Navigation Approach For Lunar Rover Based On Slip Prediction

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***Abstract*—This paper presented a method for navigation of lunar rover. This method used the real lunar data to model the virtual terrain. In addition, this method not onle considers uncertainty of sensor data, and does integrate directional slip prediction into the path planning algorithm resolving the issue of emerging higher-level behaviors such as planning a path with switch-backs up a slope. Simulation results show the feasibility and effectiveness of the algorithm in path planning for lunar rover.**

***Index Terms*—slip prediction, lunar rover; navigation**

I. INTRODUCTION

The exploration of lunar surfaces by lunar rover offers many technical challenges. One major difficulty concerns significantly increased autonomy in navigation required in order to meet future demanding mission criteria. Another major challenge for long-range traversal in highly unstructured and poorly modeled natural terrain is the large amounts of uncertainty in the rover model, terrain model, range sensor data, and rover path following errors. To this effect, the rover must possess the ability to navigate a path to a specified goal, in the presence of sensor uncertainty, while not exposing the rover to any undue risk.

The navigation is one of key technologies for lunar rover research[1]. The path planning is important component of the lunar rover navigation technology. It is the foundation which the robot carries out various mission . The existing path plan method divides into three types approximately: One kind is traditional path planning method based on the complete environmental information; Another kind is path planning method based on the behavior; The third kind is local path planning method based on the sensor information[2]. At present, in the complex natural terrain environment path planning methods of the commonly used planetary vehicle mainly have two kinds: Tangent Bug algorithm [3] and D* algorithm [4][5]. However, above two navigation methods has not considered slipping and uncertainty factors of modelling and sensing data.

Literature [6] proposed a kind of navigation method. It has considered influence of slip on the path plan.

However, it only analyses traversability of the lunar rover in the rough terrain. To be applied actually, many factors needed to consider, such as velocity of the path search algorithm, terrain parameter's online estimation and so on. This article proposed a kind navigation method of lunar rover. It planes the path using knowledge based genetic algorithm [7]. And the speed of this method was not only quick, but also it does integrate directional slip prediction into the path planning algorithm. It is the only method of present methods of path planning integrating slip prediction into the path planning algorithm.

II. TERRAIN MODELLING

The lunar terrain environment modelling is one of key technologies which the lunar rover accomplishes navigation task. It is the foundation that the lunar rover planes path. To simulate lunar rover's exploration actually in lunar environment, we must consider that lunar terrain feature, established the three dimensional lunar model, cause the lunar rover to move in above terrain, then test navigation capability of lunar rover.

A. Modelling Terrain of Triangulated Irregular Network

This article uses the satellite photography of the lunar terrain, obtains the terrain digital elevation model (DEM) data, establishes the three dimensional lunar topographical model, provides the navigation environment for the lunar rover.

This article uses in the Delaunay triangulation algorithm the commonly used insertion algorithm point by point to establish the TIN(Triangulated Irregular Network- TIN) model.

Then the model is as shown in Fig.1.Then,mesh must be simplified.

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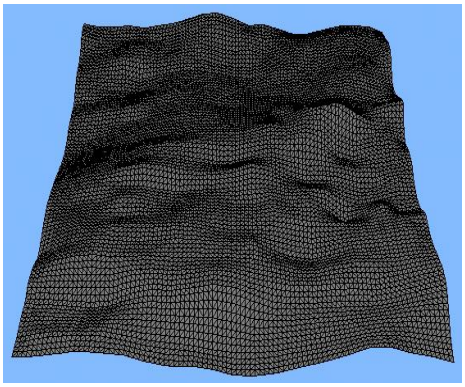

Figure 1 Lunar terrain map

B. Simplifying Mesh

This article uses the method which literature [8] proposed to carry on the terrain simplification. For a more detailed description, see literature [8].

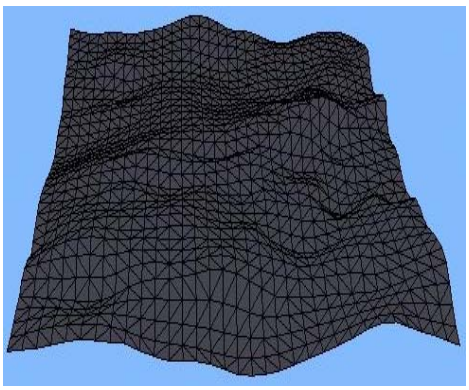

Figure 2 Lunar simplified terrain map

To fulfill the requirement of real-time computing, the algorithm for generating compact models of lunar environments from laser rangefinder is applied to reconstruct compact terrain with lunar rover. The algorithm adopted the pre-processing step leading to lower in-core memory consumption. It can be divided into the four steps as follows:

Step 1: PRE-PROCESSING Tag all the boundary triangles of the input mesh.

