Estimation of Soil Volume Change Using UAV-based 3D Terrain Mapping

○ Yuyang Shao, Yonghoon Ji, Hiromitsu Fujii (The Uiversity of Tokyo),
Shingo Yamamoto, Takumi Chiba (Fujita Co., Ltd.), Kazuhiro Chayama (KOKANKYO Engineering Co., Ltd.), Yusuke Tamura, Keiji Nagatani, Atsushi Yamashita,
and Hajime Asama (The University of Tokyo)

Abstract In this paper, we propose a novel method using unmanned aerial vehicle (UAV)-based 3D terrain mapping to estimate the soil volume change in a short time. Dealing with natural disasters (e.g., landslide, earthquake, etc.), teleoperation of an unmanned robot is a good way to execute tasks in the area of disaster, such as sediment clean-up. The management of soil volume is especially helpful for the whole process of the construction task. The main contribution of this work is to propose a novel method based on 3D registration and RANSAC-based compensation to calculate accurate amount of the change. Experimental results show that our proposed method is able to estimate the soil volume change in an allowable error.

Keyword: Volume estimation, UAV-based mapping, teleoperation

1 Introduction

In disaster area, a landslide may occur during the post-disaster construction, which cause significant damage to constructors who work in the field. Therefore, teleoperation of an unmanned construction machine is a good way to deal with such tasks. In this case, three-dimensional (3D) terrain model which is very helpful for the teleoperation can be used to represent the disaster area and its situation. On the other hand, an unmanned aerial vehicle (UAV) equipped with a camera which can provide a wide range and multi-angle images of the environment of the natural disasters[1)]. Therefore, the UAV is widely used to generate a 3D models of a disaster area. Lucieer *et al.*[2)] and Verykokou *et al.*[3)] used a structure from motion (SfM) method to generate 3D terrain model that consists of point cloud using the camera mounted on the UAV in a disaster area. When conducting post-disaster construction in a disaster area, it is important to estimate the removal volume of soil by unmanned construction machine in order to establish construction plan reasonably. Kaiser *et al.* introduced a method that calculate the soil volume change based on 3D terrain model comparison[4)]. In this research, two 3D models for same area are built at different time in order to compare them. They used ground control points (GCPs) to align two 3D models, and then enhancing the accuracy of the registration by iterative closest point (ICP) algorithm. The result of soil volume change could be calculated by comparing the distance between two 3D models[4)]. However, the borders or stones are chosen as GCPs; thus, when the environment changes, the GCPs might be disappear, which leads to decrease estimation performance.

In order to overcome this limitation, we propose a novel method that also utilizes the 3D terrain models built by UAV. First, 3D registration to align two sets of 3D point cloud is performed. However, the two 3D models cannot be perfectly registered after registration. Therefore, second, we make a compensation after registration in order to calculate the volume change accurately.

The reminder of this paper is organized as follows. Section 2 describes the overview of our method and how to estimate the soil volume change based on UAV-based SfM. Section 3 explains the experiment in a real environment and the results. Finally, we give the conclusions and future works in Section 4.

2 Soil volume change estimation

In order to represent the disaster area, a 3D terrain model is generated by SfM that uses 2D images taken by the camera mounted on the UAV. The global 3D terrain model that is built for the first time represents a wide range area of disaster areas. On the other hand, when we want to calculate the soil volume change after construction in certain area, the local 3D terrain model of corresponding area by UAV-based SfM will be re-generated. These 3D terrain models consist of the 3D point cloud. Figure 1 shows an overview of our proposed method. Our proposed method can be divided into 4 steps to estimate soil volume change as follows:

- Alignment initialization based on GPS signal.
- Coarse registration based on fast point feature histogram (FPFH) descriptor.
- Precise registration based on point feature histogram (PFH) descriptor.
- Distance compensation based RANSAC plane.

