

Traversability Analysis for Mobile Robot Navigation in Rough Terrain

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ABSTRACT

For the research described here, the road surface necessary to enable autonomous navigation by a robot in rough terrain was modeled and a method of traversability analysis of that road surface was created. As in much preceding research, this method consists of three steps, which are (1) dividing the road surfaces around the robot into grids, (2) generating a road surface model of each grid, and then (3) performing traversability analysis of those road surfaces by evaluating those models. The new contribution made by this method is that, by optimizing the grid size of the road surface to be modeled, it can assure the validity of modeling a road surface on rough terrain by means of planes. In addition, this method is robust with regard to outliers and noise near maximum and minimum values in a measurement point cloud, and the small number of setting parameters is another distinguishing characteristic. Application of this method to an environment of rough terrain, including slopes, uneven surfaces, and obstacles, made it possible for robots to correctly perform traversability analysis of road surfaces and to navigate autonomously in that environment.

1. Introduction

In the societal context of labor shortages and other such issues due to the influence of the declining birthrate and growing population of elderly people in recent years, there has been growing demand for robots to transport supplies, agricultural robots to work on farms, and other such robots that can autonomously navigate rough terrain⁽¹⁾. In order for robots to navigate autonomously in a rough terrain environment, they need to use data obtained from cameras, light detection and ranging (LIDAR) systems, and other such sensors to recognize height differences and slopes in surrounding road surfaces, and they need to perform traversability analysis of those road surfaces.

Previous research on methods of road surface traversability analysis with the objective of autonomous navigation by a robot over rough terrain can be categorized relative to the two axes: the type of information used to model a road surface and the method used to model that road surface. Road surface models are mainly built using either visual information obtained from image data, or geometric information obtained from point cloud data, or other information obtained from acceleration data and so on, or a combination of multiple types of information. Almost all the methods for building those models use either

a model-based approach founded on certain rules, or a machine learning-based approach.

Machine learning-based methods have been actively researched in recent years. These include methods of obtaining models for performing traversability analysis of road surfaces by supplying the course followed when driven by humans as training data, applied with respect to input consisting of point cloud geometric information and light reflection intensity⁽²⁾; methods of obtaining models for performing patch-by-patch traversability analysis when a height map obtained from point cloud data is converted into a grayscale image, which is divided into multiple patches, and the travel results for a robot operated in simulation are used as training data with respect to those patches^{(3), (4)}; methods of enabling traversability analysis by supplying training data consisting of the results of image-by-image traversability analysis by humans with respect to input consisting of multiple feature quantities obtained from RGB images⁽⁵⁾; a method combining this method with predicted future images⁽⁶⁾; and so on. Research has also focused on numerous methods that combine a multiplicity of information, such as a method that adds robot vibration information obtained from an inertial measurement unit (IMU) to the results of uneven surface estimation and texture estimation obtained from image data⁽⁷⁾, a method

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that uses segmentation images in combination with the geometric features of those images to judge whether an obstacle on the road surface can be traversed⁽⁸⁾, and so on.

These methods are capable of expressing traversability analysis functions that cannot readily be expressed in model-based approaches, and are therefore very useful. However, learning-based methods in general have issues with regard to applicability to unfamiliar environments of types that are not included in the learning data. For robots that navigate rough terrain, many are expected to operate in unfamiliar environments, and therefore there is concern that this method's traversability analysis results may degrade performance. It is also the case that robots have different navigation performance and, depending on requirements, differing labels on their learning data. When a method is used with a different robot, therefore, and when the requirements change, it is necessary to rebuild the learning data, which presents convenience issues for the method.

When higher priority is assigned to applicability in unfamiliar environments and to convenience, model-based methods are effective. Many model-based methods first divide the road surface around the robot into grids, and their geometric features identified from point cloud data obtained using LIDAR and depth camera are used for grid-by-grid modeling of the road surface. Then, based on those models, traversability analysis is performed. Prior research includes methods for performing traversability analysis, such as a method for modeling the slope of the road surface and its surface roughness from specific vectors and eigenvalues of the point cloud distribution covariance matrix, and performing traversability analysis by threshold values set according to those quantities^{(9), (10)}; a method for grid-by-grid modeling of the road surface by a plane equation using random sample consensus (RANSAC)⁽¹¹⁾ and then performing traversability analysis from the magnitude of the slope and the continuity of the grid⁽¹²⁾; and so on. There are also many methods that define their own, unique evaluation indices for performing traversability analysis, such as a method for analyzing traversability by defining evaluation functions such as the weighted sum from the slope, variance, or other such parameters in the road surface model^{(13), (14)}; fuzzy-based methods for judging traversability using fuzzy membership functions that define the extent of those parameters⁽¹⁵⁾; and so on. Most of these methods, however, have the three issues shown below.

