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Defining Acceleration Limits Signalling Onset of Slope Failure in Surface Mines

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Abstract: Slope failures in mines are commonly preceded by a creep deformation curve comprising primary, secondary, and tertiary phases. The final tertiary (accelerating) phase provides the strongest precursor signals of imminent collapse, but reliably identifying its onset (the Onset of Slope Failure, or OOSF) in noisy monitoring data remains challenging. Traditional early-warning systems rely on fixed displacement or velocity thresholds, but once those limits are reached, the lead-time before failure is uncertain. We propose a new algorithmic framework to detect the OOSF by analyzing real-time displacement time-series with a moving-window multi-criteria test. The method applies sequential checks on short windows of data. Only when all checks are satisfied is the window start marked as the OOSF. This systematic detection of tertiary creep onset could improve the early forecasting of slope failures.
Keywords: early-warning systems, slope stability, mine slopes, onset of slope failure

1. INTRODUCTION

Surface mine slopes often exhibit creep deformation long before collapse, following the classical three-stage creep law: an initial primary (decelerating) phase, a steady secondary phase, and a final tertiary (accelerating) phase. The tertiary phase is of particular interest because its strong acceleration can be used to forecast the time of failure (ToF).

For example, Saito (1969) and Voight (1989) formulated power-law relations in the tertiary regime, leading to the widely used inverse-velocity plotting method (Fukuzono, 1985). The basic idea is that, under constant stress, landslide deformation obeys creep theory and the acceleration of displacement follows a known curve, enabling graphical extrapolation to predict collapse. In practice, many case studies have successfully applied inverse-velocity fits to failure incidents, often assuming a nearly linear trend in the final accelerating phase. Figure 1 shows the three creep phases.

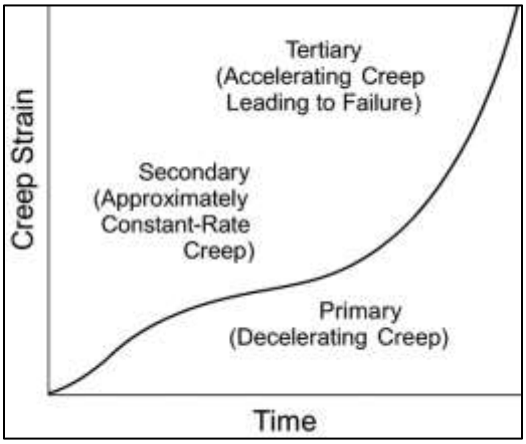

Figure 1: Primary, Secondary and Tertiary Creep

While the theory of tertiary creep is well established, its practical use in early warning is limited by data noise and ambiguity. Real monitoring data from slopes can be scattered, and the point at which one enters true accelerating creep is not always obvious. Typically, early-warning systems impose alert levels on displacement or velocity (e.g. if velocity exceeds a set threshold, issue an alarm). However, as Crosta *et al.* (2003) point out, identifying suitable thresholds is difficult due to the complex and variable nature of landslides. Worse yet, if we act only when a fixed threshold is crossed, there may be very little time before actual failure, and the precise timing remains unknown. In other words, once the highest alert level is triggered, traditional EWS approaches effectively end, leaving a critical gap.

To address this gap, it is advantageous to automatically detect the onset of the tertiary creep (i.e. the OOSF) as early as possible, using systematic analysis of the monitored displacement record. In recent years, several authors have suggested that the inverse-velocity fit should be applied only to data after this OOSF, to avoid bias from the earlier, slower phase. For instance, Dick *et al.* (2014) specifically recommended excluding pre-acceleration data when fitting linear extrapolations. Rose and Hungr (2007) similarly noted that the inverse-velocity curve tends to become linear *near* the time of failure, but that the early part of the record (before acceleration) can distort the forecast. This implies that identifying the correct breakpoint (the OOSF) is crucial: it allows us to take only the truly accelerating part of the time series into account. Unfortunately, most existing methods rely on expert judgment or simple rules to pick the OOSF. A few recent studies have proposed algorithmic frameworks (e.g. moving averages or statistical tests) to recognize the acceleration point, but these are often not general or remain in the research stage.

In this work, we propose a novel moving-window, multi-criteria algorithm to identify the OOSF in slope displacement monitoring data. Our goal is to create a more objective, data-driven trigger that can support failure forecasting. The algorithm applies a sequence of explicit checks on short time-windows of recent data, ensuring that a candidate acceleration signal is sustained and genuine before it is flagged. If all conditions are met, the algorithm marks the beginning of that window as the OOSF. The conditions are designed to filter out noise and require clear signs of positive velocity and accelerating trend.

