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Rockfall Risk Analysis in the Era of Automation and Artificial Intelligence

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Abstract

The challenge of rockfall and its associated risks has been haunting the mining industry for quite some time. It has been a significant cause of fatalities, serious injuries, and financial losses. Following the established empirical techniques is the most efficient (probably the only) approach to studying this problem. But they have their disadvantages; chief amongst them is the detailed and resource-exhausting geological studies. Recent technological developments and their introduction into mining engineering applications open the door to updating the studies. Such renovations would mainly focus on automating geological mapping of the rock surface using unmanned aerial systems and big data analysis. Also, efforts will be taken to model the potential trajectory of the fallen rocks in a semantic 3D model based on machine learning algorithms. UAV photogrammetry and LiDAR were used to gather point cloud data to build a 3D model of the rock slope and extract its geological features. Furthermore, a trajectory estimation model of rockfalls, also developed at UNR's Mining Automation lab, uses the mass and origin of rockfalls to calculate the impact characteristics and simulate a rockfall's energy changes during its fall. Both these developments rely on a combination of physics-based and data-driven models, necessitating continuous data flow. Moreover, the mine site is a dynamic environment, and changes happen daily; therefore, the information about the rock surface must be updated at timely and financially efficient intervals. The empirical methods used for generations are our best bet at calculating the rockfall probability; however, we are also exploring the possibility of improving these techniques by using machine learning to extract correlations between rockfalls and factors that affect them. One major challenge is the availability of historical data on rockfall cases. For this purpose, a geotechnical digital twin of the mine site, capable of combining a high-fidelity 3D model of the site with semantic data received from monitoring, lab tests (including coefficients of restitution), and simulations, is designed to present all this information in a single unified interface for interactive decision making and developing a rockfall risk map.

Keywords: Rockfall; Artificial Intelligence; Geotechnical; Geological Mapping; Mining

Abbreviations: AVR: Average Vehicle Risk; COR: Coefficients of Restitution; DSD: Decision Sight Distance; DBSCAN: Density-Based Scan with Noise; HAM: Hybrid Analysis and Modeling; PC: Point Cloud; RHRS: Rockfall hazard rating system; RANSAC: Random Sample Consensus; RPF3D: Rock Path Finder

Introduction

Rockfall is the continuous movement of a rock down a steep slope instigated by adverse discontinuity orientation, freeze-thaw cycles, inefficient blasting, water presence, weathering, and vegetation on the slope. The rockfall movement is categorized into free-falling, bouncing, rolling, or sliding [1]. The rockfall hazard rating system (RHRS), introduced by the US Department of Trans portation, is a uniform method to acquire the geographic locations of rockfall sites and categorize them using a two-phase process including three preliminary groups and a detailed classification to identify the most hazardous sites [1]. However, the general problem with these empirical procedures is their resource-exhaustive approach that requires a very experienced expert to yield the appropriate results. Hence, there is a need for a faster, state-of-the-art, and economical method to deliver reproducible results regardless of the raters' experience. The geotechnical DT will be a hub for a high-fidelity 3D model, an automated geological mapping algorithm of the rock discontinuities based on point cloud data, and a realistic 3D trajectory simulator for rockfalls, all combined to present the most holistic overview of the rockfall study and analyses.

By importing the historical data into this system and complementing it with state-of-the-art technologies, it would be possible to make an objective approach capable of producing reproducible results. However, the manual geological mapping of the slope is a very laborious, exhaustive, and unsafe undertaking. At the University of Nevada, Reno's Mine Automation Lab., an automated system is developed to extract the joint characteristics (orientation, spacing, and persistence) from point cloud data. The deep learning algorithm used in this system shows promising results and accuracy in recognizing joint planes on the rock slope while ignoring noises such as vegetation and debris. Of course, like any machine learning algorithm, training datasets are critical in developing this method [2]. Another significant area of interest for rockfall analysis is understanding the behavior after their fall. Simulating the rockfall paths and finding run-out zones is critical in recognizing the gullies in which rockfalls concentrate. A 3D software (Rock Path Finder (RPF3D)) was developed assuming lumped masse for rockfalls and elastic rock-surface contacts to develop a risk map of the mine site. RPF3D is designed as a quick and reliable rockfall risk assessment tool for the mine site. The objective is to address the shortcomings of available rockfall simulation tools in recognizing mining-specific needs in rockfall trajectory estimation. The software, however, is far from the final development stage, and a lot of effort is being devoted to addressing the simplifications that could tarnish the accuracy of the results. Conducting rigorous lab and field experiments to evaluate the software results is also under investigation. Nevertheless, the software capability of handling high-fidelity 3D rock slope models in an acceptable time to render detailed bounce heights and lateral movements is promising [3].

