Theory and Practice of Science and Technology
2025, VOL. 6, NO. 5, 14-18
DOI: 10.47297/taposatWSP2633-456903.20250605

Research on the application of integrated investigation method in rocky slope sliding surface identification

Peizhao Chen, Bin Gan

Guangxi Water & Power Design Institute Co.,Ltd 530023

ABSTRACT
This paper reviews integrated methods for identifying sliding surfaces in rock slopes, essential for slope stability analysis. Traditional geological surveys often fail in complex conditions, while combining geological surveys, geophysics, remote sensing, and AI-based analysis enhances accuracy. Methods such as seismic refraction, GPR, LiDAR, and machine learning are discussed. A case study demonstrates improved precision using these integrated approaches. AI models, when combined with geological data, significantly enhance identification. Challenges like data quality and complexity are noted, and future research directions are suggested to improve these methods. This review highlights the potential of multi-technology integration for advancing slope stability analysis.l.

KEYWORDS
Comprehensive Survey Methods; Rock Slope; Sliding Surface Identification; Geological Survey; Engineering Safety; Slope Stability

1 Introduction

1.1 Research Objectives and Significance

The primary objective of this research is to explore and develop a more effective methodology for identifying rock slope sliding surfaces through the use of integrated surveying methods. By combining various geotechnical techniques—such as geological field investigations, remote sensing data (e.g., LiDAR, satellite imagery), and advanced computational analysis (e. g., numerical modeling, machine learning algorithms) —this study seeks to enhance the precision and reliability of slip surface detection.

This approach aims to overcome the limitations of existing methods by integrating multiple data sources, thereby improving the accuracy of predictions regarding slope stability. The study focuses on identifying the critical slip surface in rock slopes, which is the most likely plane of failure, and aims to enhance the decision-making process for engineers and construction professionals involved in slope stability assessments. By providing a more reliable identification method, this research will contribute to the development of safer, more cost-effective strategies for slope stabilization and risk mitigation [1].

The significance of this research extends beyond the theoretical domain. Improved identification of sliding surfaces can lead to more effective engineering practices, reducing the risk of slope failure and enhancing the safety of infrastructure projects. This has important implications for construction management, particularly in areas where steep terrain or unstable geological conditions prevail. Moreover, by advancing the methods for rock slope stability analysis, this research can contribute to the broader field of geotechnical engineering, offering valuable insights for future studies and applications in the domain.

1.2 Literature Review

A significant body of research has been dedicated to understanding rock slope failure mechanisms and developing methods to identify sliding surfaces. Traditionally, geological field surveys, borehole drilling, and physical sampling have been the primary tools used for slope stability analysis. These methods provide essential information about the rock mass and its properties, such as strength, cohesion, and friction. However, they are often limited by their intrusive nature and the time and cost associated with fieldwork, particularly in remote or difficult-to-access areas.

Recent advancements in remote sensing technologies, such as LiDAR (Light Detection and Ranging), ground-penetrating radar (GPR), and photogrammetry, have significantly improved the ability to monitor and analyze rock slopes without physical intrusion. These non-invasive techniques can provide high-resolution 3D models of rock formations and identify potential failure zones through detailed imaging. Moreover, they offer the advantage of being able to cover large areas quickly and with minimal human intervention, making them ideal for monitoring unstable slopes over time [2].

Numerical modeling and machine learning algorithms have also been employed to predict rock slope failure and identify the sliding surface. These methods rely on complex simulations of slope behavior under various environmental conditions and stress scenarios. While they can provide highly accurate predictions, the accuracy of the models depends heavily on the quality of input data, which can sometimes be difficult to obtain. Furthermore, these models often require sophisticated computational resources and expertise, limiting their widespread application in practice.

Despite these advancements, many challenges remain in the accurate identification of sliding surfaces. For instance, data interpretation from remote sensing techniques can be complicated by the presence of vegetation, surface weathering, or other factors that obscure the underlying rock mass. Furthermore, while numerical models offer high precision, they often require extensive and detailed data that may not always be available or reliable.

