Abstract—Obtaining 3D sensor data of complete plants or plant parts (e.g., the crop or fruit) is difficult due to their complex structure and a high degree of occlusion. However, especially for the estimation of the position and size of fruits, it is necessary to avoid occlusions as much as possible and acquire sensor information of the relevant parts. Global viewpoint planners exist that suggest a series of viewpoints to cover the regions of interest up to a certain degree, but they usually prioritize global coverage and do not emphasize the avoidance of local occlusions. On the other hand, there are approaches that aim at avoiding local occlusions, but they cannot be used in larger environments since they only reach a local maximum of coverage. In this paper, we therefore propose to combine a local, gradient-based method with global viewpoint planning to enable local occlusion avoidance while still being able to cover large areas. Our simulated experiments with a robotic arm equipped with a camera array as well as an RGB-D camera show that this combination leads to a significantly increased coverage of the regions of interest compared to just applying global coverage planning.

I. INTRODUCTION

Creating accurate 3D models of plants is difficult due to their complex structure and lots of occlusions, e.g., caused by leaves. Global viewpoint planning approaches typically evaluate the information gain of multiple viewpoints to determine the next best view. These methods can be used for large-scale viewpoint planning, but since they consider the complete environment, they can fail in complex environments with lots of local occlusions. On the other hand, local viewpoint planning methods aim at avoiding local occlusions. For example, Lehnert et al. [1] proposed to evaluate differences in images from a camera array to find the direction that maximizes the number of visible pixels of a given region of interest (ROI) and therefore reduces occlusions. These methods can effectively avoid occlusions, but can only be used locally. Once a local maximum is reached where the view on the current target can no longer be improved, they cannot be applied to plan further viewpoints.

In this paper, to get the best of both worlds we combine both global and local planning. We use 3D Move to See (3DMTS) [1] to get a movement direction that improves the target visibility whenever occlusions of the ROI are detected. When 3DMTS reaches a local maximum, we use global viewpoint planning [2] to find the next best view and plan the camera motion to this pose. The global viewpoint planning method builds up an octree of the plants with labeled ROIs, i.e., fruits, and uses this octree to sample viewpoint candidates at frontier cells. To evaluate the viewpoints, the framework applies a heuristic utility function that takes into account the expected information gain and automatically switches between ROI targeted sampling and exploration sampling, to consider general frontier voxels, depending on the estimated utility.

Figure 1 illustrates our proposed approach. On the left image, 3DMTS uses a camera array to propose a gradient that improves the visibility of a partially occluded target. On the right, our approach either decides to follow this gradient, if the expected information gain is high enough, or samples viewpoints with the global planner instead. The source code of our system is available on GitHub\(^1\).

Our contributions are the following:

- Integration of 3DMTS [1] with the global viewpoint planner [2].
- Experimental evaluation in simulated scenarios of increasing complexity, comparing the new, combined approach with the previous global viewpoint planning method without 3DMTS in terms of number of detected ROIs as well as covered ROI volume.

As the experiments with a robotic arm equipped with a camera array as well as an RGB-D camera show, the presented combination leads to a significantly increased coverage of the regions of interest compared to just applying global viewpoint planning, since the plants are covered in a locally more systematic way.

\(^1\)https://github.com/Eruvae/roi_viewpoint_planner
II. RELATED WORK

Viewpoint planning approaches can generally be divided into global coverage path planners (CPP) that compute a complete viewpoint path aiming at covering the desired area of a known environment, and local next best view (NBV) planners that can be applied to unknown environments. An example of the CPP paradigm is the method proposed by Oßwald et al. [3] that generates viewpoints by casting rays from known object voxels towards free space. The authors use a utility function that evaluates the viewpoint candidates based on the number of visible object voxels and apply a traveling salesman problem solver to compute the smallest tour of view poses that cover all observable object voxels. Similarly, Jing et al. [4] generate viewpoints based on the maximum sensor range and compute viewing directions from the surface normals of all target voxels within a certain range. Afterward, the authors proposed to randomly sample a set of points and connect nearby points with a local planner to construct a graph. Starting with the current robot pose, the neighbors with the highest ratio of expected information gain (IG) and move cost are added to the solution path until the desired coverage is reached. There are a variety of use cases for CPP methods, i.e., path planning for cleaning robots [5] or covering a complete agricultural field with machines for crop farming [6]. Note that such CPP approaches typically rely on a given representation of the environment. However, in our agricultural use case for fruit size estimation, the environment typically changes significantly with the growth of the plants and their fruits. Therefore, in our work, we do not assume a map of the environment to be given beforehand. Instead, our framework builds a 3D map of the plants during operation.