Geotechnical Digital Twin

DT's Definition

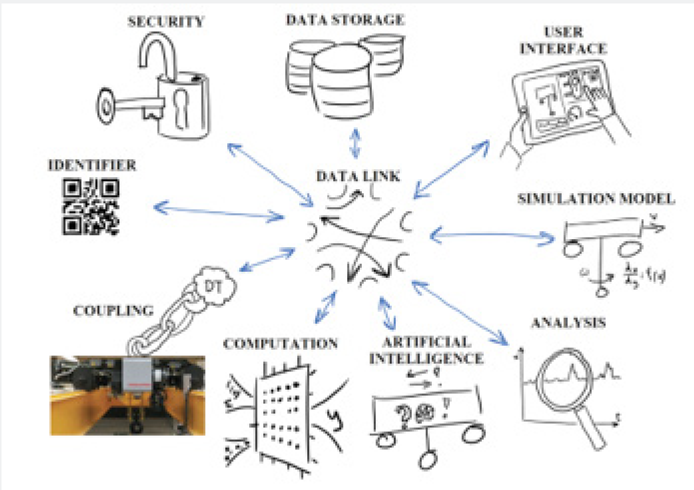

Figure 1: Schematics of "feature-based" DT framework [5].

As new technologies are being introduced to the mining industry, the challenges related to their safe assimilation and the potential changes they bring to mining techniques necessitate adjustments to the current operations. Predictive simulations are significant for understanding unforeseen scenarios and shifting costly changes from the operational stage to the design. DT methodology has gained a lot of attention in recent years. Many industries, from manufacturing to engineering and even social sciences, are adopting this approach to understand better the complex systems they are dealing with [4]. DT is a dynamic idea for implementing technologies; the level at which it is realized depends on the data and resources available and managerial decisions [4,5]. Data received from various sources (Figure 1) will inevitably have different structures and formats and be noisy. Pre-processing the information to "clean" and unify them is essential. Then, using available data processing techniques such as statistics (distribution, correlation, regression, clustering analysis, and dimension reduction techniques like PCA), neural networks (forward NN, feedback network, and self-organizing networks), machine learning algorithms, edge computing, and fog computing will help

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extract meaningful relations and correlations within the dataset [6]. Also propose a new hybrid approach to take advantage of the accuracy and universality of big data analysis while utilizing interpretable physics-based models, and they call it "Hybrid Analysis and Modeling (HAM) " (Figure 2).

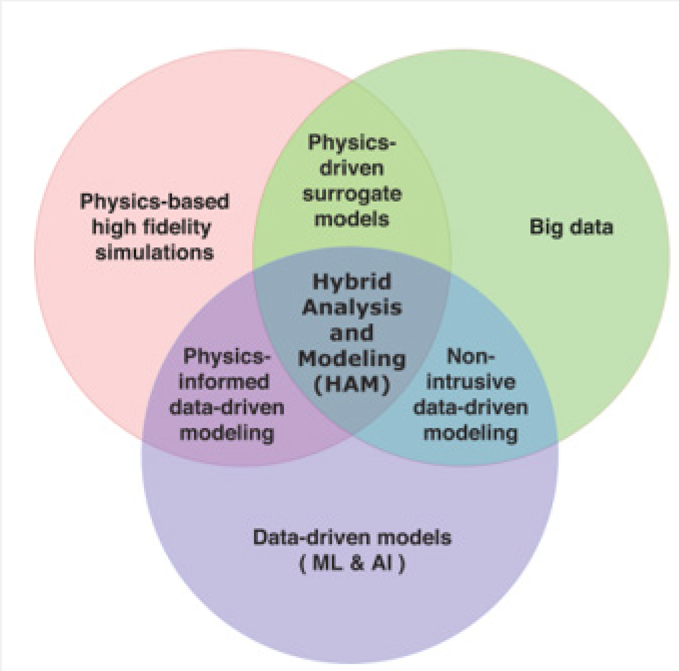

Figure 2: HAM, combining data-driven and physics-based models [6].

