Towards Multicriterial Scan Planning in Complex 3D Environments

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Abstract. As-is geometry of existing structures in the built environment can be captured with high accuracy using laser scanning. Frequent measurements and automation of data processing steps allow digital representations of physical assets to be kept up to date at a justifiable cost, even if they are subject to frequent changes. Before operators can execute stationary laser scanning, scan planning has to be performed to estimate the required effort and choose equipment, settings, and locations. In contrast to the conventional, expert-based method usually conducted as an assessment in the field, automated offline approaches aim to solve this task exclusively with pre-existing data describing the scene. These methods are more efficient, add transparency to the existing process landscape, and are a prerequisite for sensible implementation of robotic automation, enabling actual repeatability. The novel method proposed in this paper works in complex 3D environments while considering multiple criteria relevant to the feasibility of acquisition and the quality of acquired datasets. The proposed method introduces the scene as a triangulated mesh within which viewpoint candidates are automatically generated. This mesh is further used in a deterministic approach for visibility and coverage analysis between scene and viewpoint candidates. Based on this analysis, viewpoints are selected to form a solution set that fulfils all pre-defined requirements regarding surface coverage in the scene using a greedy algorithm. Connectivity in the solution is enforced to ensure the captured data will allow targetless registration. The objective function used for evaluating potential solutions allows for consideration of all necessary objectives and constraints in the greedy algorithm while retaining flexibility for applying other solution heuristics and optimization methods.

Keywords: Scan Planning · Planning for Scanning · P4S · Terrestrial Laser Scanning · TLS · Greedy Algorithm.

1 Introduction

As the digitization of the built environment progresses, methods for managing physical assets using their digital representations are evolving, and applicable solutions are penetrating the market. With a majority of projects within the domain of Architecture, Engineering and Construction (AEC) happening in the context of the existing building stock, an increasing focus lies on the challenge of keeping the digital models up to date. Capturing technology is rapidly developing in various aspects, ranging from sensor precision and acquisition speed to easy applicability; first attempts are made to perform acquisition tasks fully autonomously with the help of robotic platforms to further lower costs and enable regular updates. Furthermore, these platforms can be deployed under conditions that would make it difficult or impossible for a surveyor to perform the acquisition. For any reality capture mission to be successful, it needs to be properly planned. In the context of construction sites or industrial facilities, changes in geometry happen regularly and are of high relevance for those in charge of their management and monitoring progress. A conceptual overview of this repetitive process is depicted in Figure 1 to introduce the context. The conventional method of scan planning is expert-based and often conducted in the field only- in some cases, supported by pre-existing information, such as floorplans of the area to be scanned, which helps to ensure proper data quality in the resulting point cloud. Automating the scan planning process helps save time, approximate the required time for capture and assure sufficient quality in the resulting data in each repetition.

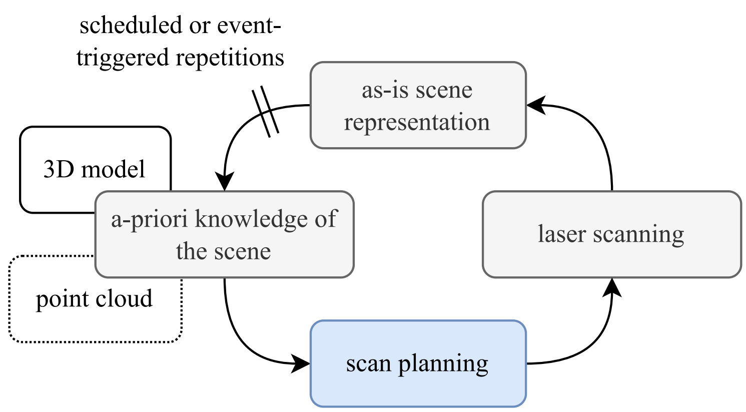


Fig. 1: Conceptual, repetitive process to keep geometric as-is scene representations updated on a regular basis; this paper introduces a novel method for scan planning

Most existing approaches that develop scan plans based on prior knowledge of the scene are based on 2D scene representations and therefore lack specific precision in geometrically complex environments. Some use actual 3D representations as input but use heavy simplifications or simulations to proceed, often leading to impractical or not generally applicable results.

To overcome these limitations, the method presented in this paper can process the scene in a full 3D representation instead of a simplifying abstraction- while taking into account multiple aspects of recording quality and equipment requirements for scan planning using a simple heuristic. Thus, this method can achieve a technically comprehensive and feasible scan plan ready for deployment in the scene.

