Tackling Geotechnical Risks in Tailings Dams Using High-Resolution UAV Imaging and Advanced Image Processing

Jose A. Gomez Llerena[1]; Milad Ghahramanieisalou[2]; and Javad Sattarvand[3]

[1]Graduate Research Assistant, Dept. of Mining and Metallurgical Engineering, Univ. of Nevada, Reno, NV. Email: jgomezllerena@unr.edu
[2]Graduate Teaching Assistant, Dept. of Mining and Metallurgical Engineering, Univ. of Nevada, Reno, NV. Email: mghahramanieisalou@unr.edu
[3]Dept. of Mining and Metallurgical Engineering, Univ. of Nevada, Reno, NV. Email: jsattarvand@unr.edu

ABSTRACT

Recent technological developments in remote sensing and image analysis and their introduction into the mining industry have opened the door for updating risk analysis techniques. The R&D team of the Mining Automation Lab of the University of Nevada–Reno develops UAV-based photogrammetry and image analysis technologies to address the geotechnical risks of the tailings dam. All procedures are based on high-resolution imaging by a special UAV control software for terrain-following and photogrammetry for 3D modeling. The system can efficiently cover large areas and capture high-resolution images as input for novel image analysis methods. This approach's biggest challenge is acquiring enough annotated samples to train a model that produces high-accuracy results in various rock types and environmental conditions. The results can be used for localized risk analysis of rockfall using available empirical models. Our team at UNR is working on including multispectral imaging and unifying all the data formats and analysis techniques under a digital twin framework.

INTRODUCTION

Proactive management is necessary for a tailings storage facility (TSF) to operate successfully. Tailings are heterogeneous and anisotropic by nature, which presents numerous difficulties for storage, design, operation, and closure. The designs of monitoring systems are adapted to the distinctiveness of each TSF and anticipated operating performance, and they range from the most basic to the most sophisticated. Implementing a well-thought-out and thorough monitoring program is necessary to evaluate TSF performance. This program must produce high-quality data, collect and retrieve data quickly and reliably, and use the proper methods to send this data to the stakeholders for analysis and evaluation (Morrison 2022).

Monitoring instrumentation and supporting systems are subjected to exceedingly demanding conditions that require the cautious design of both the setting and long-term tailings characteristics. Monitoring systems generally fall into two categories of system terrestrial-based and remote (Morrison 2022). The focus of this paper is on the remote type of monitoring systems. Several hundred tailings dams have collapsed since 1910, according to the International Commission of Large Dams and the United Nations Environment Programme. One reason is the slope's fragility. The instability of a slope might be caused by internal tailings movements (Cheng et al. 2021; Ozcan et al. 2013). External motions of embankment slopes, seismic activity, the weight of tailings, and moisture content are further factors. Hence, these places need to be kept an eye on. With the help of drones and remote sensing technology, this study presents the necessary research for a dependable and proactive tailings dam instability alert system.

There are two types of remote sensing systems: active remote sensing and passive remote sensing (Morrison 2022). The former assesses the surface feature using energy, such as laser, radio waves, or other techniques, and measures the reflected condition. On the other hand, passive remote-sensing techniques utilize naturally existing energy that is radiated or reflected from the Earth's surface and can be filtered depending on a distinct spectrum. Satellite-based systems are the most traditional and widespread method of remote sensing. The equipment used by small unmanned aerial vehicles (UAVs) for near-ground surface systems to measure or produce different types of energy for imaging has recently changed. For instance, RGB cameras, LiDAR, thermal imaging, and hyperspectral sensors are getting smaller and lighter (Society for Mining Metallurgy & Exploration 2022).

Additionally, digital twin (DT) is a dynamic idea for using various technologies to mirror a physical system in digital space. The realized level depends on available data, resources, and managerial decisions (Jiang et al., 2021). (Negri et al., 2017) argue that DT is an evolved Virtual Factory (VF). The difference is that DT goes beyond VF by including a realistic synchronization that leads to making the right decisions about the actual and future production. The data model for DT must consist of systems operations, history, behavior, and current state. Many researchers look at DT as a means of maintenance, diagnostics, and prognostics (essentially health analyses); or as a model that simulations could be run on or seen as the simulation of the system itself.

