Development of a filtered inverse velocity method analyser: A comparative study of smoothing filters in surface mines for optimisation of slope failure predictions

by M.M. Masood[1], T. Verma[2], G.Y. Raju[2]

Affiliation:
[1]National Institute of Technology Raipur, India.
[2]Indian Institute of Technology (BHU)
Varanasi, India

Correspondence to:
M.M. Masood

Email:
maneebmasood@gmail.com

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ORCiD:
M.M. Masood
http://orcid.org/0000-0002-2445-7406
T. Verma
http://orcid.org/0000-0002-3875-9704
G.Y. Raju
http://orcid.org/0000-0001-8330-9940

Abstract

The inverse velocity method has proven to be an effective approach for predicting slope failures in surface mines by analysing displacement monitoring data. However, the accuracy of inverse velocity method predictions is significantly affected by instrumental noise and natural environmental variations, which influence the identification of different deformation stages. To enhance predictive accuracy, this study applies and evaluates three filtering techniques to velocity time series data: Exponential smoothing filter, short-term smoothing filter, long-term smoothing filter and also compares it to raw data (no filtering). A refined prediction framework, that is, filtered inverse velocity method analyser, is proposed to improve slope failure forecasting in surface mining operations. The results demonstrate that filter selection plays a crucial role in optimising failure time predictions, offering valuable insights for geotechnical monitoring and early warning systems in surface mines.

Keywords

slope monitoring, slope stability radar, surface mines, early warning systems, inverse velocity method

Introduction

Slope failures in surface mines represent one of the most critical challenges in the mining industry, posing severe risks to worker safety, operational efficiency, and financial stability. Slope deformations in mines, characterised by their sudden nature, can occur both during active mining operations and long after mining cessation due to residual geotechnical instabilities (López-Vinielles et al., 20200). The instability of mine slopes is influenced by various factors, including excavation activities, geological conditions, groundwater dynamics, and external loading factors such as blasting or heavy rainfall (Tao et al., 2020). The consequences of slope failure extend beyond safety hazards, as they lead to equipment damage, production losses, environmental impacts, and increased operational costs (Yalagandala akshay kumar et al., 2019).

Maintaining high production rates while ensuring the stability of slopes is a crucial balancing act in mine planning and design. Overly conservative designs can lead to unnecessary over-excavation and increased costs, whereas inadequate slope stabilisation measures heighten the risk of catastrophic collapses (Kolapo et al., 2022; Obregon, Mitri, 2019). To manage this challenge, the mining industry increasingly relies on monitoring systems that track slope movement, displacement, and deformation trends to provide early warning indicators of failure (Prasad et al., 2021). The ability to accurately predict slope failure time is fundamental to ensuring both operational continuity and worker safety, necessitating the development of robust predictive models and real-time assessment tools (Zevgolis et al., 2018).

Among the various techniques used for slope failure prediction, displacement monitoring plays a central role. Displacement, along with its derivatives, velocity and acceleration, are widely recognised as the most reliable indicators of impending failure (Masood et al., 2023). Slope monitoring programmes often utilise global navigation satellite system (GNSS) sensors, radar, robotic total stations, and LiDAR scanning to collect displacement data at regular intervals (Dick et al., 2015; Masood et al., 2024). The analysis of this data enables researchers to identify progressive deformation trends that signify slope instability (Masood et al., Dash, 2023; Masood et al., 2024; Terzaghi, 1950; Saito, 1969). A fundamental observation in geotechnical research is that slopes approaching failure exhibit an accelerating rate of movement, a phenomenon commonly referred to as tertiary or accelerating creep (Zavodni, Broadbent, 1978; Varnes, 1982; Cruden, 1987). This behaviour forms the basis of many failure prediction models, which focus on estimating the time-to-failure (TTF) by extrapolating displacement and velocity trends (Dusseault, Fordham, 1993; Dok et al., 2011; Intrieri et al., 2019). However, traditional monitoring techniques alone do not provide explicit failure timing, necessitating the use of analytical and computational approaches to interpret displacement patterns and predict the imminence of collapse.

