Orchard Autonomous Navigation and Automatic Targeted Spraying Robot Postprint

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Abstract

To simultaneously achieve autonomous navigation and automatic target spraying for orchard intelligent plant protection machines, an orchard autonomous navigation and automatic target spraying robot was developed. Firstly, a single 3D LiDAR (Light Detection and Ranging) was employed to collect fruit tree information and determine the Region of Interest (ROI). The point cloud within the ROI was subjected to 2D processing to obtain fruit tree centroid coordinates. The Random Sample Consensus (RANSAC) algorithm was utilized to derive fruit tree row lines and determine the inter-row centerline (navigation line), thereby controlling the robot to travel along the navigation line. An encoder and Inertial Measurement Unit (IMU) were used to determine the vehicle speed and position, with the IMU correcting the collected partitioned canopy information of fruit trees. Finally, a program controlled whether the spray nozzles were activated based on the presence or absence of partitioned canopy. The results demonstrated that during autonomous navigation, the maximum lateral positioning deviation was 21.8 cm and the maximum heading angle deviation was 4.02°. Compared with conventional continuous sprayers, the applied liquid volume, airborne drift, and ground loss were reduced by 20.06%, 38.68%, and 51.40%, respectively. This study achieved autonomous navigation and automatic target spraying for the spraying robot while ensuring spray efficacy, reducing pesticide usage and drift loss through the use of a single 3D LiDAR, encoder, and IMU.

Full Text

Preamble

Autonomous Navigation and Automatic Target Spraying Robot for Orchards

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Abstract: To simultaneously achieve autonomous navigation and automatic target spraying for intelligent plant protection machinery in orchards, this study developed an orchard robot capable of both autonomous navigation and automatic target spraying. The system first employs a single 3D Light Detection and Ranging (LiDAR) sensor to acquire fruit tree information and determine the region of interest (ROI). Point clouds within the ROI undergo 2D processing to obtain fruit tree centroid coordinates. The Random Sample Consensus (RANSAC) algorithm extracts tree row lines, from which the inter-row centerline (navigation line) is derived to control robot movement. The Inertial Measurement Unit (IMU) and encoders determine vehicle speed and position, while also correcting the collected zoned canopy information. Finally, a program judges the presence or absence of canopy in each zone to control nozzle activation. Results demonstrate that during autonomous navigation, the maximum lateral deviation is 21.8 cm and the maximum heading deviation is 4.02°. Compared with conventional continuous spraying, the system reduces pesticide volume, aerial drift, and ground loss by 20.06%, 38.68%, and 51.40%, respectively. This study successfully implemented autonomous navigation and automatic target spraying using a single 3D LiDAR, encoders, and IMU, thereby reducing pesticide usage and drift.

Keywords: autonomous navigation; target spraying; LiDAR; RANSAC algorithm; robot; IMU

1 Introduction

Currently, over half of China' s orchard sprayers lack cabs, exposing operators completely to the spraying environment [1, 2]. While remote-controlled sprayers offer limited separation between human and machine, they do not achieve complete isolation, posing safety risks [3]. Autonomous navigation-enabled sprayers provide complete human-machine separation, ensuring operator safety and representing a significant market opportunity [4]. Among these, GNSS-based solutions have been widely applied in field operations [5].

Modern orchards adopt wide-row, dense-planting configurations characterized by wide inter-row spacing and narrow intra-row spacing, with closely interlinked branches forming "tree wall" structures that simplify navigation scenarios [1, 5, 6]. Current orchard autonomous navigation primarily relies on vision-based and LiDAR-based systems [7, 8]. Vision navigation captures orchard images and video, extracting navigation lines based on trunk color, texture, and shape features, then calibrating camera parameters to determine robot position relative to fruit trees for autonomous control [9, 10]. Although cost-effective and information-rich, vision sensors suffer from light interference, cannot directly obtain depth information, and cannot operate around the clock [11].

LiDAR navigation employs Light Detection and Ranging technology to scan orchard environments in real-time, achieving relative robot positioning by detecting different tree positions. Laser offers active illumination, high ranging accuracy, all-weather operation, and strong environmental adaptability [12]. Santos et al. [13] developed the VineSlam localization and mapping method and "AgRobPP" path planner for vineyards based on Simultaneous Localization and Mapping (SLAM) technology, demonstrating effective mapping and path planning for diverse robotic tasks. While 3D LiDAR-based SLAM comprehensively perceives environmental information and enhances mobile robot safety, it also increases computational burden and demands higher processing performance [13]. Saike et al. [14] achieved autonomous navigation in greenhouses through 2D processing of 3D LiDAR data. Liu et al. [15] used 3D LiDAR for navigation line extraction and autonomous navigation but did not process canopy features. These studies employed 2D LiDAR or 2D-processed 3D LiDAR for navigation without obtaining complete fruit tree feature information.

