# Automated Deterministic Model-based Indoor Scan Planning

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ABSTRACT: Scan planning describes the process of choosing equipment and locations for reality capture with laser scanners. By contrast to the traditional, expert-based method usually conducted in the field, automated approaches aim to solve this task exclusively with pre-existing data in the form of plans or 3D models of the scene. Existing approaches for automation are mostly either limited to 2D or based on simulations of laser scans, which oversimplifies respectively complicates the process to the degree that makes them inapplicable for practitioners. We aim to solve both problems by basing our solution on a 3D representation of the target scene and a deterministic approach. Thus, the workflow remains computationally feasible while the complexity of real-world scenes is sufficiently represented. We present a literature review on related research and technical guidelines for scan planning to define realistic requirements for scan planning, including point density, field of view, and depth of field limitations. To develop valuable strategies, we create a static set of candidate locations on a grid in the scene. We then perform visibility and coverage analysis and evaluate each candidate's fitness for the overall strategy based on its contribution to our pre-defined scan requirements. Finally, selected locations are combined to form an optimized strategy to fulfill these requirements following two versions. We apply two basic methods for candidate selection and investigate their implications in a descriptive experiment.

## 1 INTRODUCTION

Advances in sensor technology and data processing algorithms enable the implementation of digital methods in various fields in the domain of Architecture, Engineering, and Construction (AEC). Significant examples include progress monitoring during construction and digitization of built structures in the operations phase or before deconstruction, amongst others. This is made possible by lowering the effort required to capture the actual conditions of the built environment and transfer them to a raw but processable digital representation. Terrestrial Laser Scanning (TLS), for example, allows for capturing millions of points per second with an accuracy in the range of millimeters (Wunderlich et al. 2013). To control the process and ensure efficiency and sufficient data quality at the same time, acquisition activities need to be thoroughly planned and prepared.

Traditionally, this approach is based on the surveyor's knowledge, aiming to fulfill all requirements regarding density, and coverage but also efficiency in execution time and therefore cost. To enable the implementation of a Digital Twin (Boje et al. 2020), especially in frequently changing industrial scenes (Hellmuth, Wehner, and Giannakidis 2020; Shellshear, Berlin, and Carlson 2015), this process should be as precise and robust as possible, when data capture is not a one-shot measure but a recurring part of the process.

The finished acquisition plan is executed either by professional staff using the specified equipment or ideally using sensor-equipped robots that can localize themselves and navigate within the actual scene (Prieto et al. 2017). The acquired data can be processed for a wide range of potential use cases. In the domain of AEC, these use cases most commonly emerge in the context of Building Information Modeling (BIM) (Borrmann et al. 2018). These include the field of Scan-to-BIM, which aims to recreate a usable digital model from the captured data directly, and the field of Scan-vs-BIM, where a prior existent model is compared to the acquired information to validate or update the model (Bosché et al. 2015).

In any case, the quality of the captured point cloud is critical for the success of all further processing steps. While it is difficult to make general statements about point cloud quality (Alexiou and Ebrahimi 2018), specific aspects such as density overlap contribute to robust point cloud quality (Song, Shen, and Tang 2014). To enable successful application, we support the initial requirements of a sensible scan plan by automating the process in pre-existing, complex 3D scenes.

## 2 BACKGROUND

Preparation of scan execution helps to ensure successful and efficient capture resulting in high-quality point cloud data. In this context, a variety of aspects need to be considered; in the following, the most relevant ones are introduced in the context of the current state of the art.

### 2.1 *Point clouds in AEC*

Point clouds allow accurate and detailed capture of the current conditions of facilities in the built environment with decreasing cost and lowering effort. In the context of BIM, there is a multitude of possible applications (Volk, Stengel, and Schultmann 2014; Wang and Kim 2019), spanning the entire lifecycle of buildings from the observation of excavation works (Su, Hashash, and Liu 2006) and automated construction progress monitoring (Braun et al. 2020) to deconstruction planning (Volk et al. 2018). In general, applications of point clouds in AEC can be classified based on whether a suitable model exists. If there is no suitable model, approaches that aim to create a model from the captured point cloud alone are called Scan-to-BIM (Son, Kim, and Turkan 2015). Approaches that update, enrich, or replace the model partly based on the captured point cloud range under Scan-vs-BIM - either come with specific challenges and opportunities (Bosché et al. 2015).

