An End-to-End Framework for Landslide Erosion Analysis

Hameed Abdul-Rashid[1] and Christoph Mertz[2]

Abstract— **We present a unified framework comprising numerous state of the art algorithms which improve both respond times to landslide events as well as intervention efficacy. This results in improved outcomes following landslide events including reduced property damage and saved lives. We discuss numerous code libraries and show that our system combines this information in a way which is intuitive to domain experts. Furthermore, we show that our framework can be implemented using inexpensive and accessible hardware, including a cell phone camera as well as a general purpose laptop.**

I. INTRODUCTION

Landslides are natural phenomena characterized by the downward slope movement of soil and rock, resulting in millions of dollars of damage including loss of property and loss of life. The frequency of landslides is increasing in Pittsburgh, due in part to record rainfall as well as a confluence of geological features which make the city susceptible to such seismic activity. The Landslide risk assessment and response process is accompanied by time-consuming multifaceted inspection. This includes drilling, geophysical studies, aerial reconnaissance, lab-based testing of earth materials and so forth [3]. Given that landslide site's are dynamic landscapes, traditional inspection methods are unable to quickly capture crucial land measurements that depict erosion or gradual change in the landscape.

The Geospatial research community has made many contributions to solve this problem, the use of LIDAR or laser scanners and GPS markers to track the landslide site's kinematic displacement has achieved the best results in terms of accuracy [5, 4, 12].

However, LIDAR scanners and the accompanying equipment needed to capture both terrestrial and air-based scans in this method is inaccessibly expensive.

To reduce cost, studies on 3D reconstruction of landslide sites with high quality dslr camera equipped drones has been done with notable results [9, 14, 8, 6]. Although this method is far cheaper and only marginally less accurate than LIDAR based approaches, it is still costly and time consuming to systematically coordinate flight and image capture.

Furthermore, the image collection process is just the first step in the entire point cloud comparison procedure: images must be aggregated accordingly, an application must preform the 3D sparse then dense reconstruction (often different applications), a separate program must be used to visualize the results, numerous software applications must be used to align and segment point clouds for comparison and then finally point cloud distance can be computed. This method is inaccessible due to the technical knowledge and copious amounts of software needed to handle each step.

Fig. 1. US Route 30 Landslide in Greater Pittsburgh Area

We aim to solve such problem, by creating an end-to-end framework that handles every step of 3D reconstruction and Geometric Change Detection with the only requirements being a camera equipped smart phone and a general purpose laptop. The following sections will give a brief overview of the each step in the pipeline and open-source software and algorithms used.

II. 3D RECONSTRUCTION

A. Structure From Motion

Structure From Motion(SFM) is a technique for estimating 3D scenes from a sequence of static 2D scene images coupled with local motion and is classically preformed in three general steps.

(1) Features are detected and extracted from each image by algorithms such as SIFT [2]. (2) Features are matched between images pairs, correlating features are saved while non-matching features are disregard. This process is exhaustive for it checks each image pair for scene overlap. (3) Geometric verification validates pairs after the feature matching process. Scene overlapping projective geometry is used to estimate transformations and 3D composition of detected features.

*This work was sponsored by Traffic21

[1]H. Abdul-Rashid is studying Computer Science at the University of Southern Mississippi. hameed.abdulrashid@usm.edu

[2]C. Mertz is with the NavLab at The Robotics Institute, Carnegie Mellon University, 5000 Forbes Avenue,Pittsburgh, PA, USA. c.mertz@andrew.cmu.edu

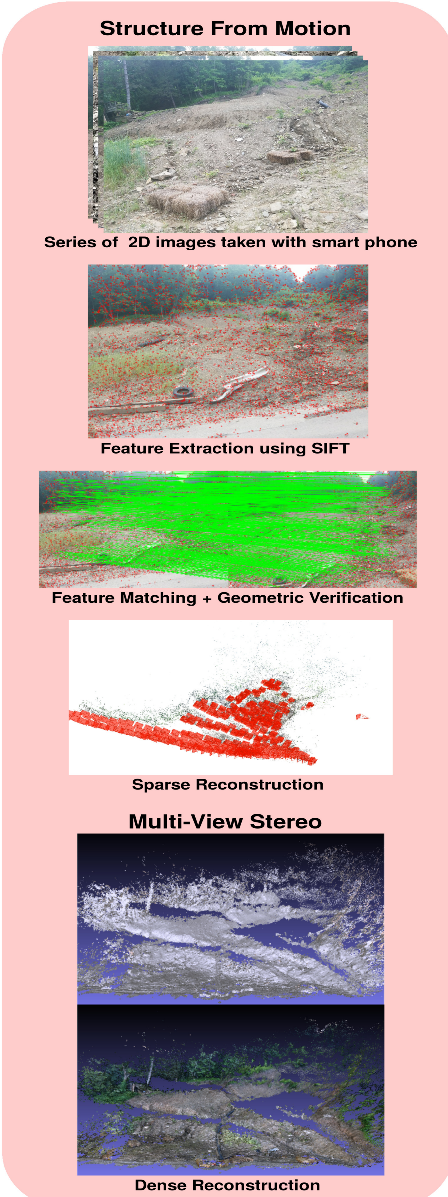

Fig. 2. 3D Reconstruction Process

B. Multi-View Stereo

The output from SFM is used to compute depth and the surface normal information for every pixel in an image with overlapping pair. Overlapping images normal and depth maps are then fused to form a dense reconstruction. Poisson Surface Reconstruction and similar algorithms can reproduce 3D geometry of the scene.

