Escaping Local Minima Using Repulsive Particles in FastSLAM for Space Rover

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***Abstract*—This paper describes the efficient strategy for guidance and control of a space rover using estimated position and a map acquired by using FastSLAM (Simultaneous Localization and Mapping) algorithm using a particle filter. A guidance law based on potential function method is also designed to cope with topographical change on a planet. Using the method, local minima problem in the potential field are frequently occurred when designing repulsive potential functions so as to avoid obstacles. To overcome the problem, we propose the new method that generates repulsive potential function at particles in FastSLAM for an exploration rover in unknown environment. Numerical results are performed to verify the validity of the proposed method for solving local minimum problem. Adaptive temperature parallel simulated annealing (ATPSA) method that is usually used to escape local minima is also applied to the system for comparison.**

***Index Terms*—component; FastSLAM; potential function method; repulsive particles; particle filter; space rover**

I. INTRODUCTION

It is practical and effective to use a space rover in exploration of a planet where manned exploration is impossible. Conventional space rover designs a path to a destination, and identifies its position by matching images of a camera mounted on a space rover with terrain images from an orbiting satellite. However, a space rover has difficulty identifying its position if mutual communication with an orbiting satellite is interrupted on account of an unexpected accident, or in the case of absence of an artificial satellite in orbit around a planet. Furthermore, the conventional method does not respond quickly to a sudden change in terrain because a space rover normally designs a path in advance.

The method using SLAM and the potential function method is considered as one of the effective methods. SLAM is the method of performing localization and mapping simultaneously with sensors mounted on a space rover, and the potential function method is the way by which a space rover is steered to the destination and avoid obstacles without a designed path in advance, i.e., a space rover can perform autonomous exploration in an unknown environment. However, an exploration of a space rover will be interrupted, and continuation of the mission will be almost impossible if it falls into local minima generated by a dense area of obstacles during the mission. ATPSA developed from SA (Simulated Annealing) that is one of the global optimum solution search method is proposed in order to solve this problem. This method requires iterative calculation to search the solution. As a result, it is difficult to implement this method in actual equipment because it takes a huge amount of time to escape local minima.

We propose the method combining the detecting local minima method with FastSLAM and the potential function method for the purpose of escaping local minima smoothly.

The number of times of resampling changes depending on the various landform when a space rover constructs the map information. This variation is applied to the detective of local minima, and a space rover escapes local minima by generating the repulsive function on particles used in FastSLAM. Comparing with ATPSA as a conventional method, the proposed method is possible to reduce the computational load.

We confirm effectiveness of the proposed method for the escaping local minima through numerical simulation.

II. GUIDANCE OF SPACE ROVER

A. Equation of Motion

Fig. 1 shows definition of a coordinate system and variable related to the kinematics of a space rover. Then, discrete-time state equation is expressed by the following equation. It is assumed that the motion of a space rover is restricted in XY plane.

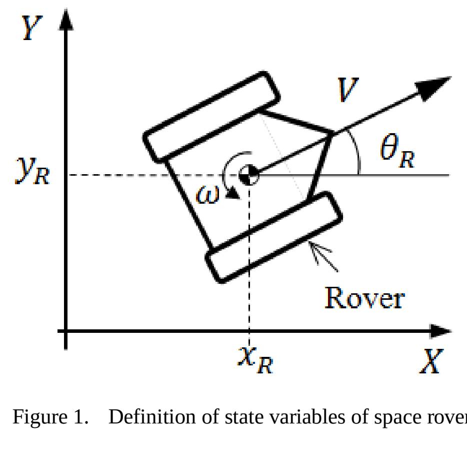

Figure 1. Definition of state variables of space rover.

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$$\mathbf{X}_R(k+1) = \mathbf{f}(\mathbf{X}_R(k), \omega(k), V(k)) + \mathbf{e}(k) \tag{1}$$

$$\mathbf{f}(\mathbf{X}_R(k), \omega(k), V(k)) = \begin{bmatrix} x_R(k) + T\,V(k)\cos\theta_R(k) \\ y_R(k) + T\,V(k)\sin\theta_R(k) \\ \theta_R(k) + T\omega(k) \end{bmatrix} \tag{2}$$

where $X_R(k) \in R^3$ shows the state vector of a space rover, $x_R(k)$ the X coordinate, $y_R(k)$ the Y coordinate, $\theta_R(k)$ the attitude angle, $V(k)$ the translational velocity, $\omega(k)$ the angular velocity, T the sampling period, $e(k) \in R^3$ the process noise of covariance matrix R. The equation of motion takes a slip of wheels of the space rover and sensor noise into account.

