

Article

Design and Experimental Evaluation of a Machine Vision-Based Delay Compensation Algorithm for Corn Row-Following Spraying

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Abstract

To address the reduction in nozzle row-following accuracy caused by sensing–execution latency during corn row-following operations, a delay compensation method based on machine vision and dynamic region of interest (ROI) adjustment was proposed. The method integrates real-time forward-velocity information from a global navigation satellite system/inertial measurement unit (GNSS/IMU), decomposes the delays associated with image processing, command transmission, and actuator motion, and calculates a visual look-ahead distance from the total response delay and robot forward velocity. Inverse-perspective mapping was used to establish the relationship between pixel and world coordinates, and the ROI position was dynamically shifted to synchronize the sensing–execution process. Indoor bench tests showed that, under variable conveyor-belt speeds ranging from 0 to 0.25 m/s, the algorithm achieved a row-following accuracy of 93.75% and a lateral mean absolute error of 0.019 m; compared with the average result of the three fixed-ROI tests, the lateral mean absolute error was reduced by 24.8%. Whole-machine tests showed that, under random platform forward speeds of 0–1.00 m/s, the row-following accuracy remained above 85.71%, with a lateral mean absolute error of 0.034 m. The results indicate that the proposed method effectively compensates for system delay under different speed conditions and reduces lateral tracking errors caused by longitudinal spatiotemporal mismatch, providing technical support for the development of precision corn row-following spraying equipment.

Keywords: precision agriculture; visual servoing; sensing–execution latency; spatiotemporal alignment; adaptive ROI



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1. Introduction

Mechanized plant protection in corn production is a key operation for ensuring stable and high crop yields. However, conventional wide-swath spraying can result in substantial pesticide drift and off-target deposition between rows, leading to pesticide waste, environmental contamination, and potential impacts on field ecosystems [1,2]. Machine vision-based row-following spraying identifies crop rows and guides the spraying device

to perform target-oriented application, thereby improving chemical-control precision. It has therefore become an important research direction in precision agriculture [3,4]. The core requirement of this technology is the real-time and accurate alignment of the spraying terminal with dynamically changing crop rows. Under variable-speed field operation, however, inherent multi-stage response delays occur from image acquisition and processing to control-command generation and actuator motion [5]. This sensing–execution latency causes the actual physical position of the spray nozzle to lag behind the target row position identified by the vision system, generating tracking errors [6] and limiting the nozzle-positioning accuracy and reliability of the system under variable-speed conditions [7,8]. Therefore, analyzing the mechanism of response delay and dynamically compensating for it are essential for improving corn row-following nozzle-positioning accuracy.

Existing studies aimed at improving corn row-following spraying systems have mainly focused on crop-row detection accuracy and system-delay compensation. In crop-row detection, traditional image-processing algorithms based on Excess Green (ExG) features and Hough transform are widely used in real-time control systems, especially on embedded platforms, because of their high computational efficiency and real-time performance [9,10]. Deep learning algorithms [11,12] perform well in complex scene recognition, but their higher computational complexity can introduce longer and more variable processing delays, which may challenge real-time control and hinder stable delay modeling [13]. For delay compensation and control, when a servo system is used to drive a spray nozzle or spray boom, the key issue is to overcome the response delay across the complete chain from visual perception to servo actuation. Classical proportional–integral–derivative and fuzzy control strategies [14,15] have been widely applied to servo-tracking control. Further studies have improved system performance by modeling and compensating for delay. For example, Wang et al. [16] developed a variable-rate spray (VRS) system for unmanned aerial applications that integrated pulse width modulation (PWM) technology with a lag compensation algorithm (LCA). The LCA was designed to counteract the droplet deposition-position lag caused by the inherent system response delay during UAV aerial spraying operations, and experimental results demonstrated that the proposed algorithm effectively reduced the deposition-position offset induced by fixed delays, improving the spatial consistency between the target area and actual spray deposition. Li et al. [17] addressed the problem of droplet deposition offset in field target-spraying operations by establishing a nozzle motion state perception model and a deposition-position prediction model based on GNSS/IMU Kalman filter signal fusion. By predicting the real-time position of the nozzle and the anticipated landing point of the droplets, the method compensated for signal-processing and system-response lag, achieving target spraying accuracies of 99.8%, 98.4%, 95.9%, and 76.5% at forward speeds of 0.5, 1.0, 1.5, and 2.0 m/s, respectively. Li et al. [18] proposed a deep learning-based precision target spraying device for weed control in soybean fields, in which a grid-based matching spraying algorithm was developed to synchronize target detection with spray actuation. The system systematically analyzed the image processing delay, communication and control delay, and spray deposition delay, and implemented a time-delay compensation strategy to dynamically adjust the triggering grid positions based on real-time vehicle speed feedback, achieving nozzle-positioning accuracy exceeding 85.88% at forward speeds of 1–4 km/h. Zheng et al. [19] designed and experimentally validated an automatic row-oriented spraying system based on machine vision for early-stage maize crops, in which a compensation model was established that explicitly accounted for communication delay, image processing delay, and mechanical movement delay. By incorporating these delay components into the control logic, the system reduced row-following errors and improved the alignment accuracy between the spray nozzle and the crop row under varying operational speeds. These studies provide

useful references for delay compensation, but some model parameters are obtained by static calibration and do not account for the dynamic movement response of the servo system. A method capable of dynamically quantifying and compensating for system delay in real time is therefore required to improve row-following nozzle-positioning accuracy.

The objective of this study was to develop and preliminarily evaluate a dynamic delay-compensation method that combines total system response delay with real-time robot forward velocity for a corn row-following system with continuously moving nozzles. The method couples the temporal relationship between system delay and target distance and dynamically adjusts the ROI position to reduce nozzle-positioning errors caused by sensing–execution latency. Indoor fixed-ROI and dynamic-ROI tests were used to evaluate the compensation mechanism, and outdoor whole-machine tests were used to assess integrated positioning feasibility under platform motion. Actual droplet deposition and field spraying efficacy were outside the scope of the present study.

2. Materials and Methods

2.1. Working Principle of the Intelligent Row-Following Spraying System

To enable real-time nozzle response under variable-speed forward motion during corn row-following spraying, an intelligent row-following spraying system integrating perception, decision making, and execution was developed. The robot operation scheme is shown in Figure 1. The row-following spraying system was mounted on a high-clearance mobile platform suitable for longitudinal field operation in corn. An industrial camera was installed along the longitudinal centerline of the platform. Two lateral alignment modules were installed symmetrically on both sides of the centerline and were used to follow the left and right corn rows, respectively.

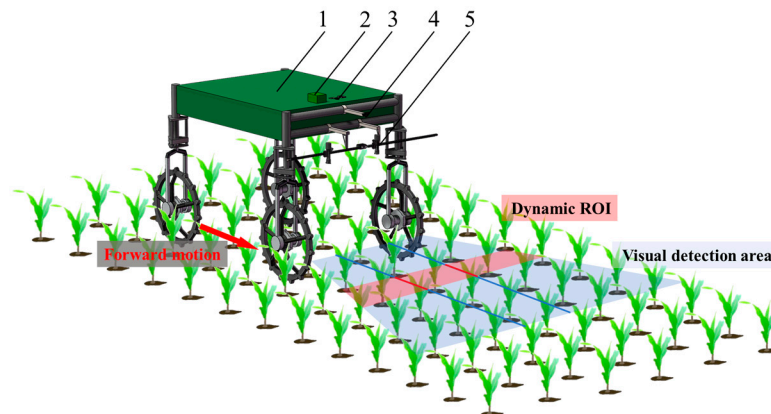


Figure 1. Schematic diagram of row-following spraying robot operation. 1. High-clearance platform; 2. control box; 3. pose-sensing module assembly; 4. industrial camera; 5. lateral alignment module.