The inverse velocity method (IVM), first introduced by Saito (1965) and refined by Fukuzono Fukuzono (1985), is a widely used approach for failure prediction, based on the inverse proportionality between velocity and time-to-failure. As a slope approaches failure, velocity increases asymptotically, and plotting 1/velocity against time often reveals a linear trend in the final accelerating phase, enabling failure time extrapolation. Although conceptually simple, IVM's real-time implementation in mining operations became practical only in the early 2000s with advancements in high-resolution displacement monitoring. Since then, numerous studies have enhanced IVM applications: Rose and Hungr (2007) demonstrated its effectiveness in predicting large-scale rockfalls, Dick et al. (2013) integrated machine learning with geodetic monitoring, Carlà et al. (2017; 2018) developed risk-based alarm strategies for open-pit mines, Zhou et al. (2020) proposed a modified IVM framework for improved accuracy, and Chen and Jiang (2020) introduced the dimensionless inverse velocity method (DINV) to enhance detection while reducing false alarms.

While the IVM has proven effective in predicting slope failures, its practical application in surface mining environments is still challenged by several limitations like sensitivity to noise and instrumentation errors, and variability in slope failure behaviour as some failures may be triggered by external shocks (e.g., seismic activity, rainfall-induced weakening, or mine blasting) leading to deviation from the expected inverse velocity trend. Many mine monitoring programmes operate on limited temporal sampling, where data is collected at daily or weekly intervals rather than real-time continuous recording (Petley et al., 2005). This can result in critical missed data points during rapid acceleration phases thus leading to under-sampling of data [Voight, 1988; 1989].

To address these limitations, this study proposes a filtered inverse velocity method analyser to enhance slope failure prediction in surface mines, identifying the optimal smoothing approach for improving time-to-failure (TTF) estimations, and validates the methodology using real displacement monitoring data. These advancements contribute to proactive hazard management, reducing operational risks in mining and geotechnical engineering applications [Segalini et al., 2018; Glastonbury, Fell, 2002].

Methodology

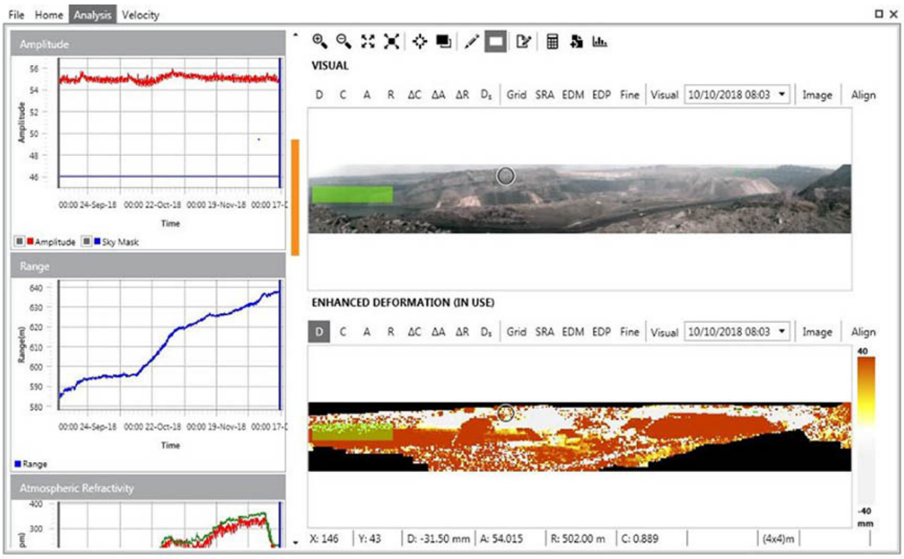
This study focuses on the analysis of deformation and displacement data, along with its derivatives, to assess slope stability and predict failure in surface mines. The dataset for this analysis comprises real-time monitoring data from three coal mines operated by South Eastern Coalfields Limited (SECL) and historical slope failure data digitised from an Australian mine. By integrating both real-time and historical datasets, this study enables a comprehensive evaluation of failure mechanisms across different mining conditions.