1. USING UAVS FOR REMOTE SENSING

By measuring an area's reflected energy (multispectral imaging) and emitted radiation (thermal imaging) from a distance, typically from a satellite or aircraft, remote sensing is the process of identifying and keeping track of its physical features (USGS 2022). Satellites may cover vast land areas but have certain downsides, such as irregular satellite visit times, limited picture quality, and a time lag between satellite flyover and sensor data reaching the end-user that can take many hours; hence, it cannot be utilized as a quick reaction resource. Moreover, cloud coverage is an essential factor in the availability of satellite data (Allison et al. 2016). Aircraft, on the other hand, can be deployed and versatile, allowing them to target critical areas and adjust as priorities shift. Aircraft frequently undertake lengthy missions and return to the target region, mainly using unmanned platforms. Unmanned aerial vehicles (UAVs), sometimes known as drones, fly at lower altitudes than traditional aircraft, which results in photos with excellent precision, flexibility, and low operational costs (Maes & Steppe 2019). Aerial remote sensing images taken by a UAV have a more excellent resolution than those taken by satellites. Compared to UAV photos, satellite remote sensing images are more complex to comprehend and larger (Lu et al. 2020a). However, the drones' short range and low endurance present a challenge when using them. The system is not designed to support longer flights delivering continuous, uninterrupted data or lengthy mapping excursions. It is essential to mention that wind has a significant role when using drones. Strong winds will drain quicker drone batteries due to more energy exerted to combat winds means faster draining. Similarly, flying an airplane requires more fuel against strong headwinds (Allison et al. 2016).

2. REMOTE SENSING: MULTISPECTRAL AND THERMAL IMAGING

To discover or describe a material's characteristics, spectroscopy investigates how light interacts with those attributes. As a result, it analyzes the target's light behavior and identifies materials based on their distinctive spectral signatures. The spectrum of the object can be used to identify these spectral fingerprints. A spectrum shows how much light is generated, scattered, or transmitted from the target by describing the amount of light at various wavelengths. Typically, it is displayed as a graph with an intensity and wavelength scale (SpecimSpectral 2019).

Because multispectral contains a wide range of spectral information, allowing you to identify specific materials, multispectral imagery enables you to collect more precise and detailed data (Shippert 2003). The ability to categorize similar materials and gather multispectral data concede sub-pixel information. The principle of reflection is an important topic. Reflectance measures how much light a material reflects (Shippert 2003) despite being absorbed or transferred. The reflectance spectrum depicts the reflectance of various materials as measured over a spectrum of wavelengths. A particular wavelength of light will be reflected by some materials while being absorbed by others. Healthy vegetation, for instance, appears green to human eyes because it has a reflectance peak in the visible spectrum's green region.

On the other hand, water bodies absorb near-infrared wavelengths, which is why there is no reflectance in this region. Certain materials can be recognized via multispectral imaging by using the reflectance value of the materials. On the other hand, thermal sensing focuses on detecting emitted rather than reflected energy. Since all matter emits temperature-dependent electromagnetic radiation at temperatures beyond absolute zero, thermal sensing concentrates on detecting emitted rather than reflected energy. The distribution maxima fluctuate inversely with temperature, and the radiance is inconsistent throughout wavelengths. The peak occurs between 8 and 12 µm at ambient temperatures, and most of the radiant energy is found at wavelengths more significant than 5 µm. As a result, the thermal imaging band refers to the wavelength range between 8 and 15 µm. The spectrum from 5 to 8 µm is unsuitable for remote imaging due to solid atmosphere absorption (Allison et al. 2016). Surface soil moisture (SSM) detection is one of the frequent applications of thermal sensors. Because moisture directly impacts the strength of the tailings, managing moisture is a crucial goal of managing these massive impoundments (Zwissler et al. 2017). Moreover, identifying early-stage seepage is crucial for the dam's security (Mainali et al. 2016).

