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NBV Planning for the detection of hidden tomatoes in greenhouses with AgriSEE

Cañadas-Aránega, Fernando[a,*], Border, Rowan[b], Blanco-Claraco, José L.[c], Moreno-Úbeda, José C.[a]

[a] *University of Almería, Department of Informatics, CIESOL, ceia3, Ctra. Sacramento s/n, 04120, Almería, Spain. (fernando.ca, jcmoreno)@ual.es*
[b] *Vision for Robotics Lab (V4RL), University of Cyprus, Kallipoleos 75, Nicosia 1678, Cyprus. border.rowan@ucy.ac.cy*
[c] *University of Almería, Department of Engineering, CIESOL, ceia3, Ctra. Sacramento s/n, 04120, Almería, Spain. jlblanco@ual.es*

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Resumen

La agricultura intensiva bajo invernadero es clave para sostener el crecimiento poblacional global. Sin embargo, el aumento de la población exige transformar los sistemas agrícolas hacia modelos más eficientes y sostenibles. En este contexto, la automatización, y en particular la robótica, se presenta como una solución para enfrentar retos del sector, especialmente en tareas monótonas, insalubres o peligrosas (*DDD: Dull, Dirty, Dangerous*). Este estudio aborda la implementación de un algoritmo Next Best View (NBV), concretamente SEE++, con el fin de generar modelos 3D mediante nubes de puntos. Se utiliza un brazo robótico UR3 de Universal Robots equipado con una cámara Intel RealSense L515, escaneando frutos dentro de un entorno de invernadero simulado. La metodología permite determinar dinámicamente la siguiente mejor vista para optimizar el proceso de escaneo. Los resultados muestran que el sistema puede detectar tomates en escenarios dinámicos simulados donde los métodos tradicionales fallan ante objetos parcialmente ocultos, sentando las bases para su futura aplicación en tareas de recolección.

Palabras clave: Robótica agrícola, Robots móviles, Robots manipuladores, Planificación de trayectorias y caminos, Construcción de mapas

NBV Planning for the detection of hidden tomatoes in greenhouses with AgriSEE

Abstract

Intensive greenhouse agriculture is essential to support global population growth. However, the increasing population demands a transformation of current agricultural systems into more efficient and sustainable models. In this context, automation, particularly robotics, emerges as a key solution to address the challenges of the sector, especially tasks that are monotonous, unhealthy, or hazardous (DDD: Dull, Dirty, Dangerous). This study focuses on implementing a Next Best View (NBV) planning algorithm, specifically SEE++, to generate 3D models using point clouds. A Universal Robots UR3 robotic arm is equipped with an Intel RealSense L515 camera to scan fruits in a simulated greenhouse environment. The proposed methodology dynamically determines the next best view to optimise the scanning process. The results demonstrate the system's ability to detect tomatoes in dynamic simulation environments, where traditional methods fail to accurately locate partially occluded objects. This work lays the foundation for future applications in automated harvesting.

Keywords: Agricultural robotics, Mobile robots, Robots manipulators, Trajectory and Path Planning, Map building

1. Introduction

The global area dedicated to greenhouse cultivation currently exceeds 490,000 hectares, with an estimated annual growth rate of 19% since 1980. Approximately 20% of this area is located in the southeastern region of the Iberian Peninsula in Spain, where greenhouse vegetable production

*Corresponding author: fernando.ca@ual.es

alone accounts for over 77,000 hectares (Moreno Úbeda et al., 2022). The predominant model in Spain is the Mediterranean-type greenhouse, which represents 92% of global greenhouse coverage and is characterised by low to medium technological levels (Sánchez-Molina et al., 2024). However, this model faces increasing competition from both highly automated systems, such as those developed in the Netherlands, and low-cost alternatives implemented in countries like Morocco or Turkey. Improving crop productivity and quality has become essential to maintaining the competitiveness of the Spanish market. Moreover, the growing demand for food—both for humans and animals—the shortage of labor in rural areas, and the rising interest in autonomous systems, partly driven by the COVID-19 pandemic, further reinforce the need to explore such technologies (Aranega et al., 2024).

Greenhouses exhibit a certain degree of structural organization but differ significantly from highly controlled industrial environments, such as automotive assembly lines. This distinction presents specific challenges that require the integration of highly automated machinery to ensure the efficient development of greenhouse agriculture. A key aspect in the deployment of robotic systems in such environments is the selection of appropriate sensors capable of detecting obstacles and localizing the robot in dynamic settings with limited communication (Ko et al., 2014; Abanay et al., 2022; Moreno et al., 2024). These systems must not only navigate autonomously but also perform complex tasks such as automated crop harvesting.

