3D RECONSTRUCTION OF A LARGE LANDSLIDE FROM UAV-BASED IMAGERY

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ABSTRACT

Remote and close range sensing are well-suited methods for monitoring natural hazards such as landslides. In particular, assessing the behavior and the dynamics of landslides through aerial imagery can considerably reduce the social and economic impacts of such events. UAVs (Unmanned Aerial Vehicle) with digital cameras on board represent an efficient, cost-effective and reliable system for 3D mapping of landslides by photogrammetry. In this study, we present the first results of the UAV-based photogrammetric processing performed in June 2016 and aimed at digitally reconstructing the Corvara landslide (South Tirol, Italy) in 3D. The data acquisition was carried out using a RICOH GR compact camera onboard an octocopter UAV platform. The photogrammetric workflow included, first, a camera calibration and image orientation using well distributed control points. Second, a dense image-matching algorithm was adopted to derive dense point clouds featuring almost 400 million points and a mean spatial resolution in the range of 1.5 cm to 2 cm. This data are now useful to perform comparisons with previous flights in order to quantify the displacements of the landslide.

Index Terms— Photogrammetry, UAV, 3D, point cloud, remote sensing

1. INTRODUCTION

In recent years, the importance of environmental monitoring to reduce the negative effects of natural hazards has widely increased. Among the geology-related natural hazards, landslides frequently occur in many areas of the world. In this regard, understanding the spatial and temporal evolution of landslides is a key point for hazard assessment [1][2]. In order to accurately and efficiently evaluate the dynamic nature and behavior of a landslide, ground-based monitoring measurements, such as terrestrial laser scanners (TLS) and Global Positioning System (GPS), and remotely sensed data, passively and actively acquired by sensors onboard satellite and aerial platforms, can be adopted. Among them, Differential Synthetic Aperture Radar Interferometry (DInSAR) is a powerful technique to detect the deformation of structural movements with the precision up to few millimeters. In particular, advanced DInSAR algorithms such as Permanent scatterer (PS) and Small BAseline Subset (SBAS) can be applied to obtain pointwise and surface deformation maps. However, finding a sufficient number of PSs in the area being monitored and overcoming the temporal and spatial decorrelation problems pose significant challenges for the use of PS and SBAS algorithms in landslide monitoring applications [3][4]. Furthermore, observable movement direction and rate by DInSAR are generally limited to the Line Of Sight (LOS) of the satellite path and to one quarter of the sensor wavelength, respectively. To overcome these limitations and complement satellite-based techniques, digital cameras onboard UAV platforms, together with state-of-the-art photogrammetric and computer vision-based algorithms, can be efficiently applied for the detailed and accurate 3D reconstruction of a landslide. In some recent studies, the capability of Structure from Motion (SfM) techniques [5] in 3D modeling of landslides has been demonstrated [6][7]. The results of UAV-based photogrammetry such as dense point clouds, DSM (Digital Surface Model), DTM (Digital Terrain Model) and orthomosaics can be used to quantifying the landslide dynamics. The adopted approaches usually rely on differential digital elevation models and image correlation on multi-temporal data in order to extract the displacement vectors of landslide [8][9]. In this paper, the first results of a UAV-based survey for landslide monitoring are presented, as pilot action within the wider EUREGIO-funded LEMONADE project (LandslidE MOnitoriNg And Data integration)[10]. The latter aims to (i) monitor landslides by adopting a selected combination of ground-based and remote sensing methods (ii) investigate the advantages and limitations of each approach and (iii) develop the best strategy for multi-sensor and multi-resolution data integration.

2. CASE STUDY

Among the three sites under investigation within the LEMONADE project, Corvara is the largest and most active landslide and is located in the Italian Alps (Fig. 1). It has been monitored for several years, recording some velocities of up to 20 m/year [11]. Starting from these studies, the LEMONADE project is currently investigating the landslide dynamics by integrating UAV-based and ground-based photogrammetry, TLS and DInSAR data.

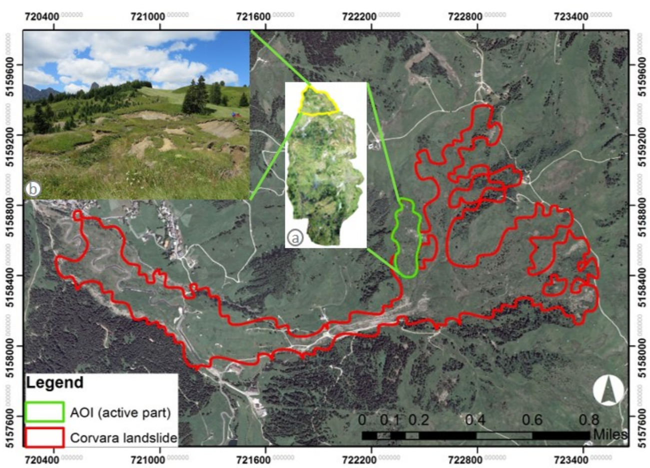

Figure 1. Location of the Corvara landslide (red boundary) and of its most active part (green boundary). The orthophoto (a) and close-up view (b) show the area surveyed by UAV and the landscape of the upper part of the landslide, respectively.

3. METHDOLOGY

3.1. UAV survey

The Corvara dataset covers an area of about 400 x 250 m and was acquired with a RICOH GR compact camera (4928 x 3264 pixels, pixel size 4.6 μm, 18.3 mm nominal focal length) onboard the octocopter Octagon x-8 produced by SoLeon GmbH with a payload of 1550 g (Fig. 2a). Five flights were performed at different heights (Fig. 2b), resulting in more than 2000 images with an average GSD (Ground Sampling Distance) of 1.9 cm. Ground truth data was provided in form of 8 GCPs and 6 independent Check Points (CPs), GNSS-surveyed with a mean positional accuracy of few centimeters (Fig. 2c).

