Digital twins in smart farming: An autoware-based simulator for autonomous agricultural vehicles

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Abstract: Digital twins can improve the level of control over physical entities and help manage complex systems by integrating a range of technologies. The autonomous agricultural machine has shown revolutionary effects on labor reduction and utilization rate in field works. Autonomous vehicles in precision agriculture have the potential to improve competitiveness compared to current crop production methods and have become a research hotspot. However, the development time and resources required in experiments have limited the research in this area. Simulation tools in unmanned farming that are required to enable more efficient, reliable, and safe autonomy are increasingly demanding. Inspired by the recent development of an open-source virtual simulation platform, this study proposed an autoware-based simulator to evaluate the performance of agricultural machine guidance based on digital twins. Oblique photogrammetry using drones is used to construct three-dimensional maps of fields at the same scale as reality. A communication format suitable for agricultural machines was developed for data input and output, along with an inter-node communication methodology. The conversion, publishing, and maintenance of multiple coordinate systems were completed based on ROS (Robot Operating System). Coverage path planning was performed using hybrid curves based on Bézier curves, and it was tested in both a simulation environment and actual fields with the aid of Pure Pursuit algorithms and PID controllers.

Keywords: autoware, simulation platform, autonomous agricultural vehicle, digital twin, autonomous robots
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1 Introduction

Autonomous agricultural vehicles can improve profitability, help alleviate labor concerns, and reduce the cost of inputs[1-3]. Significant research progress has been made in automated guidance for the agricultural vehicle in the last two decades[4], but the development of unmanned agricultural technology is limited by processes such as tillage, seeding, management, and harvesting[5]. Experiments can only be conducted at specific times of the year. Moreover, research in autonomous agricultural vehicles that are required to enable more efficient autonomy becomes increasingly demanding due to the growing simulation technology, and field trials are sometimes accompanied by safety hazards[6-8]. These problems have become restraints for the fast development of agricultural machinery technology.

Grieves et al.[9] proposed the concept of digital twins. With the development of digital twins, virtual simulation technology has played an important role in various industries, including manufacturing[10], automotive industry[11], and energy industry[12]. Simulation technology can leverage computing power and cloud platforms to reduce the costs and time of testing, and developers can also change algorithms, retrain network models or quickly perform regression testing in a virtual environment. The simulation environment allows precise control of weather, time, maps, traffic, and other conditions, which enables to generate training data for machine learning[13]. There are already a few successful digital twin applications in agriculture[14]. Zhao et al.[15] proposed a fast and accurate fishing net damage detection model that has been established based on digital twins. Tsolakis et al.[16] developed AgROS, an emulation tool based on ROS, which uses actual landscapes from digital elevation models retrieved from Open Street Maps as input. In the paper, a test was conducted for actual orchards and virtually simulated orchards and confirmed the usability of its

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ROS-based simulation system but did not deliver reliable simulation results. Jensen et al. developed a software platform named Frobomind using ROS as middleware. It is concluded that FroboMind is usable in practical field robot applications by research groups[5]. Nevertheless, due to the increasing complexity of software, the research on advanced cognition and behavior required to achieve more efficient, reliable, and secure autonomy is becoming increasingly difficult.

Simulation techniques are widely used in the automotive industry, especially in the field of vehicle dynamics, such as CARLA[17], CarMaker[18], CarSim[19], and ADAMS[20]. However, integrating developers' unmanned systems into the vehicle requires a lot of extra work and cannot be deployed on a real tractor given the safety concerns. Commercial simulators are usually not open source and usually unavailable for researchers targeting at different research goals[13]. Most of them are mainly used for car driverless testing and it is difficult to have secondary development based on field scenarios in the aspects of map, planning, and control. A simulation study of driverless agricultural machines based on Autoware has been carried out, integrating HD maps, global path planning and lateral control modules for unmanned agricultural vehicles. It will significantly decrease the development time and resources required in field experiments.

The scope of this research is to combine customized data loading with communication methods based on Autoware, and integrate the model of environments, planning, and control modules to jointly build an simulation platform for agricultural vehicles. Field experiments were conducted with the same path planning and control algorithms, and the test results were compared with the reference path to verify the feasibility of the platform for agricultural vehicles. In this sense, our tool involves following steps, which are: 1) construction of the field environment model; 2) the construction of tractor model construction and kinematic model; 3) design of inter-node communication methods; 4) field experiment validation.