Field study and historical dataset

The first dataset consists of real-time monitoring data collected from three SECL mines, where slopes are continuously monitored to track displacement, velocity, and inverse velocity trends. The monitoring system utilises a slope stability radar (SSR), which provides high-resolution deformation data. In addition to real-time monitoring, historical slope failure data from an Australian mine were digitised and incorporated into this study. These datasets include recorded failure events with corresponding displacement-time trends, allowing for a retrospective application of inverse velocity analysis. This additional dataset provides valuable insights into different geological settings and deformation patterns, facilitating a broader validation of the proposed failure prediction methodology.

Data collection

Slopes at the three SECL mines are monitored using SSR, which captures real-time displacement data to enable early warning alerts and failure predictions. The monitoring system includes continuous tracking of slope deformation, with each radar scan providing high-resolution movement data and automated data processing through specialised software called SSRViewer, which enables trend analysis, alarm triggering, and data export for further examination. Figure 1 shows the SSRViewer screen.



10/10/2018 08:03

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X: 146 | Y: 43 | D: -31.50 mm | A: 54.015 | R: 502.00 m | C: 0.889 | (4x4)m

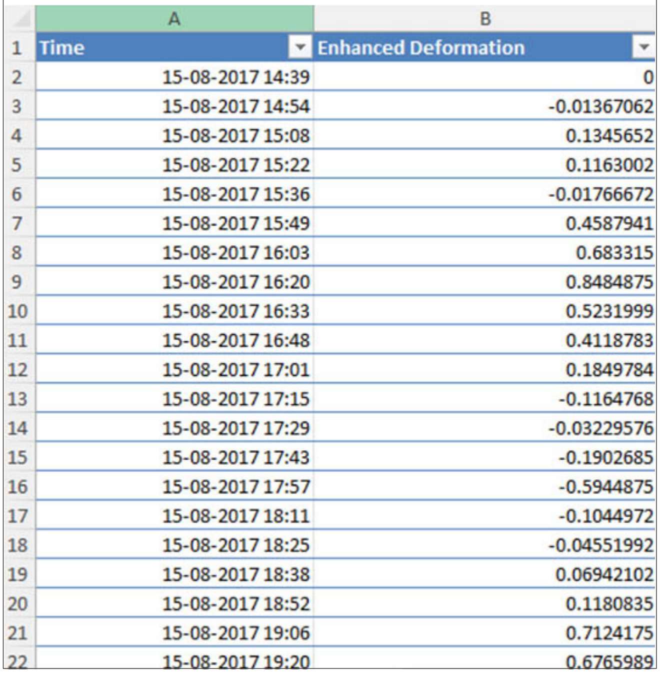
Figure 1—SSR Viewer screen showing the monitored slope

Details of the deformation data

The data collected from the mines were extracted from SSRViewer and transferred to MS Excel for further analysis. This dataset contained time vs. deformation and time vs. velocity values, depending on the type of data extracted from SSRViewer. The extraction process involved the selection of the desired monitoring area and exporting the relevant data by right-clicking on the velocity or inverse velocity (IV) graph displayed on the left panel of the SSRViewer interface. Table 1 presents a sample dataset collected from one of the SECL mines, illustrating the format and structure of the extracted monitoring data. Table 2 presents sample digitised data points, while Figure 2 illustrates its graphical representations, highlighting deformation patterns preceding past slope failures. The combination of real-time and historical datasets strengthens the reliability of the study, ensuring that the proposed filtered inverse velocity method analyser is tested under diverse conditions.