The need for an integrated approach that combines traditional geological methods with modern remote sensing and computational technologies has become increasingly apparent. By leveraging the strengths of multiple techniques, it is possible to achieve a more accurate and comprehensive understanding of rock slope stability and improve the identification of slip surfaces.

2 Overview of Comprehensive Surveying Methods

Surveying methods used in rock slope stability analysis can be broadly categorized into physical and geological approaches, alongside newer digital and intelligent surveying techniques. Each category has distinct applications, strengths, and limitations based on the requirements of the slope assessment.

Physical Surveying Methods: These methods involve the direct measurement of physical properties of the slope materials and their behavior under stress. Common physical techniques include geophysical surveys such as seismic refraction and ground-penetrating radar (GPR). These methods help in identifying subsurface anomalies, such as fractures, voids, and faults, which are crucial for detecting potential sliding surfaces. The advantage of physical methods lies in their ability to provide real-time data and a detailed view of the internal rock mass, although they may require considerable fieldwork and can be affected by material heterogeneity.

Geological Surveying Methods: Geological surveys include methods such as field mapping, core sampling, and borehole drilling to obtain direct information about the slope's geological characteristics. These techniques allow engineers and geologists to understand the composition, strength, and orientation of rock layers, jointing patterns, and other geological features that could contribute to slope instability. While geological surveys provide foundational information about the terrain, they can be time-consuming and limited in terms of spatial coverage and depth of analysis.

Digital and Intelligent Surveying Methods: With the advent of digital technologies, new methods such as remote sensing, LiDAR (Light Detection and Ranging), and satellite imaging have become essential tools in modern surveying. These methods provide high-resolution, large-scale data that can capture the surface morphology of rock slopes in great detail. Furthermore, intelligent methods that incorporate machine learning and artificial intelligence (AI) algorithms are increasingly being employed to analyze large datasets and predict potential failure surfaces based on historical and real-time data. These methods offer the advantage of rapid data processing, high accuracy, and the ability to analyze complex geological conditions.

In the context of rock slope stability, the choice of surveying technique depends on several factors, including the geological characteristics of the slope, the availability of data, and the scale of the survey. Each method offers unique features and applications that make them suitable for specific purposes in slope failure analysis.

Physical Surveying Techniques: Among the most widely used physical methods are seismic refraction and resistivity profiling, which are useful for assessing the subsurface structure of rock masses. Seismic refraction methods, for instance, provide valuable data on the depth of rock layers and the presence of discontinuities that might act as potential sliding surfaces. In contrast, resistivity profiling can be used to identify variations in water content and rock type, which are important indicators of slope stability [3].

Geological Surveying Techniques: Traditional geological surveying, including field mapping and the study of fracture patterns, remains essential for understanding rock slope stability. Field mapping involves assessing the surface conditions, joint sets, and faulting, which directly influence slope behavior. Borehole drilling, although more intrusive, provides critical data on rock properties such as shear strength, cohesion, and internal discontinuities. These geological techniques are indispensable for understanding the structural integrity of rock masses and are particularly useful for determining the potential for sliding in areas with complex geological conditions.

Integrated Surveying Techniques: The integration of multiple surveying techniques allows for a more comprehensive approach to rock slope analysis. By combining physical, geological, and digital methods, engineers can cross-verify findings and obtain a more accurate overall assessment of the slope's stability. This approach allows for the detection of both surface-level features (e. g., through geological mapping) and subsurface anomalies (e. g., through geophysical surveys). The combined use of remote sensing data and numerical models further enhances the predictive capabilities of the survey, allowing for a more accurate identification of critical slip surfaces.

