Ridge-tracking for Strawberry Harvesting Support Robot According to Farmer's Behavior

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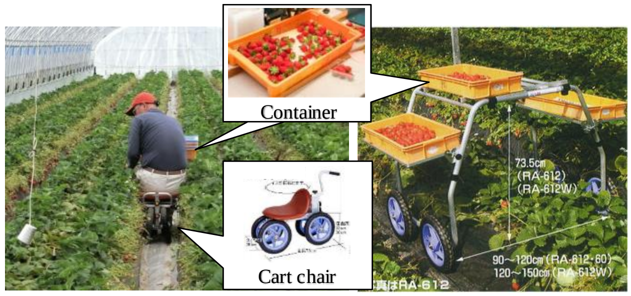
Abstract In Japan, the amount of agricultural production decreases year by year. Moreover, reduction in agricultural work population and increase of abandonment of cultivated land are major social issues. To overcome these issues, we have proposed a small agricultural robot "MY DONKEY" which supports transportation of harvested crops and records the farm work of the user and crop yield in field map while moving closer to the user. In order to move in the furrowed field, it is necessary to detect ridges and furrows where the robot can move using robot mounted sensors and follow the ridge while avoiding the ridges and crop rows. Furthermore, to realize smooth harvesting support, we propose a ridge tracking control according to user's behavior based on the recognition of the work contents of the user such as harvesting, loading of harvested crops to the robot, transportation and movement. We propose the ridge tracking control framework based on fuzzy set theory which can evaluate and integrate multiple situations and carry out experiments in strawberry farm.

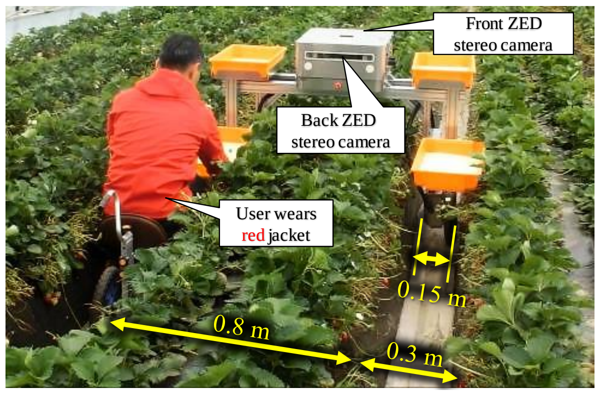
1 Introduction

The increase in global population has led to an increase in food demand, shortage of agricultural workforce due to aging, and a decline in the quality of harvested products. To overcome these issues, some researches and developments of

Ayanori Yorozu
Graduate School of Science and Technology, Keio University, 3-14-1 Hiyoshi, Kohoku-ku, Yokohama 223-8522, Japan, e-mail: ayanoriyorozu@keio.jp
Genya Ishigami
Department of Mechanical Engineering, Faculty of Science and Technology, Keio University, e-mail: ishigami@mech.keio.ac.jp
Masaki Takahashi
Department of System Design Engineering, Faculty of Science and Technology, Keio University, e-mail: takahashi@sd.keio.ac.jp



(a) Before: Strawberry harvesting by farmers



(b) After: MY DONKEY harvesting support

Fig. 1 Strawberry harvesting support

agricultural robots have been actively conducted to replace the workforce [1, 2]. In addition, for increasing the crop yield and improving the quality of crops, development of smart farming and automated agricultural technology is underway. These methods and technologies aim at constructing database of agricultural activities such as watering, weeding, harvesting, and crop yield, and automating production management [3,4].

