MODELING OF LIDAR MEASUREMENT UNCERTAINTY FOR ROVER PATH PLANNING

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ABSTRACT

A planetary rover is required to perform longer and safe autonomous drive. The autonomous drive system in the past rovers basically utilizes onboard stereo cameras for taking three dimensional terrain maps. The system then assesses terrain traversability on the map and guides the rover to a location of interest. A laser imaging detection and ranging (LIDAR) technology is also useful particularly for longer and wider mapping that can extend the capability of the autonomous drive, even though any LIDARs for the rover usage have not been flight-proven. In general, the LIDAR is carefully calibrated in its fabrication process but it is still subject to an error for distance measurement, resulting in less accurate assessment of the terrain traversability. The work presented in this paper first performs an experimental test of a LIDAR accuracy with varied distances/reflectance of objects, and empirically elaborates an uncertainty model of the LIDAR measurement as a function of distance and intensity measured. The proposed model is then incorporated into a simulation framework of a rover path planning. Paths generated from the simulation are more ramified as the uncertainty of the LIDAR measurement increases. This result indicates that the proposed model can be useful to statistically assess untraversable region while a rover performs longer autonomous drive.

1 INTRODUCTION

As a mobile robot performs an autonomous mobility task such as localization, mapping, and path planning, a LIDAR has been commonly used as a promising and primary sensor for taking geometric information around the robot. This is because the LIDAR has an advantage on detecting longer range than a stereo camera, and also, it can take various reflectance of objects, resulting in an intensity image which provides a pseudo gray-scale image being useful for tasks stated above. For these reasons, there are reasonable prospects of its use in the future space missions [1][2] although the LIDAR has some difficulties owing to its low space-qualified performance, including radiation vulnerability, limited heat tolerance, and high power consumption.

The LIDAR also possesses a range-dependent uncertainty (or error) in its measurement because of reflection intensity and background light. Such uncertainty still remains even after a careful sensor calibration. Therefore, for a long-range autonomous drive of a planetary rover with LIDAR, the measurement uncertainty should be taken into account in order for the rover to avoid hazardous regions where the LIDAR may have serious errors.

Several studies for the LIDAR measurement uncertainty have been reported. The work reported in [3] summarized that two factors are mainly related to the LIDAR measurement errors: geometric factor such as target distance and non-geometric factor such as temperature, ambient illumination, and texture of target materials. Even though the detail investigation on the LIDAR measurement accuracy was conducted, there is still an inconsistency between the theoretical accuracy of the LIDAR and the observed performance. A calibration approach for the LIDAR sensor error was also investigated [4]. This paper revealed that parameters related to the exposure time, the focal length, and the positional difference of the pixels degrade the LIDAR performance, and proposed a precise calibration approach. However, the approach is only applicable in the case where the environment data such as external temperature and ground texture data are given beforehand. Consequently, an uncertainty of the LIDAR measurement may still exist even after a careful sensor calibration, and a method dealing with the uncertainty needs to be addressed. An approach for the autonomous drive of the rover that considers system uncertainty, for instance, the rover position, the terrain model, and rover path following have been proposed [5][6]. These works assumed the worst case of the uncertain parameters so they may overestimate mobility hazard and restrict the motion of the rover. The uncertainty should be statistically considered for both robust and optimal mobility of the rover.

The work described in this paper develops an empirical-based sensor uncertainty model that considers distance and intensity measured by the LIDAR. The model is then plugged into a simulation framework for rover path planning that demonstrates a possible application of the proposed model.

The paper is organized as follows: Section 2 describes an experimental procedure of the LIDAR measurement for the uncertainty modeling. In Section 3, the LIDAR measurement uncertainty model is elaborated based on statistical analysis of the

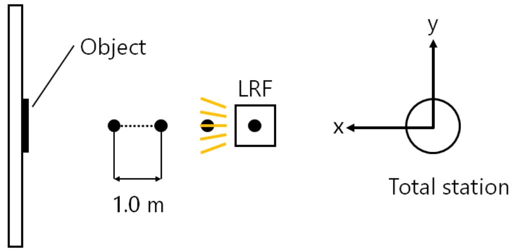


Figure 1: Top view of the experimental setup

experimental results. Section 4 describes a demonstration of the proposed model in the simulation of rover path planning.