(1) Appropriate modeling of road surfaces to include obstacles

As explained above, many model-based methods use planes as constituent elements of road surface models. When they are measuring road surfaces, with obstacles included, the planes are influenced by both the ground surface point cloud and the obstacle point cloud. With regard to the inclination of the plane, in particular, the

values can differ greatly because of differences in the proportion of the road surface taken up by the obstacle region. Unless these influences are taken into account, therefore, planes may be estimated that are not in line with the intention of the method, and the criteria for performing traversability analysis will not be met. Consequently, appropriate modeling of road surfaces when obstacles have been measured is an issue.

(2) Road surface modeling that is robust with regard to point cloud measurement noise

On rough terrain, the influence of the sunlight environment and reflection characteristics of the road surface may result in large amounts of noise being included in measured point cloud information. Of such noise, that from outliers and noise near maximum and minimum values in a measurement point cloud in particular can yield incorrect traversability analysis results. Consequently, those noise elements need to be taken into consideration as a practical matter when modeling road surfaces.

(3) Simplification of setting parameters

When parameters and indices for which explaining the physical meaning is troublesome are used for weighting with respect to road surface modeling and traversability analysis indices, tuning the parameters can be troublesome and not only does this contribute to degradation of traversability analysis performance, but it also diminishes the method's general purpose properties. Consequently, it is desirable for the setting parameters in this method to be simple and intuitive.

This paper therefore proposes a traversability analysis method that resolves these issues; that is, the aim here is to create a method that assures the validity of modeling a road surface by means of planes, that is also robust with regard to noise from outliers and noise near maximum and minimum values in a measurement point cloud, and that the parameters expressing the criteria for traversability analysis used in this method are not dependent on the robot's system integrator, but rather are judged solely by the hill-climbing performance and traversal performance of the robot.

2. Method of Traversability Analysis Appropriate for Uneven Surfaces

Like the various methods described in part 1, the proposed method is made up of three parts: (1) The part that divides the road surfaces surrounding the robot into grids; (2) the part that generates a road surface model for each grid; and (3) the part that performs traversability analysis of the road surface by evaluating the model.

In this part, Section 2.1. will first assume a road surface of natural terrain without any obstacles and describe a method for traversability analysis of that road surface. This method is like much preceding research in using planes to model road surfaces. It also includes several statistical methods, and a

feature of this method is its ability to remove the noise from outliers and noise near maximum and minimum values in a point cloud of road surface measurements.

Section 2.2. will describe a method for traversability analysis in terrain that includes obstacles. The road surface that includes obstacles has different geometric features than a road surface that does not include obstacles. Therefore, as described in the previous chapter with regard to issues faced by modeling methods, when a road surface that includes obstacles is modeled using planes, there are instances when the inappropriateness of that approach means that those planes can cause traversability analysis to produce incorrect judgments. In the proposed method, however, the division into grids in part (1) is performed with the grid divisions defined in an appropriate size. This makes it possible to perform traversability analysis without loss of the model's validity even if the method for modeling a road surface of natural terrain that does not include obstacles is applied, just as it is to a road surface that does include obstacles.

2.1. Method for Traversability Analysis in Natural Terrain

(1) Division into grids of road surface surrounding the robot
Division into square grids of appropriate size is performed. In this section, as in much of the preceding research, the division into grids is done without any need to impose constraint conditions.

(2) Generation of road surface model

The road surface is first modeled using three procedures: (a) estimating representative planes, (b) modeling the surface shape of the representative planes, and (c) separating outliers. A general view of this is shown in Fig. 1.

(a) Estimating representative planes

For each grid that has been divided, RANSAC⁽¹¹⁾ is used to estimate the representative planes. With RANSAC, the number of outliers is smaller and planes that are compatible with point clouds other than those of outliers can be obtained, so planes that are less susceptible to influence by measurement

noise outliers are estimated.

(b) Modeling the surface shape of the representative planes

Plains, ridge-top paths, slopes, and other such outdoor natural terrain have continuously changing elevations. It is assumed that the variations in elevation within each grid are based on the Gaussian distribution $N(\mu, \sigma^2)$. Here, μ is the representative plane estimated in procedure (a) while σ is approximated by the root mean square (RMS) value for the whole point cloud with respect to that μ .

