Assessing and Improving Automated Viewpoint Planning for Static Laser Scanning Using Optimization Methods

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Abstract

The preparation of laser scanning missions is important for efficiency and data quality. Furthermore, it is a prerequisite for automated data acquisition, which has numerous applications in the built environment, including autonomous inspections and monitoring of construction progress and quality criteria. The scene and potential scanning locations can be discretized to facilitate the analysis of visibility and quality aspects. The remaining mathematical problem to generate an economic scan strategy is the Viewpoint Planning Problem (VPP), which asks for a minimum number of scanning locations within the given scene to cover the scene under pre-defined requirements. Solutions for this problem are most commonly found using heuristics. While these efficient methods scale well, they cannot generally return globally optimal solutions. This paper investigates the VPP based on a problem description that considers quality-constrained visibility in 3D scenes and suitable overlaps between individual viewpoints for targetless registration of acquired point clouds. The methodology includes the introduction of a preprocessing method designed to simplify the input data without losing information about the problem. The paper details various solution methods for the VPP, encompassing conventional heuristics and a mixed-integer linear programming formulation, which is solved using Benders decomposition. Experiments are carried out on two case study datasets, varying in specifications and sizes, to evaluate these methods. The results show the actual quality of the obtained solutions and their deviation from optimality (in terms of the estimated optimality gap) for instances where exact solutions can not be achieved.

1. Introduction

Laser scanning has an increasing importance for applications in the built environment. While digital, model-based methods are becoming common practice globally, applications involving operations and refurbishment, or projects within existing structures in general face additional challenges because the digital data basis for the application of digital methods needs to be collected from the real-world environment first (Borrmann et al., 2018). Laser scanning has become an important part of the solution to this problem (Valero et al., 2022). To achieve good results both in terms of data quality and efficient execution, scanning missions need to be planned thoroughly. Especially for the case of recurring scanning in environments such as industrial facilities or large-scale construction sites with continuous progress monitoring, automating the process of scan planning is a worthwhile exercise; firstly, because the savings obtained from the implementation of an automated solution grow with each iteration, and secondly because recurring data acquisition in short cycles means that the environment is expected to change in limited extents between iterations and the data acquired in a previous cycle contains information well-suited for the planning of the next scanning mission (Wakisaka et al., 2019). Furthermore, applications on construction sites and industrial plants usually require high precision, which is only achievable with static, terrestrial laser scanning, which prohibits the application of faster but less accurate mobile laser scanning systems. Scanning missions often involve hundreds of scanning locations, as reported by Hullo (2016). In such cases, implementing an efficient scan planning strategy that effectively reduces the number of necessary scanning locations by a notable percentage can lead to substantial economic benefits.

The presented work does not describe an end-to-end method for scan planning but focuses explicitly on the last step of optimal viewpoint selection or the so-called Viewpoint Planning Problem (VPP) (Aryan et al., 2021).

The paper is structured as follows: Section 2 presents related work, focusing on scan planning and specifically on the VPP. Section 3 outlines the methodology, detailing the input data and techniques for addressing the VPP. Section 4 applies the presented methods to two distinct scenarios of varying complexity, followed by a discussion of the results. The paper concludes in Section 5, summarizing the findings and exploring their potential impact on future research in this field.

2. Related Word

The Scan Planning problem can be defined as *”the problem of finding the minimum number of predefined viewpoints that give a full coverage of the scanning targets while satisfying the data quality requirements”* (Aryan et al., 2021). This is a precondition for automated scanning using robotic platforms (Adán et al., 2019) and helps to avoid sub-optimal decision-making in the manual process (Mozaffar and Varshosaz, 2016). As introduced, for this work, we assume knowledge of the scene is

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available in the form of 3D models or prior scans, which is an assumption made in the context of our above-explained target use cases of industrial plants and construction progress monitoring and contribute to their development towards autonomous data acquisition (Wetzel et al., 2022).

Conventional approaches for Scan Planning are based on 2D floorplans, as they are the most commonly available representation of existing buildings (Jia and Lichti, 2019; Zeng et al., 2022). However, the complex reality of the built environment of construction sites, structural systems, industrial facilities, and others cannot be sufficiently depicted by such 2D representations. Solving the problem of Scan Planning in 3D poses additional problems due to the computational complexity (Jia and Lichti, 2019; Aryan et al., 2021). Therefore, instead of continuous approaches or discretization of the existing data, most 3D-based approaches make use of simplifications made possible in structures with highly repetitive element types (Li et al., 2022) or laser scan simulation (Rougeron et al., 2022; Wujanz and Neitzel, 2016; Biswas et al., 2015). Some recent works use conventional representations such as voxels (Wakisaka et al., 2019) or triangulated meshes (Noichl et al., 2024), making application possible for a wider range of input data.

