International Journal of Scientific Research in Science, Engineering and Technology

Print ISSN - 2395-1990
Online ISSN : 2394-4099

OPEN ACCESS

Available Online at : www.ijsrset.com
doi : https://doi.org/10.32628/IJSRSET2310511

The Design and Simulation of Autonomous Agricultural Vehicle for Orchards

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ARTICLEINFO

Article History :

Accepted: 08 Sep 2023
Published: 25 Sep 2023

Publication Issue :
Volume 10, Issue 5
September-October-2023
Page Number :
104-114

ABSTRACT

In recent years, agricultural producers have faced challenges due to the uncertainty of labor force access, growing demand for safe, accessible, and high-quality agricultural products, high competition with international producers, and the need to reduce their carbon footprint. To continue their competitive and profitable production, producers must invest in technology and increase efficiency. Autonomous agricultural vehicles are crucial for autonomous processes in orchards, increasing productivity, collecting data for decision-making, reducing operating costs, and carbon footprint. This study focuses on the design and simulation of an autonomous vehicle for orchards. The autonomous vehicle can map the orchards using data from odometry and light detection and ranging (LIDAR) sensors by utilizing Simultaneous Localization and Mapping (SLAM) algorithm, accurately determine its position using the Adaptive Monte Carlo Localization method, and avoid obstacles using the dynamic window approach algorithm. The autonomous vehicle is an original design for netted orchards where GPS cannot work properly and is fully autonomous, requiring no external GPS data. It is expected to provide higher efficiency by reducing environmental pollution, operating expenses, and labor force in practice. The success of the mapping and localization application depends on the update frequency of the position and the number of particles used for localization. A path-planning application was developed to reach the desired position from the autonomous agricultural vehicle's current position on the map. The Dijkstra Algorithm was used for path planning, with the Dynamic Window Approach allowing the robot to escape obstacle. The simulation studies achieved the lowest position error when the vehicle's position was updated at intervals of 2 cm, and a minimum of 500 and a maximum of 2000 particles were used. While the vehicle was moving on a straight obstacle row in the simulation environment, an average localization error of 2.1 cm was obtained. This error is convenient as it enables seamless navigation between tree rows without any collision.

Keywords: Localization, SLAM, autonomous navigation, agricultural robot, autonomous vehicle

I. INTRODUCTION

According to projections, it is anticipated that the global population would reach 9 billion by the year 2050. In order to adequately address the food, nutrition, textile, and fuel requirements of this population, it will be necessary to double agricultural production and enhance productivity in production by 25% [1,2].

With the expansion of agricultural fields, the need for automation in certain repetitive tasks, such as spraying, arose. In numerous instances, the utilization of agricultural robots may not be suitable for tasks that necessitate substantial power consumption, such as tillage, planting, and harvesting, due to their comparatively restricted size and engine power when compared to conventional agricultural vehicles. Nevertheless, agricultural robots exhibit a high level of suitability for tasks that necessitate comparatively lower power consumption. These tasks encompass monitoring and charting the growth of plants, autonomously transporting both the harvester and the harvested produce, as well as administering variable rate spraying in accordance with specific requirements.

Soil compaction is influenced by various factors, including the weight, tire pressure, and size of agricultural tools and tractors [3,4]. The primary cause of soil compaction in a field is attributed to the irregular traffic patterns of tractors, accounting for over 96% of such occurrences. Furthermore, a significant proportion of energy utilized in the production process, approximately 90%, is expended in the endeavour to alleviate this congestion. Compression inside the root zone induces alterations in the physical and mechanical characteristics of the soil. The process of compaction leads to a rise in the bulk densities of soils, but it also results in a reduction in both total porosity and drainage capabilities. The phenomenon of soil compaction has been shown to result in a mechanical impediment to the growth of plant roots, hindering the essential flow of air required by the roots to reach deeper layers of the soil [5]. Additionally, this compaction has been found to contribute to drainage issues in low-lying areas. The reduction in water infiltration into the soil caused by compaction in sloping terrain leads to an elevation in surface runoff, thereby increasing the risk of erosion. The phenomenon of soil compaction has been found to result in a reduction in plant growth and denitrification, as demonstrated by Nolte and Fausey [6]. Agricultural robots, because of their reduced weight in comparison to traditional agricultural instruments, result in decreased soil compaction [7].