The system adopted a multi-sensor fusion architecture composed of a vision sensing unit, a pose-sensing unit, an integrated image-processing system, an execution control system, and a lateral row-following system. The structural block diagram of the spraying system is shown in Figure 2.

The perception part of the system combined monocular vision with GNSS/IMU-based velocity measurement to support high-precision row-following spraying under dynamic conditions. The vision sensing unit consisted of a forward-looking industrial camera equipped with a wide-angle lens with a vertical field of view of approximately 50° . The camera was mounted above the spray nozzles to ensure that the image fully covered corn rows in the forward direction. It output 1920×1080 -pixel image sequences at 30 frames/s, providing high-quality image input for real-time row detection. The pose-sensing unit

used a combined GNSS/IMU scheme, in which data were fused using a Kalman filter [20]. This unit provided the robot with accurate three-directional velocity and pose information in real time, with a velocity-measurement accuracy better than 0.1 m/s in open farmland, and synchronized the data with the upper-computer processing unit through a serial interface. An NVIDIA Jetson Orin NX was used as the core processing unit to run the image-processing and multi-source data-fusion algorithms. It dynamically estimated the system delay, adjusted the ROI through feedforward compensation, and transmitted the resulting crop-row world coordinates to the execution module via serial communication, thereby achieving spatiotemporal alignment between the spray nozzle and the target row. The execution module used an embedded microcontroller to drive a lateral sliding mechanism. A stepper motor moved the nozzle mounted on a synchronous belt in the direction perpendicular to the forward motion. The nozzle height was set to 1.3 m and was aligned with the lower viewing plane of the camera, enabling dynamic tracking and accurate targeting of the corn row.

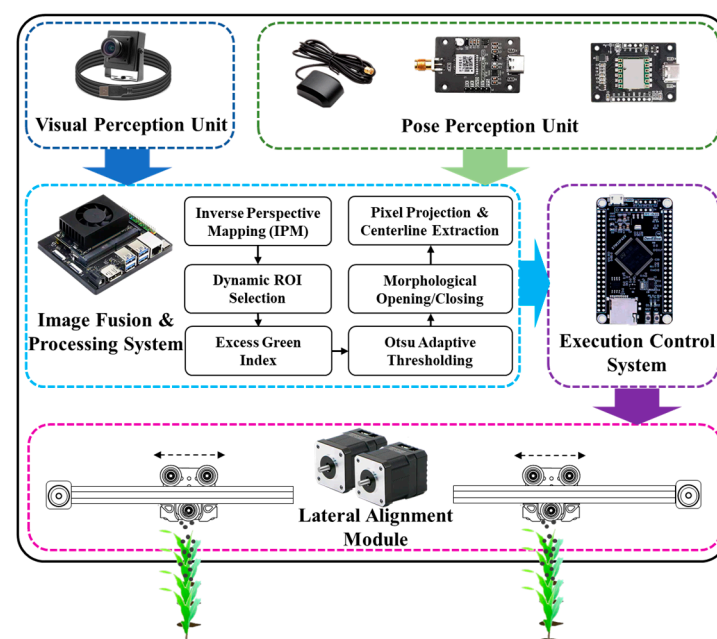


Figure 2. Overall structural block diagram of the corn row-following spraying system.

2.2. Analysis and Calculation of System Response Delay

2.2.1. Analysis of Delay Components

Row-following spraying is essentially a discrete-event control process, and inherent delay exists from visual perception to the completion of actuator motion [21]. This delay is the core factor restricting system accuracy under variable-speed or high-speed operation. To achieve accurate row-following control, the total system delay must be modeled and quantified. The timing diagram of the system is shown in Figure 3. During a single operation process, from the acquisition of the original corn-row image to the execution of nozzle targeting, the total delay mainly consists of three serial stages: image acquisition and processing, target localization and command transmission, and nozzle movement. In parallel, the nozzle also moves forward with the robot.

The time consumed from image acquisition to the output of target coordinates by the corn-row detection algorithm is defined as the image acquisition and processing delay, t_p . The exposure time of the image sensor and the image-data transmission time were very short and were ignored. Algorithm computation time was dominant, and its value was related to image complexity and ROI size. In this study, timestamps were inserted into the

main program, and the time difference was calculated in every control cycle. The delay measured in frame n was used as t_{p_n} in the prediction of the ROI position for frame $n + 1$.

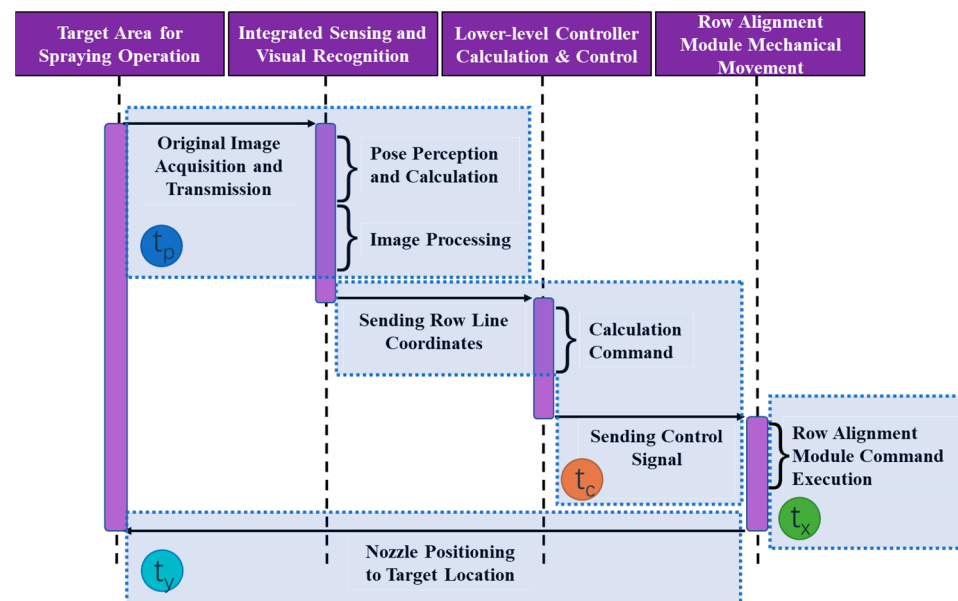


Figure 3. Timing analysis of the response delay in the corn row-following spraying system.

After visual processing, the relative target-position coordinates were obtained. The time from the output of the target coordinates by the upper computer to the reception of the rotation command by the stepper motor driver was defined as the lower-computer control delay, t_c . To quantify t_c , a dual-channel digital oscilloscope was used to synchronously capture the rising edges of the upper-computer serial signal and the lower-computer control pulse signal. The time interval between the two rising edges was measured. Repeated measurements yielded a stable communication-path delay of $t_c = 0.2$ ms. Because this delay had negligible influence on the row-following error, it was ignored in subsequent analysis.

The lateral movement delay of the row-following module, t_x , is the time required for the nozzle to move from its current position to the target position on the sliding module. This value changes dynamically and can be calculated as follows:

$$t_x = \Delta x / v_x \quad (1)$$

$$v_x = \pi d n \quad (2)$$

where Δx is the absolute difference between the target point and the current point in world coordinates, m; v_x is the lateral nozzle movement velocity, m/s; n is the stepper motor rotational speed, r/s; and d is the pitch-circle diameter of the synchronous-belt driving pulley, m. In this device, the maximum lateral movement velocity of the nozzle was calculated as $v_x = 0.3$ m/s.

While the above serial process is running, the row-following spraying robot continues to move forward. The target spatiotemporal travel time, t_y , is determined by the actual horizontal distance from the current nozzle working position to the visually identified target position, which coincides with the ROI centerline, and the robot forward velocity, v_y :

$$t_y = \Delta y / v_y \quad (3)$$

where Δy is the actual horizontal distance from the ROI centerline to the nozzle position in the forward direction, m, and v_y is the forward velocity of the robot, m/s.

