



Chapter 6

LiDAR-based Semi-Autonomous Inspection of a Coal Mine Tailing Impoundment Emergency Spillway

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Abstract Coal mine tailing impoundments are built primarily to dispose of coal refuse and have taken on the role of storing process water. In the Appalachian region of the eastern USA, impoundments are generally constructed as cross-valley embankment dams. These structures are regulated by the respective state and by the US Department of Labor, Mine Safety and Health Administration (MSHA). The tailings dams may be designed to have emergency spillways that passively maintain the required pool elevation level for structural stability and water discharge control. The emergency spillways are required to remain free of obstructions at all times. Emergency spillways of tailing dams are inspected to ensure that no objects are blocking the water discharge. To facilitate a more objective, comprehensive, and faster inspection process during sunny-day, excessive storm events, and night-time conditions, this paper presents a semi-autonomous inspection approach using Unmanned Aerial Vehicle (UAV) to identify, categorize, and geo-reference purposely placed obstructions as simulated hazards placed within the cross-section of a hydraulic spillway. The study focuses on the inspection of an emergency spillway for

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a tailing dam facility located at a permitted and operating coal mine located in Greene County, Pennsylvania, USA. Airborne Laser Scanning (ALS) of the spillway was carried out using the L1 Zenmuse LiDAR sensor mounted on a UAV. Two flight missions were planned: one to scan the spillway without anomalies (baseline), and another with simulated anomalies placed on the spillway. After collecting LiDAR datasets, three-dimensional (3D) point cloud models of the spillway were reconstructed for both missions. The point clouds of both models were registered and then the Cloud to Cloud (C2C) surface change detection algorithm was implemented to detect changes in the baseline model. It was found that the C2C algorithm successfully detected all simulated anomalies on the spillway, even the ones that were the size of a soccer ball. It is concluded that relying on such technology has the potential to minimize the dependence on subjectivity of physical inspections and reduce the safety concerns for inspectors.

Keywords UAV · Anomaly detection · Tailing dam · LiDAR

Introduction

Coal tailing dams are inspected by trained inspectors and Professional Engineers to comply with state and Federal mining regulations. The dam inspection consists of a comprehensive field review of critical aspects of the dam structure and hydraulic appurtenant structures [1]. Inspecting large dam and hydraulic control structures is time-consuming and poses hazards to the inspectors. Therefore, it is essential to investigate methods to employ the latest technological advances to facilitate this process for humans and contribute to increase the likelihood that anomalies are detected. The authors have been exploring incorporating UAVs and advanced algorithms in the inspection process of tailing dams. In this paper, the authors present a simple approach for semi-autonomous anomaly detection for an emergency open channel spillway of a tailing dam on the East Coast of the USA.

The use of UAVs in structural health monitoring has caught the attention of researchers in the past. A dam health monitoring model using UAV photogrammetry was proposed by [2]. The authors reconstructed tri-dimensional (3D) models of the dam under study from UAV photogrammetry and utilized the Multiscale Model-to-Model Cloud Comparison (M3C2) method for anomaly detection. The M3C2 method was also used in another study to explore the potential of leveraging multi-temporal 3D surveying data to monitor archaeological heritage sites [3]. A deep learning-based approach was proposed to detect rill erosion on tailing dam slopes from UAV images [4].

Matrice 350 RTK and L1 Zenmuse

The UAV platform used in this study is the DJI Matrice 350 RTK shown in Figure 1(a). This advanced drone platform has a wide range of state-of-the-art features such as a wide-range transmission system that enables triple channel 1080p HD live feeds, an efficient battery system, several safety features, and the ability to carry three payloads simultaneously [5]. These features together with the proper payload make this UAV platform a very powerful asset for flight operations such as high-precision mapping, air-to-ground coordination, and automated precision inspection.



Fig. 1 DJI Matrice 350 RTK (a), and L1 Zenmuse LiDAR sensor (b).

