A Point Cloud Filtering Method for Reservoir Bank Slopes Integrating Scene Classification and Ridge Detection

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Abstract

Reservoir bank slopes are characterized by pronounced terrain relief and dense vegetation, which lead to severe mixing of ground and non-ground points in LiDAR point clouds and pose significant challenges to accurate ground filtering and terrain reconstruction. Traditional filtering methods based on uniform thresholds often fail to balance filtering accuracy and terrain structure preservation under complex and heterogeneous terrain conditions. This study proposes a LiDAR point cloud filtering method that integrates scene classification and ridge detection. A depth image interpolated from the point cloud is used to derive directional gradients and multi-dimensional terrain descriptors, enabling automatic classification of the study area into gentle and mountainous regions. A feature-triangle-based region growing approach is developed to extract ridge lines in mountainous areas, which are incorporated as structural constraints to preserve critical terrain features during filtering. Within a progressive TIN densification framework, scene-adaptive parameter strategies are applied to iteratively extract ground points and update the TIN. Experiments conducted on UAV-borne LiDAR data from the Cheyiping reservoir bank slope along the Lancang River show that the proposed method achieves ground point misclassification rates of 0.64% and 3.42% in gentle and mountainous regions, respectively, demonstrating high consistency with manually interpreted reference data. Compared with conventional methods, the proposed approach effectively suppresses top-clipping and excessive slope smoothing, while significantly improving terrain structure preservation in complex environments.

1. Introduction

Light Detection and Ranging (LiDAR) technology, with its active sensing capability, enables the rapid acquisition of large-scale, high-density, and high-precision three-dimensional (3D) surface point cloud data. It provides reliable data for Digital Elevation Model (DEM) construction and dynamic terrain evolution analysis, and has been widely applied in geological hazard monitoring, engineering safety assessment, and environmental change studies. In this study, the term “reservoir bank slope” refers to a river-valley bank slope located within the reservoir-affected area of a hydropower project and influenced by reservoir water-level fluctuations, rather than an ordinary natural river bank.Reservoir bank slopes in mountainous canyon regions are influenced by multiple factors, including water level fluctuations, rainfall, and geological structures. They exhibit highly concealed deformation characteristics and complex evolutionary mechanisms, and their stability directly affects the safety of reservoir dams and surrounding areas. Consequently, fine-scale terrain modeling and continuous monitoring of reservoir bank slopes based on LiDAR point cloud data have become essential approaches for geological hazard prevention and mitigation in reservoir regions.Accurate mapping of these slopes is important for detecting subtle terrain deformation, identifying potential landslide-prone areas, and supporting reservoir safety management. However, reservoir bank zones are typically characterized by dramatic terrain relief, complex slope variations, and dense vegetation cover. As a result, the acquired point cloud data often exhibit uneven density distribution, high noise levels, and significant mixing of ground and non-ground points, posing substantial challenges to the accuracy and reliability of subsequent terrain reconstruction and deformation analysis. Therefore, robust and accurate ground point extraction from LiDAR point clouds in such complex environments is a critical prerequisite for achieving high-precision topographic representation and reliable deformation monitoring of reservoir bank slopes.

Existing ground point filtering methods generally construct parameterized decision rules based on the spatial distribution and local geometric relationships of point clouds. Under the assumption of surface continuity and local smoothness, reference surfaces—such as Triangulated Irregular Network (TIN) or raster-based surfaces—are first established. Metrics including point-to-surface distance, elevation difference, and local slope are then computed, and threshold criteria are applied to progressively eliminate non-ground points, such as vegetation and buildings. Representative approaches include progressive TIN densification, the Progressive Morphological Filter (PMF), and Cloth Simulation Filtering (CSF). By iteratively updating the reference surface and classification criteria, these methods gradually expand the ground point set and typically achieve stable performance in areas with relatively simple terrain structures and limited local gradient variation (Wang et al., 2021, Cai et al., 2023, Li et al., 2019).

Mixed geomorphological environments such as reservoir bank slopes exhibit interwoven gentle slopes, steep slopes, and vegetation-covered areas, resulting in pronounced spatial non-stationarity in terrain gradients. Under such conditions, filtering strategies based on uniform thresholds struggle to accommodate diverse terrain types. When thresholds are overly strict, low vegetation or subtle micro-topographic variations in gentle areas may be misclassified as non-ground points, resulting in ground point omission. Conversely, when thresholds are relaxed to adapt to steep terrains, excessive non-ground points may remain in high-slope regions, leading to insufficient filtering and reduced completeness of ground point extraction.