In recent years, a highly accurate outdoor localization for robots has been made possible by the real-time kinematic global navigation satellite system (RTK-GNSS). Techniques using the RTK-GNSS to autonomously move within the field while following a pre-planned path from the field map have been proposed [5]. Especially in large-scale farms, large-sized tractor automation technology and autonomous harvesting robots that move in the field by localization, observe the degree of crop maturity and harvest the crops using robot arms have been developed. On the other hand, approximately 70% of agricultural producers in Japan possess dispersed farms on a medium and small scale (less than 5 ha), and they often cultivate a variety of crops on these lands. Due to the scale, it is difficult to introduce large-sized agricultural machines to these farms [6]. In these medium/small-scale farms, farm works such as watering, weeding, and harvesting are performed by human workers. For example as shown in Fig. 1 (a), during harvesting, the farmer moves through the field carrying a container or a cart for loading the harvested crops, identifies the mature crops, and loads them in the container. Thus, a lot of labor is required to transport containers loaded with crops and push the cart or containers. Therefore, production management and agricultural support technology customized for small/medium-scale decentralized agriculture, different from the large-scale types, are required.

In this study, we focus on small/medium-scale farms of 2–3 ha, which account for the aforementioned 70% of Japan's farms. A consortium led by Japan Research Institute, Ltd. proposes a compact multi-functional agricultural robot called "MY DONKEY" [7]. As shown in Fig. 1 (b), this robot supports transportation of harvested crops and records the work on the farm done by the user and the crop yield of the land on the field map, based on localization, while maneuvering closer to the user. As opposed to several of the previous works on automation technology of the agricultural robot, this study focuses on designing a user's behavior–based harvest support system in a furrowed field.

To avoid collision with ridges and crops in the furrowed field, the robot must be able to detect the navigable ridges and furrows using onboard sensors and follow the ridge, by the means of a robot coordinate system. In this study, a center for ridge detection using point cloud data from a stereo camera mounted in the robot and a safe-ridge tracking control to avoid ridges and crops are proposed. Furthermore, to realize smooth harvesting support, a ridge tracking control according to farmer's (user's) behavior such as moving, harvesting, and loading the harvested crops in the robot, is proposed. For example, the robot moves to maintain a certain distance from the user, when the user moves and harvests the crops; and then stops and waits until it has been completely loaded with the harvested crops upon recognizing the farming work contents of the user. In this study, we propose a ridge-tracking control framework based on the fuzzy set theory, which evaluates and integrates multiple situations and functions. The proposed system is applied to strawberry harvesting and experiments using "MY DONKEY" on a strawberry farm are carried out.

2 Strawberry Harvesting Support Using "MY DONKEY"

2.1 Strawberry Harvesting

Fig. 1 (a) shows a typical strawberry harvesting activity. In the strawberry harvesting work, the farmer uses a cart of multiple harvesting containers. The farmer sits on a cart chair, picks the strawberries, moves while loading them into the container, and again stands up to arrange the containers filled with harvested strawberries. During the harvesting work, the farmer moves through the field carrying a container or cart for loading the harvested crops. It is desirable for the robot to move through the furrowed field and maintain a certain distance from the user when the latter is sitting, and to stop and wait when they are standing to load the containers on to the robot.

Therefore, in this study, the user's behavior is identified from the position of user (standing or sitting), and the ridge-tracking controller is designed based on the user's behavior.

2.2 System Configuration

Fig. 1 (b) shows a robot system configuration for the strawberry harvesting support. The ROS (Robot Operating System) framework is used for the robot system. As shown in Fig. 1 (b), stereo cameras (ZED©Stereolabs), which can be used outdoors and can obtain 3D point cloud data over a wide range, are equipped on the front and backside of the base module of the robot for ridge and user detection. In this study, for the robot to detect the user to follow, the user wears a red jacket.

The proposed system determines the velocity command to track the ridge according to the user's behavior based on obtained sensor data. The robot has a four-wheel, independent drive system. It is possible to steer each wheel separately. Additionally, the mass meters were mounted to measure the yield of strawberries.

3 Ridge-tracking Control According to Farmer's Behavior

3.1 Ridge Detection

Fig. 2 shows the 3D point cloud data (PCD) extracted from the ZED camera in the strawberry farm. As shown in Fig. 2, it can be inferred that it is difficult to acquire the shape of the ridge accurately because of the noise and data loss in PCD. On the other hand, the contours of both the adjacent ridges can be acquired at relatively low data loss. From experimental data, the center line of the ridge for the robot to follow is detected from the lines at the edge of both the adjacent ridges using the Hough transform in the robot coordinate system, because the ridges of the strawberry rows are straight and furrowed at regular intervals.