Viewpoint candidates are placed in the scene on rectangular grids (Jia and Lichti, 2019) or nodes generated using triangulation methods (Frías et al., 2019; Wakisaka et al., 2019). Visibility analysis can be done based on discretized scene representation directly (Jia and Lichti, 2019; Li et al., 2022) or indirectly through laser scan simulation (Biswas et al., 2015; Rougeron et al., 2022). Evaluation results can be stored in table-like format, such as the *visibility score table* described by Jia and Lichti (2019).

After this evaluation is complete, the VPP needs to be solved. The most prominent method to approximate a suitable solution is the greedy algorithm (Jia and Lichti, 2019; Wujanz and Neitzel, 2016; Frías et al., 2022). The greedy algorithm can be described as a sequential search heuristic, providing a series of choices built sequentially, selecting the option that seems most advantageous or optimal at each step without considering future consequences. This approach generally leads to locally optimal solutions, but does not guarantee a global optimality. Randomized selection algorithms, like evolutionary algorithms, offer a contrasting approach to the deterministic nature of greedy algorithms. Evolutionary algorithms use randomness and selection principles inspired by natural evolution. These algorithms start with a population of potential solutions and iteratively apply genetic operations such as mutation, crossover, and selection. The randomness in evolutionary algorithms allows for exploration of the solution space beyond local optima, potentially leading to better overall solutions than the locally-focused greedy method. This makes evolutionary algorithms particularly suitable for complex problems where the solution landscape is poorly understood. The related works of Jia and Lichti (2017); Ibrahim et al. (2022) investigate the applicability of various randomized selection algorithms to solve the VPP. Exact solutions can be achieved through optimization techniques like Mixed-Integer Linear Programming (MILP). While evolutionary algorithms can navigate large and complex solution spaces through iterative and randomized processes, MILP takes a more direct and precise approach, formulating the problem as a set of linear equations and inequalities to find an optimal solution that satisfies all constraints. This method guarantees the discovery of a globally optimal solution by exhaustively exploring the feasible solution space. Amongst others, Dehbi et al. (2021) apply such methods to solve a version of the problem considering walls as lines in 2D and floor areas; Wakisaka et al. (2019) apply MILP for scan planning based on a voxel representation that is derived from a mesh representation obtained from a prior scan. The trade-off is that MILP can be computationally expensive, especially for large-scale problems, where heuristic methods like sequential search and evolutionary algorithms might provide solutions of sufficient quality much more efficiently.

Still, the question remains of how good the results of sequential heuristics actually are – in comparison to solutions found applying exact methods. This paper aims to investigate this question by applying several sequential search heuristics to exemplary case study scenes based on a description of the VPP that allows the consideration of point cloud and overlap criteria in complex environments.

3. Method

The VPP is presented in the following form, as described by Noichl et al. (2024): The scene itself is described as a set of triangular faces $F = \{f_1, \ldots, f_m\}$ with their respective areas $a_1, \ldots, a_m$ stored in the area vector $a \in \mathbb{R}_+^m$. All viewpoint candidates are collected in the set $VP = \{\mathrm{vp}_1, \ldots, \mathrm{vp}_n\}$.

Faces in the scene that are visible and covered following the pre-defined coverage criteria are stored in the coverage table $C = (c_{i,j}) \in \{0,1\}^{m\times n}$ with

$$c_{i,j} = \begin{cases} 1 & \text{face } f_j \text{ is covered by viewpoint } \mathrm{vp}_i \\ 0 & \text{otherwise.} \end{cases} \tag{1}$$

If a viewpoint is selected, it will be used to capture a point cloud using static laser scanning. The individual point clouds should be registered using targetless registration. For $k \in \{1, \ldots, n\}$, we define $J_k = \{j \in \{1, \ldots, m\} \,|\, c_{j,k} = 1\}$ as the set of face indices visible from viewpoint candidate vp_k. The pairwise overlap between viewpoint candidates is stored in the relative overlap table $O_{\mathrm{rel}_{k,l}} = (o_{\mathrm{rel}_{k,l}}) \in \mathbb{R}_+^{n\times n}$ with

$$o_{\mathrm{rel}_{k,l}} = \frac{\sum_{i \in J_k \cap J_l} a_j}{\sum_{j \in J_k \cup J_l} a_j} \tag{2}$$

Based on this input data, we use two approximation methods and one exact algorithm to determine solutions to the VPP. All three approaches are introduced in the following. For ease of understanding, they are written in pseudo-code.

