

Enhanced Adaptive Monte Carlo Localization with Iterative Closest Point Scan Matching for Agricultural Mobile Robots

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Abstract—Accurate localization of agricultural mobile robots is difficult in plantations because repeated rows of crops or trees provide limited distinctive geometry. Previously, an Adaptive Monte Carlo Localization (AMCL) refined by the Normal Distributions Transform (NDT) was proposed for two-dimensional Light Detection and Ranging (LiDAR) localization to improve the localization accuracy of the robots. This paper extends that study by cascading Iterative Closest Point (ICP) scan matching after AMCL on every cycle the current AMCL estimate initializes point-to-point scan-to-map registration, allowing ICP to refine the pose using local tree-trunk geometry, and the refined pose is published as the output of the pipeline. The method was evaluated in a Gazebo palm oil plantation with ROS 2 Humble, a Clearpath Husky platform, and a 270° 2D LiDAR with a 30 m maximum range. Conventional AMCL, AMCL with NDT, and AMCL with ICP were evaluated against Gazebo ground truth using Absolute Pose Error, reported both after rigid-body trajectory alignment and in the map frame without alignment, and rotational and translational relative pose error. Compared with conventional AMCL, the proposed method reduced mean aligned absolute pose error from 0.413 m to 0.305 m and its root mean square error from 0.427 m to 0.323 m. Mean rotational relative pose error decreased from 1.118 degrees to 0.113 degrees, while its root mean square error decreased from 1.465 degrees to 0.223 degrees. The ICP-based extension also achieved lower translational and rotational errors than the NDT-based method, which was run from the same node with the same inputs and preprocessing. The results indicate that ICP refinement of the AMCL estimate is effective in repetitive plantation geometry, although isolated scan-matching failures remain.

Keywords—Adaptive monte carlo localization; iterative closest point; 2D LiDAR; agricultural robotics; scan matching; pose estimation; precision agriculture

I. INTRODUCTION

Autonomous ground robots are increasingly used in agriculture for monitoring, spraying, transportation, and other repetitive operations that require reliable navigation [1], [2]. Localization is a prerequisite for these tasks because the robot must continuously estimate its position and orientation before path planning, motion control, and obstacle avoidance can be performed reliably.

Outdoor agricultural environments are particularly challenging for localization. Plantation rows are often large, repetitive, and locally similar. In a palm oil field, for example, multiple robot poses may produce similar 2D Light Detection

and Ranging (LiDAR) observations because neighboring tree trunks have comparable spacing and geometry. These characteristics reduce landmark uniqueness and can cause drift or delayed correction in localization methods that depend strongly on distinctive map features. GPS-based techniques provide a global position reference, but centimeter-level accuracy generally requires additional infrastructure such as Real-Time Kinematic (RTK) positioning, while satellite signals can also degrade in obstructed areas. LiDAR-based localization therefore remains attractive for cost-sensitive autonomous agricultural robots [3], [4].

Adaptive Monte Carlo Localization (AMCL) is a probabilistic localization method that estimates robot pose using a set of weighted particles [5], [6]. Given a known occupancy-grid map, AMCL predicts particle states using a motion model and updates their likelihood according to current sensor observations. Although AMCL is widely used and computationally practical, repetitive or feature-poor environments can produce ambiguous particle hypotheses and reduce pose accuracy [7]–[9].

Scan matching provides a complementary geometric correction mechanism. The Normal Distributions Transform (NDT) models map regions probabilistically, whereas the Iterative Closest Point (ICP) algorithm directly aligns two point sets through repeated correspondence and transformation estimation [10], [11]. The two approaches therefore exploit environmental geometry differently. NDT smooths local geometry into probabilistic cells, while ICP preserves point-level correspondences that may be useful when discrete objects such as tree trunks are repeatedly observed.

Previously, an AMCL–NDT framework for agricultural mobile robots using 2D LiDAR was presented [12]. That work established the feasibility of using NDT after AMCL pose estimation and demonstrated a substantial reduction in relative pose error compared with conventional AMCL. However, the reported benchmark also showed that the evaluated NDT configuration did not reduce the main APE statistics, motivating further investigation of a different local registration mechanism.

This paper extends the previous work by focusing on ICP-based pose refinement. The AMCL estimate is used to initialize ICP, after which the current LiDAR scan is aligned to a point representation of the known map and the refined pose is published as the output of the pipeline. AMCL continues to run on its own prediction and measurement updates, so each

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registration is re-initialized from a fresh AMCL estimate. This initialization is important because ICP is a local optimizer and is sensitive to poor starting poses.

The contributions of this paper are as follows:

- 1) a cascaded AMCL–ICP localization pipeline for 2D LiDAR-based agricultural mobile robots, in which the AMCL pose initializes point-to-point scan-to-map ICP on every cycle and the refined pose forms the reported estimate.
- 2) a quantitative evaluation using APE and rotational and translational RPE against Gazebo ground truth.
- 3) a direct three-method comparison with conventional AMCL and the previous AMCL–NDT work, including a discussion of why point-level ICP behaves differently from NDT in repetitive plantation geometry.