(c) Separating outliers

Areas where the distance from the representative plane is $\pm 2\sigma$ (hereinafter referred to as an effective model area) are defined and point clouds outside those areas are removed. If the road surface model is to strictly follow Gaussian distribution, about 2.5% each of the point cloud on the largest and smallest sides of the signed distance from the representative plane will be removed. The purpose of this process is to reduce noise from outliers and noise near maximum and minimum values in a measurement point cloud. In some cases, a portion of the point cloud of the road surface model itself can also be removed, but if the terrain features are continuous and dense, then the value of the point cloud that was removed can be approximated by the point cloud within the boundary of the effective model area and close to that boundary.

(3) Analysis of traversability

Traversability is judged for the road surface model generated for each grid on the basis of the following two criteria.

$$T_1 = \begin{cases} 1 : \theta \leq \theta_{lim} \\ 0 : \text{otherwise} \end{cases} \quad (1)$$

$$T_2 = \begin{cases} 1 : d_{max} - d_{min} \leq h_{lim} \\ 0 : \text{otherwise} \end{cases} \quad (2)$$

Here, θ is the absolute value of the slope of the representative plane, θ_{lim} is the absolute value of the slope

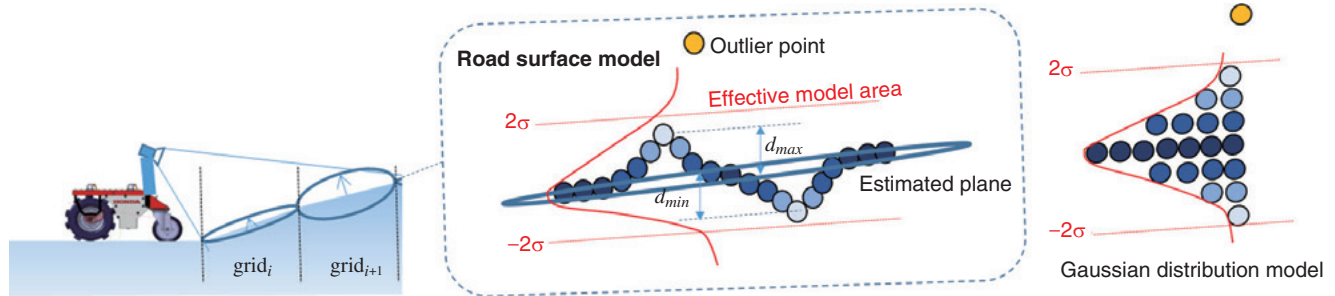


Fig. 1 Road surface model based on Gaussian distribution

angle that the robot is able to ascend and descend, d_{max} is the greatest value for the signed distance between the points included in the effective model area and the representative plane, d_{min} is the corresponding smallest value, and h_{lim} is the greatest height value for an obstacle that can be traversed by a robot. For this paper, the absolute value of the largest slope angle that can be ascended and the absolute value of the smallest slope angle that can be descended are considered to be equal, and θ_{lim} is used for these values. If the two values differ, however, then when θ is between the smallest and the largest slope angles, it will suffice to set Eq. (1) so that $T_1=1$. Equation (1) expresses the traversability analysis index for a slope, and Eq. (2) expresses the traversability analysis index for uneven ground. Preceding research used variance and standard deviation as traversability analysis indices for uneven ground instead of Eq. (2), and many such approaches assigned some kind of threshold value to those indices. The threshold value in that kind of method can carry the same implications as Eq. (2), depending on how the threshold value is assigned, in cases where the road surface model completely follows Gaussian distribution as assumed in (2)(b). When the road surface model diverges to some extent from Gaussian distribution, however, and in an environment where the extent of concavities with respect to the estimated plane are not equal to the extent of convexities, degradation of performance can be expected. With the present method, therefore, the peak-to-peak value for the point cloud within the effective model area, as in Eq. (2), is taken as the traversability analysis index for uneven ground. This enhances the method's robustness when the road surface diverges from Gaussian distribution.

The traversability analysis index is defined using T_1 , T_2 as follows:

$$traversability = T_1 \cdot T_2 \quad (3)$$

When $traversability=1$, the terrain is traversable. When it is 0, the terrain is untraversable.

2.2. Traversability Analysis in Terrain that Includes Obstacles

Obstacles on the road surface being traversed are modeled as shown in Fig. 2 (a). An actual robot would use a three-dimensional plane model. Here, however, the

explanation will use a simplified two-dimensional, straight-line model. In this model, the obstacle is represented with respect to a traversed road surface segmented into grids that have one side of length l , where a convex portion with height h exists with occupancy rate α as a proportion of the grid. In other words, a difference in level or other such obstacle can be expressed by changing the values of h and α . In this section, it will be shown that the traversability analysis method described in previous sections can be applied as it is to a road surface that includes this obstacle model if the size of the grids dividing the road surface is set appropriately.

