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Artificial intelligence applied to the detection and early warning of geotechnical instabilities in mining slopes

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Abstract

It is possible to detect and anticipate geotechnical instabilities of the slopes of an open pit from the systematic monitoring of surface displacements induced by mining excavation. In the last few years, the detection rate of large-scale instabilities has improved through the application of the radar interferometry technique. However, small-scale instabilities are the most frequent and they present a low detection rate and early warning, since they have a short activation period, and are eventually, eclipsed by environmental noise and/or the mining operation itself. For this particular case, how to improve the detection and anticipation rate was discussed based on the hypothesis that geotechnical instabilities show a 'recognisable behaviour', well-defined and mathematically expressible. This feature makes the application of artificial intelligence (AI) tools feasible, specifically neural networks, to generate models trained in the early detection of 'recognisable behaviour', under a supervised learning approach.

To develop a predictive application based on AI tools, a collaborative work dynamic was proposed between Minera Los Pelambres (MLP), belonging to the mining company Antofagasta Minerals S.A. (AMSA), and E Mining Technology S.A., a mining technical services company.

The results of the training process of neural network models showed they are capable of identifying the 'recognisable behaviour' of a geotechnical instability at an early stage. Moreover, these models, when complemented with a layer of geotechnical-mathematical criteria, were allowed to build an algorithm capable of improving the overall performance of the surface displacement monitoring system. The performance of the algorithm was evaluated over a period of eight months at the MLP open pit. In this period, it was possible to increase the detection and early warning rate from an effectiveness of 43–82% in small-scale instabilities and as a result, a decrease in the risk during the construction of slopes. In addition, a significant reduction of false positives was reached by minimising the effect in the environmental noise by 80% with respect to the performance of the current monitoring systems.

In the future, it seems reasonable to predict that with an expansion of the dataset and auscultation of new AI models and/or architectures, it will be possible to further improve the efficiency of monitoring systems.

Keywords: *slope monitoring, artificial intelligence, advanced analytics, geotechnical instabilities, early warning*

1 Introduction

The ability to detect potential geotechnical instabilities early is essential for the management of geotechnical risks during the construction of the slope in open pit mining. Early detection allows the mining operation to be alerted of the risk of geotechnical instabilities, and it avoids or reduces the potential impact on people, equipment, or the continuity of the operation. To this end, the mining industry has adopted—specifically, in its geotechnical monitoring systems—the radar interferometry technique to estimate the surface

displacements based on the gap that is produced between the emission, reflection, and reception of electromagnetic waves when interacting with the slope face.

In the case of large-scale geotechnical instabilities, where development times are longer, monitoring systems have performed well in sending an early warning of an imminent geotechnical instability. However, the results have not been satisfactory in the early detection of small-scale or 'bench scale' geotechnical instabilities. These types of instabilities, commonly developed in a short activation period, are the most frequent, and are sometimes eclipsed by environmental noise or the mining operation itself.

Statistics at Minera Los Pelambres (MLP) show that for large-scale instabilities, the detection and early warning rate reaches 100%, while in small-scale ones, only 43% is achieved, as can be seen in Figure 1. To address the challenge of reducing the risk in a mining operation near the slopes, it was planned to improve the detection and anticipation rate based on the assumption that geotechnical instabilities, in specific surface displacement curves, have a 'recognisable behaviour', well-defined and mathematically expressible. For this purpose, an algorithm was developed using artificial intelligence (AI) based on neural networks. The training process of these networks followed a supervised learning strategy to identify and detect the 'recognisable behaviour' on the displacement curves. Additionally, this algorithm incorporates a layer of geotechnical-mathematical criteria, whose purpose is to interpret the data provided by the model in the monitoring operation.

The performance of the surface displacement monitoring system, which had the support of the AI algorithm, was evaluated in MLP over eight months, the results of which will be presented in this paper.