3.1 Greedy algorithm

The greedy algorithm is a straightforward method for obtaining approximate solutions for the VPP. The value of all potential viewpoint candidate points is evaluated, and then the most valuable candidate is added to the solution. This process is repeated until the coverage requirement set in the SP is met. This principle logic structure is described in Algorithm 1, taken from Noichl et al. (2024). Due to its strictly sequential nature, this approach can also be referred to as *forward selection* and is prone to return sub-optimal solutions.

Algorithm 1: Greedy algorithm

```
initiate empty solution
while coverage criterion is not met do
    calculate score per viewpoint candidate
    append candidate with the highest score to solution
end
return solution
```

3.2 Oscillating search

Sequential search can also be executed in the opposite direction of the greedy algorithm: Starting from a complete solution, the loss connected with removing single viewpoint candidates is calculated for all viewpoint candidates in the solution. After removing the point with the least individual impact on the overall strategy, this procedure is repeated until the remaining solution no longer fulfills the coverage requirement. This approach can also be referred to as *backward elimination*. Although it is deterministic, due to the high number of necessary evaluations, it leads to high computational costs with increasing numbers of viewpoint candidate points. It is possible to combine *forward selection* and *backward elimination* to mitigate the limitations of these approaches. This approach is detailed in Algorithm 2, which we refer to as oscillating search, as described in Noichl et al. (2024).

Algorithm 2: Oscillating search

```
initiate empty solution
while solution does not meet requirements do
    for i in n_f do
        forward selection
    end
    evaluate solution
    for j in n_b do
        backward elimination
    end
end
for k in n_o do
    oscillate with a_o
    evaluate solution
    if solution OK then
        store the solution
    end
end
pick best solution from stored solutions
return solution
```

In contrast to the greedy algorithm, this approach has parameters that can be changed: n_f is the number of steps of forward selection in a sequence, n_b the number of steps of backward elimination. After the solution has reached the requirements, there are additional *oscillations*, describing subsequent phases of forward selection and backward elimination, with fixed or varying numbers of steps a_o each.

3.3 Benders decomposition

Apart from heuristics, the VPP can be solved exactly by applying a Benders decomposition algorithm. In its general form, the Benders decomposition algorithm tries to decompose a mixed-integer linear program (MILP) into a master- and a subproblem (Benders, 2005). This is done by reformulating the initial MILP into an equivalent problem such that a subset of variables is projected out. Instead of considering the complete reformulated problem, a relaxed version, called master problem, is solved to optimality. After a new solution is found, the subproblem is used to evaluate its optimality with respect to all constraints of the reformulated problem. If the found solution is not an optimal solution, the subproblem produces a violated constraint, which is added to the master problem, and the process repeats.

This method is guaranteed to converge but may come with many drawbacks, such as time-consuming iterations and slow convergence towards the end of the algorithm (Rahmaniani et al., 2017).

One possible way to decrease the necessary time per iteration is to use a branch-and-benders-cut framework. Instead of solving the master problem to optimality in each iteration, it is solved only once via the branch-and-bound algorithm. When a new (integral or fractional) solution is found, the subproblem is used to evaluate its optimality with respect to all reformulated constraints. An additional constraint, called cut, is added to the master problem if the found solution violates any of these constraints. This procedure avoids redundancies in eliminating non-optimal solutions when repeatedly solving the master problem.

Cordeau et al. (2019) develop a branch-and-bender-cut algorithm that can be utilized for a large variety of (partial) covering problems. Due to their special structure, the evaluation of a solution to the master problem and the generation of a cut can be performed in linear time. Clearly, the VPP falls into this class if only coverage constraints are considered.

In order to also incorporate overlap constraints, the master problem is initialized with additional constraints that ensure the registrability of the selected candidate points. Dehbi et al. (2021) formulate the registrability constraints by ensuring the existence of a multi-commodity-flow in a connectivity graph, that represents the sufficient overlap between viewpoint candidates. This approach is also used in this paper, hence, the master problem of the branch-and-cut-benders-cut algorithm is initialized with these constraints in order to ensure the registrability of the delivered scanning plan. The branch-and-bender-cut approach is summarized in Algorithm 3.