2 Materials and methods

2.1 Modeling of field

In order to simulate the real field environment, a field in Miyun District, Beijing was selected as a case study, as shown in Figure 1. DJI photom4 was used to collect aerial photos and then constructed High Definition maps (HD maps) of the field. The Agisoft metashape and Unity were used for map construction and accuracy verification. The UAV parameters are listed in Table 1.

Figure 1 The study area

Data acquisition was performed on a clear sky. Pix4Dcapture was used for route planning. All airfoil positioning states are fixed solutions. The flight altitude was 73 m, the course overlap rate was 80%, the bypass overlap rate was 80%, and the flight speed was 5 m/s. The flight trajectory planning is shown in Figure 2.

After the aerial photography was completed, flight inspection was conducted on the relevant aerial images, and the flight and photography quality met the specification requirements.

Table 1 UAV parameters

Items	Parameters	Values
DJI Phtom4 pro RTK	Wheelbase/mm	350
	Weight/g	1391
UAV camera	Image sensor	1" CMOS
	Effective pixels	20 million
	Maximum resolution/pixels	4864×3648
	Focal length/mm	8.8-24.0
GNSS modules	Usage frequency	GPS: L1/L2; GLONASS: L1/L2; BDS: B1/B2; Galileo: E1/E5
	Horizontal positioning accuracy/cm	1
	Vertical positioning accuracy/cm	1.5

Figure 2 Aerial film shooting locations

The image postprocessing is shown in Figure 3. After completion of the image alignment, the aerial triangulation was performed, and finally, the dense point cloud was generated (Figure 4). It is worth noting that the model restores the real scene at equal scale, rather than artificial modification and texture.

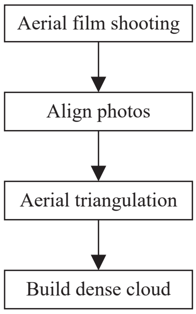


Figure 3 Data Acquisition and Processing

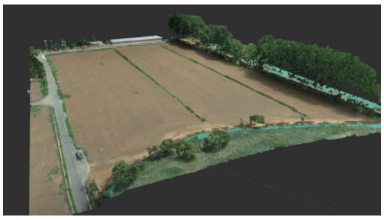


Figure 4 Field dense point cloud

2.2 The tractor motion model

In order to build an equal scale model of the tractor in the simulation system, the dimensions of the tractor in Autoware should be consistent with the field experiment. The DF2204 with stepless transmission can be controlled by CAN signal. The parameters are listed in Table 2. The Autoware-based simulator using ROS Melodic as system architecture. An isometric 3D model of a tractor was created in the Gazebo 3D scene environment (Figure 5) in Unified Robot Description Format (URDF).

Table 2 DF2204 tractor parameter

Parameters	Values
Wheelbase/mm	3042
Front-wheel distance/mm	1920
Rear wheel distance/mm	1900
One-sided brake turning circle radius/m	5
No unilateral braking steering circle radius/m	6
The maximum turning angle of front wheel/(°)	50

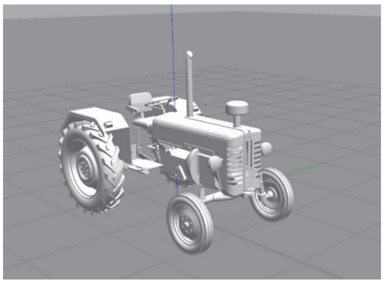
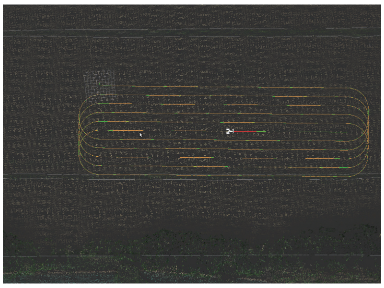


Figure 5 Tractor model in gazebo

First, the global path planning is implemented using Bézier-based hybrid curve. According to the method, the field was divided into a straight-line operation area and a turning area. For the problem of discontinuous curvature of U-turn and straight-line operation path connection, the minimum turning radius of the tractor is firstly considered to determine the number of paths skipped by a single arc turn, then the control polygon is obtained. The three-time Bézier curve is used to build a smooth connection between straight-line operation path and the turning path.

The kinematic model of autonomous tractor uses Ackermann steering. Pure Pursuit algorithm was used as the path tracking algorithm[21]. The process of agricultural machine operation is shown in Figure 6.