Recent studies have proposed terrain-adaptive filtering strategies to address these limitations. These methods partition the study area according to geometric indicators such as elevation difference, slope, and normal variation, and dynamically adjust filtering parameters based on local terrain characteristics. For example, Liu et al. (Liu et al., 2020) characterized terrain saliency using local relief and elevation variance to develop a partition-driven adaptive filtering framework. Chen et al. (Chen et al., 2021) further incorporated surface roughness indicators, including slope and curvature, to establish a dynamic threshold mechanism that enhances classification stability in both continuous and discontinuous terrain regions. Zhang et al. (Zhang et al., 2018) classified terrain types based on relief intensity and adopted differentiated filtering windows and threshold combinations to improve adaptability to terrain variability. In addition, recent studies have introduced segmentation-based strategies to incorporate both geometric and contextual information, where point clouds are first partitioned into segments and adaptive thresholds are applied according to local terrain conditions (Chen et al., 2023). Meanwhile, some methods further adjust filtering thresholds based on terrain complexity measures such as relief amplitude to enhance adaptability in areas with significant elevation variation (Li et al., 2021). Although such partition-based adaptive strategies have improved ground filtering performance in complex environments to some extent, they still rely heavily on local geometric descriptors and empirically determined thresholds. In areas with complex geomorphological structures and pronounced spatial transitions, such as reservoir bank slopes, issues including unstable partitioning, incomplete filtering, and local terrain distortion remain unresolved.

Beyond terrain scene variability, structural topographic elements such as ridges, valleys, and breaklines play a crucial role in terrain modeling and deformation analysis (Briese, 2004). However, most existing filtering methods adapt to terrain undulations primarily by adjusting search radii or relaxing thresholds related to elevation differences and slope. They lack explicit identification and structural constraint mechanisms for overall topographic features, making them prone to typical issues such as mountaintop clipping and residual non-ground points at slope toes. To overcome these limitations, several studies have incorporated structural terrain information into the filtering workflow to enhance shape preservation in complex environments. For example, Little and Shi (Little and Shi, 2001) demonstrated that structural lines derived from local curvature can be used as an initial skeleton in constrained TIN construction, reducing the number of points required to achieve a given DEM approximation accuracy while preserving important terrain structures.You and Lee (You and Lee, 2025) explicitly extracted geomorphological feature lines, including ridges and valleys, and integrated them as global constraints within the terrain modeling process, effectively mitigating structural degradation caused by local smoothing. Shi (Shi, 2018) introduced slope, curvature, and local elevation difference metrics into the progressive TIN densification framework, applying differentiated thresholds and update strategies across slope categories to reduce top clipping and misclassification in steep areas. Ni (Ni, 2017) extracted terrain edges and linear structural elements based on curvature and normal variations, using them as auxiliary constraints in point cloud classification and filtering to improve the preservation of abrupt topographic transitions. Yang et al. (Yang et al., 2016) further integrated breakline extraction with ground point filtering, jointly incorporating structural feature lines into the filtering workflow to better preserve discontinuous terrain features and improve DEM quality. In addition, anisotropic filtering strategies guided by terrain aspect have been proposed to enhance the preservation of sharp terrain edges such as terraces and ridges (Pijl et al., 2020). Although these approaches have achieved improvements in complex terrain and transitional zones, they remain largely dependent on local geometric descriptors or boundary information,such as local slope, elevation difference, surface roughness, curvature, normal-vector variation, point-to-TIN distance, and extracted breaklines or terrain edges. A systematic and robust mechanism for identifying and protecting key structural features—particularly ridges—is still lacking. Consequently, in environments characterized by pronounced spatial transitions and strong structural expression, such as reservoir bank slopes, problems including ridge-top clipping and excessive slope smoothing persist.

To address these challenges, this study proposes a point cloud filtering algorithm that integrates scene classification and ridge detection. The proposed method is specifically designed for complex terrains, such as reservoir bank slopes, by incorporating two key components: automated scene classification and ridge detection. These components are introduced to enhance the adaptability of the filtering algorithm and improve terrain preservation fidelity. The primary contributions of this research are as follows:

1)An automated scene classification method based on directional gradients is proposed: By utilizing depth images interpolated from the original point clouds and analyzing their directional gradient characteristics, the study area is partitioned into two macro-scale terrain units: "gentle" and "mountainous" regions. Combined with multi-dimensional terrain descriptors—including local relief indices and aspect consistency—this method enables fine-grained identification and categorical labeling of terrain units.

