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Using a Drone for Automated 3D Scanning

Category: Research

Abstract

This paper reviews the state-of-the-art techniques in automated 3D scanning focusing on the task of Next Best View (NBV) planning. Starting with a comprehensive overview on classic approaches mainly using geometric and heuristic methods to optimize the position of the sensor for a maximum coverage of the surface by minimal occlusion. Next, modern learning-based approaches are presented that utilize advanced machine or deep learning models to dynamically predict the most informative viewpoints. Such techniques for example try to integrate probabilistic models and real-time data to enhance the efficiency and flexibility for determining the NBV. Furthermore, various techniques are compared in terms of their efficiency but also their ability to handle different input types and complexities of the environment to scan. Finally, we conclude the paper by providing an outlook to future work in this field of research that could further improve the process of automated 3D object reconstruction.

Index Terms: Computing methodologies—Artificial intelligence—Planning and scheduling—Robotic planning; Computing methodologies—Artificial intelligence—Computer vision—Image and video acquisition3D imaging;

1 Introduction

Over the past decades, the methods for automated 3D scanning improved significantly and became very important in varying domains such as manufacturing, architecture or in the preservation of cultural heritage and the practicality of such systems is largely dependent on the accuracy as well as the efficiency of the reconstruction process of 3D models from the observed data. To achieve this, it requires strategic planning to find the optimal Next Best View (NBV) with minimal operational costs but at the same time a maximum of quality for the data acquisition should be achieved.

The question this paper aims to answer is:
What are the current state-of-the-art techniques for solving the various tasks of automated 3D scanning, including classic approaches as well as learning-based?

1.1 Motivation

One of the main motivations for improving NBV planning methods is, the increasing demand of high quality 3D scans and therefore techniques that can efficiently execute such high precision scans. However, efficiency for finding the NBV not only includes the quality of the reconstructed model itself, but also the reduction of the necessary computational power as well as the computation time, which are crucial for real-world applications. Nowadays, 3D scanning is also becoming more important in the industry and gets more integrated into various processes there, where the ability for a fast and accurate reconstruction of 3D models from a minimal set of viewpoints and a sophisticated NBV planning algorithm are crucial factors.

1.2 Overview of Classic Approaches

Classic approaches for NBV planning in automated 3D scanning are mainly relying on geometric and heuristic methods that are designed to maximize the coverage of the surface to scan, while minimizing occlusion without further knowledge of the global context of the scene. One early work in this domain is by C.I. Connolly which uses partial octree models to systematically determine the NBV, e.g. by using a spherical approach which positions measurement points on a hypothetical sphere around the object, which should maximize the scene coverage while at the same time reduce the unobserved area [2].

Another approach by Scott et al. [10] improves existing techniques by a more sophisticated sensor planning strategy, which not only considers the current sensor position and visibility of the object but also incorporate adjustments based on the relative position between the object and the sensor. This makes their method especially effective in structured environments with predictable surroundings and if there is only minor obstruction of the views by the geometry of the object itself.

However, these classic methods often lack flexibility and therefore often struggle in dynamically changing environments or with complex object geometries, where unpredictable occlusions can lead to less than optimal data. As such, classic approaches build a strong foundation for the planning of the NBV, but their limitations show, that there is a need for more sophisticated approaches, that are able to address the challenges of modern 3D scanning environments.

1.3 Overview of Learning Approaches

In recent years, learning-based approaches became more popular in NBV planning and have gained significant improvements due to the use of deep learning to determine the best viewpoints for scanning, based on learned patterns from extensive datasets. Zeng et al. for example introduced a deep learning approach based on point clouds called PC-NBV, in which they process raw point cloud data and the current state of the reconstruction to predict the information gain for each NBV candidate [16]. Since they can avoid computationally intensive tasks such as ray-casting simulations and the transformation of the volumetric data, as most traditional approaches would do, their method outperforms classic approaches in terms of quality and speed of the reconstruction.

Another approach from Song et al. integrates so-called online multi-view stereo (MVS) techniques in their approach for a real-time reconstruction of large scale structures using unmanned aerial vehicles (UAV), which makes it very flexible to adapt to new data acquired during the flight [11]. Further, Pan et al. proposed a one shot view planning method based on a set-covering model, named SCVP, which is trained to determine a minimal set of views that can guarantee a complete coverage, and for efficiency in unknown environments they use a volumetric occupancy grid as input [7].

