IMAGE BASED BEHAVIOR PLANNING SCHEME FOR AUTONOMOUS PLANETARY EXPLORATION ROVER

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ABSTRACT

Various kinds of space explorations have been performed for decades in order to understand the origin of the solar system and life as well as to seek natural resources in space. Especially, rover missions which can perform detailed planetary surface exploration are under planning around the world. However, a rover mission still has difficulty in its autonomy in spite of its potential expectation. This paper proposes an autonomous driving system for efficient exploration. The proposed system contains three topics: environment recognition, path planning and behavior planning. By processing a pair of stereo images, objects and their positions, slope and texture of the terrain are recognized. Path is planned according to the weight and value of the parameters. During driving, behaviors like new image capturing, adjusting rover's direction and path re-planning are selected according to the situation.

1 INTRODUCTION

For direct and specific exploration of planetary surface, planetary exploration rovers have been developed by space agencies worldwide. The scope of rover mission includes gathering planetary surface images, understanding detailed terrain of the planet, analyzing the surface material, and will be expanded to building base and helping human in the future. Due to long time lag between the earth and planets and limited communication capacity, efficient automation is one of the most critical technical challenges for development of planetary exploration rover.

This paper proposes a total algorithm which navigates rover to the commanded goal autonomously. In addition to our the previous achievement in autonomous rover which consists of object detection and path planning [1], a behavior planning method to enable safe and robust long-distance drive is newly discussed.

2 RELATED WORKS

There are several autonomous rovers which have been used in the practical missions. Mars Exploration Rovers operated by NASA have performed impressive exploration activities on Mars. The MERs have autonomous traveling ability[1]. The Opportunity rover, which has driven over over $45km$, is still in operation[2]. MER employs 6 cameras for traveling over Martian surface. The path planning by MER is realized autonomously by creating DEM(Digital Elevation Map)[3]. DEM enables the evaluation of traversability based on the position of obstacles and slope to plan optimal path. With the limited spec of the rover CPU, it took over a minute to create DEM and plan paths[4], and the DEM had to be created frequently.

NASA's Curiosity rover launched in 2011 is equipped with new features like slip prediction by texture analysis and recover from slip by visual odometry[5]. It also learns the relation between the terrain and slip using receptive regression technique[6].

ExoMars rover under planning by ESA will be equipped with $2m$ core drill as well as PanCam aiming subsurface life signatures of morphological and chemical types[7]. ExoMars rover's behavior flow is planned as follows[8]:

- Recognize terrain with stereo camera and plan path by connecting way points
- Look for interest points from images captured during driving
- Calculate time and distance for detailed searching of the interest point
- Decide whether to search the point considering current driving plan and mission priority
- Insert the interest point in the rover's path plan

For detecting interest points, an edge extraction and labeling is applied, and then three characteristics: structure, texture and composition.

Those parameters are referred to the table where some typical characteristics(cross-bedded sandstone, carbonate etc.) are prepared.

3 ENVIRONMENT RECOGNITION

3.1 Object detection

Objects are detected from single image using combination of some visual features. The location of each object is measured by stereo vision. First of all, the position of horizon in the image is detected. Based on the previous work[9], Prewitt filter[10] is applied to find the line of horizon. For the later image processing, only areas under horizon is taken into consideration to reduce unnecessary computation.

Combining the variance and binarization results, obstacle areas are extracted by the algorithm proposed in the previous work[9]. The areas with high variance and white pixels, and areas with high variance and black pixels are recognized as obstacles. Small objects under the size of half the rover's wheel are eliminated because the rover is able to run over such small objects.

In the proposed method, the stereoscopy is applied to only four points per obstacle for computation efficiency as shown in Fig. 1. MER described in the previous section needs over a minute to recognize environment and plan paths because it calculates stereoscopy for every pixel.

