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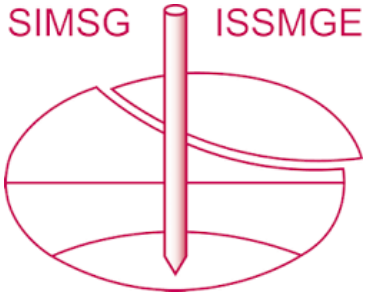


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# Rockfall monitoring using LiDAR data and AI: Opportunities and challenges

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**Abstract**

LiDAR technology has been widely adopted within the geotechnical community for field monitoring purposes since the early 2000s. The ability to obtain precise mm-level digital replicas of rock slopes in only a few minutes has placed LiDAR data among the most powerful means of monitoring surficial changes such as rockfalls. An appropriately set up LiDAR-based rockfall monitoring program enables the spatial-resolved extraction of information related to displacement magnitude, motion kinematics as well as the volume and shape of the deformed mass via advanced 3D point cloud processing methods. Although the remote control capabilities of modern laser scanners have enabled automated data acquisition, there are still steps in the process that require either human supervision or time-consuming manual effort. As the utilization of 3D point clouds for rockfall monitoring increases, increasing amounts of data are becoming available and the potential to automate tasks by training AI algorithms through deep learning grows.

This paper focusses on AI development in the field of rockfall monitoring and hazard assessment based on LiDAR data. Rockfall activity digitization via LiDAR monitoring combined with the advances in deep learning models, hardware, and cloud infrastructure brings opportunities to explore the unknown structure in the input data more deeply. Since AI defines the art of learning from data, appropriate data collection and preparation strategies have the potential to lead to applications ranging from semantic definition to geospatial forecasting. The authors review the challenges associated with the data curation along this transition to knowledge extraction. Hardware, software, survey, and semantic challenges are highlighted with examples from the early stages of development of a rockfall monitoring AI at several rock slope sites within the Railway Ground Hazard Research Program in British Columbia, Canada.

Keywords: Rockfall, Monitoring, LiDAR, Artificial Intelligence, Autonomy

## 1. Introduction

In the beginning of the 21st century, Light Detection and Ranging (LiDAR) (technology started finding its first geoscience applications mainly as a means of high spatial resolution Digital Elevation Model (DEM) creation in the form of rasterized 2.5D representations of large areas with ALS (Airborne Laser Scanning) (Jaboyedoff et al., 2012). The ability to obtain precise 3D digital replicas of the surveyed area, quickly attracted the attention of geoengineers utilizing Terrestrial Laser Scanning (TLS) for rock slope characterization, structural mapping, and monitoring (Antonio Abellán et al., 2014).

In the context of the Railway Ground Hazard Research Program (RGHRP) in western Canada, LiDAR-based rockfall monitoring has been conducted systematically at several rock slopes during the last decade (Bonneau & Hutchinson, 2019; Hutchinson et al., 2015; Kromer et al., 2015; Rowe et al., 2018). This remote sensing technique has provided a solution to the restrictions related to accessibility and visibility. Before LiDAR, the documentation of rockfall events was limited to what could be seen from the infrastructure level (Figure 1) or from infrequent aerial visual inspections. As such, identifying evidence of rockfalls was limited to occurrences that were of a significant size, or that had impacted the nearby infrastructure. Today, high resolution information about the exact source zone location, magnitude, and shape of a particular rockfall event across large areas is available to enrich rockfall inventories (DiFrancesco et al., 2020).

One of the main advantages of LiDAR-based rockfall monitoring is that it generates all the geometric/geographic data needed to digitize the evolution of a given rock slope by means of rockfall activity in a high-dimensional space. Being able to automate the data acquisition, pre- and post-processing (Kromer et al., 2017; Williams et al., 2018) and detect millimeter-level deformation (A. Abellán et al., 2009) across an entire rock slope not only supports the inventorization of rockfall events for statistical hazard assessment but also creates sequences of

spatio-temporal rockfall patterns. These sequences represent the digital footprint of the rock slope evolution and rockfall activity.

