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

M.M. Masood, T. Verma, G.Y. Raju

Introduction & Motivation: Why Slope Failure Prediction Matters?

- Slope failures in surface mines pose major safety and economic risks.
- Failures are unpredictable and can occur during or even after mining operations.
- Accurate time-of-failure (TOF) predictions are crucial for early warnings and mine safety.
- The discussed study introduces an improved method for more reliable and timely slope failure prediction, centering on the application of filtering techniques to displacement monitoring data using the Filtered Inverse Velocity Method Analyzer (FIVM-Analyzer)

Figure 1: Slope failure. Bingham Canyon Mine. Utah / USA (Source: http://www.mining.com)

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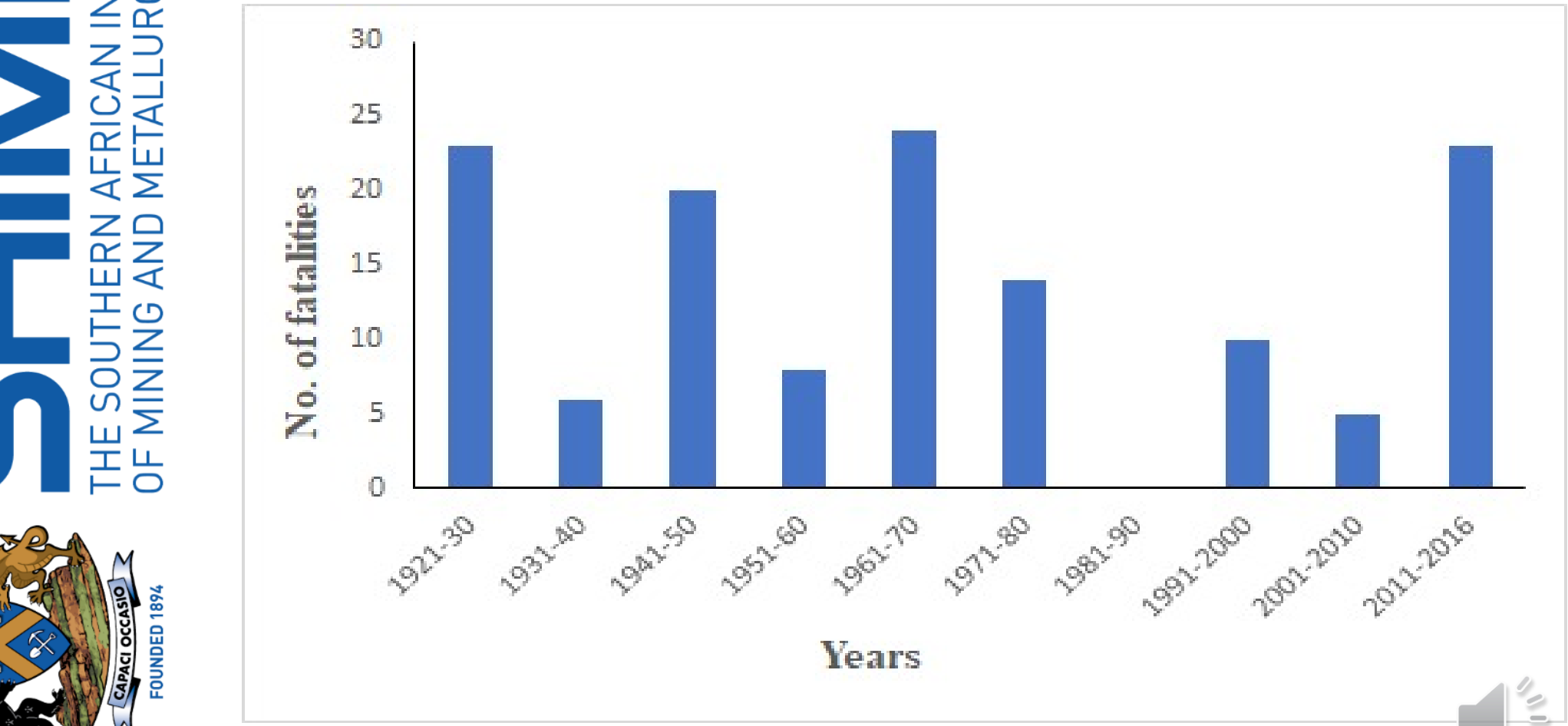

Figure 2: Loss of lives due to slope failure from 1921 to 2016 in India (23 accidents causing 143 fatalities), CURRENT SCIENCE, VOL. 117, NO. 2, 25 JULY 2019

Fortunately, mine slope failures usually give advance warning before failing.