These recent developments show the benefits of modern learning approaches in the field of NBV planning in contrast to previous classic ones. Modern learning models are not only capable of learning and adapt to new situations due to fine-tuning the models by domain specific datasets, which makes them really flexible to use, but they also outperform traditional methods in terms of precision and efficiency in automated 3D scanning.

2 Classic Approaches

One of the earlier works in the field of classic approaches is by C.I. Connolly [2], which deals with constructing comprehensive three-dimensional models from a series of depth images and was published in 1985. In this work, the authors introduce two innovative algorithms that are using partial octree models to systematically determine the next best viewing position in a sequence of views.

The first algorithm (Planetarium Algorithm) employs a spherical approach, i.e. it positions a hypothetical sphere around the object

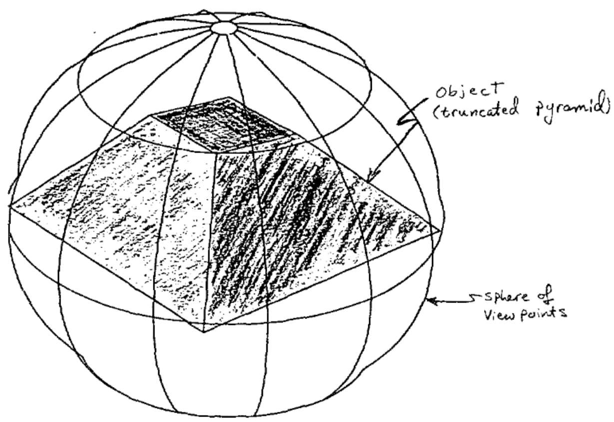

Figure 1: Illustration of the Planetarium Algorithm setup, depicting the sphere around the scene with sampled points for the generation of the optimal next view for the 3D model reconstruction [2].

and selects measurement points on this sphere to maximize scene coverage. Here, the algorithm chooses the point that would eliminate the largest volume of unobserved space and takes potential occlusions into account. Figure 1 illustrates the arrangement of the sphere and the process of selecting measurement points [2].

The second algorithm (Normal Algorithm) focuses on the visibility of invisible nodes within the octree structure. Figure 2 shows the challenges of occlusions and how the algorithm handles them, for example in the case of a self-occluding scene. The algorithm ensures that non-visible or partially visible parts are sufficiently covered in subsequent views.

By using octrees as the data structure, these methods provide an efficient and systematic approach, thus enabling significant progress in the field of 3D model reconstruction.

In the work of Scott et al. from 2003, called *View Planning for Automated Three-Dimensional Object Reconstruction and Inspection* [10], the authors target the complex process of 3D reconstruction and inspection using laser scanning distance sensors, and addresses the critical task of view planning within the context of automated and semi-automated systems for high-density 3D object reconstruction with high precision.

The described process of 3D reconstruction consists of several crucial steps beginning with the planning of a series of views, followed by adjusting the relative position between the object and the sensor. Subsequent steps include scanning the object, registering the geometric data within a common coordinate system to determine an optimal set of sensor positions and finally integrating these depth images into a comprehensive, non-redundant 3D model.

One significant aspect of the authors work is the extensive overview and comparison of existing view planning techniques, particularly those that make use of active triangulation based distance sensors. The authors evaluate approaches and emphasize their appropriateness for various purposes in reconstructing 3D objects and thus offers valuable perspectives on the advantages and drawbacks of each method which will help guiding future developments and applications.

In 2011, Vásquez and Sucar proposed a novel work called *Next-Best-View Planning for 3D Object Reconstruction* [15] to tackle the complex task of 3D model acquisition through a strategic sensor view planning by using an iterative process to select the NBV for the position of the distance sensors.