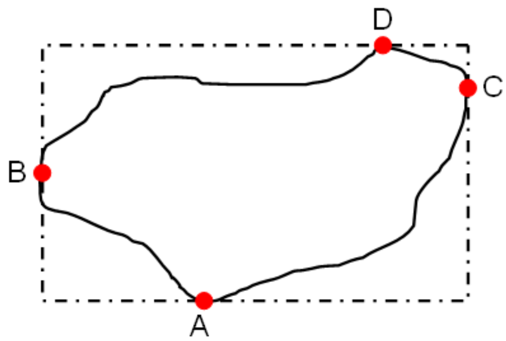

Fig. 1: Position measurement points

3.2 Slope Approximation

On the condition that there are enough numbers of objects, slope of the terrain is approximated by Delaunay triangulation. Triangular surfaces which consist of three dimensional points derived from stereoscopy are generated by Delaunay triangulation. Then the slope is estimated by calculating the normal vector of each triangular surface.

3.3 Terrain Classification

Terrain texture classification is conducted by histogram analysis and k-means clustering. To analyze the texture of the terrain, image area under the horizon is divided into 10×10 cells. Let $H(l)\,(l = 0, 1, 2, \cdots 255)$ is the histogram of each cell, the following parameters are analyzed:

- Contrast
  It is assumed that the contrast value is high in convex area which is exposed to the sun, and is low in area with less sunlight such as crater and shadow. The value of the contrast is calculated by Eq.(1).

$$CNT = \sum_{l=0}^{255} l^2 H(l) \tag{1}$$

- Energy
  The energy expressed by Eq.(2) is high in area where the pixel values are in the same level such as shadow and equable sandy area.

$$EGY = \sum_{l=0}^{255} H^2(l) \tag{2}$$

- Variance
  The variance value described by Eq.(3) is high at bumpy surface.

$$\begin{aligned} VAR &= \sum_{l=0}^{255} (1 - M)^2 H(l) \\ M &= \sum_{l=0}^{255} lH(l) \end{aligned} \tag{3}$$

Once three parameters (CNY, EGY, VAR) per each cell is derived, cells are classified by k-means clustering algorithm proposed by Steinhaus[11].

4 PATH PLANNING

In the proposed system, a path is expressed as connection of way points. The candidate of way point is selected from the four points around each obstacle considering the size of rover W.

Dijkstra' s algorithm is applied in the proposed method[12]. Dijkstra's algorithm is a well-known algorithm finding the shortest paths between nodes in a graph. When the cost of path between two nodes are defined, an overall path is derived so that the sum of the cost is minimum. For the cost definition, distance, slope and texture of the terrain are considered by Eq.(4) where L denotes the distance of the path between node $A(x_a, y_a)$ and node $B(x_b, y_b)$, S denotes maximum slope of the path and T denotes the danger parameter of the path. Let the cluster center of smooth texture be (C_s, E_s, V_s) and the texture on the path be (C, E, V), then T is described as Eq.(4). w_l, w_s, w_t are weight for each parameter.

$$
\begin{aligned}
cost &= w_l L + w_s S + w_t T \qquad (4)\\
where & \\
L &= \sqrt{(x_a - x_b)^2 + (y_a - y_b)^2}\\
S &= max(s_{roll}, s_{pitch})\\
T &= \sqrt{(C - C_s)^2 + (E - E_s)^2 + (V - V_s)^2}
\end{aligned}
$$

In the proposed system, two modes of weight determination are considered. In the case that the rover has high traverse ability or the searching area is flat, the path panning can be conducted based on only distance parameters($w_l = 1.0, w_s = 0, w_t = 0$). On the other hand, in the case that the rover's traversability has some limitation or there exist obstacles and slopes in the searching area, the path should be determined considering all parameters of distance, slope and texture like ($w_l = 0.1, w_s = 0.5, w_t = 0.4$). When these three weights are well-balanced, a short and safe path is planned.

5 EXPERIMENTAL RESULTS

5.1 Environment Recognition

The recognition ability of the proposed system is tested in an artificial test field. Also, the positions of objects could be measured with accuracy of 94.1% within the distance of $3m$ (see Fig. 2 and Table 1) and the slope of the terrain was approximated based on the object positions(see Fig. 3).