B. SLAM

SLAM is a method by which a space rover is enable to build a map of an unknown environment on the basis of information obtained from its various sensor and deduce its location at the same time [1]-[4].

In this study, we apply FastSLAM that uses the particle filter for localization and the extended Kalman filter for mapping to the space rover, and carry out the exploration mission. Fig.2 shows schematic diagram of SLAM.

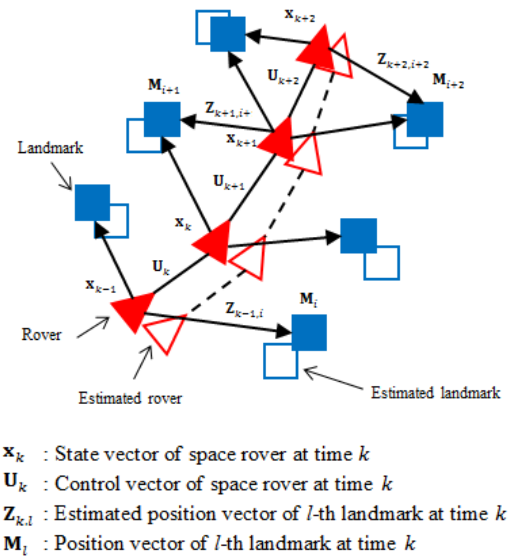


Figure 2. Schematic representation of SLAM.

C. FastSLAM

It is shown as the following equation that FastSLAM separates the localization from the building a map to calculate the probability [2-4].

$$P(x, s|z, u, c) = P(x|z, u, c)\prod_{l=1}^{n} P(s|x, z, u, c) \tag{3}$$

where x denotes the state variable, s the map, z the observed value, u the input, c the feature quantity of the obstacles, l the l-th obstacle, n the number of obstacles. In FastSLAM, the particle filter with the property of (3) can be used to estimate the trajectory of the space rover and the low dimensional EKF can be used to make a map.

In FastSLAM, p-th $(1 \le p \le m)$ particle is defined by the following equation.

$$[\mathbf{Y}_k]_p = \left\langle [\mathbf{x}_k]_p, [\boldsymbol{\mu}_{1,k}]_p, [\boldsymbol{\Sigma}_{1,k}]_p, \ldots, [\boldsymbol{\mu}_{n,k}]_p, [\boldsymbol{\Sigma}_{n,k}]_p \right\rangle \tag{4}$$

Here, $\mathbf{x}_k$ expresses variable to estimate the path of a space rover, $\boldsymbol{\mu}_{l,k}$ the mean of estimated position in l-th $(1 \le l \le n)$ landmark, $\boldsymbol{\Sigma}_{l,k}$ the covariance matrix. There are a total of m particles in the FastSLAM eventually. Filtering the posterior at time k from the one at time $(k-1)$ generates a new particle set $\mathbf{Y}_k$ from $\mathbf{Y}_{k-1}$ at time $(k-1)$. Generated particle set incorporates the input and the measurement. This update is performed in the following steps.

1) Prediction

FastSLAM uses the input u to sample state $\mathbf{x}_k$ of the space rover from each particle at time $(k-1)$, i.e., the posterior motion of p-th particle is sampled in accordance with the following equation.

$$[\mathbf{x}_k]_p = P([\mathbf{x}_k]_p | [\mathbf{x}_{k-1}]_p, u) \tag{5}$$

here $[\mathbf{x}_{k-1}]_p$ is the posterior estimate for a space rover location at time $(k-1)$. The obtained $[\mathbf{x}_k]_p$ is added to a temporary set of particles along with the previous trajectory $[\mathbf{x}_{1:k-1}]_p$.