Table 1

Deformation data from one of the slopes at SECL mines, India



	A	B
1	Time	Enhanced Deformation
2	15-08-2017 14:39	0
3	15-08-2017 14:54	-0.01367062
4	15-08-2017 15:08	0.1345652
5	15-08-2017 15:22	0.1163002
6	15-08-2017 15:36	-0.01766672
7	15-08-2017 15:49	0.4587941
8	15-08-2017 16:03	0.683315
9	15-08-2017 16:20	0.8484875
10	15-08-2017 16:33	0.5231999
11	15-08-2017 16:48	0.4118783
12	15-08-2017 17:01	0.1849784
13	15-08-2017 17:15	-0.1164768
14	15-08-2017 17:29	-0.03229576
15	15-08-2017 17:43	-0.1902685
16	15-08-2017 17:57	-0.5944875
17	15-08-2017 18:11	-0.1044972
18	15-08-2017 18:25	-0.04551992
19	15-08-2017 18:38	0.06942102
20	15-08-2017 18:52	0.1180835
21	15-08-2017 19:06	0.7124175
22	15-08-2017 19:20	0.6765989

Table 2

Digitised dataset of an Australian mine (Voight, 1989)

Time (days)	Displacement (mm)	Time (days)	Displacement (mm)
2.51	0.98	12.12	10.53
3.23	0.98	12.86	11.03
3.99	1.31	13.62	12.18
4.73	1.64	14.34	13.17
5.42	2.29	15.08	13.99
6.23	2.95	15.82	15.31
6.94	4.27	16.53	16.47
7.70	4.60	17.30	17.62
8.45	5.10	18.04	18.78
9.19	6.25	18.75	19.77
9.92	6.91	19.46	21.75
10.67	8.23	20.16	23.07
11.38	9.38	20.90	24.06

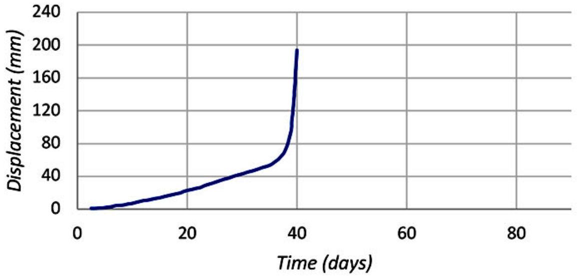


Figure 2—Plot for the digitised data set of an Australian mine

Slope failure prediction methods

Slope failures follow a progressive process consisting of three distinct stages: (i) deceleration, where movement slows down; (ii) steady-state deformation, where displacement occurs at a nearly constant rate; and (iii) acceleration, where movement rapidly increases, ultimately leading to failure. This three-stage model, validated through laboratory experiments and field monitoring, serves as a fundamental framework for analysing and predicting landslides and slope instabilities (Petley et al., 2005).

Building on this framework, Fukuzono (1985) developed a failure time prediction method by analysing the tertiary (final acceleration) stage of slope movement. A key concept introduced in this approach is the onset of acceleration (OOA) point, marking the transition from steady-state deformation to rapid acceleration. By plotting inverse velocity against time, this method enables the identification of failure trends and estimation of the time-to-failure. The acceleration phase is further classified into two segments: pre-OOA, where the slope remains stable but trends toward failure, and post-OOA, where velocity increases rapidly and inverse velocity approaches zero. To refine failure time estimation, Voight (1988; 1989) introduced mathematical models that incorporate displacement, velocity, and acceleration data to improve the predictive accuracy of inverse velocity analysis. Several researchers have since expanded on Fukuzono's approach, introducing empirical equations to better characterise failure progression. A widely adopted method involves selecting critical points on the failure curve, plotting tangent lines, and extrapolating failure timing based on inverse velocity trends.

The accuracy of these models depends largely on two empirical constants, A and α used in Equation 1, which was introduced by Fukuzono by combining the developments on his earlier work.

$$\Lambda = \frac{1}{v} = A(\alpha - 1)^{1/(\alpha-1)}\left(t_f - t\right)^{1/(\alpha-1)} \qquad [1]$$

where t_f is failure time, Λ is inverse velocity.