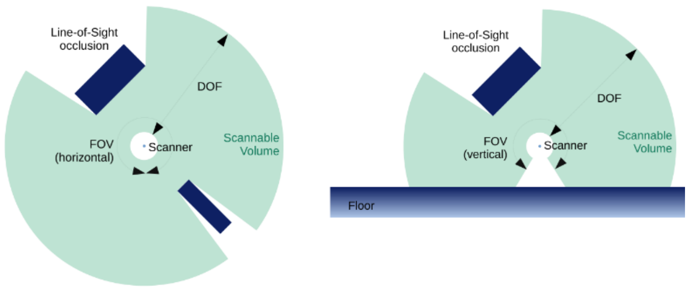
### 2.1 *Point cloud acquisition*

Point cloud-specific attributes vary largely depending on the chosen acquisition method. Well-known acquisition methods include camera-based and laser-based systems; the choice should be made in consideration of use case-specific requirements and implications (Esfahani et al. 2021). Our focus lies on indoor applications in the industrial domain, for which point density and high accuracy are more important than acquisition speed (IFF 2018), which makes Terrestrial Laser Scanning (TLS) the method of choice (Hullo et al. 2015).

### 2.2 *Point cloud characteristics and requirements*

In this paper, we investigate the Viewpoint Planning problem for the application of TLS. This sensor equipment is stationary, ground-based, usually on a tripod or similar. Modern equipment's potential field of view (FOV) usually spans 360° horizontally; vertical FOV depends on the manufacturer and model (Aryan, Bosché, and Tang 2021). Furthermore, the coverable area is restricted by the depth of field (DOF) defined by the minimum and maximum distances between sensor and surface per equipment specification.

Furthermore, TLS acquisition potential is inherently limited to the line of sight between sensor and




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

**Figure 1: Field of View (FOV) and Depth of Field (DOF) of a Terrestrial Laser Scanner (TLS), with characteristic occlusions, from (Aryan, Bosché, and Tang 2021)**

captured surface, given within its FOV and DOF, as depicted in Figure 1. Any pre-existing knowledge about the 3D geometry of the scene in question, in the form of a 3D model or similar, can therefore be leveraged directly to derive suitable acquisition strategies.

Point clouds can be generally characterized as large, unstructured datasets. If suitable equipment is chosen and necessary precision assured, the core property to be measured out of a point cloud is point density. Point density can be determined in terms of points per area as nominal pulse density (NPD, pts/m$^2$) or point-to-point distance with nominal pulse spacing (NPS, m) (Heidemann 2018). The relationship between the two can be considered as

$$NPS = \sqrt{\frac{1}{NPD}}. \tag{1}$$

Based on these metrics of point density, for further processing, concerned institutions aim to provide technical requirements to satisfy the needs of specific applications. For use in the context of BIM, the U.S. General Services Administration issued a report stating minimum point density (in this referred to as resolution and artifact size) for varying Levels of Detail and Areas of Interest (U.S. General Services Administration 2009). Specifically for industrial applications, Fraunhofer Institute for Factory Operation and Automation more recently presented guidelines for Laser Scanning in industrial facilities (IFF 2018); towards the acquired point clouds itself, the technical requirements are limited to object-dependent point density minima along with several equipment-specific maximum values for acquisition distances, presented in ready-to-use tables derived from point density calculations.

(Rashdi et al. 2022) present an extensive review of technologies and methods applicable in the context of BIM; specific applications for infrastructure have, for example, been collected in (Rashidi et al. 2020). In a more specific approach, (Rebolj et al. 2017) investigated point clouds regarding their suitability for Scan-to-BIM applications. In this, orthogonal projections are used to evaluate surface coverage; a minimum of 0.5 on a rasterized grid is assumed to be the required coverage (Rebolj et al. 2017).

### 2.3 *Scan planning*

To assure data quality and repeatability and allow reasoning about required effort and thus cost-efficiency, a suitable choice of sensor equipment and placement needs to be considered in the context of any acquisition activity. In the context of AEC, this challenge is referred to with Scan Planning (Frías et al. 2019), Planning for Scanning (Aryan, Bosché, and Tang 2021), or the Viewpoint Planning problem (Jia and Lichti 2018). In general, the underlying problem has been referred to as (TLS) Viewpoint Planning (Wujanz and Neitzel 2016) or as View Planning (Scott, Roth, and Rivest 2003) and has, for example, been approached as an Art Gallery Problem (Kröller et al. 2012), classically in 2D.