The focus of the paper is especially targeting the problems caused by positioning errors, which are particularly relevant when using mobile robots since they reduce the quality as well as the efficiency

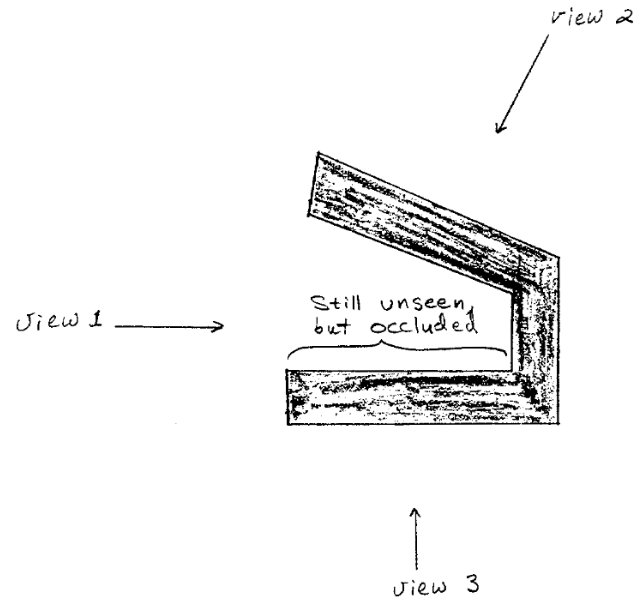

Figure 2: Illustration of a self-occluding scene, highlighting the challenges of scenarios with objects that are partially occluded [2].

of 3D reconstruction significant. To target this, the authors propose an innovative method for planning *safe views*, which are designed to be effective even in the case of positioning errors and therefore helping to enhance the reliability and accuracy of the reconstruction process.

In their approach, the authors redefine the process of the selection of candidate views for the 3D object reconstruction by re-evaluating them, but unlike other traditional methods that select views based only on the current sensor position and the visibility of the object, this method also takes neighboring views into account and represents a significant advancement over conventional methods by proactively addressing potential errors in the movement or positioning of the robot [15].

The experiments of the authors with objects of a varying complexity were promising and demonstrate that their method is able to achieve results comparable to an ideal scenario without positioning errors. Furthermore, they observed that their method require fewer views compared to standard approaches that do not consider positioning errors, while still maintaining high quality reconstruction.

In their follow-up work 2014, Vasquez-Gomez et al. address the problem of 3D object reconstruction with an innovative algorithm for determining the NBV [13]. They propose a method to enhance the reconstruction process by optimizing the position of the sensor and accommodating uncertainties in the motion of the robot. Their algorithm uses a search-based strategy to generate candidate views and selects the most suitable one for each iteration of the reconstruction process and integrates new information and constraints, such as the position, sensor properties or registration, as shown in Figure 3.

Furthermore, the paper introduces a utility function to evaluate these views, where the authors consider factors like the navigation distance and scan quality. Results of their simulation and comparisons with previous approaches demonstrate the effectiveness of the method in improving scan quality and reducing navigation distance, which highlights the potential of search-based strategies to refine the process of 3D scanning, leading to more accurate and efficient reconstructions.

The work of Kriegel et al. from 2015 present an advanced autonomous robotic system for 3D scanning that demonstrates sig-

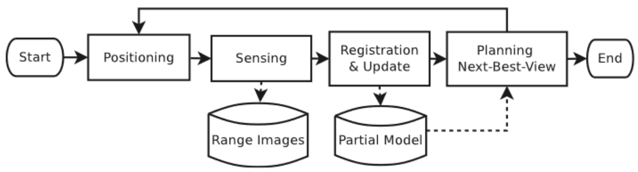

Figure 3: Illustration of the iterative object reconstruction process consisting of four main steps: positioning, scanning, registration, and planning [13].

nificant innovation in the real-time reconstruction of unknown objects [5]. The uniqueness of the system lies in its ability to stop scanning once a specific mesh quality is achieved, which optimizes both, the scanning process and the final product. Furthermore, the authors introduce a novel planning strategy for the Next Best Scan (NBS), which dynamically estimates scan paths by analyzing the evolving shape of a partially constructed triangle mesh during the scanning process.

This approach effectively combines surface-based and volumetric planning techniques. It uses the voxel space for exploration and searching for collision-free paths, while the triangle mesh helps in estimating scan paths and determining when to stop the scanning process [5]. Figure 4 shows how both, the mesh and the probabilistic voxel space (PVS) are continuously updated during the scans, which is essential for achieving a balance between exploration and accurate model reconstruction.

The contribution of Kriegel et al. is highlighted by the integration of real-time updates that minimize the errors in the position estimation and select the NBS based on information gain and surface quality [5]. Furthermore, their criteria for termination, which has the focus on the completeness and density of the model, enhance the efficiency in robotic applications.

