

UGV–UAV Bounding Box Mapping for Occluded and Dense Orchard Environments

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Abstract: Autonomous 3D mapping in agricultural environments is challenging due to dense vegetation, canopy occlusion, and degraded GPS signals, which hinder consistent spatial representation. While dense point clouds offer high fidelity, they are computationally intensive for real-time deployment. This paper investigates a collaborative unmanned ground vehicle (UGV) and unmanned aerial vehicle (UAV) mapping approach for orchard environments using a compact Bounding Box (BB)-based representation to preserve geometry for navigation. Three simulated scenarios with increasing complexity assessed robustness: aligned rows, misaligned rows, and canopy occlusion. Results showed the BB representation reduces map size by approximately 43%, maintains planar coverage above 95%, and preserves vertical canopy structure. Collaboration enhances spatial completeness, with the UGV contributing 64–79% of total coverage, complemented by UAV sensing. The BB abstractions also support simplified 2D projections and corridor analyses. Overall, the proposed BB representation is an efficient alternative, improving coverage in occluded regions for autonomous agricultural use.

Key-Words: 3D mapping; UGV–UAV collaboration; Bounding box abstraction; Occlusion handling; Vegetation density; Agricultural robotics; Orchard mapping; Autonomous navigation.

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1 Introduction

The generation of accurate 3D representations for autonomous systems in agricultural environments remains a significant challenge. This difficulty largely stems from perception and navigation limitations inherent to outdoor agricultural scenarios, [1]. These environments typically feature dense and heterogeneous vegetation, few distinctive features, and irregular terrain. In addition, degraded GPS availability further impairs reliable state estimation and spatial mapping, [2]. Consequently, developing robust and adaptive mapping methodologies is critical to support dependable autonomous operation in agricultural robotics.

Conventional agricultural mapping often relies on

unmanned ground vehicles (UGVs) and unmanned aerial vehicles (UAVs) for 3D perception, inspection, and monitoring. Their complementary viewpoints provide both near-ground and overhead coverage of vegetation. However, most 3D mapping approaches rely on dense point clouds or voxelized grids. These methods often struggle to deliver consistent performance in such environments, [3], [4], [5], [6]. Ground platforms frequently suffer from occlusions caused by canopies and vegetation, which restrict visibility and line-of-sight measurements. In contrast, aerial platforms tend to miss structural details closer to the ground, such as stems, trunks, and low branches, resulting in incomplete representations of orchard structures. Moreover, dense map

formats impose high memory and computational demands, making them unsuitable for time-critical planning and navigation in autonomous field robotics. These limitations highlight the need for compact and cooperative mapping approaches tailored to agricultural environments.

Recent research has investigated heterogeneous UAV–UGV collaboration to improve scene coverage and environmental understanding, especially in cluttered or GNSS-denied scenarios. [7] proposes Bayesian continuous–discrete map fusion to support adaptive merging, while [8] integrates octomap-based reconstruction with ORB-SLAM2 for robust indoor navigation. Other approaches use multi-stage registration or planar features for UAV–UGV point cloud fusion, providing robust reconstruction but requiring environment- or sensor-specific pipelines, [9], [10]. Complementary approaches combine LiDAR and visual sensing with pose graph optimization, ego-motion estimation, or neural data association, attaining high accuracy at notable computational cost, [11], [12].

In agricultural domains, research typically focuses on crop modeling, canopy characterization, or tree parameter estimation. [6] fuse UAV orthomosaics and UGV RGB-D data for canopy analysis, whereas [13] employ semantic octree fusion to generate multi-layer representations compatible with autonomous planning. [14] explores distributed SLAM with semantic–geometric registration to enhance global consistency, and AgriColMap, [15], aligns multimodal vegetation data through optical flow and grid fusion for precision agriculture tasks. In dynamic or partially occluded scenes, heterogeneous UAV–UGV teams have been deployed for 3D data acquisition and viewpoint planning, improving coverage and efficiency despite coordination constraints, [16].

A closer look at existing works shows a focus on high-fidelity reconstruction, which incurs high computational and memory costs. Few studies address compact 3D representations tailored for trajectory planning and cooperative navigation in structured orchards, and research in heavily occluded, dense, or low-visibility environments remains limited. This gap motivates the development of mapping approaches that balance completeness, efficiency, and task relevance for robust autonomous operation in challenging agricultural settings.

Although several UAV–UGV collaborative mapping approaches have been proposed, they primarily focus on high-fidelity reconstruction and dense representations. In contrast, the approach proposed in this paper emphasizes compactness and task-oriented abstraction, enabling efficient map representation suitable for navigation and planning

in structured agricultural environments.

