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DESIGN AND DEVELOPMENT OF AN AUTONOMOUS ROBOT PROTOTYPE FOR A POTATO FARM

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Abstract This article includes the design and development of an autonomous robotic system for intelligent navigation in a potato farm. An algorithm for stable and accurate navigation using ultrasonic sensors was designed and implemented in a laboratory-scale model. Hence, four ultrasonic sensors and an Arduino-based control system were a solution for the suggested robot to the farm's physical condition. The suggested robot was first developed with a structure that reflects the physical attributes of the farm, including four ultrasonic sensors and an Arduino-based control system. The robot was further simulated in the MATLAB/Simulink environment and ultimately modeled and evaluated under three different physical conditions. For the given scale of the robot, the maximum acceptable deviation is set at 2 cm, whereas in the unstable scenario, the deviation reaches 5 cm. Experiments were conducted with the primary goal of reducing tracking errors and oscillations while maintaining the robot's alignment with the optimal route. In addition, the mechanical component is constructed with a design that corresponds to the actual prototype in terms of structure and operation. Thus, consistency between the model and the physical system is maintained. Moreover, ultrasonic sensors are used instead of LiDAR sensors under the same arrangement of ridges in potato farms. This decision is logical and economical. Consequently, cost efficiency is improved in future agricultural applications.

Keywords: Autonomous robot, Agricultural robotics, Ultrasonic sensor, Row following, Precision farming, Smart agricultural systems, Potato Farm robots, Simulink, Smart pathway, Path tracking.

AMS Mathematics Subject Classification: 93C85.

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1 Introduction

Calculations of global population expansion require improvements in agricultural efficiency. Advancements in human safety and environmental sustainability are also needed. However, these factors are often conflicting attributes [1]. The autonomous navigation of farm robots is necessary because a wide range of activities is executed in farming areas. Furthermore, accurate navigation is difficult as a result of the unstructured characteristics of these settings. Specific challenges are identified in these environments. These include backdrop clutter, spatial occlusion, and light variations. Also, changes in appearance and dense fruit distributions are observed. Consequently, the difficulty of precise perception is increased [2, 3]. Agriculture requires automation and robotics. Information services and intelligence are also utilized. Thus, food production rates are enhanced for future demands [4]. The use of automatic vegetable transplanters is shown to reduce production expenses. Operational efficiency is also improved. Additionally, labor shortages during peak seasons frequently result in transplanting delays. As a result, considerable yield declines are observed [5]. While all agricultural systems require human interaction, this dependence leads to challenges. For this reason, exhaustion and labor shortages occur. Furthermore, detrimental working conditions are present.