2 EXPERIMENT ON LIDAR MEASUREMENT

The LIDAR measures the distance based on the Time of Flight (TOF) principle, which counts the time from an event on a light emission of the laser diode to another event on a light detection returning from an object. Based on this principle, the LIDAR can output ranging data with an intensity of the reflected light. The value of intensity is generally proportional to a reflectance of an object surface, and therefore, the LIDAR also provides a grayscale image each pixel of which contains the intensity value. The data measured by the LIDAR often includes an error due to background noise, temperature, or surface texture of an object. These errors can be compensated from a preflight sensor calibration, but in an actual environment where a planetary rover is operated, measurement errors due to extreme temperature or unknown objects are usually unpredictable and an online calibration for such errors cannot be performed since the true measurement is not available.

This section describes an experimental test on the LIDAR measurement errors with respect to varied distance and intensity values.

2.1 Experimental Procedure

The experimental setup is depicted in Figure 1. In this experimental setup, Swiss Ranger 4000 (SR4000) [7] is used as a typical LIDAR. The specification of this LIDAR is summarized in Table 1. As a target object, a gray card which has different reflectance (18%, 50%, and 90%) is used. The measurement distance varies from 1.5 m to 9.5 m at 1 m intervals. The position of the object and the LIDAR are positioned using a total station.

Two control parameters of the LIDAR are tunes: one is the Integration Time (IT), which is the length of time that the pixels on the LIDAR collect light, being set as 5.3 ms and 15.3 ms; the other one is the Modulation Frequency (MF), which defines

Table 1: SR4000 Specification

Modulation Frequency	30 MHz	15 MHz
Detection Range	0.1 – 5.0 m	0.1 – 10.0 m
Calibrated Range	0.8 to 5.0 m	0.8 to 8.0 m
Absolute accuracy	$\pm$10 mm	$\pm$15 mm
Repeatability of central pixels	4 mm (typ.)	6 mm (typ.)
	7 mm (max.)	9 mm (max.)

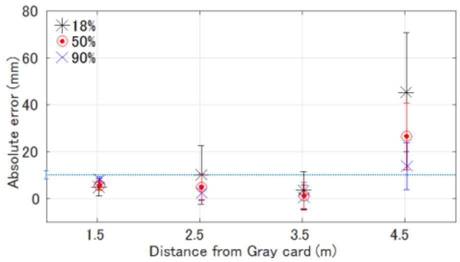
the maximum measurement range, being set to 30 MHz (max. 5 m range) and 15 MHz (max. 10 m range).

In this experiment, the LIDAR takes ranging data 100 times at each measurement position with each object. We used the data taken by the laser distance measurer, Leica DISTO D5 as a true value. The experimental result is then analyzed based on the following two statistics: the absolute error between the mean of the measured values and the true value, and the repeatability which is a measure of the spread of measurement (standard deviation) around the mean value. These two statistics are correlated with respect to the true distance and intensity value.

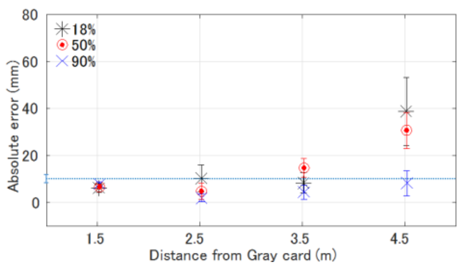
2.2 Experimental Results and Discussion

Figure 2 shows the results on the condition that MF is 30 MHz in each IT. The error bar with plots in the figure represents the repeatability. Both absolute error and repeatability increase as to the distance. For the object having a lower reflectance, both absolute error and repeatability increase. As for the influence on the difference of IT, the repeatability decreases as IT increases while the absolute error does not increase much. The SR4000 used in the experiment has the absolute accuracy of 10 mm (the dotted line in the figure) and the repeatability of 7 mm. The experimental results in the absolute error and repeatability are larger than such specifications.