Step 2: READ(*k*) takes the next *k* triangles from the input stream and inserts them into the current in-core portion (which maintains both geometry and topology) of the mesh. $N_{current} \leftarrow N_{current} + k$

Step 3: DECIMATE(*k*) performs *k* edge collapse operation on the in-core portion of the mesh according to the multiple choice optimization strategy. Each edge collapse removes two triangles from the mesh.

$N_{current} \leftarrow N_{current} - 2k$

Step 4: WRITE(*k*) removes *k* triangles from the in-core portion and writes them into the output stream. $N_{current} \leftarrow N_{current} - k$

Then the simplified model is as shown in Fig.2.

III. UNCERTAINTY OF SYSTEM

In practice, in order to effectively detect the lunar environment and accomplish a given task, the lunar rover may have to rely on a variety of sensors (such as OD, visual sensors, etc.) to perceive the lunar surface environments, and thus build environment model, then plan motion and make decision. However, due to the limitations brought about by the sensor, the information obtained by the perception of these sensors there are information uncertainty in different degrees. Perceived uncertainty of the information will inevitably lead to uncertainty of model, accordingly, planning and decision-making based on models and perception, planning and decision-making will also be containing uncertainty.

A. Uncertainty model

Probability method is an effective means by which uncertainty is described. For uncertainties in above analysis, because the ultimate result is collision which possibly come into in movement process between lunar rover and obstacles, the system certainty can be described by the relative spatial relationship of the obstacle with the rover. As specifically shown in Figure 3.

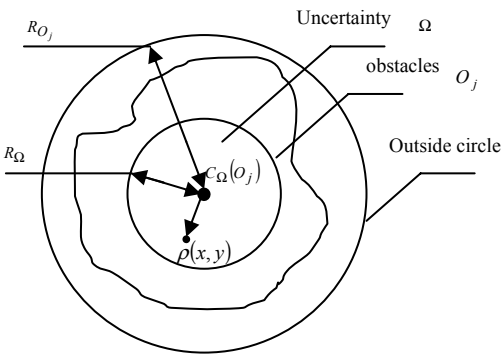

Figure 3 Uncertainty model

The probability density of Obstacle Center CΩ(Oj) is two-dimensional normal distribution as shown in formula (1).

$$\rho(x,y) = \rho'(r) = \frac{1}{2\pi\sigma^2} e^{-\frac{r^2}{2\sigma^2}} \tag{1}$$

In formula (5), $r = \sqrt{(x - x_\eta)^2 + (y - y_\eta)^2}$。

For a more detailed description, see literature [9].

B. Uncertainty Measure

To reflect the uncertainty of the system to the path planning model, and accordingly plan a safe path away from obstacles as possible, the paper proposes the concept of potentially dangerous areas, and describes the danger information which the uncertainty lead to by the introduction of risk measurement functions.

Figure 4 shows the relationship diagram between Obstacle Area, Expanded Obstacle Area, Forbidden Area, and Risky Area

The risk measurement functions $f_{G_{FD}}^{risky}$ can be defined as follows:

$$f_{G_{FD}}^{risky} = 255 \cdot \left[1 - \prod_{j=1}^{N} \left(1 - \Gamma\left(d\left(Fbd_j, G_{FD} \right) \right) \right) \right] \quad (2)$$

which,

$$\Gamma\left(d\left(Fbd_j, G_{FD} \right) \right) = \begin{cases} \iint_{G_{FD}} \rho'\left(d\left(Fbd_j, G_{FD} \right) \right) dxdy & d\left(Fbd_j, G_{FD} \right) \le D_{RA} \\ 0 & d\left(Fbd_j, G_{FD} \right) > D_{RA} \end{cases} \quad (3)$$

$$d\left(Fbd_j, G_{FD} \right) = \min_{E_n \in \partial Fbd_j} d\left(E_n, G_{FD} \right) = \min_{E_n \in \partial Fbd_j} \sqrt{\left(x_{E_n} - x_{G_{FD}} \right)^2 + \left(y_{E_n} - y_{G_{FD}} \right)^2} \quad (4)$$

For a more detailed description, see literature [9].