Note: Green line indicates the globally planned path, and the virtual tractor can make a single-arc turn and set row operations. The gray line indicates the pure pursuit algorithm search range, and the red part is the work.

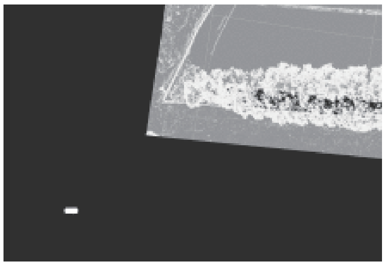
Figure 6 Emulation Interface on Autoware.

2.3 Coordinate conversion and node communication methods

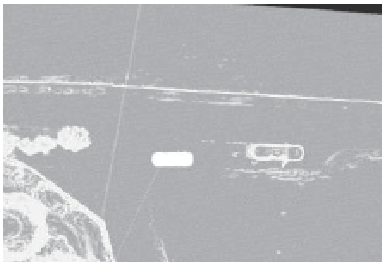
The transform system (tf), is a package that allows users to keep track of multiple coordinate frames over time. Tf maintains the relationship between coordinate frames in a tree structure buffered in time so that users can transform points, vectors between any two coordinate frames at any desired point in time on ROS[22].

Once the autonomous tractor receives the data transmitted by the sensors, like the camera or Lidar, the navigation module needs the vehicle to publish the necessary information about the coordinate system and its relationships using the tf. The tf tree starts with the world coordinate system and has many other branches. The world coordinate system is the origin of the entire tf tree and can be used to design various interactions between the tractor and the map, depending on the requirements of the research.

As shown in Figure 7 , the initialization of the tractor and base map can be completed by the relevant tf settings.



a. Before tf loading



b. After tf loading

Figure 7 Effects of vehicle and base map initialization

In order to realize the controller's function, a message format Tractor_Tf_Msg was customized based on Autoware data format, taking the specificity of agricultural scenarios into account, as listed in Table 3. *x*, *y*, *z*, yaw, velocity, change_flag, lon, and lat are the eight parameters.

Table 3 Tractor_Tf_Msg format

Field	Data type	Meanings
X	float	*x*-coordinate
Y	float	*y*-coordinate
Z	float	Elevation
Yaw	float	Yaw angle
velocity	float	speed
change__flag	uint8	State of tractor-mounted equipment
lon	float	Longitude
lat	float	Latitude

Figure 8 shows the schematic diagram of the inputs, outputs, and interfaces to implement the topic model function. The track data format is Tractor_Tf_Msg, which is read by the loading module and published to the /car_tf topic by the /tf_publisher node. The /path_publisher node receives the data in the topic and displays the

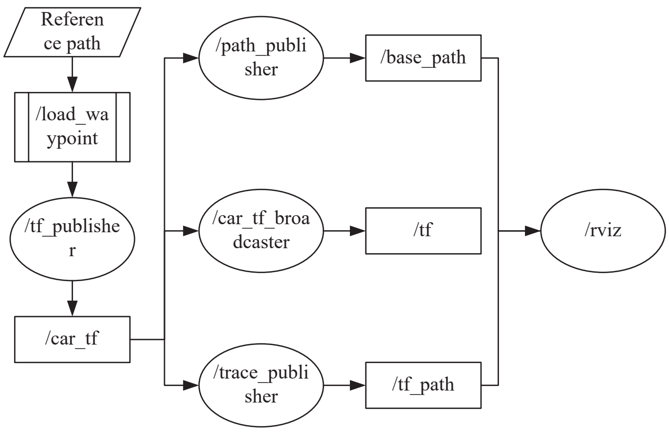


Figure 8 Topic model

global trajectory in Rviz via /base_path; /car_tf_broadcaster node broadcasts the processed heading angle, trajectory data, map coordinate system, and base_link coordinate system transformation relationship to the tf tree; /trace_ publisher node displays the path passed by the vehicle in Rviz.

2.4 Field experiment validation

In the simulation environment, the model of an experimental continuously variable transmission field tractor was tested on a specified field (Figure 9). The simulation model allows the developed module to be modally transferred and tested in real-world field together with the tractor. It passed the same route as the autoware-based simulator and work at the same speed of 2 m/s.