The scope of this study is limited to these three methods in one common simulation setup. Other enhanced AMCL methods and other ICP variants are not benchmarked.

The remainder of the paper is organized as follows. Section II reviews relevant localization and scan-matching studies. Section III presents the proposed AMCL–ICP method and experimental setup. Section IV describes the evaluation metrics. Section V presents the results together with their interpretation, the comparison between the two scan-matching configurations, and the limitations of the study. Section VI concludes the paper.

II. RELATED WORK

A. Agricultural Robot Localization

Robot localization in agriculture has been investigated using GNSS/RTK, dead reckoning, cameras, LiDAR, and multi-sensor fusion. Fasiolo *et al.* [3] reviewed technologies supporting autonomous agricultural mapping and highlighted the increasing use of LiDAR together with other sensing modalities. Three-dimensional LiDAR provides rich environmental information, but the higher data volume, hardware cost, and computational requirements can be undesirable for cost-sensitive platforms. Two-dimensional LiDAR remains a practical option when the relevant environmental structure can be represented in a horizontal plane.

LiDAR-based outdoor localization must cope with sparse landmarks, repeated structures, and partial occlusions. Ren *et al.* [4] demonstrated large-scale outdoor SLAM based on 2D LiDAR, while agricultural mapping research has increasingly combined geometric and probabilistic estimation to improve robustness. These studies indicate that the key challenge is not merely obtaining range measurements, but extracting sufficiently distinctive geometric information for stable pose estimation.

B. AMCL Enhancement

Monte Carlo localization represents the posterior pose distribution with weighted samples [5], [6]. AMCL adapts the particle population according to localization uncertainty, reducing unnecessary computation when the pose distribution becomes concentrated. Nevertheless, the method can still fail

when multiple regions of the map generate similar observations.

Peng *et al.* [7] integrated laser scan matching into AMCL for complex and unstructured environments. Chung and Lin [8] modified AMCL to improve localization precision, and He *et al.* [9] developed an enhanced AMCL method for dynamic and featureless environments. More recently, Zuo *et al.* [13] integrated a virtual motion model with AMCL, using NDT-based matching to provide additional displacement information. These works demonstrate that geometric refinement can compensate for weaknesses in the particle-filter observation update.

C. ICP and NDT Scan Matching

ICP estimates a rigid transformation between source and target point sets by alternating between correspondence assignment and transformation optimization [11]. Its main advantage is the direct use of local geometry. Its main weakness is sensitivity to initialization and local minima. Robust ICP variants therefore focus on correspondence selection, outlier handling, and faster convergence [14]. Wang *et al.* [15] proposed multi-level ICP for large-scale sparse scenes, while Liang *et al.* [16] investigated laser and inertial navigation fusion for mobile robot localization.

NDT instead divides the map into cells and represents the points in each cell using a normal distribution [10]. This produces a smooth objective function and avoids explicit nearest-neighbor matching for every map point. NDT-based approaches have been extended to complex and large-scale environments [17], [18]. In [12], the integration of AMCL and NDT applied this principle to the same agricultural localization problem considered here.

III. PROPOSED AMCL–ICP METHOD

A. AMCL Pose Estimation

Let the planar robot pose at discrete time step k be

$$\mathbf{x}_k = [x_k, y_k, \theta_k]^T, \quad (1)$$

where, x_k and y_k are the robot coordinates in the map frame, θ_k is its heading angle in radians, and $(\cdot)^T$ denotes the transpose operation.

AMCL approximates the posterior distribution of the robot pose using a set of weighted particles,

$$\mathcal{P}_k = \left\{ (\mathbf{x}_k^{[i]}, w_k^{[i]}) \right\}_{i=1}^{N_k}, \quad (2)$$

where, $\mathcal{P}_k$ is the particle set, $\mathbf{x}_k^{[i]}$ is the pose hypothesis of particle i , $w_k^{[i]}$ is its normalized importance weight, and N_k is the number of particles at time step k . The weights satisfy $w_k^{[i]} \geq 0$ and $\sum_{i=1}^{N_k} w_k^{[i]} = 1$.

At each filter update, particles are propagated according to the odometry-based motion input $\mathbf{u}_k$. Their importance weights are updated using the likelihood of the LiDAR observation $\mathbf{z}_k$ given the known occupancy-grid map $\mathcal{M}$. The weights are then normalized, and resampling is performed as required.