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These factors decrease efficiency and increase production costs. Consequently, accidents and extended working hours are recorded. To achieve sustainable agriculture, modern technologies are incorporated. These include blockchain, big data, machine vision, IoT, and machine learning. Thus, future agricultural requirements are met [6]. Conventional manual methods limit the effectiveness of cucumber harvesting. Therefore, a crop-picking robot is created. This system provides an effective and efficient solution to the issue [7]. Nearly all field operations possess fundamental functions. The robot must navigate autonomously in the field. Also, operational decisions for specific tasks are made. These operations are then executed automatically [8]. To facilitate a field robot, preliminary research is required in several domains. First, path planning algorithms are developed [9]. Second, navigation techniques are utilized [10]. Third, localization methods are examined [11]. Finally, environmental sensing of the relevant farmland is performed. As robot applications become prevalent, numerous researchers concentrate on robot navigation. The primary challenge of robot navigation is defined. It is determined how robots move from the starting point to the destination along the designated route. For this reason, localization and environmental data are acquired from external sensors. Effective navigation requires proficiency in four fundamental components. These include vision, localization, cognition, and motion control. In addition, mapping and path planning are identified as primary concerns [12]. Autonomous navigation in agricultural fields presents significant challenges because the environment is complex and unstructured. This setting is characterized by numerous types of noise and disturbances. In a previous study, the accurate identification of crop rows for autonomous robot navigation is documented [13]. The proposed method is validated through image processing techniques. Furthermore, several path-planning algorithms are implemented on the recorded images. Navigating an outdoor area is difficult. It is observed that sunlight is misleading during edge identification. Therefore, risky conditions are created when a fully camera-based navigation system is utilized [14]. Hardware constraints influence navigation performance. These include issues associated with the controller, wheel slip, and sensor inaccuracies [15]. For this reason, the design of an effective navigation system is essential. Path planning algorithms are developed and optimized for complex agricultural environments. Thus, the autonomous operation of farming robots is enabled. Research into autonomous navigation utilizes various methodologies. These include Global Positioning Systems (GPS), infrared sensors, machine vision, LiDAR, and ultrasonic sensors. For example, the GPS is integrated with the automatic navigation system of a tractor or other machinery [16]. Consequently, production costs are reduced. The integration of this system with other control modules is also enhanced. However, variations in environmental circumstances affect performance. Unfavorable weather conditions and signal blocking caused by obstacles are observed. Most crucially, low positional precision is a significant drawback of the GPS when the system is used independently. Therefore, multi sensor fusion is required for future reliability. In comparison to cameras and radars, LiDAR is commonly used in agricultural robots. High precision is achieved. Furthermore, the ability to withstand a broad range of light conditions is observed [17]. The primary contribution of researchers includes the invention of components that enhance the efficiency and precision of point cloud segmentation [18]. The LiDAR sensor determines canopy amount and structure. Leaf area is calculated. Also, crop height and production are evaluated. For this reason, LiDAR is used to assess the development and vitality of vines [19]. Despite these benefits, significant constraints are faced in agricultural practices. A major challenge with 2D LiDAR for navigation is occlusion caused by plants and branches. This issue hinders the identification of crop rows. Consequently, navigation failures occur. In addition, range sensor based navigation systems struggle to position the robot within a global reference frame. Thus, the potential for autonomous control is limited. Moreover, substantial computing power is required because raw point clouds are processed. This requirement compromise real-time performance. Also, the high cost of LiDAR sensors restricts application in large scale settings [20]. Therefore, more economical solutions are sought for future agricultural deployment. The ultrasonic sensing technique involves the emission of a brief, high-frequency acoustic pulse. This pulse traverses the air and impacts a target. Then, it returns as an echo. The distance to the target is calculated because the time gap between the emission of the sound pulse and the reception of the echo signal is measured. The primary objective of ultrasonic sensors in agricultural robots is to enable autonomous navigation in expansive and complex environments. These systems include vision, control, and mechanical components. In addition, navigation systems are examined as fundamental aspects of agricultural robots. These components enable the robots to travel and evade obstacles. Furthermore, detection is executed and designated jobs are accomplished [21]. Ultrasound range sensing is a key technique. A high-frequency acoustic pulse propagates through the air. It hits a target and returns as an echo. The electronics within the sensor calculate the distance. This is possible because the time for sound to travel from the emission point to the reception point is measured. Various studies demonstrate the use of this method in the estimation of crop metrics. These metrics include volume, density, and height [22]. Thus, ultrasonic sensors provide a functional alternative for future precision farming. In [23], the use of ultrasonic sensors on tractors is suggested. These sensors analyze the canopy densities of apple trees and grapevines in real-time. Also, ultrasonic and photoelectric sensors are examined for plant canopy detection [24]. Furthermore, ultrasonic sensors are used to identify the interstitial spaces between plants. Thus, sprayers are deactivated in the gaps between tree canopies [25]. Research also investigates the use of ultrasonic sensors in robotic arms. These sensors are used for obstacle identification and item handling [26]. These robots use an array of sensors to facilitate autonomous navigation. The list includes, Global Positioning System (GPS), Infrared (IR), Machine Vision (MV), Light Identification and Ranging (LiDAR), and Ultrasonic Sensors. The efficacy of this method is dependent on the accuracy of the sensors. Therefore, complex algorithms are required because the precision of obstacle detection must be enhanced. In addition, ultrasonic sensors are used in autonomous navigation robots for environmental awareness and route planning. Autonomous navigation is a critical capability of agricultural robots. It enhances farming automation because machines traverse and operate along crop rows consistently [27]. As a result, operational reliability is improved for future agricultural systems. Analysis of several sources determines the successful use of ultrasonic sensors in this navigation method. Pertinent research studies are outlined. An autonomous planting and watering robot is proposed with an Arduino board [28]. This robot utilizes two ultrasonic sensors. One sensor is positioned at the front and the other is placed at the base to detect obstacles. Before the system proceeds, obstacles are identified. The robot lifts itself to avoid these impediments and lowers itself after the traversal is complete. Furthermore, sensors for soil moisture and temperature are included for environmental monitoring. A study investigates an autonomous navigation system that uses ultrasonic sensors to avoid collisions [29]. The algorithm reduces route deviation. Moreover, strong performance is demonstrated even if the primary sensor fails. A hybrid navigation system is also presented [30]. This system integrates ultrasonic sensors and LiDAR to improve the precision of autonomous navigation. This combination demonstrates enhanced efficacy in settings where LiDAR alone fails. For example, transparent or absorbent impediments are detected more accurately. However, this method requires specialized hardware. In addition, further integration costs are faced. Therefore, the use of standalone ultrasonic arrays is explored for future cost-effective deployment. The research conducted by [31] examines route optimization for nondestructive robots with ultrasonic sensors. Optimization tools are used to enhance robotic performance in intricate situations. These include graph theory and K-dimensional tree (K-d tree) techniques. A self-directed harvesting method for white asparagus is introduced [32]. In this system, ultrasonic sensors are mounted to each wheel of the robot. An additional autonomous agricultural robot is developed to assist farmers [33]. The system is operated by an Arduino board. Ultrasonic sensors are used to move between crop rows and maintain a predetermined route. However, the functionality is confined to small agricultural farms. A robot is also equipped with an ultrasonic distance-based navigation system as developed by [34]. Thus, the effectiveness of sound-based distance measurement is established. For this reason, ultrasonic arrays are integrated into the current laboratory-scale model to ensure reliable navigation in future agricultural environments. This robot is designed for autonomous navigation within rows of rose crops. The trajectory is changed to the next row after the end of a line is reached. However, a significant drawback is identified in this research. A thorough evaluation of sensor performance is absent. Table 1 provides a comparative overview of the analyzed research. In this table, innovations, advantages, and disadvantages are emphasized. Current research on navigation robots and sensing technologies suggests that these tools enhance the performance of autonomous systems. This is observed especially in complex agricultural settings. In addition, ultrasonic sensors improve precision. For this reason, the design and development of a path-following robot are presented in this work. Ultrasonic sensors are utilized because the movement and navigation capabilities of robots in agricultural environments are enhanced. Furthermore, a forward-thinking approach is adopted to ensure the scalability of the system. This method is effective as long as the sensor data is processed accurately. Therefore, reliability is increased. Thus, the proposed system provides a foundation for future autonomous farming applications. Previous studies on sensing technologies and navigational robots show that ultrasonic sensors improve the accuracy of autonomous systems. This improvement is useful in complex agricultural settings. Therefore, this paper expands upon these findings. The steps to create a path-following robot with ultrasonic sensors are detailed. As a result, navigational and mobility skills in agricultural environments are enhanced. The environmental features of the potato farm provide substantial obstacles for robotic navigation. These include different types of barriers and changes in topography. For this reason, the robot is tested and validated in this specific setting. The primary goal of this research is the improvement of agricultural robot navigation. New approaches to autonomous systems are presented. One of the most innovative aspects is the body shape of the robot. This shape is designed explicitly for agricultural settings, i.e., potato farms. This layout improves the precision with which the robot traverses routes. Various obstacles are included in these routes. Furthermore, the correct integration of sensors and the implementation of navigation algorithms are important contributions. An Arduino Uno control board is utilized for this purpose. With this simple control system, navigation algorithms are refined and deployed quickly. Moreover, the system is effective in agricultural situations. Consequently, a forward-thinking solution for autonomous farming is established.