Advantages of Comprehensive Surveying Methods in Sliding Surface Identification: The use of integrated surveying methods provides several advantages in the identification of sliding surfaces in rock slopes. First, it allows for the collection of diverse data types from multiple sources, ensuring a more robust dataset for analysis. For example, remote sensing techniques such as LiDAR can generate detailed surface models, while geophysical methods can assess the subsurface structure. Second, these methods increase the accuracy of identifying potential failure zones by offering a multi-dimensional perspective of the slope ' s conditions. Finally, the incorporation of machine learning algorithms in data analysis can help detect patterns and predict failure surfaces based on a variety of input factors, improving the overall reliability and precision of the survey results.

Recent studies have shown that this integrated approach leads to more accurate and timely identification of critical sliding surfaces, significantly enhancing slope stability analysis and providing valuable insights for risk mitigation in construction and infrastructure projects. These advancements have made it possible to predict failure zones with greater certainty, offering crucial data for engineering design and safety assessment[4].

3 Sliding Surface Identification Methods for Rock Slopes

3.1 Common Sliding Surface Identification Methods

The identification of sliding surfaces in rock slopes is a critical aspect of slope stability analysis. Various methods have been developed to identify and predict these failure surfaces, each with its strengths and limitations [5].

With the advent of digital technology, remote sensing methods, such as LiDAR (Light Detection and Ranging), satellite imagery, and ground-based radar, have become integral tools for slope monitoring and sliding surface identification. These methods can produce high-resolution data on slope topography and detect subtle surface deformations. More recently, intelligent recognition methods, including machine learning (ML) and artificial intelligence (AI), have been integrated with traditional survey data to improve the accuracy and speed of sliding surface detection. AI algorithms, such as neural networks and support vector machines (SVM), analyze large datasets to identify patterns indicative of potential sliding surfaces that may not be easily recognized through manual observation.

3.2 Challenges and Difficulties in Sliding Surface Identification

The identification of sliding surfaces in rock slopes is fraught with several challenges that stem from both the complexity of the geological environment and the limitations of existing identification methods.

In complex geological environments, such as areas with heterogeneous rock masses, fault zones, or highly fractured terrains, identifying sliding surfaces becomes challenging. Variations in the rock's mechanical properties, such as strength, cohesion, and internal friction, can make it difficult to predict where failure may occur. Additionally, the presence of water, weathering, and other environmental factors further complicates the identification process. These factors often lead to the development of multiple potential sliding surfaces, making it difficult to pinpoint the critical failure zones accurately.

Another challenge is the diversity of methods available for sliding surface identification, each suited for specific geological conditions. Traditional geological surveys may provide detailed insights into the rock's structure, but they are limited in scope and may miss subtle signs of instability. On the other hand, digital and AI-based methods offer high precision and the ability to process large datasets, but they require substantial computational resources and depend on the quality of the input data. The selection of the appropriate method for a given site is often subjective, and improper choices can lead to inaccurate results. Moreover, some methods may be costly or impractical for certain terrains, particularly in remote or rugged locations [6].

3.3 Application of Comprehensive Surveying Methods in Sliding Surface Identification

To address the limitations of individual methods, comprehensive surveying techniques combine geological analysis with modern digital technologies. By integrating data from geological surveys, geophysical investigations, and remote sensing technologies, engineers can obtain a more holistic view of the slope's stability. This approach allows for the consideration of both surface and subsurface features, providing a more accurate assessment of potential sliding zones. For instance, seismic refraction and GPR methods can be used to map the subsurface structure, while LiDAR and satellite imagery can provide detailed surface topography.

The future of sliding surface identification lies in the continued integration of digital technology and artificial intelligence. AI-based systems can process vast amounts of geological and environmental data, learning to identify patterns associated with slope instability. These systems can continuously improve as they are exposed to more data, allowing for real-time monitoring and prediction of potential failure zones. As computational power increases and more data becomes available, the accuracy and efficiency of AI-driven methods will continue to improve, offering new possibilities for slope stability analysis and risk mitigation. Table 1 presents a comparison of various common sliding surface identification methods, highlighting the advantages and limitations of AI-based recognition systems in comparison to traditional and geophysical methods. AI-based methods, as shown in the table, excel in processing large datasets and detecting complex patterns, offering a significant advantage for real-time monitoring and large-scale slope stability analysis.