If they can be accurately detected, slope failures related hazards can be avoided.

Through proper knowledge of the deformation behaviour, mine slope hazards can be greatly reduced and failures can be predicted.

Slope Monitoring Approaches

- Monitoring tools: Slope Stability Radar, GNSS, LiDAR, etc.
- Displacement, velocity, and acceleration are key indicators.
- Focus on trends: *progressive movement leads to failure*.

Slope Failure Prediction Techniques

- Researchers have made various efforts in the past five decades to establish acceptable techniques for estimating the failure time of mining slopes. However, no one approach is universally acceptable.
- The difference in the models used for estimating the time to failure of mine slopes relies on the adopted function. The generally utilised functions are linear, exponential, and power law.
- Variables, such as the displacement or velocity characterising the slope behaviour before failure, are used in the models.

The Inverse Velocity Method (IVM)

- Fukuzono(1985) found that time to accelerating creep failure under gravity loading was inversely proportional to deformation rate.
- IVM relates slope movement velocity to failure time. As failure nears, velocity increases, and inverse velocity (1/v) decreases.
- Plotting 1/v against time helps estimate when the slope will fail.
- One can estimate the failure time by extrapolating the curve (1/v vs time) to the time-axis (inverse velocity = 0).

Real-time application is challenged by noisy and incomplete data.

- Fukuzono presented three inverse velocity curves shown in figure below, are defined by the equation:

$$\Lambda = \frac{1}{v} = A(\alpha - 1)^{1/(\alpha-1)}\left(t_f - t\right)^{1/(\alpha-1)}$$ where, t_f is failure time, Λ is inverse velocity

In practise, α = 2 is used since it almost never deviates, making the simpler linear fit method the one of choice, with the condition that it must be regularly updated to detect the trend shifts (Rose & Hungr, 2007a).