Navigation sensors can also collect canopy characteristics (volume, leaf area index, etc.) for precision variable-rate spraying in orchards [16-20], with LiDAR being the most widely applied [21]. Li et al. [22] and Dou et al. [23] used vertically-mounted 2D LiDAR to obtain tree feature information, achieving profile variable spraying and automatic target spraying (spraying when canopy is present, a key precision spraying technique [23, 24]), thereby reducing pesticide drift and saving chemicals. Vertically-mounted LiDAR maximizes acquisition of tree profile information but creates blind spots in the forward direction, preventing autonomous navigation [18]. Compared to 2D LiDAR, horizontally-mounted 3D LiDAR can detect more complete environmental information [16].

These studies demonstrate that LiDAR enables all-weather information collection, while 3D LiDAR captures three-dimensional information around the robot. However, none have utilized a single 3D LiDAR to achieve both autonomous navigation and automatic target spraying. Therefore, this study employs a horizontally-mounted 3D LiDAR to acquire fruit tree point cloud information, 截取 appropriate Regions of Interest (ROI), and processes the ROI point clouds through cropping, filtering, Euclidean clustering, and 2D projection to obtain tree centroid positions. RANSAC algorithm extracts left and right tree row lines to determine the navigation line, controlling robot movement along this path. Simultaneously, logical calculation of canopy presence in seven different ROIs for the same tree yields upper, middle, and lower zone information, enabling automatic target spraying based on canopy presence. Finally, autonomous navigation and spraying performance tests were conducted to provide references for intelligent orchard plant protection machinery research.

2 System Design

2.1 Hardware Design

[Figure 1: see original paper] illustrates the complete robot hardware system, comprising sensor modules, control modules, drive modules, target execution modules, and power modules. Green lines indicate power supply, while blue lines represent information transmission.

The sensor module primarily consists of encoders, an Inertial Measurement Unit (IMU), LiDAR, and RTK GNSS. LiDAR serves dual purposes: autonomous navigation and canopy feature detection. This makes LiDAR selection critical. This study employs a 16-line mechanical 3D LiDAR (RoboSense, Shenzhen) with 360° horizontal and 30° vertical field of view, 150 m detection range, $±$2 cm accuracy, and 2° vertical angular resolution. Operating at 10 Hz, it achieves 0.18° horizontal resolution, DC 9-32 V power supply, and 100 M Ethernet communication with the industrial computer, transmitting 320,000 points per second.

The central processing unit requires substantial computational power to handle 320,000 points per second while withstanding harsh orchard environments. An industrial computer with i7-10510U processor, 16 GB RAM, 1 TB SSD, pre-installed Ubuntu 18.04 Linux, RS232/Ethernet/USB/RS485 interfaces, and DC 9-36 V power supply was selected.

The microcontroller controls robot motion and automatic target spraying actuators while collecting encoder data. An M3S STM32 microcontroller (stm32f103zet6 chip) with ARM Cortex-M3 protocol, 144 pins, 512 kB flash memory, 72 MHz clock speed, CAN/USB/RS232 interfaces was adopted.

Two 800 W brushless DC servo motors (SDGA08C11AB, 48 V) provide propulsion, paired with 1:30 gearboxes (60TDF-147050-L2H, Jiaxing, China) and SDGA-21A servo drivers. E6B2-CWZ6C encoders (1000 pulses/revolution) mounted coaxially with drive wheels (24 cm diameter) provide speed information. During operation, offset, tilt, and wheel slip occur; the ICM-20948 IMU provides more accurate velocity and attitude data. With built-in Kalman filtering, it offers static accuracy of 0.05°/s, dynamic accuracy of 0.1°/s in X/Y axes, 1°/s in Z-axis (no magnetic interference), 0.02 g acceleration accuracy, and 0.06°/s gyroscope accuracy at maximum 200 Hz output (100 Hz used in this study). For navigation performance validation, a "P3-DU" RTK GNSS system compatible with six major satellite systems provides $±$1 cm horizontal accuracy at 20 Hz (used in this study) with DC 9-36 V power supply.