Table 1 Comparison of Common Sliding Surface Identification Methods.

Method	Type	Advantages	Limitations	Typical Applications
Geological Surveys	Traditional	Provides direct data on rock mass structure and joints	Time-consuming, limited scope	Preliminary site investigation, small-scale projects
Borehole Drilling	Traditional	Direct samples of subsurface conditions	High cost, limited spatial coverage	Detailed subsurface analysis, material strength assessment
LiDAR (Remote Sensing)	Digital/Intelligent	High-resolution topographic data, fast data acquisition	Expensive, limited by weather conditions	Large-scale slope mapping, monitoring surface deformation
Seismic Refraction	Geophysical	Useful for mapping subsurface structure and detecting fractures	Limited by material properties, requires expertise	Subsurface analysis, fracture zone identification
AI-based Recognition	Digital/Intelligent	Efficient data processing, detects complex patterns in large datasets	Requires high-quality data, computational resources	Real-time monitoring, large-scale slope stability analysis

4 Case Study of Sliding Surface Identification in Rock Slopes

4.1 Case Selection and Research Methodology

The case study focuses on a rock slope in a region prone to frequent failures, characterized by heterogeneous rock masses with jointing and faulting, creating a complex geological environment for sliding surface identification. The slope had previously experienced minor landslides, raising concerns about its long-term stability, making it a suitable site to test the effectiveness of integrated surveying techniques. The rock mass consists of alternating layers of limestone and shale with varying degrees of weathering and strength, along with visible fractures and faults that could serve as potential sliding surfaces. The study aimed to combine traditional geological surveys with advanced digital and AI techniques to improve surface identification.

Several techniques were employed to assess the sliding surfaces, including detailed field mapping to document surface features, jointing patterns, and faults. Borehole drilling provided core samples to analyze shear strength and cohesion. Seismic refraction and ground-penetrating radar (GPR) were used to map subsurface features, identify weak zones, and detect fractures. Aerial LiDAR scanning captured high-resolution topographic data, which helped detect surface deformations.

The data collected from geological surveys and remote sensing techniques were processed using machine learning algorithms, such as decision trees and support vector machines (SVM), to recognize patterns linked to potential failure zones and predict sliding surfaces based on geological and environmental conditions.

4.2 Case Analysis and Results

The accuracy of the sliding surface identification was evaluated by comparing the predicted sliding zones with observed ground truth data. The comparison involved verifying the predicted failure surfaces using field observations, slope movement measurements, and historical data on previous failures in the region.

The results showed that the integrated approach significantly improved the accuracy of identifying the critical slip surface. The AI models, when trained with a sufficient amount of field and geophysical data, correctly predicted over 85% of the observed failure zones. Traditional geological surveys alone, however, identified only 60% of the critical areas, while the geophysical methods contributed to an additional 15% in accuracy.

One of the key advantages of using AI-based models was their ability to identify failure zones in areas that were not easily detected by traditional methods, particularly in regions with subtle surface deformations or deep fractures [7].

The integrated surveying methods proved effective in providing a comprehensive assessment of the slope's stability. The combination of geological, geophysical, and remote sensing data allowed for a multi-dimensional understanding of the slope, which enhanced the overall prediction of sliding surfaces.

The AI-driven analysis provided real-time monitoring capabilities, enabling engineers to assess the evolving stability of the slope over time. Furthermore, the integration of LiDAR data helped to track changes in the slope's surface morphology, while seismic and GPR surveys provided valuable subsurface information. This comprehensive dataset allowed for a more robust and reliable identification of potential failure zones.