2) Measurement Update

FastSLAM updates the posterior estimation of landmarks represented by the mean $[\boldsymbol{\mu}_{l,k-1}]_p$ and the covariance $[\boldsymbol{\Sigma}_{l,k-1}]_p$. The new mean and covariance are obtained by using the EKF measurement update.

$$[\boldsymbol{\mu}_{l,k}]_p = [\boldsymbol{\mu}_{l,k-1}]_p + [\mathbf{K}_k]_p(\mathbf{z}_k - [\hat{\mathbf{z}}_k]_p) \tag{6}$$

$$[\boldsymbol{\Sigma}_{l,k}]_p = (\mathbf{I} - [\mathbf{K}_k]_p[\mathbf{H}_k]_p)[\boldsymbol{\Sigma}_{l,k-1}]_p \tag{7}$$

in which, $[\mathbf{K}_k]_p$ is the Kalman gain that is given by

$$[\mathbf{K}_k]_p = [\boldsymbol{\Sigma}_{n,k-1}]_p[\mathbf{H}_k]_p([\mathbf{H}_k]_p[\boldsymbol{\Sigma}_{n,k-1}]_p[\mathbf{H}_k]_p{}^T + \mathbf{Q})^{-1} \tag{8}$$

moreover, $[\mathbf{H}_k]_p$ is the Jacobian of observation model, $\mathbf{Q}$ covariance matrix of the observation noise.

3) Importance weight

New particles in FastSLAM are weighted to reflect measurements $\mathbf{z}_k$. The weight for each particle is defined as follows:

$$[\omega_k]_p = \frac{1}{\sqrt{|2\pi[\mathbf{Q}_k]_p|}} \exp\left(-\frac{1}{2}(\mathbf{z}_k - [\hat{\mathbf{z}}_k]_p)^T[\mathbf{Q}_k]_p(\mathbf{z}_t - [\hat{\mathbf{z}}_k]_p)\right) \tag{9}$$

with the covariance

$$[\mathbf{Q}_k]_p = [\mathbf{H}_k]_p[\boldsymbol{\Sigma}_{n,k-1}]_p[\mathbf{H}_k]_p{}^T + \mathbf{Q} \tag{10}$$

4) Low variance resampling

FastSLAM has a process restrains the estimation error that occurs when a particle variance increases. This process is called resampling. In this study, we apply the low variance resampling to restrain a sampling error.

The standard resampling selects independently some particles from temporary particle set by using random numbers. Meanwhile, low variance resampling is method selects a particle in accordance with a probability proportional to the weight with a single random number r selected from the interval $[0\ m^{-1}]$. Therefore, the index U of selecting particles is defined as the following equation.

$$U = r + (p - 1)m^{-1} \tag{11}$$

From the above equation, the particle i satisfied the following conditional expression is selected.

$$i = \underset{p}{\operatorname{argmin}} \sum_{p=1}^{m} [\omega_k]_p \geq U \tag{12}$$

New particles are selected with repeating this process m times. Fig. 3 shows schematic diagram of low variance resampling.

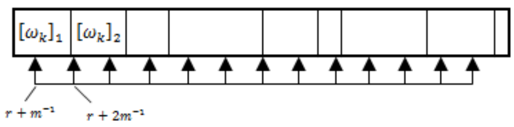


Figure 3. Schematic representation of resampling.

D. Potential Function Method

The potential function method is a way of generating an artificial potential field in an exploration area to guide a controlled object to a desired state while avoiding obstacles. In this method, the steering potential is designed to guide the controlled object to the destination, and the repulsive potential is applied to avoid obstacles. In general, the potential function $U(\mathbf{x})$ is composed of the steering potential $U^S(\mathbf{x})$ and the repulsive $U^R(\mathbf{x}_l)$ as shown in the following equation. Figs.4 and 5 show an example of integrated potential function and its velocity field [1,5].

$$U^S(\mathbf{x}) = C_a\sqrt{x^2 + y^2 + L_a} \tag{13}$$

$$U^R(\mathbf{x}_l) = C_r \sum_l \exp\left(-\frac{|\mathbf{x}_{R.l}|}{L_r}\right) \tag{14}$$