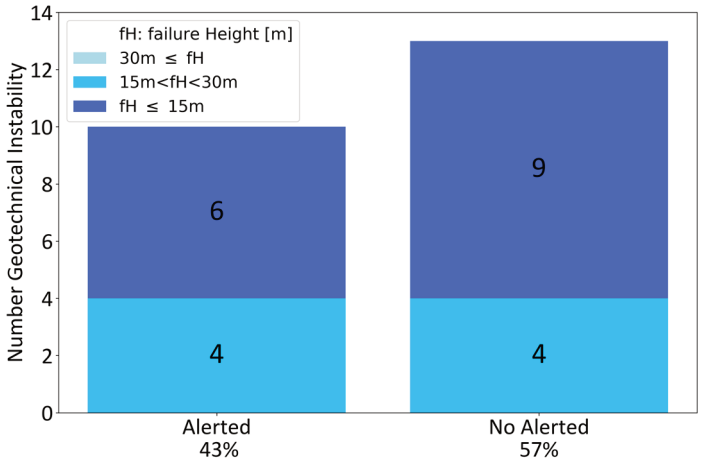


Figure 1 Geotechnical instability statistics at Los Pelambres Mine from April to December 2019

2 Radar interferometry data

2.1 Technique and basic principles

The monitoring of surface displacements in open pit mining slopes is carried out mostly by using ground-based radars. These radars support the operation thanks to the use of the interferometry technique, which compares the phase difference that occurs between two wave acquisitions due to the displacement of the slope surface. For this, a sequence of electromagnetic waves is released with well-defined characteristics that are reflected by the target surface, which upon return are received by the radar of origin. When repeating this process systematically, in every time interval (scan time), it is possible to compare the phase changes produced by the movement of the slope surface and therefore, estimate the magnitude of the displacements (Figure 2). Measurements can reach sub-millimetric accuracy and they can be altered by physical phenomena, such as atmospheric variations and mining operation itself due to the presence of equipment or material in suspension (dust.) This type of alteration is the main source of noise in interferometric measurement in open pit slopes.

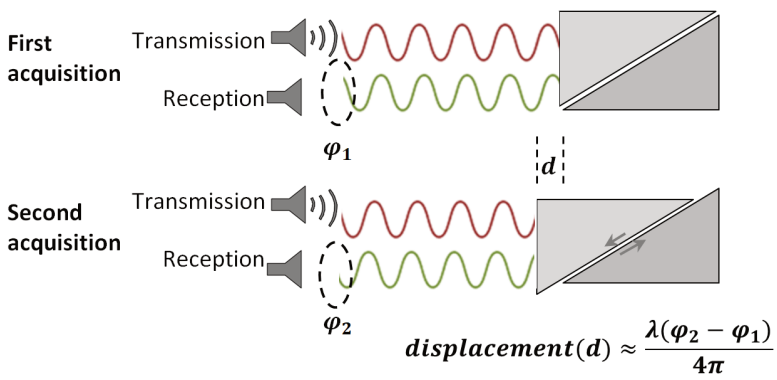


Figure 2 Surface monitor diagram using radar interferometry technique

2.2 Radar data

A relevant factor that determines the capability of the system is the physical layout and configuration of the radars. Location, orientation, and distance of the radar from the slope determine the coverage, resolution, and accuracy of the measurement. Meanwhile, the dimensions of the area of interest to be scanned define the frequency of scanning of the equipment, which is reflected in the number of acquisitions obtained.

The minimum spatial sampling unit in the interferometry technique is known as cell or pixel. This unit corresponds to the lowest possible resolution that can be reached by the instrumental capability and configuration (distance and orientation radar from the slope).

The displacement of each cell is estimated at each scanning cycle generating a sequence of displacements that are represented in a time series:

$$D_i^t = \left(d_0^i, d_1^i, d_2^i, \dots, d_{t-1}^i, d_t^i\right) \tag{1}$$

where:

d_t^i = displacement of a cell c_i at the reading time t.