To address these challenges, this paper presents a collaborative UGV–UAV 3D mapping method based on a bounding box (BB) representation to generate compact, structure-aware maps under vegetation occlusion. The approach is evaluated in three simulated orchard scenarios of increasing complexity: (S1) aligned rows without occlusion, (S2) dense canopy with occlusion, and (S3) misaligned rows introducing geometric variability. To the best of the authors' knowledge, the combination of bounding box abstraction and layered segmentation for collaborative UAV–UGV mapping in occluded orchard environments has not been explicitly addressed in prior work. One of the evaluated scenarios is partially based on a simulation environment presented in [17], and is reused here solely as a baseline for comparison under a different mapping framework.

The main contributions of this paper are as follows:

- **A task-oriented 3D mapping abstraction based on bounding boxes** for structured agricultural environments, prioritizing structural and navigational relevance over dense reconstruction.
- **A layer-based segmentation strategy** for consistent extraction of crop row structures from heterogeneous UAV–UGV point clouds under occlusion.
- **A compact multi-robot mapping framework** that integrates well-established techniques (e.g., ICP, FPFH, PCA, and clustering) into a unified pipeline, with the contribution lying in their task-oriented integration and the proposed bounding box abstraction.
- **An experimental evaluation in progressively complex orchard scenarios**, highlighting the trade-off between map compactness and spatial coverage.

The remainder of this paper is organized as follows: Section 2 presents the proposed framework; Section 3 discusses the simulation results; Section 4 analyzes and interprets the findings; and Section 5 concludes the paper with remarks and directions for future research.

2 Bounding Box-Based 3D Mapping Method

The Bounding Box (BB) method is based on the application of compact geometric structures to represent the agricultural environment efficiently.

Crop rows are abstracted and replaced by bounding boxes derived from the point cloud obtained through UGV–UAV collaboration, which can optionally be organized into vertical height layers. These boxes delineate vegetation rows and define the volumetric extent of tree canopies, providing a simplified yet information-rich spatial description of the mapped area.

As illustrated in the simplified flowchart (Fig. 1), the methodology consists of a sequence of processing steps: merging the UGV and UAV point clouds, segmenting crop rows and tree volumes, organizing the data into vertical layers, extracting and fusing 3D bounding boxes, and exporting a compact 3D map. Each step is described in detail in the following subsections.

The proposed pipeline is not intended to improve individual components such as registration or clustering accuracy, but rather to redefine how the environment is represented after fusion, prioritizing compactness and structural relevance for autonomous navigation tasks.

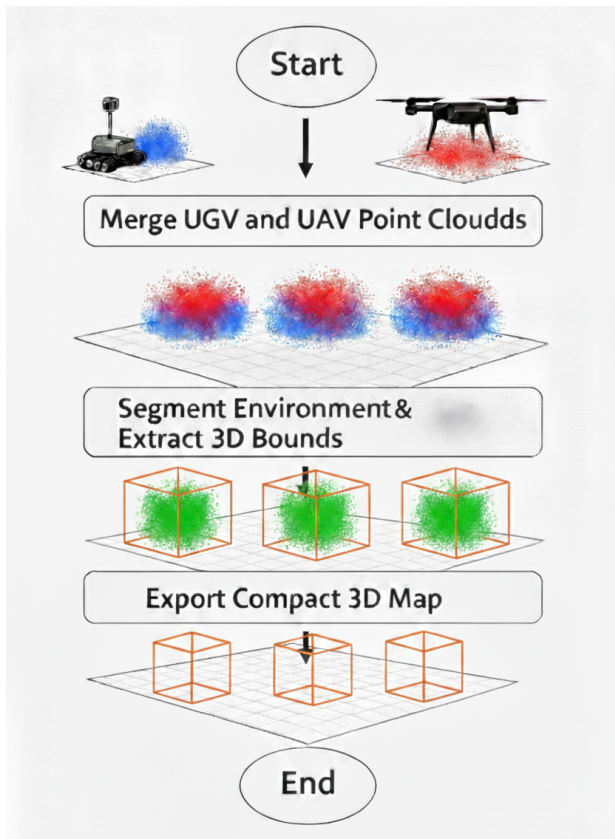


Fig. 1: Simplified flowchart of the BB method (single-layer). Source: created by the authors.

2.1 Merge UGV and UAV Point Clouds

In this first stage, point clouds captured by the UGV and UAV are registered into a common reference frame and merged into a unified representation of the environment. The pipeline begins with voxel downsampling and normal estimation, reducing redundancy and stabilizing local surface descriptors. Next, Fast Point Feature Histograms (FPFH) are computed for both point clouds to enable feature-based matching. A global alignment is first obtained using RANSAC-based registration, providing an initial transformation.