2 Related work

In scan planning, automated approaches can generally be separated into model-based and non-model-based approaches. Non-model-based approaches perform decision-making on the go with no prior knowledge of the scene, while model-based methods are informed by prior knowledge. While model-based approaches can provide solutions for the scene in its entirety, the actual quality of the proposed strategy is limited to the closeness to the reality of the input model. Non-model-based solutions generally aim for local optimality in consecutive acquisition steps; they are therefore well suited for those cases where no reliable prior knowledge of the scene is available. Either paradigm poses specific challenges that have been faced with various technical solutions. In this work, we focus on model-based scan planning; the related works are therefore selected accordingly. For a comprehensive review of relevant aspects and approaches, the reader is referred to the pertinent overview publications in the field. [1, 14]

Model-based methods for scan planning are classically treated as variations of the Art Gallery Problem. In this, an art gallery needs to be equipped with a minimum amount of guards such that the entirety of the gallery, represented by a wall polygon, can be observed [7]. In the context of scan planning, the same logic can be applied for finding optimal locations for scanner placement that minimize effort while ensuring sufficient surface coverage in the scene [11]. Amongst others, the problem has been referred to with *viewpoint planning* [11, 15], *scanning network design* [10] and *planning for scanning (P4S)* [1]; for the sake of clarity and to emphasize the application reference, we refer to it with *scan planning* like the majority of researchers in the field [17, 5, 3, 13].

Proposed solutions for the scan planning problem are largely focused on 2D floorplans as input to achieve 100 % wall coverage- predominantly using variations of the greedy algorithm [10, 16], in comparison with other optimization methods [9]. In 3D, solution approaches include the use of laser scan simulation [2, 6], or specific, repeating geometric features of the scene [12] to solve the problem. Beyond coverage alone, scan planning should consider other constraints- one important aspect to consider for terrestrial laser scanning is the acquired data's readiness for registration [15]. [10] proposed a solution for target-based registration based on a 2D floorplan representation of the scene; towards 3D, [4] includes the floor area in addition to the wall polygon and proposes an approach to assure connectivity between scanning locations through sufficient overlap.

After potential scanning locations have been evaluated with regard to the defined evaluation criteria, a selection needs to be made to form a set of points that is able to fulfil the overall requirements. [10] uses the well-known greedy best-first approach; [9] in comparison with evolutionary optimization methods, [4] define the candidates on a scanning graph and use mixed integer linear programming to find optimal solutions.

Based on this, we identify a research gap in a robust scan planning method that is versatile in terms of 3D input, works in full consideration of this 3D environment and can take into account multiple constraints. We investigated a deterministic approach to face this problem in 3D without simulation and analysed the performance of two single-criterion greedy algorithms in [13]. This paper extends the well-known greedy approach to work on multiple criteria using a graph-based objective function. This allows us to take more criteria into account- which we showcase by introducing pairwise overlap while assuring set-wide connectivity.

3 Method

In the context of construction sites or industrial facilities, changes in geometry happen regularly and are of high relevance for those in charge of their management and monitoring progress. The presented method is model-based and therefore especially suited for the context of repeated inspections, updating and extending the digital as-is representation of the scene, as introduced in Figure 1. The necessary individual steps of the scan planning method are automated and get introduced in more detail in the following sections; three main steps can be distinguished, Figure 2 provides an overview.

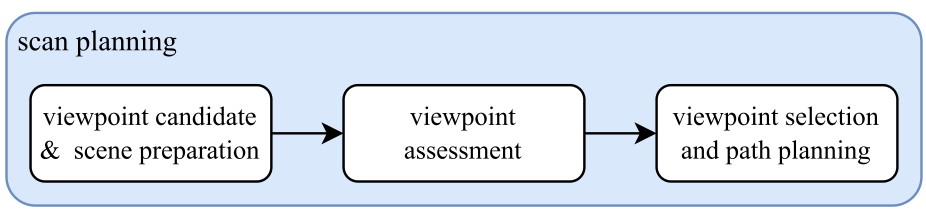


Fig. 2: Subsequent steps of the scan planning method

3.1 Viewpoint candidate and scene preparation

In the scene, a 3D viewpoint candidate grid is initiated based on model areas suitable for setting up laser scanners. First, the user needs to identify planes in the model that are suitable locations to place the scanner, which is the only remaining step that requires manual intervention. Three parameters are then used to create the candidate grid:

- r_{scene}: voxel size scene

- r_{grid}: viewpoint candidate grid resolution in the x-y-plane
- t_z: options for height adjustments on the z-axis

Points are sampled on a regular grid with grid size r_{grid} on the identified planes to create a regular-spaced grid of candidate points; the scene mesh scene is transformed into an occupancy grid with voxel sizes r_{scene}. The candidate grid points are translated along the z-axis to the first element of t_z- if there are multiple height options for the equipment, the initial grid is copied in the direction of the z-axis for each entry of t_z accordingly. An inlier test is then performed between all elements of the resulting 3D candidate grid and the occupancy voxel grid depicting the scene to filter candidate points that either collide with or lie in direct proximity of the triangulated scene. The remaining points are valid viewpoint candidates and are further processed into a viewpoint candidate graph $G_{candidate} = (V_{cand}, E_{cand})$, connecting all valid viewpoints with their immediate neighbours leveraging the pre-defined parameters of grid resolution as thresholds in the respective coordinate directions; The respective edges graph are weighted with the euclidean distance between the nodes they connect to create a weighted graph that is suited for path planning. Using this method, edges in this graph will naturally not connect nodes whose direct connection is obstructed by objects in the scene, thus allowing meaningful path planning directly within the viewpoint candidate graph.

The scene is considered in the form of a triangulated mesh. For meaningful investigation of occlusions caused by obstructions of the line of sight, triangles in the mesh should have consistent, limited sizes. To create such evenly sized faces of a limited extent, the triangulated mesh is refined by subdivision of edges such that all edges in the mesh are shorter than a pre-defined threshold value l_{max}. Using this method, the integrity of the original geometry is insured, as additional nodes are only created on existing edges; additional edges will always lie within existing faces.

3.2 Viewpoint assessment

Raycasting is performed from all candidate viewpoints to all triangle midpoints of the faces in the scene. This way, visibility between each viewpoint candidate and the scene is evaluated on a deterministic basis and independent of equipment resolution. Each ray's first intersection with the scene is stored, and the intersected face ID is stored as visible from the ray-emitting viewpoint candidate. The full visibility information is stored in the initial, binary visibility table

$$\mathbf{V}_{0_{i,j}} \text{ with } v_{i,j} = \begin{cases} 1 & \text{face } j \text{ visible from viewpoint } i \\ 0 & \text{face } j \text{ occluded from viewpoint } i. \end{cases} \tag{1}$$

The visibility table is further filtered according to the defined framework conditions:

1. equipment-specific
   - field of view
     - horizontal assumed to be 360°, negligible
     - vertical restrictions: user-defined ($\leq 180°$)
   - depth of field: minimum and maximum distance
   - minimum incidence angle
2. technical requirements
   - maximum distance
   - minimum local point density LPD

$$LPD = \frac{1}{LPS_{90}} \times \frac{1}{LPS_\alpha} \tag{2}$$

   with $LPS_{90} = SPS \times d$ for the orthogonal case and $LPS_\alpha = LPS_{90} \div \sin\alpha$ for any incidence angle; SPS denotes the distance-specific point spacing, d the scanning distance, and α the local incidence angle.

The visible faces that also comply with these requirements are collected in the initial coverage table

$$\mathbf{C}_{0_{i,j}} \text{ with } c_{i,j} = \begin{cases} 1 & \text{visible and within requirements} \\ 0 & \text{occluded or visible and violating requirements.} \end{cases} \tag{3}$$

After the initial mesh subdivision step, triangle face areas are similar but not equal. Therefore, the coverage table needs to consider the individual areas of all faces, denoted with a_j:

$$\mathbf{C}_{i,j} = \mathbf{C}_{0_{i,j}} \circ a_j \tag{4}$$

The evaluation of potential strategies is conducted over three levels of granularity between individual viewpoints (micro) and a full set of viewpoints forming a scan plan (macro).