L1 Zenmuse is a LiDAR sensor that can be mounted to the DJI Matrice 350 RTK drone platform as shown in Figure 1(b). This LiDAR sensor incorporates a Livox Lidar module, a high-accuracy Inertial Measurement Unit (IMU), and a camera with a 1-inch CMOS on a 3-axis stabilized gimbal. It has a detection Range of 450 m with 80% reflectivity and 0 klx, whilst

a lesser range of 190 m when the reflectivity is poor (10% reflectivity, and 100 klx). The effective point rate is 240,000 pts/s and it supports three different return modes: single, dual, and triple. It also offers two scanning pattern options: repetitive and non-repetitive. The RGB camera is 20 MP with 1-inch CMOS and a mechanical shutter. The payload has a vision sensor for positioning accuracy and is capable of GNSS, IMU, and RGB data fusion. According to the specs provided by the manufacturer, the system accuracy (RMS 1σ) is 10 cm at 50 m horizontal and 5 cm @ 50 m vertical, while the LiDAR ranging accuracy (RMS 1σ) is 3 cm at 100 m [6].

The open channel emergency spillway

The open channel emergency spillway shown in Figure 2 is for the tailing dam facility studied in the project. It plays an essential role in managing the disposal of excess water, particularly in times of emergency (excessive precipitation inflow). The spillway attributes are a trapezoidal cross-section with a base width of approximately 15 meters, top width of 32 meters, and side slopes of 32 degrees. The spillway length is approximately 155 meters, and discharges to an existing stream. It was constructed using concrete-filled fabric bags having a rough surface to reduce water velocity. Spillways are required always to remain free from obstructions that prevent water discharge during emergency events.



Fig. 2 Open channel emergency spillway.

Mission Planning

The DJI Matrice 350 RTK is used to execute the spillway surveying mission. The L1 Zenmuse sensor is mounted on the drone to collect LiDAR data points. The mission is initially created on the remote controller of the drone on the Pilot 2 app. The area of interest is selected on the map, and the mission and payload settings are set to build accurate 3D models of the spillway. The sampling rate is set to 240 kHz for the payload. Because the drone can do real-time kinematic (RTK) correction of the GPS signal while surveying the area of interest, no ground control points are needed to verify the drone's measurements and point cloud model accuracy. The collected LiDAR data points are stored on a MicroSD card and used later to reconstruct detailed three-dimensional spillway models.

To implement an anomaly detection method, the spillway had to have surface changes that represent potential anomalies blocking the spillway. Consequently, two surveying missions are planned and flown. For the first surveying flight, the open channel spillway was clear from any objects (simulated anomalies). Therefore, the dataset collected from the first mission served as a baseline for comparing with the datasets collected from the second mission. To create a scenario that simulates the existence of potential anomalies on the spillway, objects such as boxes and soccer balls are dispersed on the spillway, as well as some of the team members stood in different areas while the UAV was scanning to create the second dataset as shown in Figure 3.

After collecting the LiDAR datasets from the two missions, DJI Terra [7] software is used to reconstruct three-dimensional point cloud models of the spillway. These models are then exported in formats compatible with point-cloud software for



Fig. 3 Simulated anomaly locations of the spillway.

further analysis. The next step is to register the two 3D point cloud models to align and merge them into a common coordinate system. Over the years, various point cloud registration algorithms were introduced such as the classic ICP-algorithm, feature-based methods, learning-based methods, and others [8]. CouldCompare [9] software is used to register the reconstructed 3D point cloud models by manually picking at least 4 equivalent point pairs i.e. correspondences in each model. Then, the registration algorithm will find the correct translation and rotation between the two clouds.

The registered point clouds are then utilized as inputs for the Direct Cloud-to-Cloud Comparison algorithm (C2C). This is an efficient approach to compare 3D point clouds directly without gridding or meshing the data and calculation of surface normal. It compares two sets of point clouds simply by finding the closest point in the first cloud for each point in the second point cloud. Subsequently, the distances between the points indicate surface change. However, the surface roughness and point cloud density affect the closest point distance L_{C2C} between the point clouds. Therefore, this approach is well-suited for change detection for highly dense point clouds [10].