DT's Application in Rockfall Risk Analysis

Historically, the mining industry has always collected large amounts of data; however, there is a significant lack of effort and resources to analyze them. One of the critical obstacles to data analysis is the lack of communication between the wide range of mining operations. Exploring the correlations of seemingly independent processes and variables through data-driven models will enable managers and engineers to create a holistic approach to ensure an optimized solution. Admittedly, the quality of recorded data (past or present) has a significant role in the efficacy of this approach. However, a more pressing issue is the availability of representative data. Furthermore, data quality is a very fluid concept depending on specific points of view (noise, corruption, bias, etc.) [7] has explored the applicability of DT in disaster management.

In their case, DT is used as a unifying platform for all the crisis information; to implement AI in the situation analysis, decision making (including resource allocation), and cooperation of different parties; and to better understand the interactive effects of decisions and actions in disaster management. DT can help with the training and cooperation of responders in disasters; this capability is realized through "serious gaming environments" that also provide visualization. Analyzing the interaction of responders and the information they need would help with resource and task allocation. The iterative process allows the system to learn, grow, and provide predictive simulations [8]. have proposed a DT-based monitoring system for geological hazards. The evolution of the prediction methods for such hazards has led to a dynamic system capable of "real-time' analysis and prediction (using Back Propagation Neural Network to calculate the probability of a hazard). Combining data from GIS, GPS, and various remote sensing technologies (indicating the status of the topography) with historical data (landslides, subsidence, collapses, and meteorology) provides a data visualization tool (based on GIS) and a predictive simulator of the behavior of the slope (Figure 3).

Geological Mapping of the Slope Surface

Rockfalls either stem from discontinuities in the rock mass or result from erosion. In the first case, the discontinuity (>10 ft) orientation and type (joints, faults, bedding planes, and shear structures) are the critical factors that one must consider. Infillings and water pressure are also very important in subsequent rockfall events [1,9,10]. The friction of discontinuity surfaces directly affects the potential movement of a block relative to another. The friction is defined based on the features of the macro- (the undulations) and micro- (the texture). Rockfall potential is higher when the discontinuity surfaces are highly weathered and open joints

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with infilling or water dominate the rock slope [1,9,10]. As for erosion, differential erosion leads to over-steepened slopes, unsupported hang walls, or exposed more resistant rock units that could be the potential rockfall sources. The differential erosion features, alluding to protruding and irregular features on slope surfaces, may also cause rockfalls to be launched to an uncharacteristic trajectory, offsetting the benefits of safety measures. As for the causes of erosion, the experts must consider the collective influence of physical, chemical, and man-made erosion on the slope surface [1,11]. Therefore, geological features on the slope have a substantial role in rockfall events, and most empirical methods for studying rockfall depend on the measurement and characterization of such features.