In the Nav2 AMCL implementation, the particles are grouped into pose-hypothesis clusters, and the reported pose is the mean of the cluster with the largest total weight. Accordingly, the AMCL pose estimate is expressed as

$$\begin{aligned}\hat{\mathbf{x}}_k^{\text{AMCL}} &= \boldsymbol{\mu}_{k,c^*}, \\ c^* &= \arg \max_c W_{k,c},\end{aligned}\quad (3)$$

where, c denotes a particle-cluster index, c^* identifies the highest-weight cluster, and $W_{k,c} = \sum_{i \in \mathcal{I}_{k,c}} w_k^{[i]}$ is its total weight. Here, $\mathcal{I}_{k,c}$ is the index set of particles belonging to cluster c , and $\boldsymbol{\mu}_{k,c}$ is the corresponding weighted mean pose. Its positional coordinates are computed by weighted averaging within the cluster, whereas its heading is computed using a circular mean to account for angular wraparound.

In a repetitive plantation, this estimate can remain biased when multiple locations produce similar laser observations. The proposed method therefore treats $\hat{\mathbf{x}}_k^{\text{AMCL}}$ as an initial geometric estimate rather than the final pose.

B. ICP Scan-to-Map Refinement

The occupancy-grid map is converted to a point cloud from its occupied cells, and the current 2D LiDAR scan is converted to a point set in the robot base frame. Let the current scan be $\mathcal{S}_k = \{\mathbf{p}_j\}$ and the reference map points be $\mathcal{M} = \{\mathbf{q}_l\}$. The AMCL pose initializes the scan transformation before ICP iterations begin.

ICP was implemented with the Point Cloud Library class `pcl::IterativeClosestPoint` through the open-source `pcl_localization_ros2` package, selected by setting that package's registration method to ICP. The same node, and therefore the same scan and map preprocessing, is used for the NDT configuration, so the two scan-matching configurations differ only in the registration algorithm. At each iteration every transformed scan point is associated with its nearest map point using a k-d tree, and the rigid transformation is estimated by minimizing the point-to-point error [11]:

$$\mathbf{T}^* = \arg \min_{\mathbf{T}} \sum_{j=1}^m \|\mathbf{T}\mathbf{p}_j - \mathbf{q}_{c(j)}\|^2, \quad (4)$$

where, $c(j)$ denotes the map point matched to scan point j . Before registration the scan is downsampled with a 0.2 m voxel filter and restricted to the 1–100 m range, the same preprocessing applied in the NDT configuration. The transformation epsilon was set to 0.01 every other registration parameter was left at its library default, including the maximum of 10 iterations, the unrestricted correspondence distance, and the absence of any outlier-rejection filter. Because ICP is initialized from AMCL rather than from an arbitrary pose, the registration begins closer to the expected solution and is less likely to search an unrelated region of the map. Nevertheless, false correspondences remain possible in highly repetitive geometry [19].

The two components are coupled in one direction. AMCL publishes its estimate on `amcl_pose` the registration node subscribes to that topic and overwrites its current pose with it, so each registration starts from the latest AMCL estimate. The refined pose is then published on `pcl_pose` and is the estimate evaluated in this paper. AMCL itself continues to run from

Algorithm 1 AMCL with ICP Pose Refinement

```
1: Initialize particle set  $\mathcal{P}$  and weights  $W$ 
2: while robot is active do
3:   Acquire motion input  $\mathbf{u}_k$  and LiDAR scan  $\mathbf{z}_k$ 
4:   for each particle  $\mathbf{x}^{[i]}$  do
5:     Propagate particle using the AMCL motion model
6:     Update  $w^{[i]}$  using  $\mathbf{z}_k$  and map  $\mathcal{M}$ 
7:   end for
8:   Normalize weights and resample particles
9:   Compute  $\hat{\mathbf{x}}_k^{\text{AMCL}}$ 
10:  Convert  $\mathbf{z}_k$  to point set  $\mathcal{S}_k$ 
11:  Initialize ICP using  $\hat{\mathbf{x}}_k^{\text{AMCL}}$ 
12:  repeat
13:    Find nearest-neighbor correspondences
14:    Estimate the rigid transformation using Eq. (4)
15:    Transform the current scan
16:  until the convergence threshold or the maximum number of iterations is reached
17:  Output refined pose  $\hat{\mathbf{x}}_k^{\text{ICP}}$ 
18:  Publish  $\hat{\mathbf{x}}_k^{\text{ICP}}$  as the estimate for cycle  $k$ 
19: end while
```

odometry and the laser likelihood field and does not consume the refined pose. The AMCL–NDT configuration uses the same node and the same coupling, with the NDT registration method in place of ICP.

The overall AMCL–ICP localization procedure is summarized in Algorithm 1, covering the AMCL pose estimation, ICP initialization, scan-to-map refinement, and publication of the refined pose. The corresponding processing flow and sensor connections are illustrated in Fig. 1.