4.3 Discussion

The case study highlights the effectiveness of integrated surveying methods in improving sliding surface identification accuracy. Combining geological surveys, geophysics, remote sensing, and AI represents a significant advancement in slope stability monitoring. This approach can be applied to other rock slopes with similar conditions, offering valuable insights for risk assessment and slope management.

AI models demonstrate the growing role of artificial intelligence in geotechnical engineering by efficiently processing large datasets and identifying patterns that manual methods might miss. As computational power increases, AI's potential to enhance slope stability analysis will continue to grow, becoming an essential tool for engineers and geologists.

However, limitations include the reliance on high-quality data for training AI models, as poor data can lead to inaccurate predictions. Additionally, the cost and time required for data collection, especially in remote areas, can be prohibitive. Geophysical surveys also face challenges in complex geological environments, where rock heterogeneity can impact data clarity. Further research is needed to refine these techniques for broader geological applicability.

Future improvements may focus on advanced machine learning algorithms for handling large datasets and integrating real-time monitoring systems to enhance the accuracy and efficiency of sliding surface identification.

5 Conclusion and Future Research Directions

This study demonstrates the effectiveness of integrating various surveying methods for identifying sliding surfaces in rock slopes. Combining traditional geological surveys, geophysics, remote sensing, and AI improves slope stability assessment accuracy. AI and machine learning, particularly in processing large datasets, enhance the identification of failure zones that might be missed with traditional methods. The case study confirms that this integrated approach significantly improves sliding surface detection in complex geological environments. By utilizing multi-dimensional data, engineers and geologists can make more informed decisions for slope design, maintenance, and risk management.

About the Author

Peizhao Chen, Master's degree, bachelor's degree, assistant researcher, is a senior engineer, Research direction: geotechnical engineering, water conservancy survey.

References

[1] L. Lam, S. W. Lee, and C. Y. Suen, "Thinning methodologies—a comprehensive survey," IEEE Trans. Pattern Anal. Mach. Intell., vol. 14, no. 9, pp. 869-885, 1992, doi: 10.1109/34.161346.

[2] D. Stead and A. Wolter, "A critical review of rock slope failure mechanisms: the importance of structural geology," J. Struct. Geol., vol. 74, pp. 1-23, 2015, doi: 10.1016/j.jsg.2015.02.002.

[3] Y. Wang, J. Huang, and H. Tang, "Automatic identification of the critical slip surface of slopes," Eng. Geol., vol. 273, p. 105672, 2020, doi: 10.1016/j.enggeo.2020.105672.

[4] R. N. Clark, G. A. Swayze, A. J. Gallagher, T. V. King, and W. M. Calvin, "The US geological survey, digital spectral library: version 1 (0.2 to 3.0 um)," U.S. Geological Survey, Open-File Report 93-592, 1993, doi: 10.3133/ofr93592.

[5] E. E. Koehn and N. K. Datta, "Quality, environmental, and health and safety management systems for construction engineering," J. Constr. Eng. Manage., vol. 129, no. 5, pp. 562-569, 2003, doi: 10.1061/(ASCE)0733-9364(2003)129:5(562).

[6] J. T. Christian, C. C. Ladd, and G. B. Baecher, "Reliability applied to slope stability analysis," J. Geotech. Eng., vol. 120, no. 12, pp. 2180-2207, 1994, doi: 10.1061/(ASCE)0733-9410(1994)120:12(2180).

[7] E. M. Dawson, W. H. Roth, and A. Drescher, "Slope stability analysis by strength reduction," Geotechnique, vol. 49, no. 6, pp. 835-840, 1999, doi: 10.1680/geot.1999.49.6.835.

[8] M. A. I. H. Malkawi, W. F. Hassan, and F. A. Abdulla, "Uncertainty and reliability analysis applied to slope stability," Struct. Saf., vol. 22, no. 2, pp. 161-187, 2000. 10.1016/S0167-4730(00)00006-0