2.2.2. System Equivalent Time Deviation

To accurately describe the system timing logic and design the response-delay compensation strategy, a system equivalent time-deviation model was established based on the four delay components described above. The total system response delay was defined as the sum of the image acquisition and processing delay, the lower-computer control delay, and the lateral movement delay of the row-following module:

$$T_s = t_p + t_c + t_x \quad (4)$$

During system response, the robot continues to move forward at velocity v_y , which causes longitudinal displacement of the target position relative to the nozzle. The corresponding target travel time is t_y . When $T_s \neq t_y$, a timing mismatch occurs. The equivalent time deviation, T , was defined as the absolute difference between the total system response delay and the target travel time:

$$T = |T_s - t_y| = |t_p + t_c + t_x - t_y| \quad (5)$$

where T is the equivalent time deviation, s. Its value is non-negative in the range $[0, +\infty)$, and it represents the time-difference magnitude between the actual response moment and the ideal target-response moment. A larger T indicates more severe timing mismatch. When $T = 0$, the system response is fully synchronized with the target motion, representing the ideal operating state.

To distinguish the mismatch direction, a direction flag sigma was introduced:

$$\sigma = \begin{cases} 1, T_s \geq t_y \\ -1, T_s < t_y \end{cases} \quad (6)$$

The longitudinal row-following error can then be expressed as

$$\delta = \sigma \cdot T \cdot v_y \quad (7)$$

where δ is the longitudinal row-following error, m. When $\delta > 0$, the critical point of the nozzle trajectory lags behind the target point; when $\delta < 0$, it leads the target point; and when $\delta = 0$, the nozzle is fully aligned with the target. Equations (5) and (7) indicate that the magnitude of the equivalent time deviation directly determines the longitudinal row-following error, $|\delta| = T \cdot v_y$. Under variable-speed or high-speed operation, an increase in v_y increases $|\delta|$ proportionally. Therefore, dynamically adjusting the visual processing area can compensate for row-following error caused by velocity changes and drive T toward 0, enabling accurate row following under variable-speed and high-speed conditions.

2.3. Design of the Delay-Compensated Vision System

The proposed vision system combines the system response delay and the forward velocity of the robot. It corrects image scale through inverse-perspective mapping and uses the dynamic-ROI delay compensation algorithm to shift the visual processing area in a forward-looking manner. The optimal ROI is selected, and the corn-row coordinates are extracted from the optimized region, thereby compensating for longitudinal row-following errors caused by system delay. The geometric relationship is shown in Figure 4. The camera installation geometry includes the mounting height H , the vertical field of view α , and the angle θ between the optical axis and the vertical direction. These parameters define the observation baseline and are used to calculate the actual length covered by the image, L , and the actual length covered by the ROI, L_{ROI} , thereby establishing a mapping relationship between the pixel coordinate system and the field coordinate system.

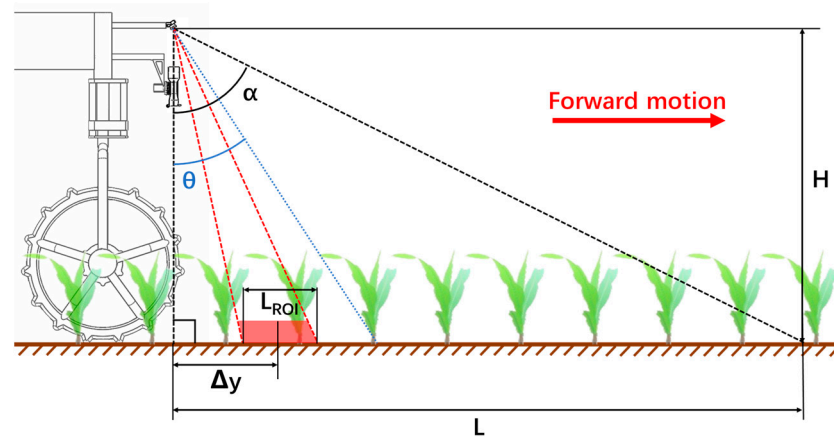


Figure 4. Schematic diagram of imaging side-view geometric relationships. α denotes the camera vertical field of view; θ denotes the angle between the camera optical axis and the vertical plane; H denotes the camera mounting height; L_{ROI} denotes the physical length covered by the ROI; Δy denotes the horizontal distance from the ROI centerline to the nozzle position in the forward direction; and L denotes the physical length covered by the entire image.

2.3.1. Inverse-Perspective Mapping Based on Planar Homography

To accurately calculate ROI translation and prepare for subsequent visual processing, a linear geometric relationship between image pixel coordinates and ground-plane world coordinates must be established. Because the operating scene satisfies the ground-plane constraint, all target points can be regarded as being located on the plane $Z_w = 0$. Therefore, an inverse-perspective mapping method based on planar homography was adopted [22]. A 3×3 homography matrix P was used to directly establish the mapping between image pixel coordinates (a, b) and the ground-plane world coordinate system (X_w, Y_w) :

$$\lambda \begin{bmatrix} a \\ b \\ 1 \end{bmatrix} = P \begin{bmatrix} X_w \\ Y_w \\ 1 \end{bmatrix} = \begin{bmatrix} p_{11} & p_{12} & p_{13} \\ p_{21} & p_{22} & p_{23} \\ p_{31} & p_{32} & p_{33} \end{bmatrix} \begin{bmatrix} X_w \\ Y_w \\ 1 \end{bmatrix} \quad (8)$$

where λ is an arbitrary scale factor, and p_{mn} represents the elements of the homography matrix P .

Matrix P includes camera intrinsic parameters, mounting height H , and camera pitch angle θ . It can be obtained directly through calibration. Then, by calculating the inverse matrix P^{-1} , image pixels can be mapped to the ground-plane world coordinate system:

$$\begin{bmatrix} X'_w \\ Y'_w \\ \lambda' \end{bmatrix} = P^{-1} \begin{bmatrix} a \\ b \\ 1 \end{bmatrix} \quad (9)$$

This transformation converts the image into a bird's-eye view and effectively eliminates scale deviation caused by perspective effects. The distance along the Y -axis, i.e., the forward operating direction, is linearly related to the world coordinate. Because the camera projection model is anisotropic, the scale relationship between world and pixel coordinates differs between the X - and Y -axes. In this study, the output bird's-eye view was defined at the same spatial resolution as the input image (1920×1080 pixels) to maintain computational compatibility with downstream processing. Therefore, the X -axis scale factor k_x (pixel/m) and the Y -axis scale factor k_y (pixel/m) were calibrated separately to provide an accurate geometric basis for subsequent calculations. Calibration was implemented in OpenCV using multiple non-collinear reference points with known ground-plane coordinates. The final calibrated values were $k_x = 400$ pixel/m and $k_y = 456.25$ pixel/m.

2.3.2. Dynamic-ROI Delay Compensation Mechanism

Because the total system response delay objectively exists, that is, $(t_p + t_c + t_x) > 0$, the ideal working state requires the equivalent time deviation to satisfy $T = 0$ according to Equation (5), thereby achieving $\delta = 0$:

$$t_y = \frac{\Delta y}{v_y} = t_p + t_c + t_x \quad (10)$$

An ideal real-time control method would complete closed-loop control within the same program cycle. In practice, however, the discreteness of the real-time control cycle imposes inherent timing constraints, and the system must adopt a forward-looking prediction strategy to overcome the inherent delay of the control chain. Using the measurable system state in frame n , the ROI required for frame $n + 1$ can be predicted. Combined with the real-time forward velocity of the current frame provided by GNSS/IMU fusion, the required look-ahead distance of the visual processing region is

$$\Delta y_{n+1} = v_{y_n} \times (t_{p_n} + t_{c_n} + t_{x_n}) \quad (11)$$

where v_{y_n} is the real-time forward velocity in frame n , m/s, and Δy_{n+1} is the look-ahead distance required for frame $n + 1$, m.

