Contour line extraction and feature tracking for real-time 4D landslide monitoring based on point clouds: Proof of concept with lab experiments

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Abstract

Landslides are a pervasive natural hazard with significant societal and environmental impacts. Several methods for monitoring landslides exist, including comparing point clouds from two different epochs directly using the M3C2 algorithm. The main challenge for existing methods is the size of point cloud data sets, which are not computationally efficient enough to process in real time. In this research, we develop an algorithm for real-time landslide monitoring by using a mixture of contour lines to cluster deformed areas and feature tracking to detect small deformations in the pre-clustered areas. The first step involves roughly identifying the deformed area because applying feature extraction and matching on the entire data set is computationally intensive and time-consuming. Detecting these small deformations in the deformed areas, which happens in the feature tracking, could be helpful in predicting the next stage of a landslide and issuing necessary warnings. The method was tested on a controlled laboratory dataset, providing an ideal environment to validate the method's precision, achieving sub-millimeter accuracy under controlled conditions. The results showed that the method is well-suited for real-time monitoring, accurately detecting the deformation's magnitude and direction.

Keywords: *Deformation Analysis, Terrain deformation, Feature Detection, Hillshade, Permanent Laser Scanning*

1 Introduction

Landslides are one of the most destructive geological hazards, leading to considerable property damage and posing serious safety risks worldwide. They occur due to the gravitational movement of material down a slope. Various factors, including heavy rainfall, earthquakes, volcanic eruptions, and human activities can trigger landslides. Their impact extends to critical infrastructure, such as roads and buildings, endangering human lives (Hosseini et al., 2023). According to the World Health Organization, between 1998 and 2017, landslides affected approximately 4.8 million people and resulted in over 18,000 fatalities. Because of that, several research studies have been done to monitor and predict the components of landslides (Casagli et al., 2023; Chae et al., 2017). One notable workflow among these methods offers high spatial resolution monitoring; however, it remains unsuitable for real-time applications. This approach involves extracting features from point clouds obtained using terrestrial laser scanners (Hosseini et al., 2023). In this study, we outline some of the limitations of this method and set forth specific goals to enhance its applicability to real-time data sets, thereby improving its usefulness. These goals include (a) modifying the algorithm to handle real-time data more effectively and (b) identifying ways to overcome its limitations to enhance landslide monitoring and prediction techniques. We evaluate this new concept based on laboratory experiments with known reference movements.

2 Literature Review

Landslide monitoring techniques can generally be classified into two main categories: real-time (permanent) and periodic (intermittent) monitoring.

Each approach has distinct advantages and limitations, depending on the application, available resources, and desired accuracy.

2.1 Real-time Permanent Monitoring

Real-time monitoring collects and analyzes data to detect deformations as they occur. Such monitoring is necessary for early warning systems and high-risk areas where immediate action is required. The most common real-time method is the Global Navigation Satellite System (GNSS), which tracks ground movement continuously to millimeter accuracy (Huang et al., 2023; Shu et al., 2023). When deployed in landslide-prone regions, GNSS stations permit 24/7 displacement monitoring. However, high installation costs caused some research to focus on low-cost GNSS for this purpose (Bellone et al., 2016). Moreover, the other main disadvantage of using GNSS for permanent monitoring is spatial coverage constraints, which limit its application to only discrete points and not the whole surface.

The other major real-time monitoring approach is Terrestrial Laser Scanning (TLS), which periodically takes high-resolution 3D point cloud data. In landslide-prone areas, TLS allows the detection of small-scale topographic changes (Anders et al., 2019; Winiwarter et al., 2023). While TLS gives detailed spatial data, data processing complexity makes real-time computation impossible. To overcome this, researchers have developed feature-based deformation tracking and automated change detection algorithms. This method is applied practically in the AImon5.0 project for monitoring a rock face located in Trier (Czerwonka-Schröder et al., 2025).

Other real-time monitoring methods use inclinometers, extensometers, and fiber optic sensors to record subsurface and surface movements such as (Wang et al., 2015). They are very sensitive instruments that need frequent calibration and maintenance and, thus, are suitable for localized studies rather than large-scale applications. Furthermore, these methods cannot detect deformation directly, and their results need to be interpreted.