The target execution mechanism mounts on both sides of the axial fan outlet, controlling nozzle activation based on canopy presence. 2W150-15 solenoid valves (24 V, ADEC, Ningbo, China) control pipeline flow, switched by N-channel MOSFETs controlled by microcontroller I/O port logic levels.

A 48 V lithium iron phosphate battery (SK-48V100Ah, 100 Ah capacity, ~55.2 V full charge) powers the system, with voltage regulators providing stable 5, 12, 24, and 48 V outputs for different modules.

The spraying system uses a 26A plunger pump for hydraulic pressure, regulated by a pressure valve. The pump is driven by the gasoline engine via a V-belt, as is the rear-mounted fan connected to a front pulley. Liquid from the tank passes through the pump into a three-way distributor, which branches into 3, 4, and 3 liquid paths to nozzles, with solenoid valves installed between nozzles and liquid paths.

2.2 Workflow

[Figure 2: see original paper] shows the robot' s workflow for autonomous navigation and automatic target spraying, with detailed implementation described in subsequent sections.

2.3.1 Coordinate Determination

As shown in [Figure 3: see original paper], the robot' s next instantaneous Cartesian coordinates and yaw angle (x, y,) in the world coordinate system are constructed based on robot kinematics:

$$\begin{bmatrix} x_{w1} \\ y_{w1} \\ \theta_{w1} \end{bmatrix} = \begin{bmatrix} x_{w0} \\ y_{w0} \\ \theta_{w0} \end{bmatrix} + \begin{bmatrix} \cos(\theta_{w0}) & -\sin(\theta_{w0}) & 0 \\ \sin(\theta_{w0}) & \cos(\theta_{w0}) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} v_x \\ v_y \\ \omega \end{bmatrix} \cdot t$$

where x_{w0}, y_{w0} are current Cartesian coordinates; θ_{w0} is yaw angle (°); r is drive wheel radius (12 cm); ω is robot angular velocity (rad/s); and t is LiDAR frame time (0.1 s).

2.3.2 ROI Extraction

As shown in [Figure 4: see original paper], LiDAR is horizontally mounted 1.3 m above ground with 150 m maximum range, theoretically perceiving approximately 7 hectares in a circular area. At 10 Hz, each frame contains 32,000 points. Since the robot only requires point cloud data within a limited forward/backward range, excessive information causes data redundancy and compromises real-time performance. Therefore, redundant information must be cropped to extract an appropriate ROI.

Orchard robot localization and navigation only require several trees before and after the robot [15]. However, this study' s ROI must also capture complete tree profile features. [Figure 4: see original paper] illustrates 3D LiDAR detection of trees on one side during operation: nearby trees show only partial canopy detection, while distant trees are fully captured. Red lines represent laser beams, black lines indicate perpendicular distance from LiDAR to tree row (half of row spacing $D/2$, with 4 m row spacing), and blue lines show linear distance from LiDAR to target trees (d). The blue line, red lines, and trees (average height H = 4.05 m) form a right triangle. The target tree is the nearest tree with complete canopy detection (the n-th tree ahead, with 1.5 m plant spacing). With LiDAR mounting height h, geometric relationships yield Equation (2). Substituting data gives $n = 7$:

$$n = \frac{H - h}{\tan(15°) \cdot r}$$

Thus, ROI ranges were set as: X [-2.5 m, 2.5 m], Y [-3.0 m, 10.5 m], Z [1.9 m, 4.8 m], with forward direction as positive X-axis. PCL' s passthrough filter cropped x, y, z dimensions to obtain the final ROI range. This simple, efficient filter iterates through each point and removes points outside specified ranges.

2.3.3 Tree Localization and Navigation in ROI

PCL' s voxel grid downsampling function reduced voxel size to (0.05 m, 0.05 m, 0.05 m), decreasing point cloud quantity and improving computational speed. Processed point clouds and corresponding world coordinates were stored in shared memory for rapid calculation.

Statistical filtering removed noise, followed by Euclidean clustering to obtain point cloud clusters P_i, with minimum distance threshold $h/3$, and minimum/maximum cluster sizes of 10 and 5500 points, respectively. After clustering, point clouds were projected onto the XOY plane, and centroids $(X_i, Y_i, 0)$ were calculated as tree positions. Based on IMU, encoders, LiDAR, and tree positions, the ROI updated when the robot reached the midpoint between tree rows. RANSAC algorithm fitted tree rows, with navigation line extraction and tracking algorithms following reference [15], ultimately transmitting specific angular velocity commands to the microcontroller.