III. Point Cloud Preparation

During the reconstruction process, the estimated camera position and orientation determine the initial transform of models. To properly compared models, the initially distance between clouds must be minimized. Methods of registration are used to reduce distance between transforms and align point clouds.

A. Local Registration

Given an initial transform and two point clouds, Iterative Closest Point Registration(ICP) roughly aligns the points [1]. However, ICP is local registration method and does not preform well if initialized transform do not converge. Colored Point Cloud Registration uses both point cloud geometry and color information and runs ICP iteratively with a joint optimization objective.

B. Global Registration

Local registration methods are not robust enough to handle point clouds with large initial distances or in congruent transforms. More sophisticated methods such as Fast Global[11] and Multiway[7] Registration handle initialization of transforms for non-converging point clouds rather well. Once global registrations provides an initialized transform, iterative local registration methods are once again applicable.

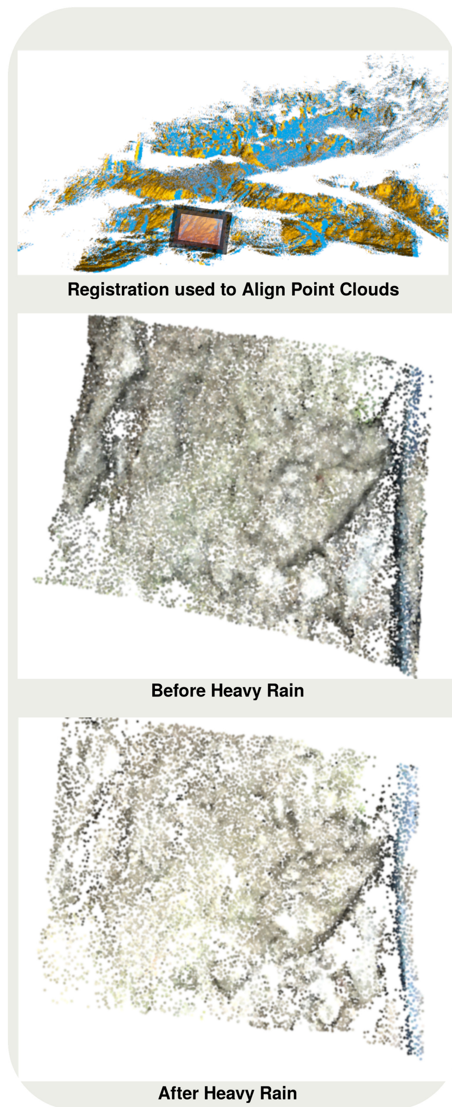

Fig. 3. Registration and Segmentation on two similar point clouds

IV. Calculated Point Cloud Distance and Change

Once the alignment of two point clouds are reduced, then the geometric comparison of two similarly structured point clouds can be used to detect change that occurred. The Hausdorff distance is a trivial solution to calculating the difference between aligned point clouds. This algorithm calculates the furthest corresponding point for each point in the compared point clouds 4.

$$\mathrm{d_H(X, Y) = max\{d(A, B), d(Y, X)\}}$$

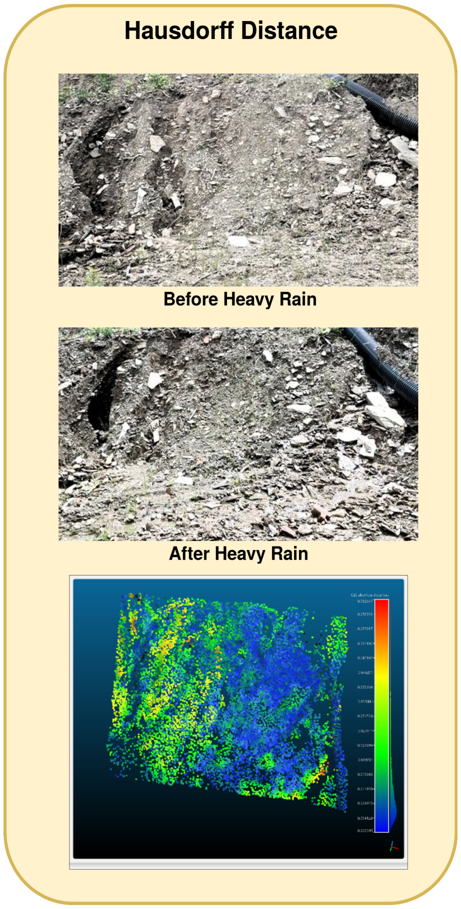

Fig. 4. Hausdorff Distance Formula and Algorithm Result

V. Framework Pipeline

(1) Image Collection. Images are captured from smart phone camera and scaled down to a 1/4 the resolution. (2) COLMAP 3D Reconstruction. The open-source tool COLMAP is used for the 3D reconstruction process [10]. It provides incremental reconstruction and bundle adjustment methods which provides state of the art performance compared to other implementations of SFM. (3) Registration and Segmentation. The Open3D [13] library provides implementations state of the art registration algorithms as well as segmentation[13]. (4) Change Detection. Cloud Compare is used to turn the calculated scalar Hausdorff distance for each point cloud into a heatmap.