The alignment is then refined using Iterative Closest Point (ICP) optimization with a point-to-plane metric. The ICP process estimates the optimal rigid transformation by minimizing the distance between corresponding points in the two point clouds, which can be formulated as follows, [18], [19]:

$$\mathbf{T}^* = \arg \min_{\mathbf{T}} \sum_i (\mathbf{n}_i^T (\mathbf{p}_i^{UGV} - \mathbf{T}\mathbf{p}_i^{UAV}))^2 \quad (1)$$

where $\mathbf{T} \in SE(3)$ represents the rigid transformation (rotation and translation), $\mathbf{p}_i^{UGV}$ and $\mathbf{p}_i^{UAV}$ are corresponding 3D points, and $\mathbf{n}_i$ is the surface normal associated with $\mathbf{p}_i^{UGV}$.

The final transformation is applied to the full-resolution UAV point cloud before merging it with the UGV data, resulting in a unified representation that serves as the basis for subsequent processing stages.

2.2 Segment Environment and Extract 3D Bounding Boxes

The merged point cloud is partitioned into a fixed number of height layers, creating volumetric slices of the canopy. A fixed number of height layers is adopted to limit memory and computational costs, as experimental tests showed that increasing the number of layers results in only marginal accuracy improvements.

Within each layer, points are clustered along the lateral axis using K-means, where the number of clusters is defined according to the expected number of crop rows in each layer to separate individual crop rows. The clustering process is performed by minimizing the within-cluster variance, [20]:

$$J = \sum_{k=1}^K \sum_{\mathbf{x}_i \in C_k} \|\mathbf{x}_i - \boldsymbol{\mu}_k\|^2 \quad (2)$$

where C_k represents the k -th cluster and $\boldsymbol{\mu}_k$ is its centroid.

For each cluster, a local Principal Component Analysis (PCA) estimates the dominant longitudinal and lateral directions, allowing the points to be aligned in a local reference frame. The principal directions are obtained from the covariance matrix, [21]:

$$\mathbf{C} = \frac{1}{N} \sum_{i=1}^N (\mathbf{x}_i - \bar{\mathbf{x}})(\mathbf{x}_i - \bar{\mathbf{x}})^T \quad (3)$$

where $\bar{\mathbf{x}}$ is the centroid of the cluster. The eigenvectors of $\mathbf{C}$ define the dominant directions used for local alignment.

Minimum-area rectangles are then fitted to the clusters in 2D. Given a set of projected points $\mathcal{P} = \{\mathbf{x}_i\}$, the rectangle orientation is obtained by minimizing the area of the enclosing bounding box:

$$\theta^* = \arg \min_{\theta} A(R(\theta)\mathcal{P}) \quad (4)$$

where $R(\theta)$ is a rotation matrix and $A(\cdot)$ denotes the area of the axis-aligned bounding box after rotation. The resulting rectangles are then extruded vertically according to the layer height to form 3D bounding boxes representing the volumetric extent of vegetation. Each cluster is represented by a 3D bounding box defined by its spatial limits:

$$\mathbf{BB}_k = \left\{ \mathbf{x} \in \mathbb{R}^3 \mid \begin{array}{l} x_{\min} \leq x \leq x_{\max}, \\ y_{\min} \leq y \leq y_{\max}, \\ z_{\min} \leq z \leq z_{\max} \end{array} \right\} \quad (5)$$

Points contained within each bounding box are flagged, and the boxes are fused with points outside them to preserve important geometric features while simplifying the overall representation. This results in a compact, structure-aware volumetric map of the environment.

2.3 Export Compact 3D Map

Finally, the processed point cloud, including the fused 3D bounding boxes, is exported as a PLY file. This compact 3D map provides a simplified yet information-rich representation of the agricultural environment, suitable for autonomous navigation, trajectory planning, and decision-making in cooperative robotic systems.

3 Simulation Results

This section presents the performance evaluation of the proposed BB-based 3D mapping approach. Section 3.1 details the simulation scenarios and the robotic platforms employed, while Section 3.2 reports the resulting 3D maps.

3.1 Simulation Scenarios

The experiments were conducted in the Gazebo Harmonic simulator integrated with ROS 2 Jazzy, [22]. Three *Orchard*-based scenarios were evaluated: Scenario 1 (S1) aligned rows without anomalies, Scenario 2 (S2) aligned rows with occlusions, and Scenario 3 (S3) misaligned rows introducing geometric variability. Fig. 2 shows the environment and the initial positions of the quadrotor (UAV) and the differential-drive (UGV). The UGV is a Clearpath Husky equipped with a 3D LiDAR, GPS, and an RGB-D camera, while the UAV carries a 3D LiDAR, GPS, IMU, and a downward-facing RGB-D camera, [17].