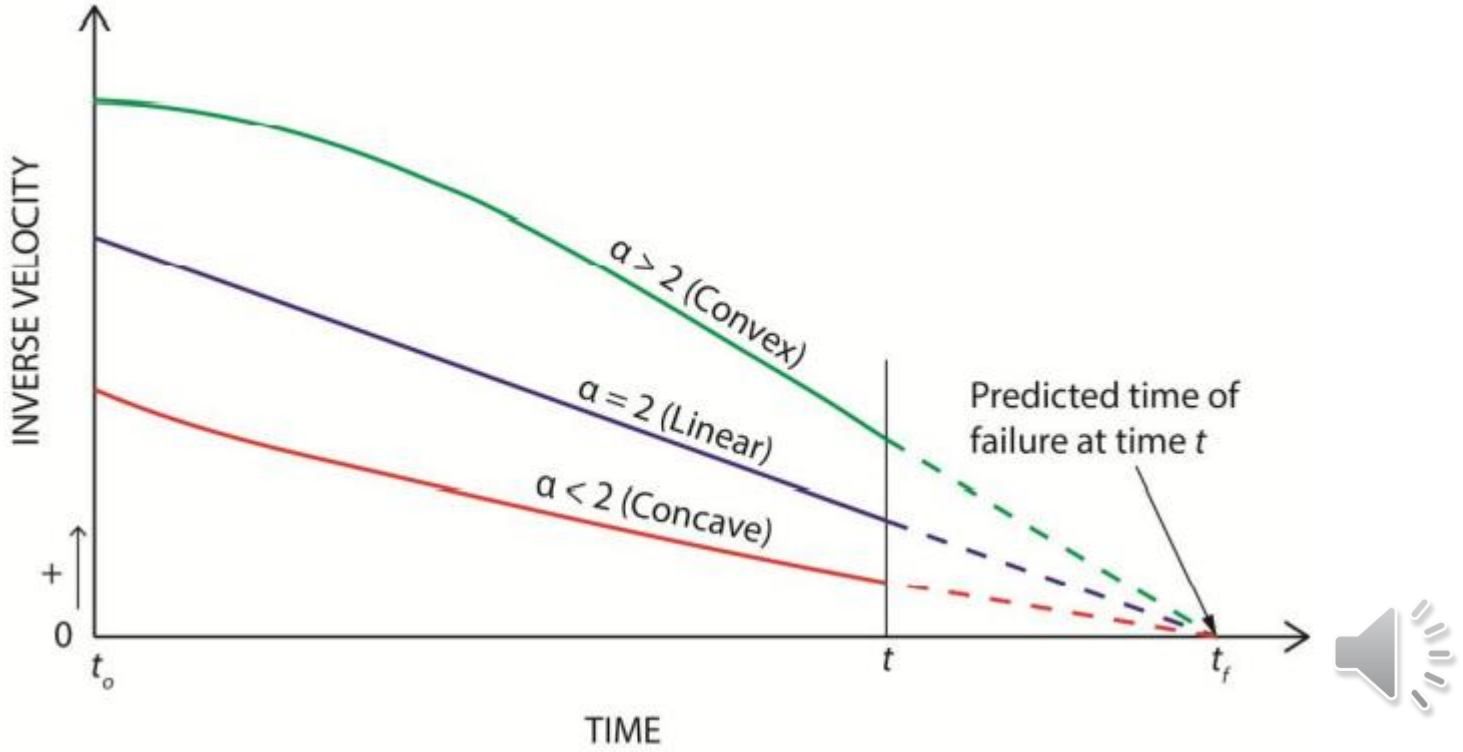

Figure 3: Inverse velocity versus time relationship related to the variation of α

Problem Statement

- Instrumental noise and irregularities disturb the IVM trend.
- Raw sensor data causes fluctuations that mislead failure predictions.
- The proposed solution: apply smoothing filters to clean velocity data before using IVM.

The Proposed Solution – FIVM-Analyzer

- A tool to process displacement data and apply inverse velocity logic.
- Features:
  - Calculates velocity, acceleration, and inverse velocity.
  - Applies smoothing filters.
  - Fits linear regression to IV curve in the acceleration phase.
  - Estimates time-to-failure.
- Evaluates accuracy across filters using real and historical mine data.

Filtering Techniques Used

1. Short-Term Simple Box Filter (SSBF/SMA)
2. Long-Term Simple Box Filter (LSBF/LMA)
3. Exponentially Weighted Moving Average (EWMA/ESF)

All compared with unfiltered (raw) data.

Methodology Overview

- Data Sources:
  - Real-time SSR data from 3 SECL mines (India).
  - Digitized historical data from an Australian mine.
- Steps:
  - Extract displacement & velocity data.
  - Apply each filter to the velocity series.
  - Convert to inverse velocity.
  - Fit regression to data.
  - Extrapolate to predict failure time.
- Computed failure prediction is compared to observed failure timelines.

Results—Filter Performance

- Raw IV data: highly erratic → inaccurate TOF estimates.
- SSF (Short-Term): Better than raw, but residual noise affected TOF.
- LSF (Long-Term): Very smooth trend, slight delay in TOF prediction.
- ESF (Exponential): Most accurate and timely prediction of TOF—closely matched real failure on March 10–11.
- Testing on other datasets also confirmed ESF consistency.