For that purpose, the size of the grid divisions first needs to be optimized, and the reason for this will be shown using concrete examples. With respect to a road surface that includes the obstacle model shown in Fig. 2 (a), the ideal representative plane with least variance, estimated by the procedure in (2)(a) of Section 2.1., will be as shown in Fig. 2 (b). Consider a robot with navigation performance of $\theta_{lim}=25$ deg and $h_{lim}=0.05$ m (a robot with this navigation performance will be referred to hereafter as Robot A) that performs traversability analysis with respect to a road surface model that includes obstacles. Figure 3 is a judgment diagram showing recognition of an obstacle of height $h=0.03$ m and occupying a proportion $\alpha=0.25$ of a grid that has one side of length $l=0.05$ m. In Eq. (1), $\theta=33.1$ deg > 25 deg yields $T_1=0$, while in Eq. (2), $d_{max}-d_{min}=0.0251 < 0.05$ yields $T_2=1$ so that according to Eq. (3), $traversability=0$. It is apparent that the obstacle is judged to be untraversable even though this is an obstacle that by its nature should be fully traversable. This is a phenomenon that can occur in all methods that express a road surface model using representative planes. The reason for it is that when the grid size is small, the slope of the representative plane on a road surface that includes obstacles becomes steep. Due to this phenomenon, a divergence occurs between the obstacle height that can be traversed based on the robot's navigation performance and the result of the traversability analysis, and the robot's traversable region is reduced. On the other hand, when the grid size becomes larger, the resolution of the road surface is correspondingly reduced so that the robot's movement becomes constrained. In performing traversability analysis of a road surface that includes obstacles, therefore, a

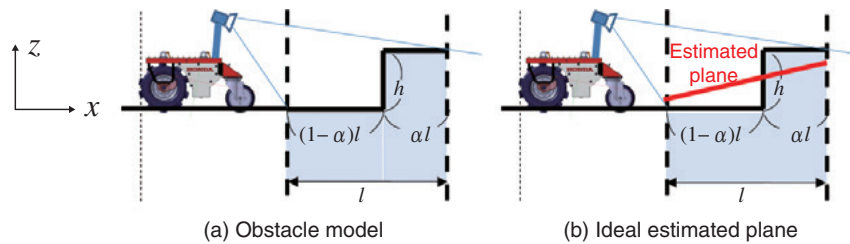


Fig. 2 Definition of obstacle model and traversability estimation of obstacle

grid division method is needed that provides for the least divergence in traversability analysis so as not to cause these issues to occur.

The proposed method has established such a grid division method. The incorrect judgment in traversability analysis described above occurs because the obstacle height, on which traversability hinges in accordance with grid size, changes so that it diverges from the actual threshold value h_{lim} . When a robot that has θ_{lim} , h_{lim} navigation performance recognizes surrounding road surfaces with grids that are of length l on one side, and performs traversability analysis by the method shown in Section 2.1., then in the case of an obstacle with the occupancy rate α , the robot will define the height that it judges internally is untraversable as $h_{internal}(\alpha, l)$. The method of derivation will be described later. In the case of the example shown in Fig. 3, for instance, the threshold value at which this robot judges internally that a road surface is untraversable is $h_{internal}(0.25, 0.05) \approx 0.015$ m, which diverges from the set threshold value $h_{lim} = 0.05$ m. The result, as discussed above, is that the traversability analysis with respect to an obstacle with height $h = 0.03$ m that is within the range of $h_{internal}(0.25, 0.05) < h < h_{lim}$ will yield an incorrect judgment.

The method for deriving $h_{internal}(\alpha, l)$ can be described by Algorithm 1 shown below.

Algorithm 1: $h_{internal}(\alpha, l)$

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1  $h \leftarrow \text{null}$ ; traversability  $\leftarrow \text{True}$ 
2 while traversability do
3    $h \leftarrow h + \Delta h$ ;
4   traversability  $\leftarrow \text{Judge}(\theta_{lim}, h_{lim}, l, \alpha, h)$ ;
5 return  $h$ ;

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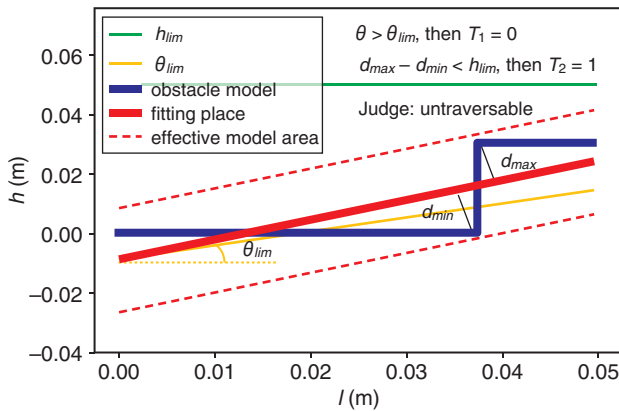


Fig. 3 Example of incorrect estimation result
($l = 0.05$ m, $\theta_{lim} = 25$ deg, $h_{lim} = 0.05$ m)

Here, $\text{judge}(\theta_{lim}, h_{lim}, l, \alpha, h)$ is a function that returns traversability analysis results when the traversability analysis method shown in Section 2.1. is applied to a robot with threshold values θ_{lim} , h_{lim} with respect to an obstacle model expressed by l, α, h as defined in this section.