2)A ridge detection algorithm based on feature-triangle region growing is developed: This approach constructs local Triangulated Irregular Networks (TINs) and identifies triangles with long-edge characteristics as candidate ridge units. Through a region-growing procedure, ridge lines representing abrupt slope variations and topographic transitions are automatically extracted. These ridge lines are incorporated as structural constraints within the filtering framework to explicitly preserve key geomorphological elements, such as ridges and gullies, thereby effectively mitigating the top-clipping effect and excessive slope smoothing commonly observed in progressive TIN densification filtering.

2. Methodology

The proposed point cloud filtering algorithm integrates scene classification and ridge detection and consists of three main components: automated scene classification based on directional gradients, ridge detection in mountainous terrain, and progressive TIN densification filtering. The overall workflow is illustrated in Fig. 1.

2.1 Scene Classification

Scene classification identifies terrain units prior to filtering and provides constraints for subsequent processing. Reservoir bank slopes typically include both gentle terrains with small slope variations and mountainous terrains with significant gradient changes. Applying a uniform filtering parameter set may lead to ground point omission in gentle regions or insufficient filtering in mountainous areas. Therefore, the point cloud is first classified

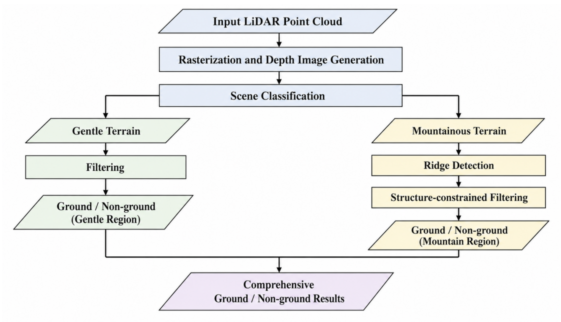


Figure 1. Flowchart of the proposed point cloud filtering algorithm combining scene classification and ridge detection.

into different terrain scenes, and the classification results are mapped back to the original point cloud.

The original LiDAR point cloud is first rasterized to generate a regular depth image. Specifically, the point cloud is projected onto a two-dimensional horizontal grid with a predefined cell size, and the elevation value of each grid cell is obtained by interpolating the surrounding LiDAR points. Empty cells caused by occlusion or uneven point distribution are filled using neighboring valid cells. The resulting depth image provides a structured elevation representation for subsequent gradient and statistical feature calculations. The central difference operator is then applied to compute horizontal gradients G_x and vertical elevation gradients G_y:

$$G_x(x,y) = \frac{I(x+1,y) - I(x-1,y)}{2\Delta} \tag{1}$$

$$G_y(x,y) = \frac{I(x,y+1) - I(x,y-1)}{2\Delta} \tag{2}$$

Where Δ denotes the pixel spacing. The combined gradient magnitude is computed as:

$$G = \sqrt{G_x^2 + G_y^2} \tag{3}$$

This indicator is used to comprehensively characterize the intensity of local slope variations.

To suppress random noise while preserving the linear structural characteristics of terrain features, directional median filtering is applied to the gradient image. The filtered gradient image is then divided into several blocks of fixed size B, and terrain features are calculated within each block. Three indicators are derived for each block:

(1) Mean directional gradient $\mu_G(B)$, representing the overall slope level of the block and can be expressed as:

$$\mu_G(B) = \frac{1}{|B|} \sum_{(x,y)\in B} G(x,y) \tag{4}$$

(2) Elevation fluctuation index $R(B)$, defined as the standard deviation of elevations within the block, measuring elevation variability.

(3) Aspect consistency index $C(B)$, defined as the degree of consistency between the local slope directions and the dominant direction within the block:

$$C(B) = \frac{1}{|B|} \sum_{(x,y)\in B} \cos\big(\theta(x,y) - \theta_B\big) \tag{5}$$

Where $\theta = \arctan\left(\frac{G_y}{G_x}\right)$,$\theta_B$ represents the dominant slope direction of the block. This indicator helps strengthen the identification of different terrain units.

Based on the above features, A composite score is constructed to quantify terrain variability within each block:

$$S(B) = \alpha \cdot \mu_G(B) + \beta \cdot \frac{R(B)}{R_{\max}} + \gamma \cdot C(B) \tag{6}$$

Where α, β, and γ are weighting coefficients, and $R_{\max}$ is the normalization factor for elevation fluctuation. The composite score is used to evaluate the degree of terrain relief and gradient variation within each block: Blocks with higher scores are classified as mountainous terrain, whereas those with lower scores are assigned to gentle terrain.

In this study, the weighting coefficients are empirically set to α = 0.5, β = 0.25, and γ = 0.25. A relatively higher weight is assigned to the directional gradient term because scene classification in reservoir bank slopes mainly depends on the intensity of local terrain variation. The elevation fluctuation and aspect consistency terms are used as auxiliary indicators to improve the characterization of terrain heterogeneity.