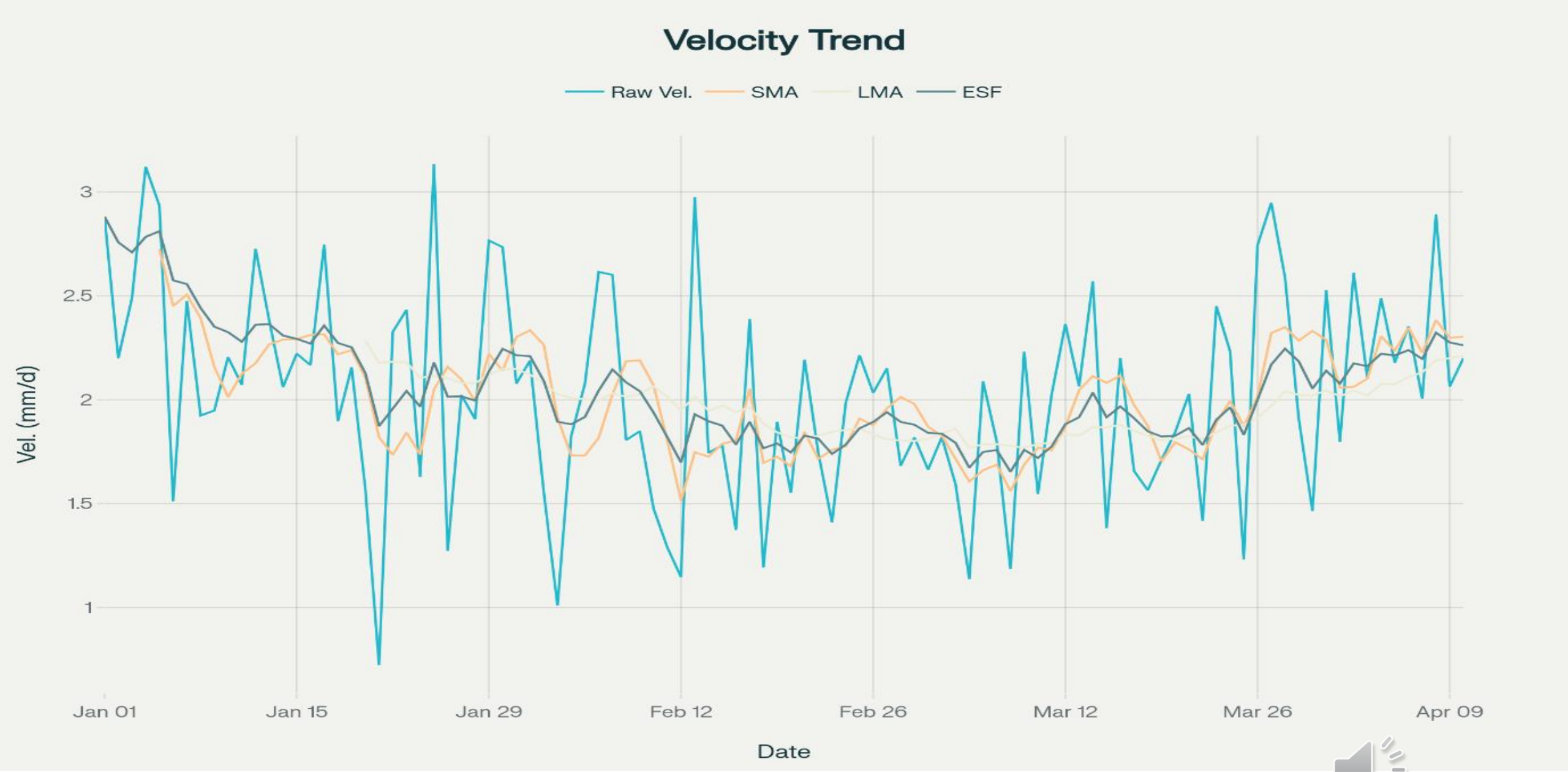

Figure 4: Comparison of raw and filtered velocity and inverse velocity trends, historical failure displacement, and multiple case study displacement trends.

Key Findings

- Filtering significantly improved the clarity and reliability of IVM predictions.
- All filters helped reduce random noise and improve regression fit.
- Exponential Smoothing Filter (ESF) is the most suitable for real-time early warning.
- Filtering compensates for sensor variability and irregular monitoring intervals.

Conclusions & Future Work

- The FIVM-Analyzer successfully optimizes slope failure prediction using filtered IVM.
- ESF offers the best trade-off between responsiveness and stability.
- Improves safety and decision-making in mine operations.
- Future research:
  - Explore nonlinear trend fitting (e.g., logistic, power-law).
  - Combine IVM with machine learning to better generalize across site conditions.

Thank you!