Algorithm 3: Branch-and-benders-cut

```
initiate master problem with registrability constraints
solve masterproblem via branch-and-bound
while branch-and-bound is not terminated do
    if incumbent solution is found then
        solve subproblem using the incumbent solution
        if incumbent solution is not optimum then
            add produced cut to master problem
        end
        else
            continue brach-and-bound
        end
    end
end
return solution
```

3.4 Preprocessing

To reduce the size of the problem and the resulting computation time, instances are simplified as follows. For all following operations, we denote the input variables by x, intermediate results by $\hat{x}$, and final preprocessing results by $\bar{x}$. The initial coverage table C is filtered in this process: Faces that are not visible from any of the viewpoint candidates are deleted from the instance, which yields $\hat{C} = \{\text{row}_i(C) \mid \exists j : a_{ij} \neq 0\}$. This step adheres to the logic of the established method of *back-face culling*, an effective standard technique in graphics processing (Vaněkčkek Jr, 1994).

If two distinct faces $f_i \neq f_j$ are covered by the same viewpoint candidate points, we call them redundant and merge them in the instance representation, which yields $\bar{C} = \{\text{row}_i(\hat{C}) \mid \text{row}_i(\hat{C}) \text{ is unique in } \hat{C}\}$.

Accordingly, for each unique row i for which the (identical) rows $k \in K$ have been removed from the coverage table, the area vector needs to be updated with $\bar{a}_i = a_i + \sum_{k \in K} a_k$.

These operations are designed to simplify the problem without actual information loss by removing superfluous and redundant information from the instance description. The only information that is lost is the geometric description of individual covered faces, which plays a role in describing *geometric contrast* in overlapping areas for targetless registration (Wujanz and Neitzel, 2016). Under the assumption of sufficient viewpoint candidate grid resolution, this can be neglected.

Further operations can be applied to simplify the problem, for example, by merging viewpoints based on coverage similarity, inversely to the above-described removal of redundant faces. To be applied effectively, it is useful to introduce certain thresholds within which loss of information is acceptable. In the scope of this paper, we only consider loss-free preprocessing and neglect the latter. In our preprocessing, the number n of viewpoints remains unchanged, while the number m of faces is reduced to $\bar{m} \leq m$.

4. Experiments

The introduced methods to find solutions for the VPP can be applied to all mentioned scene representations and candidate grid layouts introduced in Section 2. For the experimental part of this paper, simple 3D geometries are considered as the scene, represented by triangulated mesh representation; potential viewpoint candidates are located on a rectangular grid.

4.1 Datasets

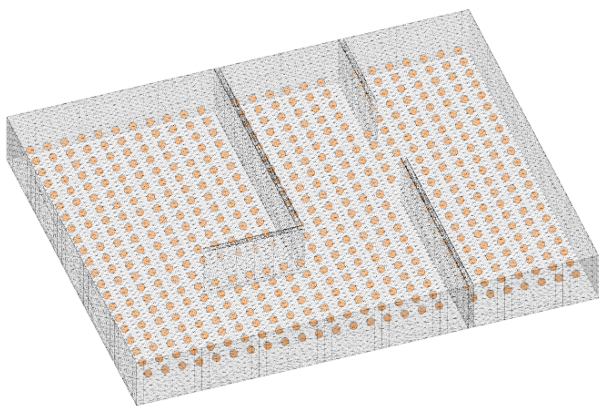

Figure 1. Experiment scene 1: Single-level building model.

Two simple building models are used in our experiments. Scene 1 depicts a simple, single-level house (Figure 1), and scene 2 depicts a more complicated geometry, where scene 1 is extended by a second floor (Figure 2). In scene 2, two openings connect the two levels: A rectangular opening (right corner) and a ramp to connect the two floors (middle, left) as depicted in Figure 2. All outer surfaces are modeled as single surfaces for simplicity and inner structures such as inner walls and the slab separating the levels in scene 2 are modeled as cuboids, requiring coverage from both sides. Both figures show the scene geometry as discretized triangular faces (black outlines) and viewpoint candidate locations (orange circles).