C. Simulation and Data Collection

The experiment was conducted in a simulated palm oil plantation. The environment was derived from an actual plantation layout and represented as a 2D occupancy map with a resolution of 0.05 m per pixel. The resulting environment measured 126.75 m $\times$ 100.7 m. Tree trunks were represented with a diameter of 1.5 m. A Clearpath Husky robot was simulated in Gazebo under ROS 2 Humble on Ubuntu 22.04. The robot carried the 2D LiDAR supplied with the Husky description, a SICK LMS1xx model configured with a 270° field of view, a 30 m maximum range, 720 beams per scan (0.376° angular resolution) and a 50 Hz scan rate.

The simulation was first executed with conventional AMCL, during which the LiDAR, odometry, and IMU data and the Gazebo ground-truth pose were recorded along a single trajectory. The recorded sensor data were then replayed to evaluate AMCL with NDT and AMCL with ICP, so that all methods were exposed to the same trajectory and evaluated against the same ground truth (Table I).

All three methods were run with the default configurations of their implementations where no parameters were tuned for this environment. AMCL used the Nav2 defaults for ROS 2 Humble [20]: a differential-drive motion model with α_1 – α_5 equal to 0.2, 500 to 2000 particles, a likelihood-field measurement model using 60 beams per scan, and filter updates after 0.2 rad of rotation or 0.25 m of translation. ICP used the

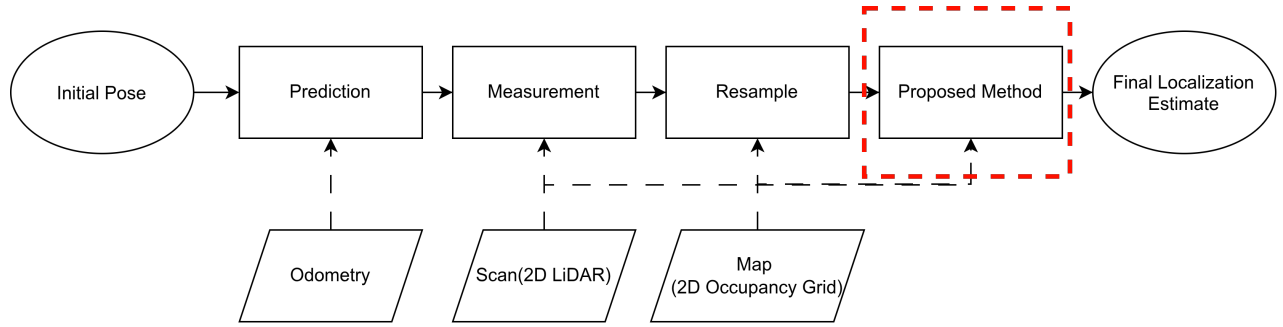


Fig. 1. Proposed AMCL-ICP localization pipeline. Odometry drives the AMCL prediction step, while the 2D LiDAR scan and occupancy map are used both for the AMCL measurement update and for building the scan/map point sets used by ICP. Solid arrows denote the main processing flow and dashed arrows denote sensor and map connections, the AMCL estimate re-initializes the registration step on every cycle, and the refined pose is the output of the pipeline.

TABLE I. SIMULATION PLATFORM AND ENVIRONMENT

Item	Configuration
Operating system	Ubuntu 22.04
ROS version	ROS 2 Humble Hawksbill
Robot model	Clearpath Husky
2D LiDAR	SICK LMS1xx
LiDAR field of view	270°
LiDAR maximum range	30 m
LiDAR angular resolution	0.376° (720 beams)
LiDAR scan rate	50 Hz
Map image	2535 × 2014 pixels
Map resolution	0.05 m/pixel
Map size	126.75 m × 100.7 m
Tree trunk diameter	1.5 m

TABLE II. LOCALIZATION PARAMETERS USED IN THE BENCHMARK

Method	Parameter	Value
AMCL	Minimum angular / distance update	0.2 rad / 0.25 m
AMCL	α_1 – α_5	0.2
AMCL	Particles	500–2000
AMCL	Laser model / beams	Likelihood field / 60
ICP	Error metric	Point-to-point
ICP	Matching	k-d tree, nearest neighbour
ICP	Outlier rejection	None
ICP	Maximum iterations	10 (library default)
ICP	Transformation epsilon	0.01
ICP	Voxel filter / scan range	0.2 m / 1–100 m
ICP	IMU / odometry	Disabled
NDT	Step size / resolution	0.1 / 2.0 m
NDT	Transformation epsilon	0.01
NDT	Voxel filter / scan range	0.2 m / 1–100 m
NDT	IMU / odometry	Disabled

settings described in Section III-B. NDT used a step size of 0.1, a resolution of 2.0 m, a transformation epsilon of 0.01, a 0.2 m voxel filter, a scan range of 1–100 m, and a fitness-score warning threshold of 2.0. Both scan-matching configurations were run from the same node and the same parameter file, so both used the same scan and map preprocessing and both had the optional odometry and inertial inputs disabled. The only differences between them are the registration algorithm and the NDT-specific resolution and step size. Table II summarizes these settings.