A. Limitations and Future Work

3D Reconstruction requires a well lit static scene. Vegetation, shaded areas, moving clouds, etc are obstructions and result in lost geometry in the reconstruction process. Therefor, this framework should only be used for sites with isolated or few areas of vegetation.

Currently, the use of the Hausdorff distance is trivial and requires accurate elimination of outlier point in the segmentation process. Our next steps are to find a more robust algorithm for distance calculation between aligned point clouds.

Improving user interface, making use of Open3D's C++ interface to improve performance and further simplify the framework pipeline are areas we look to explore.

VI. Conclusion

Our framework utilizes recent advances in open source libraries and algorithms to provide landslide responders with a single application that handles every step in the 3D reconstruction and change detection process.

References

[1] Szymon Rusinkiewicz and Marc Levoy. "Efficient variants of the ICP algorithm". In: *Proceedings of International Conference on 3-D Digital Imaging and Modeling, 3DIM* (2001). ISSN: 15506185. DOI: `10.1109/IM.2001.924423`.

[2] David G. Lowe. "Distinctive image features from scale-invariant keypoints". In: *International Journal of Computer Vision* (2004). ISSN: 09205691. DOI: `10.1023/B:VISI.0000029664.99615.94`. arXiv: `0112017 [cs]`.

[3] Lynn M Highland and Peter Bobrowsky. "The Landslide Handbook — A Guide to Understanding Landslides". In: *Landslides* (2008), p. 129. ISSN: 1067084X. DOI: `Circular1325`.

[4] Sajid Ghuffar et al. "Landslide displacement monitoring using 3D range flow on airborne and terrestrial LiDAR data". In: *Remote Sensing* (2013). ISSN: 20724292. DOI: `10.3390/rs5062720`.

[5] D. Raucoules et al. "Time-variable 3D ground displacements from high-resolution synthetic aperture radar (SAR). application to La Valette landslide (South French Alps)". In: *Remote Sensing of Environment* (2013). ISSN: 00344257. DOI: `10.1016/j.rse.2013.08.006`.

[6] Arko Lucieer, Steven M.de Jong, and Darren Turner. "Mapping landslide displacements using Structure from Motion (SfM) and image correlation of multitemporal UAV photography". In: *Progress in Physical Geography* (2014). ISSN: 03091333. DOI: `10.1177/0309133313515293`.

[7] Sungjoon Choi, Qian Yi Zhou, and Vladlen Koltun. "Robust reconstruction of indoor scenes". In: *Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition*. 2015. ISBN: 9781467369640. DOI: 10.1109/CVPR.2015.7299195.

[8] A. Stumpf et al. "Ground-based multi-view photogrammetry for the monitoring of landslide deformation and erosion". In: *Geomorphology* (2015). ISSN: 0169555X. DOI: 10.1016/j.geomorph.2014.10.039.

[9] Abdulla Al-Rawabdeh et al. "Using an unmanned aerial vehicle-based digital imaging system to derive a 3D point cloud for landslide scarp recognition". In: *Remote Sensing* (2016). ISSN: 20724292. DOI: 10.3390/rs8020095.

[10] Johannes L. Schonberger and Jan-Michael Frahm. "Structure-from-Motion Revisited". In: *2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR)*. IEEE, June 2016, pp. 4104–4113. ISBN: 978-1-4673-8851-1. DOI: 10.1109/CVPR.2016.445. URL: http://ieeexplore.ieee.org/document/7780814/.

[11] Qian Yi Zhou, Jaesik Park, and Vladlen Koltun. "Fast global registration". In: *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics)*. 2016. ISBN: 9783319464749. DOI: 10.1007/978-3-319-46475-6_47. arXiv: 1311.2901.

[12] G. Bru et al. "Site scale modeling of slow-moving landslides, a 3d viscoplastic finite element modeling approach". In: *Landslides* 15.2 (2018), pp. 257–272. ISSN: 16125118. DOI: 10.1007/s10346-017-0867-y.

[13] Qian-Yi Zhou, Jaesik Park, and Vladlen Koltun. "Open3D: A Modern Library for 3D Data Processing". In: (2018). arXiv: 1801.09847.

[14] Sharad Kumar Gupta et al. "3D Reconstruction of a Landslide by Application of UAV & Structure from Motion". In: (), pp. 1–7.