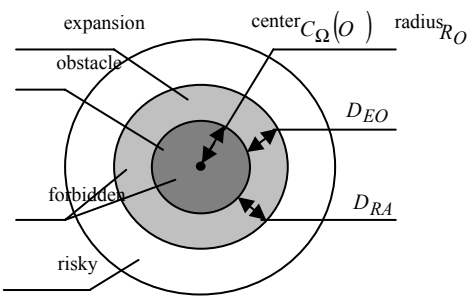

Figure 4 Obstacle area relationship diagram

IV. SLIP PREDICTION

Large amounts of slippage which can occur on certain surfaces, such as sandy slopes, will negatively affect rover mobility. Therefore, obtaining information about slip before entering a particular terrain can be very useful for better planning and avoiding terrains with large slip.

Slip is a measure of the lack of progress of a wheeled ground robot while driving. High levels of slip can be observed on certain terrains, which can lead to significant slow down of the vehicle, inability to reach its predefined goals, or, in the worst case, getting stuck without the possibility of recovery.

Similar problems were experienced in the Mars Exploration Rover (MER) mission in which one of its rovers got trapped in a sand dune, experiencing a 100% slip. In future missions it will be important to avoid such terrains, which necessitates the capability of slip prediction from a distance, so that adequate planning could be performed. This research is relevant to both Mars rovers and to Earth-based ground robots.

In this section we describe the slip prediction method using vision information. And we decided to adopt the slip prediction method of D. Kim et al.[10]. This method ,at first, use texture based classification method to extract material information from each segmentation of image of environment. By using their segmentation technique, compositional ratio of materials are obtained. This result is terrain information.Each terrain will be grouped by using compositional ratio of materials of terrains. Thus, this can be applied to predict friction coefficient usefully.Path planning of autonomous mobile robot depends on the predicted result so as to avoid slippery area.

A. Terrain classification

The approach to terrain classification is based on processing visual appearance information,namely texture and color. The te xton based algorithm is applied which uses both color and texture simultaneously to learn to discriminate different terrain appearance patches. The algorithm proceeds as follows: initially the color R,G,B values in small pixel neighborhoods are collected and the most frequent features in the whole data are selected. Then a histogram of the occurrence of any of the selected features within a patch corresponding to a map cell is built and compared by using a nearest neighbor classifier to a database of training patches. Intuitively, a patch from a bedrock class will have a high frequency of pixels typical of previously observed bedrock patches, but it might also contain a small number of pixels which are typical of an unfamiliar to the system “pebble” class which happens to be also shared with the soil class too (either of the terrain types patches might have small rocks dispersed in them). That is,this representation allows for building more complex appearance models and making correct decisions given the observed statistics from the data. In order to deal with variations in lighting conditions this algorithm uses normalized color during the training and classification steps.

B. Learning the slip models

As each terrain type has a potentially different slip behavior, a slip model for each terrain independently is learned. The slip models are built by learning a nonlinear approximation function which maps terrain slopes to the measured slip.

C. Implementation details

The algorithm is designed to provide efficient slip prediction. Because terrain classification from visual information is generally time consuming, the focus has been on decreasing the amount of computation devoted to image processing related to terrain classification. In particular, the main idea is to evaluate the terrain type per map cell, rather than evaluating the terrain type in the whole image. This design concept can give significant advantages. Some speed-up can be achieved, as parts of the image do not belong to the map. Additionally, the terrain classifier will not be invoked if slip prediction is not needed in a certain area, e.g. an area which the terraintriage has already marked as definitely not traversable. Finally, a map cell at a close range covers a large part of the image compared to the ones at far ranges and can be processed selectively to speed up the processing without hurting the overall performance. To

achieve that, the map cell structure we use saves only its 3D location and pointers to images which have observed it. When the terrain type needs to be predicted in a particular map cell, a projection of the map cell to the image is done and an image patch corresponding to this cell is retrieved.

Additionally, this paradigm allows for stereo imagery data to be received asynchronously or intermittently. It also enables more efficient computation when multiple overlapping images are acquired (as is typical with a panorama) by evaluating the terrain classification once per cell rather than once per image. The result of the terrain classification is saved with its corresponding confidence and might be combined with a potentially new evaluation if the confidence is insufficient. This is in contrast to processing fully all of the incoming images, extracting visual features and saving them to the map cells.