In modern orchards, a common practice involves utilizing a slow-moving vehicle to facilitate various maintenance tasks between rows of trees, with a driver operating that vehicle. According to Hamner et al. [8], the implementation of a self-driving vehicle capable of navigating independently through rows of trees has the potential to enhance productivity, decrease production expenses, and transition agricultural workers from a passive function, such as operating a vehicle, to a more creative and effective position.

In recent years, agricultural producers have encountered notable difficulties stemming from uncertainties related to access to the agricultural labour force, increasing customer expectations for high-quality and sustainable agricultural products, competition from international producers, and the imperative to mitigate their carbon emissions. Manufacturers are able to sustain competitive and profitable production by strategically allocating resources toward technological advancements, minimizing labour expenses, and enhancing operational efficiency. The utilization of autonomous vehicles in orchards holds significance as it enables the automation of many operations and facilitates the collection of essential data for informed decision-making [8].

While the field of robotics has extensively researched autonomous driving systems, the development of such systems specifically designed for navigating orchards and nurseries remains an unresolved challenge. Autonomous tractors and harvesters employed in wheat farming exploit their ability to acquire Global Positioning System (GPS) data without obstruction in open, and unobstructed areas. The navigation of the vehicle is facilitated through the utilization of the GPS in earlier studies [9,10,11]. Implementing GPS-connected navigation systems for orchards presents significant challenges due to the high density of tree canopies and the presence of protective covers and netting that shield the trees from hail damage. Furthermore, the limited space for movement at the end of each row and the existence of dynamic obstacles that may obstruct the path of autonomous vehicles pose significant challenges that need to be addressed to enable their effective operation inside orchard environments [12,13].

Several companies, including John Deere, Class, and Amazon, have conducted prototype experiments on autonomous farm vehicles. In our country, AKINSOFT company has developed two prototype robot models that operate on electricity. These robots are equipped with GPS technology, enabling them to navigate effectively. Their primary purpose is to facilitate the process of planting [14]. These vehicles rely on GPS technology to facilitate driving, so it is not appropriate to classify them as completely autonomous. Autonomous driving necessitates a connection to satellites in those vehicles.

This study, aims to use probabilistic robotic methods in the design and simulation of an autonomous agricultural vehicle that can be used in orchards. In orchards with a netting system, trees are systematically planted, ensuring specific distances both within and between rows. Agricultural activities in orchards, including hoeing, spraying, harvesting, etc., are conducted by agricultural vehicles that move between rows. Hence, it is necessary for an autonomous vehicle designed for agricultural operations in orchards to possess the capability to navigate between specified tree rows while effectively avoiding obstacles and also ensuring the avoidance of any collisions with trees upon returning to adjacent rows. The process of achieving autonomous navigation for robots intended for agricultural tasks is challenging due to the inherent uncertainty present in the natural world. One significant drawback of current systems is their lack of resilience in the face of these uncertainties. This study presents a developed solution to the problem through the utilization of a methodology grounded in LIDAR (laser detection and distance measurement sensor) and odometry sensors. The objective of navigation is to develop software capable of autonomous traversal through the corridor situated between two rows of trees in a netted orchard while following a predetermined route. The fundamental components of the system encompass the stages of mapping, localization, and route planning.

II. METHODS AND MATERIAL

In the study, a robot with an axle spacing of 540 mm, a length of 988 mm, a width of 670 mm, and a ground clearance of 160 mm was designed for the simulation environment using the Unified Robotics Description Format (URDF). The vehicle has a differential drive. The kinematic model is as in Fig. 1. The driving variables calculated in the simulation environment for the kinematic model are given in Equations 1,2 and 3.

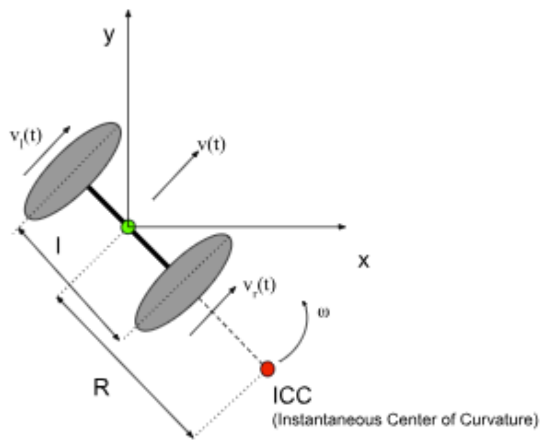

Figure 1. Kinematic characteristics of the designed autonomous vehicle

$$v(t) = \frac{1}{2}(v_r(t) + v_l(t)) \tag{1}$$

$$\omega(t) = \frac{v_r(t)+v_l(t)}{l} \tag{2}$$

$$R = \frac{(v_r(t)+v_l(t))}{2x\,(v_r(t)-v_l(t))} \tag{3}$$

$v_r(t)$: Linear velocity of right wheel

$v_l(t)$: Linear velocity of left wheel

v(t): Linear velocity

ω: Angular velocity

l: The distance between the wheel axes

R: Turning radius relative to autonomous vehicle center axis

ICC: Instant center of curvature [15]