Micro: Viewpoint coverage Based on the qualified coverage-based visibility table, the coverage can be calculated per viewpoint i as the sum of all qualified visible face areas.

$$c_i = \sum_{j=1}^{n} \mathbf{C_i} \tag{5}$$

Meso: Pairwise overlap An overlap index matrix is calculated based on the visibility lists per point for the complete candidate set as $\mathbf{O}_{\mathrm{ind}_{i,j}}$ with $o_{i,j} = \{\mathrm{ind}_i\} \cap \{\mathrm{ind}_j\}$ with ind denoting the list of row indices of visible faces in $\mathbf{V}$ and thus the faces' ID in the model; it should be noted that in this and the following equations, j is reassigned: here, indices i, j refer to viewpoint indices. For each pair of candidate viewpoints, the overlap is determined as their intersection. The respective set of face IDs can be directly accessed in the overlap table $\mathbf{O}_{\mathrm{ind},i,j}$ using the viewpoints' indices. The relative area overlap is calculated as the area of intersection over union for all pairings of viewpoint candidates in the candidate set with intersection indices $o_{i,j}$ and union indices $p_{i,j} = \{\mathrm{ind}_i\} \cup \{\mathrm{ind}_j\}$.

$$\mathbf{O}_{\mathrm{rel}_{i,j}} \text{ with } o_{\mathrm{rel}_{i,j}} = \frac{\sum_{k \in o_{i,j}} a_k}{\sum_{l \in p_{i,j}} a_l} \tag{6}$$

Macro: Set-wise connectivity Sufficient overlap must be ensured on the level of the set of viewpoints chosen as a strategy, which is evaluated in its graph representation. A complete graph $G_{select} = (V_{sel}, E_{sel})$ is built from the selected viewpoints V_{sel} as nodes, and the adjacency matrix of $E_{sel} = \mathbf{O}_{\mathrm{sel},i,j}$, populated from $\mathbf{O}_{\mathrm{rel},i,j}$. The best connectivity network of viewpoints is established as the maximum spanning tree $T = (V_{set}, E_{tree})$ of this fully connected weighted graph. The quality of cloud-to-cloud registration is evaluated by the best pairwise overlap, represented by the weighted edges in the graph. The critical overlap in the set can be quantified in the final result as the minimum weighted edge in E_{tree}.

$$o_{crit} = \min_{w} (E_{tree}) \tag{7}$$

3.3 Viewpoint selection and path planning

A greedy algorithm is applied to select viewpoints to form a suitable scan strategy. The choice for the next viewpoint is made based on an evaluation of all options successively, and at each step, the option scoring the highest value is selected for the strategy. Beyond the variables introduced above, c_{min} denotes the overall required coverage, o_{min} the minimum required pairwise overlap. S denotes the score used to make the greedy choice as follows:

The applied variations of the greedy algorithm differ in candidate evaluations. In the *standard greedy*, evaluation is performed directly on the sum of the covered areas.

$$S_{greedy,i} = \sum_{j} \mathbf{C}_{i,j} \tag{8}$$

In the proposed method, an objective function is used to evaluate the score per candidate; This approach can be directly applied in the context of other optimization methods as it allows to evaluate complete solutions in terms of coverage while taking into account the adherence to the overlapping requirement by penalizing its violation with penalty value p:

Algorithm 1: Greedy algorithm for viewpoint selection

$VP_{select} := \emptyset$
while $\sum_j \mathbf{C}_{i=VP_{select},j} < c_{min}$ **do**
  calculate S_i // calculate score per candidate
  VP_{select}.append($\max_S V_i$) // append best candidate
  $\mathbf{C}_{i,j} = 0 \; \forall \; \mathbf{C}_{i=VP_{select},j} \neq 0$ // delete covered faces from C
  if *greedy weighted* **then**
    $\mathbf{C}_{i,j} = \mathbf{C}_{i,j} \circ W$ // update coverage table with weight