Combined with the Y-axis scale factor k_y obtained by inverse-perspective mapping calibration, Δy_{n+1} was converted into a pixel translation d_{n+1} in the bird's-eye view:

$$d_{n+1} = \Delta y_{n+1} \times k_y \quad (12)$$

To clearly define the image-processing region, a rectangular region with 100% of the image width and 15% of the image height was selected as the ROI in the bird's-eye-view coordinate system, as shown in Figure 5. Because the lower boundary of the image was used as the offset reference, the ROI position $b_{ROI_{n+1}}$ was represented by the coordinate of its horizontal centerline on the b -axis. To ensure that the ROI always remained within the valid image area, its centerline b -coordinate was constrained as follows:

$$b_{ROI_{n+1}} = \begin{cases} 999, & d_{n+1} \leq 81 \\ 1080 - d_{n+1}, & 81 < d_{n+1} \leq 999 \\ 81, & 999 < d_{n+1} \end{cases} \quad (13)$$

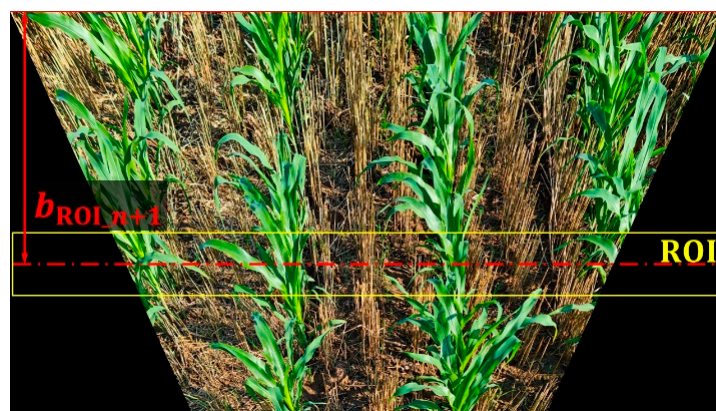


Figure 5. Dynamic-ROI delineation.

Since the image processing delay t_p may fluctuate slightly because of changes in crop-feature complexity within the ROI, abrupt variations in the estimated look-ahead distance

may occur. To improve the stability of the dynamic-ROI update, the system updates the ROI position only when the variation in the calculated look-ahead distance between two consecutive frames remains within a predefined threshold. Otherwise, the previous ROI position is retained for one frame. Because the fluctuation of t_p was generally smaller than one image frame during experiments, this simple threshold-based filtering effectively suppressed occasional abnormal peaks without affecting the responsiveness of the delay compensation algorithm.

2.3.3. Corn-Row Recognition Algorithm

Based on the spectral-reflection characteristics of corn plants, the Excess Green (ExG) feature was calculated for the ROI image to enhance the green component and suppress the red and blue components, thereby effectively distinguishing vegetation from non-vegetation regions, such as soil and shadows [23]. First, the ExG feature value of each pixel was calculated as follows:

$$ExG = \alpha G + \beta R + \gamma B, \quad G, R, B \in [0, 255] \quad (14)$$

where G, R, B are the original intensity values of the green, red, and blue channels of the pixel, respectively, and α, β , and γ are the corresponding coefficients.

Based on the spectral characteristics of the corn canopy and preliminary comparisons, the optimal coefficients were set as $\alpha = 3.0$, $\beta = -1.8$, and $\gamma = -1.2$. The calculated ExG feature image was linearly scaled to the standard 8-bit grayscale range $[0, 255]$ to obtain the grayscale image $F(i, j)$ for subsequent processing:

$$F(i, j) = \text{round} \left(\frac{ExG(i, j) - ExG_{\min}}{ExG_{\max} - ExG_{\min}} \times 255 \right) \quad (15)$$

where $ExG_{\min}$ and $ExG_{\max}$ are the minimum and maximum ExG feature values in the current image, respectively.

After this process, vegetation regions appear with high brightness in the grayscale image, providing a good basis for subsequent threshold segmentation. To convert the ExG grayscale image into a binary image suitable for geometric feature extraction, Otsu adaptive thresholding was used [24]. This method maximizes the inter-class variance between foreground and background and automatically calculates the optimal global threshold K . The segmentation process can be expressed as

$$Z(i, j) = \begin{cases} 1, & F(i, j) > K \\ 0, & F(i, j) \leq K \end{cases} \quad (16)$$

where $Z(i, j)$ is the binary result of pixel (i, j) after Otsu adaptive threshold segmentation, with 1 denoting vegetation and 0 denoting background.

Noise points and small holes within the plants often occur in the binary image and can affect subsequent row-line extraction. Therefore, morphological opening and closing operations were applied as post-processing [25]. A small 3×3 kernel was first used for opening to remove isolated noise points, and a slightly larger 5×5 rectangular kernel was then used for closing to fill small holes and smooth edges, resulting in more continuous corn-row contours.

Based on the processed binary image, the foreground white pixels were projected along the vertical direction:

$$M(i) = \sum_{j=1}^{H_{ROI}} Z(i, j), i = 1, 2, \dots, W_{ROI} \quad (17)$$

where $M(i)$ is the sum of white pixels in the i th column, and H_{ROI} and W_{ROI} are the ROI height and width in pixels, respectively. The processing procedure is illustrated in Figure 6.

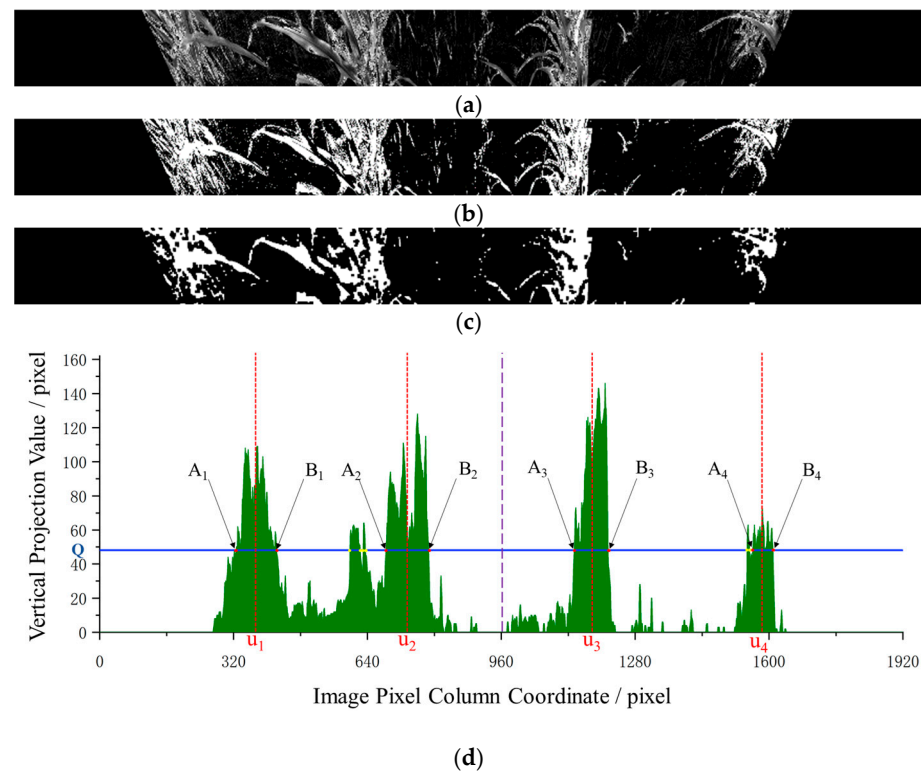


Figure 6. Visual processing procedure: (a) ExG calculation; (b) Otsu adaptive threshold segmentation; (c) morphological opening and closing operations; (d) pixel-projection histogram for centerline-coordinate selection. In panel (d), Q is the projection threshold, A_i and B_i are the left and right boundaries of the i th candidate row region, u_i is the corresponding midpoint coordinate, and the horizontal axis is the image-column coordinate (pixel).