Figure 9 Actual field experiment validation

3 Results and discussion

Figure 10 shows the path tracking results of the actual experiment by using the Pure Pursuit algorithm. It can be seen that the Pure Pursuit algorithm has a good tracking capability in the low-speed (2 m/s) environment, and the accuracy decreases in the headland. Besides, since the off-road vehicle tire-soil interaction is not accurately represented in the simulation environment, the path tracking simulated on the autoware-based emulator is better than the real tests (Figure 11).

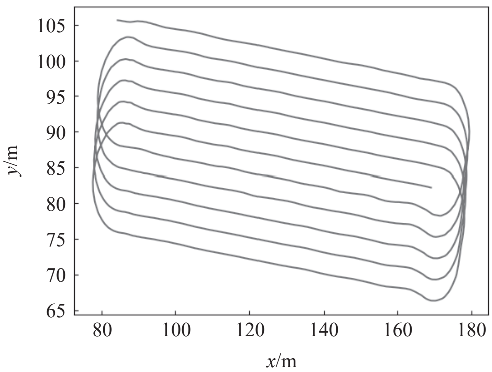


Figure 10 Actual tracking trajectory

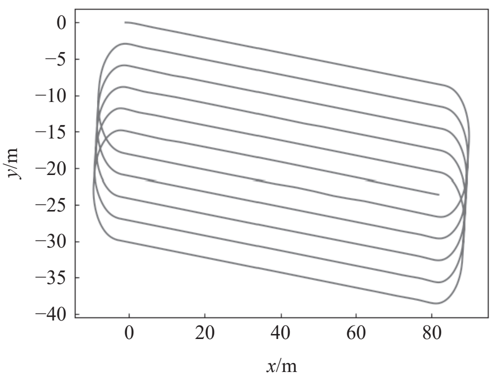
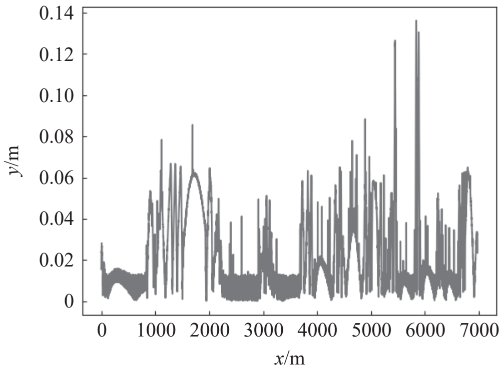


Figure 11 Tracking trajectory of the virtual simulation

The average lateral deviation of the work row is 0.072 m and the standard deviation is 0.087 m, and the average lateral deviation of the simulated work process is 0.023 m and the standard deviation is 0.001 m (Figure 12).



Note: y represents the lateral deviation of the farm vehicle from the reference path; x represents the distance walked by the tractor.

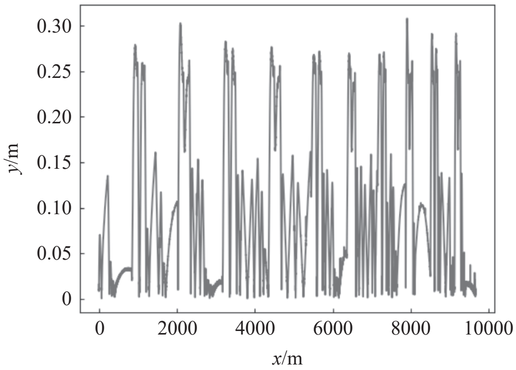
Figure 12 Lateral deviation of the simulated experiment

In the similar way, the usability of the proportional-integral-derivative controller (PID controller) in the proposed simulator was also tested. P was tested with the values of 1.0, 1.5, 2.0, and 2.5, respectively, where P stands for the proportional parameter. The variation of vehicle trajectory can be clearly seen in the operation process. When P is 1, the driving trajectory is on the outside of the planned path, and as the P value changes, the driving trajectory gradually approaches the planned path until it gradually moves away from the planned path from the other side. This has a good visual effect when performing algorithm verification, which can help the researcher to adjust the algorithm more quickly. Based on Figure 13, PID algorithm works better when P is 2.0 and 2.5 than when it is 1.0 and 1.5.