All methods for automating decision-making for scan planning can be distinguished in non-model-based and model-based approaches (Scott, Roth, and Rivest 2003). On a high level, the most noticeable aspects lie in the determination of visibility relationships, the analysis of the covered parts, and the actual selection of suitable viewpoints. For the domain of AEC, (Aryan, Bosché, and Tang 2021) present an extensive overview of proposed solutions. In the following, we present selected examples along with important aspects; an overview is collected in Table 1.

#### 2.3.1 *Non-model-based scan planning*

In non-model-based approaches, scan planning is performed without a-priori knowledge of the scene. An initial viewpoint is selected, and the following viewpoint is determined based on the content of the FOV of the initial viewpoint, following the so-called next-best-view (NBV) method, which often appears in the context of robotics and simultaneous localization and mapping (SLAM) (Aryan, Bosché, and Tang 2021). This means information on the underlying scene grows with every viewpoint. The initially achieved coverage has been evaluated and used for NBV determination in different ways: (Achakir, El Fkihi, and Mouaddib 2021) use 2D point cloud projection to generate a visibility polygon, identify and classify gaps to create NBV candidates and finally select a suitable one. In 3D (Kawashima et al. 2014), classify occupied voxels to prioritize pipes in the scene, (Prieto et al. 2017) investigate a robotic perspective room by room and use multiple classes for voxel classification in their approach.

#### 2.3.2 *Model-based scan planning*

In the case that reliable a-priori information on the scene is available, model-based approaches can be applied. Hence the knowledge on the scene is static rather than growing dynamically. Scene representations vary from sections or plan views with walls or other object segments (Jia and Lichti 2019), (Frías et al. 2019) derive sections from a 3D model, (Wujanz and Neitzel 2016) investigate a single mesh object, (Kabir Biswas, Bosché, and Sun 2015) derive mesh instances from a 3D CAD model.

Viewpoint candidates are distributed using grid-based (Jia and Lichti 2019), line-based (Wujanz and Neitzel 2016), or triangulation methods (Frías et al. 2019) to then investigate visibility relationships between candidates and scene deterministically by ray casting or using laser scan simulation. (Jia and Lichti 2019) additionally use a hierarchical approach to refine the candidate grid locally, as initially presented in (Jia and Lichti 2018). Finally, suitable viewpoint candidates are selected to form a strategy that is able to fulfill the overall scan requirements. Solutions for this range from straightforward methods like combinatorial planning (Wujanz and Neitzel 2016) the Greedy algorithm (Jia and Lichti 2019), to more advanced methods of optimization (Jia and Lichti 2017). Technical aspects like station

**Table 1: Selected characteristics of existing approaches of scan-planning in literature**

| Publication | Dimension | Scene | Visibility | Approach |
|---|---|---|---|---|
| (Kawashima et al. 2014) | 3D | Dynamic, voxel | Measurement | Next-Best View (NBV) |
| (Prieto et al. 2017) | 3D | Dynamic, voxel | Measurement | NBV |
| (Wujanz and Neitzel 2016) | 3D | Static, mesh instance | Simulation | Combinatorial planning |
| (Kabir Biswas, Bosché, and Sun 2015) | 3D | Static, mesh instances | Simulation | Integer programming |
| (Jia and Lichti 2019) | 2D | Static, wall segments | Deterministic | (weighted) greedy algorithm |
| (Achakir, El Fkihi, and Mouaddib 2021) | 2D | Dynamic, visibility polygon | Measured point cloud, projected to 2D | NBV |
| (Frías et al. 2019) | 2D | Static, object segments | Deterministic, ray casting | Backtracking algorithm |

interconnectivity (Sanhudo et al. 2020) and overlap (Wujanz and Neitzel 2016) are advanced aspects and are out of scope for this investigation.

What is still missing is a robust approach for scan planning in a 3D environment that allows taking occlusions and local point cloud quality into account. Existing approaches are either based on simulation, therefore computationally expensive and subject to randomness or handle the scene in discretized formats such as voxels that prohibit local quality investigations.

## 3 METHOD

To investigate the potential of model-based scan planning in a 3D environment, we assume a static environment with strict limitations. This allows us to perform a deterministic evaluation of visibility and coverage. The selection of candidates to form a suitable strategy is then an optimization problem that we solve with variations of a simple heuristic. The chosen method comprises several steps, as depicted in Figure 2. In the following, each step of the method is introduced to lay the foundation for our implementation and experiment.