Because the ROI height accounted for 15% of the original image height, $H_{ROI} = 162$ and $W_{ROI} = 1920$. A pixel-projection histogram was generated, and a threshold Q was set. Continuous pixel regions satisfying $M(i) > Q$ were defined as candidate row regions. To eliminate pseudo-row regions caused by incomplete plants or shadows, a lateral spacing constraint was introduced. If the horizontal distance Δa_{AB} between points A and B was smaller than 50 pixels, the projection region was discarded. The midpoint coordinate between A and B was selected as the corn-row coordinate a , representing the centerline of the candidate row region.

The two row lines closest to the vertical image centerline on the left and right sides were selected as the final output corn rows. After coordinate-system conversion, the actual row position in the X-axis of the world coordinate system was output as

$$X = a/k_x \quad (18)$$

where a is the row-line coordinate in the image pixel coordinate system, pixel, and X is the actual row coordinate in the world coordinate system, m.

The row-line pixel coordinate a can be denoted as a_L and a_R for the left and right rows, respectively. The actual world coordinates X_L and X_R were then calculated using Equation (18) and used as the upper-computer output for the left and right lateral row-following modules.

2.4. Tests of System-Delay Compensation and Nozzle Row-Following Positioning Performance

2.4.1. Indoor Bench Test for Algorithm Effectiveness

To preliminarily verify the effect of the delay compensation algorithm, bench tests were conducted in an environment without the mechanical vibration of the high-clearance mobile platform or dynamic visual-background disturbances. The tests compared the response and row-following accuracy of the system using fixed ROI and dynamic ROI under different forward speeds. The conveyor-belt test platform is shown in Figure 7. The test platform consisted of a conveyor-belt system, a lateral row-following module, a vision system, a control unit, and simulated corn plants. Biomimetic plant models with morphological and spectral characteristics similar to real corn plants were used, with an average height of 0.45 m and canopy width of 0.08–0.15 m.

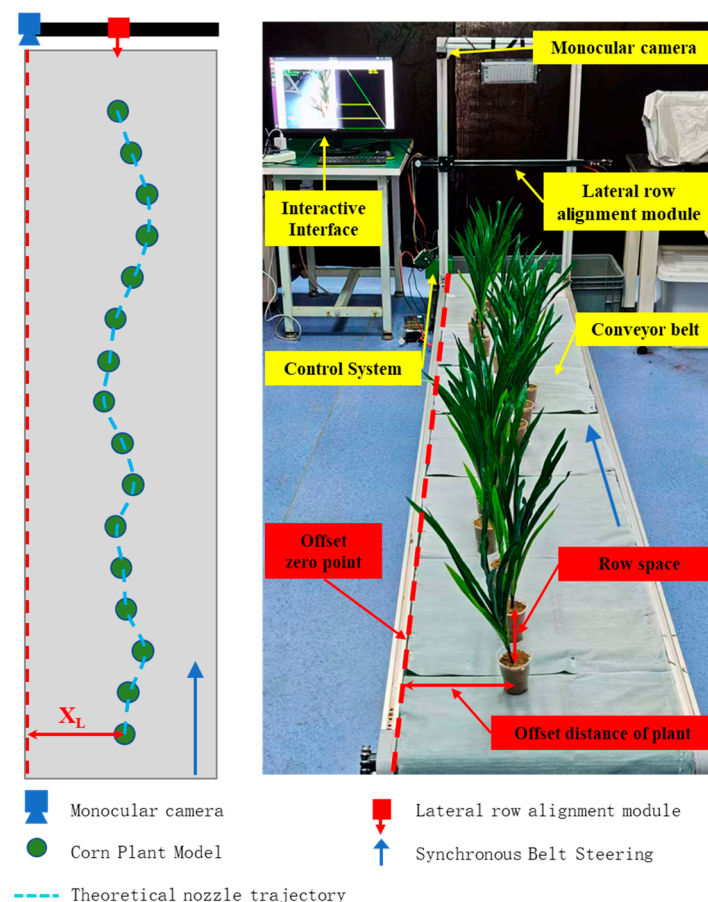


Figure 7. Single-row corn tracking accuracy test.

To isolate interfering factors and simulate the relative motion between the system and the corn plants, the corn plant models were placed on the conveyor belt, whose adjustable speed ranged from 0 to 0.25 m/s. An offset reference line was set on one side of the conveyor belt, and 16 corn plant models were placed on one side of the reference line. The longitudinal plant spacing was 0.2 m, and the distance from each plant to the reference line was randomly set to simulate the actual condition of a single corn row in the field.

The lateral row-following module was arranged on one side. The nozzle movement range was 0–0.5 m, and the adjustable movement velocity was 0–0.3 m/s. The nozzle lateral movement velocity was set to 0.1 m/s to amplify the physical response delay of the actuator and strengthen the influence of system delay on dynamic performance under the speed limitations of the conveyor belt. The camera was fixed 1 m above the side of the conveyor belt. The camera optical axis and the offset reference line were located on the

same plane, and the lower boundary of the image was aligned with the nozzle plane. The relevant parameters were recalibrated.

In the fixed-ROI test, three forward speeds were tested: low speed (0.12 m/s), medium speed (0.18 m/s), and high speed (0.25 m/s). The response-delay effect and row-following accuracy of the fixed-ROI algorithm were evaluated. To ensure that the system was not affected by other factors, the ROI width was kept consistent with the original image width (1920 pixels), and the height was set to 15% of the original image height (162 pixels). The vertical centerline of the ROI was fixed at 127 pixels from the lower image boundary. Preliminary tests showed that this ROI position corresponded to a conveyor-belt speed of 0.18 m/s, and it was therefore used as the fixed-ROI position. Low-speed (0.12 m/s) and high-speed (0.25 m/s) conditions were added to examine the sensitivity of the fixed-ROI algorithm to velocity changes, with the medium speed (0.18 m/s) used as the reference. In each test, the vertical distance from the center of each plant to the offset reference line was manually recorded. The world-coordinate output of the row-line recognition algorithm and the nozzle movement position were also recorded. The offset reference line, image centerline, and zero position of the row-following module were aligned and used as the reference for judging plant position, output coordinates, and nozzle position. The three datasets were compared to assess row-following accuracy.

In the dynamic-ROI test, the conveyor belt was set to variable-speed motion over a range of 0–0.25 m/s. The conveyor-belt speed was adjusted manually using a speed-control knob, and the motor speed was measured using an encoder and converted into real-time velocity by the upper computer. The ROI size was kept the same as in the fixed-ROI test (1920 × 162 pixels). Its initial position was aligned with the bottom of the image and was then dynamically adjusted according to the calculation result of the delay compensation system. The remaining test conditions were the same as those of the fixed-ROI test.

2.4.2. Outdoor Whole-Machine Nozzle-Positioning Test

To evaluate the integrated nozzle-positioning performance of the dynamic-ROI delay-compensation algorithm and provide a basis for subsequent field validation, a row-following platform was constructed on the high-clearance mobile robot and operated using the complete dynamic-ROI algorithm. Outdoor tests were conducted on a paved surface using artificial plants to examine the effects of controllable platform-speed changes, mechanical vibration, and unstructured visual backgrounds. The test site is shown in Figure 8. Two rows of plant models were arranged in the test area, with 21 plants in each row and a plant spacing of 0.3 m. The left and right rows were continuously and randomly placed within 0–0.5 m from the centerline to simulate irregular row-position changes. The platform traveled along a preset straight path at constant forward speeds of 0.3, 0.5, and 0.8 m/s and under random variable forward-speed conditions of 0–1 m/s. The two lateral nozzles moved in real time to follow the plant models over a test distance of 6 m. For each speed condition, three independent trials were conducted, yielding 126 paired nozzle–plant observations per condition (21 plants × 2 rows × 3 trials). The lateral absolute error was computed for each observation and used to calculate the mean absolute error (MAE), standard deviation (SD), and row-following accuracy (percentage of observations with $|\text{error}| \leq 0.05$ m). To verify the validity of pooling observations across trials, a one-way analysis of variance (ANOVA) was performed within each speed condition to test for inter-trial differences. A one-way ANOVA was also conducted across the four speed conditions to assess whether lateral MAE differed significantly with forward speed.



