, or be *'visible'*, in at least one of the scans making up the final point cloud. These *targets* can be points (e.g. corners of walls and windows), lines (e.g. slab or window boundary), or surfaces (e.g. a wall face, or the entire surface of an object). Most prior model-based P4S works implicitly consider such completeness criterion as a 'hard' constraint that all such features be fully captured [51, 52, 53].

However, it can be observed that it is often challenging to acquire entire lines or surfaces that are part of an object. Yet, acquiring a certain minimum portion or percentage of target surfaces may be sufficient for the intended purpose. For example, Son et al. [54] showed that the diameter of a cylindrical pipe can be accurately modelled as long as the points cover at least a third of its cross-section. Covering the whole cross-section is usually not necessary for deriving the radius of a cylinder. Rabbani et al. [55] also demonstrated that complete coverage is not required for modelling through their algorithm. Based on this observation, Biswas et al. [50] introduced a softer *Level of Completeness (LOC)* (or *Level of Coverage*) criterion, defined as: "the amount of surface of a scanned object of interest which is covered in the overall scan" [50]. Rebolj et al. [46], in their work on establishing point cloud quality specifications to successfully perform scan-vs-BIM processes (for object recognition), also mentioned the need for a surface coverage criterion that does not have to be set to 100%. Similarly, Heidari Mozaffar and Varshosaz [51] introduced the surface-based criterion 'Lack of Coverage', for which they also used the acronym 'LoC'. 'Lack of Coverage' is defined as the ratio of surface (descretised as points) in the scan that are not visible from the selected scanning locations over the total surfaces needed to be captured. With this description, a lower 'Lack of Coverage' figure close to %0 is desirable. Heidari Mozaffar and Varshosaz [51] employed this metric at a scene level only, while Biswas et al. [50] and Rebolj et al. [46] defined and applied LOC for each individual object of interest.

While LOC has been defined with focus on surfaces [50] we note that it is also applicable to lines, although this has never been considered in the literature.

2.2. Secondary Criteria - Accuracy and Spatial Resolution

According to scan data quality specifications developed by the U.S. General Service Administration (GSA), there are currently two major criteria that a point cloud can be evaluated against [41, 56]:

- LOA (Level of Accuracy): tolerance of positioning accuracy of each individual point in 3D point cloud data. LOA is typically defined in millimetre.

- LOD (Level of Detail or Level of Density): Minimum object size that can be extracted from the point clouds. LOD relates to *surface sampling*, i.e. how dense the scanned points are. LOD is thus typically defined as a distance (in millimetres) between neighbouring scanned points.

LOA and LOD are meaningful, only once targets have been acquired, i.e. if target completeness is achieved. For this reason, LOA and LOD can be categorised as *secondary* performance criteria.

Table 1 shows the four specification levels for LOA and LOD that the GSA has developed and that are selected depending on the intended use of the point clouds or the 3-D models derived from them [41]. Typically, for indoor applications (e.g. indoor layouts, HVAC systems), where smaller dimensions are involved, higher LOA/LOD is required. For outdoor applications (e.g. outdoor building components, building facade), that deal with larger dimensions, lower LOA/LOD is desired [28].

GSA Level	**LOA (Tolerance) mm/inch**	**LOD (Data Density) (mm× mm)/(inch× inch)**
1	$\pm 51/\pm 2$	$(152 \times 152)/\ (6\times 6)$
2	$\pm 13/\pm 1/2$	$(25 \times 25)/(1 \times 1)$
3	$\pm 6/\pm 1/4$	$(13 \times 13)/(1/2 \times 1/2)$
4	$\pm 3/\pm 1/8$	$(13 \times 13)/(1/2 \times 1/2)$

Table 1: Data quality requirements standardised by GSA.

While LOD can be assessed using the acquired survey data only, assessing LOA demands extra data obtained for a control network using another sensor with accuracy that should be an order of magnitude higher (e.g. total station). This makes LOA a dependent measure that requires additional surveying work. Also, LOA will be calculated for only a limited number of points (the control network), thus it only provides a partial assessment of accuracy. These considerations make LOA a quality measure that is difficult to predetermine during P4S. LOA and LOD are applicable in both model-based and non-model-based P4S contexts.

Precision is another metric of data quality that is often considered in the literature, often instead of LOA. This is discussed in more detail in Section 3.2.1.

Finally, in the case of model-based P4S to support scan-vs-BIM applications, Rebolj et al. [46] proposed to use another point cloud quality measure, *Level of Scatter (LOS)*. LOS estimates the percentage of points that are likely to be mistakenly matched with other objects in close proximity to the object they are actually acquired from. However, as the authors acknowledge, LOS is not an independent parameter as it depends on: (1) the matching distance threshold employed in the Scan-vs-BIM process; and (2) point accuracy (i.e. LOA). Arguably, the latter relation makes LOS redundant with LOA.

2.3. Tertiary Criteria - 'Registrability'

TLS is limited to capture only the points with a clear line of sight, therefore capturing all scanning targets requires performing multiple scans from different view points. The acquired scans are then aligned into a unified point cloud, through a process called registration. The number of scans and the quality of the scanned data play a significant role in the registration outcome. Insufficient data (quantity and quality wise) will not provide enough overlap and make registration impossible. In contrast, too many scans cost a significant, yet unnecessary amount of time. So, there is a trade-off between the number of scans and the computational efforts [23].

Point cloud registration can be conducted in one or two stages: coarse registration, possibly followed by fine registration [57]. In coarse registration, matching 3D features of the two scans are aligned. The most common method is using artificial targets inserted in the scene in such ways that they can be scanned from two or more scanning locations [58]. However, having to insert such targets increases the scanning time. Robust algorithms have also been produced that can extract and match discriminatory features (visual or geometric) that are naturally present in scenes, and therefore present in scans. This removes the need for manually placing artificial targets in the scene, which can significantly shorten data acquisition time on site. However, such feature-based registration also requires ensuring that matching features do exist among two or more scans (at least three targets need to be matched between two scans so they can be co-registered) [58].

Fine registration follows a coarse registration and results in finding a more optimal solution by using more data from the scans that the few features commonly used for coarse registration. Solutions for fine registration are commonly based on the Iterative Closest Point (ICP) algorithm [59, 60, 61] that iteratively estimates the rigid transformation that aligns point from one point cloud with the nearest points in the second point cloud. Fine registration is not commonly employed in the construction domain.