2.1 Alignment initialization

We use GPS signal of the global 3D terrain model and the local 3D terrain model to generate a partial 3D terrain model. Therefore, the registration range can be reduced. Reducing the registration range of

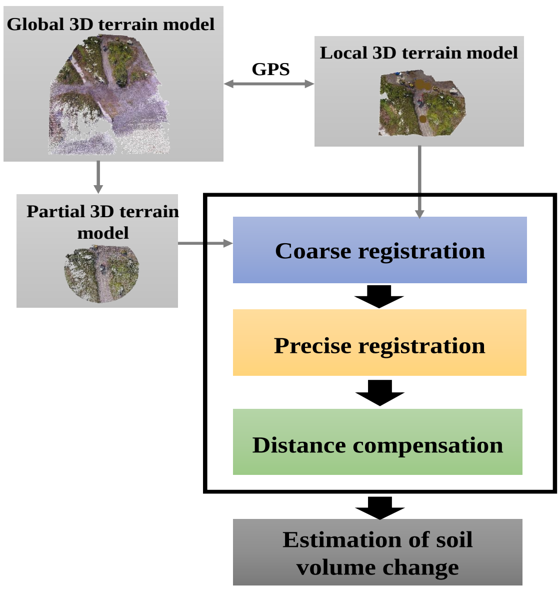

Fig. 1: The overview of soil volume change estimation. Firstly, a global 3D terrain model and a local 3D terrain model at different time are generated from images captured by a camera mounted on UAV. Then, we use the GPS signal to generate partial 3D terrain model from the global 3D terrain model. Finally, through 3D registration and distance compensation, we can estimate the soil volume change.

the global 3D terrain model can improve registration accuracy and reduce computational cost. Consequently, the same range of 3D terrain models and initial alignment between them will be determined.

2.2 Coarse registration

As we described before, the 3D models consist of the 3D point cloud, therefore, an appropriate descriptor should be defined to perform the registration between them. In order to align the partial 3D terrain model and the local 3D terrain model, we use the FPFH descriptor[5)] to perform a coarse registration. There are two steps to calculate FPFH descriptor. Firstly, the relationships between point p and its neighbors need to be calculated. The relationships called simplified point feature histogram (SPFH). In the second step, for each point, we re-determine its k neighbors and use the neighbor SPFH values that had calculated in the first step to estimate the FPFH of point p. The equation of FPFH descriptor of point is as follows:

$$FPFH(p) = SPFH(p) + \frac{1}{k}\sum_{i=1}^{k}\frac{1}{\omega_k}\cdot SPFH(p_k) \quad (1)$$

where the weight ω_k is the distance between point p and a neighbor point p_k in a given metric space. The FPFH descriptor alignment is using the sample consensus initial alignment (SAC_IA)[5)]. After performing the coarse registration, the calculated positional relationship between the partial 3D terrain model and the local 3D terrain model is used as the initial position for the precise registration which will be given in next subsection.

2.3 Precise registration

The calculation speed of FPFH descriptor is fast. However, FPFH descriptor is not robust; thus, the registration based on FPFH is not precise. After the coarse registration, the two models are not fully registered. In order to get a more accurate alignment, a precise registration need to be done. Therefore, we use PFH descriptor to make a precise registration. The PFH descriptor computation steps are as follows:

- Selecting k-neighborhood of a certain point p.
- Estimating normals of every pair of points and calculating the angle relationships between the normals.

In general, after the coarse registration of such environment, the position error is within 3 m. And the PFH descriptor based registration need at least 45 % overlap area. However, the computational complexity of PFH descriptor is high. Furthermore, in the precise registration, the size of 6m×6m area from the partial 3D model and the local 3D model in the same place will be used after coarse registration.

After computing the PFH descriptors of partial 3D terrain model and local 3D terrain model, we use the SAC_IA to align these 3D terrain models. After the coarse and precise registration, we can get the transformation matrix between the global 3D terrain model and the local 3D terrain model, then we can transform the local 3D terrain model to the global 3D terrain model based on the transformation matrix.

2.4 Distance compensation

When the registration processes are completed, the global 3D terrain model and the local 3D terrain model are almost aligned. However, a small error is still remained because of data noise which leads to a large accumulation in the calculation of soil volume change. There are many planes in the disaster environment, therefore, we consider making a compensation through based on the plane detection. Tarsha[6)] and Brenner *et al.*[7)] introduce a method to detect building roof plane based on RANSAC with a high accuracy. Therefore, we fit RANSAC plane from the two 3D models in order to calculate the compensation value. The RANSAC plane selection steps are summarized as follows:

- Selecting three points randomly, and then calculating the parameters of this plane.
- Calculating points belong to the calculated plane with a threshold.
- Repeating the steps 1 and 2 n times, and selecting the best result as the RANSAC plane.