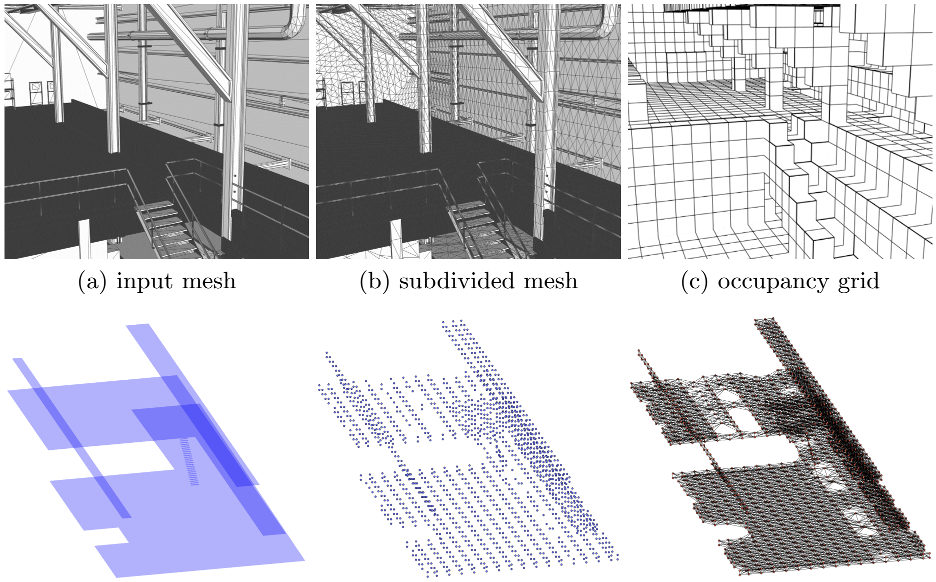
$$S_{objective} = S_{greedy,i} + f_o \text{ with } f_o = \begin{cases} 0 & o \geq \min o_{min} \\ p & \text{otherwise} \end{cases} \tag{9}$$

After a set of viewpoints is established, a suitable sequence of execution in a loop and an actual path through the scene is found using the initially created candidate graph $G_{candidate}$ by approximating a solution for the Traveling Salesman Problem (TSP) for the selected nodes V_{sel} within $G_{candidate}$. This path is inherently limited to the candidates' immediate neighbours and thus passable in the scene. Path planning is performed using existing libraries without adaption in this contribution and is not further introduced as part of the method.

4 Experiment

4.1 Setup

The evaluation of the proposed method is performed using the 3D model of an industrial facility, including several levels of steel structures, pipe and duct systems, shelves, and some clutter. The original triangulated model (overview depicted in Figure 3a, 89 000 faces and 62 000 vertices) was processed by subdivision with a threshold of max. 1 m edge length; resulting in a model with 1 030 000 faces and 530 000 vertices (Figure 3b). After suitable viewpoint areas have been identified (Figure 3d), candidate viewpoints are generated and filtered by inclusion testing with the occupancy voxel grid derived from the triangulated scene input (Figure 3c); 1730 candidate viewpoints (Figure 3e) are identified as valid input for further processing (r_{scene} =0.5 m, r_{grid} =2.0 m, t_z =[1.0 m, 2.0 m]). Due to the model's incompleteness in terms of level connectivity, some candidate areas are disconnected, and the initial graph is not fully connected. To allow automated processing end-to-end, the disconnected parts are joined automatically to their respective nearest neighbour in the remaining point set. The resulting set of viewpoint candidates is connected to immediate neighbours in 3D, forming the viewpoint candidate graph, as depicted in Figure 3f. The implementation used in this experiment makes use of Open3D [18] for geometric functionalities such as raycasting and NetworkX [8] for graph processing.



(a) input mesh (b) subdivided mesh (c) occupancy grid

(d) candidate areas (e) viewpoint candidates (f) candidate graph G_{cand}

Fig. 3: Experiment setup: Model input and intermediate processing results

4.2 Results

For all experiments, scanning equipment has a full horizontal field of view, a vertical range of 30°-180°. In the first experiment, requirements are set to overall coverage of min. 75% of the coverable surface, the minimum local required point density is set to 2500 pts/sqm, and the required overlap between two viewpoints to ensure targetless registration is assumed to be 20 %. In the objective function, a violation of this overlap constraint is penalized with $p = 100$, to make the overlap objective a limiting constraint.

The experiment is performed using a straightforward, non-constrained greedy heuristic in comparison with the greedy approach using the introduced objective function. Without objective function, the resulting strategy is able to cover the required surface with 18 viewpoints, including the constraint for sufficient overlap 25 viewpoints are required (full results depicted in Figure 5). However, cloud-to-cloud registration with our defined parameters is impossible in the former result; 10 out of 24 pairwise connections do not have sufficient coverage with any other point in the strategy.

To investigate the influence of varying overlap requirements, the experiment was repeated for a range of relative overlaps from 0 % to 30 %. The results are summarized in Figure 4 and indicate an exponential growth in the number of viewpoints required to meet the requirements. Although an investigation of the impact of such relative overlaps in terms of targetless registerability of individual point clouds is beyond the scope of this work, it has been shown that they can be accounted for within the presented scan planning methodology and have a significant impact on its results.