Maximizing the efficient use of available space within the greenhouse becomes a critical strategy for achieving optimal productivity, which in turn demands the adaptation of task-specific algorithms to the particular environmental conditions. Research on robotic tasks in greenhouses has been ongoing since 1987. It is estimated that up to 80% of operational time during the crop season is devoted to monitoring and fruit harvesting, the latter being one of the most studied tasks by the authors (Cañadas-Aránega et al., 2024c,b). The most successful developments have incorporated robotic arms for automated harvesting, typically equipped with RGB-D cameras for shape and depth detection, and/or LiDAR sensors for 3D scanning and environmental mapping (Rong et al., 2022).

Accurate environmental mapping is essential to determine the 3D position of fruits, which are then processed by object detection and classification algorithms. In Rong et al. (2022), the YOLOv5 algorithm (Ge et al., 2021) is used to detect tomato clusters from 2D images and estimate their position. In Zheng et al. (2024), the YOLOv5_SE variant is employed to identify tomatoes using RGB and depth images. Similarly, Liu et al. (2024) applies SLAM techniques to estimate distances between fruits using 2D LiDAR data. However, accurately determining the total number of fruits remains a challenge, as many are occluded and can not be detected by these technologies. This limitation has driven the development of algorithms capable of estimating occlusions and improving the efficiency of automated harvesting (Aguilar et al., 2024).

In this scenario, having an accurate 3D model of the fruit is crucial for enabling the robotic arm to plan and execute efficient trajectories. However, acquiring high-quality 3D observations remains a challenge regardless of the final application. Scene reconstruction, commonly understood as the observation of a bounded spatial region, is achieved by integrating multiple 3D measurements taken from different viewpoints. An observation is considered complete when sufficient coverage of all visible surfaces is obtained. The final coverage depends on several factors, including sensor capabilities, scene geometry, and the viewpoints from which measurements are captured (Border et al., 2018). Algorithmic view selection techniques are employed to reduce uncertainty by intelligently identifying the most informative viewpoints and selecting the next observation position that yields the greatest incremental improvement in the scene reconstruction. This is known as the Next Best View (NBV) planning problem.

This paper presents a further step forward for Agriculture Surface Edge Explorer (AgriSEE) presented in Cañadas-Aránega et al. (2025) and advances it further. In this case, a simulation environment is developed in RViz, featuring a differential-drive mobile Husky robot equipped with a UR3 robotic arm and an Intel RealSense L515 camera mounted on the end effector inside a greenhouse. The main objective is to analyse the 3D reconstruction of a tomato plant with fruit clusters using SEE++, the NBV algorithm described in Border et al. (2018) and Border and Gammell (2024). The reconstruction is performed based on point clouds generated from localised scans taken from multiple viewpoints. The experimental setup involves a simulated greenhouse environment representative of typical tomato crops in the Almería region (at the South of Spain). The results demonstrate that the AgriSEE algorithm can produce high-quality 3D observations, even in the presence of occluding elements such as leaves, providing a solid foundation for the future development of algorithms aimed at detecting and localizing partially occluded fruits (Border et al., 2024).

This paper is organized as follows: Section 2 provides an overview of the project in which this study is framed and details of the simulation experiments. Section 3 presents the simulation results for the models derived from the experimental setup. Finally, Section 4 outlines the main conclusions of this research.

2. Materials and methods

This subsection describes the materials and methods employed in this paper.

2.1. Materials

This subsection describes the materials employed during the execution of the simulation.

2.1.1. Greenhouse

To perform the simulation, a 3D model of the experimental greenhouse belonging to the AgroConnect initiative is used. This greenhouse is located in the municipality of La Cañada de San Urbano, Almería, within the facilities of IFAPA (Andalusian Institute of Agricultural, Fisheries, Food and Organic Production Research and Training), adjacent to the University of Almería. The structure corresponds to the Mediterranean-type greenhouse, which is commonly found in this region of the Iberian Peninsula. It covers an area of 1,850 square meters and features a robust steel frame and a polyethylene roof.

The interior includes a 2 meter wide central pathway, serving as the main access route, which leads to eleven aisles on each side. The aisles on the northern side are 2 meters wide and 12.5 meters long, while those on the southern side are 2 meters wide and 22.5 meters in length (Cañadas-Aránega et al., 2024a).

