Cognition of surrounding conditions for a field robot
- Slope detection using a multilayer perceptron classifier with point cloud as input-

Takumi Tomokawa
Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan

Sakmongkon Chumkamon[1], Ayumu Tominaga[2], Sylvain Geiser[1], Ryusuke Fujisawa[1], Eiji Hayashi[1]
[1]Department of Mechanical Information Science and Technology, Kyushu Institute of Technology
680-4, Kawazu, Iizuka-City, Fukuoka, 820-8502, Japan
[2]Department of Creative Engineering Robotics and Mechatronics Course, National Institute of Technology Kitakyushu Colllege, 5-20-1 Shii, Kokuraminamiku, Kitakyushu, Fukuoka, 802-0985, Japan

E-mail: tomokawa.takumi163@mail.kyutech.jp, m-san@mmcs.mse.kyutech.ac.jp, tominaga@kct.ac.jp, geiser.nathan-sylvain@mail.kyutech.jp, fujisawa@ces.kyutech.ac.jp, haya@mse.kyutech.ac.jp,
http://www.kyutech.ac.jp/

Abstract

In the Japanese forestry industry, automation of work to supplement labor is desired to achieve sustainable forest management. In this study, the field robot for the automation of forestry is developed. In the field robot, recognition of the surrounding situation is an important function for safe movement. In this paper, we focus on the recognition of terrain. The terrain in a mountainous area has various conditions such as slope, presence of weeds and trees, and unevenness. In this study, the classifier for ground and sloped surfaces using Multi Layered Perceptron (MLP) is developed. This classifier classifies each point of the 3D point cloud acquired from the RGB-D camera into the ground plane of the robot and the slope plane where the robot cannot climb. The accuracy of the classification was verified by training the classifier on a dataset acquired in a real environment.

Keywords: PointCloud, Multi Layered Perceptron, Field Robot, Forestry, ROS

1. Introduction

In the Japanese forest industry, automation of the work to decline the labor is desired to realize sustainable forestry(1). In this study, the forestry field robot was developed. Recognition of the surrounding environment such as a terrain and objects are an essential function for autonomous moving. We focus on the recognition process of the terrain because the terrain in a mountainous has various conditions such as slope, presence of weeds and trees, and unevenness. To recognize and classify these conditions, Multi Layered Perceptron (MLP) was used 3D point cloud as input which acquired from the RGB-D camera. The accuracy of the classification was verified by training the classifier on a dataset acquired in a real environment.

2. Overview of the robot

The developed robot is shown in Fig. 1, which built on an ATV (All-Terrain Vehicle) as its platform. RGB-D camera (D435, Intel Ltd. Co.) is equipped on the front of the robot. The total height of the robot is about 1.7 m, and the sensor is mounted at a height of 1.1 m. The 3D point cloud was obtained from the RGB image and Depth image obtained from this camera.

Fig. 1. Overview of the robot

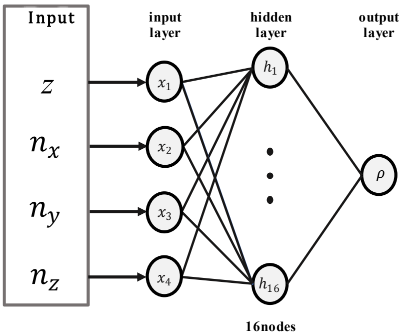


Fig. 2. Overview of the MLP built

3. Classification of ground plane and inclined plane by MLP

MLP is a machine learning framework that connects multiple simple perceptron to determine nonlinear discriminative boundaries in feature space. In this study, the slope surface is detected by treating 3D point cloud as a class classification with input data.

3.1. *MLP Design*

Fig. 2 shows the overview of designed MLP in this study. This MLP would be classify the ground plane and the inclined plane. In creating the classifier, the feature value of each point is a four-dimensional feature value shown in equation(1), which consists of the z-coordinate value (vertical direction) and each element n_x, n_y, and n_z of the local normal vectors n_i. The local normal vector is the normal vector of the approximate plane obtained from the point group contained within the radius r[m] from p_i for any point $p_i = (x_i, y_i, z_i)$ in the point group. By using such features, we can handle the relative height and angle difference between each observed point and the robot. The middle layer has only one layer with 16 nodes, and the activation function is the ReLU[(2)] function. The output layer has 1 node and the activation function is the Sigmoid function. The output ρ of the output layer takes values from 0.0 to 1.0, where less than 0.5 indicates that it is classified as a ground plane, and more than 0.5 indicates that it is classified as an inclined plane. Therefore, the teacher label for the ground plane was set to 0 and the teacher label for the slope plane was set to 1 using equation(2).

$$X = [z, n_x, n_y, n_z] \tag{1}$$

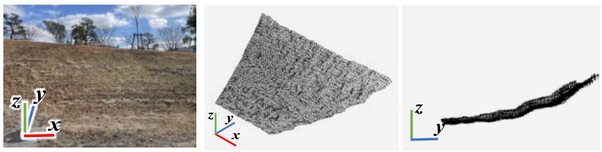
$$Y = \begin{cases} 1 \ (\rho \geq 0.5) \\ 0 \ (\rho < 0.5) \end{cases} \tag{2}$$