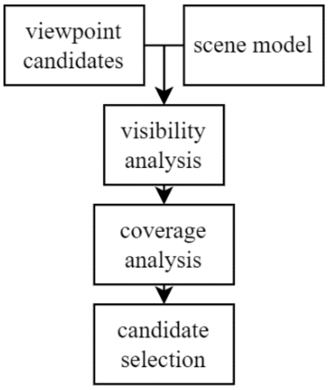



**Figure 2: Scan planning method overview from data input to final scan plan**

### 3.1 *Data Input*

The investigated scene is represented by a triangulated mesh derived from a 3D CAD model; sufficiently high mesh resolution and evenly sized faces need to be ensured to achieve useful results. Currently, this requirement is assessed qualitatively only; resolution needs to allow a sensible depiction of occlusions.

Viewpoint candidates are generated on a grid in the horizontal XY-plane with even, rectangular-shaped faces, in which the vertices' coordinates are then considered as potential sensor locations or 'viewpoints'. Candidates that are outside the area of interest, unsafe to access for scanning personnel, or lie within object geometries are removed. This step can be automated, for example, using a navigation mesh (Hale and Youngblood 2009) or similar based on the model scene geometry.

### 3.2 *Visibility Analysis*

The main shortcoming of laser scanning-based acquisition is its restriction to visible surfaces, in other words, the inability to cover surfaces caused by line-of-sight occlusion. Therefore, in the first step, visibility analysis is performed based on the two 3D inputs using ray casting. To neither rely on likelihood nor lose potentially visible faces due to point spacing, instead of following fixed angular resolutions, the direction vectors for ray casting are computed as all potential directions between each viewpoint candidate and each face in the model in a 'reverse' ray cast approach. This approach is highly computationally expensive and bears significant potential for optimization but allows uncompromised results for this initial implementation. In the next step, ray casting is performed for all potential direction vectors per viewpoint, returning the first mesh face intersected for each ray. As an effect of the 'reverse' ray cast approach, all rays intersect with at least one face. The results are collected in a complete visibility table (Scott, Roth, and Rivest 2003), comprising bilateral visibility relationships amongst all viewpoint candidates and faces of the scene.

### 3.3 *Coverage Analysis*

Not all visible faces are fit for acquisition. In the next step, visibilities are further evaluated and filtered in this regard. Limitations that are considered in this step include the equipment-specific DOF and FOV (see Figure 1). Besides those fundamental restrictions, scan quality largely relies on local point densities.

Given that a sufficient resolution is ensured in the triangulated mesh, the edge length of faces is very small in comparison to their distance from the laser scanner. Thus, we can make use of the small-angle approximation. Applying the relationship between NPD and NPS (see equation 1), we can calculate a close approximation of the theoretical local point density (LPD, pts/m$^2$) per visible face using equations 2 - 4:

$$LPS_{90} = SPS \times d \tag{2}$$

$$LPS_{\alpha} = \frac{LPS_{90}}{\sin\alpha} \tag{3}$$

$$LPD = \frac{1}{LPS_{90}} \times \frac{1}{LPS_{\alpha}} \tag{4}$$

Variables beyond the previously introduced:

| | |
|---|---|
| $SPS$ | specific point spacing |
| $d$ | scanning distance |
| $LPS$ | local point spacing |
| $\alpha$ | local incidence angle |

LPD thus depends on scanning distance, local incidence angle, and the equipment-specific scanning resolution or specific point spacing.

Finally, the result of the coverage analysis step is the above introduced local point cloud density that is then used to filter the covered faces according to the predefined requirements. The full visibility table is thus reduced to faces with qualified coverage.

### 3.4 *Candidate Selection*

To generate a decision basis for viewpoint candidate selection, the value of each viewpoint in the candidate set introduced in section 3.1 is determined in terms of its individual corresponding qualified coverage from the visibility table. Using this value, we apply a greedy and a weighted greedy algorithm to select a set of candidate points that fulfills our requirements in terms of overall model coverage as presented in (Jia and Lichti 2018). In contrast to (Jia and Lichti 2018) we do not use a Boolean score table but include the actual area of the mesh faces. For an unchanged input, the presented greedy approaches will always return the same results and can therefore be referred to as deterministic.