In the context of P4S, the main challenge in terms of registrability is ensuring that matching, discriminatory features (ideally natural features e.g. wall's or ceiling's corners) are present in pairs of scans. This ensures all scans can be collectively and robustly aligned in the same coordinate system. But, it can also be argued that, given the fact that modern laser scanners can produce individual scans that cover large FOV ($360^\circ \times 290^\circ$) [62, 63], and assuming that successive scanning locations are not excessively far from each other (which is commonly the case), then scan overlap is in fact highly likely to be present between the two respective scans, as illustrated in Figure 5.

For construction site progress monitoring, frequently acquired point clouds need to be compared against each other [64]. The point clouds are co-registered with the BIM. Any co-registration error results in wrong deviation detection (i.e. false progress monitoring). A model-based strategy, where the point clouds are co-registered against an existing as-planned model, could result in misalignment because of the potential deviations between as-planned and as-built models. To avoid inaccuracy direct georeferencing is proposed in the literature [65, 64].

Another issue which makes registration a critical step in P4S is the fact that registration error contributes to final point cloud accuracy (controlled by the LOA specification). Registration error is commonly of the order of a few millimetres. This is similar even often higher than single point scanning accuracy, which implies that registration error can impact LOA performance just as much as, if not more than, single point accuracy.

3. Parameters Impacting Data Quality Criteria

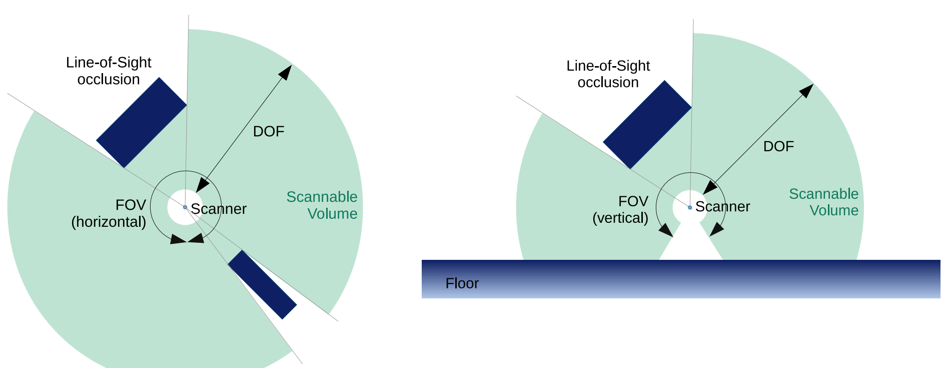
We now investigate the parameters that influence the point cloud quality criteria presented above. Section 3.1 below reviews parameters that influence point visibility, or 'scannability', as well as LOC. Section 3.2 introduces parameters influencing point accuracy (LOA), precision, and density (LOD) for objects captured in point clouds. Parameters impacting 'registrability' are discussed in Section 3.3.

3.1. Parameters Impacting Target Visibility and LOC

A point in the scene is considered visible (or 'scannable') if it is within scanning distance and without occlusion from at least one selected scanning location. There are three parameters that influence point visibility (see also Figure 2):

- Line of Sight: Only points with direct line of sight from the scanning location can be acquired.
- Depth of Field (DOF): Only points within the minimum and maximum scanning distances of the scanner can be acquired. DOF varies for different types of scanners.
- Field of View (FOV): Only points within the vertical and horizontal angle ranges of the scanner can be acquired. These ranges result from each scanner's physical and mechanical characteristics. Typical modern laser scanners (e.g. Leica ScanStation P30/P40 and FARO^{3D} Focus X330) can cover 360° horizontally and around 290° vertically, i.e. close to an entire sphere with only a small invisibility cone right below the scanner [28, 62, 63].

If a point complies with the three constraints above, it is visible from the given scanning location. The LOC criterion generalises the visibility criterion and is thus affected by the same parameters.



(a) Plan view. (b) Vertical section.

Figure 2: Parameters impacting target visibility: line of sight; depth of field (DOF) and field of view (FOV).

3.2. Parameters Impacting Point Data Quality

Scanning accuracy (LOA), precision, and detail (LOD) are affected by parameters such as: instrument technical capability and calibration, environmental conditions, object properties (e.g. surface roughness, surface reflectance, surface colour), edge effect, scanner settings (i.e. angular resolution and number of measurements per point) and scanning geometry (i.e. scanning location) [66, 67, 68, 69].

3.2.1. LOA and Precision

LOA is affected by instrument technical capability and calibration, atmospheric conditions, object properties, scanning geometry and registration quality [70, 66, 71, 72, 73, 74]. Among those, scanning geometry relates to the location of the scanner, which is possibly the parameter most easily controllable by the surveyor after instrument calibration. Scanner location impacts the incidence angle (α) and range (ρ) at which each individual point is scanned, that both have been found to have significant impact on single point scanning accuracy and precision [75].

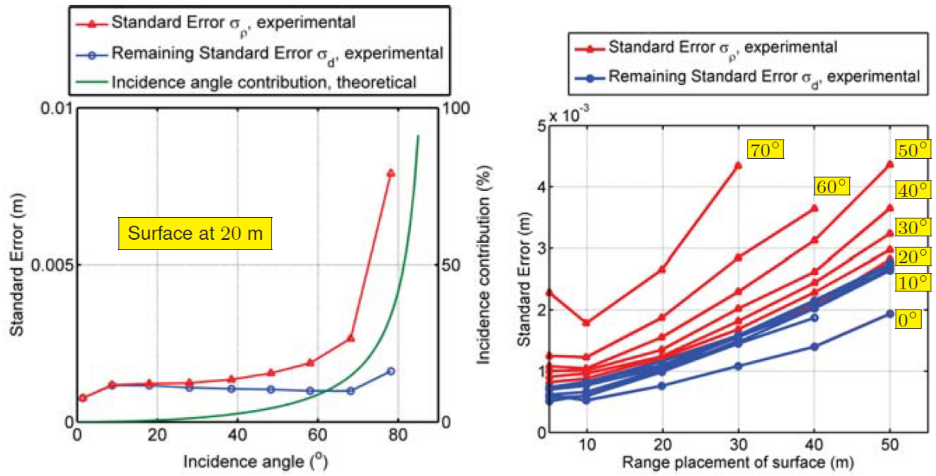
There are two components for error in laser scanner instrument measurements: systematic error and random error. Single point scanning accuracy, as specified by manufacturers, identifies the systematic error specific to each laser scanner and is typically reported without regard to any changing condition either in scanners hardware [76], geometry, atmospheric condition, or object properties. In addition to systematic error the other error component, measurements random error (i.e. precision), also impacts the final 3D point cloud quality depending on scanning geometry. To model how the scanning geometry affects the scanning measurements, Soudarissanane et al. [24] presented an approach mainly focused on incidence angle (α) and range (ρ), as the main parameters affecting the signal to noise ratio (SNR) of the measurements. Soudarissanane et al. [24] shows that higher incident angles ($\alpha > 70°$) and longer ranges to the surface result in less precise measurements. The result of Soudarissanane et al.'s work has been applied in most subsequent researches and conditions on incident angle and range are commonly considered as principal criteria for achieving specified single point accuracy and precision.