A and α influence the shape of the inverse velocity curve. The value of α determines failure prediction accuracy and follows these trends:

- ➤ $\alpha = 2$ results in a linear IV curve, simplifying failure estimation.
- ➤ $\alpha > 2$ produces a convex IV curve, where failure time becomes less predictable.
- ➤ $1 < \alpha < 2$ generates a concave IV curve, requiring additional adjustments for precise forecasting.

Studies indicate that A and α are interdependent and vary based on kinematic motion patterns, material properties, and failure scale (Segalini et al., 2018). In practical mining applications, α = 2 is often assumed to ensure real-time visual feedback for operational decision-making, as it simplifies failure predictions and aligns with standard geotechnical monitoring practices. The IVM is a simple, yet effective tool for slope failure assessment and early warning but, as explained, its accuracy is affected by noise and measurement errors. The three filter models evaluated in the study are:

- *Short-term simple box filter*: A moving average filter applied over a short window to smooth minor fluctuations in velocity data.
- *Long-term simple box*: A similar moving average approach over an extended period to eliminate noise while preserving trend stability.
- *Exponentially weighted moving average* (EWMA): A more adaptive filter that assigns exponentially decreasing weights to past observations, allowing for dynamic responsiveness to sudden changes.

By integrating real-time monitoring data, inverse velocity analysis, and advanced filtering techniques, this methodology aims to improve the accuracy and reliability of slope failure predictions.

Computational analysis of smoothing filters and optimisation of slope failure predictions through filtering methods

The computational evaluation involves programmatic implementation on python of these filters using the codes mentioned in codebox 1, followed by comparative analysis to assess their impact on IVM-based predictions (Glastonbury, Fell, 2002). Performance is measured by analysing filtered vs. raw inverse velocity trends, identifying the optimum filtering approach for early warning applications in surface mines.

The FIVM-Analyser applies computational methods to enhance slope failure prediction accuracy by analysing displacement trends and optimising inverse velocity predictions. It performs the following key tasks:

- Computes velocity and acceleration from displacement data by determining velocity and computing acceleration, essential for tracking slope stability trends.
- Computes inverse velocity for failure prediction by converting velocity values into inverse velocity (1/v) and handles zero and negative velocity values safely to avoid computational errors.
- Applies multiple smoothing methods to reduce noise.
- Estimates time-to-failure (TTF) by fitting a linear regression to inverse velocity data and accounts for measurement noise and inconsistencies to improve prediction accuracy.
- Compares predictions across all smoothing models and selects the best approach by evaluating all smoothing methods to determine the most stable and accurate prediction. Further, identifies the best model by comparing predicted failure times to the last measured time in the dataset.

Results

Analysis of slope displacement, velocity, acceleration, and inverse velocity trends

The FIVM-Analyser was applied to displacement monitoring data to analyse slope deformation trends, estimate failure time, and compare the performance of different smoothing techniques. The results demonstrate the progressive failure process, with distinct trends observed in velocity, acceleration, and inverse velocity (IV) curves. Displacement data was first processed to compute velocity and acceleration. The acceleration curve exhibited three distinct stages, showing three different stages of velocity, as shown in Figure 3:

- Initial deceleration phase, where the rate of displacement slowed gradually.
- Steady-state deformation phase, with a nearly constant velocity.
- Acceleration phase, where velocity increased significantly as failure approached.

The three stages can be seen in Figure 3, where the acceleration initially turns negative, then is zero, and in then increases continuously leading to failure.

The acceleration curve fluctuated initially but showed a clear upward trend in the final acceleration stage, confirming the onset of tertiary creep before failure. The inverse velocity (IV) curve, a key indicator in failure prediction, was computed using raw velocity data. As expected, the IV curve followed a downward trend, approaching zero as the slope neared failure. However, raw IV data contained significant fluctuations due to noise, making it difficult to precisely estimate the failure time. To improve accuracy, filtering techniques were applied to smooth the IV curve and refine failure time predictions.