3.2. Data processing

The photogrammetric processing was run with Pix4D [12] that performs the two main steps of the automatic 3D reconstruction procedure, namely image triangulation (including camera calibration) and dense image matching. The first task requires the identification of homologous points in different views of the same 3D scene; once a set of image correspondences is identified, the exterior orientation parameters of the images, interior parameters of the camera and 3D object coordinates of the feature points are automatically computed through an iterative process based on a robust Bundle Block Adjustment (BBA)[13]. In this study, the datum ambiguity was solved by including the 3D and 2D coordinates of GCPs in the BBA as observed unknowns. Furthermore, the root mean square errors (RMSEs) on CPs were computed and analyzed as measures of adjustment accuracy in object space. The horizontal accuracy of image triangulation is around 1 GSD (1.9 cm along X and 1.5 cm along Y), whereas the vertical accuracy reaches 3 cm. Finally, the dense 3D reconstruction step was performed via a Dense Image Matching (DIM) algorithm [14] able to deliver a dense point cloud ideally up to one 3D point for every image pixel. For the Corvara dataset, the DIM was carried out using images reduced at one-half of the original geometric resolution with a multiscale approach: this choice represented the best compromise between the processing time and the required point density. The derived dense point cloud (Fig. 2d and 2e) features more than 390 million points and a mean spatial resolution in the range of 1.5 to 2 cm.

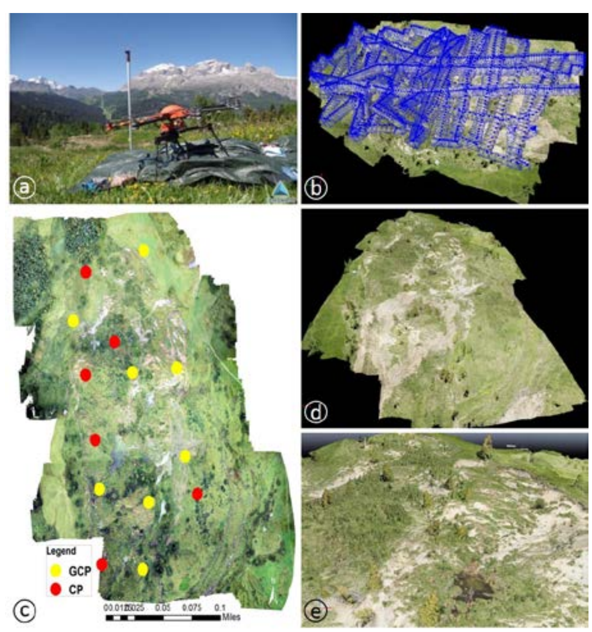

Figure 2. (a) UAV platform equipped with a RICOH GR compact camera; (b) the camera positions during image acquisition; (c) location of GCPs (yellow circle) and CPs (red circle); (d) general and (e) close-up views of the dense point cloud extracted by DIM.

3.3. Post-processing and final products

Starting from the dense point cloud, further processing steps were performed in order to refine the raw results and derive 2D/3D products useful for the LEMONADE project. The point cloud was first manually filtered, in order to remove the noise (incorrect matches) generated by DIM, which was mainly due to the presence of shadows, illumination changes and moving objects (i.e. grass and brushes). Secondly, the filtered dense point cloud was used to generate a DSM of the area (Fig. 3a), in raster and grid output format. Finally, the original images and the surface model were used to generate an orthophoto of the surveyed area (Fig. 3b). Both products (2D and 2.5D) were generated at a spatial resolution equal to the original mean GSD (1.9 cm).

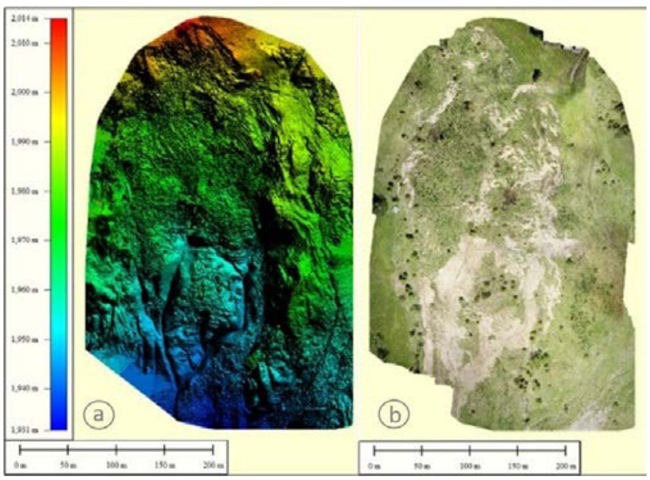

Figure 3. (a) Digital surface model and (b) orthophoto derived from UAV imagery acquired over the Corvara landslide.

3.3. Future work

The evaluation of potentialities and limitations of state-of-the art remote and proximal sensing methods is paramount to efficiently integrate their outputs for landslide monitoring. This is the overall aim of the LEMONADE project, started in February 2016 and designed to develop a novel methodology for multi-sensor and multi-resolution data fusion. Within this framework, the results presented in this paper will be integrated with those achieved in the same area by adopting other terrestrial and remote sensing techniques, i.e. TLS, ground-based photogrammetry and InSAR. Furthermore, by comparing multi-temporal data on three test-sites, landslides activating processes through seasons will be investigated. The further steps of the project and their outcomes will be the topic of future publications.

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