3.2. *Creating a Data Set*

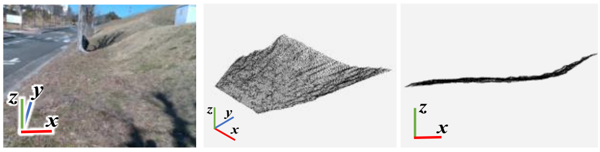
To create the dataset, we collected point clouds of the ground surface covered with weeds, including the ground surface where the robot can run and the inclined surface where the robot cannot climb (inclination angle of more than 20 degrees) within the angle of view of the camera. As shown in Fig. 3, we prepared five sets of point cloud data each for MLP training, where the inclined surface was in front, right, and left of the robot. The z-coordinate values and local normal vectors of each point were divided into the ground plane and the inclined plane in advance, and 0 and 1 supervisory labels were given.

Fig. 4 shows an example of the training data set. The evaluation data was also prepared in the same way as the training data, with five sets of each state.

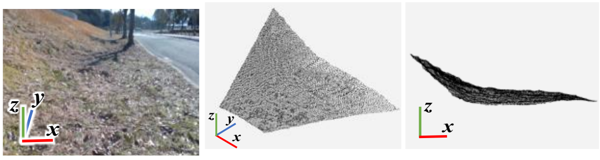
The numerical value of the local normal vector, the input to the MLP, depends on the radius of the neighborhood r[m]. Therefore, it is thought that small irregularities on the ground surface are less likely to be misidentified as slopes. Therefore, we prepared three different datasets with r values of 0.05m, 0.1m, and 0.5m, and trained the MLP with each input vector X. The number of times the MLP was trained was determined by the number of input vectors. The number of times the MLP was trained was set to 10 in each case.



(a) An inclined plane exists in front of the robot



(b) An inclined plane exists on the right side of the robot



(c) An inclined plane exists on the left side of the robot

Fig. 3. Examples of point clouds used to create the data set

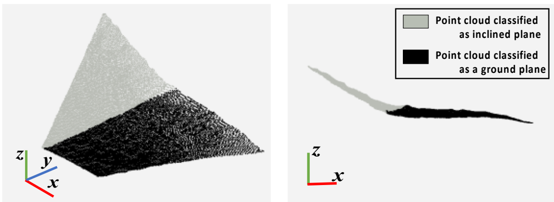


Fig. 4. Examples of created training (An inclined plane exists on the left)

4. Classification results by MLP

The classification accuracy was evaluated by IoU[3] (Intersection over Union), which takes a value from 0 to 100%. The larger this value is, the more correctly the input data is classified by MLP. Fig. 5 shows the values of IoU for each neighborhood radius r. The inclination angle of the plane classified as an inclined plane by MLP was calculated by least-squares plane fitting. If the inclination angle is more than 20 degrees, the inclination is impossible for the robot to climb. The distribution of the estimated inclination angle with respect to the neighboring radius r is shown in Figure 6. Figure 6 shows the distribution of the estimated inclination angles with respect to the nearest neighbor radius r. Figure 7 shows an example of the results of classifying the evaluation data by MLP.

5. Consideration

The IoU values in Fig. 5 do not appear to change significantly for any of the neighborhood radius r.
In this verification, however, a 1% increase in the IoU value indicates that about 1200 points were successfully classified. Fig. 7 shows that the number of points that were incorrectly classified as belonging to the ground plane decreased in the regions A and B in the classification results. The number of points incorrectly classified as belonging to the ground plane decreased. This suggests that the classification accuracy of the MLP created in this study may depend on the neighborhood radius r when the local normal vector is used as a feature of the 3D point cloud.

As shown in Fig. 6, the inclination angles estimated by the point clouds classified as inclined surfaces were distributed in the range of 18 to 31 degrees. Of these, 32 out of the 45 data for evaluation were estimated to be more than 20 degrees, suggesting that it is possible to detect unclimbable slopes with this classifier.