2. METHODOLOGY

The core of our proposed method is a sliding ("moving") window that evaluates consecutive segments of the displacement time series for evidence of accelerating motion. At each time step, the algorithm examines the most recent window of data of fixed length. The following criteria are then applied in sequence:

i. First, any negative displacement readings within the window are discarded or set to zero. In many monitoring contexts, only positive displacements (down-slope motion) contribute to creep; negative fluctuations often reflect measurement noise or recovery phases. By ignoring negative values, we ensure the algorithm focuses on sustained movement away from stability. For proceeding further at least five consecutive values of displacement should be positive.

ii. Compute instantaneous velocity: We compute the first difference (velocity) over each sub-interval in the window. These velocities represent the current trend of movement.

iii. Check for sustained movement: The window must show uninterrupted positive motion. In practice, we require four consecutive positive displacement increments (or equivalently, four positive velocity values) in the window. This ensures that the slope has been moving continuously and rules out windows with one or more stops or reversals.

iv. Check for increasing velocity trend. A hallmark of acceleration is that each velocity is larger than the previous. This condition enforces a monotonic increase in speed during the window.

v. To capture the continuous nature of acceleration, we fit a parabolic curve to the velocity data over the window. We then check that the leading coefficient a of the general parabolic equation. A positive a indicates an upward-opening curve, i.e. acceleration that grows over the window, rather than leveling off or decelerating.

vi. Finally, we identify the increase in a value for three out of four consecutive values of a.

If all the above checks are satisfied in the current window, we declare the start of that window to be the Onset of Slope Failure (OOSF). By scanning forward in time, this provides a systematic way to trigger when runaway acceleration begins. This moving-window procedure repeats as new data arrive. Only when an entire window meets every criterion do we register a positive detection. Otherwise, the window slides forward and the checks are repeated. In effect, the algorithm demands a clear, sustained acceleration before triggering, reducing false alarms from isolated fluctuations.

3. DISCUSSION

The multi-criteria moving-window algorithm provides a systematic way to flag the start of tertiary creep, with several attractive features. First, by requiring sustained positive displacements and velocity rises, it avoids false positives due to sporadic noise or brief fluctuations. Many slope monitoring records contain small movements or minor reversals; the four-point consistency check filters those out. Second, fitting a quadratic and requiring a positive leading coefficient ensures that the pattern is truly accelerating (convex upward), which is the hallmark of tertiary creep. In a standard inverse-velocity plot, we expect near-linear behaviour only after acceleration actually begins, and our algorithm enforces this by checking curvature in the raw data stream.

Our approach aligns with theoretical and empirical insights in landslide creep theory. For instance, Voight's formulation implies that the curve becomes increasingly convex as failure approaches; by explicitly testing the polynomial curvature, we operationalize that idea. As noted by Rose & Hungr (2007), when a landslide truly enters its rapid phase, the velocity-versus-time relation tends to be dominated by linear or accelerating segments. Conversely, during secondary creep, velocities are roughly constant. By demanding a positive acceleration that grows (the second derivative test), we ensure that a classical tertiary creep signature is present.

Importantly, the algorithm takes the onset issue seriously. Many forecasting errors arise when analysts include too much pre-acceleration data in a linear fit, leading to underestimation of the impending collapse date. By scanning only for windows where the criteria hold, we effectively find the breakpoint between secondary and tertiary creep. This is consistent with the recommendation of Dick *et al.* (2014) to exclude data before acceleration when forecasting. In effect, our method automatically locates that breakpoint.

The design of the checks is conservative: it will not trigger an alert unless all conditions are satisfied simultaneously. This reduces false alarms at the cost of possibly detecting OOSF slightly later than the absolute earliest moment (if data is noisy). In our hypothetical test, the window length of four steps means the detection lags the real threshold by a few time-steps (since the algorithm needs the four consistent increments to confirm). In practice, the choice of window size and sampling interval must balance timeliness with reliability. Smaller windows might detect faster but could be more sensitive to noise, while larger windows require longer sustained acceleration. These design choices can be tuned based on the monitoring frequency and noise level at a given mine site.

One potential limitation is that the method assumes the displacement trend is monotonic and gradually acceleratory. If an actual failure involves complex, non-monotonic movements (such as transient stalls or multi-phase acceleration) the strict criteria might miss or delay the detection. However, most creeping slope failures do show a generally increasing trend once tertiary phase begins. Research also shows that even very fast rock failures often have a brief tertiary creep stage, which may be missed only because standard monitoring intervals are too coarse. Our algorithm could help reveal these subtle accelerations by focusing on short windows of high-resolution data. In settings with lower sampling rates, one could lengthen the window accordingly.

Finally, the method can be integrated into a broader warning system. Once OOSF is detected, automatic triggers can initiate further analysis – for example, switching to a linear inverse-velocity forecast to estimate the failure time. Simultaneously, alert protocols (evacuation, alarms) can be activated on the assumption that collapse is imminent. Because the detection is data-driven, it adapts to the particular behaviour of each slope, rather than relying on fixed generic thresholds that may not suit all sites.

4. CONCLUSION

Accurate prediction of slope failure in surface mines depends on recognizing the precise moment when deformation starts to self-accelerate. We have proposed a new, algorithmic method to identify this Onset of Slope Failure (OOSF) by applying multiple sequential checks to real-time displacement data. The moving-window framework examines each recent data segment and enforces that motion is positive, velocities are steadily increasing, and the curvature of the trend is upward. Only when all these conditions are met is the OOSF flagged.

This approach directly targets the tertiary creep phase of landslide theory, operationalizing established concepts (e.g. that inverse-velocity should only be applied post-OOSF). In real slope monitoring, the algorithm would provide an early warning trigger that is grounded in physical behaviour rather than arbitrary limits. In practical terms, it helps bridge the gap noted by research; once a predefined alert threshold is crossed, we still lack guidance on timing. By delivering a reliable OOSF signal, our method enables timely forecasting of failure time using conventional tools, thereby enhancing the effectiveness of early warning systems.

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