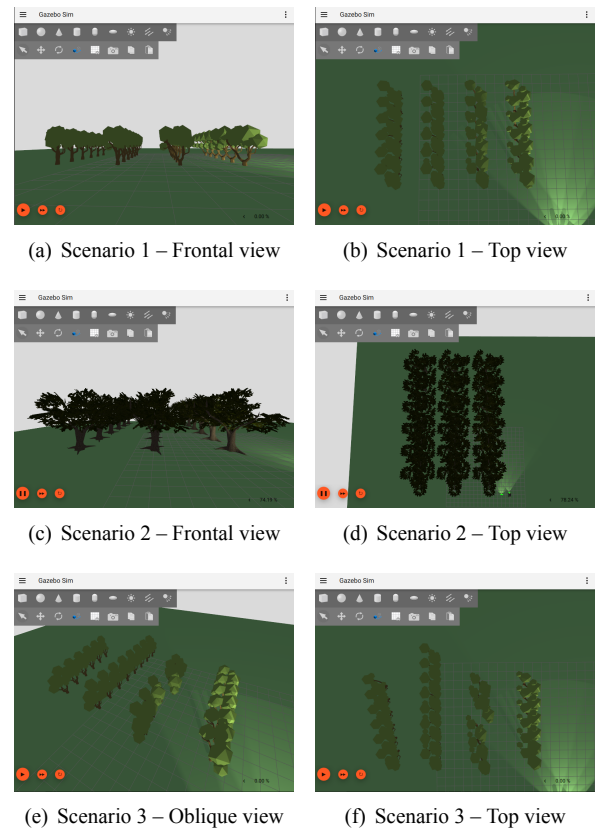


Fig. 2: Simulation scenarios used for evaluation. (S1) aligned rows without occlusion; (S2) dense canopy with occlusion; (S3) misaligned rows with geometric variability. Source: created by the authors.

3.2 3D Mapping Results

The evaluation metrics are formally defined as follows.

$$\text{Coverage}_{XY} = \frac{A_{\text{mapped}}}{A_{\text{reference}}} \quad (6)$$

$$\Delta Z = Z_{\max} - Z_{\min} \quad (7)$$

Fig. 1 (Appendix), Fig. 2 (Appendix), and Fig. 3 (Appendix) illustrate the full pipeline of the proposed BB-based approach in each scenario. The process begins with the acquisition of the individual point clouds from the UGV (a) and the UAV (b). These clouds are then merged into a unified 3D representation of the environment (c). Based on this combined map, bounding boxes are generated around the tree rows (d). The boxes are subsequently filtered to remove internal points, resulting in a cleaner and more structured layout (e). Finally, the UAV and UGV trajectories are incorporated into the map (f), highlighting the collaborative exploration carried out by the two robots.

4 Discussion

This section discusses the performance of the BB method with respect to map compactness, spatial coverage, and the benefits of UAV-UGV collaboration. The analysis focuses on how different mapping strategies affect storage requirements and the practical usability of 3D maps in structured agricultural environments.

4.1 BB-Based 3D Mapping Evaluation

Table 1 presents a quantitative comparison between the dense point cloud (Dense PC) and the BB representation across three orchard scenarios (S1–S3).

Table 1: S1–S3 Results: Dense vs. BB method. Source: created by the authors.

Metric	S1	S2	S3
Real Size Map (MB)	2.95	17.02	4.88
Reduction (%)	38.19	60.23	31.19
XY Coverage (%)	98.59	95.09	98.03
Mean Z Range (m)	0.06	0.03	0.03
Max Z Range (m)	3.15	6.82	2.88

The results demonstrate that the BB approach significantly reduces map size while preserving essential spatial and structural information. In scenarios S1 and S2, the BB representation achieves reductions of 38% and 60% in map size, respectively, while maintaining high XY coverage above 95%. Scenario S3 shows a smaller size reduction (31%), but XY coverage remains high at 98%, likely due to differences in tree density and spatial arrangement.

In addition to memory reduction, the BB representation reduces computational complexity during map handling and downstream planning tasks, as fewer primitives are required compared to dense point clouds. Although processing time was not explicitly benchmarked, the reduction in data size

directly contributes to faster map manipulation and visualization.

Vertical metrics, including mean and maximum Z range, indicate that the BB abstraction effectively preserves the height extent of crop rows and tree canopies. By capturing minimum and maximum Z limits, the BB method maintains key vertical information while filtering sensor noise and redundant points typically present in dense point clouds.

Although direct comparison with full SLAM-based or octomap frameworks was not the primary focus of this study, the proposed BB representation demonstrates significant advantages in terms of memory efficiency and structural abstraction when compared to dense mapping approaches commonly used in UAV-UGV systems.

A limitation of the proposed approach is that fine geometric details are intentionally discarded in favor of compactness, which may not be suitable for applications requiring high-fidelity reconstruction, such as detailed phenotyping or inspection tasks.