Accurate 3D modelling of the greenhouse is essential when simulating the behaviour of a mobile robot in the RViz environment. Figure 1 presents a SolidWorks representation of the structure, created using data collected from the real greenhouse described in Cañadas-Aránega et al. (2024), while Figure 8a shows the 3D model of a tomato plant, and Figure 8b shows the tomato to be scanned. This model meticulously reproduces every aspect of the greenhouse architecture, capturing its structural details with high fidelity, including the key support columns and diagonal reinforcement elements, faithfully mirroring their real-world counterparts. It is important to note that for this work, in order to speed up the simulation, only one plant with different bunches of tomatoes was used and only one bunch of tomatoes was scanned.

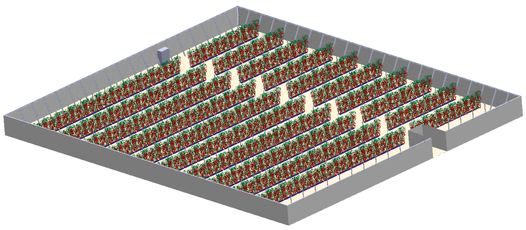
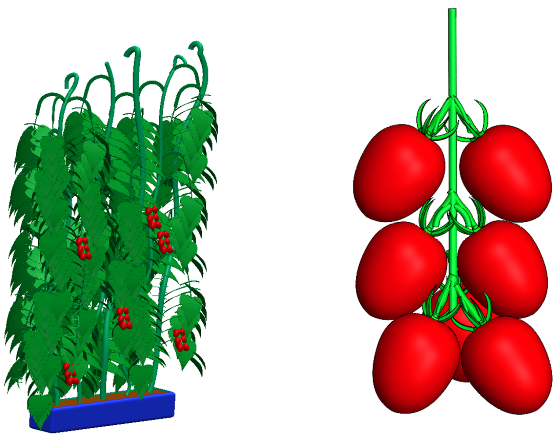


Figure 1: 3D AgroConnect Greenhouse model



(a) 3D tomato plant (b) 3D tomato cluster

Figure 2: Enviroment items

2.1.2. *Husky mobile robot, UR3 Robotics arm and Intel Realsense L515*

For this study, the Husky differential mobile robot, developed by Clearpath Robotics, was used within an RViz simulation environment. The Husky is a robust four-wheel drive platform widely adopted in research for navigation tasks in unstructured environments. In this simulation, the mobile robot is equipped with a UR3 robotic arm, enabling it to interact with the environment. These characteristics make it particularly suitable for tasks such as inspection, 3D scanning, and precise manipulation in constrained spaces (Figure 3).

Figure 3: UR3 mounted on Husky mobile robot

Also, an Intel RealSense L515 camera, based on time-of-flight technology, was mounted on the UR3 robotic arm to capture depth data during motion. Its high-resolution depth and RGB capabilities made it suitable for indoor 3D scanning. Data acquisition and synchronisation were handled using the Intel RealSense SDK 2.0 and ROS Noetic (Figure 4).

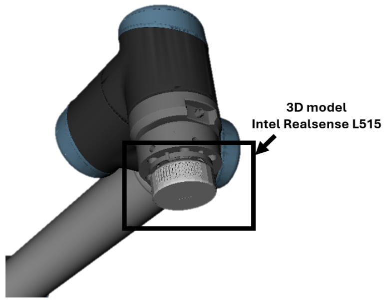


Figure 4: 3D model of the Intel RealSense L515

2.2. *Methods*

This subsection describes the methods used during the execution of the simulation.

2.2.1. *Surface Edge Explorer (SEE++)*

SEE++ is a measurement-driven NBV approach that plans viewpoints directly from sensor data to ensure a minimum required point density is obtained from the observed surface. The algorithm performs surface scanning by classifying each point individually based on the local density of neighbouring measurements. Points located at the interface between observed and unobserved regions are identified as frontier points. New viewpoints are proposed to acquire additional measurements around these frontier regions. The initial viewpoints are selected based on the geometry of the local surface and can be refined to proactively avoid known occlusions (Border et al., 2018). The experiment evaluates the 3D reconstruction of a tomato plant obtained through the application of the SEE++ algorithm in the simulation. The tested configurations were optimised to maximise surface coverage while minimising the number of viewpoints and total scanning time. Effective scanning of tomato plants requires adapting SEE to the specific geometric characteristics of the fruit. Each LiDAR measurement is classified as a core (c), frontier (f), or outlier (o) point, following the classification strategy proposed in Border and Gammell (2024). This novel breakthrough is called SEE++ as it integrates an adaptation to a real case, and will be the model to be used in this work. For a frontier point (f) to be considered valid, its normal surface vector, $\mathbf{e}_{\mathrm{n}}$, must point outwards from the tomato surface. After acquiring multiple scans from different viewpoints, SEE++ aggregates the collected data and refines the reconstruction using the Iterative Closest Point (ICP) algorithm, resulting in a consolidated 3D model of the plant (Border et al., 2024).