Based on the measurement principle of the LIDAR, a transition of distance is not relevant to the absolute error although this contradicts the experimental result that the absolute error increases as the distance increases. This contradiction may be due to a multiple reflections or multipath of the light from/to the LIDAR. The multipath is the phenomenon that the LIDAR miscounts the light reflected from an object other than a target, mainly from wall or floor. The values measured through the multipath are then distorted as longer or shorter values. The longer the distance between the object and the LIDAR, the more possibility the wall and floor are within the field of view of the LIDAR, resulting in more frequent multipath. On the other hand, the absolute error and repeatability with regard to the influence of a change of intensity can



(a) MF=30 MHz, IT=5.3 ms



(b) MF=30 MHz, IT=15.3 ms

Figure 2: Measurement error w.r.t. varying distance and different reflectivities

be calibrated by optimizing the IT.

In summary, the LIDAR measurement error cannot be completely compensated based on only a calibration table implemented in the LIDAR includes because of the inevitable and unpredictable uncertainty such as multipath.

3 MODELING OF LIDAR MEASUREMENT UNCERTAINTY

The experimental results in the previous section show that the absolute error tends to exponentially increase as the distance, and linearly decreases as the intensity value increases. Based on this observation, the LIDAR measurement uncertainty model is developed. Note that, in this work, the measurement uncertainty of the LIDAR is assumed to be affected only in terrain elevation because the change of terrain elevation has a serious influence on a rover mobility. The proposed model that consists of three equations is described in equation (1), (2), and (3).

$$z' = z + rand_{\text{index}}\, E \quad E \sim \mathcal{N}(\mu, \sigma) \tag{1}$$

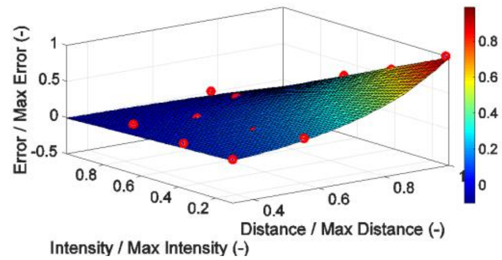
$$\mu = e_{abs}\, f(d, A) \tag{2}$$

$$\sigma = e_{rpt}\, g(d, A) \tag{3}$$

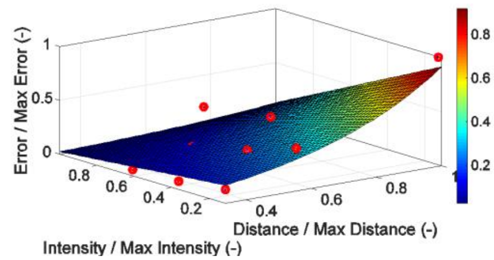
where z' represents the terrain elevation taking account of the uncertainty; z represents the terrain elevation measured by the LIDAR; $rand_{\text{index}}$ is the random number which takes a value between 1, 0, or -1 with the probability of 25%, 50%, and 25%, respectively. This expresses that the measurement uncertainty is affected in the positive direction (as it takes 1) or in negative direction (as it takes -1) or the LIDAR has no error (as it takes 0). $E \sim \mathcal{N}(\mu, \sigma)$ means that the random variable E is normally distributed with the mean μ and the standard deviation σ, where μ and σ are described in Eqs. (2) and (3). In Eqs. (2) and (3), e_{abs} and e_{rpt} represent the absolute error and repeatability defined by the LIDAR specification, respectively. The functions f and g are formulas defined as:

$$f(d, A) = (\lambda_1 A + \lambda_2) e^{\lambda_3 d} \tag{4}$$

where d represents the distance measured; A represents the intensity obtained; and $\lambda_1 \dots \lambda_3$ are the coefficients given from the curve fitting of the experimental results.



(a) Uncertainty model for absolute error



(b) Uncertainty model for repeatability

Figure 3: Curve fitting with the proposed model for measurement errors

Figure 3 shows the curve fitting result using the proposed model in regard to the experimental data for the absolute error and repeatability. The top figure represents the curved surface of the absolute error comes from the experimental result with IT=5.3 ms and MF=30 MHz. The bottom figure, which is the curved surface of the repeatability comes from the result of IT=15.3 ms, MF=30 MHz. These graphs show that the LIDAR measurement uncertainty model fairly expresses the absolute error as well as the repeatability.