The relationship between precision, incidence angle (α) and range (ρ), as well as the wider set of parameters impacting precision are often investigated individually [77, 78, 23]. Nonetheless, some researchers have attempted to provide some different insight into this matter. There are studies that focus on random error component of TLS to predict the precision of TLS by establishing the functional relation between the precision of TLS and its intensity values considering the effect of range, incidence angle, and surface properties [73, 79, 80, 81, 82]. Wujanz et al. [73] stated that, since most of the effects on precision imposed by different parameters cannot be explicitly modelled, those approaches that consider various effects separately are not practical. Soudarissanane and Lindenbergh [23] related the precision of the laser scanner measurements to the quality of the received signal. Zámečníková et al. [78] also took the same approach and considered signal strength in laser scanner error modelling. Kavulya et al. [83] investigated the effect of object colour and texture on point cloud quality. Although Kavulya et al.'s experiment is limited in scope, their results suggest that for objects with low laser return intensity surfaces (e.g. red-painted steel) quality rapidly deteriorates with range. On the other hand, the incidence angle (up to 70°) does not seem to significantly influence point cloud precision. This latter conclusion is similar to that in [66] (see Figure 3). Finally, Shen et al. [75] studied how modelling accuracy of cylinders is impacted by range, resolution, surface reflectance, shape curvature (i.e. cylinder radius, temperature, time of day (i.e. nighttime or daytime), dew point' and relative humidity. Their results show that the top five variables impacting modelling accuracy are distance, resolution, colour, intensity, and surface curvature. Their comparison of different error models as well as their limited (albeit interesting) experimental setup also confirm the difficulty to develop reliable general error models.

Among all of the studies mentioned above, most of the reviewed studies in table 2 refered to Soudarissanane et al.'s approach and considered a threshold on incident angle in order to assure the LOA they seek to achieve.

Soudarissanane et al. [66] studied the influences of α and ρ on single point precision (for a given scanner while keeping the other parameters constant), presenting the result in two separate graphs reproduced in Figure 3. These graphs can serve as baseline for estimating scanning quality results for a given plan. Although the results cannot be fully generalised (because they are obtained with a specific scanner and a limited experimental setup), they have been used to justify rejecting any scanning point for which $\alpha > 70^\circ$, as precision rapidly deteriorates beyond that angle.

The effects of incident angle, range, as well as object colour on point cloud quality have also been investigated in the manufacturing context for part inspection [84]. However, such scanning activities employ different types of scanners (e.g. line scanners mounted on robotic arm) and are conducted in



(a) (b)

Figure 3: Measurement precision with respect to (a) the incidence angle of the surface and (b) the range placement of the surface. In both figure, the remaining standard error σ_d is obtained after removal of the incidence angle effect. (Reproduced with permission from [66]).

controlled environments and at much shorter distances (e.g. 1m) than those experienced in the construction domain. Consequently, those results cannot be realistically applied nor extrapolated to the construction domain.

3.2.2. LOD

LOD can be specified by a measure called surface sampling distance (s) [28], which is mainly affected by range (ρ), angular resolution of the scanner (Δ) and incidence angle (α), with the following formula [28] (see also Figure 4):

$$s = \frac{\rho\Delta}{\cos(\alpha)} \tag{1}$$

If necessary, Equation (1) can be applied independently to obtain separate vertical and horizontal sampling distances, using the decomposition of the incidence angle into its corresponding horizontal and vertical components (and the horizontal and vertical scanner resolutions, if they are not identical).

Lichti et al. [85, 86] showed that surface sampling is also effectively impacted by the beamwidth, when the selected angular resolution is high, nearing the beam divergence angle. As a result, they introduced an alternative

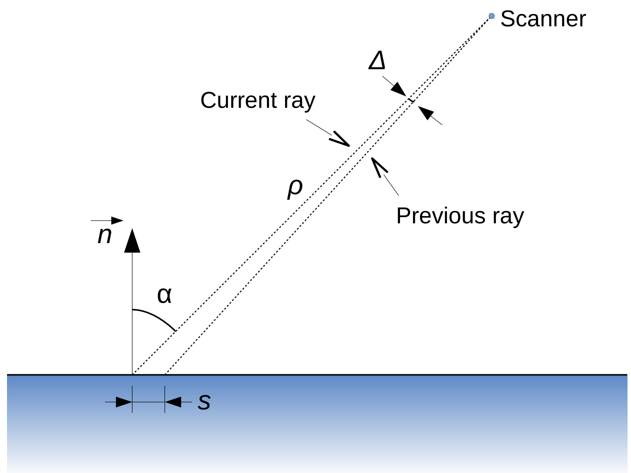


Figure 4: Parameters impacting surface sampling (s), as captured in Equation (1): range (ρ), angular resolution of the scanner (Δ) and incidence angle (α).

measure, the *Effective Instantaneous Field of View (EIFOV)*, that considers not only the scanner's angular resolution but also the laser beamwidth.

3.3. Parameters Impacting 'Registrability'

'Registrability' requires that a sufficient number of artificial or natural targets be visible in adjacent scans and be distributed as widely as possible avoiding linear configurations [52].

Researchers have suggested that this requirement is essentially impacted by the level of *overlap* between the scans — i.e. the percentage of data in one scan that is also captured in another scan acquired from another location [87, 88]. Ahn and Wohn [87] suggest to set such *Level of Overlap (LOO)* specification to 20%, and Equation 2 shows a typical LOO constraint formula presented by Chen et al. [88]. This equation guarantees that the line segments LP_i (which represent target vertical building facades on a 2D CAD model of the building to be scanned) acquired in each selected scan overlap at least $Overlap_{\%}$ (e.g. 20%) with the line segments acquired in another scan [88].

$$\min_i \left(\max_{j \neq i} \left(\frac{LP_i \cap LP_j}{LP_i} \right) \right) \geqslant Overlap_{\%} \tag{2}$$

It is important to highlight that these previous studies only consider the overlap between the data acquired of the scanning *targets* (points, lines or surfaces). This certainly guarantees a minimum $Overlap_{\%}$ but it can also be argued that, given the fact that modern laser scanners can produce individual scans that cover large FOV ($360^{\circ} \times 290^{\circ}$) [62, 63] with large DOF ($> 50m$), scan overlap is highly likely to be present between scans acquired from successive scanning locations (as discussed earlier). Scan overlap is thus not necessarily a critical performance criterion, and could in fact be discarded. For this reason, 'registrability' can be categorised as a *tertiary* criterion to assess P4S techniques. Notwithstanding, the error associated with registration is a source of systematic error impacting overall point cloud accuracy (as opposed to single point scanning accuracy), and it should be considered when assessing LOA.