NBV approaches, in general, either rely only on current sensor information or build a map of the environment while traversing it and use this map to decide on the next view. For example, Lehner et al. [1] use an array of cameras and determine the size of a given target in each frame. Based on that, their system computes a gradient to determine the direction for which the visible area of the target is increased. In our work, we combine this approach for local viewpoint planning to deal with occlusions with global viewpoint planning using a map constructed during operation [2]. In addition to the 3D structure of the plants, the map also represents the detected regions of interest, i.e., fruits, which are used for sampling viewpoints aiming at subsequently covering all fruits of a set of plants. Wang et al. [7] use both current sensor information and a built map for planning and proposed to combine an entropy-based hand-crafted metric considering ray tracing from the generated map with a local metric using a convolutional neural network that takes the current depth image as input. The two metrics are combined to evaluate candidate poses generated in the vicinity of the current camera position. While this approach combines a local planning metric with a global, map-based algorithm, the learned image-based metric is not specifically targeted at avoiding occlusions. Instead, it is meant to give an educated guess about the information gain in starting phases of planning, where information provided by the map is limited.

Monica et al. [8] consider the task of exploring the environment around a given, single object of interest with a known pose while performing 3D shape reconstruction of the initially unknown surrounding. The authors also apply an exploration behavior for unknown parts of the environment, but mainly to find new paths that may enable observations of the object of interest. Furthermore, Monica et al. [9] presented an NBV method that samples viewpoints from frontiers to unknown space. We use a similar technique to sample viewpoints for unexplored regions independently of the detected ROIs when those have been sufficiently explored. Palazzolo et al. [10] sample viewpoints on the hull of the currently known map of an area of interest and select the best point based on the estimated utility taking into account the expected IG. Bircher et al. [11] proposed to use a rapidly exploring random tree and estimate the exploration potential of a sequence of points based on the unmapped volume that can be covered at the nodes along the branches of the tree.

Similar to the approach of Sukkar et al. [12] who detect apples as ROIs through color thresholding, we also rely on automatic detection of the ROIs for viewpoint planning. Sukkar et al. proposed to evaluate viewpoints based on a weighted sum of exploration information, which is calculated from the number of visible voxels that have not been previously explored, and ROI information, which evaluates the visibility of ROIs from the selected viewpoints. This evaluation metric is then used to plan a sequence of viewpoints for multiple robot arms by utilizing a decentralized Monte Carlo tree search algorithm.

Some work also focuses specifically on viewpoint planning or analysis for fruit harvesting. Bulanon et al. [13] compare the visibility of citrus fruits when recorded with different combinations of multiple fixed cameras. Hemming et al. [14] place a single camera at multiple angles to determine which views provide the least occlusion for sweet peppers. Both approaches deliver an offline analysis of the average visibility for different views in a practical application but do not provide a method to select viewpoints online based on an observation. Kurtser and Edan [15] propose an algorithm for sensing peppers that uses camera images to determine whether additional viewpoints are necessary and selects the next viewpoint from a predefined set with the best cost to benefit ratio.

In contrast to all the methods presented above, our approach is the first one that combines an algorithm specifically targeted at avoiding local occlusions with a global, map-based approach that also considers the detected ROIs.