First of all, as represented by yellow points in Fig. 2, 2D point data at the certain height are extracted from 3D PCD. Then, as represented by the straight red lines in Fig. 2, ridge lines are detected from the 2D point data using Hough transform. Finally, as represented by light blue arrows in Fig. 2, the center of line

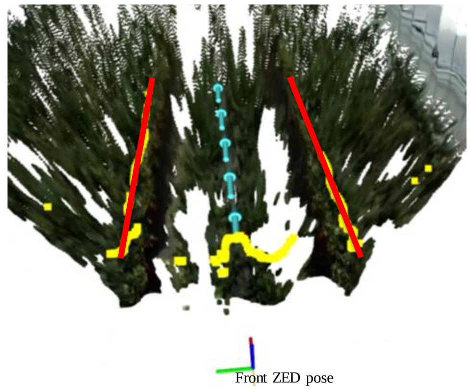


Fig. 2 Ridge detection using front ZED camera

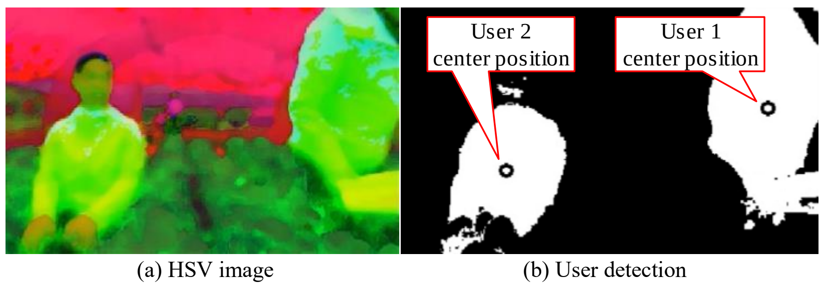


Fig. 3 User detection using back ZED camera

of the ridge, along which the robot follows, are calculated from both the detected left- and right-side lines.

3.2 User Detection

The position of the users who wear red jackets are calculated using the back ZED camera. At first, as shown in Fig. 3 (a), an RGB image from ZED camera is transformed into an HSV image, so that it could be relatively easily extracted from the red jacket. Then, as shown in Fig. 3 (b), the hue is adjusted to extract only the area of red jackets of the users. In addition, as represented by "o" in Fig. 3 (b), the jacket color area is clustered and the image centers of gravity of the color region clusters whose pixel area is larger than the threshold value are calculated. Finally, the center position of users $x^k_{user}, y^k_{user}, z^k_{user}$ in the robot coordinate system are calculated from the depth image of the ZED camera's stereo vision corresponding to the detected image center of gravity. The superscript k = 1 or 2 indicates the number of detected users.

3.3 Ridge-tracking Control Using Fuzzy Potential Method

To achieve smooth strawberry harvesting support, we propose ridge tracking control that functions by the user's behavior based on the detection of users, as shown in Sections 3.2. When the robot and user are moving between the furrowed field, it is possible to identify the user's behavior—moving and harvesting or loading containers—based on the state of the user (standing or sitting), which is nothing but the height of the center of gravity of user z_{user}^{k} . In this study, we propose ridge tracking control using the fuzzy set theory, to evaluate and integrate multiple conditions simultaneously, based on the height of the center of gravity of user z_{user}^{k} and the environment (ridges) surrounding the robot. For this study, we use the fuzzy potential method (FPM) [8], in which the membership functions (MFs) for each target action or element are generated. The horizontal axis of the MF is the yaw angle of the robot, the vertical axis of MF is the grade that indicates the priority of the target action with respect to the angle. Then, the motion (velocity command) is decided by integrating MFs.