2.2 Periodic Monitoring

Periodic monitoring, also called intermittent, epoch-wise, or campaign-based monitoring, uses scheduled observations instead of continuous data collection. This method is inexpensive and is widely applied for long-term slope stability assessment and monitoring of slow-moving landslides. The most common periodic monitoring is UAV-based photogrammetry, which takes high-resolution images at regular intervals to produce Digital Elevation Models (DEMs). UAVs are flexible, economical, and offer wide area coverage, an ideal solution for monitoring inaccessible or hazardous terrain. Moreover, there are many types of UAVs designed for specific conditions and tasks (Sun et al., 2024). However, UAV surveys are weather-dependent and require precise ground control points. Furthermore, the accuracy of the point cloud produced by the UAV's image is not as dense as that of the laser scanner point cloud.

Another common periodic method is Interferometric Synthetic Aperture Radar (InSAR), which is based on satellite-based remote sensing of ground deformation. InSAR allows large-scale monitoring and precise millimeter-level displacement measurements over long periods. However, its limits include lower temporal resolution than real-time methods and atmospheric distortion susceptibility. Also, Airborne LiDAR provides high-resolution topographic mapping for landslide-prone areas. Like TLS, which requires a ground-based setup, Airborne LiDAR can cover large areas. The cost of airborne LiDAR surveys remains a limitation, and data processing requires specialist skills.

Using GNSS and TLS is also commented on in periodic monitoring. There are several research using TLS for capturing the point cloud from the area with the purpose of periodic deformation monitoring such as (Zahs et al., 2022; Raffl, L et al., 2024)

3 Methods and Materials

This study employs a laboratory data set and a real-time featured-based method. Section 3.1 provides an overview of the study areas, while Section 3.2 details the method used for landslide identification.

3.1 Study area

In this research, we utilize a dataset that was created in a laboratory setting with the primary objective of placing multiple targets to measure all deformations using a total station simultaneously with our proposed method by using a laser scanner. This controlled environment allows for a comprehensive evaluation of the method's accuracy.

We applied several deformations in various directions to test their robustness further and create a challenging scenario. This dataset utilized a box of 1 meter by 1 meter, including tiny stones. We implemented deformation on the dataset by positioning many plastic planes beneath the layer of soil. Figure 1 illustrates four planes, each designed to apply different types of deformation (in direction and magnitude).

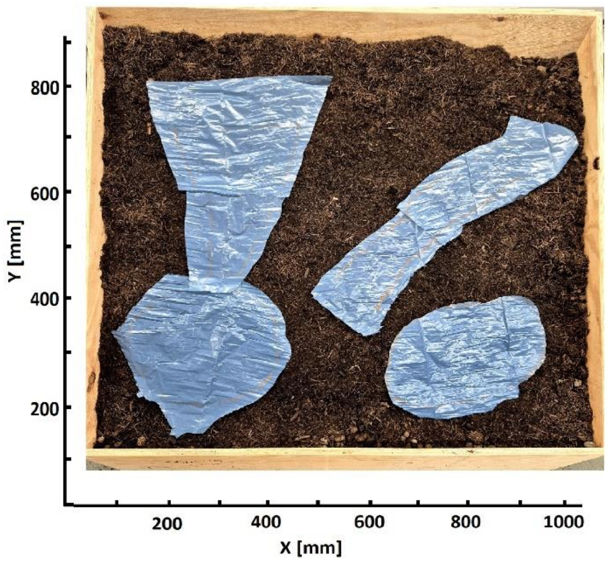

Figure 1: Locations of plastic planes under the soil

Multiple targets were positioned on the soil surface to accurately measure deformation in each area utilizing a total station (Leica Nova MS60). The Leica ScanStation P50 laser scanner was utilized to scan the dataset at every epoch. Figure 2 shows how we set the total station and laser scanner in front of our data set. A total of 20 epochs were recorded from this dataset, with deformations implemented and measurements acquired throughout each epoch utilizing both the total station and the laser scanner.

