Terrain Mapping and Classification in Outdoor Environments Using Neural Networks

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Abstract

This paper describes a three-dimensional terrain mapping and classification technique to allow the operation of mobile robots in outdoor environments using laser range finders. We propose the use of a multi-layer perceptron neural network to classify the terrain into navigable, partially navigable, and non-navigable. The maps generated by our approach can be used for path planning, navigation, and local obstacle avoidance. Experimental tests using an outdoor robot and a laser sensor demonstrate the accuracy of the presented methods.

Keywords: Terrain and environment mapping, terrain segmentation, mobile robots, laser range finders.

1. Introduction

Mobile robotics is a field of robotics focused on the development of devices capable of moving autonomously to perform predetermined tasks. In order to navigate safely, robots use perception sensors like laser rangefinders (LRF) and cameras to get information from the environment and detect potential obstacles. Usually, these sensors are also used to create internal models of the environment (maps), which allow localization and path planning.

In mobile robots navigation, maps are widely used to create terrain computer representations. Therefore, using terrain classification methods, it is possible to identify navigable portions of the land, allowing the robot to use the safest routes when navigating [12].

Most robotic mapping algorithms in the literature represent the environment with either two or three-dimensions. In 3D maps, the models are more detailed and usually applied to represent complex spaces like urban modeling. Among the most used 3D representation methods, we can cite point clouds, triangular meshes, and planar structures. The disadvantage of this representation is the requirement for a considerable storage space for modeling large environments. On the other hand, 2D maps require less computational resources, since they are generally represented by grids of cells. Thus these can be easily used to represent traversable paths [12].

One of the most important applications of maps in mobile robotics is navigation. In most cases, the robot uses a model of the environment to plan routes to a specific location avoiding obstacles. When working on outdoors, it is also necessary to avoid regions of the environment that are not appropriate for navigation like gravels, rocks and holes. In most 2D mapping approaches these features are not identified by the range sensors, once they usually only scan

a horizontal plane in front of the robot. In these cases, a 3D map of the terrain can be used to correctly represent the details of the environment.

This paper presents an extended version of the work presented in [16], which consists of a 3D terrain mapping technique and an artificial neural network-based classification approach. Our algorithm is capable of converting the 3D map of the environment into a 2D grid, where each cell is further classified into navigable, partially navigable, or non-navigable. The classification is performed by a multi-layer perceptron neural network that uses the map information as input and generate the terrain classification output. Comparing to other works in the literature, most other approaches classify each 3D point, which demands a high computational load to perform. As we classify grid cells, the number of cells to be classified is considerably lower than the number of points of the 3D map, therefore improving the computational demand during the classifications process.

1.1 Related Works

Due to its importance in robotics, environmental mapping has motivated the publication of several works by the scientific community. Among them we can cite the technique proposed by [15] to generate accurate maps of terrain using a 2D LRF. To remove noises in generated maps, a filter that removes corrupted pixels and lost data has been developed. In another approach, [11] presents a multi-robotic system equipped with a laser sensor to allow the construction of three-dimensional maps of cyclic environments in real time. To create 3D maps of urban structures with high precision, the method proposed by [2], associates images captured by a camera with data given by a LRF. Consequently, it could estimate the motion of the robot and allow the construction of detailed 3D maps.

Besides these works, there are others devoted to identification of navigable areas by extracting information of mapped terrains. Determine which ways are safe is essential for outdoor navigation. In [14], the mapping task is done using a 2D laser sensor that combines information acquired by an odometer and an IMU. In this technique, flat terrain (e.g. walkways) is classified as navigable and irregular terrain (e.g. grass, gravel) is classified as non-navigable. This classification algorithm is based on Hidden Markov Model. The work presented in [10] investigates a mapping technique that uses 3D laser range finder to make possible robot navigation in vegetated terrains. The work by [6] applies a 3D laser sensor to perform classification of the whole environment. The elements of the scene are segmented into three classes, which are, surface (e.g. ground), linear structures (e.g. cables and trunks) and dispersed structures (e.g. grass). The segmentation algorithm uses a Bayesian classifier.

Video cameras have also been widely employed in terrain classification. In [8] is presented a method for terrain segmentation that combines information obtained from a LRF and the image captured by a camera. Colors and textures extracted from the images are used to classify the land as ill-structured, gravel and asphalt. Finally, in [13] a camera and a vibration sensor have been used to classify terrain covered by the robot.