IV. PERFORMANCE EVALUATION

Ground-truth pose was obtained from Gazebo and synchronized with the estimated localization trajectories. Two complementary metrics were used: Absolute Pose Error (APE) for global trajectory agreement and Relative Pose Error (RPE) for local drift [21]. The evaluation was implemented using the *evo* trajectory-analysis package [22]. For the two scan-matching configurations, Table III reports APE from the first of the two replays and Table IV reports RPE from the second, where both replays are used in the failure-case analysis of Section V-A.

Let $\mathbf{G}_i$ denote the ground-truth pose, $\mathbf{P}_i$ the estimated pose, and $\mathbf{S}$ the rigid transformation aligning the estimated trajectory with the ground truth. APE is

$$\mathbf{E}_i^{APE} = \mathbf{G}_i^{-1} \mathbf{S} \mathbf{P}_i, \quad (5)$$

where, $\mathbf{S}$ is the rigid-body transformation determined by least-squares (Umeyama) trajectory alignment [23], without scale correction. Translational APE is reported in meters. APE is additionally reported without alignment, in the map frame, using the x and y components only, because the ground truth includes the constant 0.132 m height of the robot base, which a 2D localizer does not estimate.

RPE evaluates the change between two poses separated by interval Δ :

$$\mathbf{E}_i^{RPE} = (\mathbf{G}_i^{-1} \mathbf{G}_{i+\Delta})^{-1} (\mathbf{P}_i^{-1} \mathbf{P}_{i+\Delta}), \quad (6)$$

where, $\Delta = 1.0$ m. The rotational component is reported in degrees, and the translational component, computed in the x – y plane, is reported in meters. For both metrics, maximum, mean, median, minimum, and root mean square error (RMSE) are presented.

V. RESULTS AND DISCUSSION

A. Absolute Pose Error

Table III shows that AMCL-ICP achieved the lowest mean, median, and RMSE APE among the three tested configurations. Compared with conventional AMCL, mean APE decreased from 0.413 m to 0.305 m, corresponding to a 26.2% reduction. APE RMSE decreased from 0.427 m to 0.323 m, a 24.4% reduction. The median APE decreased from 0.430 m

TABLE III. ABSOLUTE POSE ERROR RESULTS (AMCL-NDT AND AMCL-ICP: FIRST REPLAY)

Metric (m)	AMCL	AMCL-NDT	AMCL-ICP
<i>After rigid-body alignment</i>			
Maximum	0.704	1.117	0.787
Mean	0.413	0.487	0.305
Median	0.430	0.478	0.274
Minimum	0.010	0.044	0.045
RMSE	0.427	0.516	0.323
<i>Without alignment (map frame, x-y)</i>			
Maximum	0.804	1.055	0.802
Mean	0.462	0.580	0.363
Median	0.401	0.573	0.360
Minimum	0.001	0.346	0.287
RMSE	0.492	0.588	0.366

to 0.274 m, indicating that the improvement was not caused only by a small number of favorable samples.

Compared with the previously reported AMCL-NDT configuration, AMCL-ICP reduced mean APE from 0.487 m to 0.305 m (37.4%) and RMSE from 0.516 m to 0.323 m (37.4%). The median APE was reduced by 42.7%. These results are consistent with the hypothesis that direct point correspondence can exploit local tree-trunk geometry more precisely than the probabilistic NDT representation for the tested trajectory.

Without trajectory alignment (lower block of Table III), all mean and RMSE values increase but the ranking is unchanged. AMCL-ICP has a mean APE of 0.363 m and an RMSE of 0.366 m, against 0.462 m and 0.492 m for conventional AMCL (21.4% and 25.6% lower), and AMCL-NDT remains the highest. Without alignment, the maximum APE of AMCL-ICP (0.802 m) is close to that of conventional AMCL (0.804 m).

The maximum APE provides an important qualification. After alignment, conventional AMCL recorded the lowest maximum error (0.704 m), while AMCL-ICP reached 0.787 m. The ICP trajectory therefore contains isolated scan-matching errors despite its lower central and cumulative error statistics. This behavior is consistent with ICP's sensitivity to local correspondence failures when the map contains repeated structures. This result illustrates the key accuracy trade-off of the proposed method. The lower mean, median, and RMSE indicate that ICP improves localization over most of the trajectory, whereas the higher maximum reflects a small number of local failures. In the plantation map, repeated tree spacing can create more than one plausible nearest-neighbor association, so a locally consistent ICP solution is not always the globally correct pose.

Fig. 2 shows the spatial APE distribution for AMCL-ICP. Most of the trajectory follows the reference path closely, whereas higher-error segments appear at a small number of locations, analyzed below. Fig. 3 shows that the APE remains near the lower error band for substantial portions of the run but exhibits intermittent peaks. These peaks explain why the maximum error does not improve even though the mean and RMSE are substantially reduced.