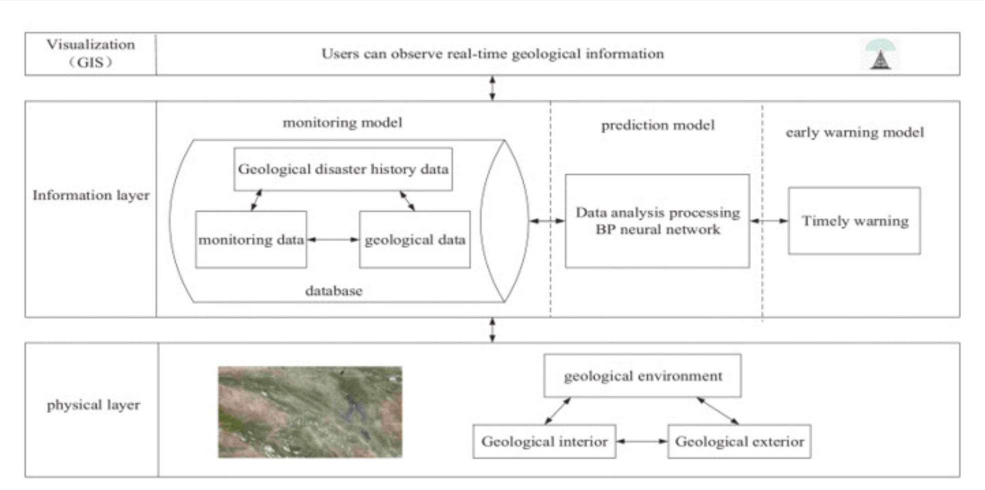

Figure 3: The DT method is used for geological disaster warning [8].

Nevertheless, the existing methods of geological studies heavily rely on manual measurements, such as scanline mapping of rock slope faces or scanning the face using handheld lasers or onboard a vehicle and analyzing them using special software. Manual methods, however, impose many problems besides being a laborious undertaking. Accessing the location under study is often challenging, if not impossible. Not to mention the increased uncertainties that come with estimation procedures inherent to extrapolating geological structures based on measurements from small sample locations [2]. Of course, there are also safety hazards related to sending geologists on foot to extreme locations on the mine site. Also, mines are dynamic environments where blasting and production happen daily, which requires established plans and schedules for new measurements [2]. Automatic or semi-automatic extraction of discontinuity parameters from the 3D rock mass models has recently gained many researchers' attention. Consequently, here at the Mine Automation Lab at UNR, a state-of-the-art algorithm is developed to extract the joint sets of the slope surface and their characteristics based on the rock mass point cloud (PC) data generated from UAV imagery and photogrammetry. The step-by-step procedure of the proposed algorithm is detailed below [2].

First, a training dataset (validated with field measurements) is prepared for developing a deep learning algorithm capable of classifying the joints on the 3D point cloud. Second, joint planes are extracted by implementing clustering algorithms like Density-Based Scan with Noise (DBSCAN). Third, the orientation of identified discontinuity planes is calculated using plane fitting techniques such as least-squares plane fitting (Random Sample Consensus (RANSAC)) or region growing methods based on local surface normal and curvature. Fourth, the orientation of joint planes is classified into various joint sets, and their dip and dip direction are measured [2].

The following steps of the procedure are currently under investigation, including calculating joints' trace length or persistence. The initial study in this area shows promising results when measuring the minimum and maximum persistence along dip and dip directions using the convex hull algorithm on extracted joint planes. The Convex hull algorithm fits all the points in the plane inside a polygon to maximize the area while minimizing the circumference. The other focal points for the ongoing research are the calculation of spacing (probably can be calculated as the perpendicular distance between joint planes), roughness, and the presence of infillings. Figure 4 (a-c) demonstrates the application of the algorithm (capable of automatically extracting the joint sets on rock slope surfaces based on their 3D PC data) in a case study to examine its effectiveness [2]. step-by-step procedure of the developed technique. Point Net (a deep neural network) is initially used to classify joint and non-joint points in the PC dataset (Figure 4a). The results clearly show the method's effectiveness in classifying the significant joints (69.64% classification accuracy) while dismissing vegetation and debris as noise [2].

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Figure 4b showcases the identified joint planes using DBSCAN (EPS of 0.5 and min Points of 100) compared to the results of the Compass plugin in Cloud Compare software on the manual orientation readings. The final step is to measure dip and dip direction (by applying RANSAC) and categorize the joints into specific joint sets [2]. The results show that 67 joint planes were marked correctly, and the rest were noisy. Also, the average error in calculating the dip angle and dip direction (on the correct joint planes) was -2.06° and -1.24°, respectively. As for the computation time, the algorithm is about an hour faster than any previously developed method, demonstrating the significant potential of deep learning for discontinuity characterization of rock slope surfaces based on PC data [2].

Figure 4a: The results of PointNet classification on the entire case study dataset [2].

Figure 4b: DBSCAN is used for identifying joint planes by clustering the segmented point cloud [2].

