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# 3D Environmental Modeling and Drivable Road Identification for a Long-Range Rover

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***Abstract*—It is necessary for a long-range space rover to model its 3D environment in order to identify drivable roads while avoiding obstacles and hazards. We present a method of modeling a 3D environment, while identifying drivable roads and obstacles, by accumulating a sequence of point clouds from stereo. The technical issues we deal with are how to avoid error accumulation in registering point clouds using visual odometry and how to keep the quality of the model under the constraint of limited number of points to carry. In this paper, we propose: 1) Digital Elevation Map (DEM) based global localization. 2) Level of Detail (LOD) based accumulation of local 3D point clouds. The application of our proposed method to Devon Island dataset [12] indicates that the error accumulation is contained within 5%.**

***Keywords*—Global Localization, Level-of-Detail-based Environmental Modeling, Obstacle Detection, and Drivable Road Identification.**

## 1. Introduction and Related Work

The farther an explored planet is, the longer it would take a commanding signal to reach from an earth commanding station to planet exploring rover. Thus, it is necessary for a space rover to be capable of autonomous and semi-autonomous decision making, such as localization, navigation, and environmental mapping. In this paper, we are interested in the problem in which a rover is required to autonomously and precisely identify its location on a planetary body, build a dense 3D map of its surroundings, and identify drivable roads and obstacles. Although dead-reckoning methods such as wheel odometry, visual odometry (VO), etc can be used with relatively good local accuracy, they are subjected to drifting error due to accumulating errors [1], and noise/mechanical disturbances in case of wheel odometry [2]. Hence, a long range exploration mission will greatly suffer from localization error unless a global localization technique is used to correct drifting error. While we dont have satellite infrastructure to form GPS on a planetary body, and orbital satellite may provide valuable Digital Elevation Map (DEM) that can be used for global localization. Multi-frame Odometry-compensated Global Alignment (MOGA) [3], Visual Position Estimator for Rovers (VIPER) [4, 5], and other approaches [6, 7] redefine the problem of global localization into a matching problem between DEM data and locally obtained data by rover sensors. [3] assumes a LIDAR is mounted on the rover and matches the dense local 3D point cloud of LIDAR with the sparse 3D point cloud of DEM. While achievable accuracy is high, LIDAR sensor is a considerable weight to be loaded on a far interplanetary exploration mission. [4–7] took advantage of DEM to render a 2D image of skyline at any given location. They compare the rendered skyline with that obtained by rover camera. Skyline approaches may not provide as much accuracy as a full 3D matching, and can be stuck in local minimum.

In this paper, we extend our previous work [8] by adding a corrective 3D matching layer that combines locally obtained 3D point cloud by stereo camera mounted on a rover, with that of DEM. We assume that rover location is coarsely known (either by VO, BA, or [8]). The proposed method aims at fine estimation of rover location, fusion of accumulated sequence of local 3D point cloud with DEM for the purpose of environmental modeling, and a simple voxel-based drivable road and obstacles identification. The paper is arranged as follows: we propose our global localization fine-tuning in section II. In section III, we propose our environmental modeling method. we propose a simple method for the identification of drivable road and obstacles in section IV. Finally, sections V and VI: show experimental results of proposed methods and conclude the paper.

## 2. Global Localization Fine-Tuning

Suppose we have a coarse estimation of rover location at a time t, i.e. ${}^{DEM}_{c_t}T = {}^{DEM}_{UTM}T\ {}^{UTM}_{Topo}T\ {}^{Topo}_{c_0}T\ {}^{c_0}_{c_t}T$ where $c_i$ is camera frame at time i, Topo is topocentric coordinate frame, UTM is Universal Transverse Mercator coordinate frame of traversed planet, and DEM is reference coordinate frame in a given DEM map. To obtain a fine estimation of rover location, we formulate a searching problem within local neighborhood of a given location with a cost function. Cost function is defined for a candidate location j on DEM as follows:

$$\begin{aligned} e(j) = \sum_{i=1}^{n} ({}_{c_t}h_i|_{DEM} - {}_{DEM}\,h(i))^2 + \\ \sum_{i=1}^{n} |{}_{c_t}n_i|_{DEM} \bigotimes_{DEM} n(i)|^2 + D(j)^2 \end{aligned} \tag{1}$$