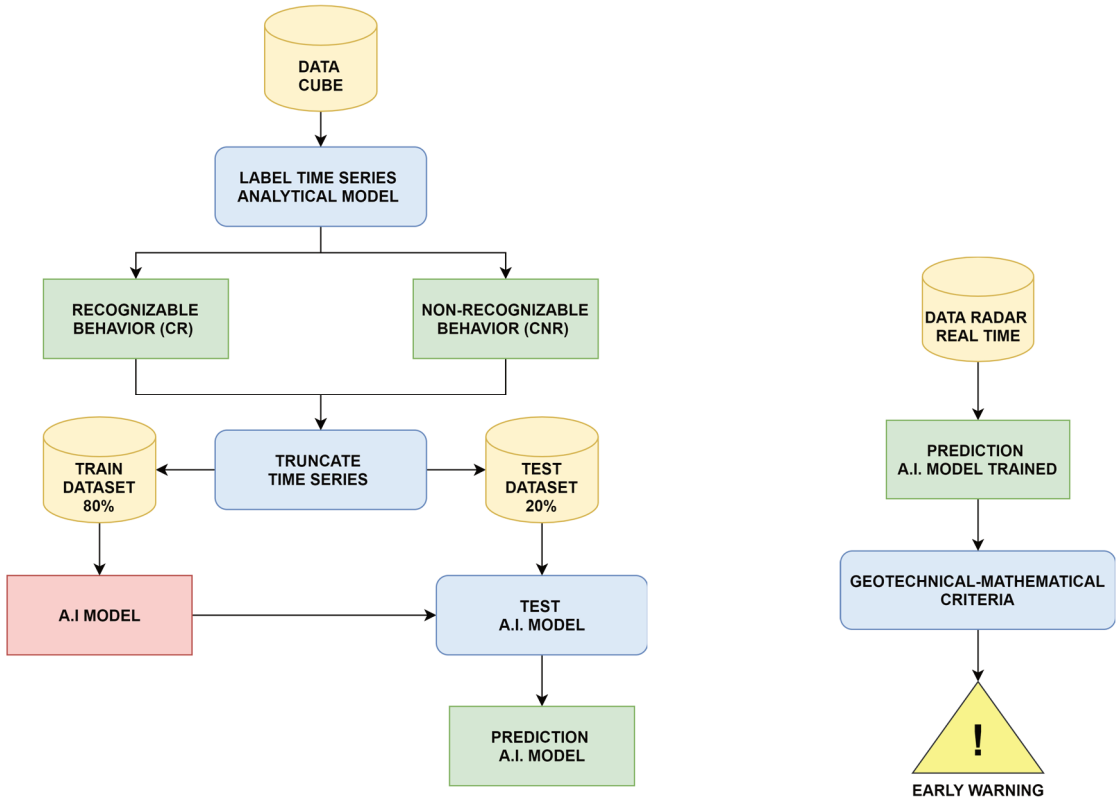
It should be noted that the data reading time t is the same for all cells in every scanning cycle. These characteristics of radar data allowed conceptualising an efficient storage structure or data cube, taking advantage that all cells present a common reading time and also spatial regularity (Figure 3). The data cube used at the present work contains information of Los Pelambres mine, corresponding to the monitoring period from April to December 2019. It is included geotechnical instabilities and also stable zones information.

$\mathbf{X-Y}$	$\mathbf{Date_1}$	$\mathbf{Date_2}$	$\cdots$	$\mathbf{Date_m}$
$x_1 - y_1$	d_1^1	d_2^1	$\cdots$	d_m^1
$x_2 - y_2$	d_1^2	d_2^2	$\cdots$	d_m^2
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
$x_n - y_n$	d_1^n	d_2^n	$\cdots$	d_m^n

Figure 3 Data cube structure

3 Methodology

The work was aimed at designing, developing, and applying a methodology that would allow us to use the extensive information available, in particular, time series of surface displacement, which collects the historical behaviour of the rock mass recorded instrumentally by ground monitoring radars. In this sense, the methodology contains the procedure of how to build an AI model (Figure 4a) with a supervised learning approach and a general scheme of the AI support algorithm that involves geotechnical-mathematical criteria (Figure 4b).



(a) (b)

Figure 4 (a) Training scheme for AI model; (b) General scheme of the AI support algorithm

3.1 Data pre-processing

3.1.1 Analytical model

Displacements associated with geotechnical instabilities follow a behaviour that can be modelled by a mathematical function of Kohlrausch (K) which is expressed as follows:

$$f(t) = \alpha e^{-(\tau t)^{\beta}} + \gamma, t \in \mathbb{R}_0^+,\ \alpha, \tau, \beta \neq 0 \tag{2}$$

where:

t = time.

$\alpha,\ \tau, \beta,\ \gamma$ = magnitude, activation time, 'abruptness', and translation parameters.

The function has different characteristic points which we will denote as t^*, t_1 and t_2 (Figure 5). These points can be obtained from the following equations:

$$\frac{\partial^2 f(t)}{\partial t^2} = 0, para\ t^* \tag{3}$$

$$\frac{\partial^3 f(t)}{\partial t^3} = 0, para\ t_1\ y\ t_2 \tag{4}$$

where:

t^* = point of maximum velocity.

t_1, t_2 = points of maximum and minimum acceleration, respectively.