The findings of the laboratory robot prototype demonstrate precision and excellent performance. These results are detailed in the latter parts of the paper. Furthermore, navigation tasks are performed with accuracy. This work represents a significant leap forward in agricultural robotics. Autonomous operations in farms are enabled because an intelligent navigation system is utilized. This system integrates accurate sensors and a complex robot design. In addition, a simple yet effective control board is used. As a result, the robot operates efficiently in agricultural settings. Therefore, the proposed design supports the advancement of farming automation. Moreover, reliability is ensured through this combination of hardware and software. Thus, a functional solution for future agricultural requirements is established.

Table 1: Comparison of research studies on autonomous robots with different sensors

Article	**Innovation**	**Advantages**	**Disadvantages**
Bai et al. (2023)	Providing intelligent path-planning algorithms to address autonomous navigation challenges in agricultural farms with complex and variable conditions	Exploring the challenges of autonomous navigation in agricultural environments under variable conditions	Problems in detecting obstacles and handling environmental disturbances, such as climate change, and inaccuracies in navigation systems in agriculture
Dong et al. (2011)	Using intelligent algorithms to enhance routing accuracy in complex agricultural farm conditions and boost the robot's capability to overcome various obstacles	Application of ultrasonic sensors in harvesting agricultural products such as asparagus	Lack of accurate data processing and inability to handle complex environmental conditions in real time
Firkat et al. (2023)	Using LiDAR sensors with suitable accuracy and lower cost for routing and obstacle detection, without requiring complex processing	Utilizing a Lidar sensor for precise measurements and better performance across various lighting conditions	Limited use in agriculture due to high costs and complex data processing (point clouds)
Hurnen (2023)	Integration of two sensors, Lidar and ultrasound, to enhance navigation system accuracy	Smaller undetectable areas, improved accuracy	Higher design demands and costs to combine two technologies
Khadatkar et al. (2021)	Robot body design and ultrasonic sensors to improve navigation in complex environments	Using autonomous robots to enhance farm productivity and decrease natural resource use	Issues with navigation system accuracy in complex agricultural settings
Palleja and Landers (2015)	Development of a routing algorithm utilizing an ultrasonic sensor for precise navigation in potato farms with complex and variable conditions	Using ultrasonic sensors to assess tree canopy density and direct robots on farms	Lack of accuracy in specific environmental conditions, such as high humidity and complex obstacles
Nadafzadeh et al. (2023)	Presenting a new routing algorithm to detect the crop row, using three preprocessing methods to remove weeds	Maintaining performance stability amid environmental and structural changes	Inability to apply data to other species with different soil and light conditions and high operating costs
Thakur et al. (2023)	Replacing GPS with ultrasonic sensors for autonomous navigation, particularly in complex agricultural environments	Exploring the use of GPS and various sensors to enhance agricultural operations	Reliance on specific GPS and radar technologies with decreased accuracy in complex conditions and high operational costs
Yasin et al. (2021)	Advanced algorithm for optimizing robot paths	Enhanced navigation with minimal route deviations	Limited performance in complex environments with multiple obstacles
Zhang et al. (2023)	Applying graph and K-D algorithms for precise routing	Enhancing routing efficiency in complex environments	Need for complex calculations and optimization algorithms
Zurey et al. (2020)	Enhancing ultrasonic sensor performance with intelligent algorithms for precise navigation in complex environments	Using ultrasonic sensors to identify gaps between plants and enhance spray performance	Problems with real-time data processing and inaccuracies in specific environmental conditions

Suggested study	Innovating robot design for specific environments like potato farms Using ultrasonic sensors instead of costly sensors such as lidar.	Designing a robot structure suitable for agricultural farms Using an ultrasonic sensor for accurate and cost-effective routing Implementing intelligent algorithms with the Arduino Uno board	Problems with real-time information processing in complex environments

2 Design of the Autonomous Robot Body

A potato farm features rows of ridges aligned in parallel, with seeds placed within the ridges and plants emerging above them. Figure 1 shows an agricultural area during the potato sprout growing phase. The movement method of a mobile robot may include legs, tracks, or wheels [35]. Nevertheless, constructing the robot with wheels has several benefits, including reduced manufacturing costs, increased speed, directional adaptability, simplicity, and enhanced control. Four-wheeled robots are often categorized into three classifications according to wheel control and power transfer mechanisms:
1. Robots equipped with four motorized wheels
2. Robots including two pairs of wheels coupled on the left and right sides (differential drive system)
3. Robots comprising two powered wheels and two non-powered wheels
Given the agricultural layout, the suggested robot must be engineered to travel independently through the open areas between the hills. Measurements taken on many farms with long, nar-

Figure 1: Potato Farm

row ridges indicate that the horizontal distance between the summits of two contiguous ridges is around 70 cm. In contrast, the elevation of each ridge is about 30 cm. Figure 2 illustrates a comprehensive depiction of the proposed autonomous robot, which has been equipped with ultrasonic sensors for navigation throughout the farm. The sensor is positioned to transmit ultrasonic waves perpendicularly onto the inclined surfaces of the ridges, which reflect, simulating the appearance of a flat surface in front of the sensor. This arrangement equips the robot with four ultrasonic sensors, two positioned at the front and two at the back (note that the rear sensors and wheels are not depicted in Figure 2).