The steps required for the viewpoint selection for both approaches are depicted in Figure 3. Starting from the qualified coverage table, the individual value of each viewpoint candidate is first calculated. For the standard greedy approach, this is a straightforward sum, for the weighted greedy approach, this value is first reduced per face depending on the frequency of hits on each face and then summed up per viewpoint candidate. The candidate with the highest value is then chosen as a viewpoint for the acquisition strategy. If the achieved coverage exceeds the required coverage, the strategy is complete; if not, the process is repeated iteratively until the coverage goal is met. Before reinitiating, the visibility table is updated: All faces covered by the selected viewpoint are discarded; the viewpoint values, therefore, need to be recalculated, along with the weights per face if applicable. For a comprehensive explanation of the process, we refer to (Jia and Lichti 2018).

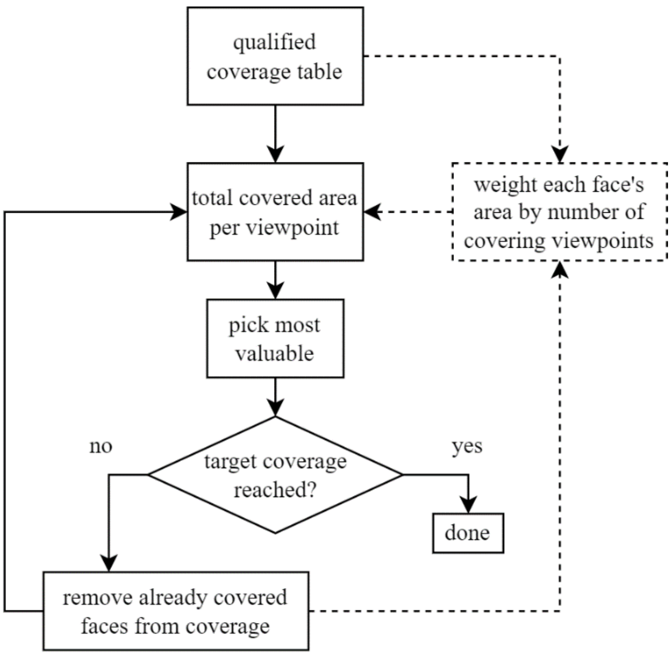



**Figure 3: Greedy viewpoint selection, dashed line indicates extra steps for weighted greedy approach**

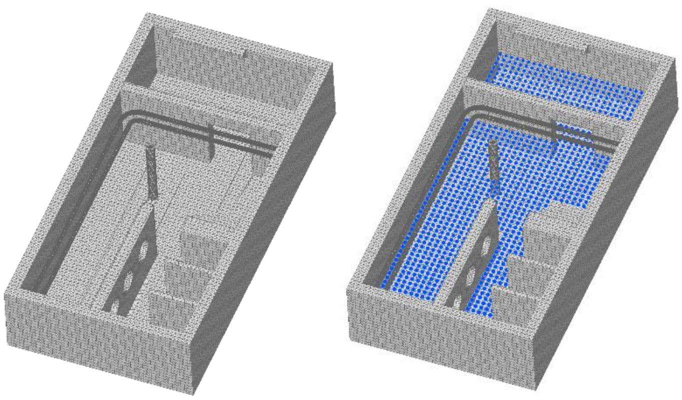
As coverage of 100% of all mesh faces in a 3D scene is hardly achievable in practice, especially as in our approach, candidate placement and requirements are fixed from the beginning, the maximum achievable coverage is defined as the area covered by all viewpoint candidates combined, with 100% coverage we refer to this reference value in the experiment.

## 4 EXPERIMENT AND RESULTS

To evaluate the presented method, we test it on a compact example. Our implementation is based on Python, and some of its standard libraries, ray casting for visibility analysis makes use of the Open3D library (Zhou, Park, and Koltun 2018). The setup of the framework and selected results are introduced in the following.

### 4.1 *Experiment setup*

Our experiment is conducted in a synthetic environment, created as a 3D CAD model using Autodesk Inventor, and exported as an ASCII OBJ file. For the baseline experiment, we create a triangulated OBJ mesh; the model is depicted in Figure X. The maximum edge length is set to 0.2m to ensure sufficient resolution. The viewpoint candidate grid is generated as a rectangular mesh and purged manually, as described in section 3.1. This setup leads to a total of 1’513 eligible viewpoint candidates and a 3D model of the scene comprising 66’676 faces with a mean area of $0.007 m^2$ and a total of $461 m^2$.