Figure 8. Outdoor whole-machine test.

No spray liquid was discharged during the outdoor tests; therefore, the experiment quantified nozzle positioning rather than deposition, coverage, off-target loss, or spray drift. Ambient wind speed was not included as a controlled factor. Future field spraying tests should simultaneously record ambient wind, platform-relative airflow, droplet characteristics, deposition, coverage, and drift.

3. Results

3.1. Indoor Bench Test of Algorithm Effectiveness

In the indoor bench test, the lateral distance between the nozzle center and the plant-model center was used as the lateral error for evaluating single-row corn tracking accuracy. The lateral mean absolute error was used as the main evaluation index. Row-following accuracy was used as an auxiliary index and was defined as the percentage of samples in which the lateral error did not exceed a preset threshold. With reference to the canopy width of the corn plant models (0.1–0.2 m), the threshold for lateral mean absolute error was set to 0.05 m, ensuring that the nozzle position did not deviate from the target width.

The results of the fixed-ROI algorithm under constant conveyor-belt speeds are shown in Figure 9, and the lateral error statistics are shown in Figure 10. When the conveyor-belt speed was 0.18 m/s, the nozzle trajectory fluctuated around the corn plant position. The maximum lateral error was 0.06 m, the lateral mean absolute error was 0.023 m, and the row-following accuracy was 93.75%. The high degree of overlap indicated that the system could effectively offset the response delay and achieve good corn-row recognition and row-following performance at the specific conveyor-belt speed of 0.18 m/s when the corresponding fixed-ROI position was used. When the conveyor-belt speeds were 0.12 and 0.25 m/s, the lateral mean absolute errors were 0.027 and 0.026 m, respectively. Once the conveyor-belt speed changed, the dynamic matching relationship between the system response delay and conveyor-belt speed was disrupted, resulting in longitudinal error and increased lateral error. In other words, when the conveyor-belt speed deviated from the speed matched to the preset ROI, the forward velocity v_y in the longitudinal-error δ changed even though the total response delay remained relatively stable, causing a spatiotemporal offset between the nozzle and the plants. Under the low-speed condition (0.12 m/s), the forward travel time t_y increased, leading to $T < 0$ and causing the nozzle action to lead the target position. Under the high-speed condition (0.25 m/s), t_y decreased, leading to $T > 0$ and causing the nozzle action to lag behind the target position. This leading or lagging relationship is reflected in Figure 9 by the distribution of plant positions on

one side of the rising or falling segment of the nozzle trajectory and in Figure 10 by the consistent polarity of lateral errors.

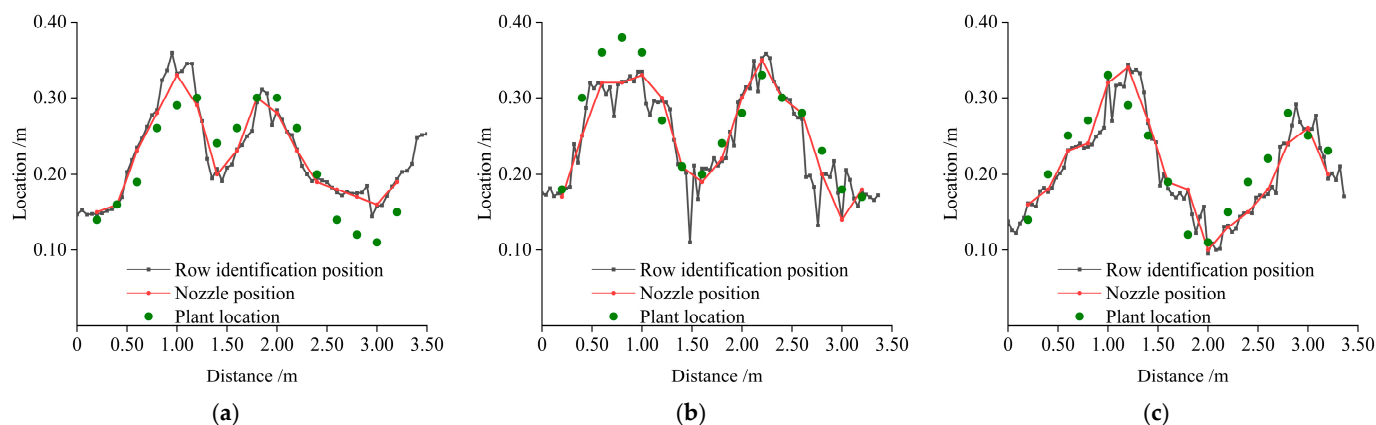


Figure 9. Row-following constant-speed test results: (a) $v = 0.12$ m/s; (b) $v = 0.18$ m/s; (c) $v = 0.25$ m/s.

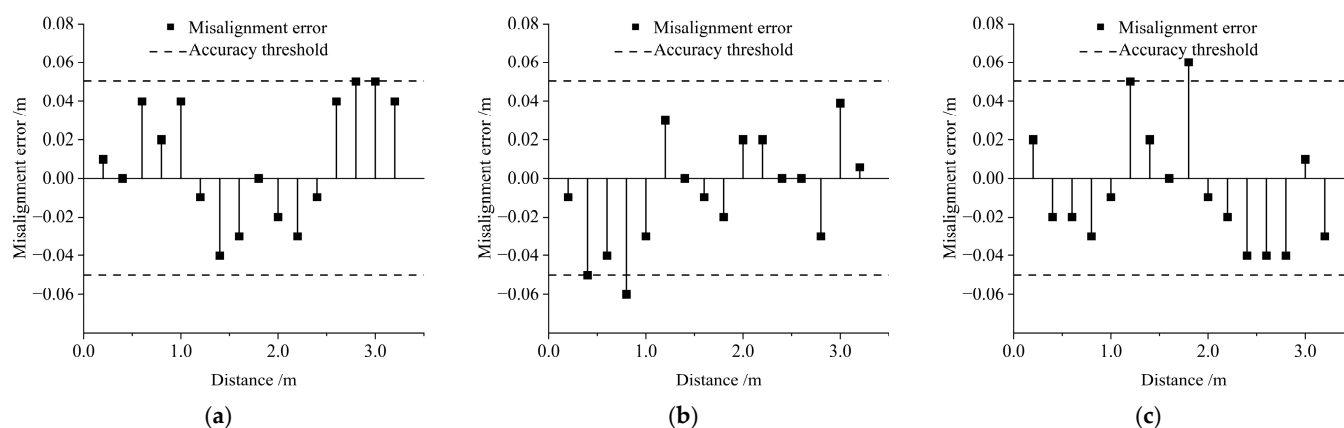


Figure 10. Lateral error statistics: (a) $v = 0.12$ m/s; (b) $v = 0.18$ m/s; (c) $v = 0.25$ m/s.

Although the row-following accuracy reached 100% at a conveyor-belt speed of 0.12 m/s, the overlap resulted from non-corresponding positional coincidence under nozzle–plant misalignment and therefore had limited comparative value. The results under different speed conditions also demonstrated the sensitivity of the fixed ROI to speed variation. The system could not adapt to changes in the relative velocity between the operating system and target, which caused offsets among plant-model position, row-line recognition position, and nozzle position. The polarity of the lateral error was also related to the direction of the nozzle trajectory change.