III. SYSTEM OVERVIEW

The goal of our work is to detect fruits of plants as regions of interest (ROI) and acquire 3D data to estimate their volume. In our application scenario, we currently use sweet pepper plants. In our previously presented approach [2], we
used depth and color images of an RGB-D camera as an input to generate a 3D map with marked ROIs from which we sample viewpoints. In the newly developed approach, we additionally apply 3D Move to See (3DMTS) [1] to better deal with local occlusions. 3DMTS relies on multiple camera images at different positions as input.

Figure 2 shows an overview of our framework and the integration of global viewpoint planning with 3DMTS. Global viewpoint planning uses the depth and color image of the RGB-D camera as input, while the camera array outputs nine color images for 3DMTS. The sweet peppers are detected in all color images (see Sec. IV-A). For the global planner, the detection is combined with the depth image to generate a point cloud with marked ROIs. The generated point cloud is forwarded to the global planning module, which uses the incoming information to build up a 3D map of the environment in the form of an octree. The octree stores both, occupancy and ROI information as described in Sec. IV-B. The planner requests a direction suggestion from 3DMTS, which is introduced in Sec. V-A. Depending on the change of the visibility of the target in the different images of the camera array, the robot arm with the cameras is moved in that direction. Otherwise, targets and viewpoints are sampled and evaluated using global viewpoint planning by sampling from frontier voxels, see Sec. V for details.

Using the MoveIt framework [16], our system plans a path for the robot arm to the best found viewpoint. The planned path is then executed by the robot controller.

**IV. PRELIMINARIES**

**A. ROI Detection**

Both 3DMTS and the global viewpoint planning approach depend on detected sweet peppers as the targets. Since the plants in our simulation experiments only had red peppers, we employ a simple color detection and find red pixels using the HSI (hue, saturation, color) color space. For the global viewpoint planning, the detected regions in the color image are transformed to 3D by using the corresponding depth image. A voxel grid filter is utilized to adjust the point clouds of the detected fruits to the resolution of the octree. For 3DMTS, only the color images are used, the detections are grouped into clusters, and the largest cluster in the central image is used as the target. For the other images in the camera array, the target is the cluster closest to the one in the central image.

**B. Octree for Viewpoint Planning**

For the global planner and fruit position and size estimation, our system builds a custom octree to store 3D information about occupancy and ROIs. The octree is updated after each movement step using a point cloud with marked ROIs that are generated as described in Sec. IV-A. The implementation is built on the OctoMap framework [17] and the octree stores occupancy and ROI log-odds. The occupancy value is updated by casting rays from the sensor origin to the points of the point cloud. For all nodes encountered by the rays, the occupancy log-odds are decreased, while for the nodes corresponding to the points of the point cloud, they are increased. Nodes with positive log-odds are considered as occupied, nodes with negative log-odds as free. The ROI probability is updated only for the nodes directly on the scanned points. For all points marked as ROI, the log-odds are increased, while for all other points, they are decreased. All nodes with log-odds above a threshold are considered as ROIs.

3DMTS does not use the octree itself, but the octree is updated with new sensor information after each step taken by 3DMTS.

**V. COMBINED VIEWPOINT PLANNING**

We now describe our combined viewpoint planning approach. In each step, we first attempt to avoid occlusions with 3DMTS if a target is visible (Sec. V-A). If no target is visible or no direction that improves the view is found, our system employs global planning instead and explores targets in the vicinity of the ROIs (Sec. V-B). If no viewpoints are found that increase the information gain, more general exploration viewpoints to discover new ROIs are sampled (Sec. V-C). In both cases, we use a utility function to evaluate the viewpoints and determine the best one (Sec. V-D).

**A. 3D Move to See**

In order to enable avoiding occlusions locally, we integrated the 3DMTS approach of Lehner et al. [1], which uses a camera array to find directions that locally improve the view on a target. In each image of the camera array, fruits are detected as potential targets, as discussed in Sec. IV-A. The cameras in the array are attached as illustrated in Fig. 3, where the offset vector $\mathbf{o} = [0.027, 0.027, 0.03]$ (for x, y and z respectively) is the same as in [1].