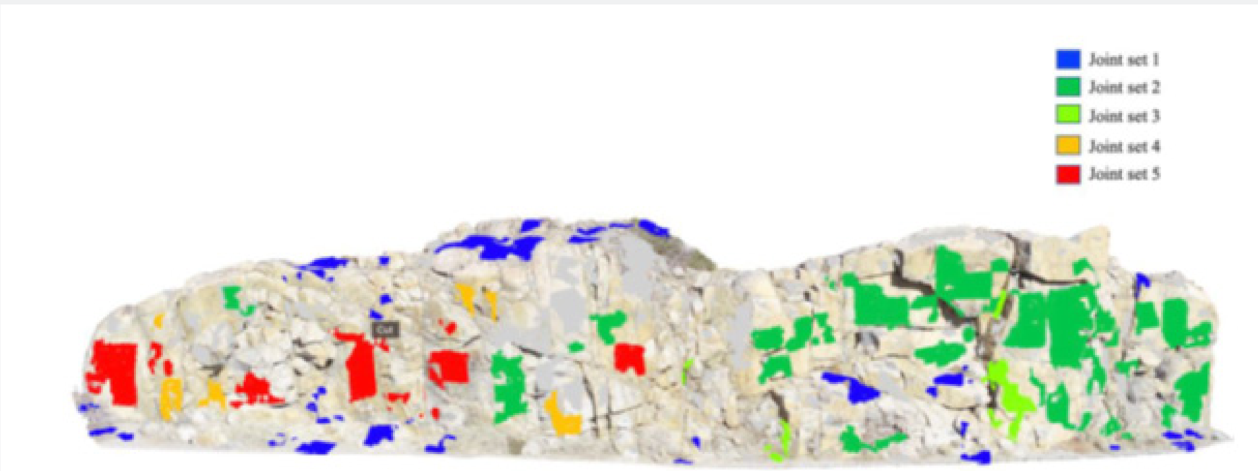

Figure 4c: Categorized joint sets on the case study point cloud [2].

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Rockfall Trajectory Estimation

Understanding the behavior of rockfalls after their fall is as imperative as studying the root causes of such events in designing mitigating strategies and measures. As rockfalls are generally unpredictable events, there is little chance to record and investigate natural incidents as they happen. Therefore, researchers have always heavily relied on the visible impact points, the gullies in which most rockfalls are gathered, and lab- or field-scale experiments. On the other hand, the existing numerical modeling and simulation tools are generally developed based on simplifications that are not good representatives of the reality of rockfall events. While providing a detailed simulation of rockfall trajectories, existing software requires specific parameters as input, which are not quickly or safely accessible. Another limitation of this software is its incapability to generate a risk heat map for possible rockfall gullies. RPF3D, a 3D simulation tool developed in the mine automation lab at UNR, addresses the shortcomings by incorporating a high-level 3D model of the rock surface to generate the "Rock Trace Map" from its simulations. RPF3D (developed in Python) can effectively read and visualize topography models consisting of many mesh elements by utilizing in-house developed algorithms that achieve high-resolution slope models. The simulation results include 3D rockfall trajectories, rockfall's bounce height, velocities, and impact points (leading to creating risk heat maps) for safety designs [3](Figure 5).