When l takes a certain value, an obstacle of height h will definitely be traversable if $h < \min_{\alpha} h_{internal}(\alpha, l)$ and will definitely be untraversable if $\max_{\alpha} h_{internal}(\alpha, l) < h$. If $\min_{\alpha} h_{internal}(\alpha, l) < h < \max_{\alpha} h_{internal}(\alpha, l)$, then traversability will change according to the value of α .

Here, consider the case when l takes a certain value and $\min_{\alpha} h_{internal}(\alpha, l) \approx h_{lim}$. In this case, the traversability analysis can be performed correctly to judge that an obstacle with $h < h_{lim}$ is traversable while an obstacle with $\max_{\alpha} h_{internal}(\alpha, l) < h$ is untraversable. On the other hand, even though an obstacle with $h_{lim} < h \leq \max_{\alpha} h_{internal}(\alpha, l)$ is untraversable, there are cases when it is incorrectly judged to be traversable depending on the value of α . If the traversability analysis update cycle is adequate, however, then even if a certain road surface has once been judged to be traversable, when the robot navigates it, the judgment can be changed to untraversable in the course of changing the value of α . Consequently, when a grid that satisfies the condition $\min_{\alpha} h_{internal}(\alpha, l) \approx h_{lim}$ has sides set to length l , then the robot will be able to perform traversability analysis of the road surface while satisfying the value h_{lim} set on the basis of the robot's navigation performance.

An objective function such as $J(l)$ in Eq. (4) is, therefore, defined and a value for l that yields the smallest $J(l)$ as in Eq. (5) is assigned as the length of one grid side.

$$J(l) = h_{lim} - \min_{\alpha} h_{internal}(\alpha, l) \quad (4)$$

$$l = \arg \min J(l) \quad (5)$$

However, Eq. (5) is considered to yield a solution under the following constraint condition.

$$h_{lim} - \min_{\alpha} h_{internal}(\alpha, l) > 0 \quad (6)$$

According to Eqs. (4) and (5), $\min_{\alpha} h_{internal}(\alpha, l) \approx h_{lim}$ is valid, so as stated above, the robot is able to perform the traversability analysis while maintaining the threshold value of h_{lim} that was set on the basis of the robot's navigation performance. Equation (6) has the role of providing for the highest road surface resolution within the range of threshold values h_{lim} that the robot is able to maintain.

For example, when the same procedure is applied to Robot A (however, with $\Delta h = 0.001$ m), then the objective function will be as shown in Fig. 4, and $l = 0.21$ m will be derived according to Eqs. (5) and (6).

Based on the above, when an obstacle model defined as in Fig. 2 (a) is assigned the constraint condition of grid size l shown in this section, then it can be judged whether an obstacle can be traversed using the same method of

traversability analysis for natural terrain shown in Section 2.1. The above method can be summarized as shown in Fig. 5.

Under the constraint condition of Eq. (6), $\min_{\alpha} h_{internal}(\alpha, l)$ will be the threshold value for the robot to judge internally that a road surface is untraversable. In practical terms, therefore, if this value is within the range of allowable values, then l will not necessarily need to be decided by Eq. (5). It will be sufficient to use a convenient figure that is close to the solution of Eq. (5).

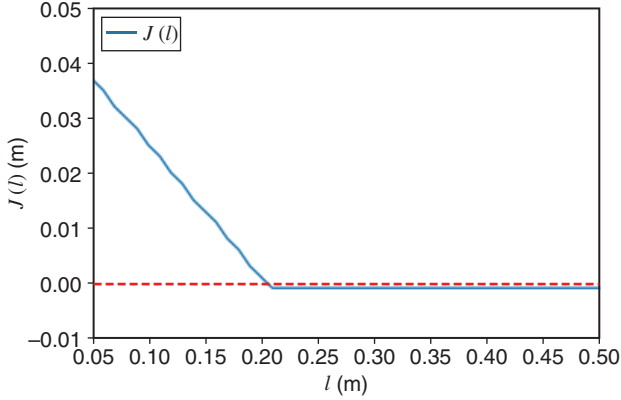


Fig. 4 Objective function of grid size optimization ($\theta_{lim} = 25$ deg, $h_{lim} = 0.05$ m)