2. Mapping

Mapping is a fundamental task to allow robot automation [11] [14]. Through the maps robots are able to estimate their own position in the environment and plan a path to a particular location [7], which are the basic functionalities to navigate autonomously. The mapping process consists on generating computer models of the real scenarios from data

collected by sensors. Most mapping techniques are based on either distance sensors (e.g. LRF and sonar) or video cameras. The work presented in this paper is based on a LRF data. This type of sensor has the advantage of having high accuracy, ability to directly acquire the distance to obstacles, and their readings are little influenced by variation of environmental conditions. Part of the mapping techniques focus on creating a computational model of the terrain. It is particularly useful when the robot navigates in outdoor environments, where the ground is not flat. In these cases, it is necessary to identify the regions that can be safely traversed by the robot. Therefore, besides the map of the terrain, it is also necessary to classify the terrain according to its navigability.

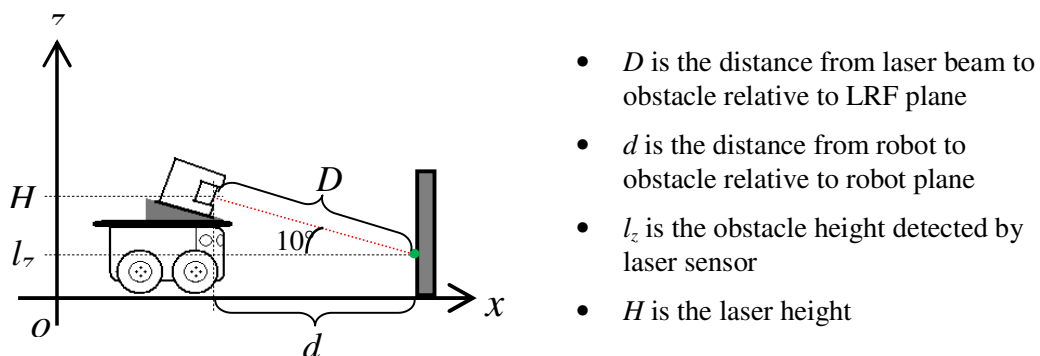Figure 1. Pioneer 3 AT Robot and SICK LMS 200 LRF used in the experiments.

2.1 Terrain Mapping

- D is the distance from laser beam to obstacle relative to LRF plane

- d is the distance from robot to obstacle relative to robot plane

- l_z is the obstacle height detected by laser sensor

- H is the laser height

Figure 2. Laser beam decomposition in *zx* surface.

In our terrain mapping experiments we have used a 2D laser sensor with –10º inclination to the ground. In this configuration, the sensor was able to detect the ground approximately up to 2 meters ahead of the robot. The LRF has been configured to perform 181 points measurements at 10Hz. Each measurement is represented by a value that corresponds the distance from the laser sensor to the detected obstacle in a particular direction. This sensor is equipped in a Pioneer AT robot, which can operate on outdoors (Figure 1). Besides the data provided by the LRF, the mapping algorithm requires robot motion information in order to

build the map. This information has been provided by the internal odometer of the robot in our tests.

The first step to build the map is the analysis of the components that form the laser beam in the *zx* surface (Figure 2)). Based on *H* and *D* values, it is possible to determine the longitudinal distance *d* and the height of the point l_z detected by laser. Through trigonometric calculations, we find:

$d = D \cdot \cos(10^\circ)$

$l_z = H - D \cdot \sin(10^\circ)$

The *x* and *y* coordinate values are directly obtained from robot position information. Figure 3 shows the same laser scanning model of the Figure 2 seen above. With the *ABC* triangle, we can determine the obstacle coordinate values l_x and l_y that has the following expression:

$l_x = p_x + D \cdot \cos(\theta + \alpha)$
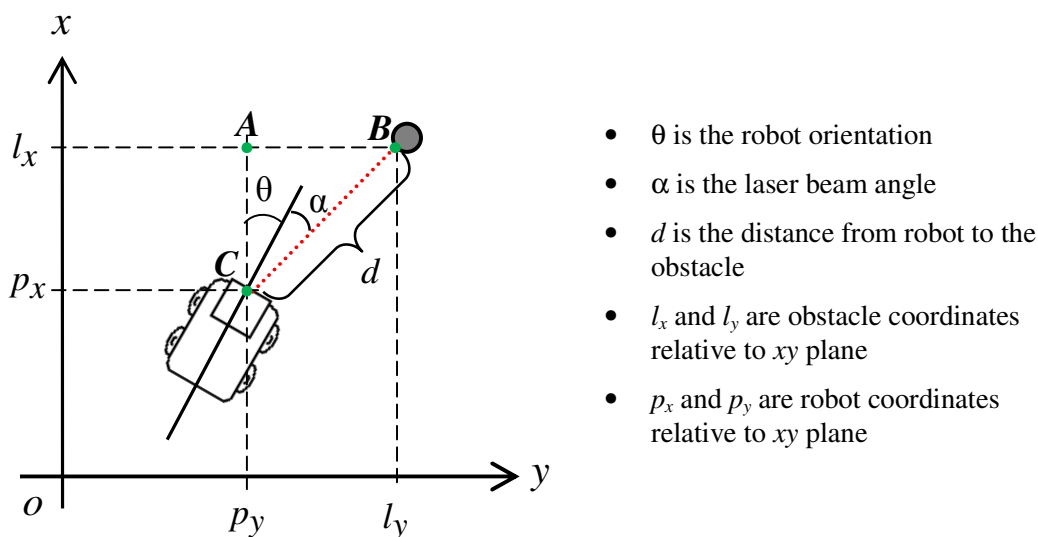
$l_y = p_y + D \cdot \sin(\theta + \alpha)$

- θ is the robot orientation
- α is the laser beam angle
- *d* is the distance from robot to the obstacle
- l_x and l_y are obstacle coordinates relative to *xy* plane
- p_x and p_y are robot coordinates relative to *xy* plane

Figure 3. Laser beam decomposition in *xy* surface

The l_x, l_y and l_z coordinates refer only to one laser reading. Thus, transformations are done in all subsequent scanned points to obtain a dense map of the environment. In this manner, the mapping algorithm is capable to obtain the values of l_x, l_y and l_z for all points obtained at each laser reading.

3. Artificial Neural Networks

Artificial neural networks (ANNs) are mathematical models inspired by the way biological nervous systems process information. Several different approaches of neural networks have been proposed in the literature for more than 4 decades [5] [1]. Most of them are composed by a large number of highly interconnected processing elements called neurons. Among applications, neural networks have been widely applied to extract patterns and detect trends

that are too complex to be identified by either humans or other computer techniques. In robotics, this approach has been successfully used in control systems. The major advantage of ANN is the capability of generalization and handle large number of data. In this work, we have used a multilayer perceptron (MLP), which is of a feedforward neural network model that maps sets of input data onto specific outputs. The MLP model consists of input, output and one or more hidden (intermediate) layers [3]. Every neuron of each layer is connected to every other neuron of the previous and the next layers with a certain weight.

In order to correctly map the input data to an expected output, it is necessary to appropriately set the connection weights of the neurons. This task is usually known as learning. As MLP consists of a supervised learning technique, it is necessary to use previously classified examples to train the neural network, so it can adapt the weights (learn) and correctly classify other data that follow the same pattern. A MLP learning algorithm is the Backpropagation technique [9], which estimates the weights based on the amount of error in the output compared to the expected results.

The standard Backpropagation algorithm is very slow and its performance gets worse to very large and complex problems. Even for fairly simple problems, normally it requires that the training patterns must be presented hundred or thousand times to the ANN, which limits its practical use. Currently, the learning algorithms employed are variations of Backpropagation like Momentum, Quickprop and Resilent Backpropagation (RProp). In this work we used RProp learning algorithm.

3.1 Map Classification

The development of rule based techniques to perform the terrain classification is a quite complex task that is subjected to errors [5]. Thus, the proposal of an ANN to make the classification justifies by not requiring creation of rules, but only data sets. This data can be generated by manually operating the robot. Finally, ANNs are robust to deal with unexpected situations and have high generalization rate.