Results

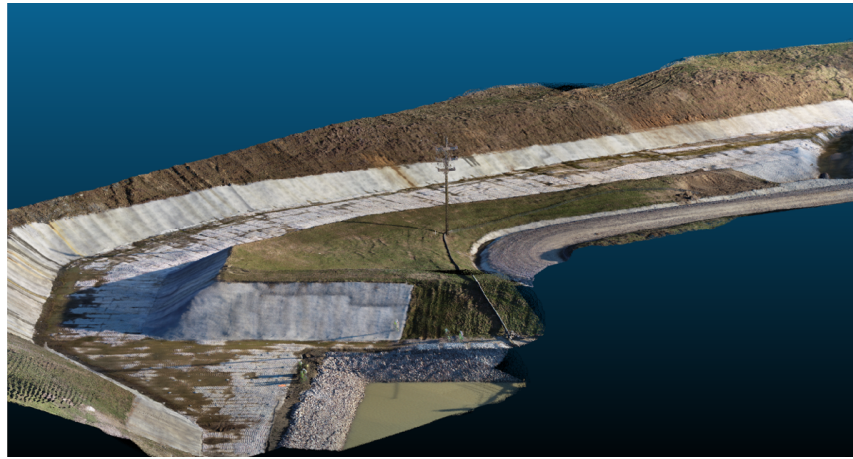
Three-dimensional model reconstruction of the spillway

The reconstructed 3D point cloud models of the spillway are illustrated in Figures 4(a) and 4(b) representing the models without and with anomalies, respectively. Each point cloud has approximately 150 million points. These high-density point clouds show fine details of the open channel spillway with remarkable clarity. In addition, the models exhibit crucial characteristics such as surface features, which makes it possible to analyze both normal and hazardous situations in great detail. Moreover, the accuracy of these reconstructions provides insightful information about the state of the spillway which enables more effective monitoring plans.

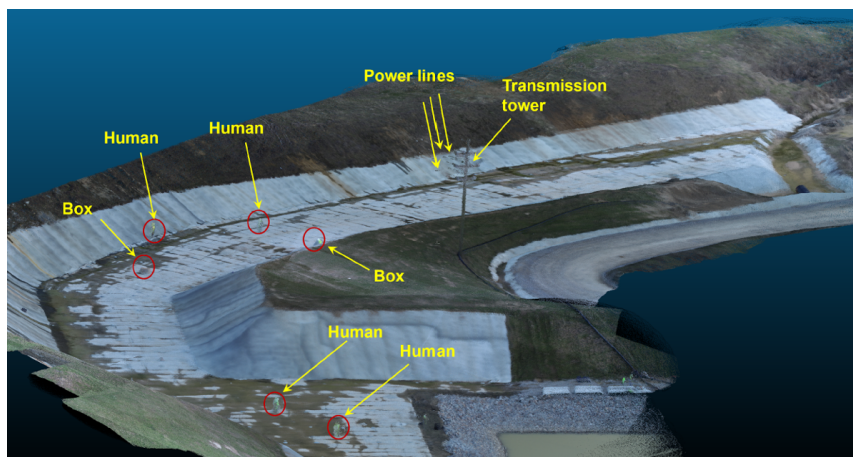
Before performing further analysis, it is imperative to investigate how well the LiDAR scan captured the anomalies with varying sizes. A close-up view of the reconstructed spillway model with anomalies shows that even an object as small as a soccer ball is clearly visible and well represented in the point cloud model as shown by the color-coded elevation map of the reconstructed model with anomalies in Figure 5. It is worth mentioning that the flight altitude for this mission is 30 m above the bottom of the spillway which emphasizes the ability of the LiDAR sensor to capture impressive details from such high altitude.