To identify the conditions under which ICP fails, the five largest APE peaks of AMCL-ICP were located along the trajectory, and the same analysis was repeated on the second replay of the recorded sensor data (Fig. 4). Three of the five

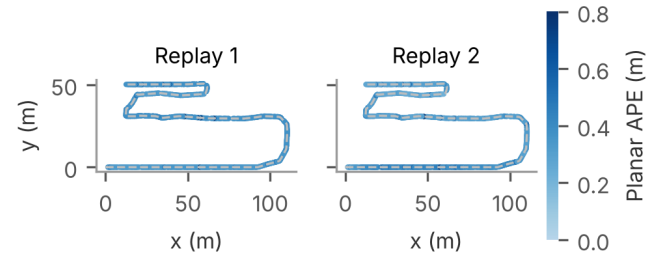


Fig. 2. Spatial distribution of translational APE for AMCL-ICP, shown for both replays of the commanded trajectory. The dashed trajectory represents the reference path, while the color scale represents error magnitude.

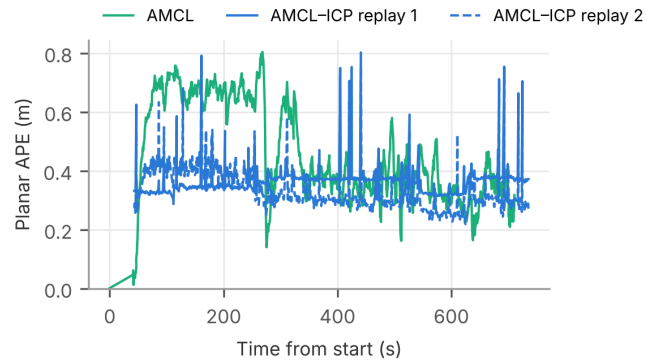


Fig. 3. Translational APE over time for conventional AMCL and for both replays of AMCL-ICP, after rigid-body (Umeyama) trajectory alignment.

peaks lie on the same row, at $y \approx 30$ m between $x \approx 47$ m and 66 m, and the peaks near (47.6, 30.7) m and (65.6, 29.6) m are among the largest errors in both replays. None of the five peaks occurred while the robot was turning. Because the largest position errors recur at the same places in independent replays, they are attributed to the local map geometry at those locations, where the visible trunk pattern can match the map at more than one offset along the row, rather than to random variation between runs. The location (57.6, 0.0) m, which is also among the five, is one of the largest error locations for AMCL-NDT without alignment, indicating a section that is difficult for scan matching in general. In contrast, the largest rotational RPE peaks occur in both replays on the left-hand section of the path, near (12–20, 32–44) m, where the robot changes direction. Turns therefore affect the orientation estimate, whereas the largest position errors arise on straight segments of the rows. Because only poses were logged, the individual scan-to-map correspondences at these locations could not be inspected.

Fig. 5 summarizes the mean and RMSE values and makes the difference among the three configurations clearer. The NDT configuration has the largest APE mean and RMSE, while ICP produces the smallest values for both statistics.

B. Relative Pose Error

The largest improvement was observed in rotational RPE. Table IV shows that AMCL-ICP reduced the maximum RPE from 4.939° to 1.927° , a reduction of 61.0%. Mean RPE

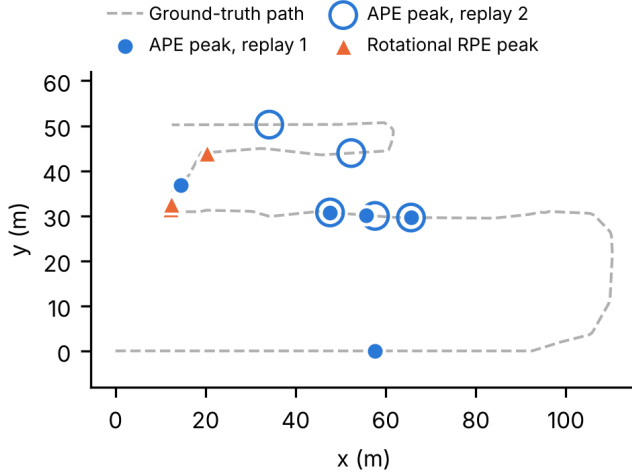


Fig. 4. Locations of the five largest APE peaks of AMCL-ICP in the first replay (filled circles) and the second replay (open circles), and of the largest rotational RPE peaks in both replays (triangles), on the ground-truth path.