Figure 4 depicts a probability distribution of the proposed model related to the uncertainty z' from two kind of inputs: the upper figure shows less measurement uncertainty while the bottom one is for more uncertainty. These figures illustrates that the probability of the uncertainty is inversely proportional to the value of μ.

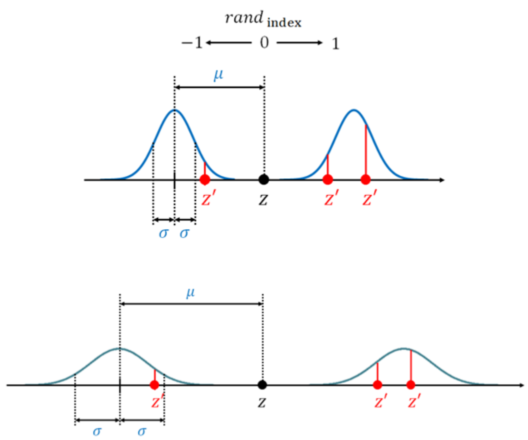


Figure 4: Probability distribution of Measurement uncertainty from the different input to the proposed model

4 PATH PLANNING WITH UNCERTAINTY MODEL

4.1 Simulation Framework with the Uncertainty Model

A general path planning process provides a path which is optimized based on a cost function composed of several indices such as traveling distance, terrain roughness, and roll and pitch angle of a rover. Each index is calculated from terrain geometry data usually taken by stereo camera pair or a LIDAR. Here, assuming that the terrain geometry data includes measurement errors, the path planning calculated from such data is also subject to the uncertainty, and it may not be able to provide an optimal path. Therefore, in this work, such path planning uncertainty is numerically evaluated by incorporating the LIDAR measurement uncertainty model proposed in Section 3.2 into a simulation framework for a rover path planning.

A basic flowchart of the path planning simulation is shown in Figure 5. As a rover loads a measured terrain data, by taking the measurement uncertainty model into account, the indices used in the cost function (terrain roughness and slope angle) significantly differ, and then, they affect the result of path generation. In this work, an original terrain data is randomly modified based on the LIDAR measurement uncertainty model in every case of the path planning simulation. Note that the intensity value in the terrain data is randomly allocated to each point on the terrain. The terrain map is generated as a 10 m semicircle (Figure 6).

4.2 Simulation Results and Discussion

Figure 6 shows the results of the path planning simulation in 100 random cases. All generated path is depicted on the original terrain data. In the case shown in Figure 6a, the longer the distance from the rover, the wider the paths diverge. In the region the paths differ significantly, it can be deduced that the LIDAR