Where ${}_{c_t}h_i|_{DEM}$ is the height/altitude (in DEM frame) of a 3D point i captured by camera at time t, ${}_{DEM}h(i)$ is the height/altitude of DEM at the exact longitude/latitude of 3D point i with respect to reference j, ${}_{c_t}n_i|_{DEM}$ is the surface normal (in DEM frame) at 3D point i captured by camera

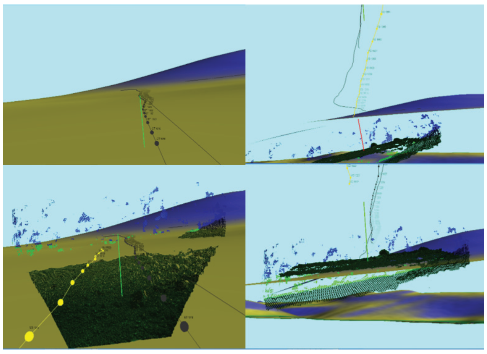

Fig. 1. An example of the result of global localization fine-tuning. Top: a locally captured 3D point cloud imposed on DEM using coarse estimated rover location. Bottom: results after apply proposed method. Left: shows the view from camera, right: shows the view from DEM ground level.

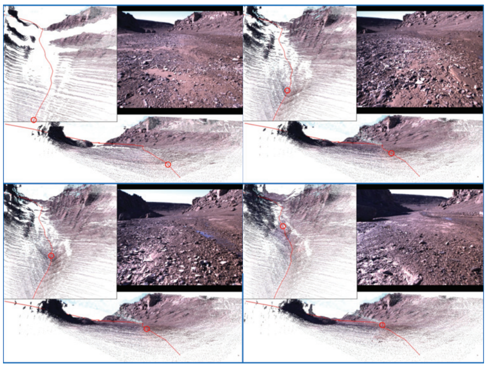

Fig. 2. An example of LOD-based accumulation of locally captured 3D point cloud. Data are from Devon Island dataset[5]. From top-left to bottom-right, propagation of rover movement (shown by red circle), and accumulated point cloud. Best viewed in color.

at time t, $_{DEM}n(i)$ is surface normal of DEM at the exact longitude / latitude of 3D point i with respect to reference j, $A \bigotimes B$ is the cross product between A and B, and D is the Euclidean distance between candidate location j, and original location suggested by the initial coarse localization. $D(j)^2$ acts as a regularization term to prevent the search from going outside error bounds of the coarse estimation, as well as bounding the searching area for more robust computation. We use bilinear interpolation to obtain a 3D DEM point at a desired location from neighboring 4 DEM points. An example of proposed method is shown in Fig. 1.

## 3. Environmental Modeling

The problem of registering accumulated point clouds for environmental modeling is not a trivial problem. With the increasing resolutions of modern stereo cameras, one may expect to get anywhere from 2∼10 million 3D points from one capture. With a minimum representation of 216 bits per point (3x4 bytes for point location in 3D: $X$, $Y$, $Z$, 3x4 bytes for surface normal at point: $N_x$, $N_y$, $N_z$; and 3 bytes for RGB color channels), a single uncompressed capture may yield a gigabyte size of data.