(a) (b) (c)

Fig. 2: 3D terrain models and initial position: (a) a global 3D terrain model, (b) a local 3D terrain model, and (c) the initial position of two 3D models.

Fig. 3: The result of coarse registration. Coarse registration of the partial 3D terrain model and the local 3D terrain model is performed based on FPFH

Fig. 4: The result of precise registration. Precise registration of the partial 3D terrain model and the local 3D terrain model is performed based on PFH

After fitting the RANSAC plane from each 3D model, we do project the 3D models to 2D grid maps. Here, the value of each grid determined as the average height of the points belong to the grid. The soil volume change can be calculated according to the formula as follows:

$$V_c = S_g \sum_{i=1}^{n} (H_g - H_l - d_i) \tag{2}$$

$$H_g = \frac{1}{m} \sum_{i=1}^{m} h_i \tag{3}$$

$$H_l = \frac{1}{m} \sum_{j=1}^{m} h_j \tag{4}$$

where V_c denotes the soil volume change in the local area, S_g represent the grid size. d_i is the distance difference between the two RANSAC planes at the same grid. n is the total number of grids that used to calculate. H_g and H_i are the value of each height assigned at same grid index respectively. H_g and H_i are the value of each height assigned at same grid index respectively. h_i and h_j are the height value of each point at a certain grid of global 3D terrain model and local 3D terrain model, respectively. m is the total number of points at a certain grid.

3 Experiment

In order to verify the accuracy of soil volume change by our proposed method, we conducted an experiment using real environment data. The global 3D terrain model and the local 3D terrain model which consist of 3D point cloud were generated by UAV-based 3D mapping that uses SfM algorithm, as shown in Fig. 2 (a) and Fig. 2 (b) respectively. The size of the global 3D terrain model is approximately 158 m×154 m, and the size of the local 3D terrain model is approximately 67 m×62.7 m. We put three pillars artificially on the local 3D terrain model in order to make the volume changes. The volume of the pillars was 1030 m^3. The initial position of the global 3D terrain model and the local 3D terrain model is shown in Fig. 2 (c). According to the comparison between true value and result based on our method to verify the accuracy of our method.

We could get the partial 3D model based on the GPS signal from the global 3D terrain model. Area radius of 30 m is selected as partial 3D terrain model. Then we performed coarse registration based on FPFH descriptor between the partial and the local 3D terrain models for matching them. The coarse registration took about 4.35 minutes, and the result of coarse registration is shown in Fig. 3.

As we described in section 2, 45% overlap area should be ensured for the precise registration. Hence, we selected an area of 6 m×6 m. The precise registration took about 13.4 minutes, and the result of precise registration is shown in Fig. 4.

After performing the registration processes, we calculated the RANSAC planes from the partial 3D terrain model and the local 3D terrain model, as shown in Figs. 5 (a) and (b), respectively. Their position