The vehicle simulation was conducted within the GAZEBO environment [16]. Fig. 2 displays the robot platform onto which the sensors have been embedded, as well as the simulation environment that has been created.

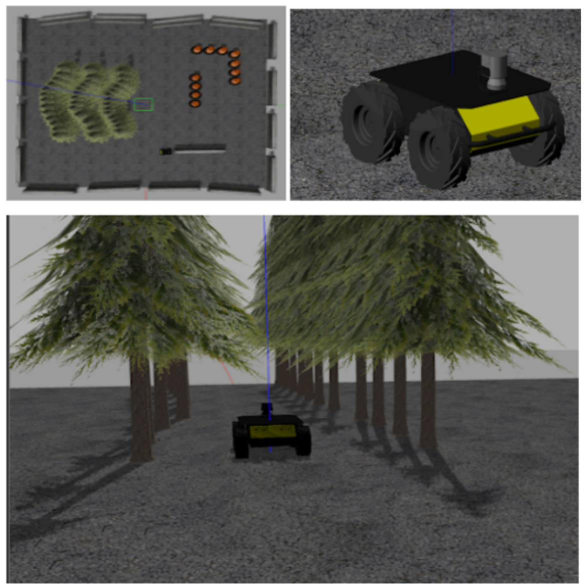

Figure 2. Simulation environment

In the context of design and simulation experiments, a computer system equipped with the Linux Ubuntu 16.04 LTS operating system, 8GB of memory, a 2.6 GHz quad-core processor, and a 2 GB graphics card was utilized.
The implementation of the software was carried out within the ROS (Robot Operating System) environment, using the Python 3 programming language. In order to conduct simulations, several sensors such as LIDAR, and odometry sensors (wheel speed, and inertia sensor) are employed. In the GAZEBO simulation environment, the

readings obtained from the sensors were subject to a random error following a normal distribution with a mean of 0 and a standard deviation of 0.03. Therefore, the objective is to simulate authentic working environments. The environment map was developed via the SLAM algorithm, as described by [17]. The fidelity of the generated map is intrinsically linked to the precision of the measurement resolution and the detection capabilities of the sensors employed. The application of an adaptive Monte Carlo Localization method, as described by Rekleitis [18], has been utilized to determine the precise location of the vehicle on the map.

Following the acquisition of a map of the surrounding environment and afterward localization of the vehicle within this map, a route planning application has been developed to facilitate the move from the current position to the desired destination(s) for autonomous driving purposes.

The task of determining an optimal trajectory for an autonomous vehicle to travel from a specified origin point A to a designated destination point B is often referred to as route planning. In the context of route planning, it is imperative for autonomous vehicles to navigate their path quickly while ensuring avoidance of obstacles present on the map, as well as those that may unexpectedly appear in their trajectory [19,20]. To execute these procedures, the process of route planning is divided into two components: global and local, each designed separately. The obstacle map, designed for the purpose of route planning, was generated by considering the computed cell values assigned to each individual cell on the map (Fig. 3). The utilization of map layers in the creation of the map guarantees that the center of rotation of the autonomous vehicle remains at a distance from obstacles that are within the predetermined tolerance threshold. This ensures that the vehicle is able to navigate without colliding with any obstacles.

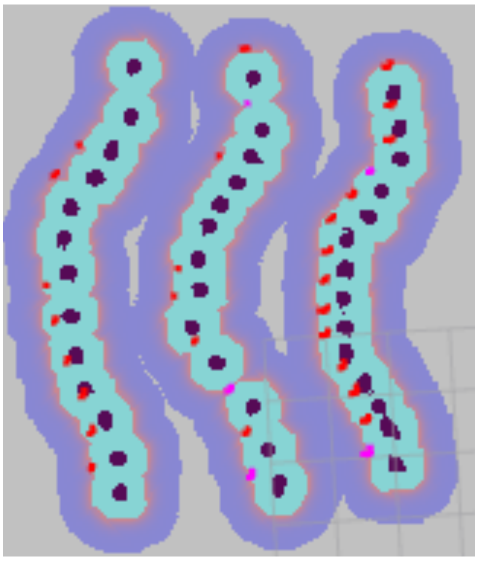

Figure 3. Visualization of the tolerance layer on the map

During the phase of global route planning, a route planning application has been devised to facilitate the navigation of autonomous vehicles from their current location on the obstacle map to the designated destination point(s). In order to fulfill this objective, the Dijkstra Route Planning Algorithm was used in route planning [21].