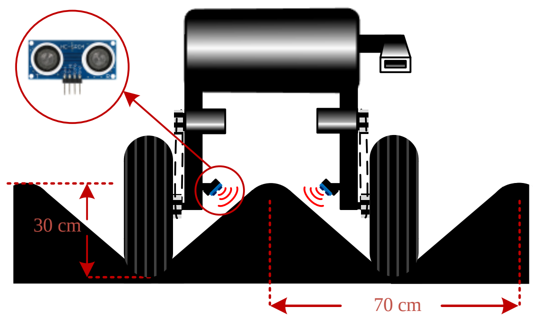


Figure 2: Proposed autonomous robot design

The robot depicted in Figure 2 utilizes two motors linked to the front wheels, employing differential drive control to maneuver and change direction by varying the rotational rates of each wheel. Furthermore, the robot is equipped with two non-motorized idler wheels, which serve only to provide stability. This robot exhibits greater stability than three-wheeled models, as its center of gravity is positioned within a rectangle formed by the four wheels. Figure 3 depicts the mechanics of this sort of robot. A two-wheel drive system provides benefits over a four-wheel drive system in terms of starting cost, component space, and energy efficiency. Consequently, with the advantages above, the more straightforward control mechanism and enhanced mobility provide the two-wheel drive system as the optimal selection for the suggested robot. In this type of robots, translational motion and rotational motion equation can be achieved using the force/torque balance relationship as (1) and (2).

$$m\dot{v} + bv = \frac{(\tau_R + \tau_L)}{R} \tag{1}$$

$$l\dot{\omega} + b_\omega \omega = \frac{L(\tau_R - \tau_L)}{R} \tag{2}$$

Where m is the mass of the robot, v is the speed of movement, b is the coefficient of friction, τ_R and τ_L are the torque of the right and left motors, respectively, R is the radius of the wheels, L is half the distance between the axles of the two wheels, l is the moment of inertia and ω is the speed of rotation around the center. These two relationships show how you can easily create translational and rotational motion by adjusting the torque of two motors without interference. For example, if the two torques are equal and in opposite directions, only rotational motion will be created, and if the two torques are equal and in the same direction, the robot will only have translational motion. This research included the construction and evaluation of a laboratory prototype of the suggested robot to verify its adaptability for subsequent farm settings. Figure 4 displays a picture of the laboratory model that was created.

3 Configuration of the Autonomous Robot

Figure 5 illustrates the block diagram of the navigation system for the proposed robot. The primary control unit of this system is an Arduino Uno. This unit is provided with energy by a 12 V DC supply through a voltage regulator module. Ultrasonic sensors function as inputs to the Arduino. These sensors supply distance data for the navigation of the robot. The Arduino Uno processes the incoming inputs. Then, the outputs linked to the DC motors are regulated. These outputs govern the direction and velocity of the motors because an L298N motor driver module is utilized. Furthermore, this configuration ensures that the robot maintains a stable

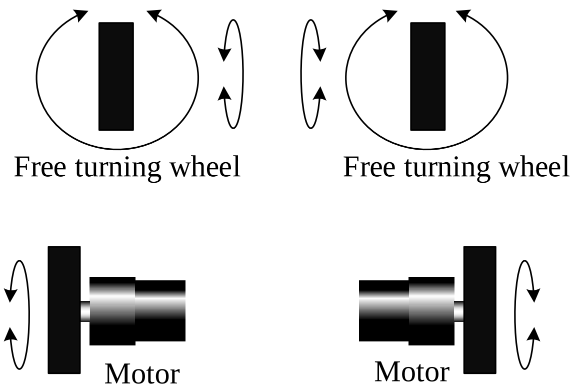


Figure 3: The robot's movement system with two active wheels and two idler wheels

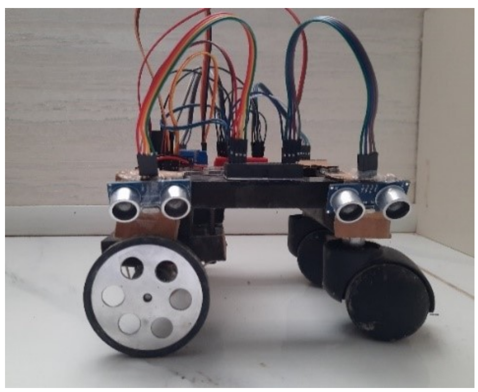


Figure 4: Proposed autonomous robot design

path. Also, power management is optimized for long term operation. Consequently, a reliable control architecture is established for future agricultural tasks. In DC motors, a gearbox either reduces torque while speed is increased or increases torque while speed is decreased. When these motors are used without a gearbox, the drive circuitry must regulate the shaft speed throughout a broad spectrum. This range exists from zero to the specified speed, e.g., 1000 rpm. The drive mechanism functions because the duty cycle or voltage level is reduced at lower speeds. As a result, torque is decreased. This drop in torque is negligible in applications such as cooling fans. However, a strong starting torque is essential for robots. Consequently, the gearbox is linked to the motor shaft so that operational complications are avoided. Figure 6(a) illustrates the installation and connection of the motors to the robot wheels in the laboratory prototype. The two rear wheels of the robot serve as idler wheels. These are shown in Figure 6(b). These wheels are used because balance is maintained and mobility is enhanced. The power source for both motors is 12 V DC. Furthermore, the parameters of the proposed autonomous robot are detailed in Table 2. Thus, the mechanical design is optimized for the physical requirements of the farm.