3. DETECTION OF SURFACE RILL EROSION ON TAILINGS DAMS USING UAV IMAGING AND DEEP NEURAL NETWORKS

Visual monitoring is highly recommended because it is the best way to identify issues. Machine learning algorithms can help automate tasks and model complex problems (L. Zhang et al. 2018).

The R&D team of the Mining Automation lab of the University of Nevada, Reno, developed UAV-based photogrammetry and image analysis technologies to address the geotechnical risks of open-pit mining, specifically rills on tailings dams. (Nasategay et al. 2021) Used the Unet architecture for semantic segmentation to effectively identify rills on tailings dams. This architecture expands the fully convolutional network and provides more precise segmentation with few training images.

TensorFlow library was employed in a Python programming environment for model design. The model was analyzed qualitatively and quantitatively. The qualitative test overlapped the predicted mask against the original image, and the quantitative test calculated accuracy, precision, and recall values. The results show that Unet could competently detect features such as tension cracks from UAV data. The value of precision (number of pixels correctly labeled to the actual pre-labeled total rill pixels), recall (correctly labeled pixels compared to the overall number of pixels predicted as rills), and F1- score (accuracy based on precision and recall values weighted together) were 83.2%, 72%, and 77.2% respectively. Figure 1 c-d shows the accuracy of the algorithm.

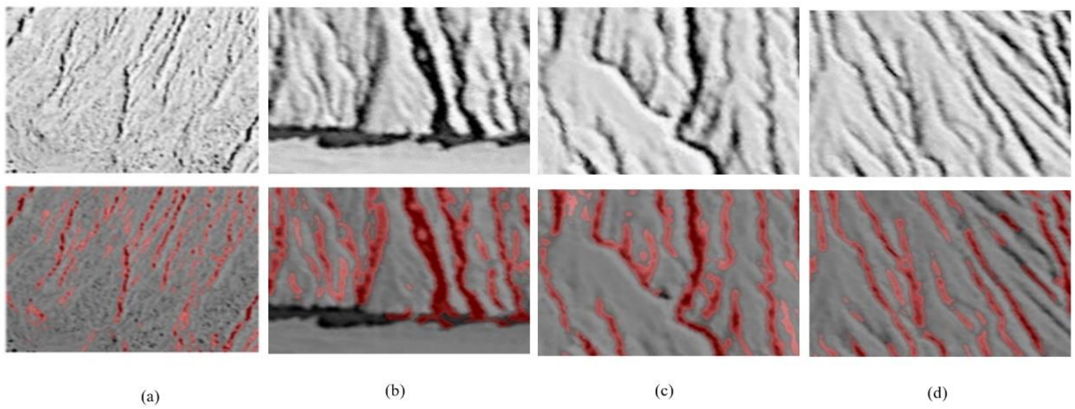

Figure 1 a - b) Training; c - d) Testing Images for the algorithm developed by (Nasategay et al. 2021)

4. DIGITAL TWIN

Since DT integrates the readings of every sensor (internal and external) and models the system and its environment, it is possible to merge data from various sources and in different formats (Negri et al., 2017). This is especially important for applications like moisture content retrieval from RGB images. DT's emergence is due to the real-time synchronization of the sensed data from the field. The Internet of Things allows electronics, software, sensors, and network connectivity to gather and transform data. The idea of the DT is to bridge the physical and virtual worlds through seamless data transmission. The information is transferred from the real world to the virtual via IoT devices and returned in processed results (Agrawal et al., 2022). Data received from various sources are inevitably going to have different structures and formats and are going to be noisy. It is essential to preprocess the information to "clean" and unify them. Then, using available data processing techniques such as statistics (distribution, correlation, regression, clustering analysis, and dimension reduction techniques like PCA), neural networks, and fog computing will help extract meaningful relations and correlations within the dataset.