According to the composite score and predefined threshold rules, the blocks are classified to obtain the initial partitioning result. Morphological closing and connected-component analysis are applied to remove isolated misclassifications and improve spatial consistency.

Finally, the classification labels are mapped back to the original point cloud so that each point is assigned either a ”mountainous” or ”gentle” terrain attribute. This scene information serves as a constraint for subsequent filtering. Considering that structural terrain features such as ridges mainly occur in areas with significant slope variations, ridge detection is performed only in regions classified as mountainous terrain, where significant slope variations are present. The detected ridges are subsequently used as structural constraints in the filtering stage.

2.2 Ridge Detection

Ridge detection addresses top-clipping and misclassification caused by abrupt slope changes and structural transitions in mountainous terrain. The process includes the construction of a local TIN, identification of feature triangles, region growing, geometric and topological optimization, and ridge line extraction.

(1) Within mountainous regions, a regular grid index is established. The lowest point within each local window is selected to construct a two-dimensional TIN, providing the topological basis for ridge analysis.

(2) Geometric evaluation is performed for each triangle in the TIN. For each triangle in the TIN, a geometric evaluation is performed. Triangles with at least two edges longer than the window scale are defined as feature triangles, and their long

edges are labeled as feature edges. These triangles are typically located in regions with abrupt slope changes and are treated as candidate ridge units.

(3) Feature triangles are used as seeds for region growing (Fig. 2). Starting from a feature edge, the adjacent triangle is examined. If the adjacent triangle satisfies the feature condition, it is incorporated into the ridge unit, and expansion continues from its other feature edges. Otherwise, growth in that direction is terminated. The process is iteratively repeated to form connected ridge regions.

For illustration, a feature edge (AC) and its adjacent triangle (ACD) are shown in Fig. 2.

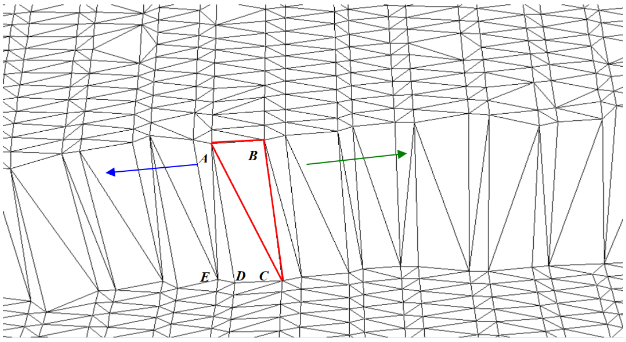


Figure 2. Illustration of feature-triangle region growing

(4) The extracted ridge units are further refined through geometric and topological optimization. Triangles with inconsistent normals are removed, and isolated misclassifications are eliminated based on elevation difference thresholds. Connected-component analysis and morphological operations are then applied to improve structural continuity and refine ridge boundaries.

(5) Ridge lines are extracted from the optimized ridge units by identifying their outer boundaries or central connection paths. The extracted ridge lines are mapped back to the original point cloud coordinate system, resulting in spatially continuous ridge representations.

2.3 Filtering Procedure

Following scene classification and ridge detection, point cloud filtering is performed using a progressive TIN densification framework with scene-specific strategies. The overall procedure is as follows:

(1) Initial ground point selection under scene constraints The point cloud is divided into gentle and mountainous regions according to the scene classification results. In each region, initial ground points are selected as the lowest points within local windows. These points are used to construct the initial TIN, which serves as the reference surface for subsequent densification.

(2) Filtering in gentle slope regions In gentle regions, standard progressive TIN densification is performed. Candidate points are evaluated based on their vertical distance to the current TIN surface and slope consistency. Points satisfying both distance and angular thresholds are added to the ground point set, and the TIN is updated iteratively until convergence.

(3) Filtering in mountainous terrain regions In mountainous regions, the filtering criteria are adaptively adjusted to accommodate larger local slope variations. Compared with the strategy used for gentle terrain, more tolerant distance and angular conditions are adopted during candidate point evaluation. Ridge detection results are incorporated as structural constraints within the progressive TIN densification framework. Because ridge lines represent structural boundaries between adjacent terrain units with changes in both slope orientation and steepness, they are used to constrain TIN updating and prevent incorrect connections across ridge-separated slope surfaces. Specifically, candidate connections that would link points located on different sides of a ridge line are suppressed during the TIN updating process. In this way, candidate points are evaluated not only according to distance and angular criteria, but also with consideration of the ridge-induced terrain structure. This strategy helps preserve ground structures near ridge lines and reduces top-clipping and excessive smoothing effects in complex terrain. Other steps remain consistent with the processing strategy used for gentle slope regions.