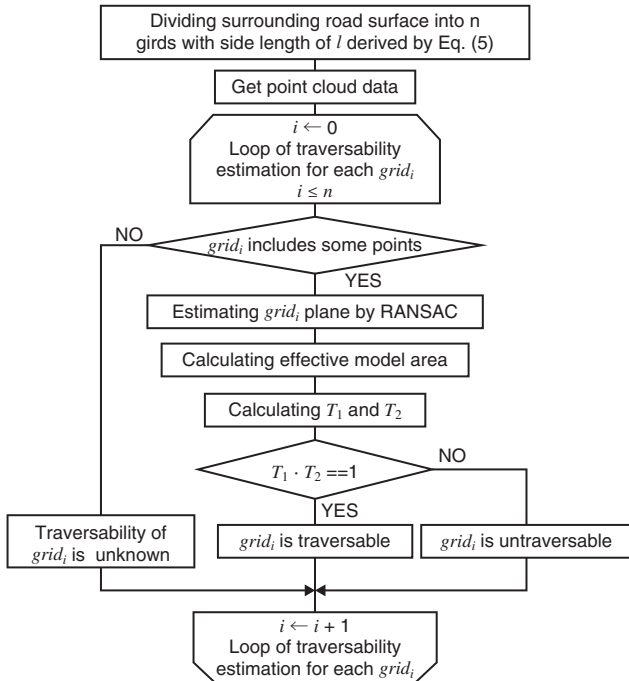


Fig. 5 Flowchart of proposed method

3. Test Conditions

Figure 6 shows the robot used in verifying the effectiveness of the proposed method shown in Chapter 2. This robot is equipped with a stereo camera, and the forward camera can be used to acquire the road surface point cloud. Fixed values $\theta_{lim}=25$ deg, $h_{lim}=0.05$ m were assigned as the threshold values for the robot's navigation performance. The threshold values were calculated on the assumption that the wheels would have sufficient grip force on the road surface and taking into consideration the radius of the wheels under the same conditions.

A square bar placed on a flat road surface was used in verifying the effectiveness of the grid size optimization method. With width 0.31 m, length 0.04 m, and height 0.04 m, this square bar was made slightly lower than the threshold value for an obstacle height that is untraversable by the robot.

In verifying the effectiveness of the robot's traversability analysis method in a rough terrain environment, a rough terrain environment like that shown in Fig. 7 was used, with gravel road, lawn, trees and tree trunks, protruding obstacles, slopes, and so on. The central illustration in Fig. 7 is a schematic view, and the proportion of the actual environment taken up by each of the road surface attributes such as lawn, surfaced road, and so on, largely matches the area ratios in the schematic view. The slopes are all uneven road surfaces. The slope angles differ, varying across a range from about 5 to 40 degrees. There was a mixture of regions with traversable slope angles and regions with untraversable slope angles. The lawn was less than 0.05 m in height, and was a traversable region. However, the obstacles on the lawn and the trees were all more than 0.05 m in height and were untraversable regions. The gravel road was surfaced with stones about 0.04 m or less in height, and much of it was traversable. However, portions of it had the stones packed closely together and overlapping so that the height exceeded 0.05 m, and those were untraversable regions. The environment in Fig. 7 does not include road surfaces that would reduce the grip force of the wheels, such as wet road surfaces, sand pits, and so on. It was an environment in which every road surface would provide the