4 Navigation System Block Diagram

A vital element of the navigation system is the route planning algorithm. This algorithm must thoroughly and impeccably integrate all the robot's automation needs, ensuring that any potential shortcomings do not result in mission failure. This algorithm forecasts all possible

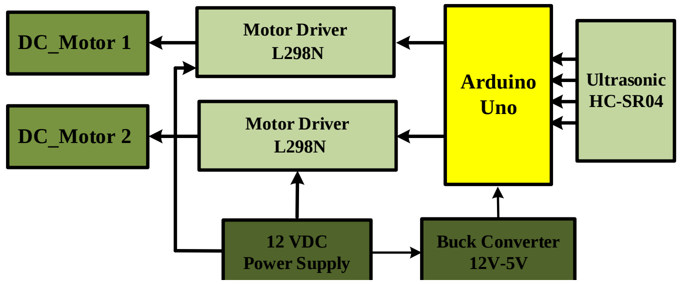


Figure 5: Autonomous robot navigation system block diagram

(a) (b)

Figure 6: Proposed autonomous robot (a) Front view of the robot (b) Rear view of the robot

events throughout the mission and formulates related reaction scenarios in a systematic way to accomplish the mission goal. Figure 7 depicts the block diagram of the constructed navigation system, accompanied by a comprehensive description below. The navigation system block diagram indicates that the robot commences its travel in an unobstructed area. Initially, before traveling the area between two ridges, it proceeds along a linear trajectory. Suppose the suggested robot does not penetrate the inter-ridge space, considering a specified distance (L) between the right and left ultrasonic sensors and the ridges. In that case, it will continue along its present trajectory. A loop is included in the block diagram for this reason. Should the robot fail to access the inter-ridge space after b attempts, its operation will be halted. Upon detecting the ridges with the front ultrasonic sensors, it is essential to precisely compute the distance from each sensor to the right and left ridges. The Arduino microcontroller initiates the turning phase by adjusting the distance between the sensors and the ridges. If the speed of the left wheel motor decreases relative to the right wheel motor, the robot turns left; if the right wheel motor slows down, the robot turns right. By keeping the sensors' distances within a specific range, the robot continues to move forward (operations in the bottom-left loop of Figure 7). Sensor data informs the two commands, which continue to operate as long as the robot remains between the ridges. As the robot nears the path's end, its frontal sensors become ineffective, and its rear ultrasonic sensors take over navigation duties. Should the rear sensors identify distances under the established threshold, the robot advances. If the distance exceeds the threshold, indicating that the robot has entirely deviated from the course, a turning maneuver is performed (as shown in the bottom-right loop of Figure 7).
Following the first phase, the robot proceeds along the trajectory using the frontal ultrasonic sensors until ridges are identified. Upon identifying the ridges, the robot re-enters the active operating zone, and the preceding processes are repeated. The mission is deemed accomplished if, after a specified time interval (b), the robot does not re-enter the inter-ridge zone.

Table 2: Specifications of the proposed autonomous robot

Specifications	Values
Robot dimensions	30*15 (cm)
Robot weight	1.7 (kg)
Height above ground level	10 (cm)
Rated motor speed	28 (rpm)