Under variable-speed conveyor-belt operation, the statistical results of the dynamic-ROI test system are shown in Figure 11. Overall, as the conveyor-belt speed changed, the look-ahead distance Δy_{n+1} corresponding to the dynamic-ROI position followed the same trend as the velocity curve, reflecting the operating mechanism of the dynamic-ROI delay compensation algorithm. The average image acquisition and processing delay was 0.140 s, and the average total system delay was 0.23 s. The total system delay showed slight fluctuations, mainly due to dynamic changes in t_p and t_x . The delay t_p was slightly affected by crop-feature complexity within the ROI, whereas t_x was positively correlated with the difference between crop-row coordinates recognized in adjacent frames. The isolated processing-time peak shown in Figure 11 remained subject to the ROI boundary constraint in Equation (13), so the target region remained within the valid image area.

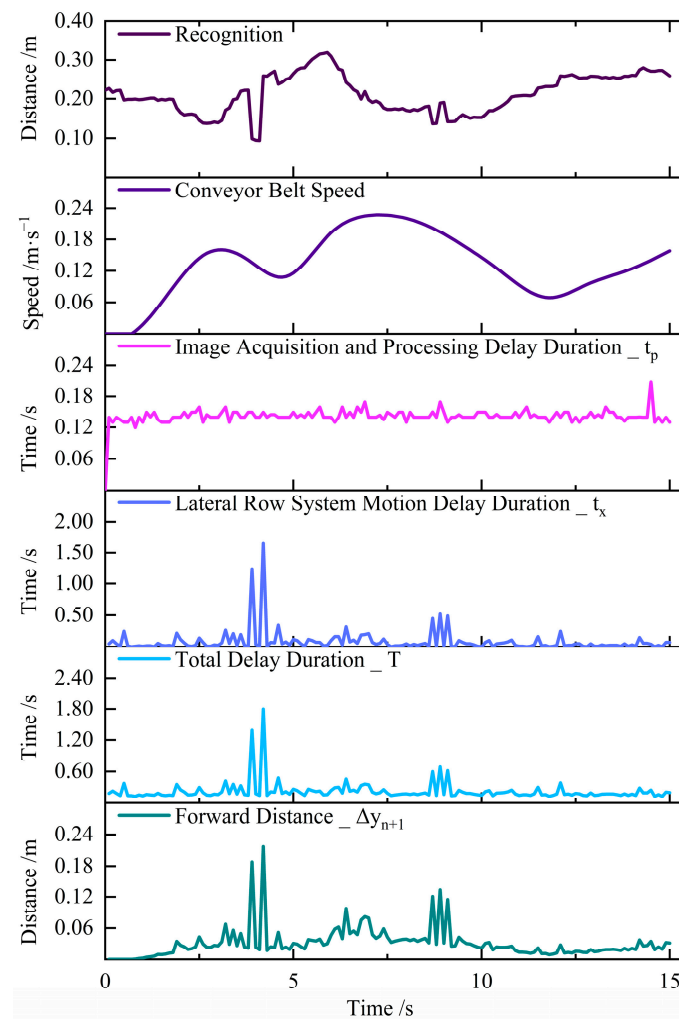


Figure 11. Operating-data statistics of the dynamic-ROI test system.

In the variable-speed test range of 0–0.25 m/s, the nozzle trajectory closely followed the plant positions, and the obvious leading or lagging phenomenon observed with the fixed-ROI algorithm did not occur. The row-following accuracy and lateral error results are shown in Figures 12 and 13. The data show that the dynamic-ROI algorithm substantially reduced the lateral row-following error without producing one-directional offset. The lateral errors were generally within 0.03 m, with a maximum value of 0.06 m, and the row-following accuracy was 93.75%. The lateral mean absolute error in the dynamic-ROI test was 0.019 m, which was 24.8% lower than the average of the three fixed-ROI tests and 0.004 m lower than the lateral mean absolute error of the fixed-ROI test at the medium speed of 0.18 m/s.

To quantify measurement variability, each of the 16 plant positions per speed condition was treated as an independent replicate, and the mean absolute lateral error (MAE) with standard deviation (SD) was computed for each condition (Figure 14). Under fixed-ROI operation, the MAE values were 0.027 ± 0.017 m, 0.023 ± 0.018 m, and 0.026 ± 0.016 m at forward speeds of 0.12, 0.18, and 0.25 m/s, respectively ($n = 16$ per condition). The fixed-ROI condition at 0.18 m/s yielded the lowest MAE, consistent with the ROI position being calibrated to this speed. Under dynamic-ROI operation across the variable-speed range of 0–0.25 m/s, the MAE decreased to 0.019 ± 0.015 m, which was 26.2% lower than the average of the three fixed-ROI conditions. The dynamic-ROI condition also exhibited the smallest standard deviation, indicating more consistent positioning performance across different plant positions. All conditions remained below the 0.05 m accuracy threshold.

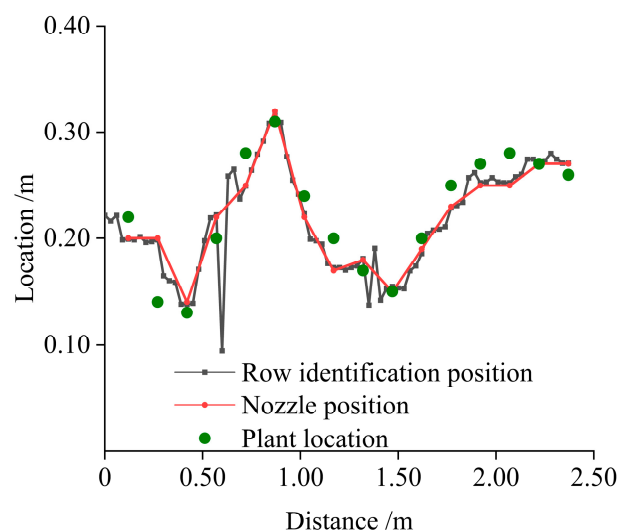


Figure 12. Row-following test results under dynamic-ROI operation.

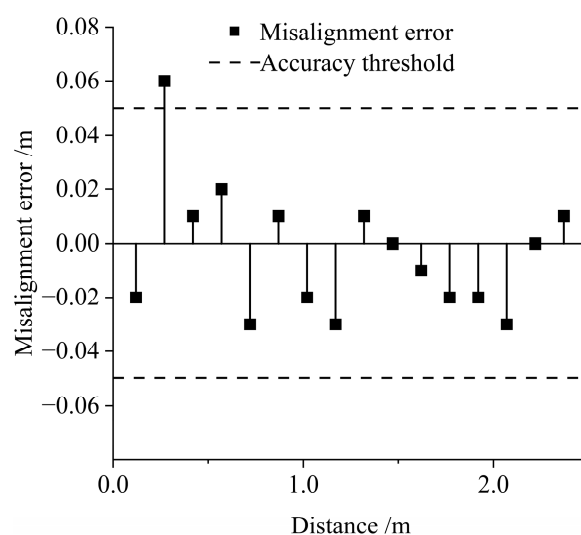


Figure 13. Lateral error statistics under dynamic row-following operation.

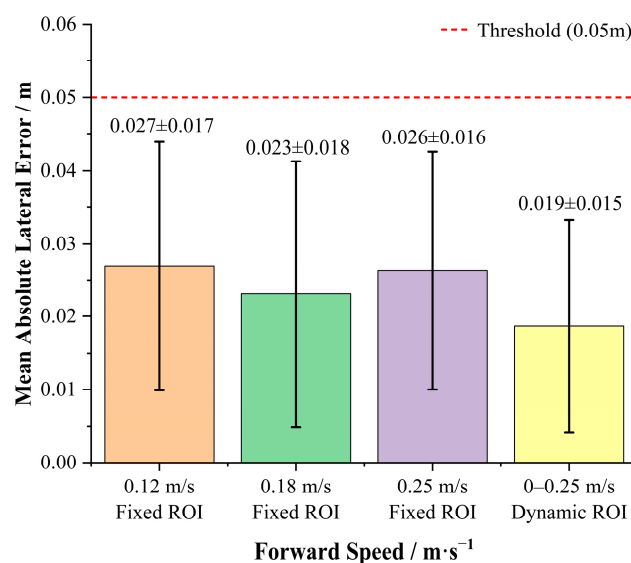


Figure 14. Mean absolute lateral error (MAE ± SD) under different test conditions (n = 16 plant positions per condition).