In the above equation, C_a expresses the magnitude of the gradient of the steering potential, L_a the gradient variation in the vicinity of the equilibrium point, C_r the gradient of the repulsive potential, L_r influence area relating to the repulsive potential. x_R denotes the position vector of the space rover, $|x_{R.l}|$ represents the relative distance between the l-th landmark and the space rover. When the gradient field of the potential function defined by the above equation is applied to the velocity field, the velocity command values to the space rover in the X direction and the Y direction are derived as follows:

$$V_X = -\frac{\partial U^S(\mathbf{x})}{\partial X} - \frac{\partial U^R(\mathbf{x}_l)}{\partial X} \tag{15}$$

$$V_Y = -\frac{\partial U^S(\mathbf{x})}{\partial Y} - \frac{\partial U^R(\mathbf{x}_l)}{\partial Y} \tag{16}$$

By using these equations, the velocity command V_d and the heading angle command θ_d for reaching the destination while avoiding obstacles are derived as follows:

$$V_d = \sqrt{{V_X}^2 + {V_Y}^2} \tag{17}$$

$$\theta_d = \tan^{-1}\left(\frac{V_Y}{V_X}\right) \tag{18}$$

III. Escaping Local Minima Method

A. Detecting Local Minima

In FastSLAM, each particle retains position information of the obstacles as shown in (4). In this way, robust mapping is guaranteed against a change in terrain with a large number of particles that keep different map information. However, if a space rover takes a long time to observe at same position, different map information that each particle retains is converged. As a result, importance weight of each particle expressed in (9) occurs biases notably. Moreover, effective sample size (ESS) expressed in (19) would decrease.

$$\text{ESS} = \left(\sum_{p=1}^{m} [\omega_k]_p^2\right)^{-1} \tag{19}$$

where m is a number of particle to be used, and if this is resampling condition, it's defined as the following equation.

$$\text{ESS} < \frac{m}{\alpha} \tag{20}$$

here α denotes threshold. This means that the frequency of resampling increases by taking a long time to observe same landmark. It is possible to utilize this characteristics as a means to detective local minima because space rover takes a long time to observe same landmark.

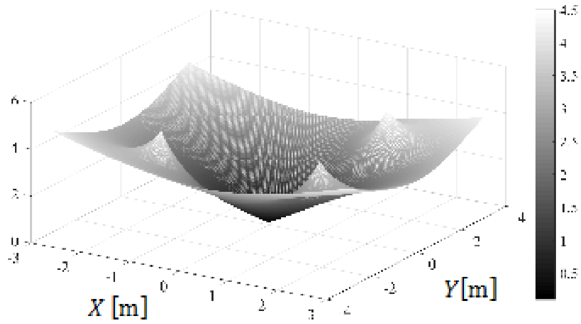


Figure 4. Integrated potential function.

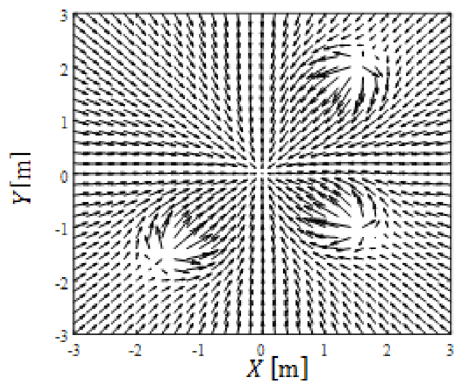


Figure 5. Integrated velocity field.

B. Escaping Local Minima

1) ATPSA

The ATPSA is an improvement of the SA (Simulated Annealing) so that the acceptance rate of a solution is 50 percent, and these methods apply the relationship between the temperature and the energy level of a substance. The ATPSA can be applied to escape local minima because the solution obtained by using this method gives a better approximation to a global optimum solution of a function given in a search space. Actually, its effectiveness has been verified by numerical simulation [1, 6, 7].

2) Repulsive Particles

The mean μ of a particle in FastSLAM used for estimating the state of the space rover is moved by $\Delta\mu$ toward the front of the space rover when the rover stops at a position that is different from a desired position. In addition, the variance value,σ^2, of a particle is also varied by $\Delta\sigma$ in accordance with the average relative distance between the space rover and landmarks. The distribution of particles that is close to the local minima is defined as,

$$f(x) = \frac{1}{\sqrt{2\pi{\sigma_a}^2}}\exp\left\{-\frac{(x-\mu_a)^2}{2{\sigma_a}^2}\right\} \tag{21}$$

where ${\sigma_a}^2 = (\sigma + \Delta\sigma)^2$ expresses the variance of a particle dispersed close to local minima, $\mu_a = \mu + \Delta\mu$ the dispersed mean. The subscript a denotes a spread particle. The particles scattered according to (21) are repulsive particles, namely, the repulsive potential is designed at particles dispersed close to local minima. Then the space rover can escape local minima by scattering repulsive particles toward the front of the rover.