Fig. 6 Test robot with stereo camera

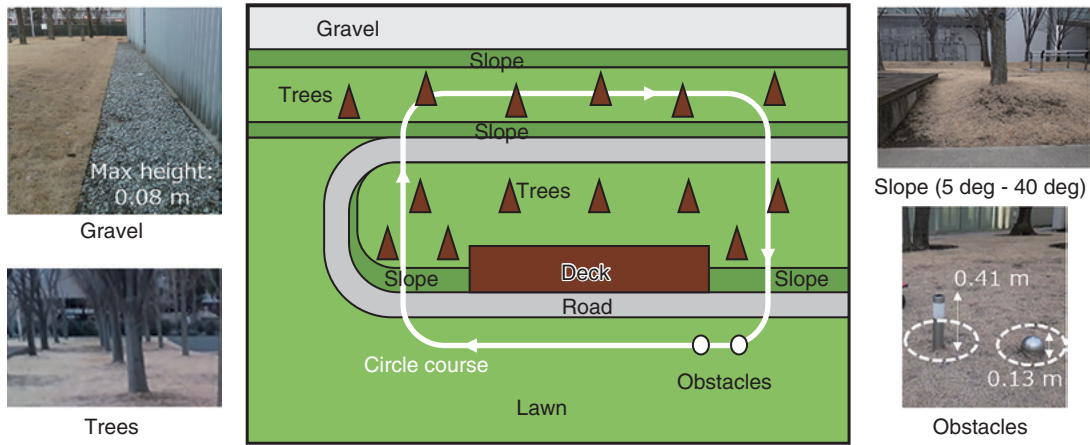


Fig. 7 Test environment

wheels with adequate grip force. The environment in Fig. 7 was configured as above to serve as the test environment. Although it did not provide a completely exhaustive rough terrain environment, it did constitute an environment of road surfaces with diverse attributes, some regions being traversable for a robot and other regions being untraversable.

4. Results and Discussion

4.1. Verification of Effectiveness of the Grid Size Optimization Method

The effectiveness of the grid size optimization method shown in Section 2.2. was verified. The method for optimizing the navigation performance of the robot shown in part 3 was first applied and the grid side was given a length of $l=0.20$ m. As described in Chapter 3, fixed values were used for θ_{lim} , h_{lim} , so the grid side length of $l=0.20$ m was also a fixed value. At this point, the threshold by which the robot would judge internally that a road surface was untraversable was $\min_{\alpha} h_{internal}(\alpha, 0.20)=0.047$ m. The case with a length of $l=0.10$ m was set up for comparison and the results of traversability analysis by the method shown in Section 2.1. were compared. Traversability analysis was performed for two patterns with square bars placed on the road surface, one with $l=0.10$ m and the other with $l=0.20$ m. The results are shown in Fig. 8. The directions of the arrows indicate the directions of the normal vectors of each grid's representative planes. The colors of the arrows are according to the definitions in Table 1.

Since the height of the square bars is lower than h_{lim} , a road surface that includes those square bars would by its nature be traversable. In the case of $l=0.10$ m, however, then, as shown in Fig. 8 (a), the slopes of the representative planes in grids that include square bars exceeded the threshold value for a slope that the robot can climb, so that $T_1=0$ and the result was that those road surfaces were judged

Table 1 Definition of arrow color

	$T_2 = 0$	$T_2 = 1$
$T_1 = 0$	Clear Red	Red
$T_1 = 1$	Clear Black	Green (traversable)

to be untraversable. This showed that when performing traversability analysis of a road surface by a method that involves dividing that road surface into grids and using the slopes of the estimated planes in each grid as factors in the traversability analysis, then an incorrect judgment could occur in the traversability analysis unless an appropriate grid size has been specified. In the case of $l=0.20$ m, on the other hand, a similar phenomenon did not occur. As shown in Fig. 8 (b), a plane including the same square bar was correctly judged to be a traversable road surface. Moreover, the judgment results did not change even when the square bars were moved to lower the occupancy rate of the square bars in a grid, or when multiple square bars were placed side by side to raise that same occupancy rate. The road surface that included square bars was correctly judged to be traversable. The above indicated the effectiveness of the method for optimizing grid size shown in Section 2.2.

4.2. Verification of the Effectiveness of the Proposed Method in a Rough Terrain Environment

The effectiveness of the proposed method was verified in the environment shown in Fig. 7. Following the previous sections, the length of one side of a grid was made a fixed value at $l=0.20$ m.

An example of traversability analysis results in natural terrain is shown in Fig. 9 (a) and (b). In this figure, (a) illustrates the recognition of the slopes in Fig. 7 and (b) illustrates the recognition of the gravel road. Figure 9 (a) has a region with green arrows that is judged to be traversable and a region with red arrows that is judged to be