2.4 Software System Design

To improve development efficiency and reduce redundant work, the software system was developed on the Robot Operating System (ROS) platform. C/C++ was used as the primary language under ROS Melodic and Ubuntu 18.04 for developing information acquisition/processing packages, tree row identification, navigation line extraction, motion control, zoned canopy logic calculation, and automatic target spraying decision packages, as shown in [Figure 5: see original paper]. The system comprises application, control, driver, and automatic target spraying layers, with the control and automatic target spraying layers being most critical.

2.5.1 Determination of Fruit Tree Zoned Canopy Presence

Determining canopy presence/absence in each zone is critical for automatic spraying. During normal operation, the ROI contains nine trees. With LiDAR 1.5 m from nozzles and requiring reaction time from data collection to spraying, point clouds from four trees behind LiDAR are discarded. IMU roll and pitch angles correct remaining canopy point clouds, recalculating tree center coordinates (trunk). Canopy distance D_s from LiDAR is compared to trunk distance D_g; if $D_s > D_g$, the area is a gap (no canopy), otherwise canopy is present.

The ROI (10.5 m length) is divided into 35 sub-zones of 30 cm each on both sides, and vertically into seven layers based on ROI update frequency, as shown in [Figure 6: see original paper]. The seven layers form seven inclined zones: upper two zones as top layer, lower two as bottom layer, and remainder as middle layer. Each zone corresponds to specific nozzles (top layer: one nozzle; middle/bottom layers: two nozzles each). Glass threads fixed on deflectors were used to verify alignment with canopy under fan airflow, with deflectors adjusted until proper alignment was achieved.

2.6 Data Plotting

OriginPro 2020 was used for plotting experimental results.

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3 Experimental Design

To verify autonomous navigation performance, validation tests were conducted on October 11, 2021, at a modern "Fojianxi" pear orchard in Xiying Village, Yukou Town, Pinggu District, Beijing. Weather conditions were sunny, temperature 17.2-18.5°C, wind speed 0.8-1.3 m/s. [Figure 8: see original paper] shows the test schematic, with a weather station 10 m from the base station and an RTK GNSS base station 15.5 m from the test area in open terrain.

3.1 Navigation Test

Before testing, RTK GNSS rover stations surveyed coordinates of first and last trees in both rows to determine tree row equations and navigation line equations. The robot was positioned mid-row at the field edge, power and engine started, then automatic target spraying program initiated. The robot traveled along the black arrow in [Figure 8: see original paper] into the 100 m × 4 m test area (10.5 m from field edge), decelerating to stop after passing 2 m beyond the test area. Three replicates were performed. Lateral deviation was defined as perpendicular distance from trajectory points to navigation line, with positive deviation indicating right-side position. Heading deviation was the angle between trajectory and navigation lines, with positive angle indicating rightward orientation.

3.2 Spray Comparison Test

To verify spraying performance, three trees in the test area were selected for spray performance evaluation. Sampling point layout is shown in [Figure 9: see original paper]. Test trees were divided into upper (3.2 m), middle (2.4 m), and lower (1.6 m) layers (average trunk height 1.15 m). Five 7 cm diameter filter papers were placed at east, west, south, north, and center positions in each layer using double clips. Three additional filter papers were placed at each tree base and 0.75 m above ground on left/right sides (spaced 0.5 m apart) to collect ground loss. A 5 m vertical pole was positioned 1.5 m from test trunks, with nine 400-mesh rectangular metal screens (2.5 cm × 7.5 cm) fixed vertically at heights of 0.2, 0.8, 1.4, 2.0, 2.6, 3.2, 3.8, 4.4, and 5.0 m (0.6 m intervals) to collect drift, grouped in sets of three.

A 3.0 g/L tartrazine solution served as tracer. Mother solution was stored in a dark box before testing. Automatic target spraying and traditional continuous spraying used the same machine, differing only by program activation. Each 100 m spray test collected samples in #6 ziplock bags.