5.2 Path Planning

In path planning step, different paths were planned according to the weight parameters of environmental factors such as distance, slope and texture. The path planning result in which only distance is considered($w_l = 1.0, w_s = 0, w_t = 0$) is shown in Fig. 4. The path which goes the main object's left is selected. On the other hand, Fig. 5 shows the path planning result where distance, slope

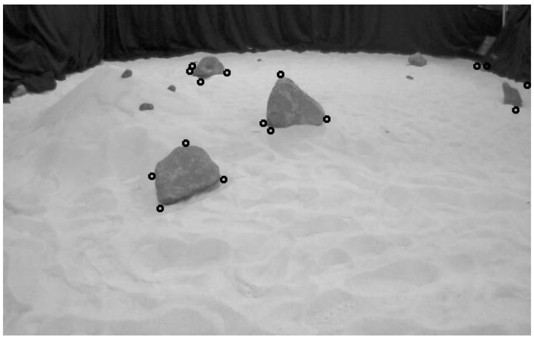

Fig. 2: Position measurement results

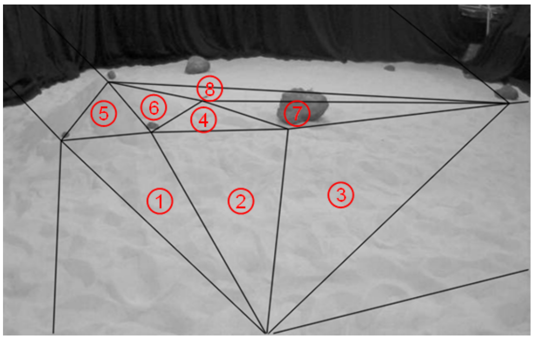

Fig. 3: Slope approximation result

and texture are considered comprehensively($w_l = 0.1, w_s = 0.5, w_t = 0.4$). The path which goes the object's right is selected in order to avoid dangerous slope on the left.

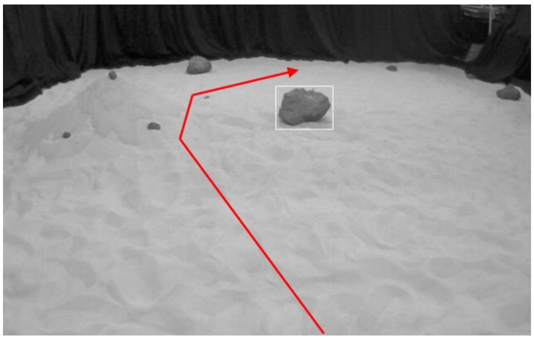

Fig. 4: Path planning result in which only distance is considered

6 CONCLUSION

An image-based autonomous driving system was proposed in this paper. In the environment recognition part, objects and their three dimensional positions were detected from a pair of stereo images. Also, slope of the terrain was approximated by three dimensional positions of the objects. In the path planning part, three parameters: distance,

Table 1: Position measurement results

Object No.	Position[m]	Position(stereoscopy)[m]	Accuracy
1	(-0.55, 1.25, 0)	(-0.57, 1.28, 0.01)	97.6%
2	(0, 2.02, 0)	(-0.12, 1.9, 0.19)	94.1%
3	(1.85, 2.9, 0)	(1.8, 3.22, -0.18)	89.0%
4	(-0.83, 3.68, 0.17)	(-0.66, 3.14, 0.19)	86.4%

Table 2: Slope approximation result

Triangle No.	$s_{roll}[°]$	$s_{pitch}[°]$
1	-10.28	-14.0
2	-5.81	-12.48
3	0.07	-12.36
4	-5.42	-10.61
5	-23.87	-54.53
6	24.18	-21.6
7	-1.25	-6.28
8	3.16	23.05

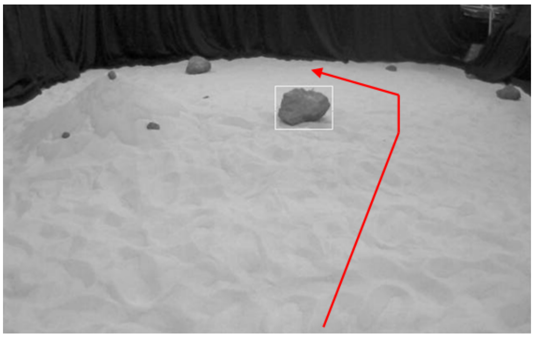

Fig. 5: Path planning result where three parameters are considered

slope and texture could be taken into the consideration to plan the safest path by the proposed algorithm. The proposed method would help long distance autonomous drive for future rover exploration mission.

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