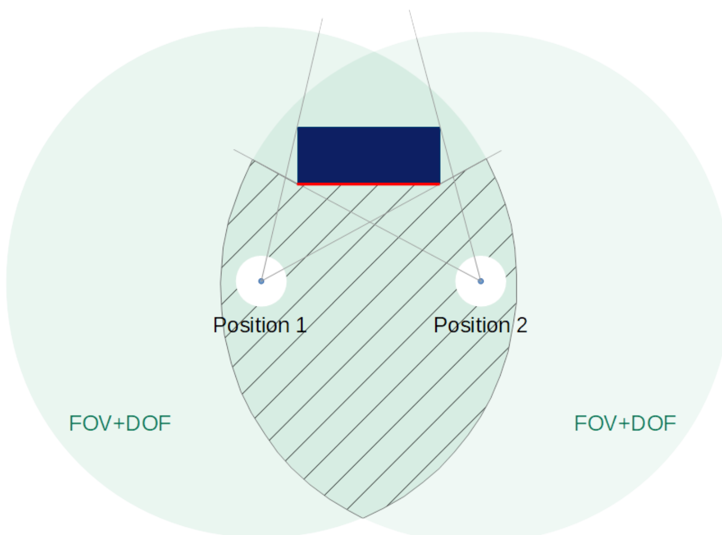


Figure 5: The overlap between the data acquired of the scanning targets (red line) typically constitutes only a part of the total overlap between two scans (hatched area).

4. P4S in Construction

P4S methods are all formulated as optimisation problems, but with different characteristics of the three main elements of optimisation problems: input, constraints, and optimisation model. This section reviews significant prior P4S methods along these three dimensions with a focus on discussing their strengths and limitations for application in the domain of construction and built environment management. Section 5 then briefly reflects on works published in the manufacturing domain.

Table 2 lists those prior works and summarises the key characteristics of prior model-based P4S approaches for application in the built environment. The characteristics of P4S methods are synthesised along three dimensions, as mentioned above:

- **Input:**
  - **Model:** whether the approach uses an existing 2D or 3D model of the facility as input to the process.
  - **Target:** whether the scanning target are points, lines or surfaces.
  - **Locations:** the set of possible scanning locations.
- **Constraints:**
  - **Primary:** whether the approach considers primary parameters, *Visibility*, or more generally *LOC*.
  - **Secondary:** whether the approach considers secondary parameters, *LOA*, *Precision* and *LOD*.
  - **Tertiary:** whether the approach considers tertiary parameters, here *Registrability*.
- **Optimisation:**
  - **Objective:** the objective function being optimised.
  - **Technique:** the optimisation techniques or algorithms employed to solve the scan planning optimisation problem.

Sections 4.1, 4.2 and 4.3 review generic P4S methods along the three dimensions mentioned above. Section 4.4 covers some P4S methods designed for specific application contexts, such as tunnel construction , inspection and as-built modelling of piping systems..

4.1. Input: Model, Target and Locations

Model. Model-based P4S techniques assume that some existing *model* of the asset or environment to be scanned is available as input. That model can be in various forms. As shown in Table 2, a number of previous works assume that the model is a 2D plan view of the asset to be scanned. This assumption is generally justified by the fact that such models are widely available [33] or they can easily be generated from sources like aerial imagery [88].

While 2D plan views of buildings are commonly available, they can lack spatial details of the scanned asset or environment for properly guiding the P4S process. In comparison, 3D (BIM) models contain more details of the scene to be scanned, and are increasingly available for applications where P4S can be model-based (e.g. dimensional quality control).

As shown in Table 2, five of the previous works assume a 3D model of the facility is available. The authors all justify this assumption based on the rapid development of 3D (BIM) models in that construction domain and their increasing availability for construction-related applications.

Targets. We observe that all reviewed methods that assume 2D (CAD) input model consider line targets. These methods attempt to plan the scanning of 3D surfaces in the built environment, but they only focus on walls, that they assume to be vertical 3D surfaces with limited height. While such assumptions limit the range of application, they enable reducing the 3D P4S problem to a 2D P4S problem where walls appear as line segments. In contrast, prior works that assume 3D input models consider targets as either points or surfaces. Only two of the studies [50, 51] have proposed a P4S method for surface targets within a 3D model. They however do this using two different approaches. Heidari Mozaffar and Varshosaz [51] discretised surfaces with homogeneously distributed point sets, reducing the problem of surface coverage to point coverage. In contrast, Biswas et al. [50] attempted to measure actual surface coverage. But, as will be shown later in section 4.3, their optimisation approach in fact presents a significant flaw.

Locations. In all reviewed works scanning locations are generated on a 2D map, typically in the form of a regular 2D grid. Instead of regular 2D grids, two other studies [33, 88] employed methods that generate locations randomly in the 2D map and one study [52] presented a hierarchical planning strategy with an improved greedy method to produce an optimal 2D grid of scanning locations.

Notably, Latimer et al. [49] took a different approach. Instead of specific scanning locations, they solve the P4S problem by considering as input only the space of 2D *intersection sets* between the *configuration spaces* calculated for all scanning targets — a configuration space is the 2D space within which the target is visible and can be acquired with the desired data quality. If an intersection set is selected in the final scanning plan, then the optimal scanning location within that intersection set is calculated (see [49] for details). The number of intersection sets is likely to be smaller than the number of scanning locations in 2D grids typically employed by other works. Therefore, using intersection sets helps reduce the complexity of the optimisation problem.

Interestingly, no existing work has yet investigated scanning locations defined in 3D, including those studies that assume 3D models as inputs.

4.2. Constraints: Primary, Secondary and Tertiary Data Quality Criteria

Primary constraints. First of all, it must be highlighted that point targets can only be acquired fully or not at all. While the visibility criterion applies to point targets, the more general LOC criterion is not applicable to them.

Looking at the works that consider line targets (in a 2D input model), they all define their optimisation frameworks with constraints demanding that all line segments be fully covered by the output scan plans (%100 line coverage), not just the end points or a portion of those lines. Although none of these works explicitly makes such suggestion, we note that their frameworks could easily be adapted to LOC constraints that require only a portion of lines to be covered.