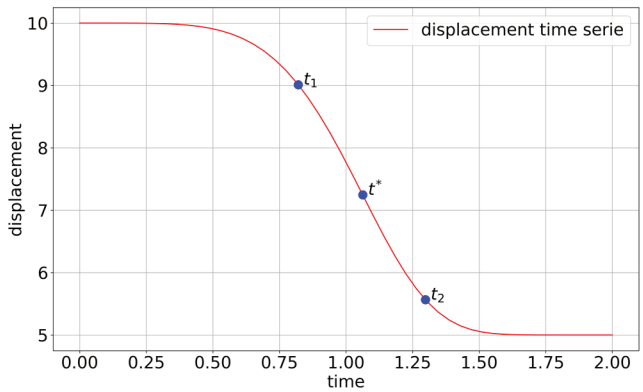


Figure 5 Characteristic points of the K function

This function can model the displacement time series for different types of instabilities. As an example, structural instability of a small-scale will follow a 'fast' model, while a large-scale instability controlled by both structural mechanism and rock mass mechanism will follow a 'slow' model, as shown in Figure 6.

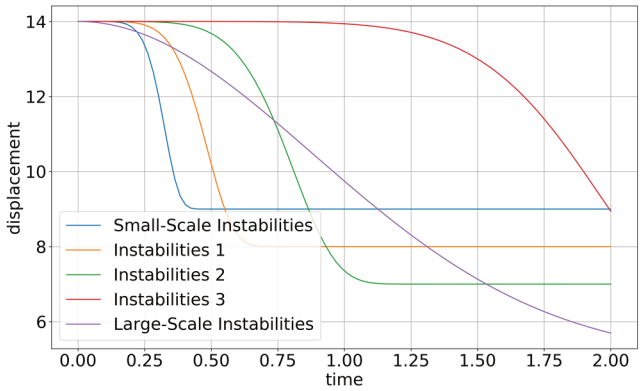


Figure 6 Examples of behaviours modelled by the K function

3.1.2 Labelling and truncating time series

To classify the displacement time series $D_i \in \mathbb{R}^n$ associated with the cell/pixel c_i it was defined as recognisable behaviour (CR) curve if there are parameters $\alpha, \tau, \beta, \gamma$ of the K function that fit D_i, otherwise must be non-recognisable behaviour (CNR).

This way, the displacement of the time series of the data cube was classified into two categories according to the following behaviours: CR and CNR. To label all the time series in CR and CNR, it was decided to automate this process by curve fitting with the K function, considering the coefficient of determination as a criteria R^2, where it is CR if $R^2 \geq 95\%$, otherwise must be CNR.

Since it is expected to build a model that allows detecting and anticipating geotechnical instabilities, it was established to truncate all the time series labelled as CR, in the mean point between the characteristic instants t_1 and t^*.

3.2 AI model and validation metrics

3.2.1 AI model

Given that the instabilities follow a recognisable and previously labelled behaviour, it was proposed to build an AI model with the supervised learning approach using the 'multilayer perceptron' neural network architecture or mlp. A classic example of the use of this network consists of recognising a number from an image containing a single value between 0–9 (Pohlmann et al. 2018).

To train the AI model, 80% of the truncated and labelled time series were used, while the remaining 20% were used for validation. The model, once trained, has the ability to predict, at each time instant, the probability or reliability (P_{CR}) that a time series will develop a recognisable behaviour or non-recognisable behaviour ($P_{CNR} = 1 - P_{CR}$). To quantify the performance of the trained model, the confusion matrix was used; a classic tool that allows visualising the performance of algorithms in the field of supervised learning. Additionally, other complementary metrics were used such as accuracy, recall, and precision of CR or CNR classification (Raschka & Mirjalili 2017).

3.3 Geotechnical-mathematical criteria

Geotechnical-mathematical criteria allow integrating the results of AI model with physical characteristics, spatial and/or temporal, detected by the monitoring system. The criteria are defined as bounds or thresholds that must be reached by a cell or a cluster of cells. Table 1 shows a summary of the main criteria used in the performance evaluation of the monitoring system with the support of the AI model.