These results show that, under relative forward-speed variation, the dynamic-ROI algorithm reduced the systematic leading or lagging behavior caused by mismatch between conveyor-belt speed and system response. The bench test therefore supports the proposed compensation mechanism under controlled conditions.

3.2. Whole-Machine Nozzle-Positioning Performance in an Outdoor Dynamic Environment

Table 1 summarizes the lateral error statistics for the outdoor whole-machine test. Under fixed forward speeds of 0.3, 0.5, and 0.8 m/s, the pooled lateral MAE values (mean $\pm$ SD, $n = 126$) were 0.037 ± 0.021 , 0.039 ± 0.020 , and 0.041 ± 0.030 m, respectively. Under random variable-speed operation (0–1.0 m/s), the lateral MAE was 0.034 ± 0.026 m, with a maximum lateral error of 0.20 m. The row-following accuracy ranged from 85.7% to 92.1% across the four conditions. A one-way ANOVA indicated no statistically significant difference in lateral MAE among the four speed conditions ($F_{3,500} = 1.851$, $p = 0.137$), suggesting that the dynamic-ROI algorithm maintained consistent positioning performance across the tested speed range.

Table 1. Outdoor whole-machine row-following test results.

Speed (m/s)	n	Lateral MAE $\pm$ SD (m)	Row-Following Accuracy (%)	Maximum Lateral Error (m)
0.3	126	0.037 ± 0.021	92.06	0.18
0.5	126	0.039 ± 0.020	91.27	0.10
0.8	126	0.041 ± 0.030	87.30	0.15
Variable (0–1.0)	126	0.034 ± 0.026	85.71	0.20

To examine inter-trial reproducibility, within-speed ANOVA was performed for each condition. No significant inter-trial differences were found at 0.3, 0.5, or 0.8 m/s ($p > 0.05$ for all), supporting the validity of the pooled analysis. At the variable-speed condition, trial 1 yielded a higher MAE (0.044 m) than trial 2 and 3 (0.030 and 0.029 m; $F_{2,123} = 4.791$, $p = 0.010$), likely reflecting initial platform stabilization; however, the overall pooled MAE remained the lowest among all conditions.

Despite low overall MAE values, transient large errors occurred. The proportion of observations exceeding the 0.05 m threshold was 7.9%, 8.7%, 12.7%, and 14.3% at 0.3, 0.5, 0.8, and variable speed, respectively. The maximum lateral error of 0.20 m occurred during trial 1 under variable-speed operation, indicating that occasional large positioning deviations coexist with low average errors. Such outliers may cause short-duration off-target misses in practical spraying and motivate confidence gating, temporal filtering, and actuator saturation handling in future implementations.

4. Discussion

Compared with the bench test, the lateral mean absolute error of the outdoor whole-machine test was larger, and the row-following accuracy under random variable-speed operation decreased from 93.75% to 85.71%. This reduction was mainly attributed to the complexity of the outdoor environment. Mechanical vibration generated by the high-clearance chassis caused camera pitch and roll oscillations and occasional motion blur, which disturbed the inverse-perspective mapping and crop-row centerline estimation. The disturbance became more pronounced at higher speeds because road-surface excitation was transmitted more strongly to the camera mount. Outdoor illumination changes and background variations further affected image segmentation and reduced system stability. Potential engineering improvements include mechanical vibration isolation or a stabilized camera mount, shorter exposure supported by supplemental illumination, IMU-assisted digital image stabilization, temporal filtering of crop-row coordinates and delay estimates,

and robust closed-loop control or state-observer methods. Future field experiments will quantify the vibration spectrum and compare these mitigation strategies under different travel speeds and field-surface conditions.

Previous studies have investigated vision-based crop-row detection and autonomous row-following systems for precision spraying applications. Compared with the vision-based row-aligned spraying system for maize seedlings reported by Zheng et al. [19], this study enhances the practical robustness of the delay compensation strategy under field-based servo row-following scenarios. While Zheng et al. treated the system response as an approximately fixed latency without accounting for speed disturbance effects, we decomposed the total response time T_s into $t_p + t_c + t_x$, and introduced the longitudinal travel speed v_y as a dynamic variable into the servo model. Crucially, validated via outdoor whole-machine tests under random forward speeds of 0–1.0 m/s, the proposed dynamic-ROI look-ahead mechanism achieves a row-following accuracy of 0.034 m, outperforming the 0.05 m row-following accuracy obtained in outdoor simulated tests reported by Zheng et al. In addition, Zhou et al. [26] proposed an adaptive multi-ROI method for maize crop-row detection, in which ROI optimization was mainly used to improve image processing efficiency and recognition robustness. Their method achieved an image processing time of approximately 0.241 s for 1920×1080 -pixel images. Under the same image resolution, the crop-row detection method proposed in this study reduced the processing time by 0.101 s, demonstrating improved real-time performance. However, previous ROI-based approaches mainly considered ROI as a spatial region for image feature extraction, without incorporating the influence of system delay and robot motion. In contrast, the dynamic ROI proposed in this study integrates motion information and system delay estimation, transforming ROI from a static image-processing region into a predictive compensation window. Therefore, the proposed method not only improves computational efficiency but also enhances row-following adaptability under variable-speed operation by reducing the leading or lagging errors caused by perception–execution mismatch.

The tests also showed that, due to camera perspective effects, the closer a plant was to the left or right boundary of the ROI, the more obvious the recognition deviation of the corn leaf center became, which increased row-following error. Increasing camera height can alleviate this phenomenon [27]. In practical operation, the robot may also exhibit small trajectory deviations, which appear as a mismatch between the vertical image centerline and the preset path. However, the system itself has a compensatory capability, and such small deviations did not affect the actual row-following effect in the tests.

5. Conclusions

This study developed a dynamic-ROI delay compensation algorithm for reducing sensing–execution mismatch in corn row-following nozzle positioning. Robot forward velocity and total system response delay were used to shift the visual ROI in a forward-looking manner. The main conclusions are as follows:

1. A visual processing method based on ROI local-image extraction was used to extract corn rows. Compared with full-image processing at 1920×1080 pixels, the average frame processing time was reduced to 0.14 s while maintaining the recognition accuracy of high-resolution ROI images at 162×1920 pixels. The adjustable ROI also provided the technical basis for establishing the spatiotemporal matching relationship required by the delay compensation algorithm.
2. The system equivalent time deviation was decomposed and quantified, and the tests demonstrated that mismatch between total system response delay and forward velocity reduced nozzle-positioning accuracy. The dynamic-ROI method reduced lateral MAE by 24.8% relative to the average fixed-ROI result in the variable-speed

bench test. In the outdoor whole-machine positioning test, the pooled lateral MAE was 0.034 m and row-following accuracy was 85.71% under random platform forward speeds of 0–1 m/s; however, the maximum error of 0.20 m indicates that transient deviations remain important. The method effectively solves the sensing–execution spatiotemporal mismatch in row-following spraying and provides technical support for the development of precision spraying equipment.

The current results primarily demonstrate feasibility under low-speed and semi-controlled conditions. Future work will conduct growing-season field trials, quantify the influence of chassis vibration and illumination variation, and evaluate mechanical camera isolation, IMU-assisted image stabilization, temporal filtering of delay and row-coordinate signals, and robust closed-loop control. Spray deposition and agronomic efficacy will also be measured to establish the real-world applicability and operating limits of the proposed method.

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Abbreviations

The following abbreviations are used in this manuscript:

ROI	Region of interest
GNSS	Global navigation satellite system
IMU	Inertial measurement unit
IPM	Inverse-perspective mapping
ExG	Excess Green
MAE	Mean absolute error

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