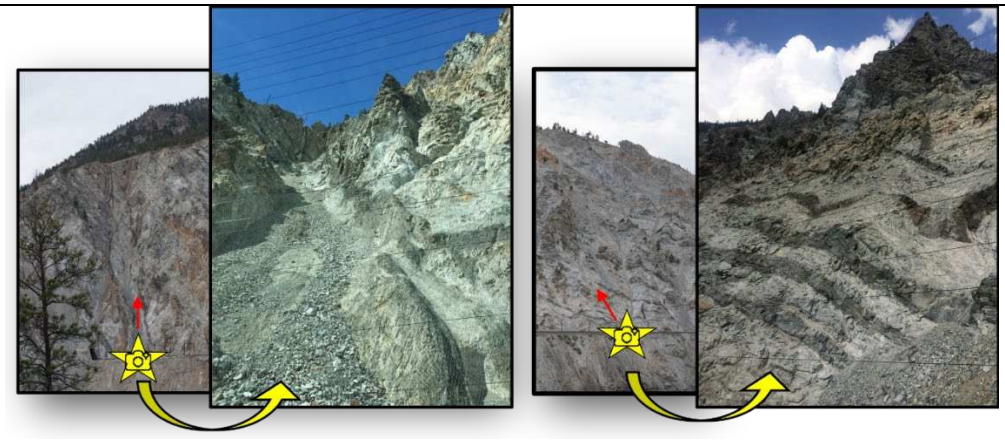

**Figure 1**: Track level view for rockfall documentation.

At the same time, modern artificial intelligence (AI) development with the use of deep learning (DL) advances rapidly by taking advantage of the wealth of available digital data in other fields such as weather forecasting leveraging long satellite-derived sequences (Liu et al., 2022; Tan et al., 2018). Since AI defines the art of learning from data, appropriate data collection and preparation strategies have the potential to lead to geospatial forecasting applications able to explore the unknown structure in the input data. This paper reviews the state-of-the-art in rockfall activity digitization with LiDAR-based monitoring and the challenges associated with the data curation along this transition of knowledge extraction though appropriately created point cloud sequences.

## 2. Rockfall Monitoring Methodology with LiDAR

### 2.1 Data acquisition

The raw data acquisition within the RGHRP LiDAR-based monitoring program has been conducted at weekly to seasonal intervals since November 2013. The surveyed railway rock slopes extend across the Frazer and Thompson Rivers in British Columbia, Canada, and thus they are scanned from positions on the opposite bank. The data have been collected with two different time-of-flight TLS systems (Optech ILRIS 3D-ER and RIEGL VZ-400i) (Kromer et al., 2017). A baseline model was taken for each scanner to avoid comparison between point clouds acquired by systems with different specifications in terms of operation wavelength, spatial precision and accuracy, range, and angular increment as per recommendations by Jaboyedoff et al. (2012).

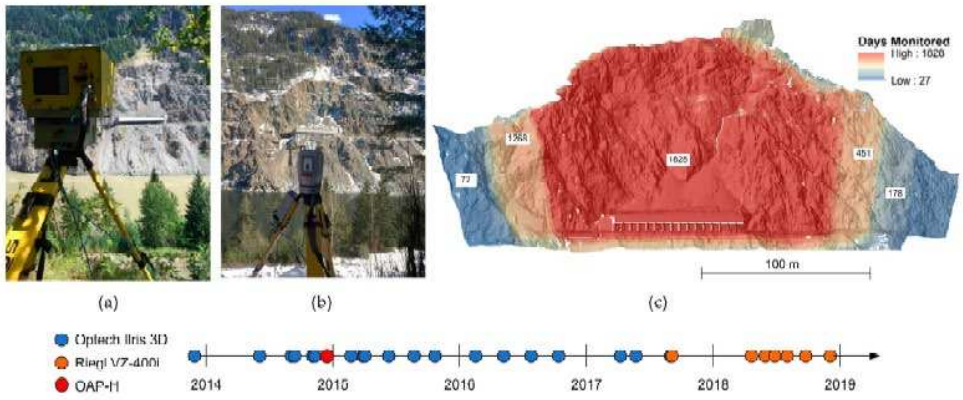


**Figure 2:** LiDAR monitoring of a RGHRP site for rockfall detection, characterization, and inventorization. (a) The Optech ILRIS 3D-ER scanner, (b) The RiEGL VZ-400i scanner, (c) monitoring duration and coverage (modified after DiFrancesco et al., 2020)

### 2.2 Data pre-processing

When the data are collected it is necessary to filter unwanted elements out of the raw point clouds. These elements mainly include points belonging to vegetation. 3D point cloud editing software packages such as RiScan Pro and CloudCompare are used for the manual segmentation of data. Subsequently, the cleaned point clouds are registered by alignment to the baseline model.