To manage the memory consumption while allowing unlimited number of 3D captures to register their point clouds on environmental map, sampling of the 3D points is required. Rather than resorting to a uniform sampling which would lead to a very low resolution of the environmental map with large number of accumulated captures, we borrow the idea of level of detail (LOD) [9] from computer graphics discipline. Level of detail is an optimization technique to reduce the complexity of a group of elements by sampling them according to a given priority criteria. We define the priority criteria as follows:

$$P(i) = \alpha \frac{1}{D_i} + \beta h_i + (1 - \alpha - \beta)|n_i \bigotimes Z| \qquad (2)$$

where $D_i$ is the distance between a point i, and current rover location, $h_i$ is the height/altitude of point i, and $|n_i \bigotimes Z|$ is proportional to the slope at point i. $\alpha, \beta$¡1. This priority criteria increases the probability of sampling a point if it is close to rover location and if it is hazardous to rover traverse (high obstacle and/or steep slope) as shown in Fig. 2.

## 4. Obstacle Detection and Drivable Road Identification

We define an obstacle as the region in which 1) traversing slope is too steep. Or 2) height step is too high for rover wheel. We define drivable road as any region that is not labeled as obstacle. Before traversing, we may generate a coarse drivable / obstacle map from DEM by analyzing the surface normal slopes. DEM, however, does not have the accuracy to identify obstacles with high step height. Analyzing local 3D point cloud obtained by rover for obstacles can be very expensive for large resolution stereo cameras. Thus, we use our fast generated octree representation [10] to down sample the point cloud into a sparse representative voxels. We measure the Z gradient of each cell, as well as the average surface normal for identifying obstacles as shown in the example of Fig. 3.

## 5. Experimental Results

To evaluate our methods, we used Devon Island dataset provided by Toronto University [11]. Devon Island is the largest uninhabitable island on Earth located at the north of Canada. Due to its altitude and terrain, it is considered one of the best planetary rover simulation sites on earth. Toronto University dataset is made using a rover (Fig. 5) mounted with a set of sensors, including Bumblebee XB3 stereo camera, in which the rover had traversed over 10km

collecting a 49,410 captured stereo images, about 20cm each. First, we generated a coarse environmental model from DEM and annotated steep slopes as obstacles and identified drivable roads as shown in top of Fig. 4. We then used visual odometry to obtain coarse estimation of rover location using SIFT correspondences. At each location, captured point cloud is used to refine rover location with respect to underlying DEM using our proposed method. Next, we identify hazardous obstacles from captured point cloud. And finally, we use LOD to register the captured point cloud, along with annotated

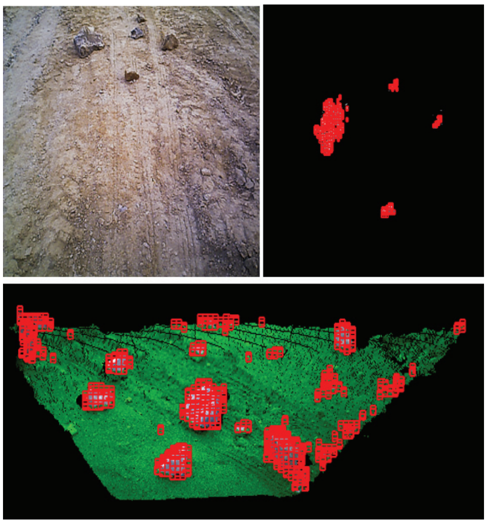

Fig. 3. An example of obstacle detection using voxel representation. top left: left RGB of input stereo image. Top right: detection of hazardous obstacles at step height of 20cm. Bottom: accumulated cloud with obstacle detection (step height: 10cm) marked in red voxels, as well as drivable roads identified in green color. Best viewed in color.