For clarity, we first describe the prediction part of the algorithm, assuming the terrain classifier and the slip models have already been learned.The slip prediction module receives stereo pair imagery and rover attitude with respect to gravity as inputs. A map of the environment is built using the stereo range data registered with the color and texture information from the input images. In particular, each cell of the map contains information about terrain elevation and points to an image patch which has observed this cell. To predict slip in a map cell, the terrain classifier is applied to all the map cells in its neighborhood. A majority voting among their responses is used as the final terrain classification response at the desired rover location.

Then, a locally linear fit in the cell's neighborhood is performed to retrieve the local slope under the potential rover footprint. The slopes are decomposed into a longitudinal and a lateral slope with respect to the orientation of the rover. The two slope angles are used as inputs to a pre-learned nonlinear slip model for the particular terrain type determined by the terrain classification algorithm. The output of this module is the predicted slip for a given orientation of the rover and a slip related cost at a given location. The slip related cost is an estimate of rover mobility without regards to particular robot orientation. It is used by the path planning algorithm by producing a slip goodness map. This map is generated by linearly combining the predicted longitudinal and lateral slip for each cell of the map and selecting the maximum slip over a range of rover yaws.

During training, the rover collects appearance and geometry information about a particular location while it is observed by the rover from a distance. The corresponding slip of the rover is also measured when this location is being traversed. We use visual odometry (VO) between two consecutive steps to estimate the actual rover velocity. The commanded velocity of the rover is computed by using the full vehicle kinematics. The collected data pairs of visual information and slip measurements are given to the learning module which learns a terrain type classifier and independent slip models for each terrain type. A rover position estimation is computed within the slip prediction module by accumulating the VO estimates. This is necessary to be able to map the current rover location to a location previously observed by the rover from a distance.

The prediction function is as followings:

$$\hat{F}(x)=\sum_{c=1}^{C}K(x,x_c)\left(b_0^c+b_1^c\right)<x_c,x> \tag{5}$$

Where x are compositional ratio of material of new terrain, and F is friction coefficient of new terrain.

The evaluaton of the slippage is mainly according to $F_{\max}^{fc}$ of the biggest friction coefficient of planetary terrain. when $\overline{F}$ of the slippage of analyzed area surpasses $F_{\max}^{fc}$, then this region is not thought to belongs to the zone, otherwise the traversable zone. And, the solution of $\overline{F}$ needs to consider the two factors. First, $\overline{F}_{patch}$ of the slippage which the analysis window (i.e. the body size of planetary rover) covers the slipping region, next $\overline{F}_{cell}$ of the slippage which in the analyzed window each triangle covers the slipping region. If maximum slipping value of all triangles is $\max\_\overline{F}_{triangle}$ in the definited analysis window, then has

$$\overline{F}=\max\left(\overline{F}_{patch},\max\_\overline{F}_{triangle}\right) \tag{6}$$

Similarly, to reflect planetary the traversablity of the rover in different slipping terrain to the path planning model, this article has introduced the sectional slipping cost function, and its definition is:

$$f_{fc}\left(\overline{F}\right)=\begin{cases} +\infty & \left(\overline{F}>F_{\max}^{fc}\right) \\ c_{\max}^{pitch} & \left(\mathrm{k}_{f2}F_{\max}^{fc}\le F<F_{\max}^{fc}\right) \\ 255\times\dfrac{\overline{F}}{F_{\max}^{fc}}, & \left(\mathrm{k}_{f1}F_{\max}^{fc}\le F<\mathrm{k}_{f2}F_{\max}^{fc}\right) \\ c_{\min}^{pitch} & \left(\overline{F}<\mathrm{k}_{f1}F_{\max}^{fc}\right) \end{cases} \tag{7}$$

In the formula, $0<k_{f1}<k_{f2}<1$. Partition evaluation of $f_{fc}\left(\overline{F}\right)$ is thought same as $f_{pitch}(\theta)$. As a result of the complexity in planetary surface environment, its terrain feature usually demonstrate the different combination of each kind of cost. Therefore, when analyzing the traversablity of the triangle, we need to evaluate the analysis result of each kind of cost. If the definition the traversable cost function of the analyzed triangle is $f_{triangle}^{trav}$, then

$$f_{triangle}^{trav}=\max\left(f_{pitch}(\theta),f_{\mathrm{roughness}}\left(\overline{D}\right),\right.$$
$$\left.f_{fc}\left(\overline{F}\right),f_{step}(RF)\right) \tag{8}$$

The detailed connents refer to the literature[9].