IV. Numerical Simulation

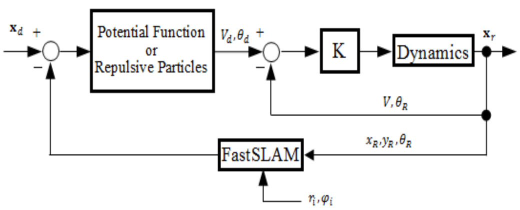
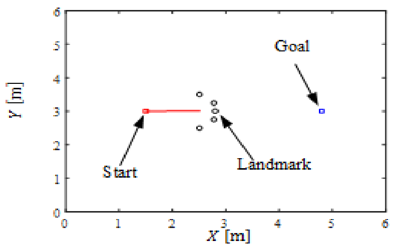
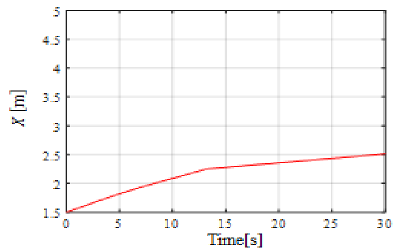


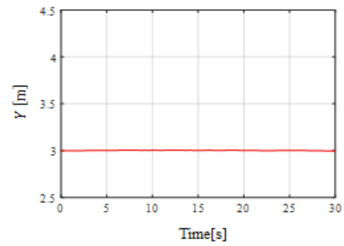
Figure 6. Block diagram of proposed control system.



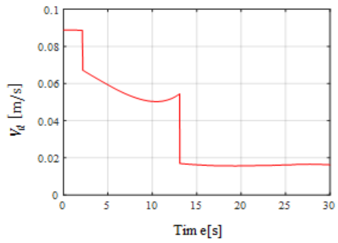
(a) Trajectory



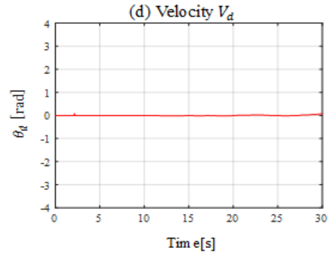
(b) Position X



(c) Position Y

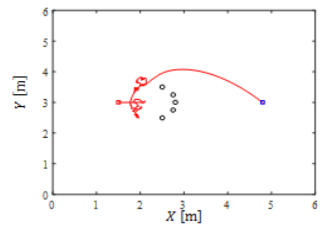


(d) Velocity V_d

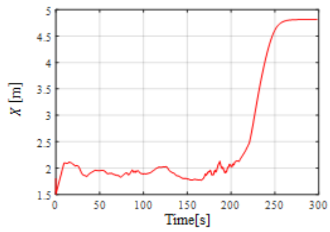


(e) Heading angle θ_d

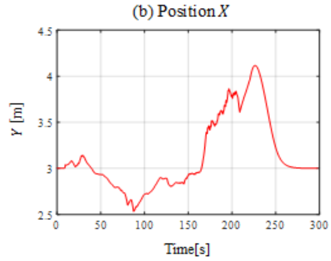
Figure 7. Without escaping local minima.



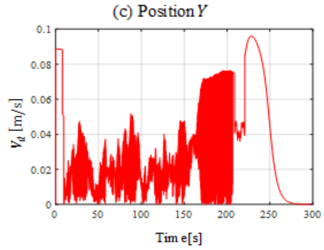
(a) Trajectory



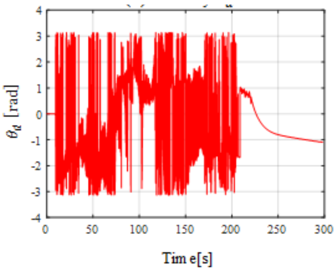
(b) Position X



(c) Position Y

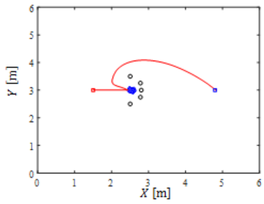


(d) Velocity V_d

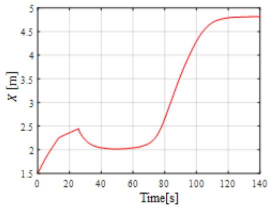


(e) Heading angle θ_d

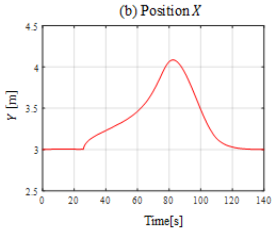
Figure 8. Escaping local minima using ATPSA



