AUTOMATIC RECOGNITION AND VOLUME CALCULATION OF LANDSLIDE COLLAPSE AREA BASED ON IMAGE SEQUENCE

Zhipeng Liang (<u>zhipeng.liang@dicea.unipd.it</u>) Central South University (China); University of Padova (Italy)

Fabio Gabrieli (<u>fabio.gabrieli@unipd.it</u>) Dept. ICEA, University of Padova (Italy)

Lorenzo Brezzi (<u>lorenzo.brezzi@unipd.it</u>) Dept. ICEA, University of Padova (Italy)

Davide Vallisari (<u>davide.vallisari@unipd.it</u>) Dept. ICEA, University of Padova (Italy)

ABSTRACT. Digital photogrammetry technology based on fixed multi-view cameras has attracted widespread attention in the field of geotechnical engineering due to its low-cost and contactless mode. For the purpose of studying the surface collapse of a landslide monitored with these low-cost cameras, we have developed a photogrammetric algorithm that can quickly detect the collapses, determine the collapse area and calculate the collapse volume. With the field data and small-scale experiments, we have verified the accuracy of the program. The method of quickly and automatically obtaining collapse information proposed in this paper will improve the efficiency of landslide monitoring system based on photos and it is of great significance for further research and the realization of a collapse prediction tool.

1. INTRODUCTION

Digital photogrammetry has become a powerful and affordable method for 3d reconstruction of objects and surfaces and thanks to advantages like non-contact and low cost, its use has recently been extended to landslide monitoring. (Antonello, M et al., 2013). The almost real-time recognition of local surficial sliding and collapsed parts of the slope is an important information for understanding the characteristics of the landslide and forecasting its possible evolution. In this perspective, time-lapse close-range photogrammetry technology offers the possibility to obtain this information automatically. Based on the comparison and analysis of image sequences taken by multiple cameras, we can quickly determine the local slip and the collapsed area, we can estimate the collapsed volume and finally we can make hypothesis about the correlation between the detachments and the driving factors (usually rainfall and piezometric levels).

In this paper, we present a tool, which can automatically analyses and process a sequence of images. Based on the image structure similarity and convolution, the program automatically identifies the collapsed area. The program is also able to automatically extract the rainfall data with the aim at analyzing the environmental conditions that characterize the collapse. With the two-month monitoring data of the Perarolo landslide, we verified the effectiveness of the algorithm, which can identify the collapse area accurately and quickly. The results make it reasonable to believe that rainfall is the main driving force of the surface sliding and collapse of Perarolo landslide. Thanks to some small-scale experiments we also tested the algorithm and implemented a stereo photogrammetric tool to estimate the collapsed volumes.

2. METHODS

Our program pursues to cooperate with fixed multi-view cameras to perform acquisition of images, collapse monitoring and early warning in a fully automatic and continuous way, without any third-party intervention or manual operation. As shown in Figure 1, there are three main steps: the collapse recognition on the image plane from image comparison, the correlation analysis between collapse events and rainfall data, the 3d reconstruction and calculation of the collapsed mass.

2.1 Collapse recognition based on image sequences

For the collapse recognition phase, the first step is to remove the area covered by trees and grass by color masking. Indeed, vegetation does not have a fixed texture due to the wind and seasonal growth that does not allow

a direct comparison between subsequent images. The second step is to use the structural similarity metric to compare two pictures for obtaining a structural similarity map (Zhou, W et al., 2004). Due to changes in contrast, saturation, lighting, etc., a lot of noise in the structural similarity map is expected, which can be removed by applying image convolution. For this purpose, we used gaussian convolution and median convolution with different patch sizes for several times (Lim, Jae S., 1990). Further collapse artifacts are caused by shadow movement which were removed on the structural similarity map. According to the statistics of the pixel values on the final structural similarity map, we are able recognize the collapsed area and get a unique structural similarity index, which can be used to determine whether the collapse has occurred between image taken at day i and i+1.



Figure 1. Steps of the collapse recognition algorithm.

2.2 Volume calculation of collapse area based on stereo vision

Once the collapse is detected, the program automatically calculates the collapsed volume. The first step of this strategy is the 3D reconstruction of the slope surface before and after the collapse using the fixed camera calibration parameters and the image disparities acquired from the two different views. After comparing the depth coordinates of the point clouds (relative coordinate of each camera system), we can find the collapsed volume. Using all the point clouds in collapse area before and after collapse, the alpha shape representing the collapsed bodies can be created and the collapsed volumes are easily estimated.

3. TESTS AND RESULTS

3.1 Collapse recognition

We have selected the image sequence acquired in the Perarolo landslide site from 08/07/2020 to 30/09/2020 (almost one image per day) for testing. The trend of structural similarity index between image at time i and i+1 is shown in fig.2, where the sudden changes represent the occurrence of collapse. The corresponding recognized collapsed areas are shown in fig.3.



Figure 2. Trend of structural similarity index.



Figure 3. (a),(b) are the collapsed area recognized by the algorithm (black area); (c),(d) are the corresponding original images before and after collapse.

3.2 Volume calculation

In order to assess the reliability of the approach we conducted a small- scale experiment to compare the volume calculated by the algorithm (see fig. 4), and the real volume. For this purpose, we have reconstructed the 3d surface of a soil pile and we have processed the stereo-images to estimate the volume of soil before and after a small excavation. As shown in fig.5, the alpha shape and its volume was automatically detected and estimated by the program. The results are consistent with volume laboratory measurements, and the average error is only 3.51%, which verifies the accuracy of the tool. Further checks and analysis about the factors affecting the accuracy of this method are still ongoing.



Figure 4.(a) Stereo camera calibration to estimate the camera parameters (b) recognized collapsed area (red line) in the rectified image.



Figure 5. (a) 3d point cloud before and after the excavation, (b) alpha shape representing the excavated mass.

3.2 Correlation between collapse and rainfall data

As shown in Figure 6, plotting the structure similarity index and the rainfall that occurred in the same days we found that the two collapses occurred exactly during the two days of maximum rainfall. This probably suggests the existence of a relationship between rainfall and the chance of collapse and makes it reasonable to believe that rainfall is the main driving force of this landslide. However, the short observation period is still not sufficient to draw firm conclusions.



Figure 6. Trend of rainfall data and of the sructure similarity index.

4. CONCLUSIONS

This paper describes a new automatic photogrammetric tool for rapid collapse detection and calculation of the collapsed volume. With the image sequence taken during two months at the Perarolo landslide and a small-scale experiment, we verified the applicability of the tool in different conditions. However, further analyses will be required in order to use this tool and obtain accurate information on the dynamics of the Perarolo landslide and other camera-instrumented landslides.

5. REFERENCE

Antonello, M., Gabrieli, F., Cola, S., & Menegatti, E. (2013). Automated Landslide Monitoring through a Low-Cost Stereo Vision System. In PAI@ AI* IA, 37-41.

Zhou, W., A. C. Bovik, H. R. Sheikh, and E. P. Simoncelli. (2004). Image Qualifty Assessment: From Error Visibility to Structural Similarity. *IEEE Trans. Image Processing*, 13: 600–612.

Lim, Jae S. (1990). Two-Dimensional Signal and Image Processing, Eng. Cliffs, NJ, Pre. Hall, 469-476.