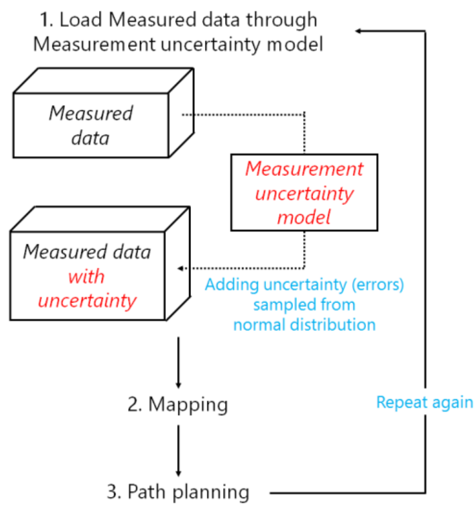


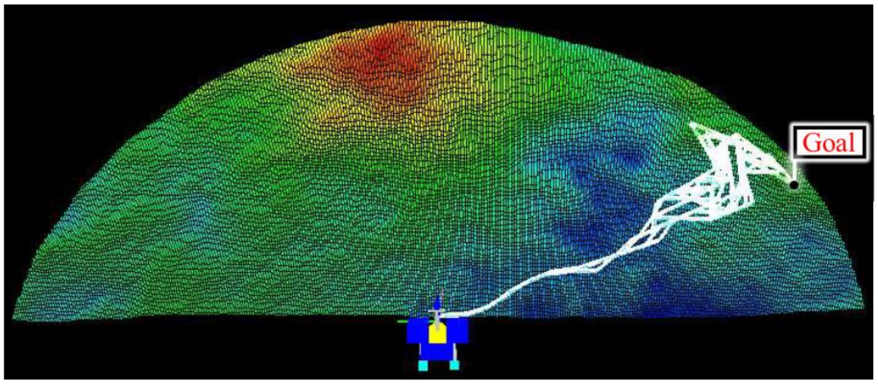
Figure 5: Flowchart of path planning with the proposed uncertainty model

has serious measurement uncertainty so that some paths may be unsafe because of the uncertainty such as the terrain is too rough to traversal, or the sloped terrain is sharp, and a potential obstacle lies on the path. The variety of paths is due to the cost function, mainly terrain roughness index modified by the proposed model. As for the case in Figure 6b, it should be noted that two kinds of paths are generated. The one detours around the hill located at the center of the terrain and the other one traverses over the hill. In general, a path traversing over the hill is not preferable for the rover because the path may often include potential hazardous due to a steep slope. Nevertheless, because of the uncertainty effect exerted from the model, the height and steepness of the hill are assumed to be lower and consequently several paths over the hill are generated.

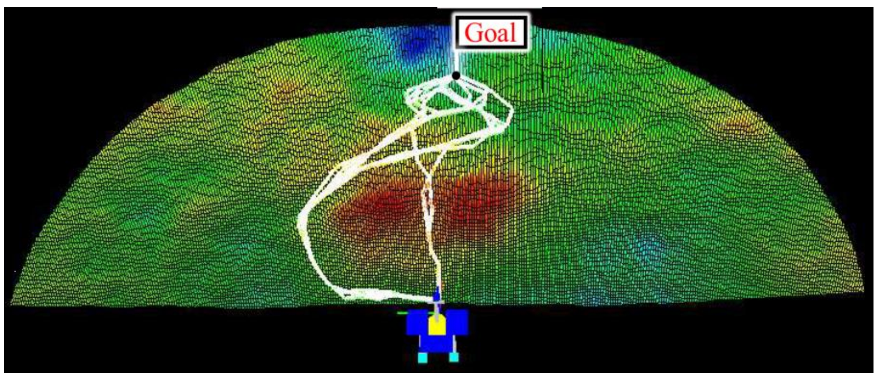
In both of these two representative results, some paths among generated 100 paths are possibly risky as stated above. Assuming an actual situation that a planetary rover drives, the unsafe path may be generated if significant measurement uncertainty is not considered in its planning. Therefore, path planning simulation with the LIDAR measurement uncertainty model decreases such risks and also let a rover detect possible hazardous region from the tendency of the paths generated. In addition, the simulation result as particularly seen in Figure 6a implies a strategy in which a rover re-plans a path at a point where the paths generated in the simulation start diverging.

5 CONCLUSION

This paper has developed the LIDAR measurement uncertainty model for a safe autonomous mobility of a planetary rover. The model has been determined by the experimental results that identify the nature of absolute error and repeatability with respect to the



(a) Case A: Path planning in 10-meter travel



(b) Case B: Path planning in an obstacle crossing/avoiding scenario

Figure 6: Simulation results of path planning

distance and intensity values. The possible application of the model has been demonstrated in the path planning simulation. The simulation result has indicated that the proposed model incorporated with the path planning suggests a re-planning location along the path, and enables a rover to avoid the possible hazardous region.

The basic approach taken in this work to elaborate an uncertainty model of LIDAR can be applied to any LIDARs since the experiment procedure on the measurement performance explicitly addressed the key factors of the LIDAR uncertainty. The uncertainty model is also applicable for a simulation framework of a rover autonomous mobility task such as localization and mapping other than path planning. Such simulation may predict possible risks due to the measurement uncertainty of the sensor in an actual environment.

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