V. PATH PLANNING ALGORITHM

The following is specific steps of path planning based on genetic algorithm presented in this paper:

Step1. Environment modeling. Do environmental modeling using grid method proposed by Simon, and Yang.

Step2. Coding and initialization.

Lunar environment is expressed by the triangular mesh model. Planning path, an undirected weighted graph is built, in which each node represents a triangle in the triangle mesh model, and edges represents connection lines between the two triangles. Each node is identified by an order number, the node's coordinates is the center coordinates for each triangle. Here

$$p = x + 10 \times y \tag{9}$$

Sequence identity number of path points is as the path encoding. We assume that there is not duplicated serial identification number in each path. For example, a path can be expressed as 0-24-36-66-74-84-99, where 0 is the starting point, 99 for the target point, and 36,66,74 and 84 for the intermediate nodes.

To encode possible paths, set the counter of evolution algebra $t \leftarrow 0$; set the maximum evolution algebra T; generated n individuals randomly as initial population $P(0)$.

Step3. Individual evaluation. Using the equation $L(a_n) = \sum_{i=1}^{N} (d_i + f_i) + \beta_i \mathrm{C}$ to calculate each individual's fitness value in population $P(t)$.

Step4. Determine whether the environment changes. If the environment changes, then run step 5. Otherwise, go to step 6.

Step5. Re-evaluation for population $P(t)$.

Step6. Tournament selection and elitist selection. To retain the best individual in parent population, run tournament selection in parent groups,.

Step7. Crossover operation. Use the single-point adaptive crossover operator on the group.

Step8. Mutation operation. Use the adaptive mutation operator on the group.

Step9. Other operations. Use other operator on group $P(t)$. After these sessions of selections, we finally get the next generation $P(t+1)$.

Step10. To determine whether it is in the dynamic environment. If it is, then go to step 4. Otherwise, run step 11.

Step11. To check if the final condition is meet If $t \le T$, then $t \leftarrow t+1$ is right, go to step 3; if $t > T$, we can consider the minimum fitness value of the individual as the optimal solution, output it and stop computing.

VI. EXPERIMENTAL RESULTS and ANALYZE

To confirm the validity of path planning algorithm which this article proposed, we have carried on the path planning experiment in the lunar environment. The main simulation parameter is as follows: The environment is 24m×24m lunar terrain; k1=0.8, k2=0.05, k3=0.75, k4=0.5. Beginning and end point coordinate respectively is beginning point(4.125,7.125), end point (14.125,16.125).One of path planning simulation results is as shown in Figure 5.

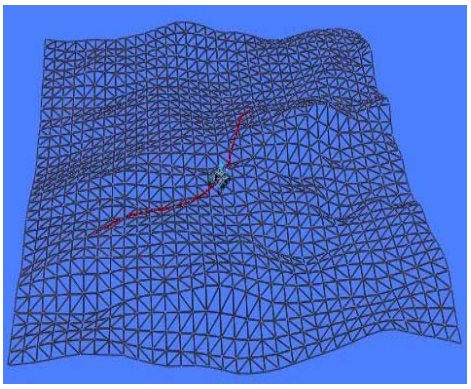

Figure 5 Typical simulation result

VI. CONCLUSION

This article proposed one kind of lunar rover navigation method based on the slip prediction. This method uses the real topographical data to modelling the lunar terrain, uses based knowledge genetic algorithm to plan the path in the three dimensional terrain environment. Simultaneously, it incorporates slip prediction into the path planning algorithm. The simulation result further shows feasibility and the validity of this method in the lunar rover navigation.

The future research work will devote to the online estimation of the contact angle of wheel and terrain, and the terrain main physical parameter.

For the time being, we do offline training of both the terrain type classifier and the slip behavior predictors for each terrain type, but our future work is targeted at slip learning in an online fashion, which has influenced the selection of the algorithms and methods in this work.Further efforts are needed to develop a better terrain classification algorithm, to avoid erroneous slip prediction due to terrain type classification errors. Visual information might not be sufficient to distinguish various terrain types and properties, especially considering Mars terrains. It can be complemented with multispectral imaging or other sensors to resolve some inherent visual ambiguities and improve on the classification results. A more advanced algorithm to consider spatial continuity of terrain classification over neighboring patches or dependent on terrain geometry also needs to be investigated.

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