We modified the original 3DMTS algorithm [1] as described in the following. Originally, the objective function of
The dot product of the weights and the objective function deltas is then computed to determine a scalar delta value $\Delta f_m$.

$$\Delta f_m = w \cdot \Delta f$$  \hspace{1cm} (5)

If 3DMTS is enabled, whenever the robot reaches a new viewpoint, the planner requests the gradient $\nabla f^*$ with the associated weighted delta value $\Delta f_m$. If the latter is above a threshold, the arm moves towards the gradient for a certain step length. The process is repeated until delta is below the threshold, the robot cannot move in the specified direction, or a maximum number of steps is reached. After that, a new viewpoint is sampled using global viewpoint planning [2], which is summarized in the following.

B. ROI Targeted Sampling

For the ROI targeted sampling, our system uses the frontiers of already detected ROIs as targets. ROI frontiers are free voxels that have both an ROI and an unknown neighbor. For each target, viewpoints are sampled by casting rays in a random direction with the specified sensor range as length. If the resulting points are within the robot’s workspace, they are considered as potential next best view, and their camera orientation is determined by rotating it so that the viewing direction aligns with the vector from the viewpoint to the target. Furthermore, a ray is cast between the viewpoint and the target point. If the ray passes an occupied node, the viewpoint is discarded, as the target is occluded.

C. Exploration Sampling

To discover new ROIs, the viewpoint planning considers general frontier voxels within the so-called exploration sampling. General frontiers are determined as free cells with both occupied and unknown neighbor cells. In this way, our system is able to find new ROIs after all previous ROIs have been sufficiently explored. After all targets have been collected, potential viewpoints are sampled and their directions are determined in the same way as for the ROI targeted sampling.

D. Viewpoint Evaluation

To evaluate the sampled views, we need to estimate their utility. To do so, we first cast rays from the viewpoint within a specified field of view of the sensor to estimate their information gain (IG). Based on the rays, we calculate the IG for the encountered voxels using the proximity count metric [2], [18]. Each unknown voxel along the rays is given an initial weight of 0.5 and if it is within a specified distance $d_{\text{max}}$ from a known ROI, the weight $w$ is increased as follows

$$w = 0.5 + 0.5 \cdot \frac{d_{\text{max}} - d}{d_{\text{max}}}$$  \hspace{1cm} (6)

where $d$ is its distance of the current voxel to the ROI. In this way, the weight of voxels close to observed ROIs is increased. Known voxels receive a weight of 0.
Algorithm 1: Viewpoint planning

\[
m2sMoves = 0;
\]
\[
\text{while True do}
\]
\[
\quad \text{if } m2sMoves < \text{maxMoves then}
\]
\[
\quad \quad \text{dir, delta = callMoveToSee();}
\]
\[
\quad \quad \text{if delta > deltaThresh then}
\]
\[
\quad \quad \quad \text{moveInDir(dir);}
\]
\[
\quad \quad \quad \text{m2sMoves++;}
\]
\[
\quad \quad \quad \text{continue;}
\]
\[
\quad \quad \text{end}
\]
\[
\quad \text{end}
\]
\[
\text{m2sMoves} = 0;
\]
\[
\text{chosenVps} = \text{sampleGlobalVps(nVps)};
\]
\[
\text{while max(chosenVps) > utilityThresh do}
\]
\[
\quad \text{vp = extractMax(chosenVps);}
\]
\[
\quad \text{if moveToPose(vp) then}
\]
\[
\quad \quad \text{break;}
\]
\[
\quad \text{end}
\]
\[
\text{end}
\]

Considering the sum of the weights of the voxels along the rays \(W_r\), the information gain of a viewpoint is defined as

\[
IG = \frac{1}{|R|} \sum_{r \in R} \frac{W_r}{N_r}
\]  \hspace{1cm} (7)

where \(N_r\) is the total number of nodes on the considered ray.