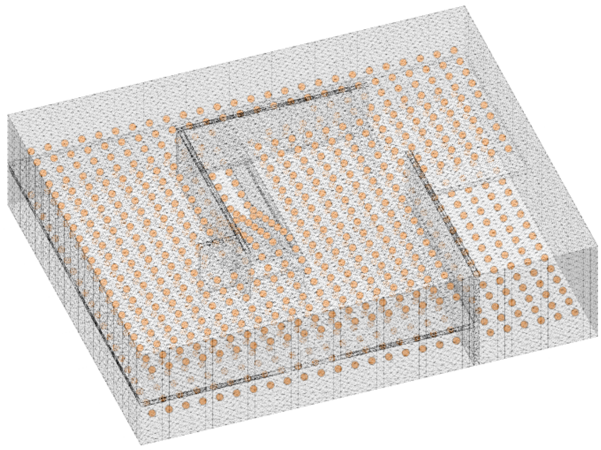

Figure 2. Experiment scene 2: Two-level building model.

dataset	scene 1	scene 2
surface area	$707.0\,\mathrm{m}^2$	$1387.7\,\mathrm{m}^2$
no. n of viewpoints	511	945
no. m of faces	50 040	104 308
$\hat{m}$ after preprocessing	31 330	71 263

Table 1. Key data of experiment scenes 1 and 2.

4.2 Experiments

All three viewpoint selection algorithms are applied to the presented problem instances to investigate their behavior in direct comparison. For the Benders decomposition algorithm, we report both the objective value of best obtained solution and the provided lower bound on the objective value of a globally optimal solution. If the two values are not equal, the algorithm cannot obtain an optimal solution within the pre-defined time limit of 30 000 s.

Before applying the viewpoint selection algorithms, the problem instances are preprocessed using the introduced filtering steps. This leads to a significant reduction in problem size by 37.4 % for scene 1 and 31.7 % for scene 2 (absolute values see Table 1).

As shown in Figure 3, the required viewpoints for scene 1 range between three and six. Both heuristic methods return the same values, and Benders decomposition reaches an optimal solution within the time limit. In a relative comparison between the methods, for a relative coverage requirement of 90 % and 99 %, both heuristic approaches require one more viewpoint candidate. Figure 5 shows the solution for 99 % obtained using the greedy algorithm as green circles in the scene.

Figure 4 summarizes the results for scene 2, where the required number of viewpoints ranges between four and 14. Within the pre-defined time limit, Benders decomposition does not reach

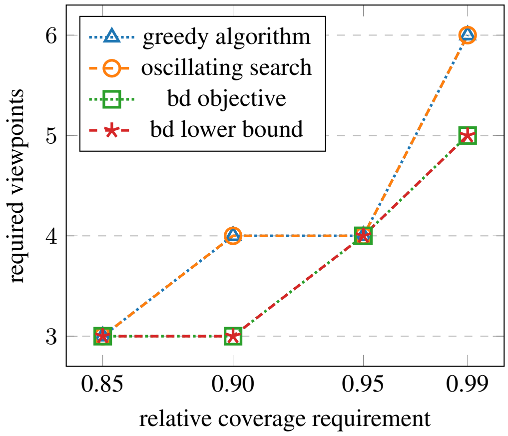

Figure 3. Evaluation of results for experiments in scene 1, bd indicates results obtained using Benders decomposition.

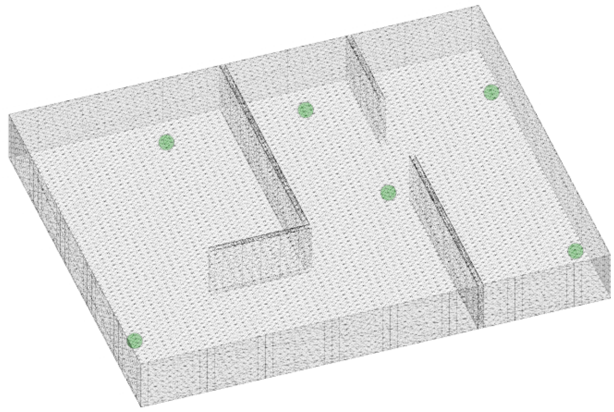

Figure 5. Experiment scene 1 with selected viewpoint candidates for 99 % relative coverage (greedy algorithm).