In this work, ANNs were applied to classify terrain portions into one of three categories: navigable (e.g. ground, pathways), non-navigable (e.g. walls, curbs) and partially navigable (e.g. grass). To facilitate this process, the 3D terrain map was converted in 2D grids, so each cell corresponds a small fragment of the land. The neural network used to classification has three layers (input, hidden and output). The input layer has two units, where one represents absolute height of grid cells and the other one characterizes the relative height between neighboring cells. Consequently this ANN depends only on altitude and slope of the land. In order to analyze the neural network performance, the hidden layer was configured with different numbers of units. Finally, the last layer is organized with three binary outputs, which each unit represents one terrain category. The JavaNNS framework was used to build and train the networks for classification. Figure 4 illustrates a classifier network with 4 and 32 hidden units used in the experiments.

4. Results

In order to validate the approaches proposed in this paper, we performed experimental tests in outdoor environments using a Pioneer 3 AT robot and a SICK LMS 200 laser range finder (Figure 5(a)). For the first experiment we tested the classifier performance for simple environments. Figure 5(a) shows this scenario (Scenario I). The mapping step generated a

precise 3D representation as it can be seen in the Figure 5(b). In this map the pathway and small obstacles (boxes) can be clearly distinguished. Before the terrain classification process, a 2D grid map has been generated based on the absolute altitude (difference between the altitude of the robot and the terrain point) and the maximum altitude difference between the 3D points in a given cell. These two values had been used as input of the ANN for terrain classification. Due to environment structure of Scenario I, the ANN was configured with two outputs, so the grid cells were classified only as navigable or non-navigable. In order to know the number of hidden units that best fits in the ANN, it was tested neural network classifiers with 4, 8, 16 and 32 hidden units. In the learning process, each network configuration was trained with 783 training patterns and 262 validating patterns. The learning algorithm was set to execute 8000 learning cycles and 1000 update steps. The MSE (mean squared error) in the learning process was below 0.01 for all topologies.

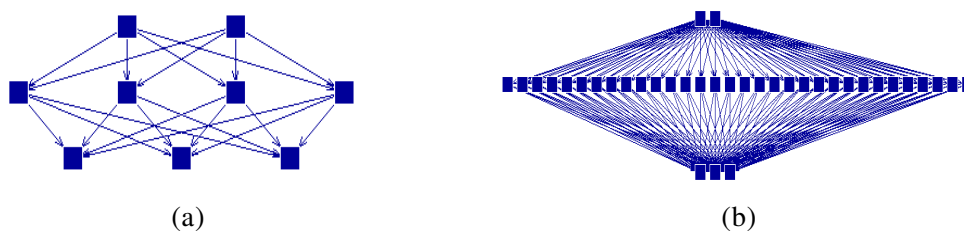(a)   (b)

Figure 4. Neural networks topologies used in terrain classification. (a) ANN with 4 hidden units; (b) ANN with 32 hidden units

Figure 6(a) and Figure 6(b) show the error graphic for ANN with 4 and 32 hidden units. In the validation step all networks obtained equal performance. Statistics of right, wrong and unknown patterns matches are listed in Table 1. Finally, we classified the 2D grid map of Scenario I with all trained networks. Due to the similar results obtained in the learning process, all classified maps were very similar. Figure 7(a) and Figure 7(b) illustrate the terrain map classified with 4 and 32 hidden neurons, respectively.

Table 1. Statistics for ANN validation results for Scenario I and Scenario II

	Scenario I		Scenario II	
Right	99.62%	261 patterns	98.62%	358 patterns
Wrong	0.38%	1 patterns	1.10%	4 patterns
Unknown	0.00%	0 pattern	0.28%	1 pattern

For the second experiment we used the environment showed in Figure 5(c) (Scenario II). In the generated 3D map (Figure 5(d)) we can notice that the lawn can be visually differentiated from the ground. Therefore, for this scenario the ANN was adjusted with one more output element to identify partially navigable regions (e.g. grass). We used the same ANN configurations and learning algorithm settings as the first experiment. For training we used 628 patterns and for validation, 363 patterns. Again, all networks topologies obtained