5. PROCESS TO INCORPORATE UAV IMAGING AND ADVANCED IMAGING TECHNIQUES

The flowchart in Figure 2 describes the process of creating a tailings dam digital twin. The exact process was used to detect surface rills described in section 3, except it ended after using

Convolutional Neural Networks and their respective interpretation and analysis. Even though the flowchart depicts the process of creating a tailings dam digital twin, it can be extrapolated to create any other digital twin in the mine site where using drones can simplify the task of acquiring data.

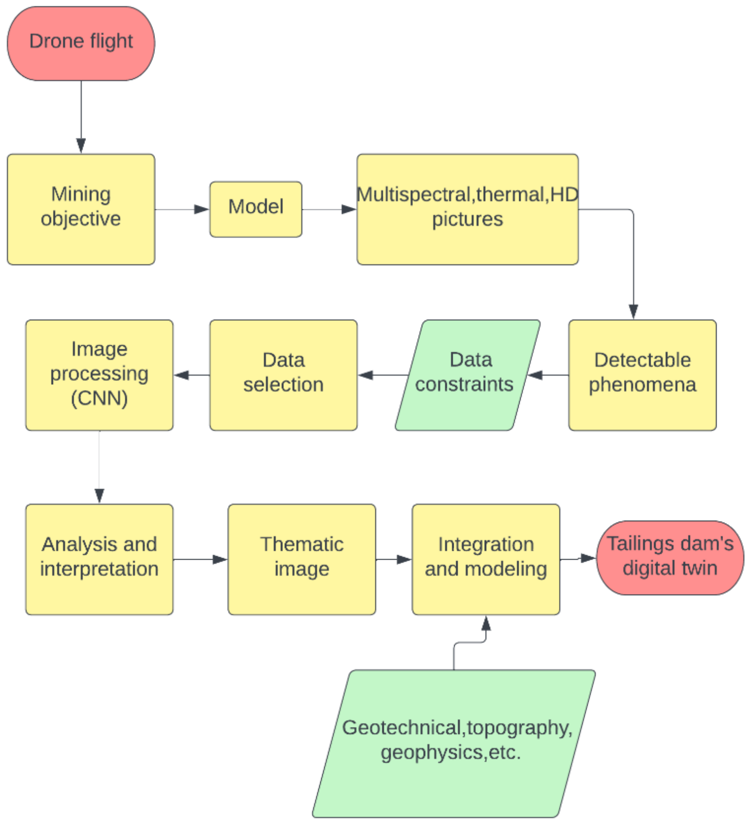

Figure 2. Flowchart to incorporate UAV imaging and advanced imaging techniques.

6. RESULTS

Figure 3 displays a thermal image that the University of Nevada, Reno's Mining Automation lab's research and development team took. Five waves—RGB, Red-edge, NIR, LWIR, and Thermal—can be captured in a multispectral image by the drone Matrice 600 carrying the Mica Sense Altum camera. In Reno, Nevada, approximately 20 liters of water were spilled upon barren ground. The red box indicates where the water was spilled and shows how simple it is for thermal cameras to identify moisture. Figure 4 shows the same spectral picture, but the Spectral Angle Mapper, or SAM, was the technique to identify moisture. This method looks at the spectral angle between the target (moisture) and the pixel in the picture; the smaller the angle, the more similar the objects are. In this picture, water is classified as blue; dry soil as yellow, purple, and magenta; black is used when the algorithm couldn't classify the object. Figure 5 depicts a different approach using a linear combination of the six bands to identify moisture (purple), dry soil (orange), not classified (white).