2.2.2. ROS and Rviz

The robotic system was developed using ROS Noetic, the latest distribution compatible with Ubuntu 20.04 LTS and designed for x86_64 architectures. ROS Noetic provided the communication framework between the nodes, enabling seamless integration of the UR3 robotic arm, the Intel RealSense L515 camera, and the data processing modules within the simulation environment. The system architecture was built on ROS topics, services, and custom messages to synchronise robot kinematics with visual and depth data streams (Mishenin et al., 2024).

RViz, the official visualization tool for ROS, was used to display the environment, the 3D model of the robotic arm, and sensor data. The URDF model of the UR3 manipulator and the point cloud streams from the RealSense camera were loaded, enabling real-time monitoring of both the robot's movements and the environment scanning process. Additionally, visual markers were employed to represent trajectories, key positions, and points of interest.

3. Simulation experiments

In this section, the process carried out to perform the simulation, as well as the results obtained, are described.

3.1. Environment design

For the design of the simulated environment, the `URDF` files corresponding to the Husky and UR3 robots were loaded, establishing a hierarchical structure that defines a coherent kinematic chain. This organization is crucial for the accurate execution of NBV planning algorithm, thereby ensuring the validity of the obtained results. Next, the target object was defined: a complete tomato plant. Only one tomato plant was included in this simulation to reduce the computational cost, which is sufficient to validate the proposed method. The 3D model of the plant was created in SolidWorks, generating an `.stl` file. Subsequently, this model was centred and scaled using CloudCompare, a tool that enables efficient and accurate transformations. The adjusted `.stl` file was then imported into Blender, where additional scaling and texture were applied, resulting in a `.dae` file suitable for incorporation into `URDF`. Finally, all the `joint` elements were defined by the established kinematic chain, resulting in the simulation shown in Figure 5.

Figure 5: Husky, ur3 and plant simulation

The scanning area was defined to enable the algorithm to capture the occluded tomato within the scene. The scanning volume was manually specified, positioning the robot at a distance consistent with that expected in a real greenhouse scenario. Figure 6 illustrates the defined scanning volume, where efforts were made to minimize the interaction with surrounding leaves.

Figure 6: Scanning volume

To enable safe interaction within the environment, specific collision objects were designed to allow ROS to detect potential collisions accurately. A rectangular volume was defined For the plant to emulate its occupied space, preventing the motion planner from colliding with the leaves. A concentric cylindrical volume was created around the tomato cluster to ensure that the UR3 does not approach too closely, which could result in measurements falling below the sensor's minimum range. A collision platform was added to cover the entire upper base the Husky robot, thereby avoiding any interference from the UR3 and preventing it from crossing this physical boundary. All of the collision boundaries were configured in the SRDF file, resulting in a complete and operational environment suitable for experimental trials.

3.2. Results

The AgriSEE algorithm was adapted to the specific objective once the entire environment was configured. As defined in Border and Gammell (2024), SEE++ aims to obtain observations of the scene with a minimum measurement density across all visible surfaces. This measurement density, ρ, is computed within a sphere of radius r. Sensor readings are acquired from a viewing distance d, and spaced at a minimum distance ϵ. As previously mentioned, given the use of the UR3 model—which has a smaller volume than the robot used in the reference work—the distance d has been reduced by 40%, which consequently lowers the value of ϵ. Since the scanned tomato is also a small object, the radius r has been decreased by 15% to improve AgriSEE's efficiency. Figure 7 presents a view obtained in the simulation using these parameters, where the initial scan of the tomato cluster is visible. Additionally, a *video*[1] is available, showing the scan processing carried out by the algorithm.