identical MSE in the training as can be seen in the Figure 6(c) and Figure 6(d). In the Table 1 is presented the validation statistics. Moreover, in the Scenario II terrain classification, all topologies generated similar classified maps. Results for 4 and 32 hidden neurons configuration can be seen in Figure 7(c) and Figure 7(d).
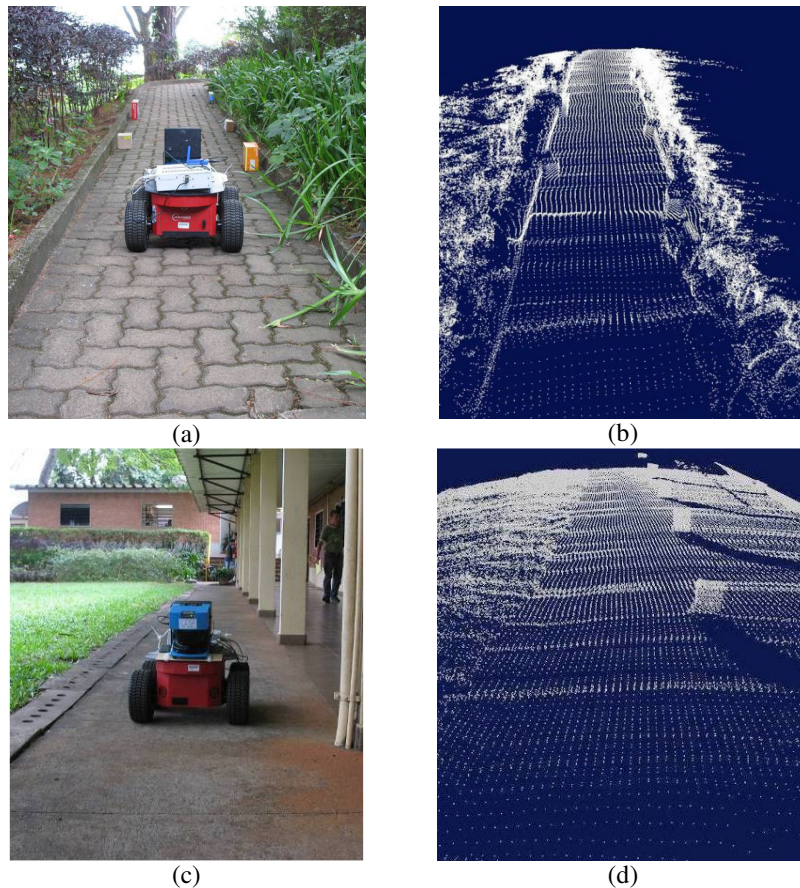

(a)

(b)

(c)

(d)

Figure 5. Scenario I: Sloped pathway with curbs and obstacles.
(a) Real environment and (b) 3D map of the environment. Scenario II: A path with
low grass in the side. (c) Real environment and (d) 3D map of the environment.

5. Conclusion

Terrain mapping is an important capability to allow mobile robots to operate in outdoor environments. This paper presented a 3D mapping technique based on LRF data. The 3D maps were capable to represent fine details of the environment, as showed in the obtained results. We also proposed a terrain classification technique based on ANNs. More precisely, we converted the 3D map into a 2D grid representation and used the information of each cell as input of a multilayer perceptron neural network. This ANN could differentiate between navigable, non-navigable and partially navigable regions. The terrain mapping and classification techniques have been validated through experimental tests and the results obtained confirm the efficiency of our approaches. Four neural network topologies have been tested and more than 98% of the cells in the environment have been correctly classified. We