(4) Termination and output The filtering process converges when no new candidate points are added during an iteration. The final output includes classified ground and non-ground points, which are used for DEM generation and terrain analysis.

3. Experiment

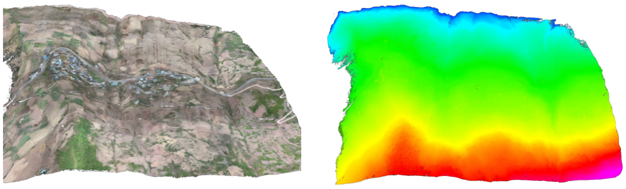
3.1 Experiment Data and Equipment

To evaluate the effectiveness of the proposed method, an experimental study was conducted in Cheyiping Village, located along the Lancang River within the reservoir-affected area of the Huangdeng Hydropower Station. The study area is characterized by complex terrain, dense residential distribution, and challenging survey conditions, including limited accessibility and concealed geological hazards.High-density point cloud data, with an average point density of approximately 100 points/m², were acquired using UAV-borne LiDAR. The filtered ground points were used to generate a digital elevation model (DEM) and reconstruct a three-dimensional representation of the study area. The location of the study area is shown in Fig. 3.

Figure 3. Overview of the monitoring area location

LiDAR data were collected in February 2023, with a total dataset size of approximately 22 GB. The raw point cloud data are shown in Fig. 4.

The LiDAR data used in this study were collected using the DJI Zenmuse L1 UAV LiDAR system. This system integrates a LiDAR sensor, high-precision IMU, and an RGB camera, enabling synchronous acquisition of point cloud and pose information. The main technical specifications of the system are summarized in Table 1.



(a) (b)

Figure 4. Raw point cloud data: (a) with texture; (b) without texture.

Parameter	Value
Laser wavelength	905 nm
Maximum range	450 m (50% reflectivity)
Point acquisition rate	240,000 pts/s
Scan field of view	70°
Ranging accuracy	±3 cm (horizontal), ±5 cm (vertical)
Laser repetition frequency	Up to 240 kHz

Table 1. Main technical parameters of the DJI Zenmuse L1 LiDAR system

For quantitative evaluation of the filtering performance, manually interpreted reference data were generated from selected regions of the original LiDAR point cloud. The point cloud was visualized and edited using DPGrid software developed by Wuhan University. Ground and non-ground points were identified through manual visual interpretation based on terrain continuity, elevation differences, and local geometric characteristics. Non-ground points, such as vegetation and other objects above the terrain surface, were manually removed to obtain the reference ground dataset.

The manual interpretation was performed by the authors. Although the authors were familiar with the proposed filtering method, the reference data were generated from the original point cloud before the quantitative accuracy assessment, and the automated filtering results were not used as direct guidance during manual labeling. The interpretation mainly relied on visual terrain cues, including local surface continuity, relative elevation differences, and geometric relationships between neighboring points. The reliability of the reference data was improved through careful inspection and repeated verification of the manual interpretation results, reducing potential misclassification caused by subjective judgment.

3.2 Scene Classification Results

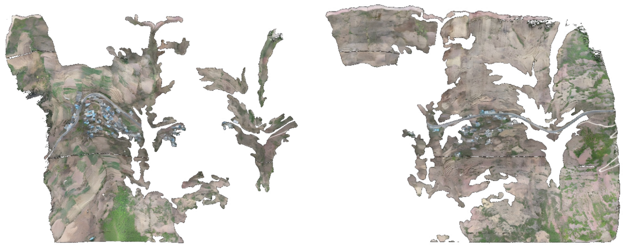
The classification results are shown in Fig. 5. The results show that the classification boundaries are generally consistent with terrain gradient variations. Mountainous regions correspond to areas with significant slope changes, whereas gentle regions are more spatially concentrated.

The classification exhibits good spatial continuity without large-scale misclassification, providing reliable constraints for subsequent filtering.

3.3 Ridge Detection Results

The ridge detection results are shown in Fig. 6. The extracted ridge lines are distributed along regions with significant elevation variation and exhibit strong agreement with actual terrain ridge structures.

The detected ridges demonstrate good spatial continuity and effectively capture structural transitions between primary and secondary slope surfaces. These results provide reliable structural constraints for the filtering process, reducing top-clipping and excessive smoothing in mountainous areas.



(a) (b)

Figure 5. Scene classification results: (a) mountainous terrain; (b) gentle terrain.