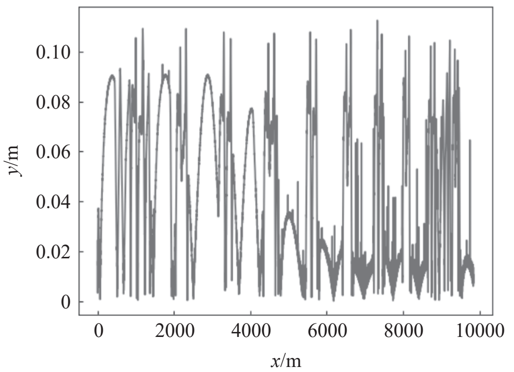
In this study, the aerial photography was adopted, which has a larger coverage area and higher efficiency compared to contact measurement methods using only GNSS receivers. The resulting 3D models also contain richer visual information. In contrast, satellite remote sensing methods have lower resolution, poor real-time performance, and lower accuracy in elevation information[23-25]. Moreover, using drones with oblique photography mode can more accurately measure the height and position information of crops and obstacles in the field. This facilitates global path planning in simulation environments, improving simulation efficiency and accuracy.

4 Conclusions

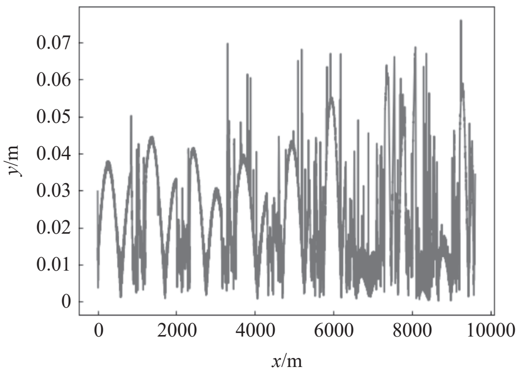
The Autoware-based digital twins have been successfully used for autonomous agricultural vehicle development. The core modules of HD maps, control and path planning are integrated in Autoware framework to build an unmanned emulation platform for autonomous tractors. In this study, the UGV adopts gazebo model with built-in DF 2204-CVT driverless tractor main parameters. The message format suitable for unmanned agricultural vehicle is defined. The inter-node communication method and input and output interfaces are designed. Spatial conversion, publishing and maintenance of the relationships between coordinate systems are performed using tf. Global path planning is implemented using a Bézier-based curve. HD maps of field are embedded in the simulation system at the same scale of real field, and virual experiments were conducted using Pure Pursuit algorithm and PID controller. The comparative analysis shows that the farm vehicle simulation platform has good workability.



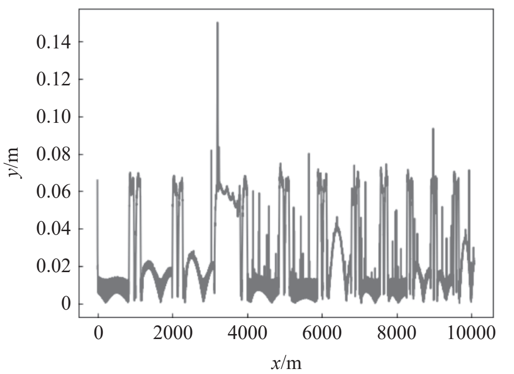
a. p=1.0



b. p=1.5



c. p=2.0



d. p=2.5

Note: y represents the lateral deviation of the farm vehicle from the reference path; x represents the distance walked by the tractor.

Figure 13 Lateral deviation of PID controller simulated experiments

In the future work, the application methods of the field road between farmlands and the hangar scene will be further studied to explore the simulation platform based on digital twins. More sensors, such as cameras, Lidar and Radar, will be used in this simulation platform to measure more agricultural vehicle operation scenarios included.

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[References]

[1] Bochtis D D, Sørensen C G C, Busato P. Advances in agricultural machinery management: A review. Biosystems Engineering, 2014; 126: 69–81.

[2] Moysiadis V, Tsolakis N, Katikaridis D, Sørensen C G, Pearson S, Bochtis D. Mobile robotics in agricultural operations: A narrative review on planning aspects. Applied Sciences, 2020; 10(10): 3453.

[3] Oksanen T, Visala A. Coverage path planning algorithms for agricultural field machines. Journal of Field Robotics, 2009; 26(8): 651–668.

[4] Bochtis D D, Vougioukas S G. Minimising the non-working distance travelled by machines operating in a headland field pattern. Biosystems Engineering, 2008; 101(1): 1–12.

[5] Jensen K, Larsen M, Nielsen S H, Larsen L B, Olsen K S, Jørgensen R N. Towards an open software platform for field robots in precision agriculture. Robotics, 2014; 3(2): 207–234.