Fig. 4 shows an example of the determination of velocity command (v_x, v_y, ω_z) by the proposed method for strawberry harvesting. First, the MF, μ_{move} , for moving to track the ridge and maintain a fixed distance from the user is generated. Next, the MF, μ_{state} , for chaining the motion according to the user's behavior is generated. Then, the velocity command is calculated based on the MF, μ_{mix} , and integrating μ_{move} and μ_{state} . Finally, the wheel speed and angle control of each wheel unit is performed based on the velocity command.

3.3.1 MF to Move Toward Center of Ridge

The MF μ_{move} , for moving to track the detected ridge and maintain a fixed distance from the detected user position in the robot coordinate system is generated.

As shown in Fig. 4 (a), the intersection point of the detected ridge center line and equation $x = x_{ridge,move}^{thre}$ is set as a subgoal, which the robot follows in the robot coordinate system. The relative angle of the subgoal from the front of the robot is denoted by θ_{ridge} . The relative distance to maintain from the user is $x_{user,move}^{thre}$. The MF, μ_{move} , is generated as a triangular MF, so that the robot moves forward in the θ_{move} direction as the user approaches the robot for moving and harvesting. Fig. 4 (b) shows an example of the MF, μ_{move} . The angle of vertex, θ_{move} , of the MF, μ_{move} , is determined to move towards the subgoal without collision, based on the detected ridge.

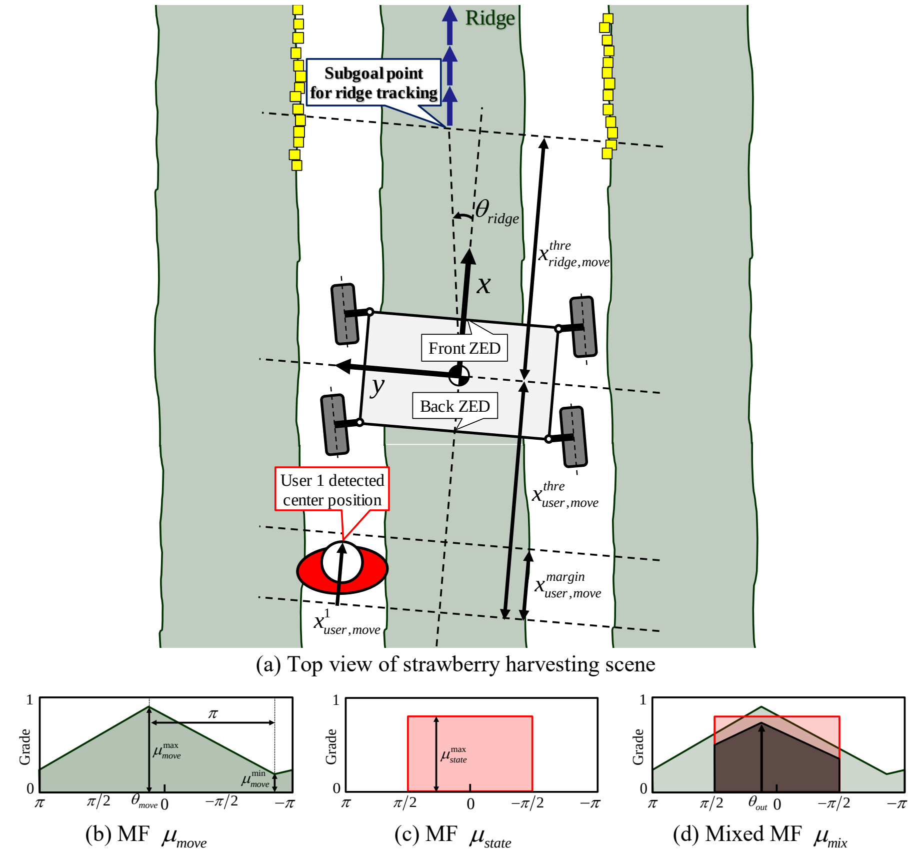


Fig. 4 Ridge tracking control according to farmer's behavior using fuzzy potential method

3.3.2 MF to Consider State

An MF μ_{state}, for chaining the motion according to the user's farming task is generated based on the user's detected height of center of gravity z^{k}_{user}.