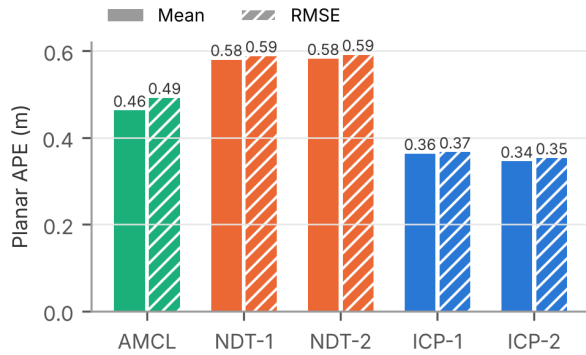


Fig. 5. Comparison of mean and RMSE translational APE for the three localization configurations.

decreased from 1.118° to 0.113° (89.9%), while median RPE decreased from 0.910° to 0.059° (93.5%). RPE RMSE decreased from 1.465° to 0.223° , corresponding to an 84.8% reduction.

AMCL-ICP also achieved lower RPE than the NDT configuration. Relative to AMCL-NDT, the ICP configuration reduced mean RPE by 25.7%, RMSE by 45.1%, and maximum RPE by 59.8%. This suggests that direct point alignment provided a stronger orientation correction for the local geometry present in the simulated plantation. The stronger rotational improvement is consistent with the geometry of the environment. Once AMCL provides an approximate position, the relative arrangement of nearby tree-trunk returns gives ICP direct orientation constraints. NDT's cell-based probability representation is smoother and less sensitive to individual point geometry, which can be beneficial for noise suppression but may weaken fine orientation cues in a highly repetitive row structure.

Translational RPE (lower block of Table IV) gives a mixed result. AMCL-ICP has the lowest mean and median (0.062 m

TABLE IV. RELATIVE POSE ERROR RESULTS (AMCL-NDT AND AMCL-ICP: SECOND REPLAY)

Metric	AMCL	AMCL-NDT	AMCL-ICP
<i>Rotational RPE ($^\circ$)</i>			
Maximum	4.939	4.799	1.927
Mean	1.118	0.152	0.113
Median	0.910	0.082	0.059
Minimum	0.001	0.0005	0.00007
RMSE	1.465	0.406	0.223
<i>Translational RPE (m)</i>			
Maximum	0.370	0.711	0.515
Mean	0.080	0.136	0.062
Median	0.066	0.069	0.027
Minimum	0.002	0.004	0.002
RMSE	0.100	0.196	0.111

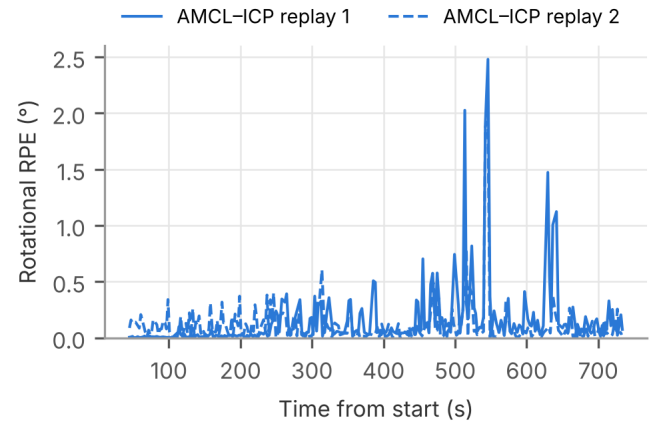


Fig. 6. Rotational RPE over time for AMCL-ICP using $\Delta = 1.0$ m.

and 0.027 m, against 0.080 m and 0.066 m for conventional AMCL), but its RMSE (0.111 m) and maximum (0.515 m) are higher than those of AMCL (0.100 m and 0.370 m). This indicates that AMCL-ICP reduces the typical position change error but produces occasional larger jumps, consistent with the isolated APE peaks discussed in Section V-A. AMCL-NDT has the highest mean and RMSE translational RPE.

Fig. 6 shows that the rotational RPE remains low for most of the trajectory, with a small number of localized spikes. The most prominent spike occurs near the later middle portion of the run but remains below the maximum observed for conventional AMCL and NDT. The spatial distribution in Fig. 7 similarly shows a trajectory dominated by low-error regions, with elevated values concentrated near turns.

Fig. 8 highlights the scale of improvement. Both scan-matching methods reduce relative rotational error compared with AMCL, but ICP gives the smallest mean and RMSE in the evaluated configuration.

C. Comparison Between the Scan-Matching Configurations

AMCL-ICP achieved lower APE and lower rotational RPE than AMCL-NDT. Both configurations were run from the same registration node with the same parameter file, so they shared the scan and map preprocessing, the 0.2 m voxel filter, the 1 – 100 m scan range, the point-cloud map, and

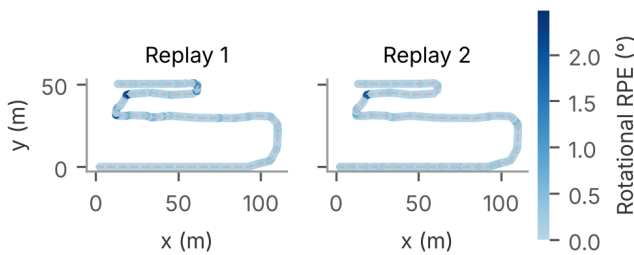


Fig. 7. Spatial distribution of rotational RPE for AMCL-ICP.