The route planning application operates in two distinct stages. Firstly, the global route planner computes a comprehensive plan, which is subsequently implemented by the local planner in order to enable the autonomous vehicle to effectively navigate and circumvent obstacles inside the LIDAR sensor's field of view. The local route planning was conducted using the dynamic window approach [22]. In the event that an autonomous vehicle encounters an obstacle, it is designed to execute predetermined rescue procedures. If the obstruction cannot be successfully overcome, the vehicle is programmed to halt its operations in order to ensure safety (Fig. 4).

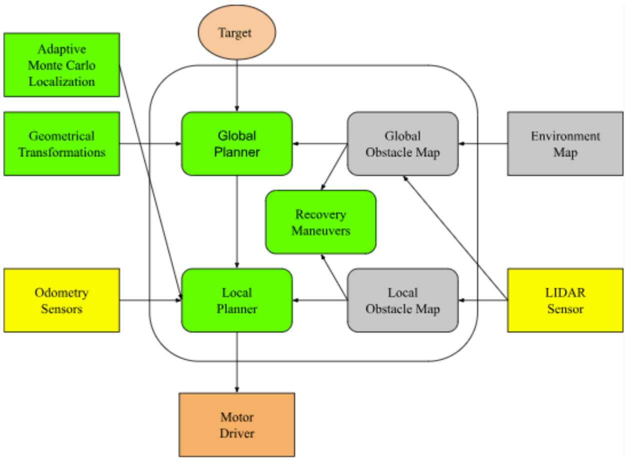

Figure 4. Autonomous vehicle software flowchart

The mapping and localization techniques employed in probabilistic approaches rely on the utilization of the particle filter-based algorithms. The study investigated the quantity of particles required for ascertaining the vehicle's position, as well as the optimal frequency for updating these particles. The optimal particle quantity and update combinations were determined by evaluating the positional errors derived from experimental trials.

III. RESULTS AND DISCUSSION

The developed mapping application automatically creates maps with the data received from LIDAR and odometry sensors. The created map is saved in PNG or JPG format. Along with the created map, an attribute file containing map size, map resolution, obstacle and free space threshold data is given as input to the map server to be provided by ROS, and the map needed by the designed navigation system is provided. The map created as an image file can be edited as desired with an editor such as Microsoft Paint. If there are tree rows or regions on the map that we do not want the autonomous vehicle to enter, these can be ignored during the route planning phase by enclosing them with a black line. The map obtained with the robot circulating in the simulation area with the developed SLAM algorithm is given in Fig. 5. White areas represent unobstructed areas, black areas represent barriers, and gray areas represent uncertain areas.

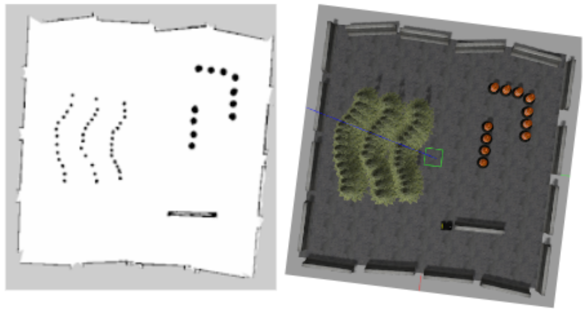

Figure 5. The map generated by the autonomous vehicle

The adjustment of the tolerance layer during the route planning phase is a crucial consideration that is dependent upon the dimensions of the autonomous vehicle's projection. The adjustment of the tolerance layer involves modifying the radius of the outer tangent circle in relation to the projection of the autonomous vehicle [23]. In order to ensure that the autonomous vehicle can navigate and maneuver without colliding with the trees, a tolerance layer width equivalent to 1.5 times the outer tangent circle is employed, given the row spacing of 1.5 m.