### 2.3 Change detection

Several techniques have been used in the geosciences for change detection, one of the most commonly used technique is the Multi-Scale Model-to-Model Cloud Comparison (M3C2) algorithm (Lague et al., 2013). M3C2 allows one scale to be utilized for determining the direction along which to calculate distance, and another scale to select the neighbourhood of points that will be used in the computation. The M3C2 technique utilizes solely the point clouds, and thus does not rely on rasterization (i.e., dimensionality reduction) or surface reconstruction (i.e., meshing) in order to define the direction in which distance is computed.

Determining the significant change on a slope thus requires a threshold to filter out the insignificant changes resulting from the measurement error and registration error. Rockfalls are digitized with M3C2 distance calculation, and subsequently filtered with the 95% confidence interval of the normally distributed registration error (Lague et al., 2013). Spatial outlier removal and manual segmentation are used to clean up noise in the change signature, before the changes corresponding to rockfall are classified. The unorganized point cloud is clustered using a density-based clustering algorithm (Ester et al., 1996), resulting in discrete rockfall objects.

### 2.4 Rockfall surface reconstruction

To assess the volume of the geomorphic changes on the study slope, surface reconstruction methods are used. These methods originate from the field of computational geometry and attempt to generate a triangulated surface mesh from an input point cloud. There are a variety of methods that can be used to generate these meshes (Berger et al., 2014). To date, most studies focus on the use of explicit polyhedron representations, with the primary methods being variants of AlphaShape (Edelsbrunner et al., 1983) and PowerCrust (Amenta et al., 2001).

Once a triangulated surface mesh has been generated, the divergence theorem is used to estimate a volume from the mesh. Work by Bonneau et al. (2019) and DiFrancesco et al. (2021) highlight the effects of different surface reconstruction methods on volume estimates for rockfall events and frequency-magnitude relationships at RGHRP sites.

## 3. Opportunities for AI

Rockfall risk management has traditionally been built upon scenarios based on statistical analysis of historic frequency-magnitude rockfall patterns. The exploitation of these patterns allows for an estimation of the return

period of rockfalls within given ranges of magnitude. The LiDAR-based rockfall monitoring methodology developed and applied during the course of the RGHRP provides multi-temporal terrain models with known rockfall locations and local geometric characteristics (≤10 cm point spacing) prior to and after each rockfall. This type of a database not only provides crucial frequency-magnitude information to quantify rockfall activity but also generates new research prospects for the development of an AI system able to incorporate the missing spatial component (geospatial forecasting) into rockfall risk analysis.

The aim is to explore the potential relationships between pre-failure local terrain characteristics and spatio-temporal failure patterns within the point cloud data, and the wealth of digital data generated by LiDAR-based rockfall monitoring generates opportunities to utilize AI in different aspects of the process. To take advantage of AI with 3D DL and advanced sequence models for spatiotemporal point cloud stream nowcasting (Zhang et al., 2019) based on LiDAR monitoring of rockfalls, an autonomous end-to-end framework needs to be designed. Terrain semantic segmentation and rockfall detection based on 3D point clouds are the two fields where AI integration has already started being investigated (Weidner et al., 2020; Zoumpekas et al., 2021; Schovanec et al., 2021; Farmakis et al., 2021, 2022). The system must be able to appropriately collect and pre-process the data, detect surficial changes, filter out non-rockfall points, calculate rockfall volumes, and store the data at a repository for the update of the predictive sequence model. However, the development and establishment of such a system has to deal with different challenges that some have already been partly addressed within RGHRP.