Samples were eluted with deionized water (50 mL per bag), sealed, and oscillated using an NMY-100A shaker to fully dissolve deposits. Solutions were pipetted into cuvettes and analyzed using a 722s spectrophotometer at 426 nm wavelength. Deposit volume V_c was determined using the method from reference [25], with unit area deposition calculated based on filter paper area. To compare spray modes, canopy deposition was normalized following references [25, 26] using Equation (4):

$$d_g = \frac{V_s \times V_z}{A}$$

where d_g is normalized unit area deposition (L/cm^2), V_s is sample deposition (L), V_z is application rate (L/ha), and A is sample area (cm^2).

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4 Results and Analysis

4.1 Autonomous Navigation Performance

[Figure 10: see original paper] presents violin boxplots of lateral deviation during autonomous navigation, showing distribution and probability density. Figure 10: see original paper shows both mean and median values were negative across three tests, indicating the robot traveled mostly left of the navigation line, with larger differences between mean and median in Test 2. Figure 10: see original paper shows absolute deviations were mostly below 15 cm, often below 10 cm, with means and medians under 10 cm, demonstrating high navigation accuracy (relative to 4 m row spacing). Tests 2 and 3 showed similar means and medians, while Test 1 differed significantly, indicating Test 1 spent the most time left of the navigation line, followed by Test 3, then Test 2. Maximum absolute lateral deviation was 21.8 cm.

[Figure 11: see original paper] shows heading deviation absolute values, with maximum 4.02°. Mean heading deviation decreased progressively across tests, likely because repeated passes compacted the rough orchard ground, reducing tilt and stabilizing heading. These results confirm the robot meets basic orchard autonomous navigation requirements.

4.2 Spray Comparison Test Results

Pesticide consumption measurements showed traditional spraying used 20.24 L while automatic target spraying used 16.18 L, corresponding to 506 and 404.5 L/ha, respectively—a 20.06% reduction.

[Figure 12: see original paper] compares actual and normalized deposition. Figure 12: see original paper and (b) show similar deposition percentages between modes, with automatic target spraying total deposition only 10.19% lower. However, after normalization, automatic target spraying showed 12.38% higher deposition than traditional spraying, indicating that while chemical savings reduced absolute deposition, spray efficacy improved because traditional spraying wasted pesticide in gaps. The actual deposition reduction in automatic target spraying may result from program delay functions and canopy presence misjudgment.

[Figure 13: see original paper] shows aerial drift quantities and percentages for both modes. Both exhibited highest drift in middle and bottom layers (47%, 42% for traditional; 41%, 49% for automatic), with upper layer drift only 11% and 10%, respectively. Traditional spray drift decreased with height because large droplets couldn' t reach upper layers, while small droplets lacked penetration to drift onto screens. Automatic target spraying showed higher middle layer drift, likely due to adjusted nozzle and deflector angles. Automatic target spraying reduced average aerial drift by 38.36%.

[Figure 14: see original paper] presents ground loss quantities and percentages. Sampling point B represents tree base, while A and C represent left/right sides between trees. Automatic target spraying ground loss was substantially lower than traditional spraying, reducing ground loss by 51.36% and significantly decreasing soil contamination. While drift percentages were similar between modes, ground loss percentages were opposite: automatic target spraying showed maximum loss at point B (43%) with similar percentages at A and C (29%, 28%); traditional spraying showed minimum at B (25%) with higher, similar percentages at A and C (38%, 37%). This occurs because points A and C are canopy gaps between trees where automatic target spraying doesn' t spray, while traditional spraying wastes pesticide in gaps. The robot reduced aerial drift by 38.68% and ground loss by 51.40% compared to conventional sprayers.

5 Conclusion

This study implemented orchard robot autonomous navigation and automatic target spraying using a single 3D LiDAR, encoders, and IMU. Navigation and spraying performance tests demonstrated the robot fully meets orchard requirements. Key conclusions:

1) During autonomous navigation, maximum lateral deviation was 21.8 cm and maximum heading deviation was 4.02°, satisfying basic orchard navigation requirements.

2) Compared to conventional sprayers, the robot reduced pesticide volume by 20.06%. Although canopy deposition decreased by 12.38%, spray performance improved with 38.68% less aerial drift and 51.40% less ground loss, reducing environmental contamination.

3) While aerial drift percentages were similar between automatic target and traditional spraying, ground loss percentages differed markedly: automatic target spraying showed maximum ground loss (43%) at tree bases, with lower loss (29%, 28%) between trees, whereas traditional spraying showed the opposite pattern.

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Note: Figure translations are in progress. See original paper for figures.