In their follow-up paper from 2017, Vasquez-Gomez et al. introduce a novel approach to 3D object reconstruction using a mobile manipulator robot, focusing on the strategic planning of the Next Best View or State (NBVS) in 3D space [12]. Therefore, the authors implement a mobile manipulator with eight degrees of freedom, enhancing the ability to reconstruct various objects with high accuracy [12]. Furthermore, the technique involves generating a set of potential views or states within the state space, then selecting the most promising based on their estimated utility and further refine this process by employing Rapidly-exploring Random Trees (RRT) to create collision-free paths [12].

A major aspect of their approach is the robustness of the method against positioning errors, that allow more reliable and accurate scanning in complex environments using a robot. Figure 5 shows the different stages of the reconstruction process by using the Stanford Bunny as target object. It demonstrates the transformation from initial scanning to the planned NBVS and subsequent scanning. Furthermore it highlights the efficiency of the approach in navigating and scanning unknown and occupied spaces.

Vasquez-Gomez et al.'s work combines traditional motion planning with a novel approach to view respectively state selection and enhances the overall efficiency and accuracy of 3D object reconstruction, making it a crucial development in the field of robotic scanning systems [12].

3 Learning Approaches

Isler et al. introduce a novel approach in 2016 called *An Information Gain Formulation for Active Volumetric 3D Reconstruction* [4] for selecting the NBV in the field of volumetric 3D reconstruction using mobile robots and represents a significant advance in the field by integrating learning-based methods with robotic vision and

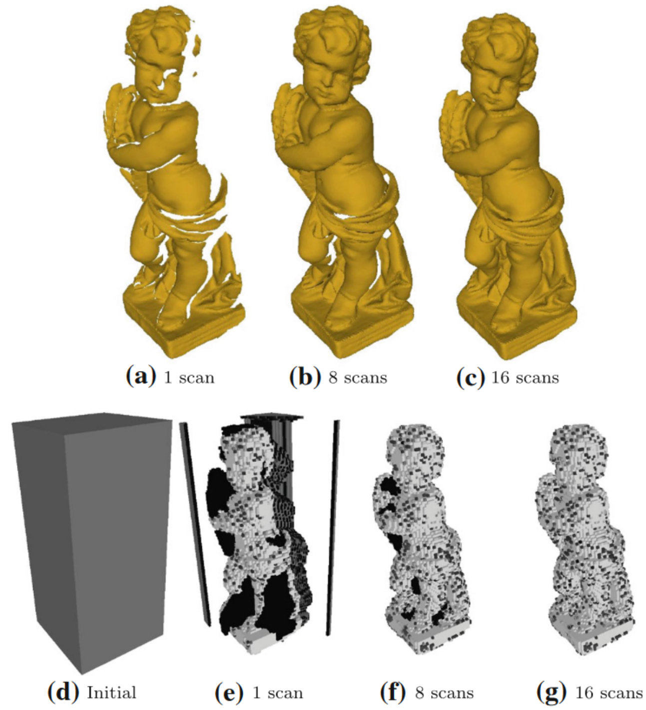

Figure 4: Illustration of the sequential progression of the model reconstruction during the scanning process, where the upper sequence shows the evolving mesh after each laser scan and the lower sequence shows the probabilistic voxel space (PVS) developing from an initial state of unknown voxels. The probability is visually encoded from black (nearly free space) gradually to white (occupied space) and free space shown as transparent [5].

navigation.

The focus of the authors is the development of a probabilistic volumetric map, which is generated in real-time and which enables the robot to evaluate the potential information gains from various candidate views [4]. This evaluation is crucial for determining the most effective position for the camera of the robot to capture new and valuable data about the object that should be reconstructed. The authors propose several metrics to quantify this information gain, including the likelihood of visibility, which evaluates the probability of successfully observing different parts of the object and the likelihood of viewing previously unseen parts, enhancing the variety of the model.

A major innovation of the work of Isler et al. is the integration of these information gain metrics with the costs of the motion of the robot by formulating utility functions that balance between exploration and efficiency. The decision making process of the robot is therefore guided by these utility functions and aim for an optimization between the discovering of new parts of the object and minimizing movement costs of the robot itself.