## 4. Challenges for AI

### 4.1 Survey challenges

The survey challenges within a rockfall prediction AI are mainly related to the frequency of data collection. Exploring the complex unknown structure in the input data, a LSTM (Long-Short-Term Memory) (Gers et al., 2000) model can learn the long-term dependencies of dynamic sequences to predict the next state (i.e., next frame prediction (Wang et al., 2017)). As such, the training sequences must be collected at a regular basis with constant time intervals. Modern laser scanners with programmable interfaces offer the possibility to automate the data collection (Kromer et al., 2017). However, the definition of the appropriate time intervals is not only a function of the time required from scan to rockfall detection but also a hyperparameter of the predictive model. For instance, sequences of states extracted every $t$ hours to be used for the prediction of the next $t$-hour state.

On the other hand, long time intervals between scans will not detect independent more frequent and lower magnitude events, which instead appear as cumulative volume loss at the same location. The training pattern would be biased at least towards lower frequency and higher magnitude than the reality. Therefore, the survey interval $t$ must be thoroughly investigated with respect to both the rockfall activity intensity and the learning process of the sequence model.

### 4.2 Semantic challenges

The most important component of an autonomous monitoring system relies on the semantics of the surveyed area. Semantic information is usually injected into the models through daunting manual segmentation processes that require human inspection. Vegetation removal is the first semantic step in the data processing chain. Bonneau (2021) presents a method for vegetation extraction in mountainous terrain using handcrafted features to identify the individual tree points. Furthermore, DL semantic segmentation methods such as PointNet (Qi et al., 2017) could also be a choice for vegetation removal.

After the changes are detected, it is important to separate rockfall events from other changes recorded (debris movement, fallen tree, etc.). Farmakis et al. (2021) proposed an unsupervised object-based framework for the semantic segmentation of a rock slope where discrete geomorphologic features such as large erosion channels are formed and are responsible for changes related to debris movements. Such a semantic segmentation method (Figure 3) can be used to generate terrain models to mask the detected changes based on the origin area. The study shows that this method outperforms point-based supervised learning.

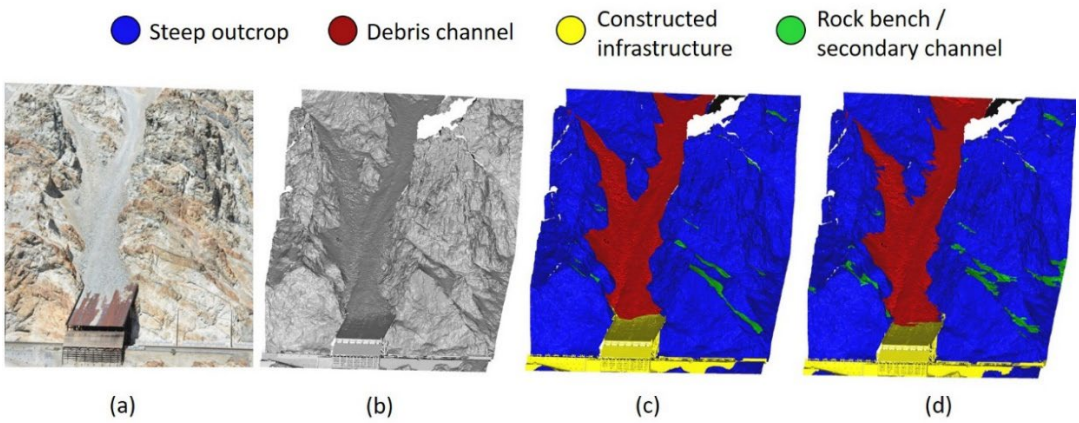


**Figure 3**: Automated terrain model generation. (a) RGB photo; (b) Raw point cloud; (c) Ground truth; (d) Prediction (modified after Farmakis et al., 2021)).

However, due to the fact that the above method is not very time efficient and complex rock slopes present more challenging geomorphologic features, the rockfall detection problem should be addressed as a point cloud classification problem. In their study, Farmakis et al. (2022), integrated deep neural networks to develop an AI for the detection of rockfall clusters after the shape reconstruction of the detected changes. The role of AI was to assign a rockfall or non-rockfall label to each individual change point cloud based on the global shape characteristics of the deformed volume. The Rockfall Detection PointNet achieved prediction scores over 90% for 2 RGHRP sites providing high confidence in the method, especially for change volumes above 1 $m^3$. Moreover, the study showed that rock slopes with unique characteristics generate change clusters with different shapes and thus site-specific AI development for rockfall detection is encouraged.