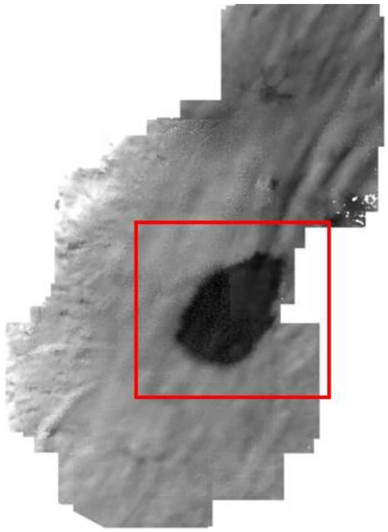

Figure 3. A thermal picture was taken with MicaSense Altum

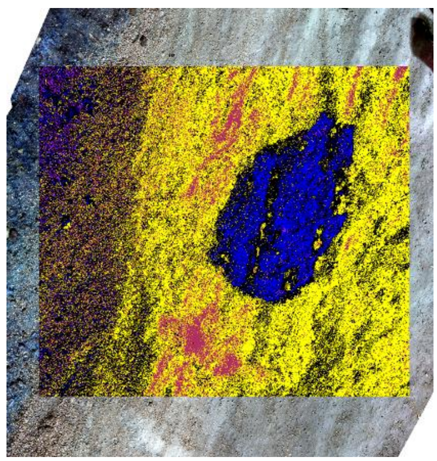

Figure 4. Spectral Angle Mapper

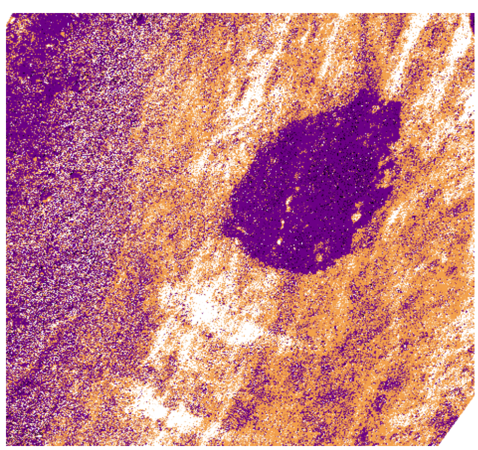

Figure 5. Soil moisture using equation of six bands

7. DISCUSSION

(Rasheed et al. 2020) Identify four challenges that must be addressed for DT's full applicability. 1) a DT model must be a mirror image of the physical asset and easy to operate, 2) as the physical asset evolves, the model must also update itself (yet be backward compatible), and 3) any decision that is made using DT or by the DT itself, must be interpretable and explainable to human beings, and 4) there must be a two-way connection between the twins for continuous updates. The model's fidelity and timely update depend on the quality and quantity of the data transferred between the twins. Moreover, remote sensing is a valuable tool for monitoring moisture as a sign of instability, as depicted in figure 3. However, lighting and other environmental conditions can affect the identification techniques, as shown in figures 4 and 5, generating misclassification; hence in figure 5, part of the dry soil was classified as wet. In figure 4, part of the wet soil was not identified.

CONCLUSION

Remote sensing technologies using drones allow mine sites to obtain accurate results when physical access is limited because of logistics, geometry, or hazardous conditions. Drone-based monitoring is more effective than manual or satellite-based systems regarding time and data accuracy. Small unmanned aerial systems are becoming more robust and airworthier, lightweight, maneuverable, and versatile. In combination with high-resolution RGB cameras and thermal and multispectral sensors, it is possible to detect moisture content, one of the reasons for slope instability, causing tailings storage facilities to fail. Moreover, machine learning algorithms and image processing methods are valuable tools for retrieving reliable results.

Additionally, a DT of the mine environment will be an exact up-to-minute replica of the mine's physical state, enabling managers and engineers to make their modeling, calculation, and simulations in this safe space and make decisions either themselves or via an AI algorithm. In the case of moisture content retrieval, DT will not only act as a data storage and processing unit, but it will also help train CNN and increase the interpretability of the results. DT will also help analyze the unknown datasets to receive the soil moisture content and verify them based on either an expert's or a machine learning algorithm's judgment. This will inevitably increase trust in the system and its results. Moreover, while 2D images will be used for moisture content retrieval, the results will be presented in a semantic, high-fidelity 3D model containing the moisture content and other geotechnical and geological information.

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