The development of the localization application involved a comparison of data acquired from LIDAR and odometry sensors with the map in order to determine the position of the autonomous vehicle. Ensuring accurate initialization of the beginning position facilitates the fast convergence of the estimated position and the actual position of the autonomous vehicle.

The accuracy of the map is enhanced with an increase in the number of particles employed in the mapping procedure. However, it should be noted that as the number of particles is augmented, the computational resources necessary for processing also experience exponential growth. Quigley et al. [24] have proposed the utilization of a minimum of 50 to 200 particle pairs, depending on the specific obstacle configuration within the outdoor setting, for the purpose of adaptive Monte Carlo Localization applications.

The localization application utilized the particle filter-based Adaptive Monte Carlo Localization method. This approach allows for automatic adjustment of the number of particles within predetermined limitations based on position precision. Upon analysis of the positioning error in the simulation across various particle quantities, it is observed that the average error is 15.3 cm for the configuration employing 5-20 particles, 10.2 cm for the configuration that includes 50-200 particles, 3.5 cm for the application utilizing 500-2000 particles, and 2.3 cm for the application employing 5000-20000 particles (Table 1). A mean inaccuracy of cm was observed. As the quantity of particles employed rises, there is a corresponding reduction in the average error; nevertheless, there is an exponential increase in the computational resources needed. The preferred configuration in the created localization application involved the utilization of 500-2000 particles.

Table 1. Localization error for different number of particle settings

	Localization Error (cm)			
	Min:5 Max:20 particle	**Min:50 Max:200 particle**	**Min:500 Max:2000 particle**	**Min:5000 Max:20000 particle**
Mean	15.3	10.2	3.5	2.3
Standard Deviation	17.7	10.5	4.9	3.0
Minimum	0.0	0.0	0.0	0.0
Median	14.4	10.8	3.5	2.5
Maximum	59.1	32.5	18.8	9.7

The success of localization is influenced by an additional factor, namely the updating of position information when the autonomous vehicle performs movement [25]. When the frequency of updates is increased within the limitations of sensor measurements, there is a linear rise in the necessary computational power, accompanied by an improvement in position accuracy. The minimum average positional error was 3.5 cm in the configuration with a position update every 2 cm. The largest average position error was 9.2 cm in the configuration where the position update was made every 8 cm (Table 2).

Table 2. Localization error for different position update frequencies

	Localization Error (cm)		
	Position update for 2 cm interval	**Position update for 4 cm interval**	**Position update for 8 cm interval**
Mean	3.5	7.2	9.2
Standard Deviation	4.9	7.7	12.7
Minimum	0.0	0.0	0.0
Median	3.5	7.0	9.0
Maximum	18.8	33.0	46.0

The errors seen in Tables 1 and 2 belong to the configuration in which the robot makes a U-turn. Since the developed system has differential driving, higher standard deviation and maximum error were obtained compared to going between rows [26]. It was considered an outlier because the maximum errors were more than 2.5 standard deviation [27].

The route planning application comprises two components, namely the global and local route planner, which operate together. The global planner provides the overall plan, which is determined based on the presence of barriers, the autonomous vehicle's location, and the desired destination, to the local planner. The data obtained from the sensors is analyzed by the local planner to ensure that the autonomous vehicle effectively navigates the environment by avoiding any impediments within the range of the sensors. The local planner uses the dynamic window technique. This approach involves the creation of local route options that can be utilized during the designated simulation timeframe. These options are generated by sampling the speed space of the autonomous vehicle. Increasing the duration of the simulation necessitates a higher computational capacity and enhances the accuracy of the generated routes [28,29]. The selection of a simulation timeframe of 4 seconds has been noted to enhance the maneuverability of autonomous vehicles when navigating through confined passageways (Fig. 6).

During real-world implementation, there may arise circumstances in which the autonomous vehicle is unable to circumvent the obstacle. In the aforementioned instances, the software for the autonomous vehicle incorporated a two-stage recovery and escape strategy for execution. The initial action involves resetting the local planner and attempting to generate a new global plan. In the event of a failure, the autonomous vehicle will initiate a change in direction and proceed to explore alternative routes. In the event that the autonomous vehicle is unable to execute a turnaround maneuver due to the potential hazard of collision, it terminates its route planning and remains still while sending an error signal.