Although the aforementioned early attempts to inject semantic information into LiDAR-based rockfall monitoring provide promising results, there is one factor that makes semantic automation challenging. The lack of implicit ontological definitions of geologic/geomorphologic elements may always lead to disagreements even between experts in the field. Different terrain interpretations can produce various semantic segmentations. This fact contradicts the state in other fields such as automotive where semantic segmentation has been decisive in advancements such as autonomous driving, as there is no disagreement between human beings on what is a stop sign, a vehicle, or a pedestrian within a scene. What is a rockfall within a point cloud, however, might be debatable.

### 4.3 Software challenges

Pipelines for segmenting 3D information from point clouds can be rather complex. With increased complexity and number of processing stages, brings the opportunity for unwanted errors to propagate. DiFrancesco et al. (2020) demonstrated that the M3C2 change detection parameters can drastically alter the rockfall inventories that are derived from point clouds in a semi-automated workflow. There is thus a challenge in selecting suitable 3D algorithm parameters that are robust and suitable for the quality of data, the scale of the geomorphological process being analysed, and the characteristics of the study environment (i.e. rock structure; topographical features).

Work by DiFrancesco et al. (2021) found that there can be variability in the success of reconstruction algorithms depending on the size of the rockfall. In their work, they found that small magnitude rockfall events caused the PowerCrust algorithm to be unable to produce watertight meshes. A watertight manifold mesh is required to be able to compute an accurate volume (Bonneau et al., 2019). Therefore, a combination of surface reconstruction methods was used to ensure that a watertight mesh was constructed.

Further work is required to investigate the viability of implicit and explicit surface reconstruction by comparing their precision, accuracy, and ability to automate. Nevertheless, a sound understanding of the processes and algorithms being used to facilitate the surface reconstruction and subsequent volume estimates is needed in order to have confidence in digital rockfall databases. As methods continue to be automated, additional checks and parametric analyses are required to ensure the software is producing accurate results. In many cases, the propagation of errors starting with change detection can have an impact on the ability to generate a mesh and compute an accurate volume.

An additional challenge is that in many cases, each institution or research group has their own processing pipeline of point cloud data to create rockfall databases. While the overall workflow generally remains the same, the computation of change and resulting volume in either 2.5D or 3D can produce different results. Therefore, a common database format for rockfalls does not exist between sites. Standardization is required to be able to leverage more data, across more diverse sites to generalize AI approaches.

### 4.4 Hardware challenges

The computational demand of 3D processing is generally high. In the case of rock slope monitoring, with the datasets often reaching hundreds of millions of points, this demand becomes a challenge for commercial hardware. In recent years, cloud infrastructure with 5G network can provide a solution to fast data transfer and processing of large amounts of data. LiDAR-based rockfall monitoring represents a typical application that can benefit from 5G networks and cloud servers.

## 5. Conclusions

LiDAR-based rockfall monitoring provides high-resolution geometric information of the rockfall activity of a given rock slope. However, the elapsed time between acquisitions may lead to coalescence of events into a set of larger events that do not represent the typical single rockfall shape and also bias the digital activity pattern. In particular, the terrain models (3D point clouds) labelled with the rockfall locations extracted from change detection constitute spatiotemporal rockfall pattern sequences for potential rockfall pattern nowcasting with LSTMs. All the information needed to investigate the potential of approaching rockfall nowcasting as visual next state prediction model are extracted within RGHRP.

LiDAR-based rockfall monitoring generated data have the potential to lead to AI development to address the ultimate geotechnical goal of future rockfall time and locations prediction. Therefore, there are significant challenges in the process, mainly related to semantics. The lack of ontological definitions and the complex nature of geomechanical data might be an obstacle to the development of generalizable AI. However, site-specific development is encouraged. Computational challenges related to software development for change detection and volume estimation as well as hardware requirements also constitute an important component within the application of an autonomous rockfall monitoring program.

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