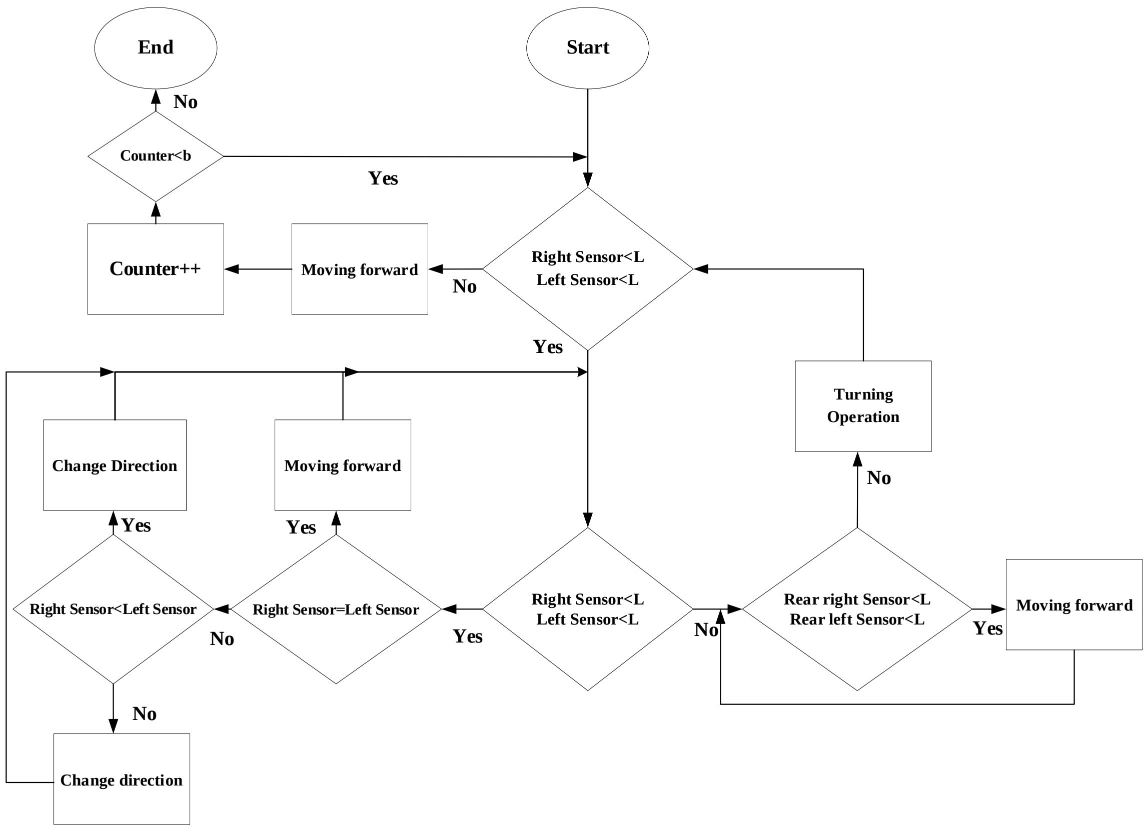


Figure 7: Proposed robot navigation system block diagram

5 Simulation and initial testing

Three separate cases of a potato farm are simulated in Simulink. This is done because the mechanical structure and control loops of the robot must be evaluated. The schematic block diagram is portrayed in Figure 8. The GetDistance block computes the distance from each sensor to the nearest wall. Then, the control block calculates the left and right wheel speeds. This calculation is based on the position error, i.e., the difference between the sensor distances. The diff-drive block computes the change rate of the Cartesian position and the heading angle of the robot. This model approximates robot behavior under various conditions through the use of different modular subsystems. Furthermore, the simulation ensures that the control logic is valid before physical implementation. Also, the integration of these blocks allows for precise path correction. Consequently, the stability of the autonomous system is confirmed for future field applications. The inputs to the model are the robot's initial coordinates (x0, y0), initial orientation (?0), target point, the path to be followed, and the operation mode. These act as inputs to begin motion and navigation. The input data is processed within the performance module. In this module, position and orientation deviations from the reference path are visually identified. Errors are then computed. These errors are forwarded to the control module, which dictates corrective behavior. The controller utilizes either a PID or other intelligent control algorithms. Command signals are published to the eff drive unit. This unit provides the kinematic or dynamic model of the robot. Furthermore, the position and heading are updated. In the middle part of the model, modules are designed because the detection of emergency conditions and obstacles is required. Also, controller performance is monitored. These modules currently display error warnings in Simulink blocks and require debugging. Therefore, system reliability is verified through this iterative simulation process. The system outputs are transferred to a unit called Logged Record. These outputs include the path, position values, and angle of the robot. This transfer is performed for performance analysis, storage, and plotting. The general model provides a comprehensive structure for animated robot navigation and control. Furthermore, the model is expanded to include additional sensors or sophisticated navigation algorithms. More complex environments are also integrated. The system serves as a practical foundation for the physical realization of control approaches. Also, the application of intelligent or learning based control strategies is enabled. In fact, this architecture allows for the rapid testing of future theories. Therefore, a robust platform for the development of autonomous agricultural technology is established.

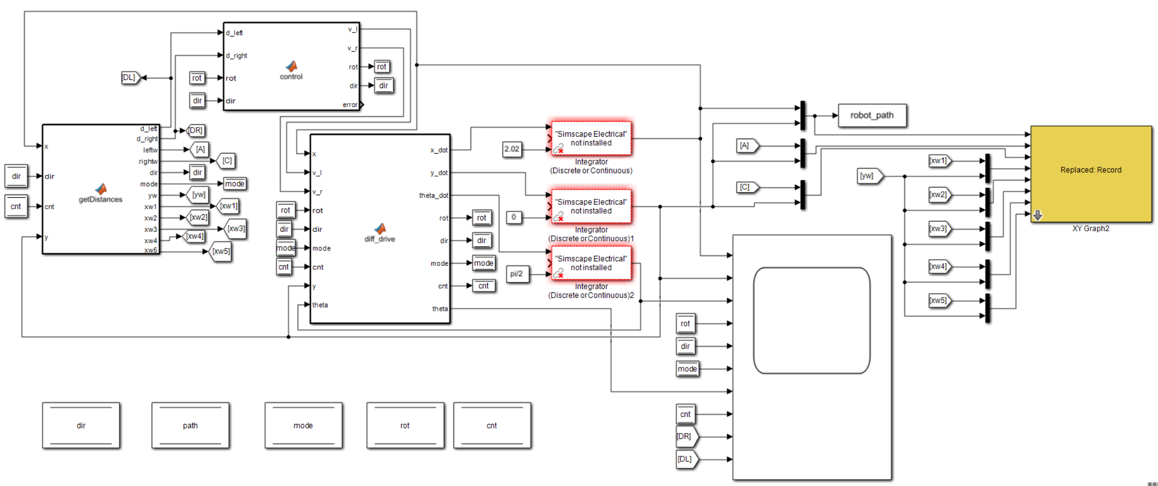
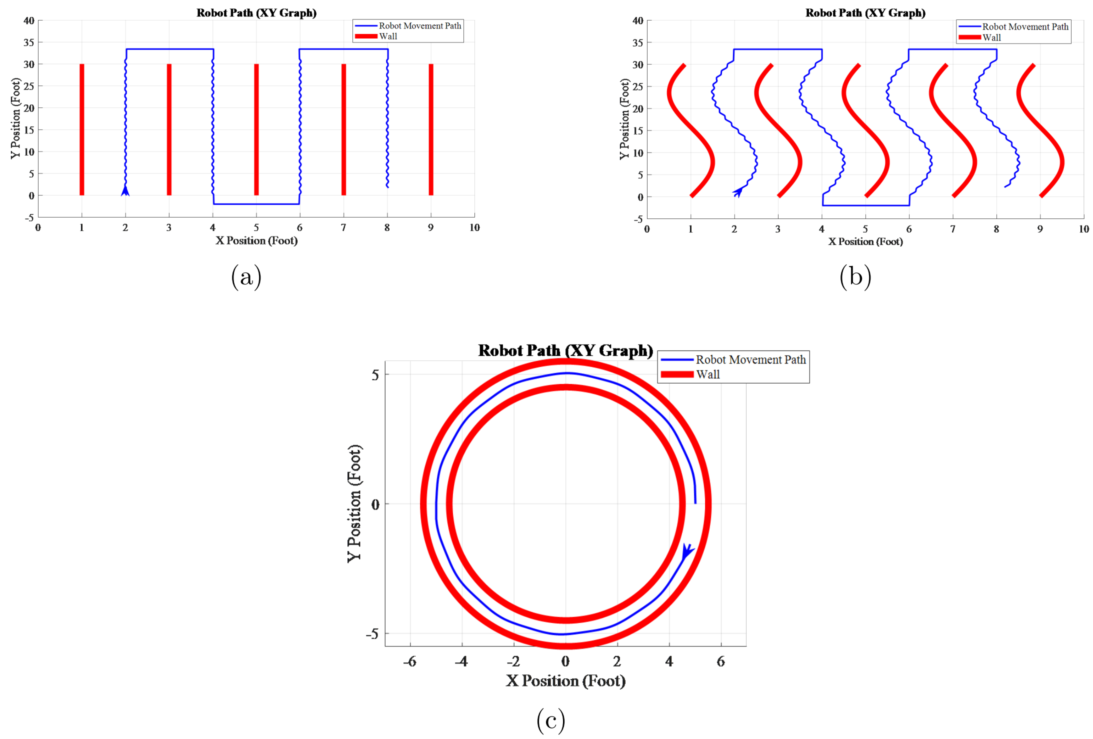