Point cloud registration

To align both models of the spillway with and without anomalies, 4 pairs of points are selected from each model at identical locations. To minimize registration errors, these points are strategically picked at distinct locations of the spillway such as the spillway's corners and key features. Subsequently, the models are aligned and registered accordingly, and the software dis-



(a)



(b)

Fig. 4 Reconstructed 3D point cloud models of the spillway without anomalies (a), and with anomalies (b).

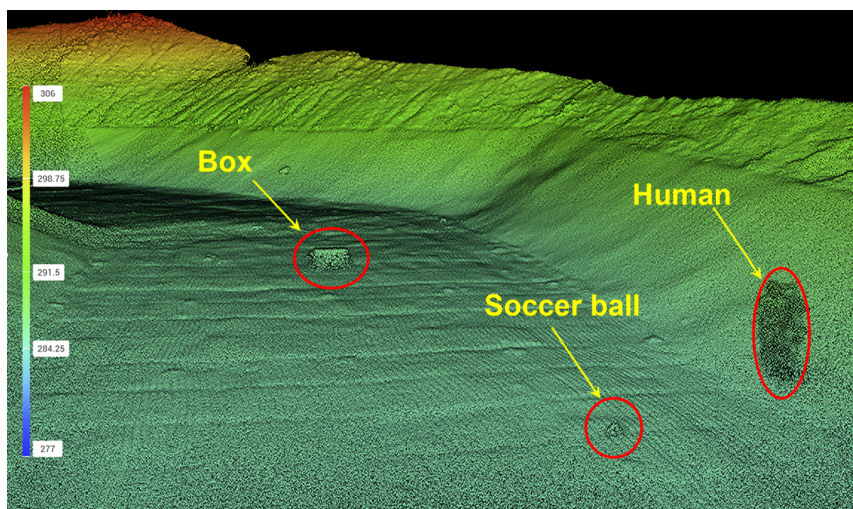


Fig. 5 Color-coded elevation map of the reconstructed 3d with anomalies model.

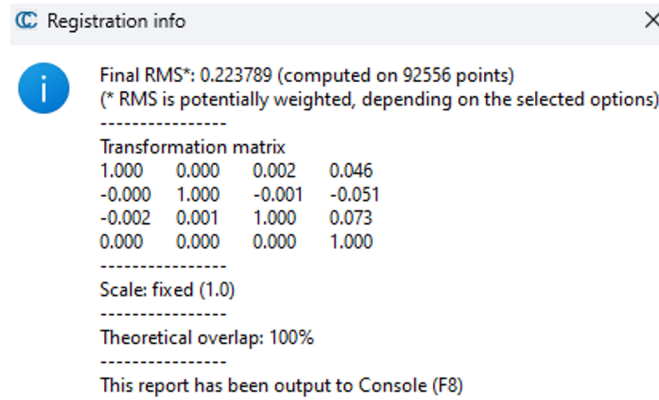


Fig. 6 Registration RMS error and transformation matrix.

plays the registration information as shown in Figure 6. The final root mean square error (RMS) for the registration process is computed based on nearly 46,000 points, yielding an RMS error of 22.37 cm. This degree of accuracy is considered adequate for identifying the existence of anomalies impeding the hydraulic discharge that are detected using the C2C algorithm, as it ensures the alignment is accurate enough for reliable comparison and assessment of the spillway models.

Implementing the C2C algorithm

The C2C algorithm is applied to the registered models to identify changes in the surface between the baseline model (without anomalies) and the model with anomalies. This algorithm highlights surface changes between point cloud models where these discrepancies represent anomalies in our case. Figure 7 illustrates a color-coded map of the compared models generated by the C2C algorithm. The map clearly shows distinct color variations corresponding to the locations of the simulated anomalies. Therefore, this indicates that the C2C algorithm successfully detected all surface changes including the smallest object such as the soccer ball. This robust detection ability is essential for evaluating the spillway's integrity and making sure that all pertinent anomalies are found and handled effectively.