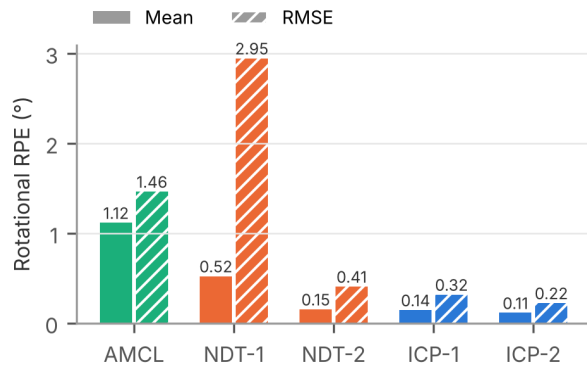


Fig. 8. Comparison of mean and RMSE rotational RPE for AMCL, AMCL-NDT, and AMCL-ICP.

the AMCL initialization, and in both the optional odometry and inertial inputs were disabled. The difference is therefore attributable to the registration algorithm and to the NDT-specific resolution and step size, rather than to unequal sensor inputs. Once AMCL narrows the global pose hypothesis, ICP matches individual LiDAR returns from tree trunks directly to map points, whereas NDT represents those points statistically within 2.0 m cells, which smooths fine geometric detail in a repeated row structure. The residual confound is the NDT cell resolution: a 2.0 m cell is coarse relative to the 1.5 m trunk diameter, and no resolution sweep was performed, so the comparison reflects NDT at its package-default resolution rather than NDT at its best achievable setting.

D. Limitations

AMCL provides probabilistic global tracking and a suitable initial guess, whereas ICP performs local geometric correction on top of it. Because the refinement is not returned to AMCL, each cycle is corrected independently and a registration error is not propagated into the particle filter, but neither does a successful refinement improve the next AMCL prediction. The higher maximum APE of AMCL-ICP and the isolated peaks in Fig. 2 and 3 show that this correction is not uniformly beneficial: occasional convergence to an incorrect correspondence is a known limitation of ICP in ambiguous geometry [14], [19].

Several further limitations should be considered. First, the experiments were conducted in simulation. The simulated LiDAR returned clean ranges from rigid, cylindrical trunks, whereas real plantations contain fronds, undergrowth, and

irregular trunk shapes that add spurious returns and change the apparent trunk geometry. These would increase false correspondences for ICP and noise in the AMCL likelihood field. Dynamic objects such as workers, animals, and moving vegetation were also absent. Second, the simulated ground was even and non-slip. On uneven terrain, robot pitch and roll tilt the 2D scan plane so that it intersects trunks at varying heights or reaches the ground, and wheel slip degrades the odometry used by AMCL and by the ICP prediction step. Third, the evaluation used one palm oil layout and one trajectory, and repeated trials sufficient for confidence intervals or statistical significance testing were not performed where other orchards, vineyards, and row crops were not represented. Fourth, all methods were run with default parameters, and runtime and processor load were not measured, so real-time suitability on an onboard computer is not claimed.

VI. CONCLUSION

This paper presented an AMCL-ICP localization method for 2D LiDAR-based agricultural mobile robots. The proposed pipeline uses the AMCL estimate to initialize ICP scan-to-map registration, combining probabilistic global localization with point-level local refinement.

In the simulated palm oil plantation, AMCL-ICP reduced mean APE by 26.2% and APE RMSE by 24.4% relative to conventional AMCL. The improvement in rotational consistency was larger: mean RPE decreased by 89.9% and RPE RMSE by 84.8%. AMCL-ICP also achieved lower mean, median, and RMSE APE and RPE than AMCL-NDT, which was run from the same node with the same inputs and preprocessing. Overall, the results indicate that ICP refinement can make effective use of local tree-trunk geometry once AMCL has provided a sufficiently good initial pose.

Future work should sweep the NDT cell resolution so that the two scan-matching configurations are compared at their respective best settings rather than at the NDT package default, repeat the experiments over multiple trajectories and runs to allow statistical testing, validate the method on a physical agricultural robot, quantify real-time computational cost, and evaluate point-to-line, generalized, and adaptive ICP variants under dynamic vegetation, uneven terrain, and varying crop layouts.

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DECLARATIONS

Use of generative artificial intelligence: Generative artificial intelligence tools were used only to support early drafting, language polishing, and manuscript organization. The authors critically reviewed, revised, and verified the entire paper and take full responsibility for the accuracy, originality, references, analysis, and final content of the manuscript.

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