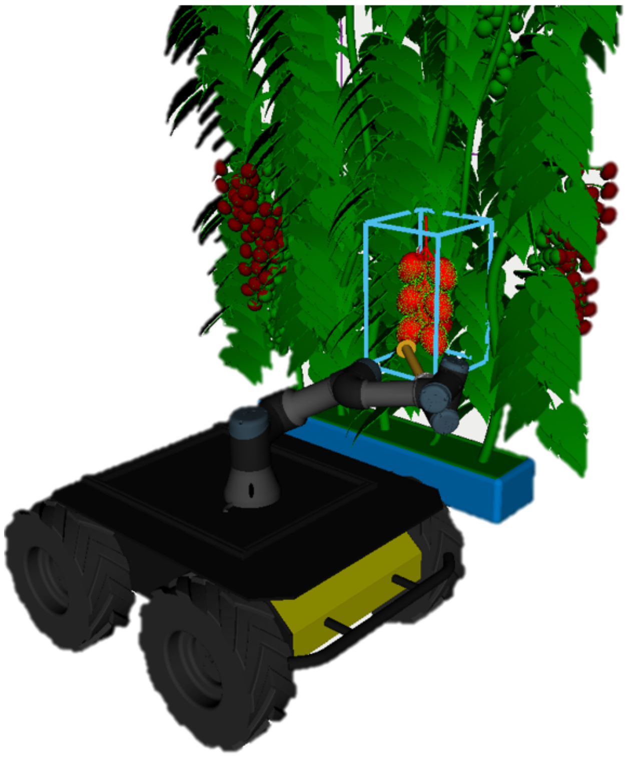
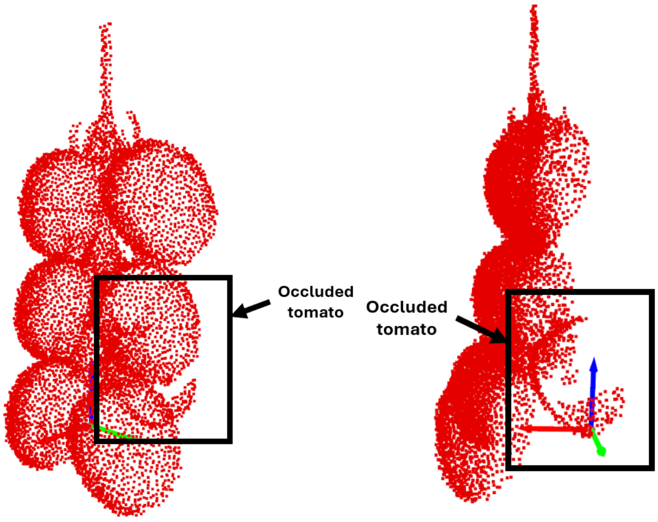


Figure 7: AgriSEE scanned tomato cluster

Once the scanning process is completed the resulting `.ply` file is processed using the Point Cloud Library (PCL) algorithm (Rusu and Cousins, 2011) to remove the points corresponding to the leaves, leaving only the tomato cluster. The result is shown in Figure 8.



(a) Isometric view (b) Lateral view

Figure 8: Scanned tomato

Although the occluded tomato is not fully detected, a significant portion of it has been identified through the point cloud generated by AgriSEE. Compared to the ground truth, 63% of the 3D model of the tomato plant was examined in 72 seconds in 12 views, covering a total distance of 8 metres. This result provides the foundation for identifying and recognizing the partial position of occluded tomatoes by providing their spatial coordinates. Such an outcome addresses one of the significant challenges in current agricultural robotics, as it enables the detection of nearly 100% of the tomatoes on each plant. Consequently, this advancement opens the door to the automated harvesting of a wider variety of horticultural crops, overcoming the limitations of previous approaches, which were mainly effective only for fruits growing in isolated or non-clustered arrangements.

4. Conclusions

This study has demonstrated the feasibility of applying the AgriSEE algorithm within a simulated greenhouse environment for the 3D reconstruction of tomato plants, using a mobile robot equipped with a UR3 robotic arm and an Intel RealSense L515 camera. The structural environment in which agricultural robots operate has been faithfully replicated by employing a realistic 3D model of the experimental greenhouse from the AgroConnect initiative.

The results show that AgriSEE is capable of identifying frontier points in partially occluded regions, such as tomato clusters hidden among leaves, and generating new viewpoints that improve surface coverage. The adaptation of the algorithm's parameters to the scale of both the robot and the scanned object—reducing scanning distances and evaluation radii—has been crucial for optimizing scanning efficiency and minimizing the number of required viewpoints.

[1]Simulation video: https://youtu.be/FDF8YRBGnvM

The integration of the SEE++ algorithm with standard ROS Noetic tools, along with the preparation of the simulated environment using CAD models and point cloud processing software such as CloudCompare and Blender, establishes a reproducible and extensible methodology for future research focused on computer vision in agricultural robotics.

This first simulated step is crucial for implementing the technique in a real environment. In this case, a camera will be pointed at the crop to identify the cluster, characterize the 3D space it occupies, and launch the algorithm. The result, with its post-processing stage, will need to account for the influence of sensor noise and foliage pricing at different times.

Finally, the partial reconstruction of occluded tomatoes obtained in the simulation represents a significant advance for the precise localisation of fruits in dense agricultural environments, paving the way for automated harvesting of cluster-grown crops. This approach overcomes the limitations of previous methods, which were mostly effective only for isolated and unobstructed fruits.

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