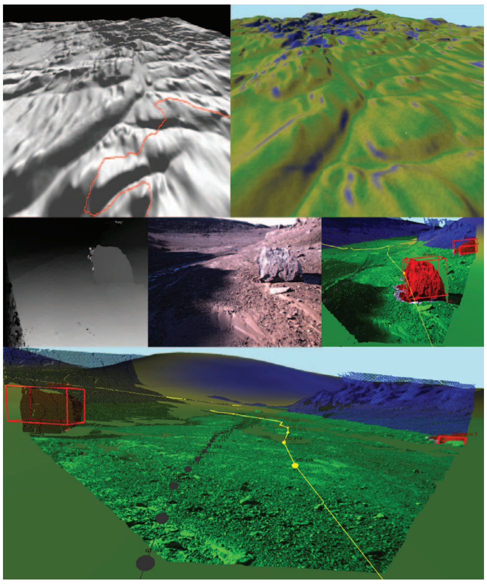

Fig. 4. Top left: 3D model of Devon Island DEM. Top right: results of obstacle detection on DEM. Green: drivable road. Yellow: steep slope (from 20∼45 degrees). Blue: very steep slope (over 45 degrees). Middle left, middle, and right: an example depth map and left RGB image of a captured stereo picture, and the result of obstacle detection. Obstacles are marked in red and blue as they trigger high step height and steep slope respectively. bottom: final result of environmental modeling after registering accumulated point clouds, obstacles and drivable road on global environmental map.

obstacles and drivable roads onto global environmental map as shown in middle

and bottom of Fig. 4. Videos of both experiments shown in Fig. 2 and Fig. 4 are referenced in [12, 13]. We have evaluated our global localization technique on Bundle 2 of Devon Island (image frame 2093∼3764) and found that proposed method maintain a bounded error of about 10m of traversed distance,

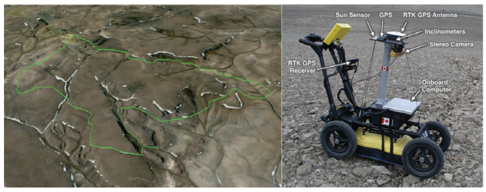


Fig. 5. Left: about 10km traverse map shown in green on an orbital image of Devon Island. Right: Toronto University experimental rover.

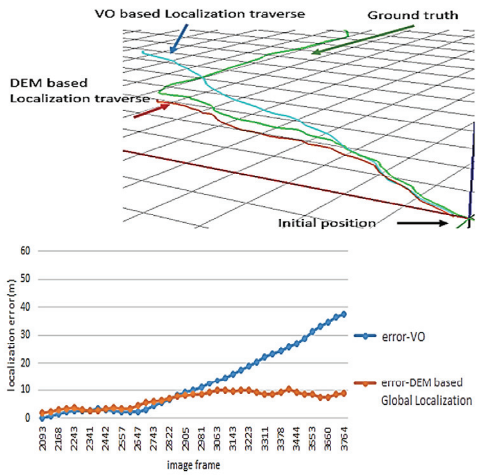


Fig. 6. Localization error using VO and global localization on Bundle 2 of Devon Island dataset [5]. Top: 3D trajectory of ground truth (green), VO (blue), and global localization correction of VO (red). Bottom: error accumulation over distance for both VO only, and with global localization.

while traditional visual odometry has an accumulating error as shown in Fig. 6.

## 6. Discussion and Conclusion

In this paper, we presented a method for fine global localization using locally captured 3D point clouds with stereo camera, and a sparse DEM 3D point cloud. We also used LOD for point cloud registration and environmental mapping. We showed a simple voxel-based method for obstacles and drivable road identification. We demonstrated our methods on Devon Island dataset and evaluated the error bound of our global localization method used to refine VO estimation.
The DEM used for Devon Island experiment has a resolution of $13 \times 24$ meters per pixel. We argue that a higher resolution DEM would reduce the error bound and produce more precise estimation of rover location. The proposed obstacle detection is simplified to work with 3D point cloud. Further work may be needed in obstacle detection by leveraging a deep convolutional neural network to identify further obstacles such as wet, slippery, and rocky surfaces from RGB images. Additionally, the use of global bundle adjustment can further enhance the localization accuracy.

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[12] A demonstration of Planetary Global Localization, Environmental Mapping, Obstacle Detection, and Drivable Road Identification on Toronto University’s Devon Island dataset: https://youtu.be/C8o-_aFYWP0

[13] This is a demonstration of LOD based Registration and Environmental Mapping using Toronto University’s Devon Island dataset: https://youtu.be/80ub32h-1U8