Among all other reviewed model-based scan planning methods that use 3D models as inputs [51, 50] considered surface targets and are thus the only ones that can meaningfully apply the LOC criterion. Heidari Mozaffar and Varshosaz [51] applied LOC at scene level, meaning their optimisation algorithm (Greedy algorithm; see Section 4.3) attempts to optimise surface coverage irrespective of which object the covered surface comes from. In contrast, Biswas et al. [50] set LOC requirements per object, which steers the algorithm to more rapidly ensure all objects get sufficient coverage.

Secondary constraints. Two main accuracy measures, i.e. single point scanning accuracy and registration accuracy, impact LOA. [27, 48, 49] and [51] all discarded the LOA criterion in their framework. A number of other scan planning approaches [18, 23, 33, 50, 52, 53, 87], and [89] took the LOA criterion into account indirectly using a simple model based on incidence angle α and/or range thresholding (e.g. discard any portion of a line segment for which $\alpha > 70°$). However, incidence angle is only one of the many factors that can significantly impact accuracy. Therefore these scan planning approaches only consider basic metrics for LOA (i.e. incident angle that indirectly affects measurement accuracy) which is referred by $\times$ in Table 2. On the other hand some other studies consider more complete metrics for assessing LOA (where both measurement accuracy and registration accuracy are considered) and this can be identified through an $\bigtimes$ (big) in Table 2.

Regarding LOD, [48] and [27] automatically defined 'feasible spaces' (i.e. constraints) within which each given feature can be acquired with the required LOD level. These feasible spaces are then fed into the optimisation engine to generate an optimal scanning plan. Chen et al. [88] utilised sweep-ray algorithm to satisfy LOD along with LOA as part of the visibility check on line targets. Notably, while [27, 48, 87] and [88] considered both range and incidence angle to indirectly assess LOD (which is shown by a $\bigtimes$ (big) in LOD column in Table 2), the other studies follow a less robust approach by not explicitly considering LOD but by only considering either one [49, 51, 18, 50] or both of the range and the incidence angle [23, 88, 89, 52, 33, 53] as part of their visibility check. [49, 51] only considered range, while [18, 50] considered incident angle only. This is recorded in the LOD column of Table 2 with: an $\times$ (small) when α and ρ are both considered; an $\times^\star$ when only α is considered; and an $\times^\dagger$ when only ρ is considered.

Surprisingly, Blaer and Allen [33] and Biswas et al. [50] do not seem to explicitly consider LOD. Yet, this could have easily been done using the same approach as [87, 88], since they already assessed incidence angles for the LOA criterion.

In a different approach, although not explicitly mentioned as LOD, Giorgini et al. [89] defined a 2D cell grid that includes a set of line segments representing elements only above the scanner height, considered as the ground. They then estimate the number of horizontal scan lines in each cell and propose a new function so called ‘ground coverage function’ for every scan station (location). Ground coverage is calculated as the ratio between the difference of the vertical angles of the outer beams that hit the cell, and the vertical angular resolution (refer to [89] for the formula). Although the approach does not assess explicitly LOD, the coverage function addresses LOD in some way.

Tertiary Constraints. Table 2 shows that only one of the approaches designed for a 3D input model takes into account overlap [49]. All the other approaches that account for registrability in their constraints are those designed for a 2D (CAD) input model and line targets [87, 88, 33, 52, 89]. In [88] and [33], the authors’ proposed algorithm embeds the overlap constraint as a constraint within the optimisation algorithm. This approach differs from the cases in other studies [49, 89, 52, 87] in which that condition is satisfied only a posteriori, after the optimised set of locations is found. [87] and [88] used the same approach to address the registrability constraint, i.e. overlap of target line segments. In a different approach, Giorgini et al. [89] defined the overlap constraint as a function of cell coverage and calculate the ratio of the ground coverage common between each scan and all previous scans and compares it against a threshold value (33%).

In contrast, in [48] and [27], the authors did not attempt to ensure that at least three or more target points acquired in one scan have also been acquired in at least one other scan. Similarly, [50] and [51] did not attempt to ensure that a minimum surface acquired in one scan has also been acquired in at least one other scan. This lack of consideration for overlap seems to be the result of the observation made in Section 3.3 that laser scanners with large panoramic field of views have better chances of generating sufficient overlapping between successive scans. Nowadays, software packages provided by scanner manufacturers make registration of point cloud very straightforward [51]. As a result, ensuring successful registration is less critical.

Jia and Lichti [52] considered artificial targets for the purpose of point cloud registration. The authors' propose a hierarchical design system to provide a near-optimal solution for scanner network configuration as well as target placement. Their target placement algorithm updates the preliminary near-optimal target arrangement to minimise the number of required targets. The algorithm begins with creating a target-point grid in the area of scanning. Then for every potential scanning location (selected view-points obtained in the first stage) the target-points alternatives are saved as potential target-points only if they are visible from the corresponding scanning location. From the potential scanner locations (i.e. first part of the study) the ones that observe the minimum number of target points (set as four) are saved as benchmark geometry. A (near)-optimal target-point selection algorithm for every scanning location of the benchmark geometry picks four randomly-selected potential target-points within the area of that scanning location in every iteration. Near-optimal target point set (i.e 4 target points in this case) are the first ones that satisfy the predefined criterion of not being distributed collinearly or near-collinearly.

Then, the algorithm moves to the next potential scanning location and generates the target point set for that location. Finally, some trimming happens in order to remove redundant target points from the final pool of all selected sets for all scanning locations.

4.3. Optimisation Approaches

Objective Function. As can be seen in Table 2, most of the prior P4S works set their optimisation objective function to minimise scanning time. All approaches except one [27] assumed fixed scanner settings (e.g., spatial resolution, noise level parameters at any give scanning locations), which means

Approach		Input			Constraints				Optimisation	
Publication	Year	Model	Target	Locations	Primary LOC	Secondary LOA	Secondary LOD	Tertiary Overlap	Objective	Method
Zhang et al. [27]	2016	3D	Points	Grid 2D			×		Min. time	D&C + Relaxed Greedy
Song et al. [48]	2014	3D	Points	Grid 2D			×		Min. scans	Greedy
Latimer et al. [49]	2004	3D	Points	Sets 2D			×†	×	Min. sets/scans	Greedy / SA
Soudarissanane et al. [23]	2011	2D	Lines	Grid 2D	×	×	×		Min. scans	Greedy
Giorgini et al. [89]	2019	2D	Lines	Grid 2D	×	×	×	×	Min. scans	Greedy
Jia and Lichti [52]	2019	2D	Lines	Grid 2D	×	×	×	×	Min. scans	Weighted Greedy
Chen et al. [88]	2018	2D	Lines	Random 2D	×	×	×	×	Min. scans	Greedy+ / SA
Ahn and Wohn [87]	2016	2D	Lines	Grid 2D	×	×	×	×	Min. scans	Greedy (interactive)
Blaer and Allen [33]	2009	2D	Lines	Random 2D	×	×	×	×	Min. scans	Greedy
Jia and Lichti [18]	2017	2D	Lines	Grid 2D	×	×	×⋆		Min. scans/Min. α	SA/PSO/GA
Kim et al. [53]	2014	2D	Lines	Grid 2D	×	×	×		Min. scans	GA
Heidari et al. [51]	2016	3D	Surfaces	Grid 2D	×		×†		Min. sets/scans	Greedy
Biswas et al. [50]	2015	3D	Surfaces	Grid 2D	×	×	×⋆		Min. scans	Integer Programming