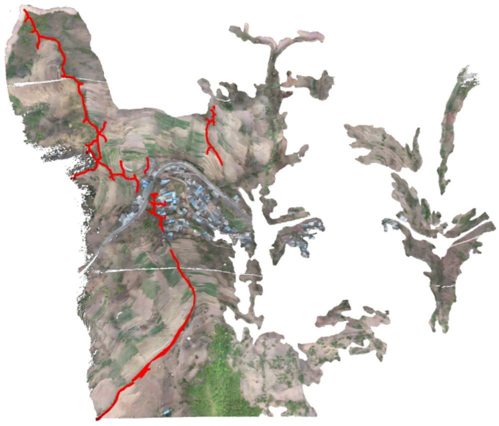
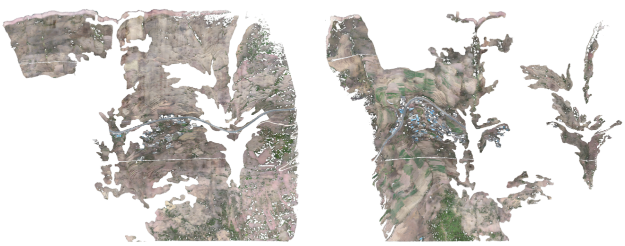


Figure 6. Ridge detection results

3.4 Filtering Results

3.4.1 Scene-Based Filtering Results: Filtering results for gentle and mountainous terrains are shown in Fig. 7. In gentle regions, non-ground points such as vegetation are effectively removed, while ground points remain continuously distributed and the terrain morphology is well preserved. No obvious omission or misclassification of ground points is observed, indicating reliable filtering performance in relatively flat areas.

In mountainous regions, ground points are reasonably distributed along slope surfaces without significant elevation anomalies or discontinuities. No evident abnormal elevation or structural breaks are observed at slope toes, mid-slopes, or slope crests. Even in areas with large slope variations, the terrain structure remains well preserved, demonstrating the robustness of the proposed method under complex terrain conditions.



(a) (b)

Figure 7. Filtering results under different terrain conditions: (a) gentle terrain; (b) mountainous terrain.

Local comparisons are presented in Fig. 8, where representative regions with manually interpreted reference data are selected. In gentle regions, the proposed method accurately distinguishes ground points from low vegetation, and the filtering results show strong agreement with manually interpreted reference data in terms of overall terrain morphology.

In mountainous regions, despite complex terrain and dense vegetation cover, the method maintains continuous and consistent ground point distribution. Notably, in ridge neighborhoods, the incorporation of ridge constraints prevents TIN connections from crossing different slope aspects, ensuring that points from different slope directions are not incorrectly merged. This effectively suppresses top-clipping and excessive smoothing, while preserving ridge structures and maintaining clear terrain transitions.

Quantitative evaluation results are summarized in Table 2. The ground point misclassification rate is 0.64% in gentle regions and 3.42% in mountainous regions. Despite the increased complexity of mountainous terrain, the proposed method maintains high classification accuracy. These results show strong consistency with the manually interpreted reference data described in Section 3.1, confirming the effectiveness of the method in both simple and complex terrain conditions.

Terrain type	Total points before filtering	Remaining points after filtering	Manual reference points	Ground point misclassification rate (%)
Gentle region	1 915 369	1 444 167	1 434 973	0.64
Mountainous region	56 526 191	43 202 792	41 752 378	3.42

Table 2. Statistical results of ground point extraction in different terrain scenes.

3.4.2 Comprehensive Filtering Results and DEM Generation:

The overall filtering results of the LiDAR point cloud are shown in Fig. 9. The extracted ground points exhibit continuous spatial distribution and accurately represent the terrain morphology of the study area.

In gentle regions, ground points are extracted with high completeness, and non-ground points such as vegetation are effectively removed. The resulting terrain surface is smooth, with no obvious residual noise.In mountainous regions, ground points are continuously distributed along slope surfaces. No significant elevation anomalies or discontinuities are observed at slope toes, mid-slopes, or slope crests. This indicates that the proposed method effectively preserves terrain structure across different slope positions, even under conditions of large gradient variation.

Based on the filtered ground points, a high-resolution DEM was generated (Fig. 10). The DEM preserves fine-scale terrain features and shows no significant artifacts, demonstrating the effectiveness of the proposed filtering approach for terrain reconstruction.

3.5 Discussion

Although the proposed method demonstrates strong performance in both gentle terrain and mountainous terrain, certain limitations remain when it is applied to more complex or extreme geomorphological conditions.