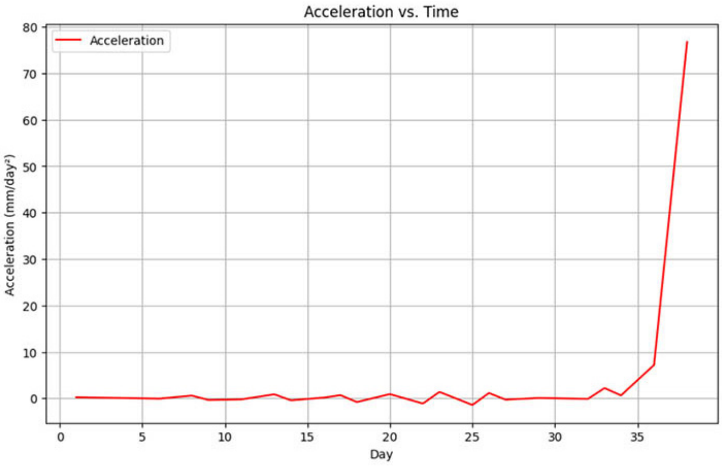


Figure 3—Acceleration vs. time plot of one of the datasets

Evaluation of smoothing filters for failure time prediction

To reduce noise and improve failure time prediction accuracy, three smoothing filters (short-term moving average, long-term moving average, and exponentially weighted moving average) were applied to the velocity data. The effectiveness of each filter was evaluated by comparing their impact on failure time estimation and trend stability. Filtered inverse velocity curves showed significant improvements over raw data, reducing erratic fluctuations while preserving acceleration trends. The short-term moving average filter effectively smoothed short-term variations but retained some noise. The long-term moving average filter produced the most stable trend but slightly delayed failure time estimation. The exponentially weighted moving average filter, with its adaptive weighting, provided the best balance between noise reduction and responsiveness to acceleration. Failure time was estimated by applying a linear fit to the inverse velocity curve in its final phase. The slope constant ‘A’ was computed as the rate at which inverse velocity decreases, representing the acceleration characteristics of the failure process.

To determine the most effective filtering approach, predictions from all models were compared against historical failure data. Raw data predictions fluctuated significantly, reducing reliability. Short-term moving average and long-term moving average filters produced reasonable estimates, but short-term moving average retained fluctuations, while long-term moving average slightly delayed predictions. The exponentially weighted moving average filter predicted failure closest to 10 and 11 March, confirming its suitability for real-time failure detection, when the slope actually failed. To further validate, two other datasets were used and similar results were observed. An example from the study's dataset has been plotted. The visualisation that follows in Figure 4 illustrates:

- Raw velocity data points
- Filtered velocity data using three distinct techniques:
- Short-term moving average (SMA)
- Long-term moving average (LMA)
- Exponential smoothing filter (ESF)

These trends are compared to visually demonstrate the effectiveness of each smoothing approach on noisy velocity data. Further, the corresponding inverse velocity trends are also shown, which are crucial for accurately identifying the time-to-failure in slope stability assessments.

The visual comparison of filters and raw data in Figure 4 clearly distinguishes between:

- *Raw data:* This line denotes the direct output from the slope monitoring system, including all instrumental noise and environmental fluctuations.
- *Short-term moving average filter:* Effectively smooths out minor, short-term fluctuations, providing a clearer trend while maintaining sensitivity to recent changes.
- *Long-term moving average filter*: Produces a very stable long-term trend but can lag in detecting rapid accelerations (critical for predicting imminent failures).
- *Exponential smoothing filter:* Strikes a balance, providing both stability and responsiveness, making it ideal for real-time early warning systems as supported by the study’s findings.

This comparison allows direct visual inspection of each filter’s ability to clean noisy data and enhance the reliability of failure time predictions.