In addition to the IG, we compute the cost \(C\) for reaching the point. Since computing the joint trajectory to reach the viewpoint is too time-consuming to be done for each sampled view, we use the Euclidean distance of the camera to the point as an approximation. Finally, the utility of a viewpoint is computed as the weighted sum of the IG and the cost scaled by a factor \(\alpha\):

\[
U = IG - \alpha \cdot C
\]  \hspace{1cm} (8)

E. Viewpoint Selection

In our proposed approach, we combine 3DMTS for local occlusion avoidance with the two global sampling methods, ROI targeted sampling and exploration sampling, as summarized in Alg. 1. As long as 3DMTS does not exceed a maximum number of steps, our planning system requests a direction suggestion from it. If the returned delta value is above the specified threshold, the camera is moved in that direction. Otherwise, global viewpoint sampling is executed using ROI targeted and exploration sampling, and the best viewpoint based on the computed utility is selected. If no plan to reach this viewpoint with the arm can be computed, the next best viewpoint is used, until either the planner is successful, or no viewpoints above the utility threshold are left. In the latter case, new viewpoints are sampled.

VI. EXPERIMENTS

A. Simulated Environment

We evaluated our viewpoint planning approach in simulated scenarios with an RGB-D camera as well as a camera array mounted on a robotic arm, i.e., the UR5e arm from Universal Robots. The arm has six degrees of freedom and a reach of 85 cm. To compute the workspace of the arm, the first 5 joints were sampled at a resolution of 10°. The 6th joint was ignored, as it only rotates the camera and therefore does not change the viewpoint. Like in [2], we set the resolution of the octree that stores occupancy and ROI information to 1 cm.

Three environments with different workspaces were designed for the simulated experiments. The first two environments are the ones we used in [2], the third one was added as a more complex scenario. In the first scenario, the arm is placed on top of a static 85 cm high pole (see Fig. 4a). This allows the arm to exploit most of its workspace, except for the part blocked by the pole. The first 5 joints were sampled at a resolution of 10°. The 6th joint was ignored, as it only rotates the camera and therefore does not change the viewpoint. Like in [2], we set the resolution of the octree that stores occupancy and ROI information to 1 cm.

The third scenario has the same setup for the arm, but instead of only four plants with a lot of space in between, two rows of six plants each are used. Only every second plant in each row has fruits.

B. Evaluation

For the evaluation, we use two of the metrics from [2]:
Fig. 5: Results for Scenario 1. For each tested approach, 20 trials with a duration of 2 minutes each were performed. The plots show the average results. Here, the results with 3DMTS are slightly below the ones from the global planner, but the difference is not significant.

Fig. 6: Results for Scenario 2. Like in Scenario 1, 20 trials were performed for each approach and the plots show the average results. As can be seen, the covered ROI volume of the combined approach is consistently above the one from the global planner. This difference at the end of the planning period is significant.

Fig. 7: Results for Scenario 3. Here, the difference between the combined approach and the global planner is even clearer. The covered ROI volume is significantly higher and, furthermore, the number of detected ROIs is significantly improved.

TABLE I: Quantitative results over 20 trials. Bold values show a significant improvement compared to the other approach.

| Scenario | # Det. ROIs | Covered ROI volume |
|----------|-------------|---------------------|
| Sc. 1 (14 ROIs) | 13.0 ± 0.7 | 0.72 ± 0.06 |
| | 12.8 ± 0.7 | 0.75 ± 0.07 |
| Sc. 2 (28 ROIs) | 25.6 ± 3.1 | 0.76 ± 0.14 |
| | 25.0 ± 3.3 | 0.71 ± 0.13 |
| Sc. 3 (42 ROIs) | 33.9 ± 4.3 | 0.50 ± 0.13 |
| | 28.6 ± 5.4 | 0.37 ± 0.07 |

VII. CONCLUSIONS

We introduced a novel viewpoint planning strategy that combines 3DMTS as an approach for local occlusion avoidance with a global planner to allow larger coverage. Our experiments show that combining these strategies leads to an improved fruit coverage in large, complex environments compared to using only a global planner.
For future work, we plan to implement this approach on our existing robotic platform to enable more accurate scans of fruits in a commercial glasshouse environment.

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