Figure 2: Location of MS60, P50 and lab setting

This dataset serves two primary purposes: it enables us to assess deformations utilizing our methodology with the laser scanner's point cloud, and subsequently, we can evaluate our findings with the control point deformations recorded by the Leica Nova MS60. This data set enables us to assess the method's accuracy under laboratory conditions. Secondly, there were no registration complications since the Leica ScanStation P50 laser scanner and the Leica Nova MS60 were stable throughout the procedure. We employed several targets in the laboratory to guarantee the accurate alignment of the coordinate systems of the total station and the laser scanner.

3.2 Methodology

This work concentrated on enhancing feature-based approaches for monitoring landslides in relation to temporal changes in the area using time series data. The prior feature-based methodologies, although practical, were not intended for real-time processing and necessitated considerable computational resources and time (Hosseini et al., 2023). Our novel methodology mitigates these constraints by implementing a more efficient and prompt strategy for real-time applications. Figure 3 briefly shows the flowchart of this method.

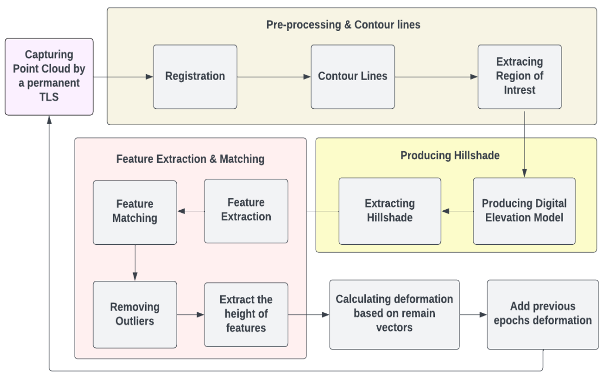

Figure 3: Flowchart of proposed workflow

3.2.1 Preprocessing and Contour Lines

This step includes registration, contour lines, and extracting the region of interest. In the first step, we must register two epochs of the point cloud before going to the next steps. The main reason for this is that if the same feature is extracted from both epochs and there is no deformation at that area, this feature should have exactly the same coordinates in these two epochs. So whenever there is a difference in the coordinate of one feature in two epochs, we consider that deformation.

Afterward, the next step is extracting the contour lines. Contour lines run between points of equal elevation on a terrain surface and are used for topographic mapping and deformation analysis. Herein, contour lines were mathematically derived from elevation values from a digital elevation model (DEM) via grid-based interpolation to derive contour positions. Linear interpolation between grid cells was performed to obtain contour locations at predefined elevation intervals for terrain representation. The utilization of contour lines is crucial for narrowing the search region in feature extraction algorithms, as the feature extraction and matching operations represent the most time-intensive elements of the algorithm. During this step, contour lines are generated from the point clouds.

One of the key points in this step would be the distance between producing contour lines. The smaller the distance between contour lines, the smaller the scale of deformation that they can detect. In the absence of deformation, the contour lines from the two epochs should match. Consequently, any inconsistency among identical contour lines over epochs signifies deformation in that area. These deformed areas will be extracted and used for the feature extraction step. By using them, we won't extract features from the whole area, increasing the method's efficiency for real-time purposes.

3.2.2 Producing Hillshades

Once the area of interest is determined, a Digital Elevation Model (DEM) is taken from the point cloud. The accuracy of this DEM, which increases with the point cloud density, enhances the precision of the feature height obtained from this DEM. This will also increase the resolution of the generated hillshade, so the 2D coordinates of features taken out of it are more exact. By imitating exactly how sunshine casts shadows across the ground, the hillshade model utilizes the DEM to visually illustrate the topography as shaded relief pictures, showcasing the topographic attributes (Horn et al., 1981).

In this particular procedure, illumination values for every cell of the DEM are computed taking into consideration the observer perspective and the incident light angle. The sun generally changes at the azimuth and height (horizontal angle) so that most landscape features can be seen. Both parameters were selected for this dataset to get the best results during the feature extraction stage.

3.2.3 Feature extraction and matching

The scale-invariant feature transform (Lowe, et al., 2004) and nonlinear scale space keypoint detection and Description (Alcantarilla, et al., 2012) feature extraction methods are then used to extract features from the hillshades. Both methods can be used to extract features from the data. However, KAZE produces more features than SIFT, which is why it was used in this study.