From a computational perspective, dense point clouds require $O(N)$ memory, leading to large storage demands as the number of points increases (e.g., up to 760,781 points in S2, Table 2). In contrast, the proposed BB representation reduces the problem to $O(K)$ primitives, achieving memory reductions of up to 60.23% while maintaining over 95% spatial coverage (Table 1). This supports the scalability of the proposed approach for real-time applications.

4.2 UGV-UAV Collaboration Assessment

Table 2 summarizes the percentage of points contributed by the UGV and UAV, the total number of points in the merged map, and the number of points obtained using only the UGV.

Table 2: UGV-UAV Collaboration in 3D Mapping. Source: created by the authors.

Metric	S1	S2	S3
UGV (%)	79.2	64.2	75.9
UAV (%)	20.8	35.8	24.1
Merged Points	173,134	760,781	234,483

The results show that the UAV provides a complementary contribution to the UGV, filling gaps that would otherwise remain unobserved, particularly in elevated or occluded areas. UGV-only mapping would yield lower point density, as indicated by the relative UGV contributions (64–79%), which highlights the added value of UAV data. This demonstrates that multi-robot collaboration ensures sufficient point density for an accurate BB-based

mapping, improving completeness and reliability of 3D maps for autonomous navigation.

4.3 2D Map Projections / Visualization

One of the advantages of the BB methodology is the ability to generate simplified two-dimensional maps from the 3D layers, which are useful for *path planning* and *task planning*.

For space considerations, Fig. 3 shows the results only for scenario S2. Five maps obtained from cumulative layers can be observed, each with a height of 1.28 m. That is, layer n corresponds to the cumulative projection of layers 1 through n . This visualization highlights the spatial distribution of vegetation at different levels, allowing a simplified assessment of vertical coverage that is useful for robot path planning and task assignment.

4.4 Geometric Interpretation of the Results

The effectiveness of the bounding box abstraction can be interpreted from a geometric and probabilistic perspective. In structured agricultural environments, crop rows exhibit strong spatial regularity.

Under occlusion, point cloud measurements are incomplete but still preserve the spatial support of the structure. By approximating each cluster with a bounding volume, the method captures the support region of the geometry.

From a probabilistic viewpoint, the bounding box acts as an envelope estimator of occupied space, providing a robust approximation of navigational constraints while filtering noise and outliers.

Therefore, the BB abstraction preserves navigation-relevant features such as free space corridors and obstacle extents, even under partial occlusion. This interpretation is consistent with the results in Table 1, where spatial coverage remains above 95% despite significant map compression.

5 Conclusions

This paper presented and validated a compact 3D mapping method for agricultural environments using UAV–UGV collaboration and based on BB representations. Evaluation in three orchard scenarios (S1–S3) demonstrates that:

- The BB representation significantly reduces map size compared to dense point cloud representations, achieving reductions of 38%, 60%, and 31% in scenarios S1, S2, and S3, respectively, while preserving high XY coverage above 95%.
- Vertical structure is effectively maintained, with the BB abstraction preserving mean and maximum Z ranges that capture the height of tree canopies and crop rows.

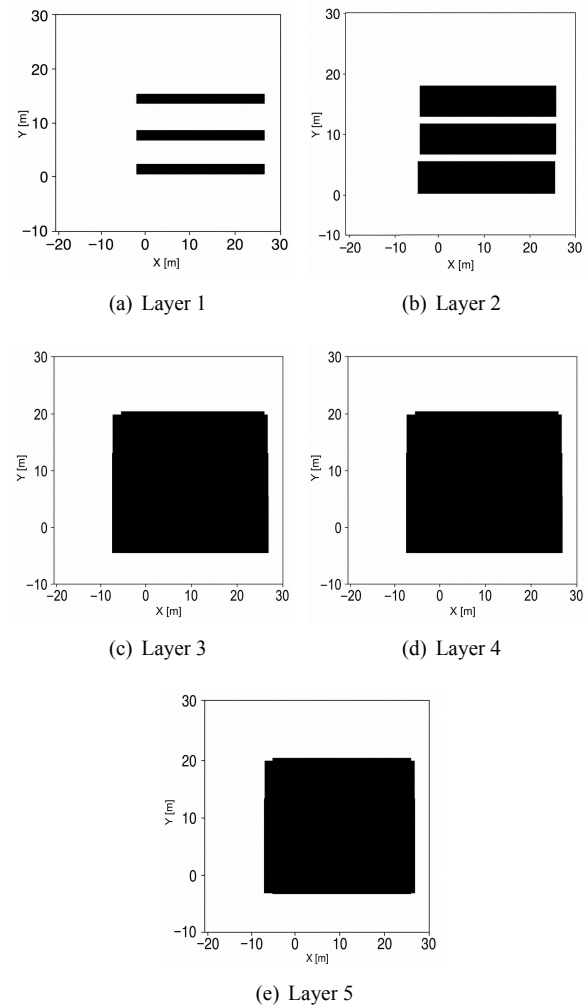


Fig. 3: Cumulative 2D map projections for scenario S2. Each layer corresponds to the cumulative projection from layer 1 to layer n , highlighting vertical vegetation distribution and providing simplified information for robot path planning and task assignment. Source: created by the authors.