Table 2: Scanning criteria and optimisation approaches considered in published model-based P4S works. ⋆: incidence angle only. †: range only.

that scanning time is the same at all locations. As a result, these scan planning approaches simply minimise the number of scans. One of the exceptions to this approach is [27], in which the authors set the scanning resolution setting as an additional parameter to be optimised for each selected scan. This means that their algorithm must maintain the objective function as minimising scanning time, but it also has consequences on the complexity of the problem.

Optimisation Method. The P4S problem is normally defined as a constrained non-linear optimisation problem, for which the objective function is generally linear (with the number of locations) but the constraints are non-linear. Solving such optimisation problem is complex. Such complexity is mainly due to the large number of variables and exponentially large number of possible value combinations among them (e.g., combinations of possible spatial resolution values of the scanner and large number of possible scanning locations).

As summarised in Table 2, almost all existing P4S works, except [50, 53, 18] employed a *greedy algorithm* to find a solution in their optimisation model. Greedy algorithms do not normally produce an optimal solution, but have shown in practice to efficiently yield reasonable local optimal solutions. Greedy algorithms are based on iterative processes that employ the heuristic of making a locally optimal choice at each stage. In the case of P4S, the greedy algorithms employed by prior studies usually select the first scanning location by choosing the location that covers the most targets with the required data quality. Then, at each iteration, they select the next scanning location by choosing the one that provides the best improvement towards the fulfilment of the goal, e.g. the coverage of the scanning targets with the specified data, or minimising occluded spaces. The process normally ends once the scanning targets are all visible with the specified data quality, in at least one of the scans. A second termination criterion is normally added that stops the algorithm in cases when the problem is in fact infeasible — i.e. when one or more targets are not visible with the specified quality from any location. A third termination criterion is also sometimes employed to stop the algorithm when the improvement after each iteration is too small.

Song et al. [48], and Blaer and Allen [33] considered a standard greedy algorithm; the other studies proposed some variants or enhanced approaches. Latimer et al. [49] first employ a greedy approach implemented using a depth-first traversal of an intersection set tree, which appears equivalent to the greedy approaches employed in the other, more recent studies. This process is then followed by a *Simulated Annealing (SA)* algorithm. The *SA* algorithm iteratively alters the initial solution based on their coverage of the scanning targets (to be maximised as the objective function). Sets of locations that collectively cover all the targets of interest are selected as the initial solution candidates. Through the *SA* process, at each iteration, if the randomly selected initial solution shares the same targets covered by another alternative location set, then the algorithm reduces the number of potential solutions to choose from and reflects the change in the next round of location set selection.

Chen et al. [88] investigated two ways to improve the standard greedy algorithm. First, they suggest a *greedy algorithm with backtracking (GS-BT)* which, after the addition of each new scanning location, searches and removes any now-redundant scanning location. Secondly, similarly to Latimer et al. [49], the authors suggest to follow the GS-BT process with a SA algorithm. The SA algorithm randomly removes a scanning location from the GS-BT solution and then assesses whether small changes in this reduced set of scanning locations can yield solutions to the P4S problem. Their experiments show that the GS-BT found a better solution in 50% of the 64 cases considered in their study. Regarding the application of SA, it found a better solution in 15% of the cases, albeit at the cost of almost 10 times longer computing time. From an optimal solution viewpoint, SA thus also seems valuable, although its additional computational time could become a concern for large-scale facilities and workspaces.

Ahn and Wohn [87] employed a human-in-the-loop *interactive* approach to enable the user to contribute additional knowledge to the optimisation. In their approach, the algorithm ranks the best possible next scanning locations, but the user is responsible for selecting the next scanning location. The location selected by the users might not necessarily be the one ranked the highest by the algorithm. Arguably, this makes the approach only semi-automated.

Jia and Lichti [52] proposed a hierarchical strategy along with an improved greedy algorithm (so called *weighted greedy*) to optimally select the scanning view points. In their proposed weighted greedy algorithm each scanning view point is assigned a visibility score, calculated as the weighted sum of objects of interests that are visible from that view point. For each object, the weight is set as one divided by the the total number of locations (view points) that have a clear line of sight to that object. For instance, if one object is visible from three different locations then the visibility score for each of those three locations is 1/3. As any other greedy algorithm, the view point with the highest visibility score is selected and the visibility scores are updated for the next iteration.

While most of the works assumed a fixed angular resolution (Δ) setting for all scans, Zhang et al. [27] and Chen et al. [88] did not make that assumption. Zhang et al. [27] relaxed that constraint and instead set Δ as an optimisation parameter. This relaxation makes the optimisation problem significantly more complicated, minimising data collection time now depends not just on the set of possible scanning locations but also on the set of possible scanning resolutions to be selected for each candidate location. The authors solve this new problem by wrapping the greedy algorithm within a *Divide-and-Conquer (D+Q)* strategy that splits the overall problem into independent, smaller problems that can be solved faster. In the 'Divide' stage, targets (points) with the same data LOD specifications are grouped in clusters according to some visibility analysis. In the 'Conquer' stage, within each cluster, the greedy algorithm is employed to find the optimal set of locations. The minimum Δ required to acquire all point targets with their specified LOD is then found, with the same Δ set for all scanning locations within each cluster.

Notably, Zhang et al. [27] also relaxed the local optimisation problem by not requiring that the greedy algorithm finds a solution that covers all targets. Instead, they employ a stronger termination criterion on the minimal improvement in the coverage of targets that each additional location must make to the solution. This leads to targets (points) being discarded from clusters. An additional 'garbage collection' process collects the discarded point targets and initiate a search for scans to cover those discarded 'garbage targets'. That search uses the same local optimisation (greedy) algorithm. This relaxation of the local optimisation problem may in some cases yield better scanning plans (fewer scanning locations), although the authors of that study do not experimentally demonstrate the level of improvement this yields. Besides, it must be highlighted that the D+Q strategy enables the approach to scale well to much larger problems, and is independent of the method used for solving each local optimisation problem.