It's crucial to remember that more features do not always mean better quality. Excessive feature extraction may result in a significant correlation between them and reduce computing efficiency. The size and roughness of the research region are two of the many variables that influence the selection of an appropriate feature extraction algorithm. Notably, the precision and dispersion of the results are greatly influenced by the texture of the area. The features that were retrieved from the preceding part are then matched using SIFT.

The 2D features are then brought back into 3D space by extracting appropriate height values for the matched features in the first and second epochs from the digital terrain models. The displacement values of characteristic object points can be ascertained at this step.

Notably, a certain proportion of the matches are inaccurate; that is, a false match joins two features that do not correspond to the same spot on the surface of the object. These inaccurate matches may affect the results' qualitative and quantitative interpretation. Therefore, in order to solve this problem, we will use Histogram analyses (Hosseini et al., 2023) to remove outliers.

4 Results

The approach is applied to the laboratory data set in this part. The existence of control points and controlled settings for the laboratory dataset allows for a clearer evaluation of various algorithmic components. By comparing the detected deformations with the known locations of the control points, these conditions also enable us to verify the accuracy of the approach. This aids in verifying the method's effectiveness in a controlled setting.

4.1 Registration and contour lines

Given that all 20 epochs were recorded under controlled laboratory settings and the positions of both the laser scanner and the dataset remained constant, all epochs were aligned with one another. This guarantees that the method's precision may be assessed without the impact of registration errors. The fundamental purpose of utilizing the laboratory dataset is to eradicate registration errors from the study. In this configuration, contour lines were placed on the dataset for each epoch pair to mark the deformed and stable regions (Figure 4), establishing the foundation for the subsequent feature extraction phase.

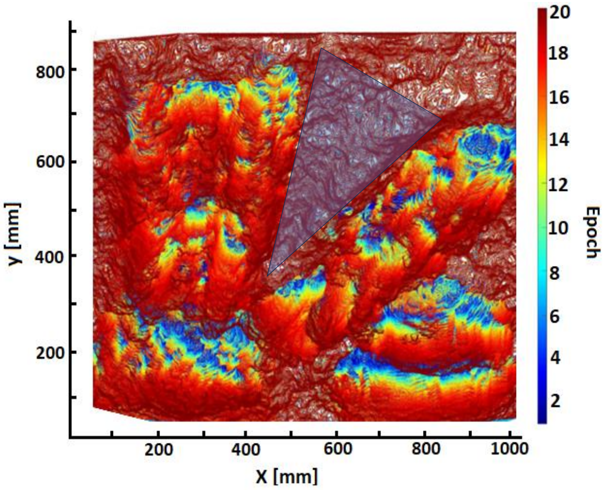

Figure 4: The stable area identified by contour lines

4.2 Feature Extraction and Matching

Following the generation of the DEM and hillshade from the point clouds, as detailed in the methodology section, the KAZE feature extraction method was implemented on this dataset. Although the total number of features covers all of the areas for this study, the distribution of features in certain areas was below average. Figure 5 depicts the location where features were obtained and matched after outlier removal by histogram analysis during two consecutive epochs. The movement of these features from one epoch to the next can show us the direction and magnitude of deformation in each area.

4.3 Evaluation of accuracy

In this section, control points located on the dataset will be used to evaluate the method's accuracy. These control points are measured in each epoch after applying deformation independently using Leica Nova MS60. For this purpose, a 20 mm by 20 mm area around each control point was selected. Features within these areas were then extracted (Figure 6). Subsequently, the movement of these features between each pair of epochs was compared to the movement of the corresponding control point located in the same area. Given the small size of the selected area, it is expected that the average movement of each group of features will closely match that of the adjacent control point.