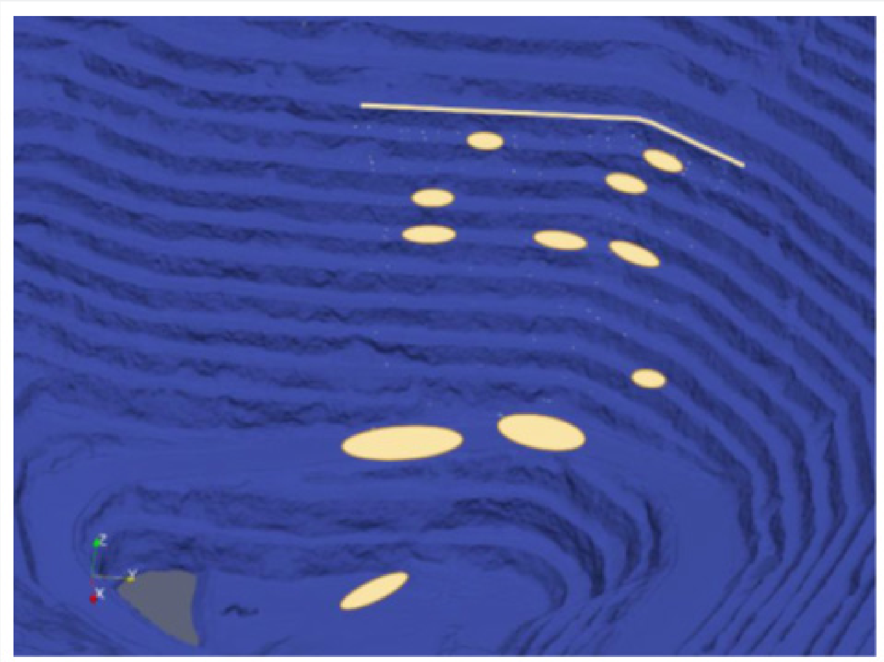

Figure 5: Potential gullies in the pit. (The yellow line represents the origin of rockfall incidents.) [3].

Moreover, future work will also focus on developing a detailed understanding of the influence of the terrain model resolution and using generalized coefficients of restitution (COR) vs. localized CORs (e.g., different CORs for the bench face and berm).

Discussion and Conclusion

The RHRS procedure defines the potential rockfall locations as any uninterrupted slope along the highway in which the number of rockfall occurrences and their category are the same. In the case of a mine site, the continuous slope geometry where the rock type and geotechnical features are relatively similar would fall in that category. However, extra care must be given to determining the number of rockfalls and their cause, as they could change dramatically within a long, uninterrupted slope. RHRS also recommends that two experts oversee the classification process; one conducts the initial and detailed rating of the site. The second familiar with the history of rockfalls, the safety measures, and their maintenance, will determine the frequency and the type of rockfall events. The official RHRS report sheet must be filled in along with the experts' comments. The subjective nature of this kind of categorization demands highly experienced people who would demonstrate solid judgment in their reports. Between the historical data and the estimated potential of rockfall, precedence is always given to the latter. The expert must report their opinion on the estimated size of the rockfall, the number of rockfalls per event, and the efficacy of safety measures [1].

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If historical data is absent, the expert must estimate the number of rockfalls yearly while providing information about when rockfall events peak. Also, in some situations, the existing database does not include smaller events that were overlooked or not recorded, as they did not cause harm. The experts must carefully examine the recorded data, compare it to their opinion, and make the necessary adjustments. One good indicator is always the frequency of ditch maintenance and cleanup, which is usually closely recorded and preserved [1,9,10].

After assigning the initial rating to all the slopes along with the highway project, in the second step, the slopes are further classified based on slope height, average vehicle risk (AVR), sight distance, roadway width, block size, the volume of rockfall events, ditch effectiveness, geologic characteristics, structural condition, rock friction, differential erosion features, differences in erosion rates, the climate and presence of water on the slope, and the history of rockfall. Following is a brief introduction to some of the parameters mentioned above [1,9,10,12]. AVR depends on the slope length, speed limit, and daily traffic and determines the amount of time a car will spend in a risky area. When calculating the AVR, the slope length must be measured cautiously, as any error would cause over- or under-estimation [1].

Decision sight distance (DSD) is the space a driver needs to see, perceive an object (rockfall), and bring the vehicle to a complete stop. It is worth mentioning that horizontal and vertical curves and obstructions like slope outcrops and vegetation will further limit the driver's ability to see potential hazards [1]. This paper examined geotechnical DT as a hub for detailed rockfall study, capable of unifying all the necessary information, risk analysis, and mitigation techniques in one environment [13-15].

The monitoring data are essential in determining the potential of rockfall in a site and the efficiency of mitigation measures installed at the site. Having all the data in a centralized space will enable further study of the risk factors and their effect individually and collectively. The geotechnical digital twin showcases excellent potential as a developing idea, and at the University of Nevada, Reno, genuine interest and effort are being devoted to further defining the parameters of such a system and exploring its effect on the mining industry. We hope that developing the geotechnical DT will enable us to expand the application of DT to other areas of the mining industry, such as fleet management and drilling and blasting optimization [16,17].

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