As shown in Fig. 4 (c), a convex MF with grade $\mu^{\max}_{state}$ in an angular range from $-\pi/2$ to $\pi/2$, because the users are harvesting continuously as they move forward in the strawberry rows. The grade $\mu^{\max}_{state}$ is designed to be slow down and stationary for loading yield crops or to move and maintain the certain distance from the user according to the height of user z^{k}_{user}.

3.3.3 Velocity Command based on Mixed MF

As shown in Fig. 4 (d), the velocity command (v_x, v_y, ω_z) is calculated based on the MF, μ_{mix} , and integration of μ_{move} and μ_{state} .

The moving direction, θ_{out} , and the translational moving speed, v_{out} , are calculated as follows based on the mixed MF.

$$\theta_{out} = \arg\max \mu_{mix}\left(\theta\right) \tag{1}$$

$$v_{out} = v_{robot}^{\max} \mu_{\max}\left(\theta_{out}\right) \tag{2}$$

where $v_{robot}^{\max}$ is the maximum translational speed of the robot. Then, the velocity command is calculated as follows.

$$v_x = v_{out} \cos\theta_{out} \tag{3}$$

$$v_y = v_{out} \sin\theta_{out} \tag{4}$$

$$\omega_z = \begin{cases} K_\omega \theta_{out} & if \ \left|K_\omega \theta_{out}\right| < \omega_{robot}^{\max} \\ \omega_{robot}^{\max} & else \ if \ K_\omega \theta_{out} > \omega_{robot}^{\max} \\ -\omega_{robot}^{\max} & else \end{cases} \tag{5}$$

where $\omega_{robot}^{\max}$ is the maximum angular speed and K_ω is an angular velocity gain.

4 Experiments

We carried out the experiments using MY DONKEY robot in a strawberry farm. As shown in Fig. 5, we verified the strawberry harvesting support of two users. Table 1 shows the system parameters.

In this study, we created a two-dimensional occupancy map in advance on the ROS gmapping package using 2D point cloud data transformed from 3D point cloud data of a front ZED camera. The localization of the robot was performed using the adaptive Monte Carlo localization in the field coordinate system during the movement for harvesting support.

Fig. 5 shows examples of the user detection results and MFs. Fig. 6 (a) to (c) shows the time history of robot localization, ridge-detected position (subgoal position), and user-detected positions in the field coordinate system. In Fig. 6 (a) and (b), the black line indicates the robot position, the red line indicates the position of detected user 1, and the blue line indicates the position of detected user 2. In Fig. 6

Table 1 System parameters

Parameters	Values
Subgoal distance $x^{thre}_{ridge,move}$	1.5 m
Maintain distance from user $x^{thre}_{user,move}$	-1.4 m
Maximum translational speed $v^{\max}_{robot}$	0.25 m/s
Maximum angular speed $\omega^{\max}_{robot}$	0.05 m/s
Angular velocity gain K_{ω}	0.5
Wheel radius r_{wheel}	0.135 m
Sampling time Δt	0.05 s