Chen et al. [88] started with an initial constant angular resolution for all scanning locations. Based on this initial value an initial scan plan is generated. Then that initial angular resolution in the generated scan plan is refined for every scanning location through a greedy search algorithm. The conditions on LOD, visibility, and overlap are satisfied with every refined angular resolution. Although this greedy approach provides flexibility for surveyors in refining the angular resolutions for all scanning positions, the final scan plan would not be optimal. To address this issue it is suggested, for the future work, to consider different angular resolutions while running visibility check; This approach would embed angular resolution into the problem formulation [88].

Genetic algorithm (GA) has been investigated as another optimisation method in [53, 18]. In [18], the authors compared three heuristic optimisation methods for their performance in a small-volume indoor network design of TLS: SA, GA and Particle Swarm Optimisation (PSO) The optimisation goal is set to find the minimum scanning locations that provides complete coverage for the objects of interest with a minimal sum of incident angles. For the problem they defined, SA performs the worst, while GA is the preferred optimisation method as it could provide an optimal solution requiring fewer parameters to tune.

In contrast to all other works, Biswas et al. [50] and Giorgini et al. [89] employed a different optimisation algorithm, *Integer Programming (IP)*. The main issue with IP is that it is NP-complete, which means that it does not scale well to large problems. However, Giorgini et al. [89] successfully applied their IP-based model in large scale environments capturing internal structures. Through their experimental evaluation they claim their algorithm, which is purposefully implemented taking advantage of GPU, can achieve the required coverage in reasonable times.

Regarding [50], the way the authors formulated their optimisation problem means that IP in fact leads to incorrect solutions. This is because their optimisation model fails to take into account the coverage overlaps between surfaces from the selected scanning locations. Notably, were those coverage overlaps taken into account, the problem would then not be solvable using IP.

4.4. Context-specific Approach

The above methods aim to solve generic P4S problems. In contrast, Cabo et al. [90] proposed an approach to optimise P4S of tunnels with circular or elliptical sections and straight or curved axis. Their fully automatic method identifies the optimal scanning locations throughout a tunnel while ensuring the satisfaction of LOD and Precision criteria over the entire surface of the tunnel. This approach is specifically designed for tunnels application and does not generalise to other environments (e.g. as buildings). For this reason, we do not include this method in Table 2.

5. P4S in Manufacturing

P4S approaches have also been proposed for application in manufacturing, typically for defining scanning plans for part inspection [22, 91]. Scott et al. addressed some of the early works on sensor-based view planning techniques for specified inspection goals [22]. Although the P4S problem in the manufacturing domain outdates that in the construction domain, the solutions are not really transferable. In manufacturing, scanners are mounted on a robotic frame or arm and have narrow FOVs — they can only scan individual points, small lines or small surface areas at a time [92]. Furthermore, the cost (in terms of time) of moving the scanner to any new position and scan from it is small. This implies that the number of scanning locations is not critical, and an optimal scanning location could be defined for distinct target areas of the object. As a result, the P4S problem for part inspection is more about optimising the scanner's path from one location to the next until all locations have been visited (travelling salesman problem). In contrast, in the context of construction TLS, the (time) cost of moving the scanner and conducting a scan is high, but each scan is 360-degree and can capture data at long distances, so that multiple scanning targets can be acquired from one location at once. This means that, in the construction context, the problem of minimising the number of scanning locations is more meaningful.

Despite these significant differences, approaches employed in the manufacturing domain might still give valuable ideas on how to approach the P4S problem in the construction domain, since they normally work with 3D input models. For example, Son et al. [92] propose a laser scanning system for part inspection that assumes a 3D CAD model of the part as input. Their proposed automated system generates a scan plan including the number of scans, the scanning directions, and the scan path. To generate a scanning plan, a 'Divide and Conquer' approach is employed where each complex part is initially divided into functional surfaces, and individual scan plans are then generated for each functional surface. Each functional surface is represented by a point set sampled from that surface, and the system aims to minimise the number of scans necessary to capture all those sampled points. After generating the initial scan plan, the algorithm checks DOF (i.e. distance from the laser source to the surface) and occlusion constraints, and modifies the scan plan to assure all the points will be acquired and measured with the expected precision. This 'Divide and Conquer' strategy is similar to that employed by Zhang et al. [27].

6. Discussion

Section 4 reviewed prior approaches to develop automated P4S algorithms for the usage of TLS in construction. In this section, we review these holistically to identify gaps in knowledge.

6.1. Input:

While a number of works assume a 2D input model, which is justified by the general availability of such models, recent works have increasingly considered 3D input models. However, while the approaches developed for 2D input models are all focused on line targets (which are the 2D representations of vertical surfaces), that line targets have not been considered by any prior work that used 3D input models. Heidari Mozaffar and Varshosaz [51] and Biswas et al. [50] considered surface targets within 3D input models. However, since the optimisation method of [50] gives incorrect solutions, the approach of Heidari Mozaffar and Varshosaz [51] is the only one that fills the gap for solutions to the P4S problem for surface targets in 3D input models.

For approaches that consider 2D input model, it is logical that potential scanning locations be also defined in 2D (plan view) only. However, we observe that no work that considers 3D input model has yet attempted to consider scanning locations defined in a 3D space. Although none of the prior authors specifically discuss this decision, it is arguably justified by two observations. First, TLS is a ground-based technology operated on a tripod that can only be extended a few metres, which limits the range of locations the scanner can be positioned at along the vertical axis. Secondly, those prior studies assume only contexts where the environment to be scanned is large with little geometric variation along the vertical axis (e.g. building exteriors), which implies that sampling locations along the Z axis (within the limited extension capability of typical tripods) would unlikely provide any significant benefit. However, these assumptions are arguably inadequate in a number of other contexts, such as when scanning interiors with MEP components or in industrial environments. In such contexts, considering potential locations in 3D may in fact be necessary to ensure that the optimisation problems are feasible.

6.2. Constraints:

LOA. The first observation is that there is not yet any general parametric formula relating single point accuracy (LOA) to all factors — or at least the main factors — that can impact it. This means that the claim from most prior works that their frameworks can account for accuracy is somewhat misleading. In practice, only approximate metrics are used, the main ones being to reject points with incidence angle $\alpha > 70^{\circ}$ (60° is also suggested) and range higher than a scanner-specific value (e.g. $\rho > 50m$). Shen et al. [75] showed that important factors impacting accuracy also include surface reflectance. Some other studies [73, 80, 81] also included the effects of range and surface properties as well as incidence angle on range precision of TLS.