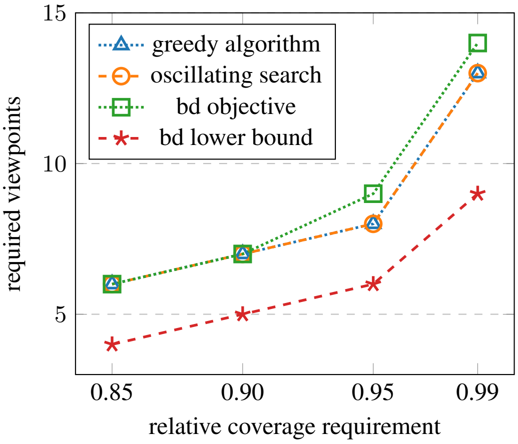

Figure 4. Evaluation of results for experiments in scene 2, bd indicates results obtained using Benders decomposition.

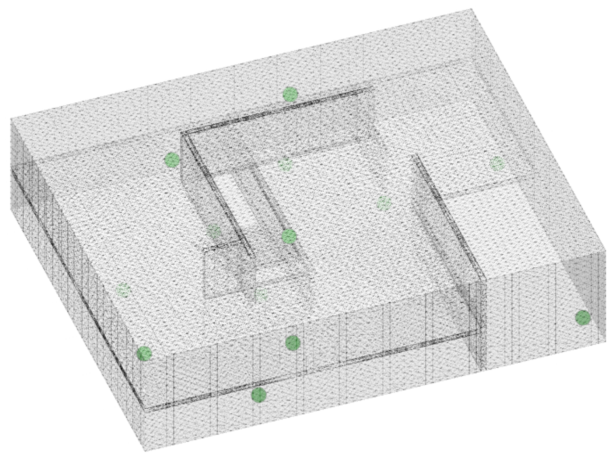

Figure 6. Experiment scene 2 with selected viewpoint candidates for 99 % relative coverage (oscillating search).

an optimal solution; the two heuristic methods return equal results consistently. For values of 85 % and 90 % relative coverage, the required number of viewpoints are equal for the solutions returned by Benders decomposition and the two heuristic approaches. Above 90 %, the heuristic methods lead to solutions that each require one viewpoint less to fulfill the coverage requirement. For scene 2, the provided lower bound on the objective value of a globally optimal solution ranges between four and nine viewpoints and is not reached by any of the generated solutions. Figure 5 shows the solution for 99 % obtained using the greedy algorithm as green circles in the scene.

Between the heuristic methods of the greedy algorithm and oscillating search, there is no difference in the results for scenes 1 and 2. Other studies have found that oscillating search can lead to improvements compared to the conventional greedy algorithm (Noichl et al., 2024), but in the presented examples, this is not the case.

5. Conclusion

This paper presents an approach for determining the exact solution for the Viewpoint Planning Problem, considering sufficient pairwise overlap as a constraint for viable solutions. Beyond the introduction of methods to find solutions to the problem by using optimization techniques, we explain existing heuristic methods to find suitable solutions and perform experiments on two simple scenes represented by 3D models to investigate performance and solution quality.

In our experiments, heuristic methods matched the exact solution in terms of the required number of viewpoints for half of the coverage requirement values tested for both scenes. In instances of deviation, solutions from Benders decomposition outperformed heuristic approaches in scene 1, showcasing their effectiveness in less complex scenarios. For the more complex scene 2, no method achieved the estimated lower bound. Here, conversely to scene 1, for the non-identical results, heuristic solutions required fewer viewpoints than those generated by Benders decomposition, indicating their efficiency in more complex environments.

While further investigation is necessary to provide more comprehensive data to support these findings, the results show that the presented heuristics are able to find sensible solutions efficiently. With increasing complexity, heuristics-based solutions deviate from the estimated optimal solution – but in some cases less so than the much more computationally expensive exact solutions using Benders decomposition.

A limitation of the presented preprocessing method is that it exclusively considers the faces of the scene and does not consider viewpoint candidate point simplifications. While including such simplifications might introduce some loss of information, it would be an interesting extension to this work – the same pertains to an extension of the presented method for model redundancy reduction.

In future work, it could be interesting to investigate the extent of problems that exact methods like the ones presented here can be applied to and whether combinations between different algorithms can outperform the existing ones.

Related research in the field of drone operations and data acquisition for photogrammetric processes includes benchmark data that are openly accessible, which allows easy comparisons of results (Rocha and Vivaldini, 2022). This could be another worthwhile addition to the literature on the topic of scan planning and the VPP for static laser scanning.

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