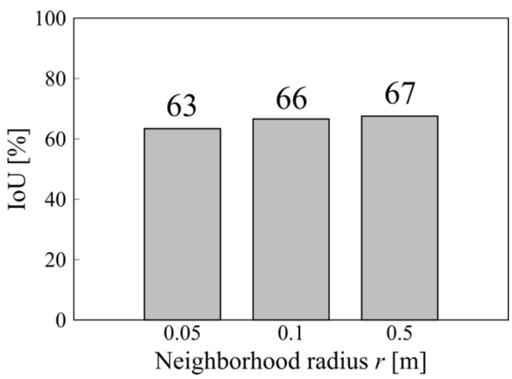


Fig. 5. IoU calculated from classification results

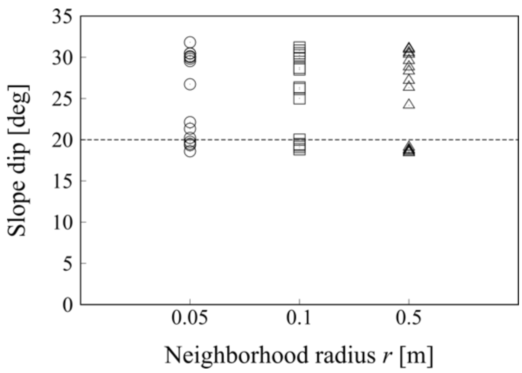
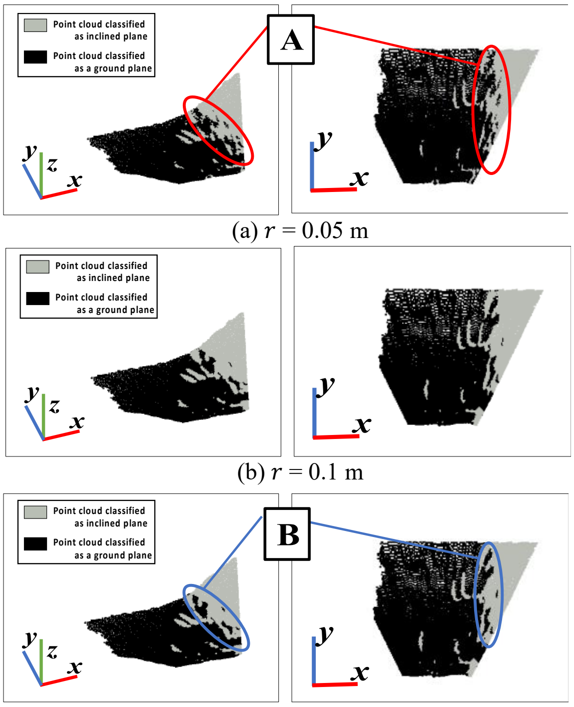


Fig. 6. Distribution of slope angle estimated from point clouds classified as inclined planes



(a) r = 0.05 m
(b) r = 0.1 m
(c) r = 0.5 m
Fig. 7. Classification Results

6. summary

In this study, we created a classifier using MLP with each point of the point cloud as input and attempted to detect inclined surfaces that cannot be traveled on. As a result, it was suggested that the radius of the neighborhood of the local normal vector, which is the input vector of the classifier, can reduce the false detection of unevenness of the ground surface and that MLP can detect slopes of more than 20 degrees.

In the future, we will study the optimal feature values to further improve the classification accuracy. In addition, we will verify the real-time performance of the system, which is important when the robot moves autonomously in mountainous areas, and we will also study terrain recognition in other environments composed of sand, such as the coast.

References

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Authors Introduction

Mr. Takumi Tomokawa

He received bachelor degree in Engineering in 2021 from mechanical system engineering, Kyushu Institute of Technology in Japan. He is currently a Master student at Kyushu Institute of Technology and conducts research at Hayashi Laboratory.

Dr. Sakmongkon Chumkamon

Dr. Sakmongkon Chumkamon received Doctor of Engineering degree from Kyushu Institute of Technology in 2017. He was a postdoctoral researcher at Guangdong University of Technology in 2017-2019. Presently he is a postdoctoral researcher in Kyushu Institute of Technology since 2019. His research interests include factory automation robots and social robots.

Projected Assist. Prof. Ayumu Tominaga

Projected Assist. Prof. Ayumu Tominaga is a professor in Department of Creative Engineering Robotics and Mechatronics Course at National Institute of Technology Kitakyushu College. He received the Ph.D. (Dr. Eng.) degree from Kyushu Institute of Technology in 2021. His research interests include Intelligent mechanics, Mechanical systems and Perceptual information processing.

Mr. Sylvain Geiser

He studied Engineering and Computer Science in Ecole des Mines de Nancy, France, between September 2018 and June 2020. He is currently a Master student at Kyushu Institute of Technology, Japan, and conducts research at Hayashi Laboratory.

Assoc. Prof. Ryusuke Fujisawa

Assoc. Prof. Prof. Ryusuke Fujisawa is an associate professor in the Department of Intelligent and Control Systems at Kyushu Institute of Technology. He received the Ph.D. (Dr. Eng.) degree from The University of Electro-Communications in 2009. His research interests include Swarm intelligence, Swarm robotics and Distributed autonomous system. He is a member of Japan Society of Civil Engineers (JSCE), Information Processing Society of Japan (IPSJ), The Society of Instrument and Control Engineers (SICE) and The Robotics Society of Japan (RSJ).

Prof. Eiji Hayashi

Prof. Eiji Hayashi is a professor in the Department of Intelligent and Control Systems at Kyushu Institute of Technology. He received the Ph.D. (Dr. Eng.) degree from Waseda University in 1996. His research interests include Intelligent mechanics, Mechanical systems and Perceptual information processing. He is a member of The Institute of Electrical and Electronics Engineers (IEEE) and The Japan Society of Mechanical Engineers (JSME).