Therefore, developing more robust single point accuracy models is necessary. Since accuracy can vary widely among scanner, such models should ideally be developed by scanner manufacturers. But, researchers could also contribute by developing more general (albeit maybe still somewhat approximate) models for typical groups of scanners. Furthermore, in contexts where P4S input models are BIM models, information about surface materials could be obtained from the model and factored in the optimisation framework to ensure that objects with challenging materials are scanned accordingly.

LOD. In contrast to accuracy, most prior works are able to account for LOD more robustly. Interestingly, these studies all use an LOD metric that depends solely on the scanner's angular resolution, with no work having used the Effective Instantaneous Field of View (EIFOV) introduced in [85]. Nonetheless, it seems that employing EIFOV would only be critical in cases of high LOD, where the specified surface sampling distance can be smaller than the beamwidth.

LOC. Although LOC, in particular surface LOC, has been shown to be critical to ensure scanned data can support successful Scan-vs-BIM applications [50, 46], Biswas et al. [50] and Heidari Mozaffar and Varshosaz [51] are the only ones that have attempted to develop a P4S framework that takes surface LOC into account.

However, as mentioned earlier and further discussed below, there remains a significant research gap in P4S solutions that can consider 3D surface targets and corresponding surface LOC specifications.

6.3. Optimisation

Objective Function. All prior works are in agreement that the main P4S objective is to minimise the time necessary to scan all necessary targets with the specified quality (LOA, LOD, LOC). Minimising scanning time is critical to minimise interruptions of other activities on site. In the majority of cases, minimising the number of scans is used as a proxi objective function.

The use of such objective functions assumes that all activities on site will be stopped for all scans in the scanning plan to be performed before all activities can resume. This is however likely sub-optimal. Instead, it would be preferable to come up with scanning plans and programmes (order of scans) that can fully utilise the gaps between other on-site tasks (e.g construction activities) so that those activities do not have to be halted to allow for data collection. This would first require conducting studies to understand how data collection can influence construction productivity (e.g. see [2]). These studies would then inform how the P4S optimisation problem could be revised with additional constraints so that the scanning plans are optimally interwoven with field workflows, fully utilising the idling time gaps and spaces between tasks to achieve an effective balance between data quality, data timeliness, and overall field productivity. Such problem may be approached using some temporal Divide-and-Conquer strategies (as opposed to spatial 'Divide-and-Conquer' strategies like the one in [27]).

Optimisation Method. As reported earlier, the greedy algorithm is commonly used to solve P4S problems in the built environment domain. While it does not guarantee optimal solutions, it does commonly achieve reasonable ones. Enhancements to the greedy algorithm, e.g. using weighted greedy, back-tracking or SA, have also shown to be able to effectively find more optimal solutions. We note that other methods for solving constrained non-linear optimisation problems, such as evolutionary algorithms (genetic algorithm, etc.), have hardly been investigated, except for the comparison study of Jia and Lichti [18] and a minimal case study in [53]. They could be employed either on their own or possibly in combination with other methods, such as the greedy algorithm or the Divide-and-Conquer strategy [27].

Most existing works have looked at medium-scale and generally reasonably simple P4S problems (i.e. few P4S inputs, and somewhat simple input 3D models). While the greedy algorithm they employ does help maintain P4S problem to tractable levels, the Divide-and-Conquer approach of Zhang et al. [27] offered a solution that better scales up to larger P4S problems. Such approach could be considered more systematically, and possibly alternative Divide-and-Conquer strategies could also be considered.

6.4. Other Consideration - Progressive P4S

Model-based P4S approaches can only work when the input model matches the real environment well. However, often this may not be the case in practice, due to: (1) *discrepancies*, e.g. due to construction having not progressed as planned or suffered some changes or errors; (2) *clutter* that prevents targets to be scanned from certain locations as expected, or (3) *uncertainties* due to approximations in actual scanner placement on site. This implies that there is a need for solutions to the *Progressive P4S* problem, where the plan is reassessed and potentially altered after the acquisition of each new scan on site. Such problem is in effect an *online* model-based *view planning* (or NBV) problem. While the non-model -based view planning problem has received significant interest in the literature (e.g. [93, 94, 95, 96, 97]), solutions to the proposed new problem of *Progressive P4S* may require specific adjustments and dedicated research.

7. Conclusion

In this paper, we first have motivated the need for automated P4S methods for application in the built environment domain. We have then conducted a detailed review of the types of performance criteria that such method should meet (Precision, LOD, LOC and registrability) and of the parameters impacting those criteria. This was followed by a review of significant prior P4S methods, with focus on thirteen particular studies published in the last decade (eight of which in the last five years). The types of input, constraints and optimisation problem formulations they consider were detailed, and this led to a final extended discussion on the achievements of those methods and identifications of the remaining key areas where further research is required. The following main conclusions (including areas for further research) are drawn.

3D input models and targets: While the problem of 2D model-based P4S has been well developed with mature solutions, there is a need for methods to be developed that are able to handle 3D input models, in particular BIM models, and that can provide plans for 3D targets that can be points, but also lines and surfaces. The need for methods that can work with 3D input models is particularly important for complex environments both indoors (e.g. scanning MEP systems located in ceilings) and outdoors (industrial sites).

Accuracy mathematical models: Mathematical models for calculating LOD and LOC are robust, but there is also a need to develop better accuracy models. While such models may still trade robustness for generalisability, this would be preferable to the overly simplistic approach of rejecting points on the basis of incidence angle alone. There are also some studies which modelled random error of TLS based on intensity values of laser [73, 80, 81], but they can't be applied to estimate LOA as they deal with precision.

Robust and scalable optimisation methods: Regarding optimisation methods, the work of Zhang et al. [27] has shown that it is possible to develop better methods that the basic greedy algorithm, using additional heuristics or well-designed Divide-and-Conquer strategies. Other optimisation algorithms, for example evolutionary algorithms, should also be investigated more closely.

Temporal constraints: We noted that the current P4S problem tends to be approached as a temporally static one. It would however be beneficial to extend it with additional temporal constraints to minimise interferences between data collection and other site activities.

Progressive P4S: Finally, while useful to prepare for site scanning activities, current scanning plans can arguably often be inadequate due to unforeseeable circumstances (discrepancies, clutter) and various uncertainties. As a result, there is a need to conduct research developing Progressive P4S methods that are able to reassess and potentially alter the plans in real time after the acquisition of each new scan on site.

The authors expect that the identification of these gaps in knowledge will motivate individuals and groups around the world to research them and propose P4S methods that are better than the current state of the art.

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