It should be noted that the study area in this work focuses on reservoir bank slopes, where the terrain is inherently inclined rather than strictly flat. Therefore, the classification of “gentle terrain” and “mountainous terrain” in this study is not based on the absolute slope magnitude, but rather on the intensity of local terrain variation (i.e., the degree of topographic relief). This classification strategy emphasizes spatial variability of terrain instead of slope magnitude alone. While such a scheme improves the adaptability of the proposed method to heterogeneous landscapes, it may still encounter limitations under extreme conditions.

One limitation arises in areas characterized by near-vertical slopes or highly fragmented terrain, where elevation changes are extremely abrupt and the assumption of local surface continuity underlying the progressive TIN densification framework may no longer hold. In such cases, large elevation differences between neighboring points and unstable local geometric relationships may lead to misclassification of ground points or insufficient representation of critical terrain features, such as steep scarps or cliffs.

Another limitation is related to the ridge detection method based on feature-triangle region growing, which relies on local TIN structures and geometric characteristics such as long-edge features. In regions with uneven point density or data gaps, the completeness and accuracy of ridge extraction may be affected, thereby weakening the effectiveness of structural constraints during the filtering process.

Furthermore, the proposed method involves multiple processing steps, including depth image generation, gradient computation, scene classification, ridge detection, and iterative TIN updating. This multi-stage workflow increases computational complexity and may limit its applicability in large-scale data processing or real-time scenarios.

Future work will focus on improving the robustness of the method under extreme terrain conditions by incorporating more advanced terrain descriptors or integrating machine learning-based strategies. In addition, efforts will be made to optimize computational efficiency and explore the integration of the proposed method into real-time LiDAR data processing systems for dynamic terrain monitoring applications.

4. Conclusion

This study proposes a point cloud filtering method that integrates scene classification and ridge detection for reservoir bank slopes characterized by strong terrain relief, large slope variations, dense vegetation cover, uneven point cloud density, high noise levels, and severe mixing of ground and non-ground points. By incorporating terrain scene information and structural constraints, the proposed method improves the robustness of ground point extraction and the preservation of terrain morphology in complex reservoir bank environments. The Cheyiping reservoir bank slope along the Lancang River was selected as the experimental area, and UAV-borne LiDAR data were used for evaluation.An automated scene classification approach based on directional gradient features derived from point-cloud-generated depth images was used to partition the study area into gentle regions with relatively small gradient variations and mountainous regions with pronounced slope changes. A ridge detection algorithm based on feature-triangle region growing was then applied within the mountainous regions. This procedure automatically extracted ridge lines representing abrupt slope variations and topographic transitions, which were embedded as

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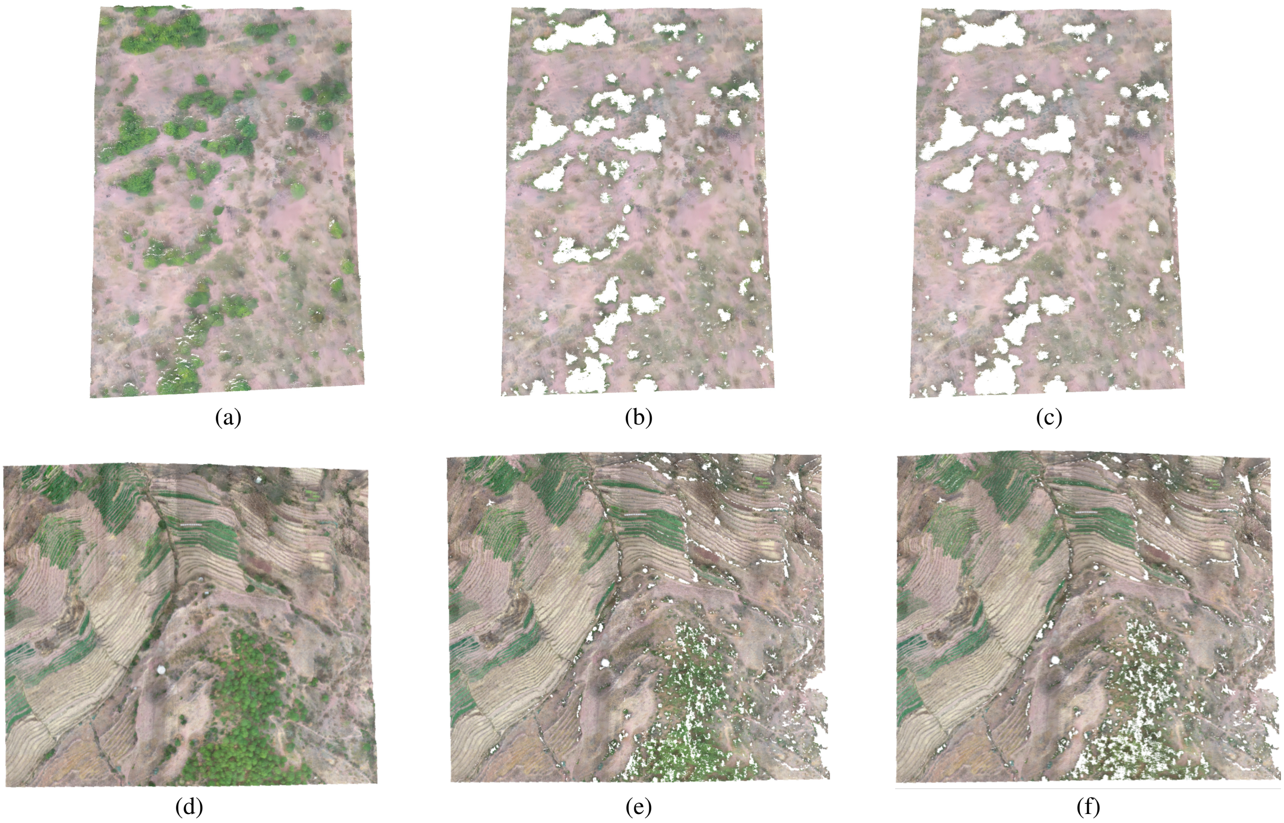