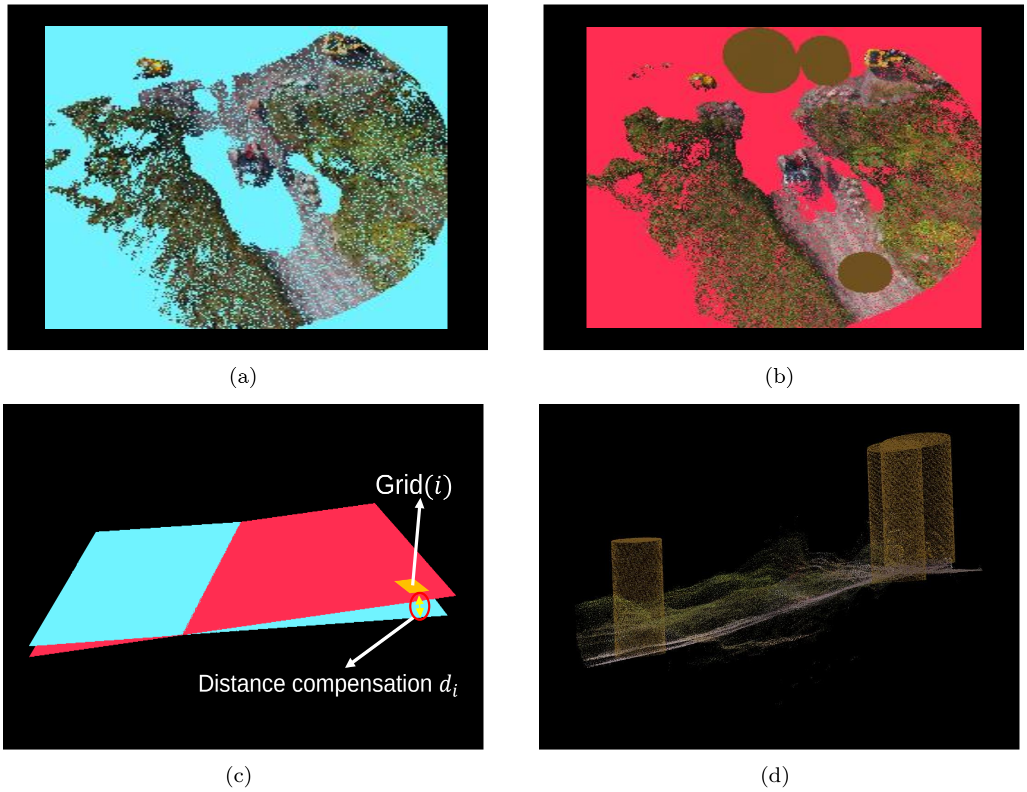

Fig. 5: RANSAC planes from each of 3D models and position relationship: (a) the RANSAC plane from the partial 3D terrain model, (b) the RANSAC plane from the local 3D terrain model, (c) position relationship between two RANSAC planes, and (d) position relationship between two models.

relationship between two RANSAC planes is shown in Fig. 5 (c). The red one and blue RANSAC plane are from the local and partial 3D terrain models, respectively. Figs. 5 (d) represents the positon relationship between two models. Then, the distance compensation based on these RANSAC planes is calculated as we described in the previous section. We conducted comparative experiments that produce the results with distance compensation and without distance compensation, as shown in Table 1. After the coarse registration and precise registration, the error of estimation result with RANSAC plane compensation was 9.42 %, and the error of estimation result without RANSAC plane compensation was 22.5 %. According to the Table 1, a better result was produced with RANSAC plane compensation.

Table 1: Estimation results of soil volume change

Condition	Estimation	True value	Error
With compensation	1127 m^3	1030 m^3	9.42 %
Without compensation	798 m^3	1030 m^3	22.5 %

4 Conclusions

In this paper, we introduced a method to estimate the soil volume change using UAV-based 3D terrain mapping. Through the 3D registration and the distance compensation, we can produce an accurate estimation result with an allowable error compared to a method without the distance compensation. The result is very helpful for us in order to build the construction tasks. In the future, we will apply this method to update a large area in a limited time.

References

1) Wu J, Zhou G: Real-time UAV video processing for quick-response to natural disaster, Proceedings of the 2006 IEEE International Conference on Geoscience and Remote Sensing Symposium, 976/979 (2006)
2) Lucieer A, Jong S M, Turner D: Mapping landslide displacements using Structure from Motion (SfM) and image correlation of multi-temporal UAV photography, Progress in Physical Geography, 38-1, 97/116 (2014)
3) Verykokou S, Doulamis A, Athanasiou G, et al: UAV-based 3D modelling of disaster scenes for urban search and rescue, Proceedings of the 2016 IEEE International Conference on Imaging Systems and Techniques, 4-5, 1392/1410 (2012)
4) Kaiser A, Neugirg F, Rock G, et al: Small-scale surface reconstruction and volume calculation of soil erosion in complex Moroccan gully morphology using structure from motion, Remote Sensing, 6-8, 7050/7080 (2014)
5) Rusu R B, Blodow N, Beetz M: Fast point feature histograms (FPFH) for 3D registration, Proceedings of the 2009 IEEE International Conference on Robotics and Automation, 3212/3217 (2009)
6) Tarsha-Kurdi F, Landes T, Grussenmeyer P: Hough-transform and extended ransac algorithms for automatic detection of 3d building roof planes from lidar data, Proceedings of the ISPRS Workshop on Laser Scanning and SilviLaser, 407/412 (2007)
7) Brenner C: Towards fully automatic generation of city models, International Archives of Photogrammetry and Remote Sensing, 32-3, 85/92 (2000)