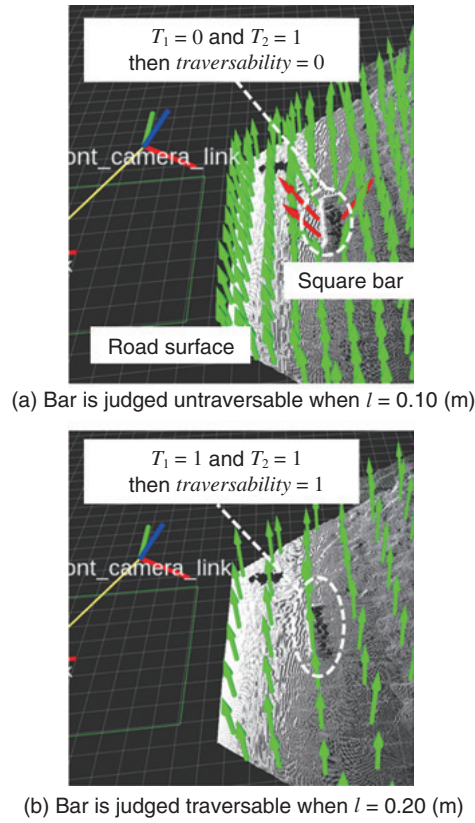


Fig. 8 Grid size optimization

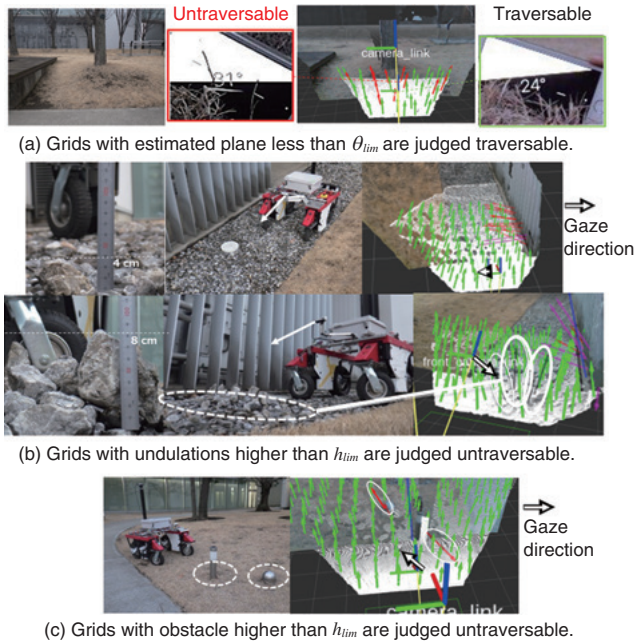


Fig. 9 Result of traversability estimation

untraversable according to the Eq. (1) index. In the green region, the slope is 24 degrees. In the red region, the slope is 31 degrees. The judgment of the slope's traversability can be considered to occur with $\theta_{lim}=25$ deg as the approximate boundary.

Figure 9 (b) has green arrows indicating the judgment of traversable with respect to a road surface on uneven ground with height differences of approximately 0.04 m. On the other hand, a road surface on uneven ground with height differences of approximately 0.08 m has clear black arrows, indicating that it was judged untraversable by Eq. (2).

Autonomous navigation by a robot was tested on the circular course shown in Fig. 7. In addition to performing traversability analysis of slopes, lawns, and other such natural terrain, the robot performed traversability analysis of road surfaces including trees, tree trunks, and other obstacles shown in Fig. 7 [Fig. 9 (c)] while successfully traveling around the circular course at a rate of 0.85 m/s.

For the future, measures will continue to be taken to verify the usefulness of this method by various means. These would include (1) testing in environments that include obstacles of a variety of shapes and sizes in order to verify the comprehensiveness of the environments for application of the method; (2) testing in environments that are more likely to produce measurement noise from sensors in order to verify the robustness of the method; and (3) testing of traversability analysis using a variety of robots in order to verify the convenience of the method; and so on.

5. Findings

This paper has proposed a method whereby a robot models surrounding road surfaces and performs traversability analysis of that model. Most existing methods that use estimated planes as elements of a road surface model face issues of inadequacy in the road surface model when measuring obstacles, and the proposed method indicates a way of resolving these issues by placing constraints on how surrounding road surfaces are divided into grids. This approach successfully assures the validity of modeling road surfaces using planes, and the proposed method is unique in this respect.

It is also the case that this method is theoretically robust with regard to noise from outliers and noise near maximum and minimum values in measurement point clouds. In addition, the parameters required by the method are determined solely on the basis of the obstacle height h_{lim} that can be traversed by the robot and the largest slope angle θ_{lim} that the robot can ascend and descend, so this can be considered a highly convenient method that is not dependent on the specific robot.

For the future, continuing measures will be taken to verify the usefulness of the method by verifying its comprehensiveness in terms of the environments and robots to which the method is applied, verifying the robustness of the method, and so on.

6. Conclusion

This paper will conclude with remarks on the prospects for this research. The proposed method determines the size of grids created when dividing the road surface surrounding the robot based on the values θ_{lim} , h_{lim} that express the robot's navigation performance. Traversability analysis is then performed of that road surface. It is to be anticipated, therefore, that if θ_{lim} , h_{lim} could be estimated from the material properties and state of the road surface, which were outside the bounds of this research, then robots will become capable of performing traversability analysis while dynamically changing θ_{lim} , h_{lim} using information about the road surface and changing the size of the grids accordingly. Expanding the method in such ways will further enhance the comprehensiveness of the environments to which the proposed method is applied and realize traversability analysis methods with a wider range of universal applicability.

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