Figure 8: Proposed robot block diagram and its navigation system in Simulink

Figure 9 reports the performance of the proposed robot across three potato-farm configurations, based on the algorithm defined in the flowchart in Figure 7, assuming the sensors are operational and provide valid, usable data. These plots illustrate the robot's circuit-tracking and obstacle-avoidance capabilities. The robot's path is indicated by blue, and obstacles and walls are shown as thick red. In Figure 9(a), the robot operates among overlapping vertical obstacles one at a time. The blue path indicates that the robot navigated among the vertical obstacles without collision, demonstrating that the robot controller can respond quickly to environmental changes through a zigzag motion. In Figure 9(b), the same case is recomposed with a more continuous, smoother path curvature, demonstrating improved control performance and stability with reduced oscillations. In Figure 9(c), the robot travels along a circular trajectory maintained by ring-shaped walls. The robot again tracks a circular path while maintaining continuous motion without contacting any walls, thereby confirming the control performance during curved and confined motion. The above findings confirm that the designed controller successfully tracked the robot's path while avoiding obstacles. The practical implementation of the fabricated robot, as shown in Figures 4 and 6, may have a greater impact on performance when deployed in a potato-farm-like environment. In the next section, three experimental settings similar to those in Figure 9 will be presented to inform the practical implementation of the robot for real-world evaluation.



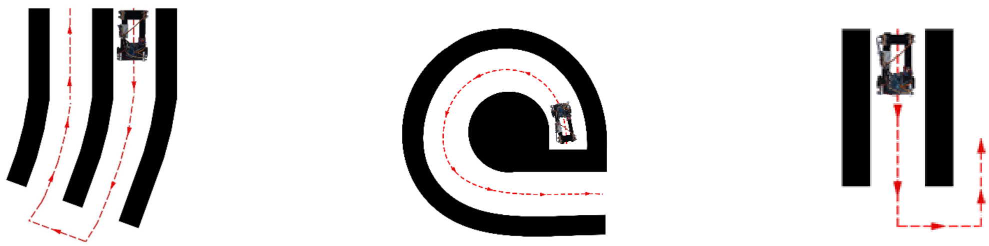
(a) (b) (c)

Figure 9: Simulation results of the proposed robot and controller model performance in Simulink. (a): First scenario, (b): Second scenario, (c): third scenario.

6 Results and discussion

Figure 10 presents the experimental results for the applied animated robot across three environmental conditions. This figure illustrates the real-life animated robot and its ability to follow a specified path while avoiding obstacles. The red dashed line shows the robot's trajectory, while the image of the robot shows its instantaneous position in the photograph. In Figure 10(a), the robot follows a curved, multi-branched path. In addition, the robot's selection of a trajectory and its smooth movement through curves demonstrate that the control system manages the complexities of paths and motion without significant deviations. This experiment illustrates the robot's capabilities to navigate in environments that require precision and continuous curvature. Figure 10(b) depicts the robot following a closed, spiral-like path to evaluate the stability of the robot and control system during continuous turning.
The test motion showed that the robot remained stable, with minimal lateral deviation from the starting point and a safe distance from the wall. This is a repeat evaluation to demonstrate that the controller achieved the desired outcome, even while the robot was in a roll. Figure 10(c) shows the robot navigating through an environment with sharp angles and corners. This test was performed to evaluate the controller's ability to respond to sudden changes in direction. The robot's ability to navigate around corners and avoid walls suggests that the control algorithm is effectively implemented and that the motion system can also perform

these actions. All results shown in Figure 10 reaffirm the robot's successful operation under real test conditions. The tests performed demonstrate that the simulation results presented in Figure 9 can be realized within the robot's physical capabilities and that the modeling of the control system led to feasible control algorithms suitable for the robot being evaluated.



(a) (b) (c)

Figure 10: Implementation of the proposed robot laboratory prototype in three different paths, (a): First path, (b): Second path, (c): Third path.

Figure 11 depicts the measured difference between the robot's lateral distances to the two crop rows (captured by the front-mounted ultrasonic sensors) for each of the scenarios in Figure 10, along with the corresponding right and left motor speeds (as a percentage of rated speed). Here, Figures (a) to (c) correspond to the first scenario, figures (d) to (f) correspond to the second scenario, and figures (g) to (i) correspond to the third scenario. The path-tracking algorithm is primarily designed to keep the robot aligned within the crop rows of the modeled farm. To maintain real-life conditions, soil-based walls were built, introducing naturally occurring irregularities such as soil clods and pebbles. When the robot encountered these irregularities, they caused minor errors in distance measurements, as shown in the distance differences plotted in Figure 11(a,d,g). Disturbances such as these can never be eliminated, so a filtering feature was used to confirm that only accurate outlier readings were sampling. Figure 11(a) shows a relatively severe deviation at second 27, corresponding to the end of the first row in the first scenario. Then, from the 27th to the 30th second, the robot turns around and enters the second row. During the movement in the second row, the largest deviation occurs at the 43rd second, which is about 2 centimeters.