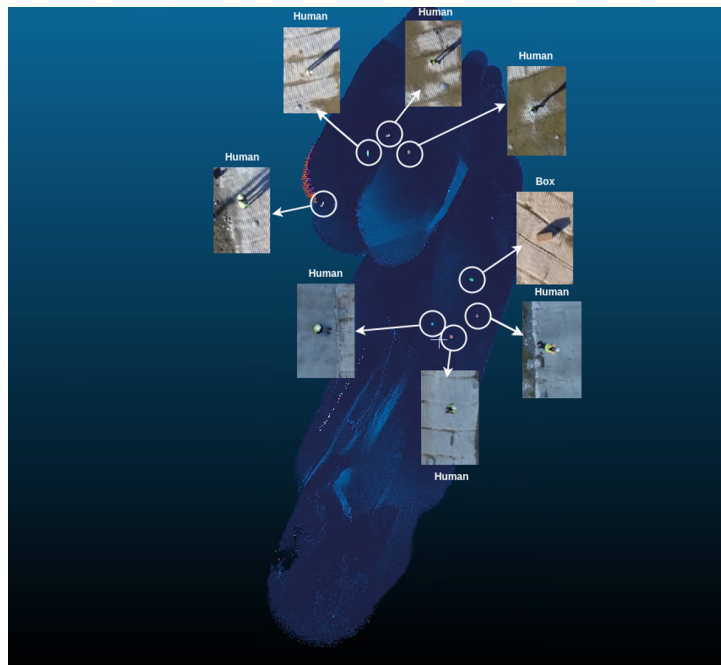


Fig. 7 Color-coded map generated by C2C algorithm.

Conclusions

In this paper, the authors introduce an approach to utilize an ALS LiDAR in the inspection of an open channel emergency spillway at an existing coal mine tailing impoundment. With this approach, accurate 3D point cloud models of the spillway are reconstructed and the C2C algorithm is utilized to compare them. In conclusion, this work provides insights into the efficiency and practicality of employing ALS LiDAR in structural health monitoring and damage detection applications. Also, the findings demonstrate that relying on such technology has the potential to minimize the dependence on the subjectivity of physical inspections and reduce the safety concerns for inspectors. In the future, the authors plan to investigate additional hazards associated with coal mine tailing impoundments such as leakage and seepage. Furthermore, they aim to develop a user-friendly software interface to facilitate hazard detection in these environments.

References

1. Quaranta, J. D., Stawovy, J., & Fourie, A. (2022). Study on mine tailings classification effected by co-disposal of drilling wastes with geochemical cations. *Mining, Metallurgy & Exploration*, 39(4), 1391–1402.
2. Zhao, Sizeng, et al. "Structural health monitoring and inspection of dams based on UAV photogrammetry with image 3D reconstruction." *Automation in Construction* 130 (2021): 103832.
3. Lercari, N. (2019). Monitoring earthen archaeological heritage using multi-temporal terrestrial laser scanning and surface change detection. *Journal of Cultural Heritage*, 39, 152–165.
4. Nasategay, F. F. U. (2020). Detection and monitoring of tailings dam surface erosion using UAV and machine learning (Doctoral dissertation, University of Nevada, Reno).
5. Matrice 350 RTK. DJI. (n.d.). <https://enterprise.dji.com/matrice-350-rtk?site=enterprise&from=nav>
6. Support for Zenmuse L1 - DJI. (2014). DJI. <https://www.dji.com/support/product/zenmuse-l1>
7. DJI Enterprise. (2024). (V 4.2.5). [DJI Terra]. <https://enterprise.dji.com/dji-terra>
8. Li, L., Wang, R., & Zhang, X. (2021). A tutorial review on point cloud registrations: principle, classification, comparison, and technology challenges. *Mathematical Problems in Engineering*, 2021(1), 9953910.
9. CloudCompare project. (2024). (V 2.14.alpha). [CloudCompare]. <https://www.cloudcompare.org/>
10. Lague, D., Brodu, N., & Leroux, J. (2013). Accurate 3D comparison of complex topography with terrestrial laser scanner: Application to the Rangitikei canyon (NZ). *ISPRS journal of photogrammetry and remote sensing*, 82, 10–26.

