Behavior Mode Selection based on Environment Map for Planetary Rover

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Abstract

This paper proposes a behavior mode selection method for improving the driving efficiency of the planetary exploration rover. In the conventional method, the behavior modes of the exploration rover are specified by the operator. Therefore, every time the surrounding environment changed, operator intervention was required, and it took time to move to the destination. In this study, in order to improve the driving efficiency of the rover, a method to select the behavior mode by the environmental map was proposed. The simulation study verified the effectiveness of the proposed method and showed that the traveling time to the destination can be shortened.

惑星探査ローバのための環境地図に基づく行動モード選択法

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摘要

本稿では惑星探査ローバの走行効率向上のための行動モード選択法を提案する．従来手法では探査ローバの行動モードはオペレータによって指定されていた．そのため周囲の環境が変化するたびにオペレータの介入が必要となり，目的地までの移動に時間を要した．本研究では，ローバの走行効率向上のため，環境地図を深層学習により理解することにより行動モードを選択する手法を提案する．提案手法の有効性を検証するためのシミュレーションを行い，目的地までの走行時間を短縮できることを示した．

1 Introduction

In the planetary rover mission , it is required to drive safely to the destination. In order to obtain many scientific results, it is necessary to fully bring out the unique advantage of the rover that it can move on the surface of the celestial body. Advanced rough terrain driving technology is required to travel on unknown and rough terrain surfaces. In addition, the one-way communication delay between Earth and Mars is 4 to 20 minutes, and it is difficult to control real-time remotely. Therefore, the exploration rover has a navigation system that can autonomously traverse to the destination. The Mars Exploration Rover (MER) mission and the Mars Science Laboratory (MSL) mission conducted by NASA/JPL demonstrated navigation in which the rover autonomously performs localization, environment recognition, and path planning [1–3]. The effectiveness of the autonomous navigation system is verified in these missions. Research on navigation is currently being actively conducted to improve the driving efficiency of the rover [4, 5].

In order to improve the driving efficiency of the rover, it is necessary not only to improve individual navigation technologies but also to have the flexibility for the environment. More efficient driving becomes possible by switching navigation mode. However, in the past exploration rover, the method of switching the navigation mode according to the environment has not been used. In the Mars exploration rover Curiosity, the mode was changed in the near area where the operator can confirm and the distant area beyond the visual limit [6, 7]. This method only changes the behavior mode according to the distance. If the navigation mode can be switched according to the surrounding environment such as the presence or absence of obstacles and the geological condition, improvement of exploration efficiency can be expected.

Based on the above discussion, this paper proposes an autonomous behavior mode selection method for the planetary exploration rover in order to realize more efficient exploration. This study focuses on local path planning and global path planning. Traveling time is reduced by deciding whether or not to implement them according to the amount and placement of obstacles. In addition, by understanding the environmental map by deep learning, appropriate behavior mode selection is realized.

2 Behavior modes

In the proposed method, three behavior modes were prepared depending on whether local path planning was performed and global path planning was performed(**Table 1**). Local path planning plans a path to drive to a waypoint, and global path planning repositions waypoints when significant detours are needed. Directed is a mode in which neither local path planning nor global path planning is performed, and it moves straight toward the destination. It can move very fast because it requires almost no computational load, but there is a risk of collision with obstacles. Therefore, it can be used only in places where safety is guaranteed. Guarded is a mode that local path planning is performed. In Guarded mode, the rover drives along the path. Obstacles can be avoided by sensing, but there is a risk that the rover will not be able to escape when entering complex terrain such as dead-end because global path planning is not performed. AutoNav constantly performs local path planning and global path planning, then moves to the destination along the path obtained by the path planning. While it can move safely and reliably to the destination, it has the disadvantage that it takes a longer time to drive than Directed or Guarded due to the heavy calculation load.

Table. 1 Behavior Modes

Mode	Local Path Planning	Global Path Planning
Directed		
Guarded	✓	
Autonav	✓	✓

In this study, the above three behavior modes are selected according to the environment.

3 Behavior mode selection

The objective of the proposed method is to select an appropriate behavior mode so that the rover successfully traverses to the destination and minimizes the traveling and calculation processing time. Therefore, the proposed method selects the behavior mode according to the mode transition diagram shown in **Fig. 1**.

First of all, sensing is performed to confirm the presence or absence of obstacles. If there are no obstacles, there is no need to perform local path planning, so the rover drives by Directed. If there are obstacles, then an environment map is built to determine global path planning is required or not. An example of an environment map is shown in **Fig. 2**. To determine global path planning is needed from an environment map, deep learning was used. A convolutional neural network (CNN) consists of 4 convolutional layers and 3 fully connected layers, and its input is an environment map and its output is whether global path planning is necessary. If global path planning is needed, AutoNav is selected. If not, Guarded is selected.