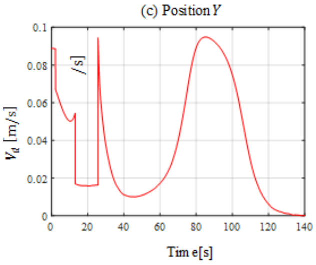
(a) Trajectory



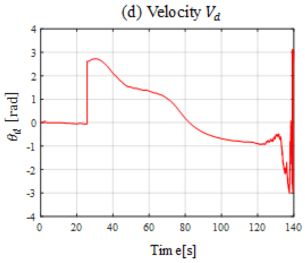
(b) Position X



(c) Position Y



(d) Velocity V_d



(e) Heading angle θ_d

Figure 9. Escaping local minima using repulsive particles

Fig. 6 shows the block diagram of the proposed control system. Here, $\mathbf{x}_d$ expresses the command of the state vector $\mathbf{x}$, V_d and θ_d the command velocity and heading angle found by the potential function method, respectively. x_R, y_R, θ_R, and V denote the position of the X coordinate, the position of the Y coordinate, the attitude angle, and the velocity of the space rover. r_i and φ_i are the relative distance and the relative angle of a landmark measured by the distance sensor. These values are applied to FastSLAM to control the rover based using measured data.

In the numerical simulation, the proposed method is compared with ATPSA that is one of conventional method for escaping local minima. Tables I to III represent values of parameters used in the numerical simulation. Figs. 7 and 9 show results in the case of without escaping local minima, with ATPSA, with the proposed repulsive particles, respectively. Fig. 7 (a) show that the space rover stopped at local minimum that is close to landmarks. On the other hand, it is clear from Figs. 8 (a) and 9(a) that the space rover succeeded in escaping the local minimum and reached the destination in both methods. However, using the proposed method, the space rover escaped the local minima smoothly in comparison with the result of ATPSA. Moreover, it is found that the calculation time to reach the destination is about half the time when using ATPSA.

TABLE I. PRAMETERS OF POTENTIAL FUNCTION

C_a(attractive gradient)	0.09
C_r(repulsive gradient)	0.06
L_a(sharpness)	0.3
L_r(area of influence)	0.4

TABLE II. INITIAL POSITION

Rover position $[x, y, \theta]$	[1.5,3.0,0]
Goal position $[x, y]$	[4.8,3.0]
Landmark 1 $[x, y]$	[2.78,3.25]
Landmark 2 $[x, y]$	[2.78,2.75]
Landmark 3 $[x, y]$	[2.5,2.5]
Landmark 4 $[x, y]$	[2.5,3.5]
Landmark 5 $[x, y]$	[2.8,3.0]

TABLE III. PRAMETERS OF FASTSLAM

Number of particles, M	100
Covariance matrix of observation, Q	$\begin{bmatrix} 0.01 & 0 & 0 \\ 0 & 0.01 & 0 \\ 0 & 0 & 0.01 \end{bmatrix}$
Covariance matrix of predict, R	$\begin{bmatrix} 0.1 & 0 \\ 0 & 0.01 \end{bmatrix}$
Threshold of resampling, α	2
Mean of repulsive particles, μ_a	[2.7,3.0]
Variance of repulsive particles, σ_a	0.1

V. CONCLUSION

We proposed the novel method that uses repulsive potential generated at particles in FastSLAM for solving local minima problem. The method was applied to a space rover in unknown environment. The numerical results showed that the space rover completed escaping a local minimum quickly in comparison with ATPSA that is often used for obtaining a global optimum solution. It was, however, also recognized from numerical results that the obtained path using the proposed method was able to compensate optimality such as minimum time for a mission. We will design an optimal path with escaping local minima for a space rover, and conduct experiments using the developed space rover in our future work.

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