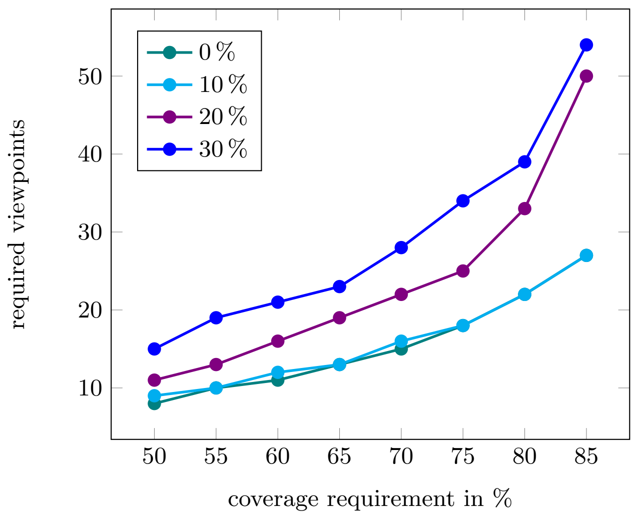
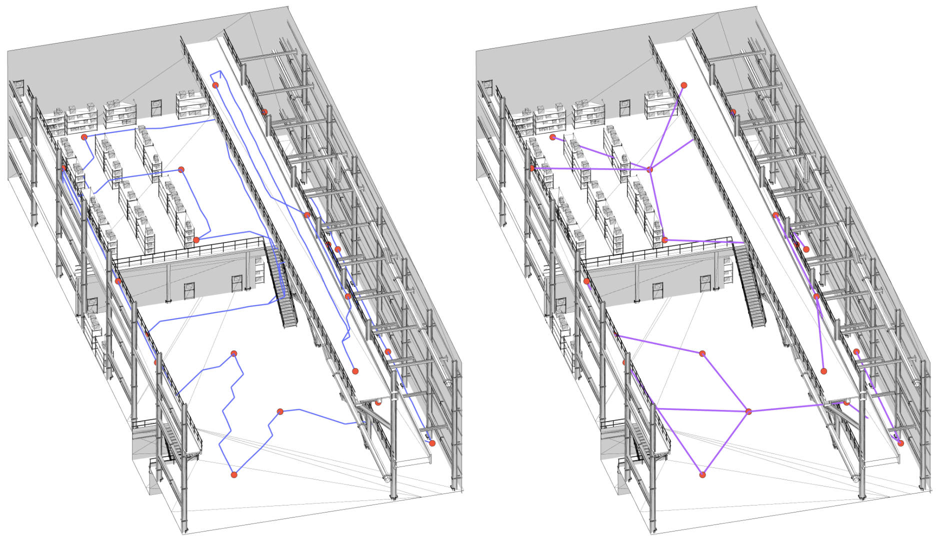


Fig. 4: Experiment results for varying overlap requirements (legend) and coverage requirements



(a) (b)

Fig. 5: Aspects of scan planning results in the context of the original experiment scene (before subdivision, two walls and roof structure removed for visualization): (a) selected scan points with shortest path visiting all selected points, (b) connectivity graph indicating best pairwise overlaps

5 Discussion & Outlook

This paper introduces a method for model-based scan planning in complex 3D environments. Beyond existing approaches, it is able to work directly with a standard 3D representation of the scene, in which the input viewpoint candidate grid is generated as a 3D graph automatically with minimal required user input. In the method, three granularities of quality metrics are considered to choose a set of viewpoints forming a scan plan, including the shortest round trip through the candidate graph as a proposed scanning sequence. With coverage and point density, local and global point cloud quality considerations are taken into account while ensuring sufficient overlap for targetless registration of the resulting point clouds. The competing objectives of this setup are considered as constraints and part of the objective function used for decision-making in the greedy heuristic. In a short experiment, it is shown how this method performs in an exemplary industrial scenario.

As the underlying computation is static and performed as an initial step, it is quite computationally expensive in its current implementation. Through the static and comprehensive basis, however, it provides a robust basis for further investigations of alternative methods for optimized viewpoint selection- which is a promising outlook, especially for more complex scenarios of competing goals.

Going forward, sensible extensions of this work are therefore identified in a) the extension of constraints and criteria to achieve more specific industry-relevant solutions along with b) the investigation of methods that are eventually able to consider all these criteria in finding suitable solutions.

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