The authors evaluate their proposed approach through both, simulated and real experiments, and demonstrate the efficiency and flexibility of their method in various scenarios of robotic based 3D reconstruction. Furthermore, the authors contribute to the field by releasing their implementation as open source, making it adaptable and applicable to other robotic platforms and reconstruction problems [4].

In 2020, Zeng et al. address the problem of finding the NBV by proposing a deep neural network (DNN) based on point clouds, named PC-NBV [16]. With this approach, the authors can avoid the computationally intensive volumetric data transformations and ray-

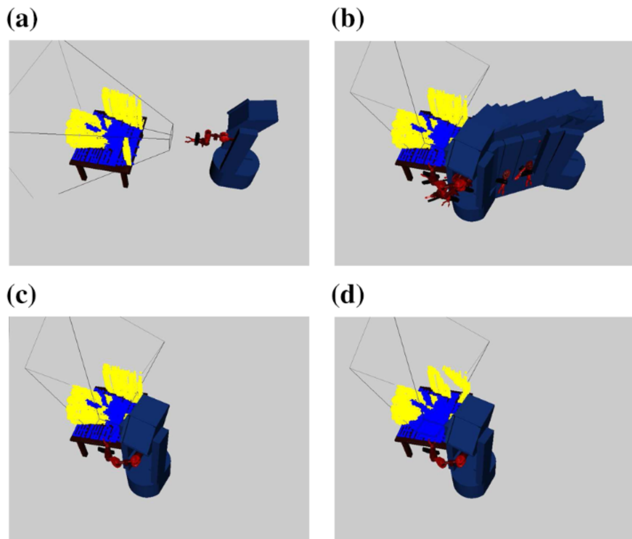

Figure 5: Illustration of the various stages of the reconstruction process of the Stanford Bunny. Starting with the initial scanning phase, followed by the planned path of the robot, the strategically chosen Next Best View or State (NBVS) and the resulting scan after this phase. Unknown areas are visually encoded in yellow, where occupied spaces are visually encoded in blue [12].

casting simulations, which are traditionally used in NBV prediction.

The basic idea is, that the DNN processes the raw data of the point cloud and uses the current states of view selection as input and directly predicts the information gain of potential views [16], as shown in Figure 6. To achieve that, the authors designed their PC-NBV to implicitly learn 3D structural patterns from their extensive training data to enhance the performance in view planning. Furthermore, the authors take care of the robustness of the network against noise and its adaptability to multi-view systems without further modifications of the network architecture or the need of retraining for varying scenarios [16].

The authors could outperform previous methods in experiments, showing a twenty-fold increase in inference speed and enhanced reconstruction quality [16]. Furthermore, tests with ShapeNet, ABC dataset, as well as complex models from MIT and Stanford database confirm that their approach outperforms other NBV in terms of efficiency as well as generalization capabilities and it also performs very good on models it has never encountered before [16].

Vasquez-Gomez et al. introduce in 2021 an innovative data-driven approach for the challenging problem of automated 3D object reconstruction, where the focus of their work is on the NBV issue in the domain of 3D scanning [14]. One main aspect of their work is the construction of geometric representations of physical objects and the critical task of determining an optimal sensor location for a complete surface observation. On the contrary to that, traditional single-image approaches for object reconstruction are indeed capable of predicting object surfaces but often result in incomplete models, especially in the case of uncommon objects like ancient artifacts or art sculptures.

The method the authors propose is using a 3D Convolutional Neural Network (3D CNN) for regressing the position of the NBV [14]. The method stands out by using previous reconstructions to train the network, rather than only relying on heuristic algorithms. The trained 3D CNN evaluates partial models and determines the position for the next optimal viewpoint to enhance the completeness and accuracy of the model [14]. Figure 7 shows the result for a selected object along with its ground truth, illustrating the precision and efficiency of the proposed technique.