Discussion and conclusions

This study applied filtered inverse velocity analysis to improve slope failure prediction in surface mines, utilising short-term moving average (SMA), long-term moving average (LMA), and exponential smoothing filters (ESF) to mitigate noise in velocity data. The results revealed that filtering significantly enhances the accuracy and stability of failure time estimates, compared to raw displacement trends. All three smoothing methods effectively reduced random fluctuations in the raw data, making it easier to identify the acceleration phase in slope deformation. Short-term moving average and exponential smoothing filter strike a good balance between smoothing out erratic signals and preserving the essential slope acceleration behaviour. Short-term moving average captures recent changes well but can leave minor fluctuations that slightly affect the final failure time estimate whereas Long-term moving average produces a very stable trend, albeit at the expense of slightly overestimating the actual failure time in rapidly accelerating

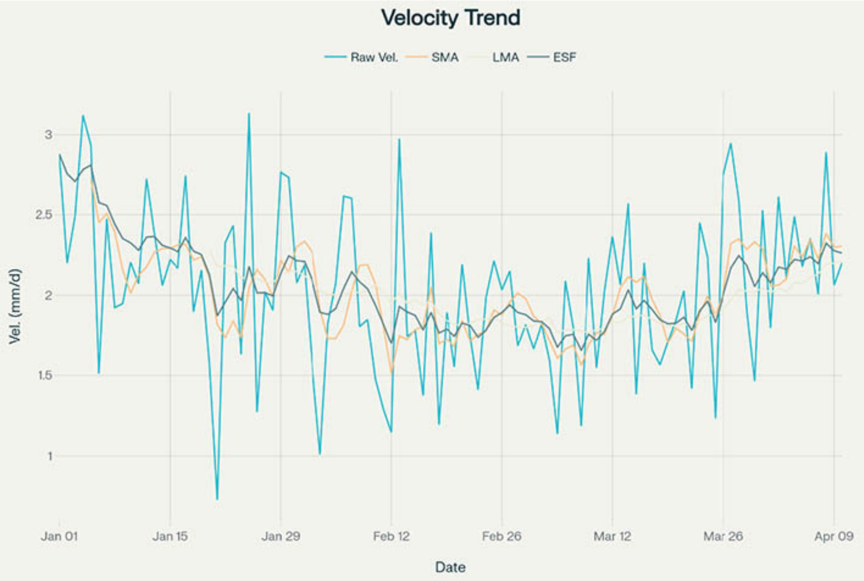


Figure 4—Comparison of raw and filtered velocity and inverse velocity trends, historical failure displacement, and multiple case study displacement trends

slopes. The exponential smoothing filter demonstrates superior adaptiveness to velocity changes, typically providing the most accurate and timely predictions relative to field observations.

The best-performing filter (exponential smoothing filter) consistently predicted failure times closest to the observed collapse scenario while the raw data predictions were less reliable, highlighting the necessity of applying a suitable smoothing technique for early warning systems. Implementing filtered inverse velocity enhances the robustness of slope monitoring, reducing false alarms and misjudged failure times. Exponential smoothing filter is especially valuable in near-real-time applications, where rapid detection of accelerating slopes is critical for mine safety. Further work could explore nonlinear fitting (e.g., power-law or logistic models) to accommodate complex or multi-stage acceleration patterns. Hybrid approaches combining machine learning with classical inverse velocity methods might further refine slope failure prediction for diverse geotechnical environments.

Declarations

Conflict of interest

The authors declare that they have no conflict of interest.

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Data availability statement

Data sharing is not applicable to this article as no datasets were generated or analysed during the current study.

Author's contribution statement

All authors contributed to the design and implementation of the research, to the analysis of the results, and to the writing of the manuscript.

Cover letter

This manuscript is the authors' original work and has neither been published, nor has it been submitted simultaneously elsewhere. All authors have checked the manuscript and have agreed to the submission.

Ethical approval

The paper has been submitted with full responsibility, following due ethical procedure, and there is no duplicate publication, fraud, or plagiarism. None of the authors of this paper has a financial or personal relationship with other people or organisations that could inappropriately influence or bias the content of the paper. This article does not contain any studies with human participants or animals performed by any of the authors.