(a) (b)

**Figure 4: Experiment setup (a) triangulated mesh model (b) with candidate grid overlay, blue**

### 4.2 *Requirements configuration*

The experiment is based on assumptions regarding values for the considered limitations, both for equipment restrictions and requirements for coverage. The specific parameters and values designated for the baseline experiment are collected in Table 2.

**Table 2: Experiment setup parameters**

| Parameter type | Parameter | Value |
|---|---|---|
| Equipment | $DOF_{min}$ | 1.5m |
| Equipment | $DOF_{max}$ | 50m |
| Equipment | Resolution / Point spacing (at 10m) | 10mm |
| Equipment | $FOV_{vertical}$ | 150° (30-180°) |
| Equipment | $FOV_{horizontal}$ | 360° |
| Coverage | Min. incidence angle | 15° |
| Coverage | Min. local density | 45'000pts/m$^2$ |
| Coverage | Relative coverage goal | 80% |

## 4.3 *Visibility and Coverage Analysis*

The maximum achievable coverage of the scene is limited by our initial choice of viewpoint candidates; of the total surface area of the model (461m$^2$), 246m$^2$ (53.4%) are visible and can theoretically be covered

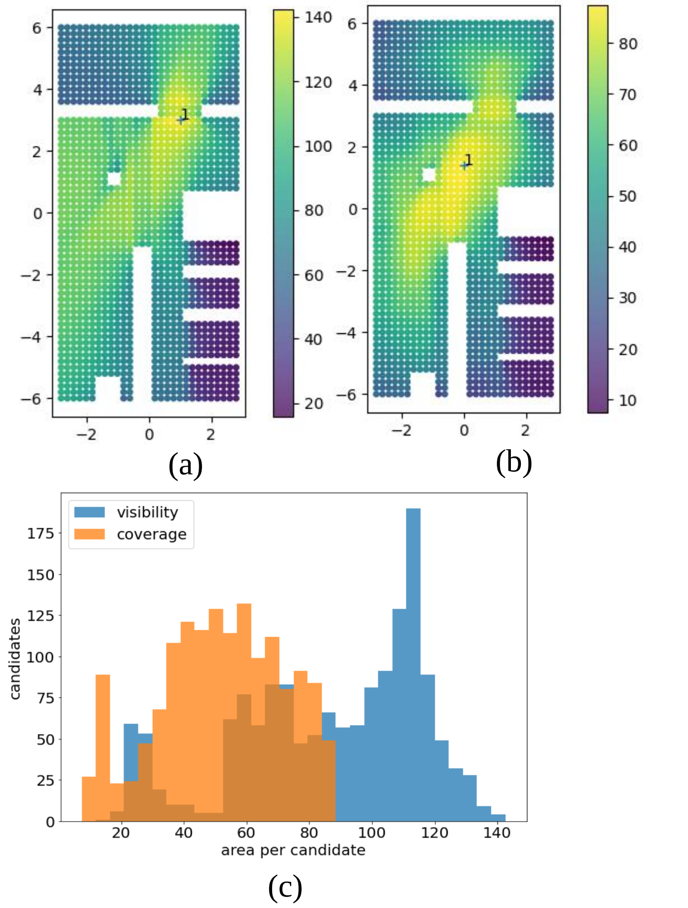



**Figure 5: Visibility and coverage results (a) initial visibility area and (b) coverage area. Total area per viewpoint color-coded, first best viewpoint marked (c) comparison of area distribution visibility and coverage**

with the defined set of viewpoint candidates. Each candidate's theoretical coverage is subsequently further reduced according to the defined coverage parameters. All parameters in use are collected in Table 2. For the full set of candidates, this changes the area slightly further to 243m$^2$ (98.6% of the visible area).

Depending on the individual viewpoints' location in the scene, both the theoretical and valid coverage changes- and the reduction of the area from visibility to coverage is significant. Figure 5 depicts the color-coded visibility and coverage area per viewpoint candidate before and after this step in comparison.

## 4.4 *Scan Planning results*

Following the greedy algorithm, viewpoints are then selected consecutively as per their individual coverage until the required overall coverage of 80% is achieved. For the presented set of parameters, the weighted greedy approach requires seven viewpoints, the standard greedy solution reaches the goal with five viewpoints, and the final scan planning results are depicted in Figure 6.