The system that was designed has an average inaccuracy of 2.1 cm across tree rows, as shown during the localization tests conducted in the simulation environment. At the U-turns, the system is capable of ascertaining its position with an average deviation of 3.5 cm. The maximum errors obtained in all three test configurations were considered outliers because they were greater than 2.5 standard deviation (Table 3). The precision spraying applications are well-suited for this technology because to its ability to achieve a high level of location accuracy comparable to GPS standards [30].

Table 3. Localization error for different position update frequencies

	Localization Error (cm)		
	Straight Row Movement	Curved Row Movement	U-turn Movement
Mean	2.1	2.2	3.5
Standard Deviation	2.3	2.9	4.9
Minimum	0.0	0.0	0.0
Median	2.0	2.1	3.5
Maximum	6.8	9.8	18.8

Since the size and weight of the developed agricultural autonomous vehicle is less than conventional tractors, it will both provide maneuvering advantage and cause less soil compaction. The autonomous vehicle design can be used both without a driver and with a driver [31].

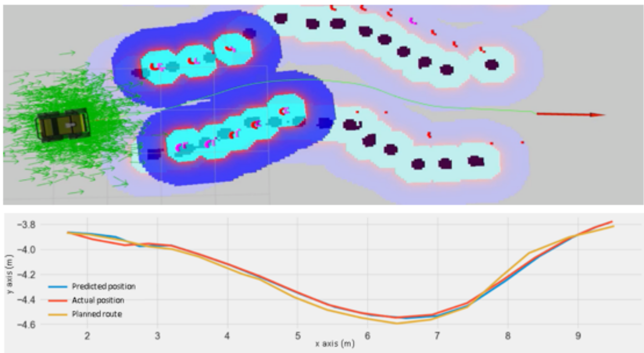

Figure 6. Movement of autonomous agricultural vehicle on a curved line

The system utilizes solely LIDAR and odometry sensors to facilitate the navigation process within rows of trees in orchards. The implemented system possesses the capability to be extended to various differential drive vehicles in a modular fashion through the straightforward process of altering the robot's dimensions and the sensor placements within the software. Sensors such as real-time kinematic (RTK) GPS require a periodic fee for data reception, whereas the created system operates independently without reliance on external data sources. Due to this reason, in contrast to robots reliant on GPS technology, the robot in the study can be categorized as entirely autonomous since it exclusively relies on its internal sensors to determine its location and navigate towards its given goal. The primary objective of the designed system is to go along specified routes through orchards, switching between rows. In this context, the vehicle that has been designed can serve as a platform for the transportation or towing of agricultural machinery engaged in various agricultural activities, including but not limited to hoeing, spraying, and harvesting. Additionally, the orchard can be accurately mapped using the data collected by the robot's sensors. This enables the creation of an obstacle map that can be customized and organized as required, eliminating the necessity for a sophisticated geographic information system.

The acquired results belong to the simulated environment. To enhance the convergence of simulation results with real-world scenarios, random errors were introduced to the sensors and a friction coefficient was applied to the simulated ground within the environment. The utilization of simulation environments plays a crucial role in facilitating the transition of these vehicles from a design stage to real-world implementation. When the results obtained in the prototype studies seen in the literature are examined, it shows that the designed system can easily converge to the simulation results after appropriate adaptations are made [32,33].

IV. CONCLUSION

The outcome of this study has led to the development of an autonomous vehicle and software system that facilitates the independent execution of diverse tasks within orchards. The main goal of the established system is to navigate predetermined routes through orchards and effectively move between rows. Within this particular framework, the developed vehicle possesses the capability to function as a platform for the carriage or towing of agricultural machinery involved in diverse agricultural endeavors, encompassing, yet not restricted to, tasks such as hoeing, spraying, and harvesting. A software system has been developed that includes a mapping application, a localization application, and a route planning application. The mapping application displays the distances between obstacles in the environment. The localization application allows the autonomous vehicle to determine its own position on the map generated by the vehicle. The route planning application facilitates reaching desired targets while avoiding obstacles.

V. ACKNOWLEDGEMENT

This article has been produced from Ph.D. thesis of Eray Önler.

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Cite this article as :

Eray Onler, Ilker Huseyin Celen, "The Design and Simulation of Autonomous Agricultural Vehicle for Orchards ", International Journal of Scientific Research in Science, Engineering and Technology (IJSRSET), Online ISSN : 2394-4099, Print ISSN : 2395-1990, Volume 10 Issue 5, pp. 104-114, September-October 2023. Available at doi : https://doi.org/10.32628/IJSRSET2310511

Journal URL : https://ijsrset.com/IJSRSET2310511