Figure 8. Local filtering comparison. Gentle terrain subregion (a-c): (a) raw point cloud, (b) proposed method, and (c) manual reference. Mountainous terrain subregion (d-f): (d) raw point cloud, (e) proposed method, and (f) manual reference.

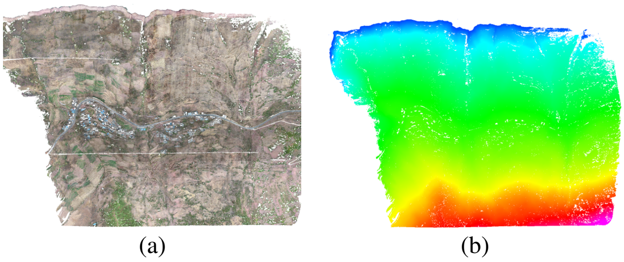

Figure 9. LiDAR point cloud filtering results: (a) with texture; (b) without texture.

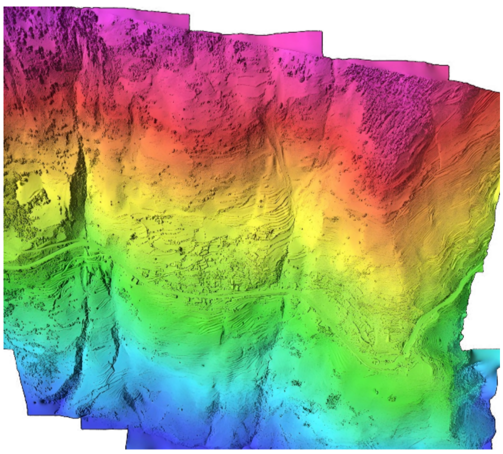

Figure 10. High-resolution DEM generated from LiDAR data of Cheyiping Village

structural constraints into the subsequent filtering framework. Based on the progressive TIN densification framework, differentiated processing strategies were implemented for different terrain scenes, enabling progressive ground point extraction and iterative TIN updating. Experimental results indicate that the proposed method effectively distinguishes ground points from non-ground points in both gentle slope segments and complex mountainous terrains. In ridge-dominated areas, the proposed method significantly suppresses top-clipping and excessive slope smoothing commonly observed in traditional filtering approaches.Compared with manually interpreted reference data, the ground point misclassification rates are 0.64% in gentle regions and 3.42% in mountainous regions. The overall topographic structure remains highly consistent with the reference data, satisfying the requirements for fine-scale terrain modeling and deformation analysis of reservoir bank slopes.

Beyond improving filtering accuracy, the main significance of the proposed method lies in its ability to preserve fine-scale terrain structures that are critical for reservoir bank slope analysis. More reliable extraction of ground points and ridge-related topographic details can support the generation of high-quality DEMs, which are essential for detecting subtle terrain deformation, identifying potential instability zones, and monitoring geomorphological changes under reservoir water-level fluctuations. Therefore, the proposed method can provide more dependable topographic data for reservoir bank deformation monitoring, landslide risk assessment, and engineering safety management in hydropower reservoir areas. These improvements are particularly valuable for survey engineers, geohazard analysts, and reservoir management agencies who require accurate terrain information for long-term slope stability evaluation and disaster prevention.

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