could also evidence that an ANN with four hidden units is enough for terrain classification task. Future works include the use of other machine learning techniques to improve the terrain classification results and the integration of the terrain classifier to assist in planning algorithms.
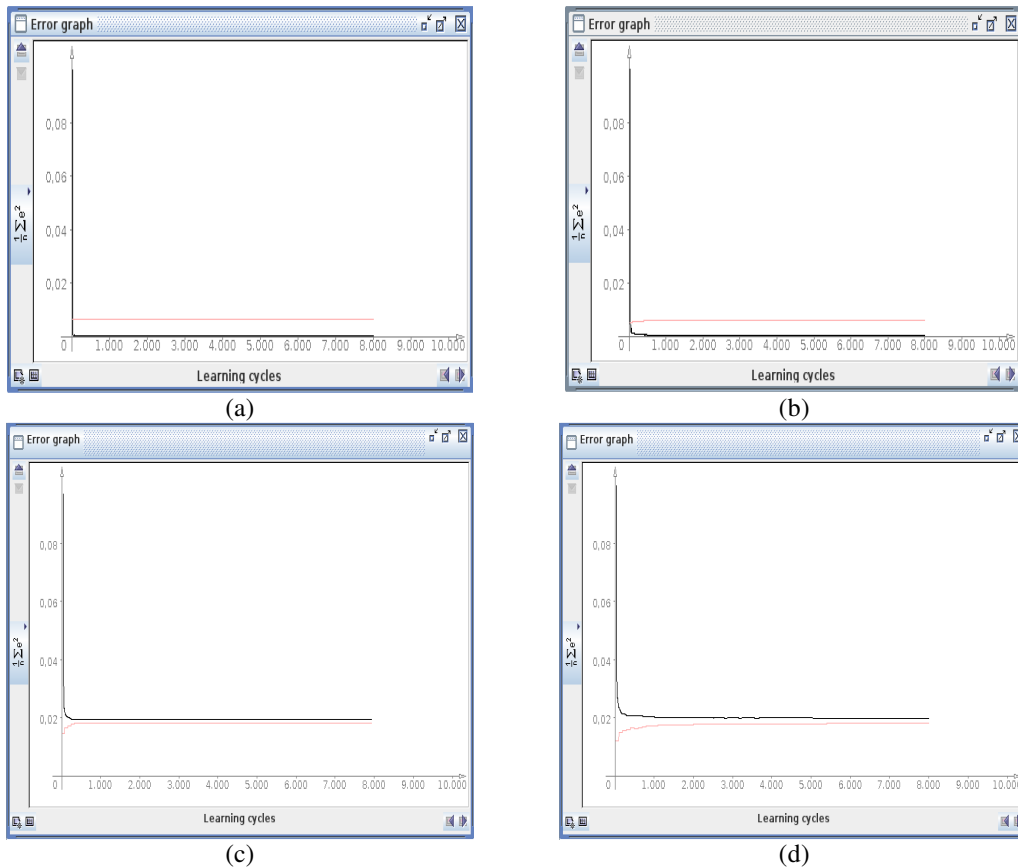

(a)   (b)

(c)   (d)

Figure 6. MSE error graphs for learning process. Scenario I classification errors: (a) Using 4 and (b) 32 hidden neurons. Scenario II classification errors: (c) Using 4 and (d) 32 hidden neurons. The red line corresponds to validation set error and the black line corresponds to training set error.
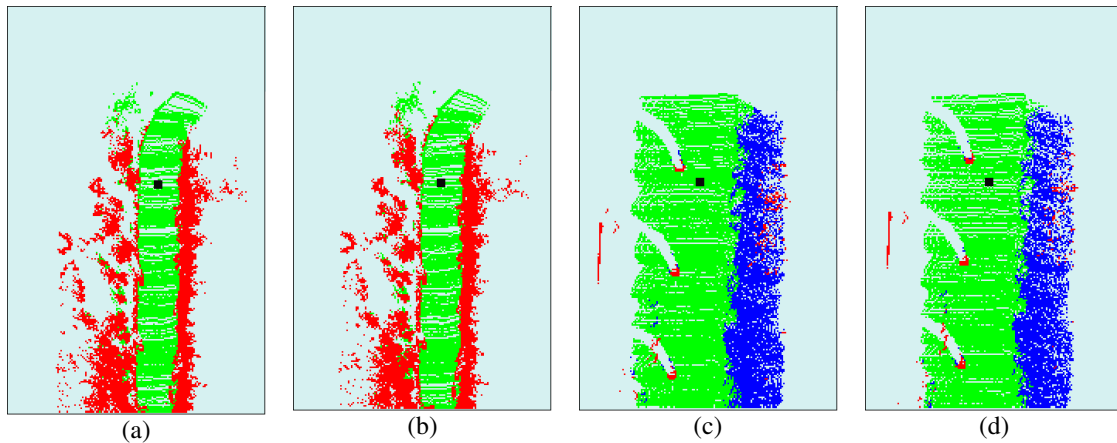
Acknowledgements

| (a) | (b) | (c) | (d) |

Figure 7. Classified maps of Scenario I: (a) using 4 hidden units and (b) 32 hidden units. Classified maps of Scenario II: (c) using 4 hidden units and (d) using 32 units. Green color corresponds to navigable terrain, red color corresponds to the non-navigable terrain, and blue color corresponds to partially navigable terrain.

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