- Integration of UAV and UGV data enhances spatial coverage and map completeness. UGV contributions ranged from 64% to 79%, while UAV contributions ranged from 21% to 36%, highlighting the complementary nature of aerial and ground sensing.
- The BB-based methodology allows the generation of simplified 2D map projections from cumulative layers, supporting practical path and task planning for autonomous robots, with detailed corridor metrics enabling assessment of navigable space at different heights.

These results indicate that the BB abstraction

provides a compact and information-rich 3D representation. It offers a favorable trade-off between map size and environmental fidelity. The combination of heterogeneous robotic platforms further enhances coverage and accuracy, particularly in structured agricultural environments such as orchards.

Future work will investigate the method in more complex and irregular agricultural layouts and integrate semantic information to support precision agriculture applications and higher-level robotic tasks.

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Contribution of Individual Authors to the Creation of a Scientific Article (Ghostwriting Policy)

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Conflicts of Interest

The authors have no conflicts of interest to declare.

Originality and Reuse Statement

The authors declare that this manuscript is an original contribution and has not been published elsewhere. The methodological pipeline is based on well-established techniques, including ICP registration, FPFH descriptors, PCA, and clustering methods, which are properly cited.

No previously published text has been reused without appropriate modification and citation. The simulation environments, datasets, and implementation used in this work were specifically developed for this study, unless otherwise stated. The present manuscript clearly distinguishes its contributions from prior works by focusing on a compact and task-oriented mapping representation rather than high-density reconstruction.

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APPENDIX

This appendix presents the complete mapping results for scenarios S1–S3, referenced throughout the main text as Figure 1, Figure 2, and Figure 3.