Table 1 Main geotechnical-mathematical criteria

Criteria	Observation
Reliability	The reliability of cells (P_{CR}) estimated by the AI model
Spatial contiguity	A number of cells that are right next to each other and share the same vertex (neighbours cells)
Persistence	The minimum time that a number of active cells are above the reliability threshold

4 Results

The results indicate that neuronal network models can recognise the characteristics associated with the recognisable behaviour (CR) of a time series of displacements. The selected model (once several models were trained) has a performance that can be appreciated in the confusion matrix, represented in Figure 7. The model has the ability to classify cells correctly, such as CR (recall) 82% of the time, i.e. only 18% are not classified correctly. Cells that were classified as CR result in CNR (false positives) reaching only 2% of the population. The precision indicates that 75% of the predicted instabilities are correct.

		PREDICTED CATEGORY	
		CR	CNR
TRUE CATEGORY	CR	TRUE POSITIVE (TP) 9	FALSE NEGATIVE (FN) 2
	CNR	FALSE POSITIVE (FP) 3	TRUE NEGATIVE (TN) 141

Figure 7 Confusion matrix of selected neuronal network model

Once the AI classification model with an acceptable performance was chosen to classify the series as following or not following a recognisable behaviour (CR or CNR), a support algorithm was connected into the monitoring system. This algorithm integrates the results of the AI model with geotechnical-mathematical criteria to support the search for instabilities that follow a recognisable behaviour. The general results in the process of detection and early warning post-AI algorithm support at Los Pelambres Mine are shown in

Figure 8. Most events are of small-scale reaching 85% of the measured cases, which increases in the early warning rate from 43–82% in an eight months evaluation period.

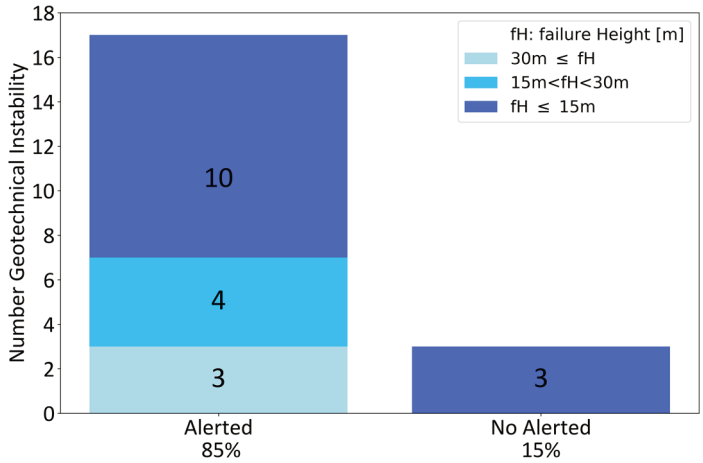


Figure 8 Geotechnical instability statistics at Los Pelambres Mine from April to December 2020

The final results show a significant improvement in the performance of the monitoring systems when reducing false positives in potential small-scale events. This can be clearly seen in Figure 9 which shows the results of the investigation period in a confusion matrix.

TRUE POSITIVE (TP)

Small scale instabilities with early warning

Before A.I. (2019)	After A.I (2020)
43% (10/23 instabilities)	83% (14/17 instabilities)

FALSE NEGATIVE (FN)

Small scale instabilities without early warning

Before A.I. (2019)	After A.I (2020)
58% (13/23 instabilities)	17% (3/17 instabilities)

FALSE POSITIVE (FP)

False early warning

Before A.I. (2019)	After A.I (2020)
150 - 250 (with 9 contiguos cells)	30 - 40 (with 4 contiguos cells)

TRUE NEGATIVE (TN)

True stable zone

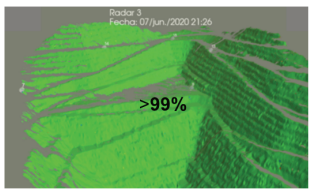


Figure 9 Comparison of monitoring results 2019–2020

5 Conclusion

The improvement in the detection rate of instabilities of small-scale represents a great progress for the safety of the people and equipment in the open pit mining operations. The achievement of using AI methodology, where the use of advanced analytics merges with the historical monitoring data, represents a technological breakthrough in the field of geotechnical slope monitoring. In this sense, it seems encouraging to continue investigating new models and expand the dataset including a wide variety of geotechnical instabilities.

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