4 Simulation Study

A simulation was performed to show the effectiveness of the proposed method. The

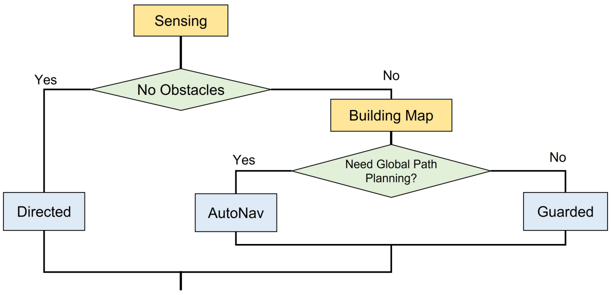


Fig. 1 Behavior Mode Selection Method

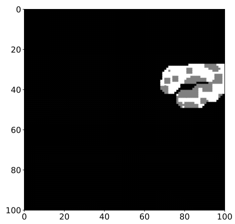


Fig. 2 Environmental Map

details are shown below.

4.1 Creating a pseudo-Mars environment

The simulation environment assumes a flat surface, and it is assumed that there are two types of terrain, an obstacle area where the rover cannot traverse and an area where the rover can traverse. In this simulation, nine simulated environments were prepared, and obstacles were randomly placed based on the obstacle occupancy rate. **Fig. 3** shows an example of a pseudo-Mars environment. The black area represents an obstacle, and the white area represents a traversable area. The pseudo-Mars environment is represented by a grid map, and the size of the map is 100 grids both vertically and horizontally. The size of the rover is the same as that of 1 grid, and the sensing area is omnidirectional with a radius of 5 grids.

4.2 Evaluation method

AutoNav mode only was used for comparison of the proposed methods. To evaluate the performance of each algorithm, traveling time is prepared(**Eq.1**). Traveling time represents the time required for the rover to traverse to the destination, and the smaller it is, the better.

$$TT = \sum_{i=0}^{i_{end}} \text{distance}(g_i, g_{i-1})\text{Cost}_{\text{M}}(g_i) \quad (1)$$

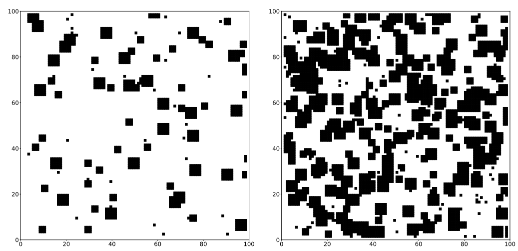
$$Cost_M(g_i) = \begin{cases} 1.0 & \text{if w/o sensing, w/o path planning} \\ 1.2 & \text{if w/ sensing, w/o path planning} \\ 5.0 & \text{if w sensing, w/ path planning} \end{cases} \quad (2)$$

$Cost_M$ represents the traveling time per unit distance. The traveling time per unit distance was set to a larger value as the calculation load increased, and was set based on the traverse record of the Mars exploration rover Curiosity [3]. Note that the traveling time was calculated only for the case where the rover successfully reached the goal.

In this paper, traveling time in each method was obtained by Monte Carlo simulation. In the Monte Carlo simulation, an episode simulation in which the rover drives from the start to the goal was performed 100 times for each method and each map. In addition, the start and goal were randomly arranged for each episode simulation and the direct distance between the start and goal was set to be separated by at least 100 grids.

4.3 Simulation result

The result of the Monte Carlo simulation is shown in **Fig. 4**. The traveling time became longer as the obstacle occupancy rate increased. Since AutoNav constantly performs sensing and path planning, the traveling time was long even in an environment with a low obstacle occupancy rate. On the other hand, the proposed method was able to significantly reduce



(a) 10% (b) 40%

Fig. 3 Pseudo-Mars environment and Obstacle occupancy

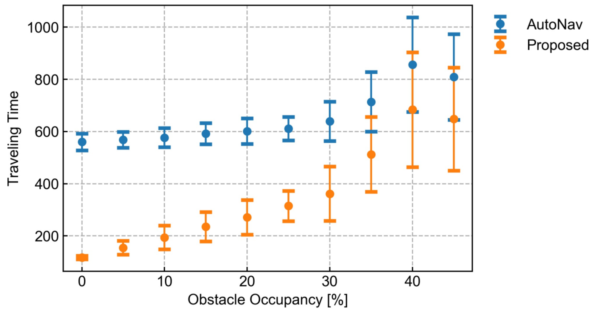


Fig. 4 The relation between occupancy rate and traveling time

the traveling time, especially in an environment where the obstacle occupancy rate is small. This is because the ratio of selecting Directed or Guarded mode is high in an environment with few obstacles. From the above, it was shown that the proposed method is effective even in an environment where there are many obstacles.

5 Conclusion

This paper proposed a behavior mode selection method for exploration rover navigation according to the surrounding environment and showed that driving efficiency can be improved. In this method, the surrounding environment is estimated from the sensed information, and it was decided whether to conduct local path planning and global path planning. The calculation processing is reduced by not performing local path planning. In addition, it was judged whether or not global path planning should be performed by understanding whether or not it was a dead-end from the environmental map by deep learning. In the future, it will be conducted that the realization of a behavior mode selection method that takes into account the uncertainty of sensing and the uncertainty of self-position estimation, assuming a more realistic environment.

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