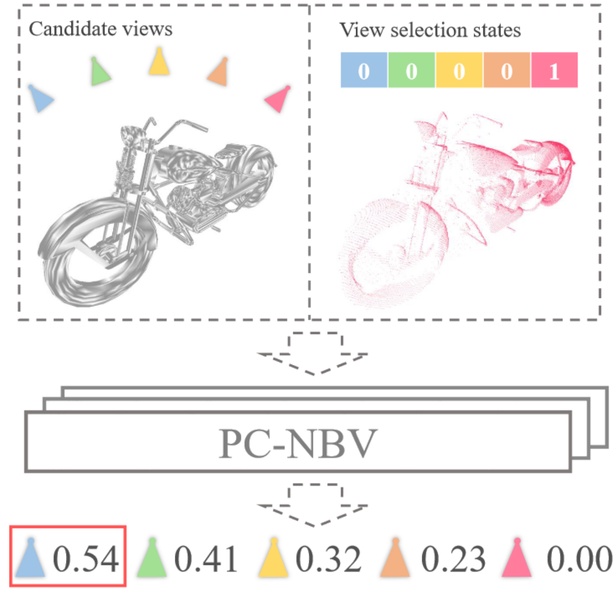

Figure 6: The illustration shows the fully assembled motorcycle model that represents the target for the reconstruction on the left, where the right side shows the current state of the reconstruction of the partial point cloud. The proposed PC-NBV network estimates the potential information gain from each possible viewpoint using the partial point cloud data and the states of view selection to guide the reconstruction process [16].

One main advantage of this method is the ability of the construction of a complete 3D model in a single scanning pass without the need of further re-scanning, which is a significant improvement over existing methods, especially for the completeness of complex structures. The experimental results by Vasquez-Gomez et al. also highlight that their method surpasses other state-of-the-art methods and provides a more efficient and accurate solution for 3D scanning of large scale structures as well as detailed and complex structures [14].

Monica and Aleotti introduce a novel approach in 2021 for solving the problem of NBV planning in 3D scanning by using a combination of deep learning and a probabilistic occupancy map [6]. They combine a Convolutional Neural Network (CNN) with ray-casting techniques to optimize the position of a depth camera for an efficient and complete scan of the environment, where in comparison, traditional methods typically rely on heuristic or simulation based algorithms [6].

In more detail, the authors invent a Convolutional Encoder-Decoder architecture for object completion, which infers the occupancy probability of spatial areas that have not yet been observed and combine that with algorithms based on ray-casting to evaluate the information gain from potential sensor viewpoint positions, which allows more accurate and detailed exploration of the environment in comparison to traditional methods [6]. The authors demonstrate the efficiency of their approach in various 2D and 3D environments using a variety of public available datasets and outperforms several existing methods, including (modified) versions of the City-CNN algorithm adapted for depth cameras. Figure 8 shows the experimental setup and the progress of environmental representation, demonstrating the applicability for real-world scenarios.

A big advantage of their method is the efficiency and predictive power and unlike in traditional NBV algorithms they do not require sensor simulation, but their method can learn environmental pri-

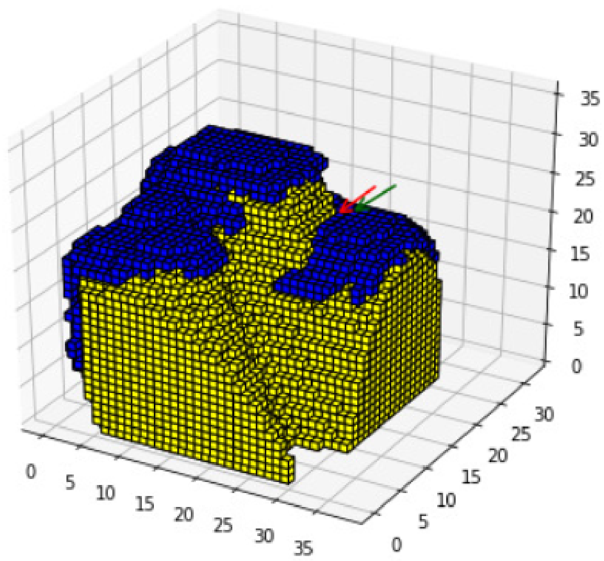

Figure 7: Illustration of predicted NBV showing the probabilistic grid with blue voxels for scanned surfaces, yellow for unknown areas. The predicted NBV for the next scan with a maximum of information gain is marked with a red arrow and a green arrow indicates the ground truth [14].

orities fast and predict the NBV by the occupancy probability of unknown voxels [6]. However, there are also limitations in the approach of Monica and Aleotti like the prediction of the view position as it does not always guarantee sufficient information gain for the convergence of the NBV and therefore could lead to an incomplete exploration of the environment.