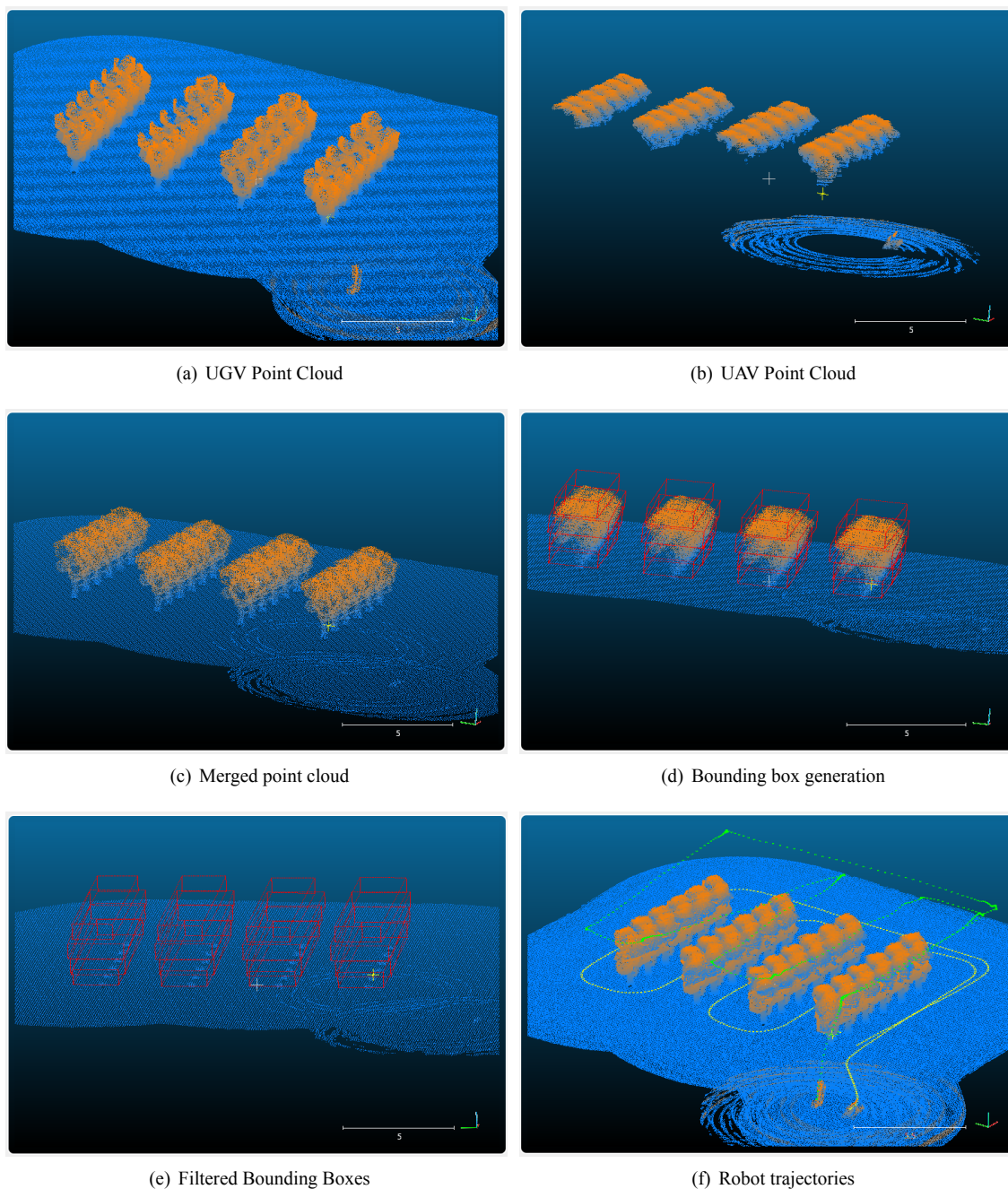


Fig. 1: Orchard scenario (S1): (a) UGV point cloud; (b) UAV point cloud; (c) Merged point cloud; (d) Bounding boxes with 4 layers; (e) Filtered bounding boxes; (f) Robot trajectories. Source: created by the authors.

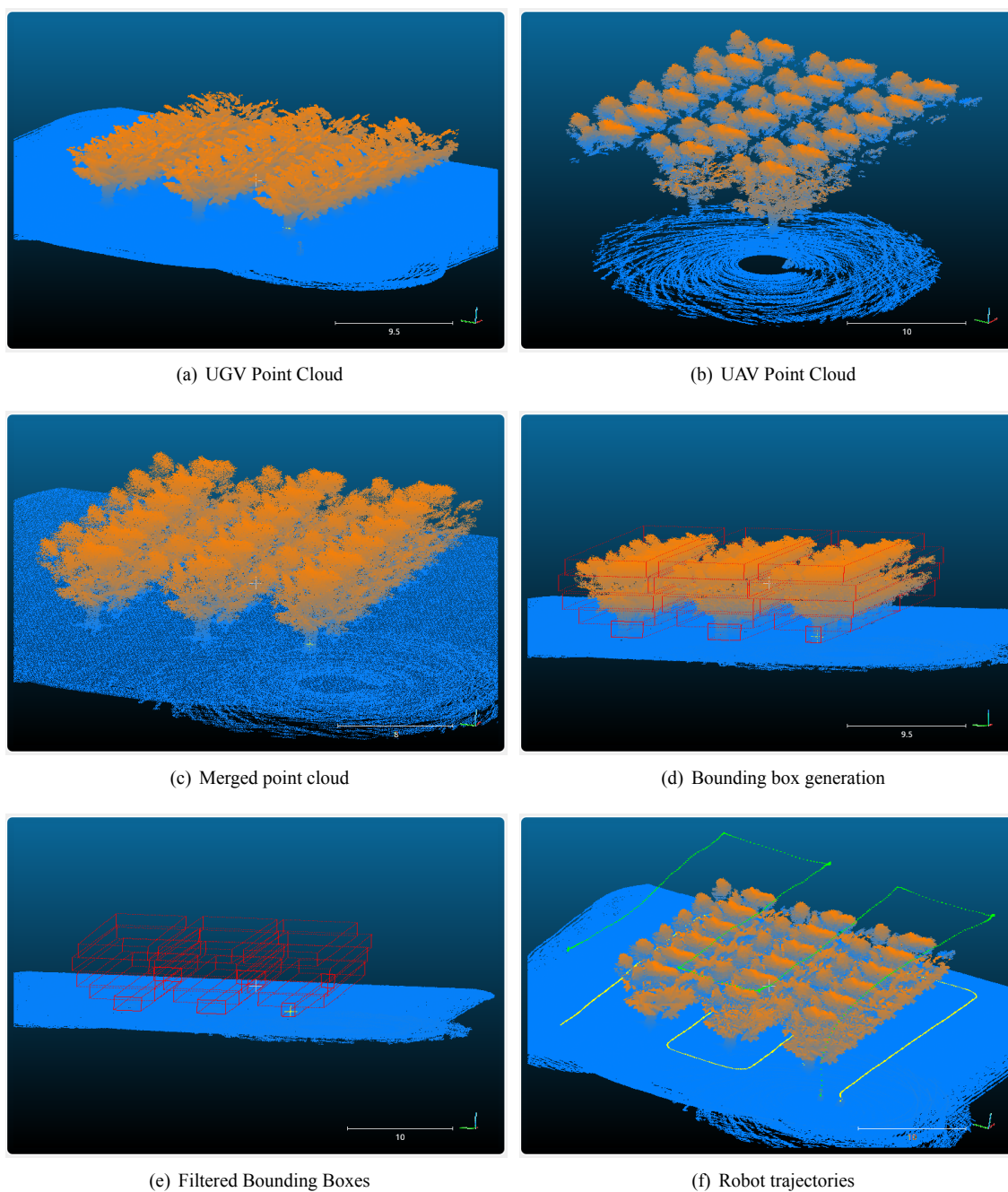


Fig. 2: Dense Canopy (S2): (a) UGV point cloud; (b) UAV point cloud; (c) Merged point cloud; (d) Bounding boxes with 5 layers; (e) Filtered bounding boxes; (f) Robot trajectories. Source: created by the authors.