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Consent to Participate

Not applicable

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Appendix

```
import numpy as np
from scipy.optimize import curve_fit
from scipy.ndimage import uniform_filter1d
from scipy.signal import lfilter
def compute_velocity(time, displacement):
"""Computes velocity (mm/day), handling division by zero."""
delta_time = np.diff(time)
velocity = np.divide(np.diff(displacement), delta_time, where=delta_time>0,
out=np.zeros_like(delta_time))
return velocity, time[:-1] + delta_time / 2  # Midpoints for velocity times
def compute_acceleration(time_vel, velocity):
"""Computes acceleration (mm/day^2), handling division by zero."""
delta_time = np.diff(time_vel)
acceleration = np.divide(np.diff(velocity), delta_time, where=delta_time>0,
out=np.zeros_like(delta_time))
return acceleration, time_vel[:-1] + delta_time / 2  # Midpoints for acceleration
times
def compute_inverse_velocity(velocity):
"""Computes inverse velocity (1/v), safely handling zero and negative values."""
return np.where(velocity > 0, 1 / velocity, np.nan)
def apply_smoothing(velocity, method="SMA", window=3, alpha=0.5):
"""Applies different smoothing techniques to velocity data."""
if method == "SMA":
return uniform_filter1d(velocity, size=window, mode='nearest')
if method == "LMA":
return uniform_filter1d(velocity, size=window * 2, mode='nearest')
if method == "ESF":
return lfilter([alpha], [1, alpha - 1], velocity, axis=0)
return velocity  # Default: No filtering if invalid method
def linear_fit_inverse_velocity(time, inv_velocity, num_points=6):
"""Fits inverse velocity to a linear model, handling NaNs."""
def linear_func(t, A, tf): return A * (tf - t)
t_fit, inv_v_fit = time[-num_points:], inv_velocity[-num_points:]
valid_mask = ~np.isnan(inv_v_fit)
if np.sum(valid_mask) < 2: return np.nan, np.nan
try:
popt, _ = curve_fit(linear_func, t_fit[valid_mask], inv_v_fit[valid_mask])
return popt[0], popt[1]  # A, t_f
except RuntimeError:
return np.nan, np.nan
def analyze_slope(time, displacement, num_fit_points=6):
"""Performs slope deformation analysis & compares smoothing methods."""
velocity, time_vel = compute_velocity(time, displacement)
acceleration, time_acc = compute_acceleration(time_vel, velocity)
inv_velocity = compute_inverse_velocity(velocity)
# Apply different smoothing methods
smoothed_results = {method: {"inv_velocity": compute_inverse_velocity(apply_
smoothing(velocity, method, 3))}
for method in ["Raw", "SMA", "LMA", "ESF"]}
# Fit inverse velocity to estimate failure time
for method in smoothed_results:
smoothed_results[method]["A"], smoothed_results[method]["tf"] = \
linear_fit_inverse_velocity(time_vel, smoothed_results[method]["inv_
velocity"], num_fit_points)
# Determine best method (closest predicted failure time to last measured time)
valid_methods = {m: res for m, res in smoothed_results.items() if not
np.isnan(res["tf"])}
best_method = min(valid_methods, key=lambda m: abs(valid_methods[m]
["tf"] - time[-1])) if valid_methods else "None"
# Print results
print("\n### Slope Deformation Analysis Results ###")
print(f"Final displacement: {displacement[-1]:.2f} mm over {time[-1]:.2f} days")
    print(f"Best smoothing method: {best_method}")
for method, res in smoothed_results.items():
print(f"{method}: Predicted failure time = {res['tf']:.2f} days, A = {res['A']:.6f}"
if not np.isnan(res['tf'])
else f"{method}: Prediction failed (insufficient data)")
```

Codebox1 - filtered inverse velocity method analyser