In 2022, Song et al. published a novel approach to view path planning in the domain of 3D scanning, where they focus on large scale structures using unmanned aerial vehicle (UAV) platforms and address the problems associated with multiview stereo (MVS)-based 3D scanning [11]. Typically, traditional approaches follow an Explore-then-Exploit strategy, where a coarse model is generated in a first step in a straightforward overhead scanning and then followed by the planning of an inspection path to fully cover the complete surface of the model. This strategy is optimal in terms of the inspection path, however it cannot guarantee a complete and accurate reconstruction of the model due to factors such as occlusions, surfaces with lack of texture or inadequate parallaxes [11].

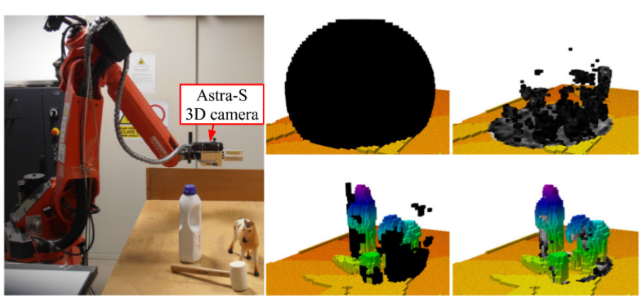

Figure 8: Illustration of the experimental setup (left), showing the environment at the start of the experiment and after the fifth NBV (middle column, top and bottom), where the right column displays the corresponding probabilistic maps predicted by the Encoder-Decoder CNN, with unknown cells in black and predicted occupied cells in grayscale, where the brightness is proportional to the occupancy probability [6].

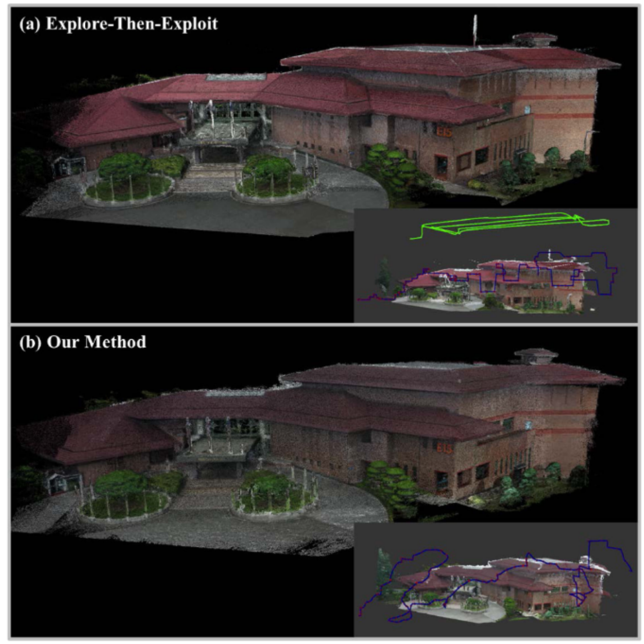

Figure 9: Comparative visualization of the 3D scanning process: (a) shows the traditional Explore-then-Exploit method using offline MVS, resulting in a two-stage model creation and (b) presents the approach proposed by Song et al. using online MVS for efficient real-time model reconstruction in a single scanning pass [11].

To overcome these limitations, the authors propose an innovative method of view path planning integrated with an online MVS reconstruction algorithm, which is capable of reconstructing the target model incrementally and online by iteratively planning view paths and analyzing the current (partial) reconstruction [11]. A unique feature for this approach is the ability of the continuous analysis of the quality of the model and the capability of identifying inaccurately reconstructed surfaces. Furthermore, it guarantees the complete coverage of these areas while maximizing the efficiency of MVS. Figure 9 demonstrates the efficiency of their approach and how superior it is in comparison to traditional Explore-then-Exploit methods in a real-world 3D scanning scenario.

A major benefit of their method is the ability to create a complete 3D model within a single scanning pass without the need of additional re-scanning, which is a significant improvement over existing methods, especially in terms of completeness of models with complex structures [11]. The experimental results of their work further support the efficiency and accuracy of their approach for 3D scanning of large scale structures, surpassing other state-of-the-art methods.