[6] Zhang Y H, Wang J, Wang X N, Dolan J M. Road-segmentation-based curb detection method for self-driving via a 3D-LiDAR sensor. IEEE Trans Intell Transp Syst, 2018; 19(12): 3981–3991.

[7] Yao L J, Hu D, Yang Z D, Li H B, Qian M B. Depth recovery for unstructured farmland road image using an improved SIFT algorithm. Int J Agric Biol Eng, 2019; 12(4): 141–147.

[8] Yang L L, Li Y B, Chang M S, Xu Y Y, Hu B B, Wang X X, et al. Recognition of field roads based on improved U-Net plus plus Network. Int J Agric & Biol Eng, 2023; 16(2): 171–178.

[9] Grieves M. Digital twin : Manufacturing excellence through virtual factory replication. Digital Twin White Papaper, 2014; 7p.

[10] Kritzinger W, Karner M, Traar G, Henjes J, Sihn W. Digital Twin in manufacturing: A categorical literature review and classification. IFAC-PapersOnLine, 2018; 51(11): 1016–1022.

[11] Caputo F, Greco A, Fera M, Macchiaroli R. Digital twins to enhance the integration of ergonomics in the workplace design. International Journal of Industrial Ergonomics, 2019; 71: 20–31.

[12] Sivalingam K, Sepulveda M, Spring M, Davies P. A review and methodology development for remaining useful life prediction of offshore fixed and floating wind turbine power converter with digital twin technology perspective. In: 2018 2nd International Conference on Green Energy and Applications, 2018; pp.197–204.

[13] Rong G D, Shin B H, Tabatabaee H, Lu Q, Lemke S, Možeiko M, et al. LGSVL simulator: A high fidelity simulator for autonomous driving. 2020; pp.1–6. doi: 10.1109/ITSC45102.2020.9294422.

[14] Pylianidis C, Osinga S, Athanasiadis I N. Introducing digital twins to agriculture. Computers and Electronics in Agriculture, 2021; 184: 105942.

[15] Zhao Y P, Lian L K, Bi C W, Xu Z J. Digital twin for rapid damage detection of a fixed net panel in the sea. Computers and Electronics in Agriculture, 2022; 200: 107247.

[16] Tsolakis N, Bechtsis D, Bochtis D. Agros: A robot operating system based emulation tool for agricultural robotics. Agronomy, 2019; 9(7): 403.

[17] Dosovitskiy A, Ros G, Codevilla F, López A, Koltun V. CARLA: An open urban driving simulator. In: 1st Conference on Robot Learning (CoRL 2017), PMLR; 2017; 78: 1–16.

[18] Ziegler S, Höpler R. Extending the IPG CarMaker by FMI compliant units. In: Proceedings of the 8th International Modelica Conference, Dresden: Technical Univeristy, Citeseer, 2011; pp.779–783. doi: 10.3384/ecp 11063779.

[19] Benekohal R F, Treiterer J. CARSIM: Car-following model for simulation of traffic in normal and stop-and-go conditions. Transportation Research Record Journal of the Transportation Research Board, 1988; 1194: 99–111.

[20] Ryan R R. ADAMS—Multibody system analysis software. In: Multibody Systems Handbook, Springer, 1990; pp.361–402.

[21] Yang Y, Li Y K, Wen X, Zhang G, Ma Q L, Cheng S K, et al. An optimal goal point determination algorithm for automatic navigation of agricultural machinery: Improving the tracking accuracy of the Pure Pursuit algorithm. Computers and Electronics in Agriculture, 2022; 194: 106760.

[22] Foote T. tf: The transform library. In: 2013 IEEE Conference Technologies Practical Robot Applications (TePRA), Woburn: IEEE, 2013; pp.1–6. doi: 10.1109/TePRA.2013.6556373.

[23] Hu H M, Kaizu Y, Zhang H D, Xu Y W, Imou K, Li M, et al. Recognition and localization of strawberries from 3D binocular cameras for a strawberry picking robot using coupled YOLO/Mask R-CNN. Int J Agric & Biol Eng, 2022; 15(6): 175–179.

[24] Bao X L, Leng J S, Mao J C, Chen B Y. Cutting of sheep carcass using 3D point cloud with dual-robot system. Int J Agric Biol Eng, 2022; 15(5): 163–171.

[25] Omasa K, Ono E, Ishigami Y, Shimizu Y, Araki Y. Plant functional remote sensing and smart farming applications. Int J Agric & Biol Eng, 2022; 15(4): 1–6.