In figure 11(d) due to the sharp bend in the test row, a slight perturbation was observed around the second 45. These inconveniences are related to when the circular path ends and the robot must move the end of the path in a straight line. The point that can be understood from doubts 11(e,f), as well as 11(b,c), is that despite applying some severe oscillating voltages to the motors, their dynamics prevent sudden changes in the robot's direction of motion. In Figure 11(g), the robot reaches the end of its path at second 15 and starts to turn around. After the turning process is complete, which lasts until about the 32nd second, the robot continues to move straight for about 10 seconds and then stops the motors based on the information in Figures 11(h) and (i).

In summary, it can be claimed that in all three scenarios considered in Figure 10, the robot with the algorithm programmed in it is able to follow the rows of the farm well and in the worst case, it has a deviation of 5 centimeters in one row. It is obvious that the scenarios considered in Figure 10 are among the three severe scenarios that are rarely seen on a real farm.

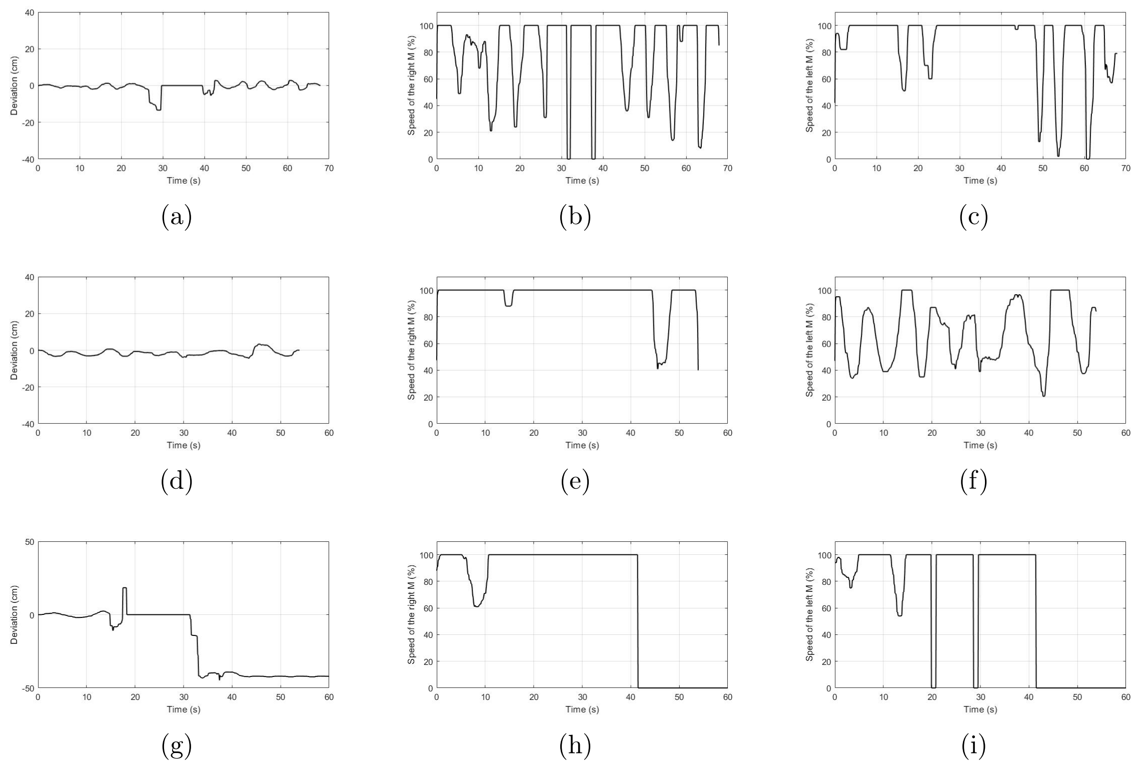


Figure 11: Results of prototype robot implementation in three proposed paths. (a): Deviation from the row on the first path, (b): Relative speed of the right motor on the first path, (c): Relative speed of the left motor on the first path, (d): Deviation from the row on the second path, (e): Relative speed of the right motor on the second path, (f): Relative speed of the left motor on the second path, (g): Deviation from the row on the third path, (h): Relative speed of the right motor on the third path, (i): Relative speed of the left motor on the third path.

7 Conclusion

This research indicates that an autonomous robot operates accurately, steadily, and economically. The system is equipped with ultrasonic sensors and a control scheme. It moves through narrow and complex paths in potato farms. After laboratory and farm data are analyzed, it is apparent that the path-tracking algorithm produces a position error of less than 5 cm even in challenging situations. Even with a simple electronic architecture and inexpensive components, the practical implementation of this system is optimized. The Arduino and a simple control program are utilized. Therefore, the upscaling of this technology for real-world agricultural systems is facilitated. Furthermore, this design proves that high precision is achievable with low-cost hardware. As a result, the accessibility of autonomous solutions for farmers is increased. Thus, a forward-thinking model for sustainable and automated agriculture is established. To improve accuracy and reliability, machine vision systems, noise filters, and multi sensor data fusion are suggested. These technologies enhance environmental perception and adaptive control in future work. In conclusion, the results of this research provide a foundation for on-farm agricultural automation. Contributions are made to the acquisition and precision of navigation in row crops, e.g., potatoes. This method is effective because it remains functional in complex topographies. Furthermore, the integration of advanced filters will mitigate environmental noise. Therefore, the proposed system serves as a scalable model for automated farming. Consequently, the reliance on manual labor is reduced. Thus, a forward-thinking path for the modernization of the agricultural sector is established.

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