To expand on this, we investigate the discrepancy of results for the greedy algorithm with and without

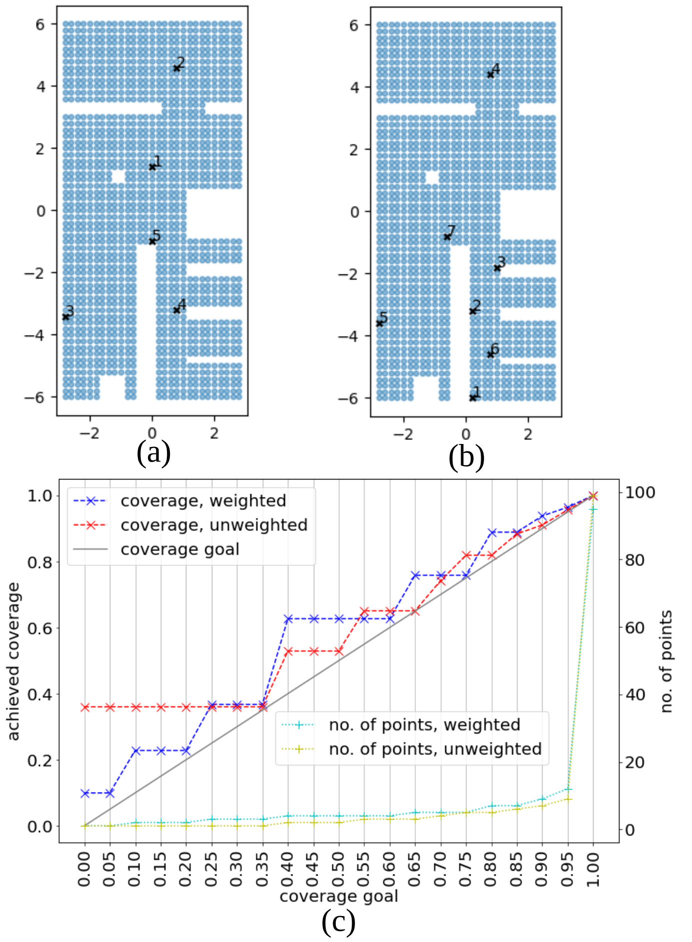



**Figure 6: Scan planning experiment results (a) standard greedy (b) weighted greedy approach (c) coverage achieved and required number of viewpoints for standard and weighted greedy approach**

weighting for the full spectrum of possible coverage goals, the result with regard to achieved coverage and required viewpoints is collected in Figure 6. It is obvious that the standard greedy approach outperforms the weighted version up to a certain degree; If 100% coverage is required, the weighted approach requires less viewpoints, which is in line with the findings presented in (Jia and Lichti 2019), where 100% coverage are assumed as a fixed requirement, albeit in a different setup with limited complexity. As introduced in the context of visibility and coverage, we find that 100% is not a sensible requirement for coverage in a complex 3D environment.

## 5 CONCLUSION AND OUTLOOK

### Conclusion

This paper presents a method for model-based scan planning that works in 3D and is fully deterministic. In comparison to other approaches, the complete information of visibility and coverage between the scene and viewpoint candidates is calculated without randomness by taking into account scene-specific occlusions and local point densities by making use of sensible approximations for calculation and a triangulated mesh instead of a voxel-based scene representation. Our approach is comparably lightweight; results are fully reproducible. The case study shows a comparison of two basic, well-known approaches for viewpoint selection and offers insights into under which circumstances one can outperform the other.

### Limitations

The approach is, however, clearly limited in some aspects. For one, the static choice of viewpoint candidates, in the beginning, limits the overall potential of coverage- a poor or insufficient selection of candidates will lead to objectively poor results that cannot be identified as such. The viewpoint selection using a greedy best-first selection is straightforward and popular but will not produce globally optimal solutions.

### Outlook, next steps

To extend the presented approach, we will extend our experiments to real-world examples, furthermore, other methods of strategy forming will be investigated. The viewpoint candidate grid will ideally be created automatically based on the underlying 3D model and a set of given restrictions and requirements. Object-specific point cloud requirements can be included by adding semantic-specific requirements and including semantics in the geometric processing. We will further investigate the applicability of the presented approach to meshes of other sources, for example resulting from initial, rough captures using mobile sensors.

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