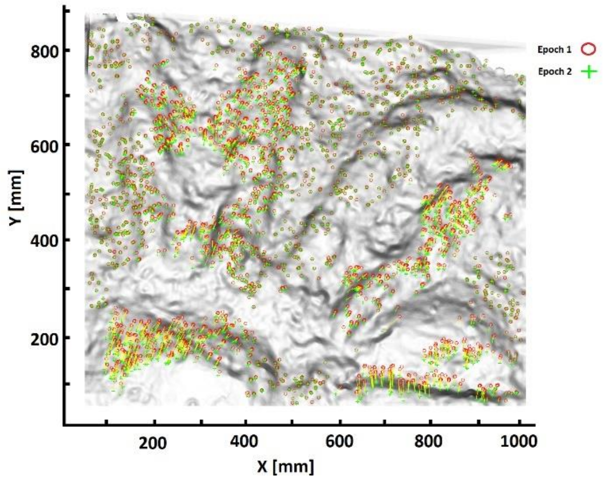

Figure 5: Distribution of features on the hillshade of the laboratory data set

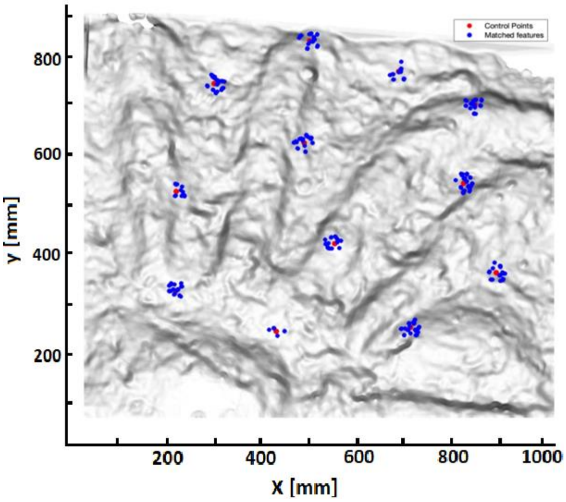

Figure 6: Control points (red) and extracted features in their neighborhood (blue)

The comparison of the average deformation of features with the deformation of each control point reveals that the difference between them is under 1 mm each epoch. Moreover, overall differences across 20 epochs do not surpass 2 mm for any control point. Figure 7 delineates the discrepancies between the deformation seen at control point 7 and those computed from their neighboring features.

5 Discussion and Conclusion

The results show that the proposed real-time landslide monitoring method can detect deformations with sub-millimeter accuracy under controlled conditions. The approach uses contour line clustering and feature tracking to isolate deformed areas with minimum computational load for real-time applications.

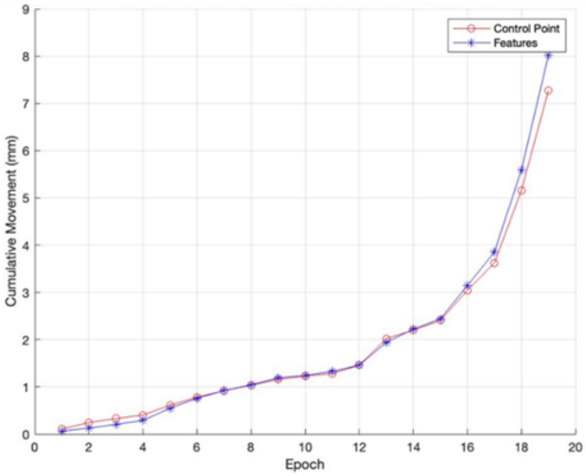

Figure 7: Detected deformation by using control point and neighboring features

Its main advantage is that feature extraction is performed only on deformed regions instead of on the whole dataset. Traditional approaches, such as M3C2-based methods, are computationally intensive because point clouds are large. Our method lowers processing time but maintains high accuracy and is suitable for rapid landslide monitoring and early warning systems.

All these advances bring challenges, though. Surface texture variations affect feature extraction and matching accuracy and result in uneven feature distribution in some locations. KAZE feature extraction yields sufficient features, but distribution may be a limitation in more complex natural environments. Optimal feature selection to achieve uniform coverage across the dataset is another improvement.

Another limitation lies in the dependence on controlled laboratory conditions where external factors like weather conditions, lighting variations, and sensor misalignment are not present. Although this approach performed well in a static setup, further research could test the approach under real field conditions to assess its robustness against environmental uncertainties. Furthermore, although histogram analysis can remove false matches completely, further refinement of this filtering via machine learning-based outlier detection could improve reliability, especially in more complex terrains.

Overall, this study offers a promising real-time landslide monitoring approach balancing computational efficiency and accuracy. Work should continue on field validation, automation enhancements, and integration with other sensing technologies like GNSS and UAV-based photogrammetry for further spatial and temporal coverage.

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