Pop and Tamas introduced in 2022 a method called *Next Best View Estimation for Volumetric Information Gain* to estimate the NBV using deep learning with focus on the volumetric estimation of parallelepipedic objects in previously unknown spaces [9]. Therefore, the authors use a data-driven deep learning approach to address the inherent complexities of 3D volumetric analysis and aim to reduce the uncertainty in the volume estimation of regular geometric shapes significantly, especially in the case of parallelepipedic or box-like objects, as shown in Figure 10.

Innovative for their approach is, that it is able to dynamically determine the most informative viewpoint in a sequence of observations, which is crucial for the optimization of the NBV estimation

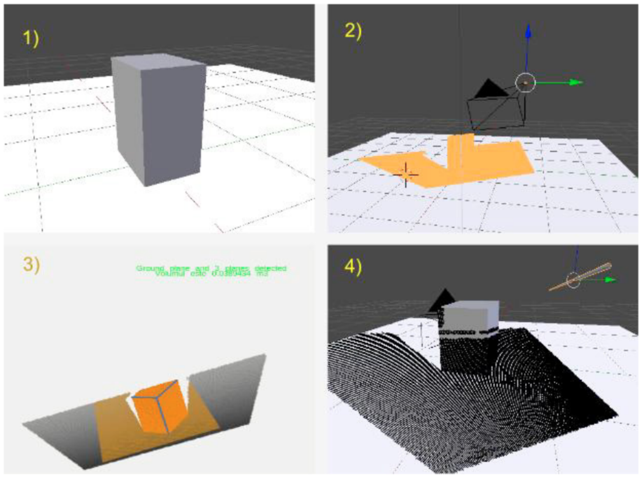

Figure 10: Illustration of the scanning process and the estimation of the NBV for a box-like object [9].

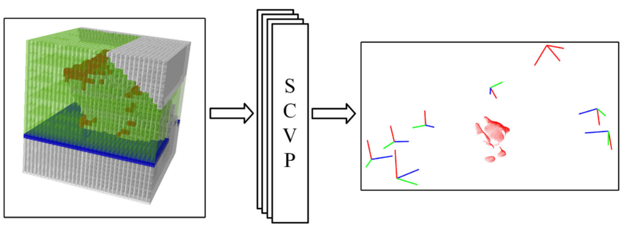

Figure 11: Illustration of the function of the SCVP network starting with the visually encoded input image displaying already scanned areas in red, the desktop in blue, empty areas in green and unknown areas in gray. The output of the SCVP network shows the scanned surface in red as wells as the visited view with a red axis and a set of predicted views for further scanning with a red-green-blue axis [7].

for the scanning of the target object. By systematically reducing uncertainties associated with the volumetric data, the proposed method enhances the accuracy as well as the completeness of the reconstruction. Another feature of their approach is the flexibility in handling different object shapes and environmental contexts which allows practical applications in fields such as robotic vision, automated inspection or spatial modeling.

In 2022, Pan et al. introduce an innovative One Shot View Planning (OSVP) method that is using deep learning to address the challenge of View Planning (VP) in active robotic vision [7]. The main challenge in VP thereby is to get a complete coverage of the surface area of the target object within an unknown environment. That is such a task, where traditional NBV planning often fail because they are unable of global path planning and they are inefficient due to the time consuming ray-casting process and high movement costs [7]. To overcome this, the authors present the SCVP neural network, which is trained on a Set-Covering (SC)-based approach to achieve OSVP. Figure 11 illustrates the process, where the neural network uses a volumetric occupancy grid as input and directly predicts the minimum number of views that are required for a complete coverage of the target object.

The authors generate the training data automatically by using methods from the SC optimization in combination with a priori geometric knowledge from 3D models. Furthermore, the authors introduce a method for the global path planning to reduce the amount of redundant movements to enhance the efficiency of the reconstruction process. Experiments with varying datasets show that their proposed SCVP approach surpasses traditional NBV methods in terms of movement costs as well as inference time and achieves at least comparable or even a superior surface coverage of the target object [7]. Further real-world tests also confirm that the proposed method is faster in the reconstruction of objects in more practical scenarios compared to other existing methods [7].

TODO:

- Han et al. [3]
- Pan et al. [8]
- Border et al. [1]

4 Comparison

TODO:

- Comparison of classic approaches
- Comparison of learning approaches
- Comparison between classic and learning approaches

5 Conclusion

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