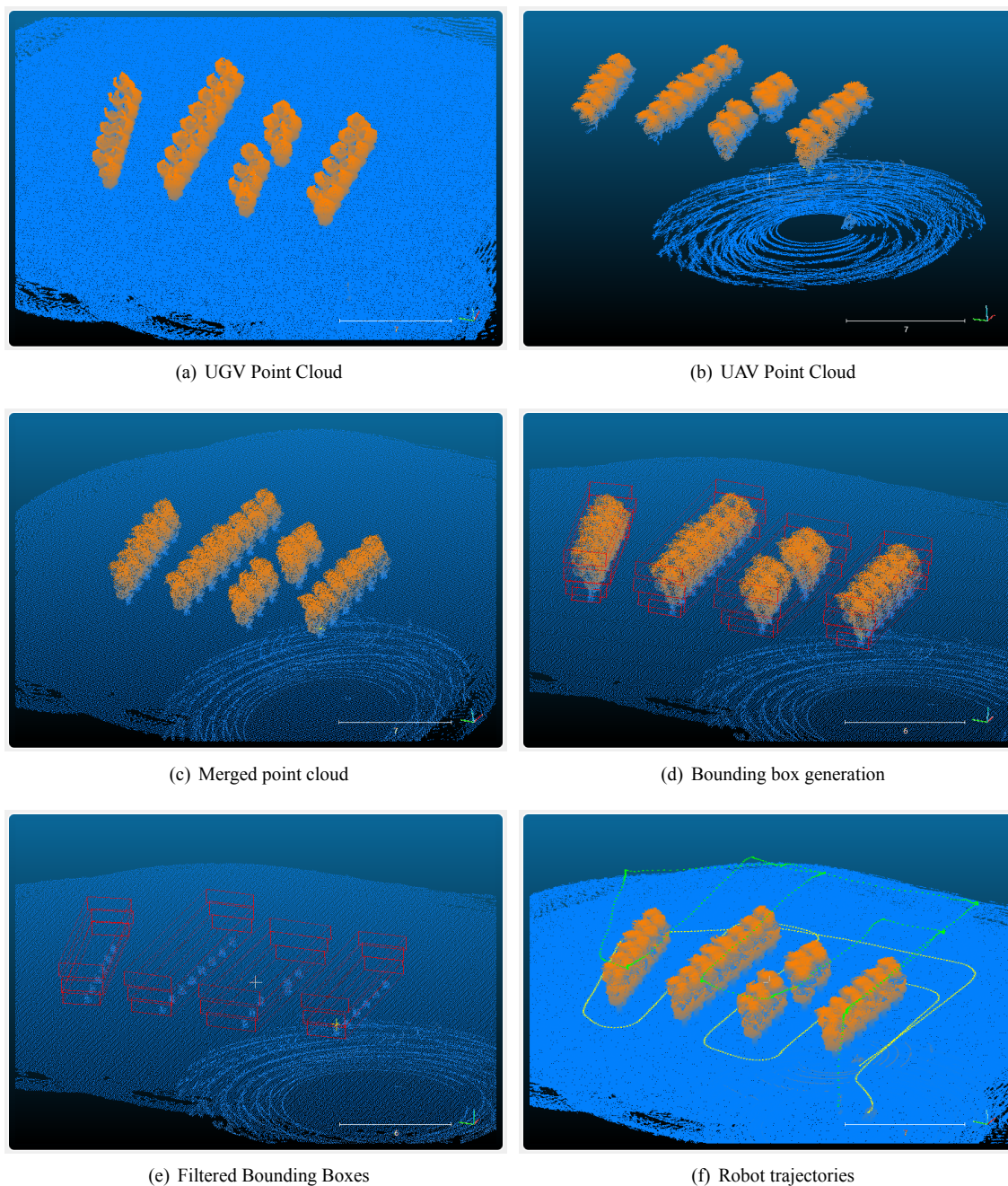


Fig. 3: Orchard scenario (S3): (a) UGV point cloud; (b) UAV point cloud; (c) Merged point cloud; (d) Bounding boxes with 3 layers; (e) Filtered bounding boxes; (f) Robot trajectories. Source: created by the authors.