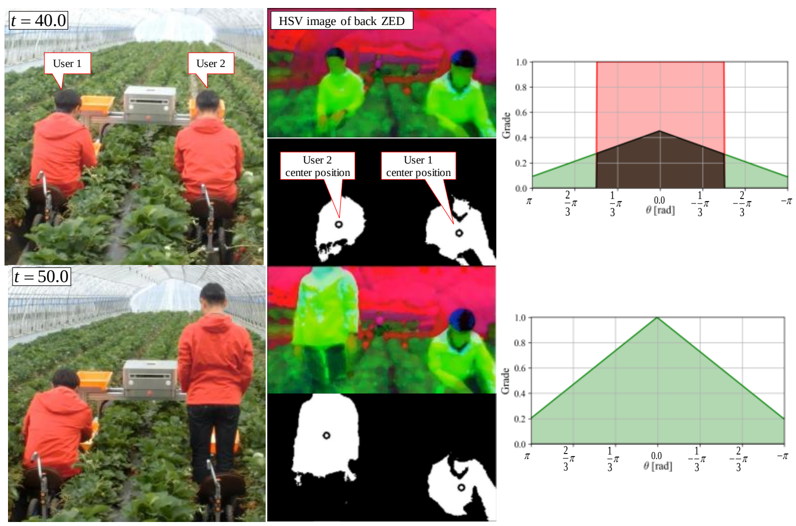
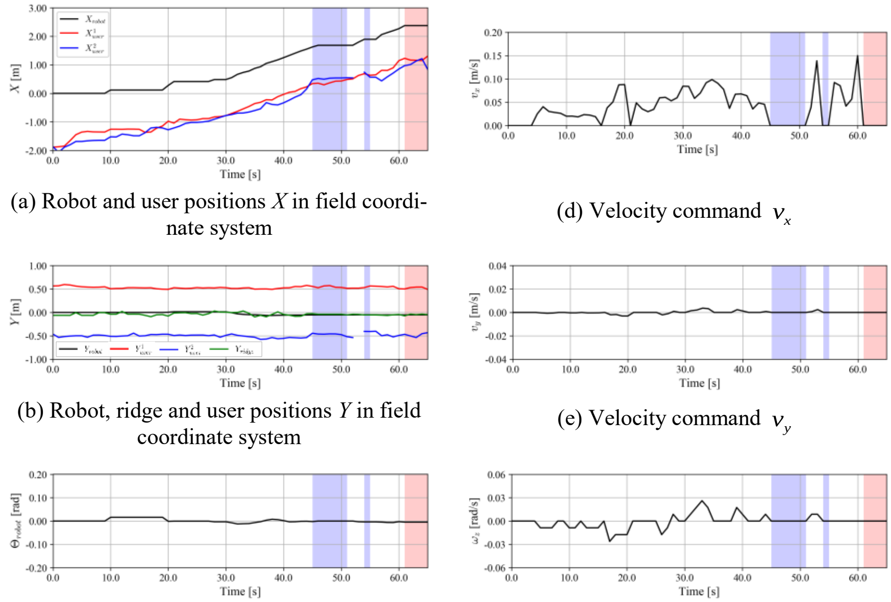


Fig. 5 Actual situations, user detection results and MFs in strawberry harvesting with two users

(b), the green line indicates the detected center position of ridge. Fig. 6 (d) to (f) shows the time history of velocity command. In addition, the light-red highlights in Fig. 6 indicate the time period where the robot recognized user 1 standing. In addition, the light-blue highlights in Fig. 6 indicate the time period where the robot recognized user 2 standing.

As shown in Fig. 5 at time t = 50.0, user 2 stood up and performed containers loading. At the time as shown in Fig. 5, the height of the convex MF μ_{state}, considering the user's behavior was 0.0. Then, it was confirmed that the velocity command was calculated to be (0.0, 0.0, 0.0) and the robot had stopped and waited until the user sat down and moved, as shown in Fig. 6 (d) to (f).



(a) Robot and user positions X in field coordinate system

(d) Velocity command v_x

(b) Robot, ridge and user positions Y in field coordinate system

(e) Velocity command v_y

(c) Robot yaw angle Θ in field coordinate system

(f) Velocity command ω_z

Fig. 6 Time history of robot position and velocity command

In addition, as shown in Fig. 6 (b),(e) and (f), it was confirmed that the robot could track ridge without collision, by adjusting the velocity command v_y, ω_z according to the detected ridge position even where the furrow was quite narrow with respect to the width of the wheel shown in Fig. 1 (b).

5 Conclusions

In order to realize smooth harvesting support, a ridge-tracking according to the user's behavior, such as movement, harvesting, and loading the yield crops is required. In this study, the ridge tracking control framework based on fuzzy set theory which can evaluate and integrate multiple situations was proposed. The proposed method was applied to strawberry harvesting support and experiments were carried out at a strawberry farm using a compact multi-functional agricultural robot "MY DONKEY". From the experimental results, it was verified that the robot could track the ridge without collision according to the user's behavior by the proposed method.

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